
Cranfield University

Yoseph Tafesse Azene

***Work Roll System Optimisation using
Thermal Analysis and Genetic Algorithms***

School of Applied Science

PhD Thesis

School of Applied Science

Manufacturing Department

PhD Thesis

2011

Yoseph Tafesse Azene

***Work Roll System Optimisation using
Thermal Analysis and Genetic Algorithm***

**Supervisor: Professor Rajkumar Roy
May 2011**

This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy.

© Cranfield University, 2011. All rights reserved. No part of this document may be reproduced without the written permission of the copyright owner.

Abstract

In today's highly competitive business environment it is vital to have smart and robust decision making framework for companies to be competitive or even to stay in the business. Profit margin increase is no longer a result of producing and brings more products to the market. Instead it is also a result of reducing cost, in particular manufacturing tooling cost. In order to succeed with this, industry needs to look to innovative intelligent systems to enhance their process development so that maximum utilisation of tools can be achieved. Tooling is part of a process hence having an optimal process design is one ideal strategy for best utilising of manufacturing tools. In design optimisation however the presence of uncertainty in design variables and in the mathematical model (used for representing the real life process) is inevitable. For a reliable design solution to be found this process complexity need to be addressed. This research is to understand work roll system optimisation issues within rolling system design, and develop Genetic Algorithm (GA) based framework to deal with the challenges.

The thesis has proposed a framework for generating approximate models from numeric finite element (FE) data. Using the proposed framework a number of single pass quantitative work roll system thermal analysis and optimisation models were generated and used in subsequent optimisation process. In the absence of a suitable multi-pass model that exhibits the features of a multi-stage process; this research has also developed a quantitative multi-pass models to simulate the work roll system thermal analysis and optimisation problem that represents the relationships between passes.

The research has developed a novel Genetic Algorithm based optimisation framework that deals with the constraint quantitative problem as well as the uncertainty, in the design space and fitness functions. The study identifies the challenges in incorporating uncertainty information in the optimisation process.

The research also proposed a post GA result analysis methodology for identifying the final best optimal design solution for the research many objective high dimensional problems. The performance of the proposed frameworks was studied and analysed through case studies. The research also identifies future research directions in the subject area.

Acknowledgement

I would like to express my thanks and deepest gratitude to Professor Rajkumar Roy, my supervisor and my mentor. He has being a constant source of inspiration to me. His support, advice, and encouragement have always provided me with new hope.

I am most thankful to my industrial sponsor, Dr Didier Farrugia, and my industrial contact, Dr Christian Onisa who provided me the resources and case study for the work roll system design.

I am thankful for the financial support for this research, which was provided through a sponsorship from Engineering and Physical Science Research Council (EPSRC) and Tata Steel-Europe.

It was a great pleasure to work with my colleagues in the Decision Engineering Centre at Cranfield University. It is impossible to list all of them but particular thanks to Dr Jorn Mehnen and Dr Ashutosh Tiwari. Thanks also to all the staff of the Department of Manufacturing and staff in the IT and Grid Computing.

This work would not have been completed without the support of my friend. Her companionship and commitment is the motivating force for my accomplishments. I express my deepest thanks to Saba.

Above all, I give thanks to the Almighty God I journey on my way, and for the wonderful gifts He bestows on me.

List of Publications

Azene, T.Y. Roy, R. Multi-stage, multi-objective process optimisation, Genetic and Evolutionary Computation Conference, GECCO-2010 (companion), Oregon, USA, 2010, p. 2063-2064, 2010, ISBN 978-1-4503-0073-5.

Roy, R. Azene, T. Y. Farrugia, D. Onisa, C. And Mehnen, J. “Evolutionary Multi-Objective Design Optimisation with Real Life Uncertainty and Constraints.” CIRP Annals-Manufacturing Technology, Volume 58, Issue 1, 2009, p. 169-172.

Azene, T.Y. Roy, R. Farrugia, D. Onisa, C. Mehnen, J. and Trautmann, J. “Work Roll Cooling System Design Optimisation in Presence of Uncertainty and Constraints.” CIRP - Journal of Manufacturing Science and Technology, Competitive Design, Special Issue, Volume 2, Issue 4, 2009, p. 290-298.

Azene, T.Y. Roy, R. Farrugia, D. Onisa, C. Mehnen, J. and Trautmann, J. “Work Roll Cooling System Design Optimisation in presence of Uncertainty.” Proceedings of the 19th CIRP Design Conference 2009, Cranfield University, UK, 2009, p. 57-64, ISBN 978-0-9557436-4-1.

Azene, T.Y. Roy, Tiwari, A. and Goteng, G.” Evolutionary Computing in Engineering Design.” Handbook of Computational Intelligence in Manufacturing and Production, Global Information Science Reference, 2007, ISBN: 978-1-59904-582-5.

Suardi, S. Roy, R. Azene, T.Y. and Mehnen, J. Uncertainty based Evolutionary Optimisation. Genetic and Evolutionary Computation Conference, GECCO-2011, Dublin, Ireland, 2011. (Accepted for publication)

Contents

ABSTRACT.....	I
ACKNOWLEDGEMENT.....	II
LIST OF PUBLICATIONS.....	III
LIST OF FIGURES.....	VIII
LIST OF TABLES.....	XIII
NOMENCLATURE.....	XVII
ACRONYMS	XIX
1. INTRODUCTION	1
1.1 THE SPONSORING COMPANY.....	3
1.1.1 <i>Steel Production Global Perspective in the last Decade</i>	<i>4</i>
1.1.2 <i>The Research Initiative and Tata Steel-Europe Research Development & Technology (RD&T)</i>	<i>4</i>
1.1.3 <i>The Proposed PhD Research as part of Tata Steel – Europe Strategic for New Product Development Project.....</i>	<i>5</i>
1.2 INTRODUCTION TO METAL FORMING.....	7
1.2.1 <i>Overview of Work Rolls and the Rolling Process</i>	<i>9</i>
1.2.2 <i>Fundamentals of Rolls in Hot Metal Rolling</i>	<i>13</i>
1.2.3 <i>Roll Types Selection for Hot Rolling Applications.....</i>	<i>16</i>
1.2.4 <i>Introduction of Roll Cooling System in the Rolling Process.....</i>	<i>19</i>
1.2.4.1 <i>The Roll Cooling System Operation</i>	<i>20</i>
1.3 INTRODUCTION OF ENGINEERING DESIGN OPTIMISATION	22
1.3.1 <i>Classification of Engineering Design Optimisation Problems</i>	<i>22</i>
1.3.2 <i>Engineering Design Optimisation in presence of Uncertainty</i>	<i>28</i>
1.3.3 <i>Design Optimisation in the presence of Constraints</i>	<i>30</i>
1.4 SUMMARY OF RESEARCH INITIATIVE.....	30
1.5 THESIS STRUCTURE	31
1.6 CHAPTER SUMMARY	34
2. LITERATURE REVIEW.....	35
2.1 FEATURES OF THE WORK ROLL SYSTEM OPTIMISATION USING THERMAL ANALYSIS AND GENETIC ALGORITHMS (GA).	36
2.2 EXISTING WORKS AND RESEARCH GAPS IN WORK ROLL SYSTEM OPTIMISATION USING .. THERMAL ANALYSIS AND GA.	38
2.3 UNCERTAINTY IN THE WORK ROLL SYSTEM DESIGN, OPTIMISATION AND THERMAL	40
ANALYSIS PROBLEM.	40
2.4 MODELLING APPROACHES FOR WORK ROLL SYSTEM DESIGN USING THERMAL	41
ANALYSIS	41
2.4.1 <i>Finite Element (FE) Methods</i>	<i>42</i>
2.5 ENGINEERING DESIGN OPTIMISATION APPROACHES	47
2.6 DESIGN OPTIMISATION APPROACHES: A COMPARATIVE OVERVIEW OF TECHNIQUE’S	51
DEVELOPMENT IN THE LAST DECADE	51
2.7 DESIGN PROBLEMS REPRESENTATION IN COMPUTING BASED DESIGN OPTIMISATIONS..	53
2.8 MULTI-OBJECTIVE DESIGN OPTIMISATION	54
2.9 UNCERTAINTY IN MULTI-OBJECTIVE DESIGN OPTIMISATION	59
2.10 RESEARCH GAP	62
2.11 CHAPTER SUMMARY.....	63
3. RESEARCH OBJECTIVES & METHODOLOGY	66
3.1 RESEARCH SCOPE AND PROBLEM STATEMENTS.....	66
3.2 RESEARCH OBJECTIVES	67

3.3	RESEARCH METHODOLOGY	68
3.3.1	<i>Literature Review</i>	69
3.3.2	<i>Knowledge Elicitation for Research Problem Realisation</i>	70
3.3.3	<i>Identifying Research Aim and Objectives</i>	70
3.3.4	<i>Industry Survey</i>	71
3.3.5	<i>Documentation and Proposed Solution Framework</i>	71
3.3.6	<i>Modelling & Optimisation Framework Development</i>	71
3.3.7	<i>Validations</i>	74
3.4	CHAPTERS SUMMARY	74
4	CURRENT PRACTICE STUDY	76
4.1	CURRENT PRACTICE STUDY INFORMATION GATHERING METHODOLOGY	77
4.2	ENGINEERING DESIGN OPTIMISATION & TECHNIQUES CURRENT PRACTISE.	79
4.2.1	<i>Selection of Companies</i>	79
4.2.2	<i>Departments Need to Participate within the Company</i>	81
4.2.3	<i>Selection of People/Experts</i>	81
4.2.4	<i>Questionnaire Development Procedures</i>	83
4.2.5	<i>Implementation of Questionnaires</i>	84
4.3	ANALYSIS AND PRESENTATION OF RESULTS	85
4.3.1	<i>Survey, State of the Art Design Optimisation Techniques in Industry</i>	86
4.3.2	<i>Observations</i>	88
4.4	KNOWLEDGE ELICITATION IN THE RESEARCH PROBLEM DOMAIN.....	88
4.4.1	<i>Knowledge Elicitation Exercise, (Questionnaires and Experts Feedback Transcript ...</i>	92
4.4.2	<i>Observations</i>	95
4.4.3	<i>Key Issues and Challenges</i>	97
4.5	CHAPTER SUMMARY	98
5	WORK ROLL SYSTEM, SINGLE PASS THERMAL MODEL DEVELOPMENT	
5.1	DESCRIPTION OF THE FEA MODEL	100
5.1.1	<i>Problem Approximation (FEA Model) and Its Specifications</i>	100
5.1.2	<i>Purpose of the Thermal Quantitative (Functional) Model</i>	103
5.2	APPROXIMATE MODELLING FOR WORK ROLL SYSTEM THERMAL ANALYSIS AND DESIGN PROBLEM	103
5.2.1	<i>Rolling Process Factors Relevant to Roll Temperature Variations</i>	105
5.2.2	<i>Description of the Final, Independent process Factor usedt in Work Roll System Rolli Modelling</i>	108
5.3	THE DESIGN OF EXPERIMENT (DOE) FOR WORK ROLL SYSTEM DESIGN THERMAL	116
5.3.1	<i>Response Surface Methodology</i>	117
5.3.2	<i>Problem Definition</i>	117
5.3.3	<i>Specify Design Matrix</i>	118
5.3.4	<i>The FEA Experiments</i>	120
5.3.5	<i>Experimental Set-Up</i>	123
5.3.6	<i>Response Data from Finite Element (FE) Simulation</i>	12128
5.3.7	<i>Procedures for Response Data from Experimental Simulations</i>	132
5.3.8	<i>Meta-Model Construction</i>	139
5.3.9	<i>Model Validations</i>	141
5.4	CHAPTER SUMMARY	144
6	SINGLE PASS WORK ROLL SYSTEM OPTIMISATION, WITH PRESENCE OF UNCERTAINTY AND CONSTRAINTS USING THERMAL ANALYSIS AND GA.....	146
6.1	ROBUST NON DOMINANCE CRITERIA TECHNIQUE FOR OPTIMISATION	148
6.1.1	<i>Application of the Technique in the Work Roll System Design Problem in presence of Uncertainty</i>	151

6.2	APPLICATION OF THE TECHNIQUE IN THE SINGLE PASS WORK ROLL SYSTEM DESIGN	
	OPTIMISATION PROBLEMS IN PRESENCE OF UNCERTAINTY AND CONSTRAINTS.	154
6.2.1	<i>The Single Pass Problem</i>	154
6.2.1.1	<i>Objective Functions</i>	155
6.2.1.2	<i>Constraints</i>	156
6.2.1.3	<i>Principle of Central Limit Theorem (CLT) to deal with Uncertainty in the Problem</i> .	157
6.2.2	<i>Application of the Techniques to Two Objective, Single Pass Design Optimisation</i>	
	<i>Problems with presence Uncertainties</i>	160
6.2.2.1	<i>The Optimisation Initial Conditions</i>	166
6.3	EVALUATING CRITICALITY OF CONSTRAINTS TO OPTIMUM DESIGN SOLUTION POINT	177
6.3.1	<i>Application of the Constraint Criticality Analysis Technique to the Work Roll System ..</i>	
	<i>design Problems</i>	175
6.3.2	<i>Sensitivity Analysis Result and Discussions</i>	175
6.3.3	<i>Section Summary, Two Objectives Problem Optimisation in presence of Uncertainty</i>	
	<i>and Constraints</i>	176
6.4	APPLICATION OF THE TECHNIQUE TO THE MANY OBJECTIVE, SINGLE PASS WORK ROLL ..	
	SYSTEM DESIGN OPTIMISATION PROBLEMS WITH PRESENCE OF UNCERTAINTY.	177
6.4.1	<i>Experimental Details</i>	1180
6.4.2	<i>GA Results</i>	1183
6.4.3	<i>Post GA Result and Analysis</i>	1184
6.4.4	<i>Post GA Result Analysis, for Final Optimal Design Solution/s</i>	1185
6.4.5	<i>Observations</i>	191
6.5	CHAPTER SUMMARY	192
7	MULTI-PASS MODEL DEVELOPMENT AND OPTIMISATION	195
7.1	QUANTITATIVE MODELLING FOR MULTI-PASS WORK ROLL SYSTEM DESIGN	
	OPTIMISATION PROBLEM.	197
7.1.1	<i>Multi-Pass Work Roll System and Modelling Characteristics</i>	199
7.1.2	<i>Multi-Pass Regression Model</i>	204
7.1.3	<i>Multi-Pass Model Validation</i>	20208
7.2	OPTIMISATION SOLUTION SEARCH STRATEGY FOR MULTI-PASS WORK ROLL THERMAL .	
	ANALYSIS AND DESIGN PROBLEM.	210
7.2.1	<i>Experimental Details</i>	211
7.2.2	<i>GA Results</i>	213
7.2.3	<i>Post GA Result and Analysis</i>	215
7.2.4	<i>Results and Analysis</i>	222
7.2.4.1	<i>Results</i>	222
7.2.4.2	<i>Discussion of the Results</i>	242
7.3	CHAPTER SUMMARY	229
8	FURTHER VALIDATION OF RESULTS.....	231
8.1	SUMMARY OF THE STATISTICAL AND EXPERIMENTAL VALIDATIONS.....	231
8.2	OPTIMISATION RESULT VALIDATION BASED ON EXPERT OPINION.....	233
8.2.1	<i>Methodology for Result Validation</i>	234
8.2.1.1	<i>Establishing what needs to be validated</i>	235
8.2.1.2	<i>Extract data from the optimisation results for validation</i>	235
8.2.1.3	<i>Manage requirements for validation</i>	235
8.2.1.4	<i>Implementation of Questionnaires</i>	239
8.2.2	<i>The Validation</i>	239
8.2.2.1	<i>Extract of Validation Questions and expert response</i>	242
8.3	CHAPTER SUMMARY	252
9	DISCUSSIONS AND CONCLUSIONS	254
9.1	RESEARCH FINDINGS AND OBSERVATIONS	254
9.1.1	<i>Understanding the Research Problem</i>	255
9.1.2	<i>Quantitative Model Development</i>	257
9.1.3	<i>Uncertainty Information in Design Optimisation</i>	257

9.1.4	<i>Validation of the Quantities Model</i>	258
9.1.5	<i>Quantitative and Uncertainty Information in Work Roll Thermal Analysis and Optimisation</i>	258
9.1.5.1	<i>Single-Pass, Multi-objective Optimisation using Quantitative and Uncertainty Information for Work Roll System Thermal Analysis and Optimisation Problems</i>	259
9.1.5.2	<i>Multi-Pass, Many-objective Optimisation using Quantitative and Uncertainty Information for work roll system Thermal Analysis and Optimisation Problems</i>	260
9.1.5.3	<i>Post GA Result Analysis for Identifying Optimal Design Solution</i>	262
9.1.6	<i>Research Validations</i>	263
9.2	RESEARCH ACHIEVEMENT AND CONTRIBUTION	265
9.3	BUSINESS BENEFIT	266
9.4	LIMITATIONS.....	26266
9.4.1	<i>The Approximate Model for Work Roll System Thermal Analysis and Optimisation (Single-Pass)</i>	26268
9.4.2	<i>The Approximate Model for Work Roll System Thermal Analysis and Optimisation (Multi-Pass)</i>	269
9.4.3	<i>The Optimisation Framework for Single and Multi-Pass Problem</i>	269
9.5	RECOMMENDED FUTURE WORK.....	269
9.6	CONCLUSIONS	270
REFERENCES		273
APPENDICES		286
APPENDICES A: INDUSTRY SURVEY, DESIGN OPTIMISATION CURRENT PRACTISE		286
	<i>Design Optimisation Techniques in Industry, Questionnaire</i>	286
	<i>Transcript A</i>	289
APPENDICES B: INDUSTRY SURVEY WORK ROLL SYSTEM DESIGN CURRENT PRACTISE ..		294
	<i>Survey Questions Themes and Probe Aim</i>	294
APPENDICES C: WORK ROLL SYSTEM PROBLEM, FEA MODEL		296
	<i>Model Assembly Specification</i>	296
APPENDICES D: WORK ROLL SYSTEM DESIGN FACTORS STUDY		299
	<i>Factors Mathematical Definition and Functional Relationship Display</i>	299
APPENDICES E: SINGLE PASS PROBLEM OPTIMISATION FLOW		302
	<i>Programme Code</i>	302
APPENDICES F: USER INFORMATION GUIDE FOR RUNNINF THE PROGRAMME		306
APPENDICES G: POST GA RESULT ANALYSIS DESCRIPTIONS		309
	<i>Programme Code</i>	309
APPENDICES H: MULTI-PASS MODELLING REGRESSION MATRIX		313
APPENDICES I: MULTI-PASS PROBLEM OPTIMISATION FLOW		317
	<i>Programme Code</i>	317

List of Figures

Figure 1.1: Global total steel production in the last decade	4
Figure 1.2: Roll breakage due to high temperature gradient/high residual stresses....	6
Figure 1.3: Steel making and the rolling process.....	8
Figure 1.4: View of single pass rolling	9
Figure 1.5: View of cylindrical work roll.....	10
Figure 1.6: View of sequence of 6 high rolling process involving 4 passes	12
Figure 1.7: Rolling mill configurations	16
Figure 1.8: Thesis structure	32
Figure 2.1: FEA in metal forming process	43
Figure 2.2: Finite Element Method papers survey in the last 5 years	46
Figure 2.3: Development trends of techniques in the last decade.....	53
Figure 2.4: Percentage share of techniques surveyed.....	53
Figure 3.1. Summary of the research methodology	69
Figure 3.2: Single and multi-pass modelling, optimisation & validation.....	75
Figure 4.1: Current practice study categories	78
Figure 5.1: Original approximate problem (FEA) model.....	102
Figure 5.2: Meta-modelling flow chart for work roll system modelling.....	105
Figure 5.3: Rolling process factors brainstorm for roll thermal design	106
Figure 5.4: Cause and effect of temperature variation in rolls	107
Figure 5.5: Simulation response data points from the roll after simulation	122
Figure 5.6: Log in to the GRID from the PC using personal ID.....	124
Figure 5.7: Sending and running jobs on the GRID.....	124
Figure 5.8: Showing post analysis results sent back to the PC by the GRID	125
Figure 5.9.A: Typical error which may happen that will give misleading results..	127

Figure 5.9.B: Instance where data, Radial stress from the roll should be taken after simulation run	128
Figure 5.9.C: Instance where data, temperature from the roll should be taken after simulations run	128
Figure 5.10: Finite element plots for roll profile temperature at the surface of the roll, 9mm and 15mm below the surface of the roll.....	133
Figure 5.11: Finite element plots for roll profile radial stress at the surface.....	133
Figure 5.12: Probe value report temperature from FEA simulation run	134
Figure 5.13: Temperatures response at calculated depth from temperature / true distance along the path graph	134
Figure 5.14: Probe value report Radial stress (S11) from FEA simulation run.....	135
Figure 5.15: Temperature tread along the heat affected area	139
Figure 6.1: Concept of robust dominance criterion with noisy fitness functions ...	151
Figure 6.2: Concept of robust dominance criterion with noisy fitness functions ...	153
Figure 6.3: Solution search strategy for multi-objective problems with uncertainty....	153
Figure 6.4: Simulation run with sample size 30.....	158
Figure 6.5: Simulation run with sample size 50.....	159
Figure 6.6: Simulation run with sample size 70.....	159
Figure 6.7: Simulation run with sample size 90.....	160
Figure 6.8: Design variables representation sequence in the optimisation of single pass 2 objective problem.....	162
Figure 6.9: Map generated by grid exploration of the decision and objective space....	164
Figure 6.10: Uncertainty in the Decision Space without the Application of CLT..	166
Figure 6.11: Uncertainty in the Decision Space & Application of CLT-1.....	167
Figure 6.12: Uncertainty in the Decision Space, & Application of CLT-2.....	168

Figure 6.13: Uncertainty in the Fitness Function, No Application of CLT-1	169
Figure 6.14: Uncertainty in the Fitness Function, No Application of CLT-2	169
Figure 6.15: Uncertainty in the Decision Space and Fitness Function, No application of CLT	170
Figure 6.16: Uncertainty in the Decision Space and Fitness Function, with application of CLT-1	171
Figure 6.17: Uncertainty in the Decision Space and Fitness Function, with application of CLT-2	172
Figure 6.18: Criticality of constraint in the decision space	174
Figure 6.19: The optimisation with uncertainty & constraints in the decision space	176
Figure 6.20: Optimisation with constraints and uncertainty in the design and objectives	176
Figure 6.21: Design solution search strategy	180
Figure 6.22: Design variables representation sequence in the optimisation of single pass 6 objective problem	182
Figure 6.23: Initial solution from GA (400 populations)	187
Figure 6.24: The highest weight vector average solutions.	188
Figure 6.25: The 2 nd highest weight vector average solutions	188
Figure 6.26: The 3 rd highest weight vector average solutions.	189
Figure 6.27: The 4 th highest weight vector average solutions	189
Figure 6.28: The 5 th highest weight vector average solutions	189
Figure 6.29: The 6 th highest weight vector average solutions.	190
Figure 6.30: Single pass 6 objective problem solutions in the objective space	190
Figure 6.31: Roll surface Temp (change in Temp + bulk initial roll Temp)	192
Figure 7.1: Multi-pass rolling arrangements involving three passes showing inter-pass distance and stock reduction after roll stock contact	198

Figure 7.2: Solution search strategy for multi-objective problems with uncertainty....	211
Figure 7.3: Design variables representation sequence in the MP optimisation	213
Figure 7.4: Initial solutions from GA (400 pop).....	217
Figure 7.5: The highest weight vector average solutions	217
Figure 7.6: The 2 nd highest weight vector average solutions.....	218
Figure 7.7: The 3 rd highest weight vector average solutions.....	218
Figure 7.8: The 4 th highest weight vector average solutions.....	218
Figure 7.9: The 5 th highest weight vector average solutions	219
Figure 7.10: The 6 th highest weight vector average solutions	219
Figure 7.11: The 7 th highest weight vector average solutions	219
Figure 7.12: The 8 th highest weight vector average solutions	220
Figure 7.13: The 9 th highest weight vector average solutions	220
Figure 7.14: The 10 th highest weight vector average solutions.	220
Figure 7.15: Temperature change in rolls along the 5 passes (°C).....	223
Figure 7.16: Total temperature in rolls along the 5 passes (°C).....	223
Figure 7.17: Roll speed trend in 5 passes	227
Figure 7.18: Stock temperature trend in 5 passes	227
Figure 7.19: Delay time trend in 5 passes.....	227
Figure 7.20: Roll / stock contact trend in 5 passes.....	228
Figure 7.21: Roll / stock contact HTC trend in 5 passes	228
Figure 7.22: HTC cooling trend in 5 passes	228
Figure 7.23: Roll bulk temperature trend in 5 passes.....	229
Figure 8.1: Procedure followed for result validation.....	235
Figure 8.2: Single pass results for change in temperature and radial stress at surface and depth below the surface.....	243
Figure 8.3: Single pass final roll temperature profile.....	243

Figure 8.4: Multi-pass temperature change results, in rolls ($^{\circ}\text{C}$).	244
Figure 8.5: Total temperature profile in rolls at each passes, in ($^{\circ}\text{C}$).	245
Figure 8.6: Multi-pass roll speed profile	246
Figure 8.7: Multi-pass stock temperature profile.	247
Figure 8.8: Multi-pass delay time profile.	248
Figure 8.9: Multi-pass Roll / stock contact profile.	249
Figure 8.10: Multi-pass Roll / Stock contact HTC profile	250
Figure 8.11: Multi-pass HTC cooling profile.	251

List of Tables

Table 1.1: The top 10 steel producers in 2009 (source (world steel association)	3
Table 1.2: Roll types and their characteristics when used in hot rolling	14
Table 1.3: Summary of the classification and classification complexities	27
Table 4.1: Pre survey conditions	82
Table 4.2.A: Surveyed companies and participant expertise	82
Table 4.2.B: Surveyed companies and participant expertise	82
Table 4.2.C: Surveyed companies and participant expertise.	83
Table 4.2.D: Surveyed companies and participant expertise	83
Table 4.3: Sample questions, survey, state of the Art design optimisation techniques in industry.....	84
Table 4.4: Questions themes and survey aim.....	86
Table 4.5: Questions themes and survey aim.....	86
Table 4.6: Initial arrangements for knowledge elicitation.....	91
Table 4.7: Sample questions, work roll system in rolling process.....	92
Table 5.1: FEA problem model meshing part boundary condition.....	102
Table 5.2: FEA problem model part interaction property	103
Table 5.3: Work roll system independent design variables used in the model.....	109
Table 5.4: Design simulation 3 level matrix inputs.....	109
Table 5.5: Design matrix for FEA simulation ($L-27 = 7^{3-1}$)	119
Table 5.6: Input Setting for the FEA Simulation	120
Table 5.7: Expected responses from the FEA simulation.....	121
Table 5.8: Independent design variables set used in the FEA simulations.....	122
Table 5.9: The experimental simulation initial conditions	122
Table 5.10: Expected heat penetration depth in to the roll	130
Table 5.11: FEA simulation responses	135

Table 5.12: FEA results for Meta-model prediction.	136
Table 5.13: Material property value ranges considered for the simulation	137
Table 5.14: Simulation matrix and property values for the selected material types	137
Table 5.15: Simulation run input factors.	137
Table 5.16: FEA Simulation run matrix	138
Table 5.17: Responses from simulation with different roll material types at roll surface and various depths below the roll surface	138
Table 5.18: Model validation summary.....	141
Table 5.19: Validation runs input data set (factors and factors parameters)	142
Table 5.20: Calculated depth at the roll surface, for data taking.	142
Table 5.21: Validation FEA simulation run Response	143
Table 5.22: Validation results	144
Table 6.1: Optimisation details for single pass work roll design problem	162
Table 6.2: Level of uncertainties used in the optimisation	162
Table 6.3: Percentage error values for design factor parameters used in the optimisation	163
Table 6.4: Design solution at three random points along the true Pareto front	165
Table 6.5: Design solution at three random points along the true Pareto front	171
Table 6.6: Design details of single pass work roll design problem.....	182
Table 6.7: Sample array from good solutions found by the GA, (Objective space).	183
Table 6.8: Sample arrays from good design solutions found by the GA, (Design space)	184
Table 6.9: Post GA percentage reduction, within the objective space for final design solution.....	187
Table 6.10: Best optimum design factors identified (Design space).....	191
Table 7.1: Inter-pass factor relationships for modelling multi-pass model.	201
Table 7.2: Inter-pass speed in multi-pass rolling	201

Table 7.3: Inter-pass delay time under normal circumstances	202
Table 7.4: Inter-pass stock temperature in multi-pass rolling.....	202
Table 7.5: Design variables of multi-pass problems (5 passes)	203
Table 7.6: Objective for multi-pass problems.....	203
Table 7.7: Response data values from FEA simulation.....	205
Table 7.8: Response data values used for generating the multi-pass models	206
Table 7.9: Model statistical validation	209
Table 7.10: Sample array from good solutions found by the GA, (Objective space. Obj-1 - Obj-10).....	214
Table 7.11: Sample arrays from good design solutions found by the GA, (Design space)	215
Table-7.12: Post GA percentage reduction, within the objective space for final design solution.....	216
Table 7.13: Objective weight vectors samples showing population reduction before identifying best optimal solution good for all objectives in the search space	221
Table 7.14: Roll change in temperature (surface temperature) and total roll temperature profile after optimisation (Objective space).....	222
Table 7.15: Best optimum design factors parameters (Design space).....	224
Table 8.1A: Validation questionnaires theme and aim.....	236
Table 8.1B: Validation questionnaires theme and aim.....	237
Table 8.2: Pre survey arrangements for validation (People and establishments) Company A.....	238
Table 8.3: Pre survey arrangements for validation (People and establishments) Company B.....	238
Table 8.4: Multi-pass factors chosen for verification.....	240
Table 8.5: Optimisation result selected for multi-pass problem validation	240

Table 8.6: Validation questionnaire, single pass rolling design optimisation main objective (change in temperature)	244
Table 8.7: Questionnaire 1. Multi-pass change in temperature in rolls, result trends along the 5 passes	245
Table 8.8: Questionnaire 2. Multi-pass exit speed design factor result trends along the 5 passes.....	246
Table 8.9: Questionnaire 3 Multi-pass stock temperature design factor result trends along the 5 passes	247
Table 8.10: Questionnaire 3. Multi-pass delay time design factor result trends along the 5 passes.....	248
Table 8.11: Questionnaire 4. Multi-pass contact length design factor result trends along the 5 passes	249
Table 8.12: Questionnaire 5. Multi-pass Roll/Stock contact HTC design factor result trends along the 5 passes	250
Table 8.13: Questionnaire 6. Multi-pass HTC- Cooling design factor result trends along the 5 passes	251

Nomenclature

C _p	Specific heat capacity (j/kg.k)
E	Elastic module (MPa)
h	heat (joule)
HTC-1	Roll / Stock contact Heat Transfer Coefficient (kW/m ² K)
HTC-2	Cooling Heat Transfer Coefficient (kW/m ² K)
i	Residual stress (MPa)
L	Contact length (mm)
NT11	Nodule temperature (°C)
P	Roll pressure (MPa)
q	Heat removal (joule)
R _i	Heat affected depth / radius of roll (mm)
r _i	Steady state depth/ radius of roll (mm)
r	Roll radius (mm)
S ₁₁	Roll radial stress (MPa)
S _{11_{15d}}	Roll radial stress at 15mm below the roll surface (MPa)
S _{11_{9d}}	Roll radial stress at 9mm below the roll surface (MPa)
S _{11_{allowable}}	Roll material allowable stress limit (MPa)
S _{11s}	Roll radial stress at the roll surface (MPa)
S _{11s1}	Radial stress at roll surface at pass 1 (MPa)
S _{11s2}	Radial stress at roll surface at pass 2 (MPa)
S _{11s3}	Radial stress at roll surface at pass 3 (MPa)
S _{11s4}	Radial stress at roll surface at pass 4 (MPa)
S _{11s5}	Radial stress at roll surface at pass 5 (MPa)
t	Roll stock contact time (s)

T_0	Roll initial temperature ($^{\circ}\text{C}$)
T_1	Roll temperature after roll / hot stock contact ($^{\circ}\text{C}$)
T_c	Temperature of coolant ($^{\circ}\text{C}$)
T_r	Temperature of roll ($^{\circ}\text{C}$)
T_{rs}	Temperature of roll surface ($^{\circ}\text{C}$)
T_s	Temperature of stock ($^{\circ}\text{C}$)
ΔL	Change in length (mm)
ΔT	Change in temperature ($^{\circ}\text{C}$)
ΔT_{15d}	Change in temperature at 15 mm below the surface ($^{\circ}\text{C}$)
ΔT_{9d}	Change in temperature at 9mm below the roll surface ($^{\circ}\text{C}$)
ΔT_s	Change in temperature at the roll surface ($^{\circ}\text{C}$)
ΔT_{s1}	Change in temperature at roll surface at pass 1 ($^{\circ}\text{C}$)
ΔT_{s2}	Change in temperature at roll surface at pass 2 ($^{\circ}\text{C}$)
ΔT_{s3}	Change in temperature at roll surface at pass 3 ($^{\circ}\text{C}$)
ΔT_{s4}	Change in temperature at roll surface at pass 4 ($^{\circ}\text{C}$)
ΔT_{s5}	Change in temperature at roll surface at pass 5 ($^{\circ}\text{C}$)
α	Thermal diffusivity (w/mk)
ε	Thermal expansion (mm)
λ	Material conductivity (w/m.k)
ρ	Density (kg/m^3)
σ_c	Stress circumferential direction (MPa)
Ω	Roll speed (rad/sec)

Acronyms

ANOVA	Analysis of Variance
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CLT	Central Limit Theorems
DAT	Data information file
DoE	Design of Experiment
DS	Decision Space
EC	Evolutionary Computing
FE	Finite Element
FEA	Finite Element Analysis
FF	Fitness Function
GA	Genetic Algorithms
HTC	Heat Transfer Coefficient
INP	Input information file
MP	Mega Pascal
MSG	Message file
mt	Million Tonnes
NPD	New Product Development
NSGA-II	Non-Sorting Genetic Algorithms two
ODB	Output Data Base
PhD	Doctor of Philosophy
PRT	Part information file
R	Coefficient of Determination of Least Square Fit
R^2	Coefficient of Multiple Determination of Least Square Fit

RD&T	Research, Development & Technology
RMS	Root Mean Square
RMSE	Root Mean Square Error
RSM	Response Surface Methodology
SME	Small and medium size enterprises
STA	Statistical information file
2D	Two dimensional
3D	Three dimensional

1. Introduction

Nowadays, the consumer wants more - with the best quality and at a low cost. Industries have to cope with this. As a forming expert in one of the leading car manufacturing companies, Tekkaya (2000) summarized the current pressure on this industry as follows: "In the past, we introduced 3 new models every 10 years, now we introduce 10 new models every 3 years." Steel product development is no exception; the pressure on other manufacturing sectors has a direct impact on steel product development. The ever-increasing demands for the steel products by these industries forces the steel makers to respond faster to fulfil the demand. Responding faster requires continuous production and use of production tools hence, more tooling cost. In the rolling process, the tooling cost is one of the main factors that lower the profit margin. An increased margin can be achieved through production cost reduction, particularly tooling cost. In order to succeed in such a complex endeavour, therefore, industry is seeking innovative intelligent systems to enhance their new product and process development strategies more than ever. Since efficient uses of existing resources are key competitive drivers in industry, it is necessary that any techniques and methodologies used to keep the efficiency are capable of delivering high quality solutions, but at low cost. However, the traditional search and classical optimisation approaches in the steel industry, for monitoring tool life and roll thermal behaviour in particular, find it very difficult to satisfy these requirements. This is mainly due to the complex and uncertain nature of the problem. Roll thermal analysis is a complex problem due to the non-deterministic nature of the process and the large number of processing conditions and uncertainty involved. The problem complexity and uncertainty requires a robust and flexible approach to address it. The Algorithm based framework is expected to alleviate the key features of the problem, such as uncertainty. GA based techniques adopted in the thesis due to its ability to deal with multi-objectivity high dimensionality in the optimisation problems, and its flexibility in application hence complex problem characteristics such as uncertainty can be addresses. GA is also a technique currently in use by the sponsoring company. In the survey conducted by this research author on research paper published about engineering design optimisation techniques, the results clearly indicate that over the

years the GA based techniques popularity increased sharply. The survey conducted by Oduguwa (2003) also reveals the popularity of evolutionary computing (EC), particularly GA based techniques in industry for real-life optimisation problem applications. The survey shows that 95% of the techniques reported are GA based. Thermal profile study is the most important feature for the roll life. This is due to the fact that thermal related stresses are a major cause of work roll wear and cost of roll due to thermal wear is a concern to steel industry. Despite its importance however the subject is not fully investigated.

Uncertainty in the Work Roll System Design

Uncertainty in rolling particularly in data acquisition is inevitable. Rolling is a process that takes place in extremely hot and high disturbance uncertain environment. In this situation measuring accurate data live is challenging. As observed in Tata Steel Research, Development & Technology data acquisition is mainly using of measuring tools such as CNC machines and data taken during redressing off the processing line. Inter-stand data measurements are mainly calculated using assumed inter-stand relationship. Other very important rolling thermal variables such as roll speed and heat transfer coefficients are measured using encoders. The encoders convert the computer characters and commands in to digital forms. On the other hand roll profile is not directly measured, only estimated from models. These lead to data accuracy uncertainty. Due the complexity of the real life rolling processing environment, where empirical study is difficult to do, using approximate model is inevitable. Approximate models are however prone to forced accuracy compromises, as well as being known as model uncertainty. In this research context uncertainty is defined as the variability inherent in a physical system due to the range of expected outcome. To deal with the design challenges such as uncertainty, therefore, the research:

Aim to develop a framework for work roll system optimisation using thermal analysis and genetic algorithm.

The chapter introduces the context of the research domain studied to address the aim, and is organised as follows: Section 1.1 introduces the sponsoring company business portfolio and its product development culture, as well as its association to the PhD project. Section 1.2 introduces metal forming technology and gives an overview of what constitutes the forming process. Section 1.3 introduces of engineering design optimisation and real engineering design problem complexities Section 1.4 Summery

of research initiative Section 1.5 present the thesis structure. The chapter concludes by outlining the thesis structure in Section 1.6.

1.1 The Sponsoring Company

TATA Steel - Europe, previously known as Corus is Europe's second largest steel producer, among the top ten in the world, with annual revenues of around £12 billion and a crude steel production of over 20 million tonnes. Corus was formed on 6th October 1999, through the merger of British Steel and Koninklijke Hoogovens. On April 2 2007, Corus became a subsidiary of Tata Steel, with 37, 000 employees worldwide, and has manufacturing operations in many countries, with major plants located in the UK and the Netherlands. The group operates through 20 business units and has an extensive product portfolio and services, including carbon steel, engineering and stainless steel, as well as aluminium. Corus comprises three operating divisions, strip Products, long products and distribution & Building Systems, and has a global network of sales offices and service centres. Tata Steel - Europe is a leading supplier to many of the most demanding markets, including construction, automotive, packaging and engineering. Rolling is the main manufacturing process undertaken, in which up to 15% goes to manufacturing tooling cost. The main collaborator of this research is Tata Steel - Europe, Research, Development and Technology (RD&T) Centre, located in Swinden, Rotherham, North of England, and UK.

Table 1.1 The top 10 steel producers in 2009 (source world steel association)

Rank	Million metric tonnes	Company
1	103.3	Arcelor Mittal
2	37.5	Nippon Steel ¹
3	35.4	Bao steel Group
4	34.7	POSCO
5	33.3	Hebei Steel Group
6	33	JFE
7	27.7	Wuhan Steel Group
8	24.4	Tata Steel ²
9	23.3	Jiangsu Shagang Group
10	23.2	U.S. Steel

(1) - includes part of Usiminas (2) - includes Corus

1.1.1 Steel Production Global Perspective in the last Decade

There are around 80 companies worldwide known to be involved in the steel production, according to World Steel Association. The sum total of the annual production coming out of these companies amounted to 1219.715mmt in 2009. Although as indicated in the chart below, there is a downward growth from 2009 due to global recession. The latest update suggests that the world's total crude steel capacity, by the end of 2012, may grow by 251mmt to 1470.715mmt compared to 2009. Corus, despite its leading position, ranking eighth in the world steel production, has only 2% of the global market share.

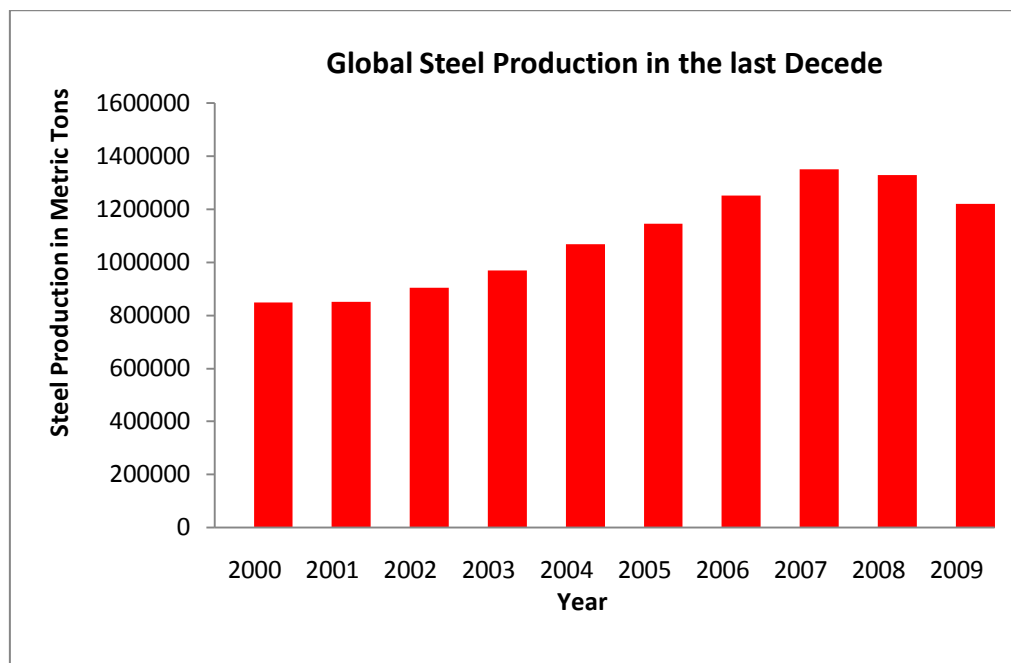


Figure 1.1 global total steel productions in the last decade (world steel association 2009)

1.1.2 The Research Initiative and Tata Steel-Europe Research Development & Technology (RD&T)

As stated in the section above, the Tata Steel - Europe is comprised of three main divisions and 20 business units. One of the units is the Tata Steel - Europe RD&T, set to provide research, development and technology, and hence, to improve knowledge. The aim of the unit is to promote innovation and the development of new ideas to find optimum cost effective technologies based process solutions for the company as well as to continuously improve production processes development, and also protection of

the environment. The unit is stretched beyond Tata Steel - Europe, and collaborates with universities and other research councils to advance its research goals. As part of fulfilling these goals, the RD&T initiate a long term research product, aiming to develop a process modelling techniques covering long product rolling to provide a robust modelling environment for roll life improvement. Some of the tasks necessary to achieve the project objective are stated as follows.

- To develop a modelling environment for rolling scheduling and optimisation. This is primarily aimed at the new product development (NPD) and process improvement of long products.
- To capture knowledge (uncertainty for accuracy, etc) within the rolling and modelling environment.

Therefore, to satisfy these objectives, Tata Steel - Europe RD&T collaborated with Cranfield to develop the PhD project. The relevance of the PhD project to the new process development project is discussed in the next section.

1.1.3 The Proposed PhD Research as part of Tata Steel – Europe Strategic New Product Development Project

The PhD project was initiated to provide support towards achieving some of the new process development project objectives introduced by Tata Steel - Europe RD&T. Rolling system design is a core skill, which significantly influences the ability to improve process, product and tool life. Currently, the rolling system design has been conducted by skilled experts using their experiences. Although in recent years, the system has been improved based on scientific approach, this approach, does not include the roll thermal effect. Currently, the roll damage due to heat can only be dealt with by mechanical means like dressing - this type is costly, time consuming and reduces the size of the roll unnecessarily. Most importantly, it does not include some important real life design problem characteristics, such as uncertainty. Motivated by these necessities, therefore, the PhD project is designed to fill the gap by developing a rolling system design, thermal effect and uncertainty, based on scientific approach. By doing this, the PhD research contributes knowledge to the overall Tata Steel - Europe RD&T NP & D in the following areas:

- Fulfil the increasing need to develop solutions, using scientific approaches in favour of traditional approaches, to advance effective utilisation of work rolls, overcoming thermal effect.

-
- To strengthen capability to search a design space to deliver robust, multiple, good solutions, regardless of the presence of uncertainty.

Hot rolling is a process, driven by friction, in which large plastic strain occurs in the work piece when the roll exerts pressure at the bite region. The resulting plastic work is converted into heat energy, while friction heat is generated at the interface due to the relative motion between the work piece and the roll. Depending on the roll speed and material properties at the point of contact, a fraction of this heat is transferred toward the roll. Finally, the heat is taken away from the roll by the cooling system (either water cooling or air). It is important to emphasize that high heat flux, generated at the interface; results in substantial variations in the work piece and roll surface temperature, whereas roll bulk temperature remains more or less unaffected. The roll surface is subjected to significant variation of thermal stresses that ultimately cause roll damage, and shortening of roll life. It is obvious that such rolls decrease the productivity of the rolling process, thereby increasing the number of roll changes, and thus influencing product quality and cost. The cost of rolls and rolling take a significant portion of the overall production cost. A single roll costs £8000 and the rolling process estimated to have absorbed 5% to 15% of the production cost. Therefore, it is important that heat flow during the metal rolling process be studied, in order to design work roll thermal analysis and optimisation so that its working life can be improved. Although many studies have been carried out to model thermal behaviour of rolling processes that involve either modelling of roll or strip, few attempts have been made to couple thermal modelling of the roll, product and, most importantly, incorporate uncertainty and constraints in the modelling and optimisation. Therefore, this PhD research is designed and fills these gaps.



Figure 1.2. Left to right: Roll breakage due to too high temperature gradient/high residual stresses and fire cracks rolling rails (Schroeder, 2005).

1.2 Introduction to Metal Forming

Metal forming is a complex manufacturing process requiring a simple geometry to be transformed into a complex one. But what are the details of the forming and the important characteristics involved in the process? Metal forming is normally performed after the primary processes of extraction, casting and powder compaction, and before the finishing process such as: cutting, grinding, polishing, painting and assembly (Avitzur, 1979). So, the forming process is an intermediary stage, but it is also a very important stage because the main objective of metal forming process is to give the dimension desired of the work piece to obtain the best final product. The forming process is defined as an operation where the shape of a metal experiences changes via plastic deformations using specially made forming tools called work rolls. To describe the details involved in the forming process and the deformation phenomena, plasticity theory can be employed (Leisten *et.al.*, 2001). However, this is beyond the scope of this research. The forming process includes typical processes like rolling, forging, stamping, drawing and extrusion. During all these processes, deformation is induced by external compressive forces from work rolls. Work rolls are an important part of the forming process. The forming process can be divided into two categories:

- Hot working
- Cold working

The main focus area of the research is in the hot metal rolling process, highlighted in Figure 1.3, particularly the roll used to cause the deformation in the product and the cooling system associated to it.

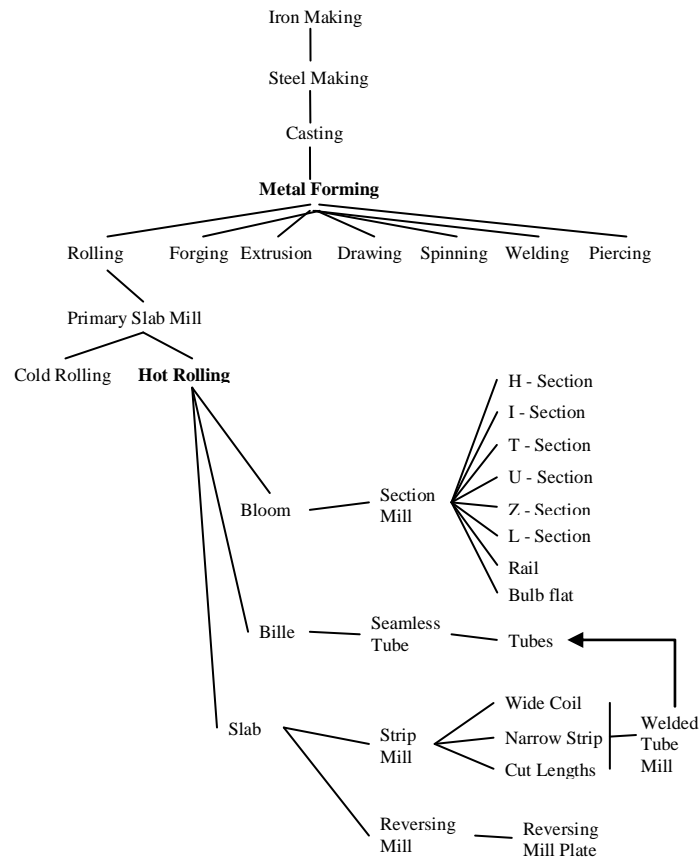


Figure 1.3. Steel making and the rolling process

Hot Working Process

This is a process by which a microstructure, thermal and thermo mechanical, transformation of a material occurred due to heat. During the process, the material is deformed above its re-crystallization temperature. Although the condition varies depending on the working condition and material type, the temperature can reach up to 1500°C during hot working. In hot rolling, the mechanical, thermal and physical properties, as well as boundary conditions, are temperature related. Therefore, heat is the major issue in the hot rolling. Thermal effect also has a trigger for the presence of stress; therefore, the heat flow and stress analysis cannot be analysed separately. The analysis requires a thermally coupled approach (Chen *et.al.*, 1998). Since work roll is the integral part of the working process, it is exposed to all the effects of the above mentioned features of the working process. To protect the roll from these effects, therefore, it is necessity to have an optimal rolling thermal design that can overcome the effect and protect the roll from damage. Major hot-working processes that are of major importance in modern manufacturing include the following: **Rolling**, Forging, Extrusion and upsetting, Drawing, Spinning, Pipe welding, piercing.

Cold Working Process

Cold working is defined as a plastic deformation of metals below the recrystallization temperature. In most cases of manufacturing, such cold forming is done at room temperature. In some cases, however, the working may be done at elevated temperatures that will provide increased ductility and reduced strength, but will be below the recrystallization temperature. In the majority of cases, no heating is required in the cold working process.

1.2.1 Overview of Work Rolls and the Rolling Process

The rolling operation is a high-speed process where the material referred to as the stock, is passed between two work rolls driven at same peripheral speed in opposite directions. Each roll exerts compressive stresses and forces the work piece to reduce in cross section, as shown in Figure 1.4. The stock leaves the work rolls with a reduced thickness and uniform cross section. Since the stock is driven by the roll speed the velocity (V_{out}) of the stock (after it comes out of the roll gap) is higher than before entering the gap (V_{in}) or can be written as ($V_{out} > V_{in}$). Heat from the rolled product to the roll is the maximum at roll bite. The rate at which the heat transferred is depending on various factors, collectively called heat transfer coefficients (HTC). Other parameters such as roll stock contact length and roll speed also influence the heat transfer from stock to the work roll. This topic discussed in detail in Chapter 5.

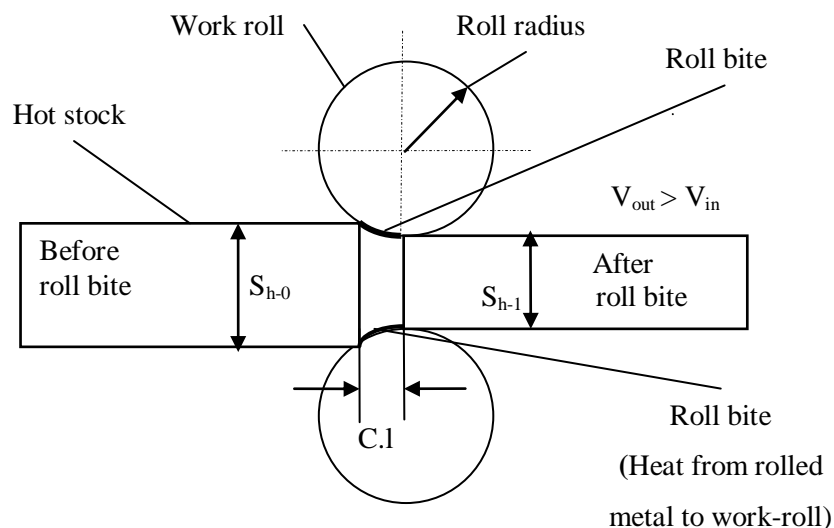


Figure 1.4. View of single pass rolling featuring roll/ stock contact length (C.L), roll radius, roll gap, stock before and after bite.

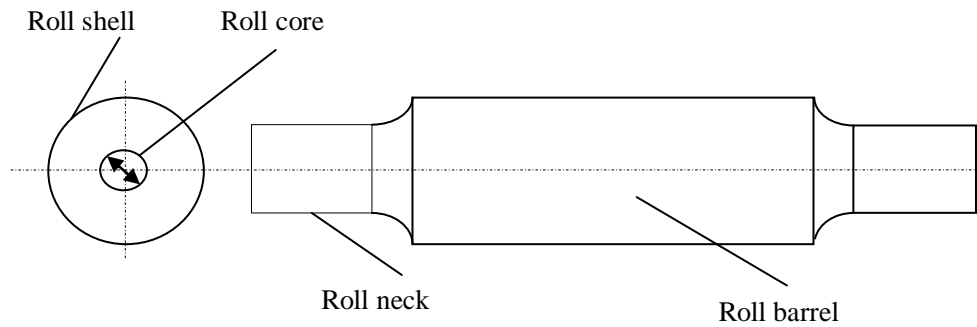


Figure 1.5. View of cylindrical work roll.

Work rolls are a forming tools designed to change the shape and size of the rolled metals depending on forming requirements. Achieving the final shape of the product in minimum number of passes, within the constraints of the mills is the main criteria for designing rolls. Typical roll type, shown in Figure 1.4 and 1.5 consists of the following parts: Roll barrel, Roll neck, Roll shell and Roll core.

Roll barrel – is the part of the roll that is in direct contact with the rolled product and makes the forming. Roll barrel can be sectioned in to two; these are the shell or the surface of the roll and the core or internal part of the roll.

- **Shell** - is the surface or outer part of the of the roll barrel which is in direct contact with the hot stock during rolling. The temperature at this section rise above bulk (initial temperature of the roll as high as half of the stock temperature. The extent of the temperature rise and depth of penetrations is depending on various process factors. For example the speed in which the roll runs, the contact time the roll has with the hot stock, and the cooling conditions are some of the main factors determined the heat affected area on rolls. The roll running at lower speed with longer roll / stock contact time led to the higher the amount and depth of heat in to the roll. The section also acted up on by the cooling system to remove the excess heat from it, absorbed from the stock when in contact. This constant change in temperature and occasional non-uniformity of coolant application on the surface cause the shell highly prone to thermal related failure.
- **Core** - is the inner part of the roll. The core expected to retain the bulk / initial roll temperature throughout the rolling process. In practise this is true only if the temperature increase in the shell is managed. Heat passed and accumulated

to the core or at the interface between shell and core will cause roll thermal shock, particularly when the coolant applied to it or during the cooling period.

Roll neck- is section at two end of the roll which is used to attach the roll in the roll mill and load applies to it so that the roll can press the rolled product when it pass through the roll gap.

Rolls are manufactured by casting and are varies in size and texture/grades. The variation is an important behaviour of rolls because the choice of rolls for application in rolling is depend on it. For example selection of work roll differs depending on requirements of products to be rolled and section of the rolling process. The main drivers of rolls selections are the ability to resist wear, thermal shock and withstand stress. In the last decade the use of work rolls in hot rolling has improved. This is due to the roll grade development by using enhanced roll materials. For example due to the roll size and production demand placed on the rougher rolls, high chrome steel 70-75 ShC has been gradually replaced by new grades like carbide enhanced high chrome steel 75-80 ShC, and the finishing passes have seen a development from high chrome cast iron 70-75 ShC to carbide enhanced high chrome cast iron 75-80 ShC, and a variety of other enhanced materials (Ziehenberger and Windhager, 2006). The development is necessary since it improves the surface quality of the roll; as a result it runs much longer campaigns and improves the efficiency of the entire mill. However improving the roll material or/and selecting compatible roll type for particular product and section of rolling may not guarantee that the roll behaviour could be fully realised. There are uncertainties. The uncertainties are due to imperfection in the roll manufacturing and developing as well as during the forming process. According to Ziehenberger and Windhager the following are roll manufacturing concerns, which may have impact on roll life when used in the hot rolling process.

- Double poured work rolls are big and very complex castings. The bigger the casting, the more likely the inner part of the casting will show imperfections.
- Shell (outer layer of rolls) and core material have different alloying contents resulted varying temperatures and thermal expansion. This leads to high residual stress, compression stress in the shell, tensile stress in the core.
- High residual stress and imperfections in the inner part of the shell or in the transition zone, shell and core interface may increase the risk of roll failure.

The uncertainties, which are related to roll thermal behaviour, can only be improved if it is addressed in rolling process planning of campaigns that includes searching for robust, optimal process design. The work rolls in the mill are subjected to periodic loading that is accompanied with abrasion by scale and fluctuations in temperature (Hitchcock, 1935). Various factors cause the temperature fluctuations. Design variables such as roll speed, roll/stock contact length, stock temperature the cooling regime, delay time and other related process factors. Parameter variability in those design factors is also a source of uncertainty that cause thermal variation in rolls during rolling. Figure 1.6 shows a 6 high, 4 passes hot rolling process arrangements consisting of roughing, intermediate and finishing stands.

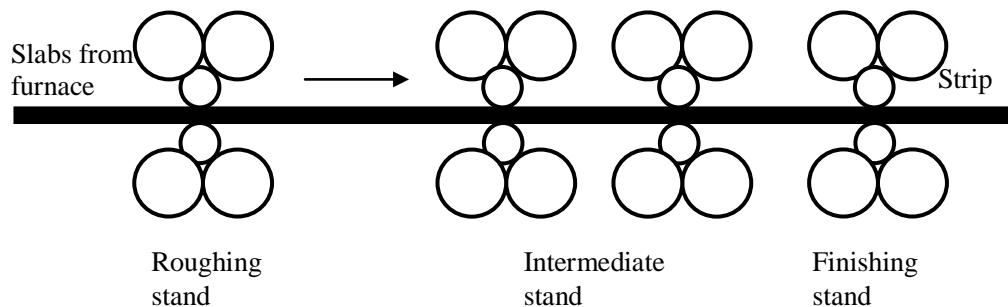


Figure 1.6. View of sequence of 6 high rolling process involving 4 passes.

The main drawback of the process is the tool life. During hot metal forming work roll service life is dramatically shortened by thermal and mechanical cycle, excessive metal flow and decrease in roll hardness. The roll life and degree of wear are also influenced by uncertainty. Uncertainty in the system design factors, as well as uncertainty in real life rolling practise, may cause unexpected load (thermal or mechanical) on rolls. In hot metal forming, the process takes place in a very high temperature, up to 1500°C , environment, and hence, the temperature is becoming a primary subject to research for improving roll life. Today, the advancement of computer software and statistical tools has made it possible to foresee forming process behaviour in advance. For example, predicting the temperature field during the forming processes is an important phenomenon, since it influences the lubrication/cooling conditions, the material behaviour during deformation, the quality of finished part, and above all, the service life of work rolls (Jeong, 2001). Work roll cooling system is an integral part of the rolling process design to protect the roll from thermal damage. Effective utilization of rolls can only be maintained by having a

rolling thermal design model that incorporates compatible roll cooling system. Section 1.2.4 introduces the roll cooling system, its operation and disadvantages of the current system.

1.2.2 Fundamentals of Rolls in Hot Metal Rolling

Since the beginning of the technology era where metal forming become known to mankind, the forming process was always, and still is, dependant on the work rolls acting on the workspace to give it the required shape and form. Since then, however, the technology has enabled rolls to be made better and in accordance with the interests of the material to be rolled. The roll can be improved by blending, mixing different alloys together, so that stronger and better rolls can be made. In the early days, before the mid eighteenth century, cast iron rolls with different hardness (alloy properties) were used. These iron rolls, in comparison to modern era roll, exhibited low hardness and poor wear resistance. In the early part of the eighteenth century, with the introduction of the metal chill mould, the increased cooling rate at the surface of the roll produced a structure with about 40% iron carbide, a hardness of about 60%, and improved hardness. However, even though there was overall improvement in the roll, it was still characterized by low mechanical strength. As a result, to avoid roll breakage, relatively small drafts were taken during the rolling operation (90 % pearlite and 10 % graphite). In the mid nineteenth century, the cast steel rolls with a carbon content of about 0.5% were introduced. The introduction tripled the strength of the cast iron, due to the absence of graphite and massive carbides, but with a relatively low hardness. Towards the end of the nineteenth century, forged steel rolls were introduced. These exhibited a greater resistance to breaking, but not much in resistance to wear. However, improved strength and resistance to wear were provided by appropriate heat treatments, such as grain refining, annealing, as well as normalizing, and by careful control of composition, particularly with respect to carbon, manganese and chromium. In practice, even though the current materials used for rolls are much improved for reasons mentioned above, and equally important characteristics such as presence of bearings (roller bearings for work rolls and use of oil film bearings for back-up rolls) during operation, there are still problems associated with rolls that are visible mainly after certain temperatures build-up in the work roll during hot rolling. Some of the characteristics of those roll types and problems associated with them when used in hot rolling are shown in Table 1.2.

Table 1.2. Roll types and their characteristics when used in hot rolling
(Hickley and Porthouse, 1975).

Metal	Temperature range ($^{\circ}\text{C}$)	Problems in rolling
Carbon steel	1300 - 850	Fire cracking, abrasive wear, shock load during roughing
Low-alloy steel	1300 - 850	Fire cracking, abrasive wear, shock load during roughing
Stainless steel	1250 - 950	Several thermal conditions as cooling is often restricted

The rolling operation is a deformation process, the deformation of the work-piece accomplished by two rolls rotating with equal speed in the opposite direction. The frictional effect drags the work piece in to the roll bite and forces it out through the narrowest end of the bite. In the absence of any tensile stresses and friction between the rolls and work piece, rolling would not be possible, since deformation energy could not be transferred from the rotating rolls to the work piece. It is also learnt that the nature of the rolling process where the work piece passes through the rolls rotating in opposite directions, involves the flow being mainly restricted to the direction of rolling, and thus, there is a lateral constraint applied to the work piece (except near its edges). In hot rolling, however, tensile stresses are usually created by adjacent roll stands acting on the same work piece as it is processed in continuous mills. Such stress must not be very large since it will cause necking. A reduction in the cross-sectional area of the work piece may also be the cause for roll crack and damage (Schroeder, 2005 and Muller, 1959). In principle, rolling is a process where mass flow of work piece entering the roll bite is equal to that leaving it. Thus, a fractional increase in the speed of the work piece created by a rolling process corresponds to the fractional increase in the cross-sectional area of the piece. Thus, if v_1 and v_2 denote the work piece speed entering and leaving a mill pass and r is the reduction in the cross-sectional area (expressed in decimal fraction) $v_2 = v_1 / (1-r)$. While the peripheral speed of a work roll in a mill stands remains constant, the surface speed of a point, on the surface of the work piece increase as it passes through the bite until usually on exit from the bit, then it exceed the speed of the roll. The work-pieces are then said to exhibit forward slip (Muller, 1975). Rolls can be chosen depending on the type and size of material to be manufactured. Based on the type of material to be manufactured, rolls can be classified as follows.

Iron rolls- There are various rolls made of iron, differing from one another based on alloy content, method of manufacture and the character of the chill.

High-chromium rolls – high chromium is a material introduced in the 1970s and exhibiting a very high degree of wear resistance (due to chromium carbide in the shell). Today, because of these characteristics, in comparisons, high chromium rolls have better acceptance by industries. High chromium rolls have the following advantages:

- Lower roll replacement and roll grinding costs.
- Improved product quality because of better roll surface.
- Reduced roll changing delays.
- Some internal cast high-chromium rolls exhibit twice the life of grain iron rolls (McManus, 1980; Davis, 1981 and Linhart, 1972).

Steel rolls – steel rolls are widely used, mainly in manufacturing products such as high-lift blooming mills, roughing mills and slabbing mills. There are various steel rolls available, varying in property. The variation is due to the process involved in the manufacturing of the rolls; the manufacturing processes include heat treatments and follow up tempering processes.

Forged cast iron and steel rolls – to provide the toughness required in many hot-rolling situations, certain types of both iron and steel rolls are frequently forged after casting. Although quite brittle at certain temperatures, cast iron can be plastically deformed by hot working.

Carbide rolls, tungsten carbide – cobalt grades is a roll type mostly used in hot rolling. In hot rolling, carbide rolls are currently used only in the finishing, and rarely extended to the intermediate stand. However, due to the nature of the property of the material, a carbide roll must always be cooled during hot rolling. Pass arrangements in the rolling process are various, depending on the type of material to be rolled, section of operation and size of products. Typical roll arrangements commonly used are shown in Figure 1.7.

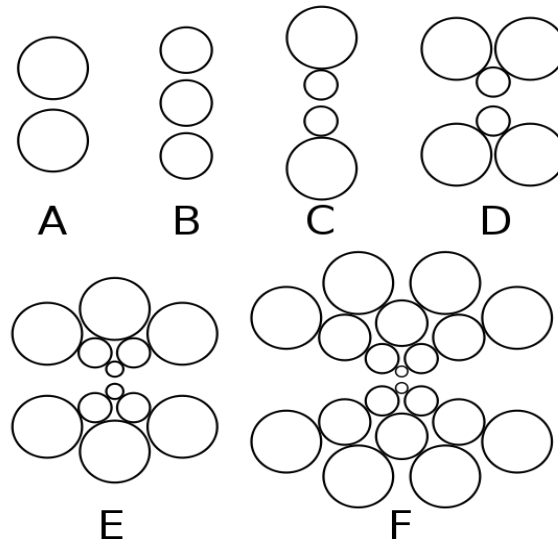


Figure 1.7. Rolling mill configurations

1.2.3 Roll Types Selection for Hot Rolling Applications

As discussed in the previous chapter, there are various types of rolls, and the variation is dependent on the material type and the suitability for particular applications. Therefore, to maintain longer roll life, the roll is selected depending on the section of the rolling process and the type of material intended to be rolled. Roughing is considered to be the most severe rolling operation next to high slabbing and blooming. High carbon grade material would be a solution for this type of process. However, its ability to grip to the work piece and resistance to fracture should be improved by alloying and heat treatment so as to refine the microstructure (Thieme and Ammareller, 1966). Generally, the selection of rolls for the rolling process requires the fulfilment of the following: with the section that exerts high stress to the roll, steel rolls mainly with low carbon contents are essential, while with the section where the stress is moderate, the steel rolls and a few specific types of cast iron whose property is compatible to steel may be appropriate. Where the stress exerted to the roll is less, any type of rolls, including cast iron, can be used. However, the choice of rolls for specific rolling operations may be difficult and require experimentation. In principle, under normal circumstances, if the right type of roll is selected for a specific type of rolling process, and with the right form of cooling conditions, the temperature of rolls remains in the outer layer of the roll. Temperature below the surface/shell at the radius should remain insignificant. Thus, it is assumed that only the outer layer with certain thickness, depending on the process factors, experiences thermal cycling.

There are various contributing factors determining the depth of the heat affected area. If the heat penetration zone reaches beyond certain radius and is accumulated at the core, it causes rapid damage to the roll. Depth of the heat penetration zone can be determined experimentally, and also as used in this research, using mathematical relationships of thermal, mechanical and process factors of the rolling process. Roll consumption represents a major part of rolling cost - much research in the field shows that thermal deterioration of the rolls is more severe than other wear mechanisms. In hot rolling, temperature and stress are mainly the results of the thermal and mechanical property of the roll material. Even though some materials such as cemented-carbide rolls are good enough to withstand thermal stresses, due to their excellent heat conduction property, however, the cooling problem, due to thermal shock, is much more severe, since more heat is conducted into the roll body. The thermal conditions at the interface between work rolls and the stock have been studied by a number of researchers and all universally accepted that rolling temperature is an important factor in determining roll wear and roll life (Hill and Gray, 1981; Pallone, 1993; Troeder *et.al.*, 1985). If the temperature concentration in the outer layer of the roll is not timely controlled with adequate cooling, it can lead to fatigue, and hence, shorter roll life. The most noticeable roll wear due to heat is the thermal fatigue (Tseng *et.al.*, 1991).

Thermal fatigue is widely known as a mechanism of roll wear. It is the major form of roll wear occurring in rolling. During the hot rolling operation, any point on the roll surface is heated when contacting the hot stock and cooled by water. As the result, compressive and tensile stresses are generated at a frequency of the roll rotation. If the compressive stress exceeds the compressive yield limit of the roll material during the heating stage, the outer layer will deform plastically. In cooling, a high tensile stress will be imposed on the roll surface. The ductility of the roll material is significantly decreased at these lower temperatures. When the fatigue limit of the material is reached, crack begins and the characteristic overall “fire crack” pattern will result (Tseng *et.al.*, 1990). Heavy bending stresses will accelerate the process of crack propagation and the subsequent roll damage. There are a number of processes, as well as operation factors and uncertainties in those factors, which directly or indirectly influence the variation in temperature in rolls, and hence, subsequent wear in rolls. But what is roll wear?

Roll wear measures the loss of rolls’ ability to roll and produce metal (in tons), due to

thermal fatigue. The rate at which work rolls wear in a hot mill, due to thermal fatigue, is of considerable economic importance because of roll purchase and grinding costs, together with the costs associated with roll change. Roll wear can be measured / estimated by the amount per ton rolled in rolls' expected normal life time. For example, under normal circumstances, cast iron is expected to roll up to 70,000 to 130,000 tons, grain-iron rolls between 95,000 and 160,000 tons, and cast steel rolls 105,000 and 165,000 - just to mention a few. This is just a rough estimate and often rolls damage before reaching this amount. Wear of the roll is greatly affected by some process parameters such as work-roll diameter and product dimension, as well as improper cooling that cause fire cracking. Keller (1955) believed that during hot rolling, heated surface layers expanded radially and contracted in the axial tangential direction. If the residual stress exceeds the tensile strength of the roll material, the condition leads to fire cracking. The correlation between the fire cracking and thermally induced stress (thermal fatigue) in the roll surface would be the main reason for untimely roll wear. If the plastic deformation in the roll surface is small, the stress in the circumferential direction, σ_c due to thermal effect and the roll pressure P will be $\sigma_c = 1,43\alpha (\Delta T) E + 0.39P$, where E represents elastic module of the roll material and α is coefficient of thermal expansion. The difference between the roll surface and body temperature, ΔT can be approximated using the following relationships: $\Delta T = H (t/k\rho C)^{1/2} (T_s - T_r)$ where H is the heat transfer coefficient between the roll and stock, t contact time, T_s initial temperature of the stock, T_r roll temperature and k, ρ , C are thermal conductivity, density and specific heat of material, respectively, (Williams and Boxall, 1963). The above relation indicates that there are number of important process factors such as heat transfer coefficient (H), influencing wear and roll life. The work also presents that the temperature condition in rolls are dependent on process sections. For example, maximum thermally induced stress occurring at the 2nd stand and dropping to the lowest in the last stand, corresponding to that the roll contact heat transfer coefficient h at the first stand, is less than half in comparison to the subsequent stands. The justification for these behaviours is partly because of the additional cooling of the stock surface by the descaling spray ahead of the first stand. Normally, protecting the roll from excessive heat is the job of the cooling system. Water cooling is the most common way of removing the heat and keeping the roll cooled. Heat removal from the roll, according to the Newton's law of cooling, can be defined as the difference of the roll-surface and the coolant temperature, T_{Rs} and T_C

respectively. With the heat transfer coefficient, H , mathematically, the relationship can be expressed as $q = H (T_{Rs} - T_C)$. Many researchers believe that the heat transfer coefficient, H is proportional to a fractional power to the amount of heat removed, or the difference between the roll surface and coolant temperature, and is mathematically expressed as $q = h (T_{Rs} - T_C)^n$. The n value will vary depending on the flow of the coolant measured by the jet, high or low speed. Hence, the effectiveness of the cooling, and thus, the temperature in the roll, has high dependency with the heat transfer coefficient. Other important factors to be considered are: type of material used for the nozzle, the flow rate required and the distance between the sprays to the surface of the rolls. A similar experimental study in the field listed the following three spray cooling parameters as the main factors that affect the roll temperature. These are: the position of the spray around the roll, the water-spray density and the length of contact of the spray with the roll (Teseng, 1999). However, there are other process factors and parameters that can determine the overall thermal behaviour of rolls. Detailed descriptions of the main factors in the rolling process influencing rolls' thermal characteristics, are discussed in Chapter 5.

1.2.4 Introduction of Roll Cooling System in the Rolling Process

Continuous developments in roll making technology have now made it possible to provide a wide range of cast and forged rolls varying in hardness. Rolls may now be selected to be appropriate for any given set of rolling conditions, so that the limitation in mill productivity attributes to roll-surface deterioration may be minimized. However, one factor which is still a critical concern and not fully explored in the operation of hot mill, is the cooling of rolls. Rolling is a heavy duty manufacturing process and takes place in a high disturbance and extremely hot environment. In the absence of proper cooling, roll intimate contact with high-temperature work pieces would result in attainment of relatively high temperatures, and consequently, such problems as excessive fire cracking, roll deformation causing rapid wear of the roll surface, damage to bearings and seals, difficulties in obtaining proper thermal crowns for the rolls and unacceptable surface on the rolled product. Proper roll cooling can obviate, or at least alleviate, most of these problems. Rolls are estimated to contribute about 5% to 15% of overall production cost in product rolling; hence, establishing an effective cooling system for optimum roll temperature is vital. However, observations of industrial real life rolling practise and literature shows that current roll cooling

practise is conventional and inadequate for potential saving of roll related costs. The cooling system is operates by continuous spraying of water on to the work roll. The spraying of water remains throughout the rolling process. Although it is clearly understood that having an efficient cooling system for keeping temperature variation in the roll surface at a minimum is vital, the cooling practice remains unsatisfactorily explained (Parke and Baker, 1972). The cooling process, as observed in real life rolling practise is a continuous flow of water in the roll during rolling, whether the roll is in contact with the stock or not. Continuous flow of water on the roll remains questionable because of the damaging effect of the increased thermal gradient, causing the roll to be prone to thermal shock, or generally known as thermal fatigue. The main issues of the current cooling techniques and gaps in the system are summarised as follows:

- Although it is clearly understood that temperature variation around and across the roll surface is detrimental, extremely wide differences in cooling practice remain unsatisfactorily explained.
- The cooling system is conventional and performed by continuous spraying of water on to the work roll, regardless of requirements and without taking in to consideration other related issues such as uncertainty, constraints and design factors.
- Although in recent times, soft computing techniques are emerging as a solution alternative for solving real world rolling problems; existing soft computing based rolling system design has not been fully utilized to include the work roll system.
- A more sophisticated problem of the optimisation of the work rolls via modelling with thermal, thermo mechanical parameters and uncertainty has not been explored.

1.2.4.1 Roll Cooling System Operation

Roll cooling is a process within the rolling system, designed to keep the roll temperature constant while it is in operation. The cooling system is carried out by continuous flow of water/coolant from a number of (usually 6) sprays through nozzles known as orifices at a given rate and pressure in to the rotating rolls. Consideration has to be given to a number of factors in selecting coolant sprays for best cooling result; these factors, as well as being known as heat transfer coefficient (HTC) of

cooling, include: type of material, flow rate and pressure, distance from the surface of the rolls and condition of oxide scale on the stock are of the most required. However, even though roll cooling is an important part of rolling system design in terms of keeping the roll in long lasting condition, observation of the real life rolling practice indicates that the system is not an innovative and intelligent system based operation. The system is mainly conventional and its application is characterised by various uncertainties. The presence of uncertainties hinders achieving a cooling regime that is efficient enough for full utilisation of rolls' working life. Main issues needing to be addressed and tackled here are the causes of insufficient cooling, or over cooling of rolls resulting in higher change in temperature, as well as the stress during rolling. There are a number of factors causing an inefficient roll cooling process. The main areas of interest needing to be investigated are parameters related to tools and the work piece, parameters related to the manufacturing environment, as well as parameters and uncertainties in the forming process. In addition, it is vital to understand complexity among factors (mechanical, thermal and thermo mechanical). For example: to understand temperature distribution of the tool, it is vital to know the initial temperature of both tool and stock parameters, as well as other properties associated to them such as the heat conductivity, density and thermal conductivity of the materials. According to Chen *et.al.* (1992) for a single rolling pass, the temperature distribution in the stock and rolls is influenced primarily by heat conduction across the roll-stock interface. There are also some process parameters which have to be taken into account, the period of contact between tools and materials and /or contact length (Rosochowska *et.al.*, 2004). For example, the longer the contact is, the more the temperature transfers to the tool. Geometric parameters are also important, like position and size of the tool. Those parameters will have an influence on the time and place of contact, and can change the distribution of the temperature on rolls. The delay time, the time where stock stops coming through the roll for known or unknown reason, is also one of the main contributors of temperature variations on rolls. All these behaviours and causes of thermal behaviours described above make the rolling system design for optimum roll cooling challenging and complex issues to deal with. Detailed review of the literature in the research domains i.e. rolling system design for optimum roll cooling and other relevant topics associated to it, are presented in the next chapter. Lists of factors of the rolling process influencing rolls' thermal behaviour, as well as complexity of factors, are also discussed.

1.3 Introduction of Engineering Design Optimisation

The concept of design was born the first time an individual created an object to serve human needs. Today, design is still the ultimate expression of the art and science of engineering. From the early days of engineering, the goal has been to improve the design so as to satisfy the needs, within the available means. The design process can be described in many ways, however, the common denominator that certain elements in the process that any description must contain are: recognition of needs and a selection of alternatives. The selection of the “best” alternative is the phase of design optimisation (Chinyere, 2000). Optimisation is the act of obtaining the best result under given circumstances and desired requirements. In the design of any engineering system, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimisation can be defined as the process of finding the conditions that give the maximum or minimum value of a function (Deb, 2001). Optimisation search methods assist the designer at all stages of the design process. Today, there are a number of optimisation tools to support the design of a variety of products, including that requiring high structural integrity, such as the metal forming and rolling process. These tools will allow the designer to trade-off amongst contradictory product requirements to find the optimal design. Few examples of product design requirements include such elements as performance against cost, quality against durability, quality against quantity, production tool life against product output and/or combination of all. Over the years, the act of finding the optimal design has shown a substantial improvement in terms of reducing optimisation process time and cost, as well as accuracy. This is due to the availability of powerful computers, together with the advancement of artificial intelligence.

1.3.1 Classification of Engineering Design Optimisation Problems

Real world engineering design optimisation problems, such as roll cooling system design problems, can be seen as a problem of multiple characteristics, each characteristic with its own unique contribution to the problem. Chapter 2 describes classifications of design optimisation in terms of problem solving approaches. This

section discusses the classification which the problem is associated with. Classification allows engineers to understand design optimisation problems according to certain characteristics and problem solving philosophy, and facilitates organisation and reuse of knowledge in the design process. It also enhances the representation of knowledge and capturing of the reasoning schemes behind designs. Classification also helps engineers to compare different design methods and tools and come up with suggestions on how best to use computer aided systems in designs. Ullman (1995) proposed four classifications, namely structure of engineering design optimisation, problem focus, range of independence and level of support. Structure of engineering design optimisation itself consists of three sub classes, namely decision space, abstraction level and determinism, as well as preference model. The preference model in itself consists of an objective function. A classification of the engineering design optimisation problem is necessary and essential to select the right optimisation approach for the problem. Tiwari (2001) further categorized and proposed 10 classifications for engineering design optimisation problems. An enhanced version of the classification is summarised by Roy *et.al.* (2008) is presented in Table 1.3. The enhanced classification is developed based on five basic schemes and two viewpoints. The basic schemes are: design variables, constraints, objective functions, problem domains and the environment for the design. The two viewpoints used are design evaluation effort and the degrees of freedom of the design optimisation problem. The five major classification schemes and their categories are discussed as follows:

Design variable plays a major role in engineering design optimisation. The number of design variables, their natures, permissible values and mutual dependencies can affect the overall complexity of the optimisation task. Most of the real life or industrial design optimisation problems are likely to be multi-dimensional (Roy, 1997). In static or parameter optimisation problems, the design variables are independent of each other, whereas in trajectory or dynamic optimisation problems, the design variables are all continuous functions of some other variable(s). Another perspective of this classification is provided by Schütz and Schwefel (2000), based on time-dependence of the optimisation problems. Depending on the values permitted for design variables, the engineering design optimisation problems can be categorised as integer-valued, real-valued and mixed-integer (that involve both integer and real variables). Variable dependence occurs when the variables are functions of each other. It is often observed

that there are variable dependencies among real life design problems. This has an effect of constraining the search space (Oduguwa *et.al.*, 2007).

Existence of constraints in an engineering design optimisation problem affects the optimisation approach to be used. The constraints can be in-equality and equality types. They can also be linear or nonlinear in nature. A mixed-integer programming (MIP) problem is one where some of the design variables are constrained to have only integer values (i.e. whole numbers such as -1, 0, 1, 2, etc.) at the optimal solution. Constraint programming defines "higher-level" constraints that apply to integer variables. The most common and useful higher-level constraint is the all-different constraint, which applies to a set of variables, say x_1 , x_2 , x_3 , x_4 and x_5 . This constraint assumes that the variables can have only a finite number of possible values (say 1 through 5), and specifies that the variables must be all different at the optimal solution, therefore it can be either 5, 4, 3, 2, 1 or 1, 2, 3, 4, 5. Travelling salesman is an example of the constraint programming type optimisation problem. The presence and types of constraints make optimisation much more difficult. Number of constraints, constraint development and evaluation time are factors that affects the optimisation significantly (Coello, 2002 and Landa *et.al.*, 2006).

Objective functions are used to evaluate a design solution within the optimisation context. Number of objective functions, their nature and whether they are separable determines the complexity of the optimisation task. In real life, most of the optimisation problems are multi-objective. The multi-objective optimisation becomes more challenging with more than 10 objectives for a problem (Corne, 2007). Quantitative objective functions can be further classified as simulation based (e.g. FEA, CFD) (Zaeh *et.al.*, 2004). Analytical (e.g. mathematical models created from the first principle and with domain knowledge) (Roy *et.al.*, 2003) and empirical (where models are created based on experimental data) (Roy, 1997). One of the major challenges in engineering design optimisation is to deal with computationally expensive objective functions. Typically, simulation based model stake a long time to evaluate. The nature of search space also classifies the engineering design optimisation problems as uni-modal and multimodal, based on the number of optimal solutions that the problem has. The multimodal problems can also be categorised as sensitive and robust. A multimodal problem is sensitive if it has mostly very sensitive optima, whereas a robust problem would have at least one robust optimum. The nature of the search space can also be classified as linear, nonlinear, geometric and quadratic,

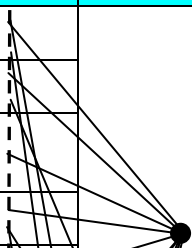
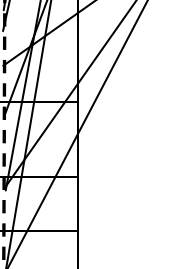
based on the nature of underlying equations in the objective function. Based on this criterion, the engineering design optimisation problems can also be classified as continuous and discontinuous, depending on whether the equations involved in the problem have any discontinuities. A function is said to be separable if it can be decomposed into functions that involve groups of variables rather than just a single variable. Inseparability manifests itself as cross-product terms, and makes the effect of a variable on the function dependent on the values of other variables in the function.

Problem domain brings different physics consideration within the optimisation. Multiple domains require a multi-disciplinary approach to the optimisation. Establishing interdependence between the domains for real life design problems and optimising them simultaneously, such as roll thermal process design, requires significant effort and makes the optimisation more complex than single domain optimisation.

The optimisation environment involves considerations like uncertainties in the design, level of knowledge available about the design solutions, importance of designer involvement and finally the nature of the environment. Lately, there is significant interest in design optimisation with uncertainties (Yong *et al.*, 2007). The uncertainties can be associated with the design variable definition, as well as in the model development (Beyer and Sendhoff, 2007). Knowledge about the design environment is often lacking for real life problems such as rolling and roll cooling system design. Only in the case of test examples, the nature of the design space and the location of the optimum are often known. Not knowing about the design space and the location makes the optimisation task more challenging. Some design tasks require designer involvement to improve their confidence and also to involve them in qualitative design evaluation; this is called interactive optimisation (Brintrup *et.al.*, 2007). The involvement increases the degrees of freedom of the optimisation due to non-uniform behaviour of human experts, and also involves significant effort from the expert designer. Finally, the nature of the environment could be static or dynamic. The dynamic environment will impact the design variables, as well as the design evaluation. If it is dynamic, the optimisation would require more effort and would involve more degrees of freedom than a static environment. The design evaluation effort viewpoint includes aspects such as computational effort required to evaluate a design model, including any constraints and the effort required to develop a model due to the nature of the objective functions, design variables and constraints

(complexity of the problem). Whereas, degree of freedom of an engineering design optimisation problem includes the number and types of design variables, constraints, objective functions, problem domains, and environmental factors like uncertainty and dynamicity. As presented in Roy *et.al.* (2008) there are two categories of design evaluation efforts. These are: inexpensive and expensive, and another two categories for the degrees of freedom: small and large. Based on these two view points, engineering design optimisation problems are classified as small-scale problem, expert dependent, algorithm dependent and large-scale problem (Koch *et al.*, 1999). Table 1.3 presents the summary of classification of engineering design problems and complexities. The classification is an important step in understanding the research design problem complexity. Table 1.3 presents the characteristics in which real life engineering design optimisation can be classified. As presented in the research scope, this research is based on the real life case study of a process design in an engineering domain where the classification introduced in the section, such as design variability, estimation of constraints, multi-objectivity, as well as consideration of optimisation environment in the design, is directly related to the research problem. Consideration of the optimisation environment, such as uncertainty in the process, believed to have significant impact to the roll thermal design, is the main part of the research. Uncertainty is associated with the design variable definition, as well as in the model development. Therefore, the design optimisation classifications presented in the section, are directly related to the research problem under investigation.

Table 1.3. Summary of the classification and classification complexities
(Roy *et.al.*, 2008).

Classification Schemes Based on		Categories	Engineering Design Optimisation Problem Classification based on two view points
Design variables	Number of Variables	<ul style="list-style-type: none"> Single-dimensional Multi-dimensional 	
	Nature of Design Variables	<ul style="list-style-type: none"> Static Dynamic 	
	Permissible Values of Design Variables	<ul style="list-style-type: none"> Integer-valued Real-valued Hybrid 	
	Dependence among Design Variables	<ul style="list-style-type: none"> Independent-variable Dependent-variable 	
Constraints	Existence of Constraints	<ul style="list-style-type: none"> Constrained <ul style="list-style-type: none"> In-equality Equality Linear Non linear Separable inseparable Unconstrained 	Design Evaluation Effort - Inexpensive
Objective functions	Number of Objective Functions	<ul style="list-style-type: none"> Single-objective Multi-objective <ul style="list-style-type: none"> ≤ 10 objectives Large scale Multi-objective (> 10 objectives) 	Design Evaluation Effort - Expensive
	Nature of Objective Functions	<ul style="list-style-type: none"> Quantitative <ul style="list-style-type: none"> Simulation based Analytical <ul style="list-style-type: none"> Linear non-linear Empirical 	Degree of Freedom - Small
		<ul style="list-style-type: none"> Qualitative Hybrid 	
		<ul style="list-style-type: none"> In-expensive Computationally Expensive 	
		<ul style="list-style-type: none"> Uni-modal Multimodal 	
		<ul style="list-style-type: none"> Linear Non-linear Geometric Quadratic 	
		<ul style="list-style-type: none"> Continuous Discontinuous 	
	Separability of Objective Functions (for Quantitative and Hybrid Problems)	<ul style="list-style-type: none"> Separable Inseparable 	Degree of Freedom - Large
Problem Domain	Physics of problem	<ul style="list-style-type: none"> Mechanics Thermo fluids Electromagnetic Multi-physics 	
Environment	Uncertain	<ul style="list-style-type: none"> Without uncertainty Uncertain Robust Reliability based 	
	Existing knowledge about the problem	<ul style="list-style-type: none"> Known Search Space Unknown Search Space 	
	Designer confidence required	<ul style="list-style-type: none"> Interactive Qualitative 	
	Nature of the environment	<ul style="list-style-type: none"> Static Dynamic 	

1.3.2 Engineering Design Optimisation in presence of Uncertainty

The challenge in achieving “the best” result in engineering design optimisation is the presence of uncertainty. Uncertainty information such as design tolerance, significantly impacts the success of the design process. Such uncertainty and its presence is certain and unavoidable, and if not considered in the optimisation of the design, the obtained solution is likely to be more “high risk” than optimal. In real life, engineering designs also have to satisfy constraints and select the best design solution against multiple objectives. Literature review conducted in the subject area, shows that there is a lack of research in multi-objective design optimisation that addresses uncertainties and the constraints together. The challenge in uncertainty may not be their presence only, but also the difficulties in quantifying them, as well as introducing the uncertainty representations in the optimisation (Helton, 1997; Apostolakis, 1994; Trucano, 1998 and Hazelrigg, 1999). Based on the visibility or clarity of uncertainty in the design and the degree of complexity in dealing with it, uncertainty in engineering design can be categorised broadly in to four classes. These are known-known, known-unknown, unknown-known and unknown-unknown type. The underlined part represents the visibility of the uncertainty, and the other for the complexity in dealing with or quantifying the uncertainty. A brief description and examples of each classification are given as follows:

Known-known refers to the type of uncertainty in design that has clarity and is relatively easier to quantify and introduce in the optimisation. Noise and variability could be considered as an example for known-known type uncertainty. Known-known uncertainty also can be manageable to deal with using appropriate means. Known-unknown type is the uncertainties in design that have clarity in their presence, but it is complex or not known as to how to represent and quantify them. An example of known-unknown type uncertainty would be epistemic uncertainty in non-deterministic systems, which arises due to ignorance, lack of knowledge or incomplete information. Unknown-known is the type of uncertainties in design that one knows well how to represent and quantify the uncertainty, but it may be too complex or their presence not known. An example of the type unknown-known uncertainty would be error, also known as numerical uncertainty. Error, although one may not say the degree of the error but its presence, can be addressed by introducing robustness in the design so that a solution can be found that overcomes error or variation. Unknown-unknown type is

the type of uncertainty where it is complex to realize its presence, and also one may not have a clear idea how to represent or address it. Uncertainty in design can be from various sources. For example, uncertainty can be inherited from the design factors and passed to the model, from model structure and model error, such as approximation and tool selection. Design uncertainty is comprised of *design* imprecision, uncertainty in choosing among alternatives, and stochastic uncertainty, usually associated to measurement limitations. Stochastic uncertainty arises from a lack of exact knowledge of a parameter in the process where the designer has no direct control or choice over (Agarwal *et al.*, 2004; Jin *et al.*, 2003; Stephen; *et al.*, 2000 and Michele *et al.*, 2002). This summarises the inevitability of uncertainty in design variables and variables parameters. If a reliable optimal solution is to be found, this inevitability must be considered in the optimisation. Prior to optimisation, therefore, it is vital to know the types of uncertainty encountered how to compute under this uncertainty, and the way to represent their presence, mathematically. Broadly speaking, there are several general sources that contribute to the uncertainties in design optimisation. These contributors can be categorized as follows:

- Variability of input values x (including both design parameters and design variables), called “input parameter uncertainty”
- Uncertainty due to limited information in estimating the characteristics of model parameters p , called “model parameter uncertainty” and
- Uncertainty in the model structure $F(x)$, including uncertainty in the validity of the assumptions underlying the model, called “model structure uncertainty”.

Over the years, a number of techniques have been developed to deal with uncertainties in the engineering design. The first and most important step in that is the quantification or recognition of their presence. The goal of uncertainty quantification is to assign an appropriate mathematical meaning to real-world information with respect to objective, and make it available to be used in the decision making. The quantification procedure is a combination of established methods from mathematical statistics for specifying the random part of the uncertainty. The choice of an appropriate uncertainty model primarily depends on the characteristics of the available information. That is, the underlying reality with the sources of the uncertainty dictates the model. Information can be, for example, objective, subjective, incomplete, imprecise, fluctuating, data-based, or expert-specified (Oakley *et al.*,

1998). In each particular case, this information must be analysed and classified before quantification.

1.3.3 Design Optimisation in the presence of Constraints

The problem of handling constrained problems in design optimisation has been studied and presented many times in the literature. Many of the proposed methods are evolutionary computing based, some are general and applicable to a wide range of optimisation techniques, and some are designed for use with specific optimisation algorithms. Cello (2002) gives the survey of constraint-handling methods. The survey highlighted the most popular technique such as penalty functions, decoders repair algorithms, and constraint preserving algorithms. In addition to the three categories, there are also number of methods, such as multi-objective optimisation, since constraint satisfaction and multi-objective optimisation are very much two aspects of the same problem. Real life engineering problems such as rod rolling thermal analysis and optimisation are often constrained by various restrictions, usually imposed in the decision variables. It is also true that sometimes constraints are imposed in the objectives space in the form of fitness functions - for example, to limit the allowable stress and temperature to the level the material can handle. Constraints usually fall in to two major categories; the two main categories are also classified in to two main types. Problems can be associated to one, few or all types of these constraint types: the two constraint types are:

- Domain constraints - Referring to the definition of the domain of the objective function and
- Preference constraints - Referring to the additional preference imposed in the optimisation solution.

Constraints in design optimisation can be categorised as equality or inequality constraints. The forms can be expressed in $f(x) = g$, $f(x) \leq g$ respectively, where $f(x)$ is the fitness and g is the constraints.

1.4 Summary of Research Initiative

Work roll system thermal analysis and optimisation is a critical concern in the rolling system design, particularly in the operation of hot mills. Untimely loss of rolls is a common occurrence during the hot rolling process. Main sources of these phenomena are the severe temperature variations and the resulting thermal stresses experienced by

the roll during the rolling process. To control roll thermal stresses and roll life, it is necessary to know the temperature variations in the work-roll during the hot rolling process. Work rolls are one of the main contributors of the overall production cost in product rolling. Hence, the need for a mechanism to minimise this cost is important. Real life rolling is a heavy duty manufacturing process and takes place in a high disturbance, extremely hot environment, and is characterised by uncertainty and constraint. Most of the roll deterioration is a direct consequence of these process behaviours. Therefore, establishing an optimum work roll system design in the process is vital. In today's competitive environment, achieving that is only possible through a more scientific and robust approach than the traditional/conventional means, although skilled experts, relying on their many years experience, have been trying to come up with practical solutions, mainly by trial and error, but such solutions acquired only offer satisfying solutions. The approach is not capable of delivering multiple optimal solutions for this complex engineering design problems, and is costly and time consuming. The key features such as multiple objectives, multiple pass search capabilities in the presence of uncertainty and constraints, are required within a robust optimiser for obtaining optimal work roll system design solutions. This can be a solution for the challenges experienced by the traditional search methods. However, it is not well understood and defined how these features can be addressed. This represents a significant gap in the use of optimisation techniques for obtaining an optimal work roll system designs using thermal analysis and algorithm based technique. The research is to develop work roll system optimisation using thermal analysis and GA and by doing so, the key features presented above can be alleviated. To help understand the flow of information and fulfil the research objectives, the thesis structure presented in Figure 1.8 has been developed and used.

1.5 Thesis Structure

The thesis structure is the description of the thesis layout that gives an overview of the thesis framework. The thesis structure, shown in Figure 1.8, is designed to demonstrate the fundamental path of the research, from hypothesis/introduction up to the thesis findings, validations and conclusions. The description of the thesis structure is illustrated as follows:

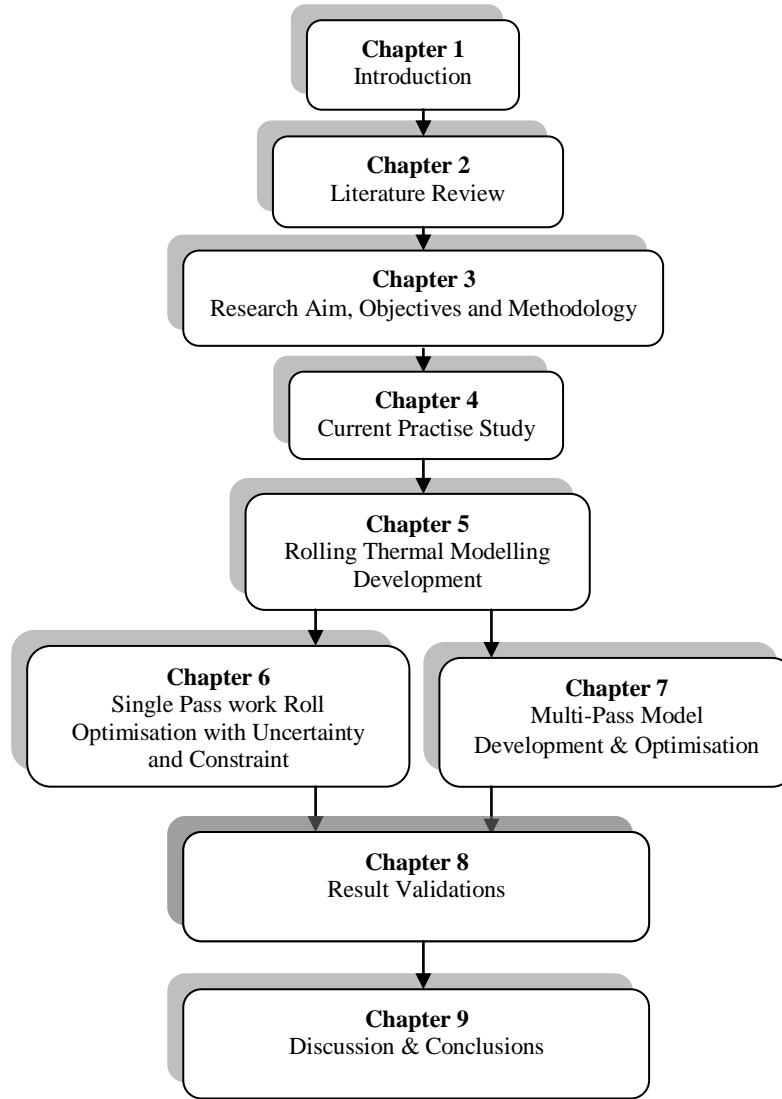


Figure 1.8. Thesis structure

Chapter 1. **Introduction:** Introduces the main issues of the research, the company, and highlights the hypothesis that leads to the research findings and contributions. Intuitively discusses the industrial problems of rolling system design and the cooling system, as well as the aim and objectives of the study.

Chapter 2. **Literature Review:** Provides a detailed review of literature in the main domain area of the research subject and associated topics of the research. The main topics include, but are not limited to, areas such as engineering design optimisation, roll cooling system design, optimisation under uncertainty and constraints, rolling system design, evolutionary based single and multi objective optimisation techniques. The review also identifies and addresses limitations in the current techniques and methods used in the roll cooling optimisation.

Chapter 3. **Research Aim, Objectives and Methodology:** The chapter identifies the research objectives necessary to satisfy the research aim. The nature of the real world problem is discussed, with the features of the work roll system design and optimum using thermal analysis and Genetic algorithms, guided by the aim and objectives. Finally, the chapter discusses the methodology that has guided the main activities of this research to fulfil the objectives.

Chapter 4. **Current Practise Study:** In order to understand the philosophy of work roll system thermal optimisation within rolling system design activities, the research developed an AS-IS process realization study with the sponsoring company. The study was based on eliciting rolling system process knowledge from suitable engineers identified from Corus Research, Development & Technology design and the rolling plant. The methodology adopted for the knowledge elicitation exercise is described in Chapter 4. The elicitation also extended to other engineering industries to include current activities the in engineering design optimisation and techniques in industries. This leads to the development of the optimisation technique compatible to the research problem. The knowledge elicitation exercise from the sponsoring company was applied to map the process involved in the rod-roll system optimisation selected by the client organisation for investigation. The collaborative activities with the engineers contributed towards identifying likely areas of the research problem.

Chapter 5. **Work Roll Thermal Modelling Development:** This chapter presents a framework for generating a quantitative model from finite element data. The chapter provides detailed procedures followed in the real life problem simulations, model building and description of the implementation of the framework. The chapter also provides analysis and validation of the models.

Chapter 6. **Single Pass Roll Cooling Design Optimisation with Uncertainty:** Here is presented a multi-objective optimisation approach to address the work roll system thermal analysis and optimisation problems with presence of uncertainty and constraints. This chapter begins by describing the challenges in the work roll system thermal analysis and optimisation problems with presence uncertainty and constraints; it then presents detailed description of the optimisation frameworks. Several work roll system thermal analysis and optimisation problem models developed, and a case study is provided to illustrate and validate the solution and solution methodology.

Chapter 7. **Multi-Pass Model Development & Optimisation:** This chapter presents a multi-objective optimisation framework for multi-pass optimisation problems capable of handling high dimensional problems with uncertainty. The chapter also presents details of the procedure for the development of multi-pass work roll system analysis and optimisation problem models.

Chapter 8. **Validation of Results:** The chapter presents the strategy followed for the validation of results. The validation is based on expert knowledge and experience. Questionnaires are developed to ask experts to comment on the result obtained and its relevance to the research real life case study problem. Questionnaires and scripts from expert feedbacks are presented in the chapter.

Chapter 9. **Discussion and Conclusions:** This chapter concludes the thesis with a discussion of the applicability of the research, contribution to knowledge and limitations of the research with respect to the proposed optimisation frameworks and process models. Finally, the future research directions that would extend the work reported in the thesis are presented.

1.6 Chapter Summary

This chapter introduced the research scope, the industrial problem domain and provided an overview of the company business strategies, as well as the core business unit associated to the research project. The chapter also introduced the main topics relevant to the project, the rolling process cooling system design optimisation, and highlighted the hypothesis that leads to the proposed research investigation. The chapter concluded by presenting the aim and the structure of the thesis. The next chapter presents the review of literature in the research domain.

2. Literature Review

Having optimal work roll thermal design in the rolling process have a significant importance in ensuring increased work roll life, eliminating unnecessary time required to replace rolls and overall rolling cost. Today motivated by the need to deliver a high quality design solution at low cost, by effectively utilizing the available resources, industries are increasingly shifting to scientific approaches over the traditional approaches. Several algorithmic optimisation approaches are emerging to deal with the complex search space properties of real world process optimisation problems such as work roll system optimisation. The inevitability of uncertainties and constraints in the real life engineering problems, which have a significant impact in achieving a best set of process design parameters, makes the complexity even greater. As part of the exploration of the fundamental issues of the research problems, work roll system optimisation using thermal analysis and genetic algorithms, the research conducted extensive literature reviews. The review is designed to understand evidently the current state of work roll thermal design and optimisation, the research gaps and the techniques and methods available to fill the gaps. In brief, the review aimed to achieve the followings:

- Explore and Identify fundamental features (factors and factor parameters) of metal forming and the rolling system design.
- Understand existing practice in the roll cooling design optimisation, identify uncertainty and cause of uncertainty, and explore existing techniques and methods available for roll cooling design problems providing the design solution.
- Review current state of engineering design optimisation and multi objective optimisation in research.

The review chapter is organised as follows:

The chapter begins with section 2.1, which explores features and complexities of work roll system optimisation using thermal analysis and GA. Section 2.2 reviews existing works and research gaps in work roll system optimisation using thermal analysis and GA. Section 2.3 explores uncertainty in the work roll system design, optimisation and thermal analysis problems. Section 2.4 presents modelling

approaches for work roll system design using thermal Analysis and GA. Section 2.5 reviews engineering design optimisation approaches. Section 2.6 presents design optimisation approaches: A comparative overview of technique's development in the last decade. Section 2.7 discusses design problems representation in computing based design optimisations. Section 2.8 reviews multi-objective design optimisation. Section 2.9 explores uncertainty in multi-objective design optimisation problems. Section 2.10 identifies the research gap and Section 2.11 concludes the chapter with a summary of the main points.

2.1 Features of the Work Roll System Optimisation using Thermal Analysis and Genetic Algorithms (GA)

This section explores the features of the work roll system optimisation using thermal analysis and GA as well as system complexity. The section also gives the relationship among features identified, and the challenges posed to the optimisation. Work roll thermal analysis and optimisation can be formulated as a process optimisation problem. Due to the fundamental nature of the rolling and load involved in the process, the problems can be identified as mechanical, thermal, and thermo mechanical in nature. Like most real-world process optimisation problems, it is also prone to uncertainty. Sections 2.2 explore some of the main rolling system features that influence the work roll system optimisation using thermal analysis. Feature of the rolling process, temperature variation on the roll, type and degree of roll wear, are a direct result of the normal pressure on the roll surface and friction. Average rolls rolling pressures can be considered to be in the range of 100-300 MPa. The corresponding cyclic stresses, amplified by thermal cycles, in roll surfaces are estimated to amount to 500 MPa (Kihara *et al.*, 1983; Kuhn and Weinstein, 1970). Cyclic loads result in material fatigue and other forms of surface deterioration, unless regulated using, for example, a cooling system. However, application of coolant in these extremely hot conditions will have a potential to cause the roll to go through various behaviours - for instance, excessive thermal, mechanical and thermo-mechanical changes. Improper cooling, such as under cooling, would lead to compressive stress on the roll, resulting in subsequent roll surface deformation, whereas over cooling, on the other hand, results in tensile stress and roll thermal shock when coming in contact with hot stock. Over cooling also triggers unexpected

thick oxide scale on stocks, where, above a critical thickness, the upper layer of the oxide scale breaks by thermal and mechanical fatigue, and spalls under the shearing. The repetition of this damage requires the machining of the roll after a certain running in the mill, and contributes to the reduction of the roll lifetime. Besides this, however, the coefficient of friction generated between the work rolls and the rolled product usually tends to decrease with the increase in thickness of the oxide scale on the rolls. This decrease in friction results in a reduction in the rolling force and, therefore, the torque applied to the rolls, which, in turn, saves energy. To some extent, the oxide scale also could limit the amount of heat transferred in to the rolls. In this way, the creation of an oxide scale on the roll has a direct impact on the operating cost of a hot mill, by reducing the damage on the rolls. Research confirms that the irregularity of this type is significantly decreased by optimally measured cooling regimes. Under normal circumstances, the aim of cooling is to keep the temperature in the roll in a balanced condition, i.e. heat entering the roll is expected to be balanced by heat exiting the roll (Devadas and Samarasekara, 1986). In real life engineering design, such as rolling, however, it is a challenge to achieve this phenomenon. This challenge is multiplied by the high dimensionality, non-linearity and high uncertainty. Heat may enter the work roll to raise its temperature above ambient as a result of flows coming from many sources, such as radiation from the work piece entering and leaving the roll bites, by conduction from the work piece through a layer of oxide, by frictional effects along the arc of contact in the roll bite and from other sources such as friction in the roll-neck bearings and rolling friction at the work roll/backup roll contact. During the rolling process, the large amount of heat generated in the roll bite transfers to work rolls (Tercelj *et al.*, 2003; Komori and Suzuki, 2005, Komori, 1999 and Arif *et al.*, 2004). Work rolls are cooled by a cooling medium in both entry and exit sides of the mill. Transient cooling behaviour of the roll affects temperature distribution and thermal profile. Review shows that apart from thermal profile, roll life is influenced by other issues. Troeder (1985) in his work presented the justification that rolls are subjected to stress fluctuations, thermal cycles, contact abrasion, and other chemical influences. Since the early 40's, the basic wear mechanism has been investigated by many qualitative studies. These also proved that there are independent quantitative factors present in the rolling process. These factors, such as scale size, spray nozzle temperature, and coolant pressure (part of cooling heat transfer coefficient), which

may be difficult to quantify, but need to be considered when searching for cooling regime that guarantees a longer roll life.

This section has shown the importance of the following rolling characteristics roll life determining factors:

- Rolls are subjected to stress fluctuations, thermal cycles, contact abrasion, and other chemical influences.
- Under normal circumstances, heat entering the roll is expected to be balanced by heat exiting the roll. In real life process however, it is a challenge to achieve this phenomenon. This challenge is multiplied by the high dimensionality, non-linearity, and uncertainty in the process.
- Work roll thermal analysis and optimisation can be formulated as a process optimisation problem. Due to the fundamental nature of the rolling and load involved in the process, the problems can be identified as mechanical, thermal, and thermo mechanical in nature.

2.2 Existing Works and Research Gaps in Work Roll System Optimisation using Thermal Analysis and GA

As shown in Section 2.1, over the years, a number of studies have been conducted and very visible developments have been recorded in improving the rolling process in general, and tooling behaviour in particular; however, very little attention has been given to the work roll thermal system analysis and optimisation in hot rolling. Cooling of rolls is a critical concern in the rolling system design - particularly in the operation of hot mills. In the absence of water cooling, roll crack and untimely loss of rolls is a common occurrence. Main sources of these phenomena are the severe temperature variations and the resulting thermal stresses occurring as a result of work-rolls and hot stock contact (Parke and Baker, 1972). To control roll thermal behaviour, and hence, roll life, it is important to understand the temperature variations and source of variation in the work-roll during the process. There are a number of published studies on temperature field in the work-roll, and how it affects the roll life during hot rolling. Parke and Baker (1972) applied a computational method for determining the temperature field in the finishing pass work-roll. The results from their model were then used to design the optimum water spray condition. A two-dimensional finite element method was used by Sluzalec (1984) to predict the temperature distribution

within the work-rolls in a roll forging process. Devadas and Samarasekara (1986) used a one-dimensional heat transfer model that was based on the finite difference method. The model was coupled with the assumption of homogenous work to estimate the steady state temperature distributions in the work-rolls and the rolled metal during the finishing stage. Teseng *et al.* (1990) and Teseng (1999) combined experimental and numerical methods to predict temperature distributions in work-rolls, In another research work, Teseng (1991) used an analytical method to solve the heat transfer using partial differential equations, and thus determine the temperature field in a work-roll for a single pass hot strip rolling process. The cooling of both the work-rolls and the product was simulated with the aid of a mathematical model, and the results are presented in Teseng *et.al.* (1992). In that paper, the temperature fields in the work-roll and the rolled metal are predicted and the effects of various cooling conditions on roll temperature variations are determined. Serajzadeh and Mucciardi (2003) coupled the unsteady state heat transfer equations with time dependent boundary conditions with a two-dimensional finite element method to predict the work-roll temperature distribution during the continuous hot slab rolling process. In all of these research works, however, the result shows only single pass work-roll temperature transfer prediction and estimates, how it affects the work roll life. Moreover, most of these works are focused on theoretical single objective problems, and have little or no assessments of uncertainty of the forming process and the potential effect it has on work rolls. The major gaps in the existing research work are summarised as follows:

- Main sources of roll damage are the severe temperature variations and the resulting thermal stresses occurring as a result of work-rolls and hot stock contact. To control roll thermal behaviour, it is important to understand the temperature variations and source of variation in the work-roll.
- Lack of exploring and documenting the uncertainty and source of uncertainties in the rolling process that have a potential impact on rolls' thermal behaviour.
- The investigation lack in addressing real life high dimensional multi-pass roll cooling system design problems with uncertainty and constraints.
- Genetic algorithm based technique is not fully explored to include process parameter optimisation of multi-pass, multi-objective work roll system thermal analysis and optimisation problems.

2.3 Uncertainty in the Work Roll System Design, Optimisation and Thermal Analysis Problem

Uncertainty is inevitable in some form in any engineering systems. The existence of uncertainties has a big impact on the system performance - if their existence not taken in to consideration and dealt with, the quality and reliability of the system will be compromised. Uncertainty may arise from various sources. The sources can be classified in to three main categories: variability in the input variables, uncertainty due to the limited information in estimating the characteristics of model design parameters, as well as known as parameter uncertainty and model uncertainty (Wood, 1989). In the latter, the uncertainty can arise from two scenarios: either due to the scientific and technical assumption adopted for developing the model or due to the fact that simulation is an approximation of a real life process where forced accuracy compromises are inevitable. Over the years, various approaches have been developed and tested to deal with uncertainty in engineering systems, for example the min-max approach for searching robust solution, making design or the system least sensitive to the uncertainty without eliminating the sources of uncertainty (Ong, 2004). The Maximum-Minimum (Max-Min) interval approach of variables is used to obtain the complete probabilistic information of the final output in term of distributions of the uncertainty. Sampling techniques such as Monte Carlo simulation is mostly used for sampling out of the distribution so that a fairly close sample can be selected. But the technique is very expensive. Other sampling techniques include improved Monte Carlo simulation, reliability based method and design of experiments. Although these techniques have reduced sampling techniques, they can still require a large amount of samples for complex problems (Chen *et.al.*, 2004). The work roll system optimisation using thermal analysis and GA with presence of uncertainty is a complex engineering system, with a large number of uncertain variables involved, and is a multi objective, multi-stage and multi disciplinary system. Uncertainty due to design parameter variability and real life approximation, are the most common problems, hence those techniques discussed above have shortcomings to address it. Small variability in design variables could have a big impact on finding an accurate design solution. In practice, the properties of a solution may be subject to a certain amount of variation because its implementation cannot be realized with arbitrary precision. This can occur due to various reasons, such as precision tolerances. If instances of a certain solution

are considered in the design, which have slightly differing decision variable values, and then these instances are evaluated, the corresponding objective vectors might differ widely, even though the variation in the decision space is not huge. In this case, it can be said that the solution is sensitive to the variation in design variables. Today, there are various methods to address sensitivity in design. The most familiar method is robustness. A robust solution satisfies the following: 1) selecting proper design variables such that the objective functions is not sensitive to tolerance, i.e. objective robustness; 2) assuring that the design variables are able to satisfy the constraints under the existence of tolerance, i.e. feasibility robustness (Du and Chen, 2000). In this study context, therefore, a robust design solution is defined as: a feasible design alternative that is optimum in its objectives and whose objective performance or feasibility (or both) is insensitive to the parameter variations. However, finding the design solutions that are insensitive to parameter variation requires careful decision making procedures in the following two important issues: 1) the selection of an appropriate robust measure and 2) an appropriate means of incorporating the selected measure or defining robustness in the context of the problem at hand (Du and Chen, 2000). There are various measuring techniques in the literature that can be used generically in many engineering problems. Two major approaches in finding robust design are stochastic and deterministic approaches. Stochastic approaches use probability information of uncertainty parameters. These approaches are commonly used in the objective robust optimisation to deal with design variables variation, while feasibility robust optimisation is used to improve reliability and a trade-off, based on an evolutionary approach, between performance and robustness using variance information. Although there are a number of studies have been conducted to address the engineering design optimisation problems with uncertainty discussed here, not many literatures found for work roll system optimisation using thermal analysis in presence of uncertainty. The existing few are focused only on uncertainty analysis for the single objectives rolling process design problem.

2.4 Modelling Approaches for Work Roll System Design using Thermal Analysis

A rolling system is a heavy duty manufacturing process, taking place in high disturbance and extremely hot environments. Since any live experimental research for improving the process, tools, and product in an engineering process of such nature is

unrealistic, a need for modelling the process in a less costly and easy to use form is essential. The modelling, although it is an approximation of the real life scenarios, is the best way of representing the engineering process with such complexity. Literature shows that there are many form of modelling techniques used often in the modelling of complex engineering processes such as the rolling system. Even though each modelling technique has its own advantages and shortcomings, depending on the type of process to be modelled, all are proved useful. Among them, however, due to its simplicity, less cost and ease of use, the Finite Element Analysis (FEA) is the most popular and widely used form of modelling. There are various types of FEA, where each type is uniquely selected depending on the type of problems and cost of modelling involved. Details of various types of FEA techniques application is discussed in the next sub section.

2.4.1 Finite Element (FE) Methods

The FE method is based on the idea of discretisation where the deformation zone is divided into a finite number of sub-zones called elements. The elements are connected together at the corners and at selected points at the edges called nodes. For each element, the individual relationship between the applied nodal forces and the resulting nodal variables are calculated and the element property obtained. These important properties made it possible for response variables to be realistically realized. The finite element method is a numerical analysis technique for obtaining approximate solutions to a wide variety of engineering problems. Although originally developed to study stresses in complex airframe structures, it has since been extended and applied to the broad field of problems in other areas. Because of its diversity and flexibility as an analysis tool, it is receiving much attention in engineering research and in industry. The first finite element analysis came in the late 1960s and early 1970s, with the so-called elasto-plastic method (Huang and Leu, 1995; Xing and Makinouchi, 2002). During the 1970s and 1980s, FEA progressed extensively. The metal forming industries' worldwide views in the late 1970s and early 1980s, were considerably different than the current ones in the areas of analytical capabilities, process control and application of technology (Tang *et al.*, 1994). In 1978, the first FEM software and also the first FEM program, called ALPID Analysis of Large Plastic Incremental Deformation were created. In the years between 1980 and 1990, the use of computers in industries increased considerably. Computers became cheaper, faster and available.

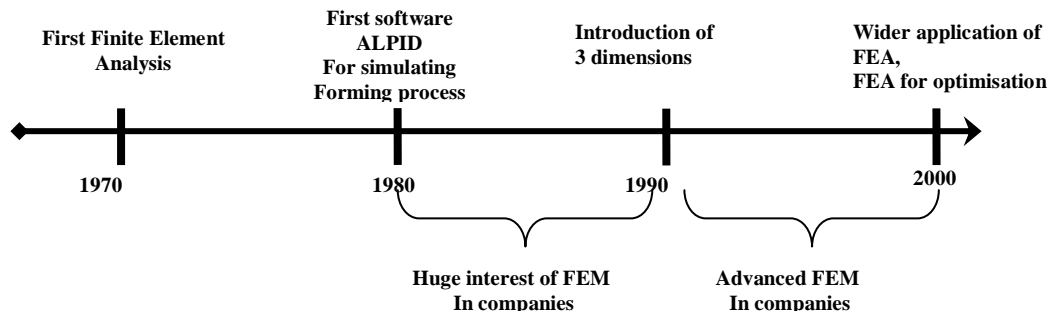


Figure 2.1. FEA in metal forming process (Tang *et al.*, 2004)

More and more companies were able to obtain one. Although several software applications were born during the 1980s, many of them were not fully utilised until 1990. The problems solved were only 2-dimensional problems. After 1990, analysis of 3-D problems began to emerge. Nowadays, the availability and capacity of software and computers makes it easier for companies to deal with problems more adequately. However, even if FEM is a very efficient technique to analyse the roll temperature distribution, there are still some drawbacks (Aretz *et.al.*, 2000). The characteristic of FEM is the mesh, but when this one becomes distorted, the FEM presents some limitations. Another kind of drawback would be the computation time. Because of the huge amount of calculations and depending on the problem, analysis can take several days. For example, during the preliminary stages, a response time of less than one hour is required, whereas for the main design stage of a complex problem, over-night would be tolerated. Nowadays, however, industries expect more from FEM code, due to research made in the field makes usage of the codes much simpler and faster. It also fulfils the desire that the thermal modelling techniques become more and more accurate. Moreover, it enhances the speed of the computational time required for the software to do the job. Today, there are various FEA methods and software to choose from, depending on the type of problems and systems of equations, such as linear or non linear and/or symmetric or non symmetric. The most common FEA techniques used today and survey of the various techniques, each with advantages and drawbacks are presented next.

Direct method

These methods are used only for systems with a reasonable size, because the calculation time is proportional to the cubic of unknown. Direct search methods are a nonlinear method that requires neither explicitly nor approximate derivatives for the

problem to be solved. Instead, at each iteration a set of trial points is generated and their function values are compared with the best solution previously obtained (Huang, 2006). This information is then used to determine the next set of trial points. Due to its computational time, the method is only taken as a last resource to be used in the modelling and optimisation.

Incremental method

The incremental method, which is used in the final design stage to verify the feasibility, needs detailed design parameters, and enormous time and cost is required to perform the numerical trial-and-error (Yang *et.al.*, 1950). This method is used for large size systems where the calculation time would be huge for a direct method. It is a compromise between an exact solution and calculation cost. Therefore, for these methods, there is another parameter to take into account: Time. Explicit and Implicit methods are two different classes of method which deal with the time. The difference between the two methods is the way to calculate the derivation. For the explicit method, the calculation is simple, but the solution is less stable than for the implicit method. But for the implicit method, the calculation needs an iterative method, which means that the calculation time is very high (Chen *et.al.*, 1998). The implicit method employs a more reliable and rigorous scheme in considering the equilibrium at each step of deformation. The implicit method appears more efficient for 2D analysis than the explicit method.

Inverse method

The principle of the inverse method is simple. As Castro *et.al.* (2004) indicated in their paper, the inverse method uses, as entry parameters, the specifications of the final product, and then it determines the design parameters that produce the required final product. That means that the method searches the initial parameters for the tool and the material (Sousa *et.al.*, 2006). This method is quite recent. The main drawback of this method is the accuracy of the result, which is quite low in certain cases. However, different advantages exist, which are explained by Yang and Nezu (1998). One of them is that the geometric definitions of the tools and the initial blank are not necessary, so the FEA model is easier to build. This method is often used at the very first stage of the design process to evaluate the feasibility of the concept.

Rigid-plastic flow method

The formulation of this method and its implementation is very simple (Makinouchi, 1996). Another advantage is its computational time. This method is faster than explicit method (Samuel, 2004). Even though this method is often used for metal forming; its application is not universal - i.e. some analyses are not applicable to it.

Static implicit method

This method is the first method used in simulation of the metal forming process. The static-implicit method, based on the equilibrium at each step of deformation, brings the most accurate result. For this reason, this method is the more used to solve 2D problems. The static-implicit method is difficult to apply to complex shapes, severe contact problems, and large and difficult convergence problems, because of the computation time to obtain a solution taking so long (Jung, 2002). For 3D analysis, it is not the most useful method. This method is often used for the analyses of the final stage of design, where accurate results are expected.

Static explicit method

The static explicit method was introduced and limited to solve the problem of the static implicit method. The static explicit method solves the equation without iteration at each time integration step. As the convergence is not checked, this problem is avoided with this method. The contact friction problem is easily treated with the application of very small time interval (Jung, 2002). So, the main advantage of the static explicit method is the reduction of computation time in comparison with the static implicit method, which can be ten times faster.

Dynamic explicit method

The Dynamic-explicit method is based on the dynamic balance equation with small time interval in each stage. The most important advantage of this method is the computation time. Indeed, this method is speedy and the memory requirement is less than the static-implicit method (Tekkaya, 2000). Moreover, large deformation and 3D contact constraints are relatively easy to implement in an explicit procedure. However, a very important drawback that exists with this method is the accuracy of the result. Each time this method is used, the results have to be studied just to be sure that they are meaningful. The explicit method is more effective for analyses of more complex cases (Yang, 1995).

Summary of techniques survey

In conclusion, there are various simulation techniques in existence, each with their own advantages and drawbacks. The very first method, the static-implicit method, is very accurate, especially for 2D problems and applicable to all section of the rolling process. Due to its accuracy, speed and generic applicability the implicit method has been chosen and applied for FEA modelling of this research. Nowadays, some methods, like the dynamic-explicit method, exist to address problems unable to be solved with the other FEA methods presented above. This method is less precise, but a lot quicker. In most of the metal forming process, the analyses (temperature, loads and strain) are not done by only one Finite Element Method. During the first stage of the design, where only the question of the feasibility is asked, a quick method is used. Although, for the final stage of the design where precise analyses are requested, the most accurate methods are used - even if these methods have a long computational time. The inverse method is one of the most recent methods and approaches for quicker and less computational time. Statistics show that, in recent years, there are a number of research applications of finite element analysis for the metal forming process. Figure 2.2 show the sample of the proportion of research papers that survey about the different methods explained above. There are 44 papers considered in the survey. As it is shown, a larger proportion is about the static-implicit method - as it was the first method and it is the most accurate one.

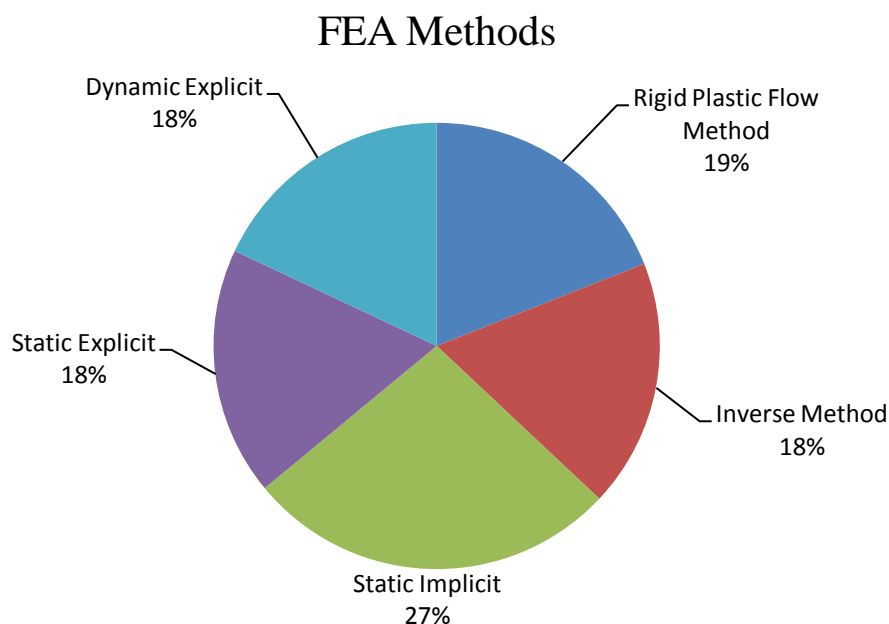


Figure 2.2. Finite Element Method research papers survey (2004-2009)

2.5 Engineering Design Optimisation Approaches

The concept of design optimisation deals with betterment and improvement. A major goal driving current design optimisation technique research is to significantly decrease the cost and time, and increase quality of products and service. To achieve these, there is a need for new techniques and approaches. Over the years, with the advancement of computer technology, the era has arrived of new state of the art design and design optimisation techniques that attract attention from across the industry sectors. In the past, extensive developments have been seen in computational applications, in order to improve the efficiency of a design process, e.g. FEA; CAD/CEM; and virtual modelling. Over the years much research has been conducted in optimisation. The introduction of optimisation in design was revolutionary in terms of aiding both the efficiency and creativity of a designer, improving the quality of a design itself. Today, the new evolutionary state of the art optimisation and search methods can assist the designer at all stages of the design process to reach the final optimal product - the final product that meets the performance requirements most. The designer can choose the optimisation and search methods by tacking in to consideration the nature and type of problems that need to be solved. In a nut shell, there are three main optimisation techniques that the designer can choose from. These are: A classical technique, Evolutionary computing and Hybrid technique. Research shows that these three techniques are all popular in industry, based on the ability each technique has, depending on problems that need to be solved. A survey of design optimisation approaches: “a comparative overview of technique’s development in the last decade” presented in Section 2.6 indicates that over the years however due to the fact that current engineering design problems are large scale, multi-objective and complex in nature, industries are leaning fast towards evolutionary computing techniques particularly GA based techniques, due to its popularity. It is also learnt that hybrid techniques are getting equal consideration as a solution for current optimisation problems. Hybrid techniques develop by combining two or more techniques together; to create a tailor made technique able to solve particular design optimisation problems.

The classical methods of optimisation may be useful in finding the optimum solution of continuous functions. These methods are analytical and make use of the techniques of differential calculus in locating the optimum points. Since some of the practical

real life problems, involve objective functions that are not continuous the classical optimisation techniques have limited scope in practical applications. On the contrary, genetic algorithms (GA) are robust and powerful global optimisation techniques for solving large scale problems. GA also has flexibility and adaptability to the task at hand, and ability to create multiple solutions in a single run - a characteristic that makes GA technique better suited to deal with current design optimisation problems. A survey conducted by this research author, shows that, in the last decade in particular, the research and development on GA techniques has grown considerably. The industry survey also shows that genetic algorithm is emerging as a new engineering computational paradigm, which may significantly change the present and future design optimisation practice. A brief overview and comparison survey results of techniques are presented in the following section.

Genetic Algorithms

The section above briefly discussed advantages of using genetic algorithms based optimisation technique over its counterpart the classical technique and its functionality in the applications - but what is evolutionary computation? Briefly, GA is a part of evolutionary computation refers to a collection of stochastic search algorithms whose designs are gleaned from natural evolution, i.e. genetic inheritance and the Darwinian principle of the survival-of-the-fittest (natural selection) (Holland, 1962 and Holland, 1972). It is a part of the several different styles of evolutionary algorithms, such as genetic programming (GP), neural network (NN) and fuzzy logic (FL), each share a common feature, i.e., modelling the search process by mimicking a biological evolution process which is operated over the solution space. They are different, mainly in the evolution operators involved and the representation of the solution space. For example, in genetic programming, each solution is represented by a computer program, and hence, the evolution process is implemented on a society of computer programs. In terms of application, however, to generate designs, they are all commonly popular in many different disciplines. Unlike the traditional methods, which are often employed to solve complex real world problems that tend to inhibit elaborate exploration of the search space, GA based optimisation is generating considerable interest for solving real world engineering problems. They are proving robust in delivering global optimal solutions and helping to resolve limitations encountered in traditional methods. The noticeable highlight the GA possesses

compared to other optimisation techniques, such as classical, is that where most classical optimisation methods maintain a single best solution found up to a point, genetic algorithm maintains a population of candidate solutions. Only one of these is ‘best,’ but the other members of the population are ‘sample points’ in other regions of the search space, where a better solution may later be found. The use of a population of solutions helps the algorithm avoid becoming trapped at a local optimum, when an even better optimum may be found outside the vicinity of the current solution. Over the last decade, Hybrid methods in engineering design optimisation also have matured considerably, and when coupled with the marked advance in computing hardware, permit the numerical solution of complex industrial problems. The main characteristics of the hybrid technique are briefly discussed as the following.

Hybrid Technique

Another optimisation technique, emerging as equally important as evolutionary optimisation, is a Hybrid technique. Hybrid is a tailor maid technique, developed by combining two or more optimisation techniques to deal with the real world engineering design optimisation problems. Hybrid is becoming popular because it is considered as a technique that can fill the gap and drawbacks (such as computational time and cost) that both evolutionary computing and non-evolutionary techniques are having. Hybrid techniques are mainly used in problems where qualitative aspects of the problem need to be incorporated in to the deterministic part of the problems. For example, Odugua (2003a) developed and successfully applied a hybrid optimisation technique, by combining genetic algorithms with fuzzy logic, to deal with roll pass design problems. In the last decade in particular, the technique shows a steady growth in applications due to its flexibility and adaptive nature. The research paper survey shown in Figure 2.3 supports this fact and presents trends the technique has shown in the last decade.

Classical Technique

Real world engineering can be characterized as having chaotic disturbance, randomness and complex non-linear dynamically discontinuous. Most industrial processes are usually large scale, high dimensional, non-linear and highly uncertain, and these characteristics may not be fit to the classical approach (Deb, 1999). This approach relies on the use of the analyst’s qualitative knowledge to explore the design

space - often through trial and error. Previous research work shows that classical optimisation often performs better for problems with many constraints than GA based techniques. However, there is also a drawback in classical optimisation techniques, such as; analyses are cumbersome and often invoked repeatedly during the search process, making the optimisation and concept exploration time consuming. In addition, classical techniques have common difficulties in terms of robustness, hence unable to deal with work roll system design problem characteristics such as uncertainty, compared to GA and hybrid techniques. Broadly, the classical optimisation methods can be classified into two distinct groups: these are: direct methods and gradient-based methods. The classification is based on guide on search strategy. Examples of the two classifications are described in (Spendley *et.al.*, 1962) and (Marquardt, 1963) respectively.

Summary of Advantages and Disadvantages of Techniques

From the review, it is understood that, there are various optimisation techniques available to choose from, depending on the problem at hand and time and cost available. Each technique has its own advantages and disadvantages in terms of application and speed and time required. However, generally, the optimisation techniques are divided in to two main groups, namely manual optimisation and algorithm based techniques. Although, in some circumstances, engineers also develop tailor made hybrid techniques to deal with a particular design optimisation problems.

Main features of the two techniques are summarised as follows:

Conventional/Manual Techniques

- The procedure in a conventional manual design process typically consists of taking an existing design and further developing, by modifications, to meet the new requirements. Optimisation is achieved through past experience and trial and error through iterative process, in some cases employing user driven computational analysis programs iteratively until a suitable solution is found.
- Most real world engineering design optimisation problems are complex and incorporate a significant number of strongly correlated design variables, each with conflicting performance targets. This presents a challenging problem if an optimal solution is to be sought. The application of the traditional iterative process can be inefficient, resulting either in a lengthy and costly design phase or a compromised optimal result at the expense of time and cost.

Algorithm based Optimisation

- Optimisation algorithms offer the potential to improve the overall efficiency of the design process by reducing the time spent manually iterating towards a suitable optimised design.
- Algorithm based techniques are able to search a number of potential optimal design solutions in one go, making the decision process faster. This can be automated by integrating numerical simulation and performance analysis,
- The technique offers a choice of solving multi objective, high dimensional problems with presence of uncertainty and constraints, finding a compromised robust solution for conflicting objectives.
- Unlike conventional techniques, algorithm techniques would make the optimisation jobs easier, thereby making them less dependent on the designers' skills and experience.

The literature review in this section indicates that the algorithm based approach is favoured over the conventional approach to deal with complex engineering optimisation problems, such as work roll system design optimisation. A few of the major advantages of the techniques are savings in time and cost, and finding the best/optimal result. It also gives benefits in dealing with complex, many objectives and high dimensional design problems.

2.6 Design Optimisation Approaches: A Comparative Overview of Technique's Development in the Last Decade

This section presents a review and comparative analysis of the main engineering design optimisation approaches, and the rationale behind why one approach is preferred over the other. The review was conducted in line with the industry survey, so that current optimisation techniques states, both in industry and academic research, can be understood. The review is based on research papers published in engineering design optimisation in the period between 2001 and 2009. Over 300 papers have been considered for the review. The main source of the review includes: Conference papers, Journals, E-journals and other Technology research databases. The resources are categorised according to methods and techniques they belong to - namely, Genetic

Algorithm based technique (GA), Non-Evolutionary computing and Hybrid techniques. The survey was conducted to fulfil the following objectives.

Objectives of the Review are as Follows:

- To understand current states of engineering design optimisation techniques, methods and tools available.
- As part of a literature review, to find out techniques and methods, if any, relevant to the PhD research and that can be used as a reference in finding gaps in existing optimisation techniques.

Conventional numerical optimisation methods have the known advantage of their efficiency; however, they are very sensitive to the starting point selection and are very likely to stop at non-global optima. The search for algorithms that are capable of escaping from local optima has led to the development of stochastic optimisation techniques via the introduction of probabilistic factors in the search process, that encourage global exploration. In addition, stochastic techniques, unlike conventional numerical optimisation methods, produce new design points that do not use information about the local slope of the objective function, and are, thus, not prone to stalling at local optima. Further, they have shown considerable potential in the solution of optimisation problems characterized by non-convex and disjointed or noisy solution spaces. The survey, conducted as part the research, also confirms this fact. In recent years, that GA application trend has shown a considerable increase compared to its conventional and hybrid counterpart. As shown in Figure 2.3 the technique is emerging as a new engineering computational paradigm, which may significantly change the present and future design optimisation practice. It is also learnt from the survey that due to its robustness, powerful global optimisation capacity for solving large scale problems, flexibility and adaptability to the task at hand, GA based techniques are better suited to deal with current design optimisation problems, as compared to their classical and hybrid counterparts. The trend, the black line in the graph, demonstrates exactly that. Hybrid methods, shown in the blue line in the graph, have also matured considerably over the years. Hybrid technique combined two or more from the various types' of evolutionary techniques, to create a method that suit a particular problem. For example genetic algorithms and fuzzy logic are used in Odugua (2003a) to deal with the quantitative and the qualitative aspects of the problem respectively, in the rolling system pass design problem.

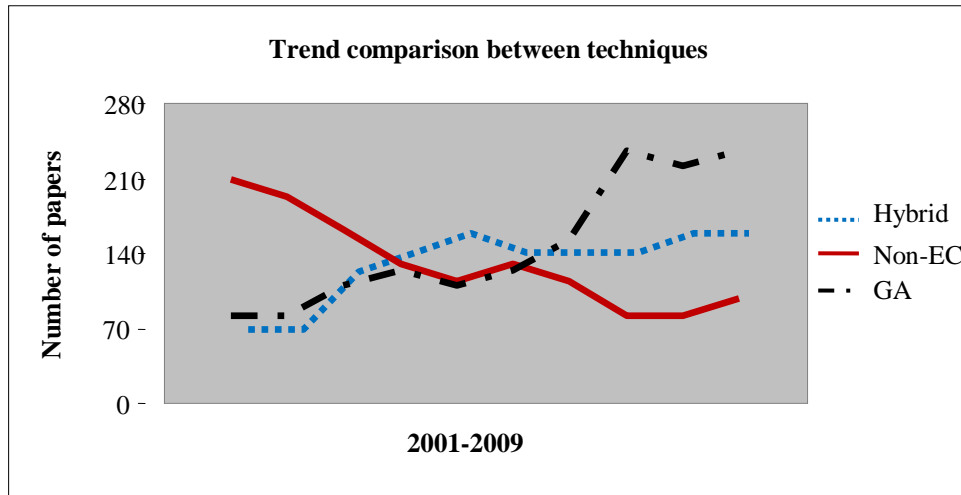


Figure 2.3. Development trends of techniques in the last decade (2001-2009)

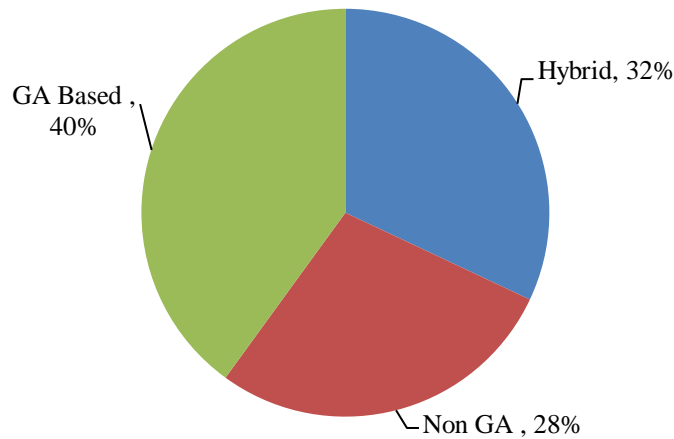


Figure 2.4. Percentage share of techniques surveyed

Figure 2.4 demonstrates the percentage share of each technique of the total number of papers surveyed. Out of the total surveyed, 40% fall in the category of genetic algorithms based techniques. This indicates the growing trend of the techniques in academic research. The trend is also in line with the survey engineers' feedback in terms of the states of algorithm based techniques in industry.

2.7 Design Problems Representation in Computing Based Design Optimisations

Solutions in design optimisation are only as good as the information provided in the optimisation. That information is usually delivered in the optimisation process in the form of representations. Therefore, accurate and complete problem representation is a

crucial stage in the process. Today, there are two well known approaches used to enquire and address real world engineering design problems (Robson, 2002). These are: qualitative and quantitative approaches.

Quantitative Approach

Quantitative is a scientific research, characterised by numerical approach to data analysis. It expresses an optimisation problem mathematically, by identifying variables and fixed parameters, systematically estimating unknown data, formulating an objective function, and identifying constraints on the variables. In today's complex engineering problems, such as work roll system design optimisation, the quantitative approach play a vital role in representing the process mathematically for optimisation, which otherwise would have been difficult to do in real life.

Qualitative Approach

Qualitative state is a set of propositions that characterise a qualitatively distinct behaviour of a system. Quantitative models are very popular in real world design optimisation problems; even though such models have been very useful in providing detailed information about the design problems, they can be ineffective in situations when the mathematical formulation of a design problem is not available or is partially defined. In such case, qualitative information can provide a valuable access to the design problem by taking advantage of human approximate reasoning to improve the complex design problem representation (Oduguwa, 2003a). Qualitative reasoning creates representations for continuous aspects of the real world engineering problems, such as time and quantity, which support reasoning with very little information. In complex and large scale engineering problems, such as work roll system design, where a quantitative approach can only represent the numeric nature of the problem, it is vital to consider the qualitative reasoning aspect of the process in order to have continuous and full information of the problem. In turn, the consideration of continuous and full information (qualitative, quantitative) nature of the process will give a strong base for better decision making.

2.8 Multi-Objective Design Optimisation

In real life most of the process optimisation problems are multi-objectives and in majority of the cases these objectives are conflicting. The objectives are may be

minimisation or a maximisation of interest in the process. For example one may wish to minimise production cost of a part while at the same time maximising the quality of the part. Objectives in the optimisation can be two or many in number. Generally it can be expressed mathematically as, a multi-objective optimisation aims to minimise, under certain constraints, the elements of $f(x) = (f_1(x), \dots, f_n(x))$, of a vector function f (in the objective space) of a decision factor x in the decision space and n is the number of objectives. In practice each of the objectives shown above may have different optimal solution in the optimisation. However in the multi-objective optimisation the solution will be a trade off, as well as known as Pareto optimal set, among the objectives. This means that the value of solution of any of the objectives cannot be improved without deteriorating one or more of the others. Objective optimisation works in the principle of dominance. For example let us assume that an optimisation seeks to maximise a single objective problem, where the objective space is a subset of real number, the principle of dominance can be expressed as $x1 \in X$ is better than another solution $x2 \in X$ if $y1 > y2$; where $y1 = f(x1)$ and $y2 = f(x2)$. In a single objective case although there are a number of solutions in the decision space they all are mapped in to same vector in the objective space. Hence there is only one optimal in the objective space. This is however not a straight forward as this is in the multi-objective case. Comparing two solutions $y1$ and $y2$ is more complex. In multi-objective optimisation to conclude that a solution $y1$ is dominate solution $y2$ the following conditions have to be fulfilled.

- If no component of $y1$ is smaller than the corresponding component of $y2$ and
- At least one component $y1$ is greater than $y2$.

By the same way, we can say that $x1$ dominates $x2$ if $f(x1)$ dominates $f(x2)$. These will produce many optimal objective vectors representing different trade-offs between the objectives. The solutions mapped in to the objective space and then form the Pareto front. The front then helps the decision makers to choose a compromised solution. Multi-objective optimisation becomes more challenging with high number of, more than about 10, objectives. Evolutionary algorithms seem particularly suitable to solve multi-objective optimisation problems because they deal simultaneously with a set of possible solutions (population of solutions), which allows finding an entire set of Pareto optimal solutions in a single run of the algorithm, instead of having to perform a series of separate runs, as in the case of the traditional technique (Deb, 2001). The

most common and relatively original evolutionary multi-objective optimisation techniques that are popular among researchers and widely mentioned in the literature, include the following: Aggregating functions; vector evaluated genetic algorithms, which was originally developed by Grefenstette (1984) as a simple genetic algorithm and which Schaffer (1985) extended to include multiple objective functions, Fonseca and Fleming's MOGA, a multi-objective genetic algorithm (Fonseca and Fleming, 1993); and Srinivas and Deb's NSGA, a non-dominated sorting genetic algorithm (Srinivas and Deb, 1994). In comparison, however, NSGA-II Deb *et al.* (2002) is the preferred technique for solving multi-objective optimisation problems for the following reasons. The technique is a fast elitist solution algorithm that uses explicit-preservation strategy to maintain diversity among solutions in the non-dominated front that is able to find much spread solutions over the Pareto-optimal front and it also requires low computational requirements. In the elitist strategy, the population is sorted into different non-domination levels and each solution is assigned fitness equal to its non-domination level (where one is the best level). Binary tournament selection, crossover, and mutation operators are used to create offspring population. Other important features of the algorithm include crowding distance assignment procedure (for estimating the distance between two points in the solution space) and the crowded tournament selection operator (guides the selection process towards a uniformly dispersed Pareto-optimal front). This algorithm is more applied to real world problems compared to most reported multi-objective algorithms. Main advantages of the techniques can be summarised as follows:

- Flexibility and adaptability of key features of the techniques makes it possible for wider application and more complex problems such as optimisation problem with presence of uncertainty and constraints.
- Relatively less in complexity and computational time. This algorithm is more applied to real world problems compared to most reported multi-objective algorithms.
- Use the non-dominated sorting concept in GAs; (Srinivas and Deb, 1994).
- Use the crowded tournament selection operator to preserve the diversity among non-dominated solutions in order to obtain a good spread of solutions.
- Results from experimental work conducted by various researchers in the literature conclude that, the NSGA-II has out-performed the Pareto-Archived

Evolution Strategy (PAES) and other multi-objective EA with the explicit goal of preserving spread on the non-dominated front (Deb *et al.*, 2002).

These important characteristics and consideration suggest that The NSGA-II based algorithm is adopted in this thesis. Other extended forms of multi-objective optimisation include: Horn and Nafpliotis' elitist NPGA, multi objective optimisation using the niched Pareto genetic algorithm (Horn and Nafpliotis, 1993). Zitzler and Thiele's suggestions of an elitist multi-criterion EA with the concept of non-domination, called strength-Pareto EA, SPEA & SPEA 2 (Zitzler and Thiele, 1998). Generalised regression GA (GRGA) by Tiwari and Roy (2001) is another multi-objective optimisation technique, developed to handle complex multi-objective optimisation problems having high degree of inseparable function interaction. An interaction occurs when the effect a variable has on the objective function depends on the values of other variables in the function (Knowles *et.al.*, 2000). Pareto Archived Evolutionary Strategy, PAES is another techniques developed to deal with multi-objective optimisation problems. The technique is based on an evolutionary strategy. The Pareto Archived Evolution Strategy (PAES) is a multi-objective optimizer which uses a simple (1+1) local search evolution strategy. The technique is capable of finding diverse solutions in the Pareto optimal set because it maintains an archive of non-dominated solutions which it exploits to estimate accurately the quality of new candidate solutions. There are three versions, (1+1), (1+lambda) and (mu+lambda)-PAES have been developed. The Pareto archive has several roles in an MOEA: it often takes part in the generation of new solutions (i.e. "parents" are drawn from it); it can be used to estimate the quality of new solutions (Knowles and Corne, 2004). In a nut shell the functionality of PAES can be described as follows: it can be described as having one parent and one child. Both are compared, and if the child dominates the parent, it becomes the new parent and the iteration continues. If the parent dominates the child, the child is discarded and a new child created by mutation. However if either of them dominates each other the choice is made by comparing them with the archived best solutions found so far. If the child dominates any member of the archive, it becomes the new parent and the dominated solution eliminated from the archive. If the child does not dominate any member of the archive, both parent and child are compared for their proximity, with archive solutions. If the child resides in the least crowded region in the parameter space among the archived member it becomes the parent and a copy added to the archive (Knowles and Corne,

2003). Those optimisation techniques discussed here, even though there is a difference among the techniques to a degree in terms of functionality, they all are suitable to solve multi objective optimisation problems, dealing with the problems simultaneously with a set of possible solutions - the so-called population. These techniques are capable of tackling a wide range of problems and they form the key research areas in evolutionary-based multi-objective optimisation research, the likes of this research. Next discussed is the strength and weakness of the evolutionary based optimisation techniques in tackling current complex multi-objective optimisation problems.

Strength and Weakness of Pareto based Optimisation Techniques

The main strength of the techniques can be summarised as follows:

- algorithms based techniques are particularly suitable to solve multi-objective optimisation problems because they deal simultaneously with a set of possible solutions (population of solutions), which allows finding an entire set of Pareto optimal solutions in a single run of the algorithm, instead of having to perform a series of separate runs, as in the case of the traditional technique
- In majority of cases the techniques satisfy the two fundamental requirements of multi-objective optimisation principles: convergence to the Pareto-optimal front and maintenance of population diversity across the front.
- They handle multiple variables involved in optimisation problems. As Zitzler and Thiele (1998); and Peng (2007) have confirmed, that in solving multi-objective optimisation problems these techniques perform better than most others.

However having considered the overall capacity and flexibility, in dealing with today's engineering design problems complexity, such as handling uncertainty and real life engineering constraints, however, the techniques lack maturity. Most complex problems arising in modern technologically developed science and engineering have multiple sources of distinct nature. Although algorithm based techniques have proven to be an efficient and powerful problem-solving strategy, as shown in the example above, they are not a problem free tool. GA based techniques do have certain limitations; in particular in the following areas:

- The first, and most important, consideration in creating a genetic algorithm is defining a representation for the problem. The language used to specify

candidate solutions must be robust; i.e., it must be able to tolerate random changes such as uncertainty in the decision variables and models used as fitness functions. This is the most common characteristics of real world engineering design problems. The techniques as they are lack addressing these characteristics.

- Another weakness are that the algorithms they use iteration for checking non-dominance in a set of feasible solutions, (in the case of uncertain problems) are computationally very expensive, and as the population size and the number of objectives are increased their performance exhibit slowness. In a number of cases, the performance of these approaches is also dependent on the values of control parameters. In a highly chaotic and uncertain engineering process environment, use of a mathematical model is unavoidable. However, the mathematical model is a numerical representation which is prone to forced accuracy compromises. This compromise needs to be addressed in the optimisation. If the fitness function is chosen poorly or defined imprecisely, the genetic algorithm may be unable to find a solution to the problem, or may end up solving the wrong problem.

To address the weaknesses particularly multi-objective problem optimisation in presence of uncertainty, there have been various attempts by number of researchers so that the techniques to be able to handle problems complexity. The next section discusses uncertainty in multi-objective optimisation and review of techniques to deal with multi-objective optimisation in presence of uncertainty.

2.9 Uncertainty in Multi-Objective Design Optimisation

It is often the case that due to the various uncontrollable variations of parameters involved, real-world engineering design problems, such as work roll system optimisation using thermal analysis and GA, are usually characterised as multi-criterion and multi-objective in nature. The variations, controllable or uncontrollable, in parameters are as a result of presence of uncertainty in the problem. The aim of solving such problems is to obtain solutions, in terms of objectives and feasibility, which are as good as possible and, at the same time, are least sensitive to the parameter variations (Fiacco, 1983). Such solutions, also known as robust optimum solutions, are found following trade-offs among the objectives, performance or may be combination of other criterions. Many methods and approaches have been

proposed in the literature to deal with optimisation in presence of uncertainty. For example techniques for searching robust solution, that is, feasible design alternatives that are optimum in their objectives and whose objective performance or feasibility (or both) is insensitive to the parameter variations. Various classifications of uncertainty in design optimisation have been suggested by researchers in the past few years (Jin and Branke, 2005; Ben-Haim, 2004 and Ben-Haim, 1996). Jin and Branke (2005) described four types of uncertainty. They are: noise in fitness function, uncertainty in design and/or environmental parameters, approximation errors in fitness function, and time-varying fitness function. The first three types of uncertainty, the main focus of this research, have been studied by various researchers and possible solution suggested. Over the year's robust optimisation, which is frequently attributed to Taguchi (1978) and many other techniques have been developed, out of which the majority of them are probabilistic methods. Since Taguchi work, many other methods have been developed. A significant portion of the literature in this area reports on probabilistic methods that optimise statistical measures of expectation (or presumed probability distribution). However in the last few years there are few exceptions where the methods do not require a presumed probability distribution for parameter variations, and is applicable even when the variations are beyond the linear range. Gunawan and Azarm (2004) presented "Non-Gradient Based Parameter Sensitivity Estimation for Single Objective Robust Design Optimisation". Their research presents a new method for estimating parameter sensitivity of a design alternative and then use that estimate in an optimisation scheme to obtain a robust design solution. The method is non-gradient based: it is applicable even when the objective function of an optimisation problem is non-differentiable and/or discontinuous with respect to the parameters. Also, the method does not require a presumed probability distribution for parameters, and is still valid when parameter variations are large. The sensitivity estimate is developed based on the concept that, associated with each design alternative there is a region in the parameter variation space whose properties can be used to predict that design's sensitivity. Their method estimates such a region using a worst-case scenario analysis and uses that estimate in a bi-level robust optimisation approach. However this technique is applied only in single objective problems and as the authors concludes the feasibility assumption may not hold if the method applied in multi-objective optimisations. The method is later improved by Lim *et.al.* (2006), in the Inverse Multi-Objective Robust evolutionary design (IMOR). Here the

computational cost reduced greatly. ‘Robust Non-Dominance Criterion Technique for Multi-objective Optimisation of Weld Bead Geometry for Additive Manufacturing by’ Mehnen and Trautmann (2008) is another recent technique in which they propose a robust non-dominance technique for two objective problems with uncertainty in the fitness functions. The robust dominance criterion is a technique, designed to utilize the new robust multi-objective evaluation technique to generate robust best compromise solutions for problems with noise and uncertainty. Brief overview of the technique and its initial application is described as follows:

In the case of noisy fitness functions (f_1 and f_2), the conventional Pareto criterion is not able to decide whether a point x is dominating another point x^* because it can only compare two discrete solutions at a time. The robust dominance criterion takes uncertainty of the fitness function values into account by calculating median estimates and the convex hull around a solution in the objective space. The convex hull represents the area of uncertainty of a solution. To calculate the Pareto-non dominance properties of any two solutions x and x^* , the median of all noisy fitness values are calculated. The problem at hand is then to estimate the true Pareto front from a set of k noisy samples ($f_k|x, q$), $i = 1, \dots, m$ which cover true Pareto front. In order to introduce a dimension of the point clouds (due to noise) in the objective space, the mean distances of all points on the convex hull from the median representatives are calculated. Then, the measure of uncertainty of a solution in m -dimensional objective space can be introduced by taking say $P := \text{med}(f_k)$ as a robust estimate of a solution, and the Convex Hull $\text{CHP}(P)$ of all k sample points around P describes a worst case representative of solution P containing all k samples (Barber *et.al.*, 1996). The absolute distances in each dimension of all points in $\text{CHP}(P)$ to P can be used to define the uncertainty vector. Given the uncertainty vectors around a solution P , all points within the box formed by uncertainty vectors are represented by P . This implies that the conventional Pareto-dominance definition may not hold any more if any two points, P and say Q , are inside the uncertainty vicinity of each other. Although these points may dominate each other in a noise-free case, in the case with noise it is impossible to tell which point dominates the other. Therefore, in this case, both points are considered as potential solutions (Pareto set). However the method has only been applied in two objective problems with uncertainty in the fitness function. Many other researchers have developed deterministic methods for obtaining robust design solutions. These include approximation-based methods by Parkinson *et al.*

(1993); Hirokawa and Fujita (2002); sampling-based methods by Tsutsui *et.al.* (1997); reliability-based methods by Du and Chen (2000); Jin *et al.* (2002); Choi and Youn (2001). Deterministic approaches obtain an objectively robust optimum design by analytically measuring the robustness of a design alternative using its first-order derivative or other non-statistical measures and then incorporating those measures into the approach. The section presents existing methods in the literature for multi-objective optimisation problems in presence of uncertainty. These techniques are Pareto based and use either deterministic methods or probabilistic strategy to address the uncertainty in problems. The section summarised as follows:

- Uncertainties present in many real-world design problems, such as work roll system and practically impossible to avoid. In the case where a solution is very sensitive to small variations either in design variables, approximate model or operating conditions, it may not be desirable to use this design because they are likely to perform differently when put into practice. Therefore optimisation without taking uncertainty into considerations produces a risky design than optimal.
- There have been attempt for addressing fitness function uncertainty in multi-objective and design variable uncertainty in single objectives optimisation. The existing techniques are design to manage uncertainty without eliminating uncertainty from the system. Various methods have been suggested of which the majority are using either deterministic methods or probabilistic strategy to address the uncertainty. Although no research work found for handling uncertainty in the work roll system design, the information from the literature on existing techniques give background knowledge for developing a technique to deal with the uncertainty in the design variable and fitness functions of many objective work roll system design optimisation problems.

The next section point out the weakness in the existing techniques for dealing with uncertainty in multi-objective optimisation and highlights the research gaps.

2.10 Research Gap

Section 2.9 presents the inevitability of uncertainty in design optimisation, the state of uncertainty in multi-objective design optimisation and main existing techniques available to address uncertainty in multi objective optimisation problems. As indicated in the section, there are various research works in the field and successful

implementation of the techniques to deal with the MO problem with presence of uncertainty. However there is research gap in the existing approaches, particularly in the following areas.

- Existing approaches for addressing design parameter uncertainties are limited for single objective optimisation.
- Existing approaches for addressing multi-objective optimisation problems with presence of uncertainties are limited to uncertainties in the fitness functions.
- Existing approaches for addressing uncertainty and constraints in multi-objective optimisation are mainly theory based and lack real life case study.
- As observed in the review that the existing approach are not implemented in high dimensional, many objective (single and multi pass rolling) optimisation problems with uncertainty in the design variables and in the fitness functions. None of the existing approaches are implemented in the work roll system thermal design and optimisation problem with uncertainty in the design variables and fitness function.
- Literature review revealed that in a complex and highly uncertain engineering process environment such as rolling system, a mathematical simulation is often required as the empirical study is very difficult.
- Real life rolling is a process carried out using multi-pass stands. Although various approximate based models exist in the literature for real life work roll system thermal design and optimisation problems, there is no suitable approximate quantitative model for the multi-pass hot-rolling design problem, considering the relationship between passes, for conducting GA based optimisation search.

2.11 Chapter Summary

Real life engineering design optimisation such as work roll system is a challenging discipline. The obvious challenge is in decision making. Decision making is even more difficult due to presence of uncertainty and constraints. Uncertainties, such as due to input variability, model approximation are common occurrence in real life engineering process design. Real life engineering processes are characterised by high disturbance; therefore, design optimisation in a real life process is a complex task to do. Thus, the need to develop a representative mathematical model is unavoidable. However, the mathematical model is an approximation of the real life process scenarios. This approximation and the inherited input variable variability are the

sources of uncertainty in the model. The chapter reviewed the literature in engineering design optimisation, optimisation complexities such as presence of uncertainty and constraints, it also explore optimisation techniques available to deal with this complexity. The field of evolutionary computing is rapidly growing and has become the essential technique as a solution search for complex engineering design problems. The chapter also presents the review of literature in the subject area of the research case study. It explores features of work roll process optimisation using thermal analysis and GA and highlights work roll system design and optimisation problem challenges. Existing techniques for work roll system optimisation using thermal analysis, recent developments, and shortcomings of techniques are explored. The review is a prerequisite for the research problem statement, is indentifies the gap in the research domain and techniques for optimisation and highlights the following main points:

- Knowledge elicitation in the steel industry revealed that work rolls are estimated to contribute about 5% to 15% of overall production cost in product rolling. Hence, establishing an optimum work roll system design is vital for longer roll working life, minimised machine down time, eliminate repair and replacement time and hence, minimised production cost.
- Rolling is a heavy duty manufacturing process and takes place in a high disturbance and extremely hot environment. Due to these characteristics, an approximate mathematical model is considered appropriate to represent the complex behaviour of the process in a simplified and controllable manner. The model represents the underlying characteristics of the problem and above all, since it is based on response surface, it provides insights in to the relationship between the output and input variables. However, most of the approximate, quantitative modelling approaches, such as finite element FE based methods, are based on quantitative information only. It is difficult to accommodate most of the complex factors unexplainable by quantitative information, such as uncertainty. Therefore the model is prone to accuracy compromises that need to be considered in the optimisation.
- Current approaches for searching solution for multi-objective optimisation problems are not simultaneously dealing with high dimensional problems with uncertainty in the design variables and fitness function.

-
- Existing GA based techniques in the rolling system design optimisation has not been fully utilised to include problems of work roll system optimisation using thermal analysis and GA.
 - In multi-pass rolling system design, the inter-pass relationship, factors complexity and related uncertainty between passes has not been fully addressed in the work roll system thermal analysis. Design and optimisation.

Following the review, the research attempts to fill the gaps in the following areas:

- Explore the rod rolling process, study process factors and factor complexities to develop an approximate model for single pass work roll system optimisation problem.
- Investigate uncertainty and sources of uncertainty information in the rolling process relevant to roll thermal behaviour, as well as in the approximate mathematical model, so that to improve the design acceptance.
- Explore the rod rolling process, study process factors and factor complexities to develop an approximate model for multi-pass work roll system optimisation problem, that consider inter-pass relationship.
- Develop GA based optimisation framework for Multi-pass work roll system optimisation problems with uncertainty in the design variable and fitness function.

These gaps define the main focus of this research. As mentioned in the introduction, the research aims to develop a framework for work roll system optimisation using thermal analysis and genetic algorithm to deal with the design problem.

This chapter reviewed the subjects in the research domain and identify research shortcomings. The outcome of the review form the focus of this thesis and the research aim outlined. In the next chapter, the objectives of the research and the methodology used to meet these objectives are presented.

3. Research Objectives & Methodology

The previous chapter reviewed the literature for current states of the main subjects in the research domain, such as engineering design and optimisation problems, challenges and existing techniques, the rolling process and roll thermal process design. The chapter also presented the gaps identified in the current techniques. The observations from the review led to the drafting of the direction of the research, the follow-up objectives, as well as methodology required to achieve the objectives.

The chapter consists of four sections and is structured as follows. Section 3.1 discusses the research scope and problem statements. Section 3.2 outlines the objectives of the research. Section 3.3 presents the methodology used to guide the research objectives. The main highlights of the sections and a summary of the Chapter are presented in Section 3.4.

3.1 Research Scope and Problem Statements

It has been learned from the literature review that although there are few scientific based solution search strategies in place to deal with the rolling system design problems, such as pass design, the existing techniques have not been fully utilised to include single pass and multi-pass hot rolling work roll system design optimisation and thermal analysis. It is also learnt that the uncertainties and constraints in the rolling system design, which have a potential to influence the work roll thermal behaviour, have not been extensively explored. Although real life industry system application review and industry expert reports indicate the presence of techniques, they are manual and address only single pass, single objective problems without consideration multi-pass rolling and the effect of uncertainty. These phenomena, described above, are the main drive for the research. The research is industry case study initiated by the sponsoring company for further investigation. The sponsoring organization, Tata Steel-Europe, Swinden technology centre's (STC) main role is process and product development, and setting the standards for steel research, as well as competence and programmes. Since there is very little research work reported in the literature concerning the research problem area, the pre-specified research domain was considered an interesting topic for the research. In order to understand the scope of the research within the rolling process and the roll thermal process design activities

of single and multi-pass rolling process, the author elicited rolling system process knowledge from suitable engineers from the sponsoring company, particularly Swinden technology centre R&D plant, Rotherham. Following the elicitation, the researcher developed a full proposal of the research, with detailed outline of aim, objective, methodology, as well as the philosophy behind the research deliverables. Post knowledge elicitation and literature review in the research domain led to outlining the research objective and methodology to achieve the objectives. The current activity study and knowledge capture with engineers in the research sponsoring company is presented in Chapter 4.

3.2 Research Aim and Objectives

Aim

The Research Aims to Develop a Framework for Work Roll System Optimisation using Thermal Analysis and Genetic Algorithm

Research objectives identify outputs and outcomes for key research challenges. The goal of this research is to develop a GA based framework for delivering solutions for real life work roll system thermal analysis and optimisation problems characterised by constraints and uncertainty. This is addressed from the perspective of the following objectives:

- Deliver a critical analysis of existing research in the work roll system thermal analysis and optimisation, addressing quantitative and uncertainty, as well as sources of uncertainty aspects in the single pass and multi-stage rolling process environment. Identify current GA based optimisation approaches and their relevance to this research domain.
- Develop approximate quantitative model for single pass work roll system design and thermal analysis problem that can be used within the optimisation framework.
- Develop GA based optimisation framework for searching optimal solution in presence of uncertainty for single pass work roll system design problem.
- Develop a multi-pass quantitative model for work roll system design and thermal analysis problem that represents relationships between consecutive passes.

-
- Develop GA based many-objective, optimisation framework to search for optimal solutions in presence of uncertainty for multi-pass work roll system thermal analysis and optimisation problem.
 - Apply the framework to real life case studies and result validations.

3.3 Research Methodology

In order to fulfil the objectives outlined above, the need for a structured research methodology is paramount. The methodology needs to address the various issues such as quantitative, qualitative, as well as uncertainty, associated with the real life heavy duty engineering practice. With this in mind, the methodology presented below (covers from problem realisation to solution implementation) is designed as a guide for the research. The methodology is designed to fulfil the requirements for real-life case study problems. The research reviewed several methodologies reported in the literature, due to the specialised nature of the real life optimisation problem in the research however, the AS-IS methodology reviewed not fully address the research problem requirements. The requirements include study of current states of the research (Literature review) in the research domain, study of the real life rolling practises in the research domain: where extensive knowledge elicitation from engineers for the process behaviours, such as quantitative, uncertainty and multi-pass rolling system modelling, and the problem understanding is required. The methodology also addresses the study findings and gaps in the research topic. The methodology is expected to give a solution proposal to fill the gap and the steps followed to achieve it. The research also carried out a second industry survey involving various engineering and design companies, including the client company, in order to have a broader knowledge context - in particular, the current state of the art design and optimisation in industry today, evolutionary computing and evolutionary computing based design and optimisation. The study provides information about the current activity of GA based design optimisation, and used as a platform for developing the optimisation framework utilised for searching solutions for the research problem. Details of the methodology that has guided through the main activities of the research are discussed in the following. The graphical illustrations of the research methodology, summarising the link between steps, within the methodology, and detail descriptions of the modelling, optimisation and validation are presented in Figure 3.1 and Figure 3.2 respectively.

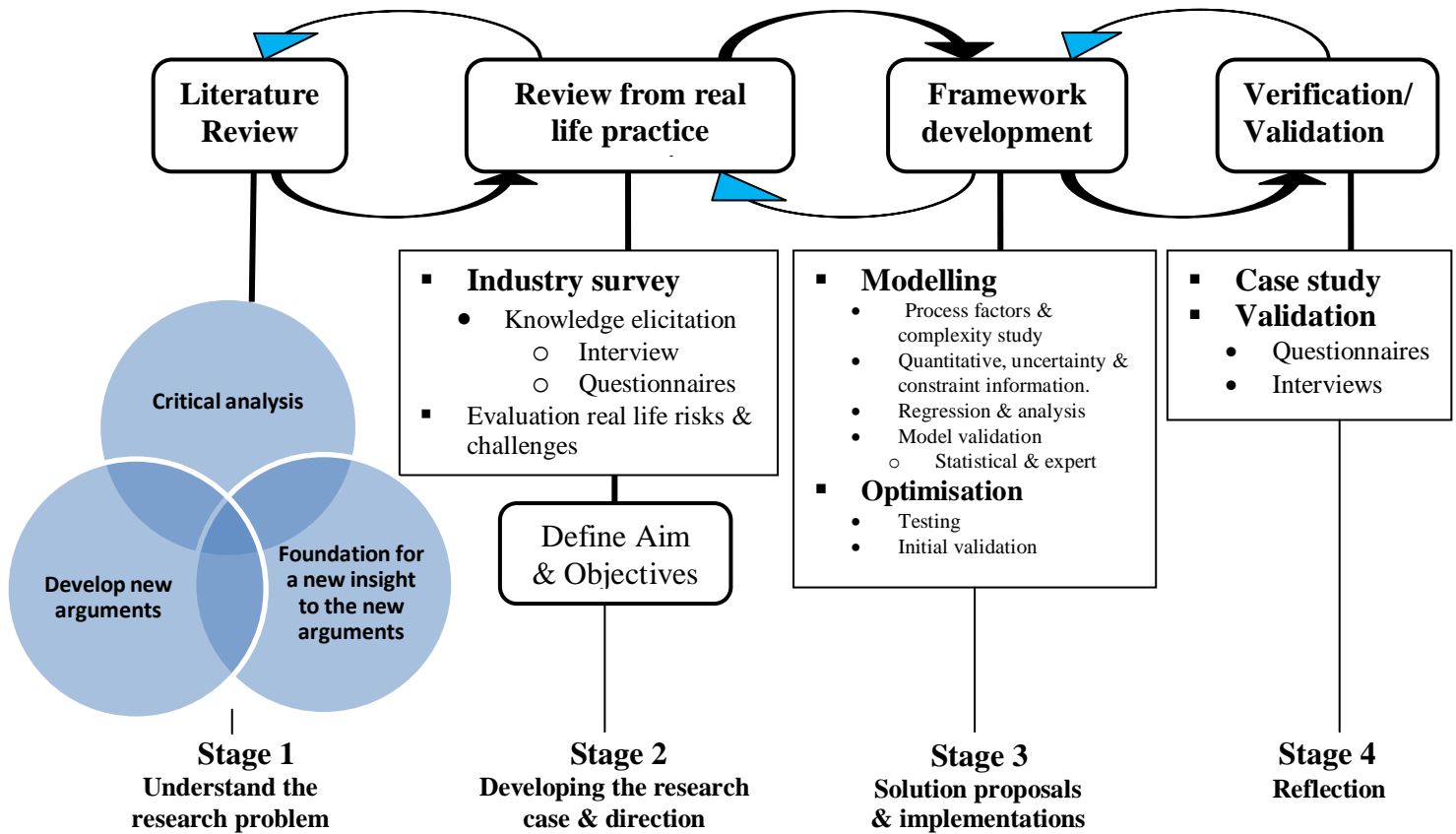


Figure 3.1. Summary of the research methodology

3.3.1 Literature Review

The research includes a comprehensive review of literature throughout the research program. The review demonstrates detailed background knowledge in the industry initiated case study subject area of the research. The review also identifies and addresses limitations in the current techniques and methods used in the optimisation. A review of literature showed that very little work has been reported in work roll system optimisation using thermal analysis and GA. It also indicates that there is not much evidence that the uncertainty information and constraints are considered in rolling single and multi-pass system thermal analysis and optimisation. However, since the researcher is an outsider, it was important that specialist rolling design knowledge was acquired in order to verify the review findings and formulate the research problem. To fulfil this, therefore, the researcher made repeated visits to the client organisation. This was necessary in order to develop the specialist rolling knowledge and to capture how the rolling engineers deal with rolling thermal design and optimisation problems, and most importantly, how uncertainty and constraint information are dealt with in the real life process design.

3.3.2 Knowledge Elicitation for Research Problem Realisation

As mentioned above, this research case study is based on a real life problem. To define the issues to be investigated and build the case, it is vital to put in place a process for first hand real life understanding of the rolling process and acquiring knowledge from the experts. Therefore, the initial phase of the research includes a knowledge elicitation exercise, which was conducted with rolling engineers and software developers from various sections of the organization, at Tata Steel-Europe, Swinden technology centre. The primary objective of the exercise is to assess the current status of work roll system optimisation, system thermal analysis and optimisation techniques in place. This is important to devise a strategy for linking the aim of the research with the knowledge gap expected to be filled. The exercise was carried out through industrial visits and direct interviews supported by tailor made questionnaires. The questionnaires and details of interviews were sent to the engineers in advance so that the engineers would have time to prepare in the specific area of interest. The details of the elicitation exercise are discussed in Chapter 4. The industry interaction is designed to achieve the following:

- To identify the main problem areas from engineers working in the problem domain.
- To understand the current level of model development and optimisation activities in Tata Steel Europe and resources available.
- To survey the current state of the art algorithm based optimisation techniques in industry.
- Since the work roll system thermal design optimisation is a specialist subject, in addition to the literature on the rolling process, it is important to get a real-life perspective on issues influencing formulation of the research problem.

3.3.3 Identifying Research Aim and Objectives

The survey of literature and problem definition highlights the main research issues that need to be addressed for handling single and multi-pass work roll system thermal analysis and optimisation problems in presence of uncertainty and constraints. This enables the precise identification of the research aim and objectives to be achieved. Knowledge elicitation, particularly, helps to formulate the research problem and requirements.

3.3.4 Industry Survey

The aim of this industry survey is to support review of literature for grounding the research within the industrial context. The survey also is designed to attain a broad perspective on evolutionary computing. Particularly GA based engineering design optimisation, and share information on issues concerning development, validation and implementation of GA based design optimisation techniques in industry. The survey was carried out through industry visits in multiple companies, for face to face interviews with experts, as well as phone interviews followed by questions. Details of the procedures followed for the survey are presented in Chapter 4.

3.3.5 Documentation and Proposed Solution Framework

Here, the identified problems, limitations and knowledge gap in the research domain are documented. Based on the knowledge acquired in the literature and industry survey, the key rolling features relevant for work roll thermal system design will be identified and classified as either deterministic or uncertainty drivers. The driver's complexities of these two types were studied extensively. The section also proposes a methodology for functional work roll system thermal design modelling and a GA based optimisation framework for searching best optimal design solution.

3.3.6 Modelling & Optimisation Framework Development

Over view of the modelling, optimisation and validation strategy is shown in Figure 3.2. The quantitative model is developed to represent the complex behaviour of a real life rolling process in a simplified and controllable manner. The developed alternative/surrogate model represents the underlying characteristics of the issues being investigated. Modelling, although it is an approximation of the real life process, is still considered by many as the best way of representing processes with high disturbance and noise, such as rolling systems. Information from literature and industry real practice survey and observations were the main background source for the development of the model. The review helped to understand the historical characteristics of the rolling process in general, and the problem of the work roll system optimisation using thermal analysis in particular. As seen in the previous chapter, the rolling process is a process that the quantitative model on its own cannot address the underlying issues investigated. A better result is only possible if the information that is in the process, but not addressed in the quantitative model, is

included in the optimisation framework. The research followed a modelling and optimisation framework where both the quantitative information and uncertainty are addressed; therefore, better decisions can be made. Modelling and optimisation without taking in to account uncertainty and variability, would lead to solutions that cannot be said to be optimal, as they are likely to perform differently when put in to practice.

Modelling framework is referring to the structure used to from the surrogate models and model validation based on regression analysis. The structure, as well as known as Design of Experiment (DoE) as part of the modelling process, conducts various FEA runs and the responses from runs are later used to build the models. The FEA runs in the DoE are originated from the process model supplied by the sponsoring company. Details of the DoE and model validation are discussed in Chapter 5.

A Quantitative Modelling and Optimisation for Single Pass Work Roll System using Thermal Analysis and GA

The aim of this section is to develop quantitative models that represent single pass problems and explain different aspects, such as uncertainty as well as rolling system factors that are relevant to work roll system thermal characteristics. An important aspect of the model development process is to capture knowledge from the rolling engineers, so that current knowledge, in terms of work roll system design, can be accommodated in the development process. This is necessary because it would help in bridging the gap between the researcher's views acquired in the literature review and the user in the real world rolling practice. The single pass model developed is used primarily as a representation of the fundamental of the real world work roll system design problem. It is also used as the source for the development of multi-pass problem models. Single pass design and optimisation consist of a quantitative model, DoE and a validation stage. The models developed are later used as a fitness functions in the optimisation for searching solutions for the research single pass design problem in presence of uncertainty and constraints. Description of the single pass modelling process, model validation, and searching solution in the optimisation, as well as subsequent improvement of the model by incorporating real world work roll system design problem characteristics such as uncertainty and constraint, are presented in Chapter 5 and 6 respectively. Summary of the multi-pass modelling and optimisation is described as follows.

B Quantitative Modelling and Optimisation for Multi-Pass Work Roll System using Thermal Analysis and GA

The multi-pass rolling is an ordered multi-stage process, using a multi-stand rolling arrangement. The arrangements let the product pass from one to the other sequentially, where the output stock of one pass is fed as input stock into the subsequent pass. Due to this characteristic, solving multi-pass problems will increase the complexity and problem size - i.e. number of variables involved in the process. As the problem size increases, so does the level of uncertainty Oduguwa (2003a) in his work on roll pass design optimisation and sequential optimisation, studied extensively the characteristics of multi pass problems and techniques available in the literature to deal with the problems. The techniques are such as: FE method, backward tracing by Wusatowski (1969), forward tracing by Park *et.al.* (1983) and a derivative based approach by Han *et al.* (1993). Although these techniques are solely applied in the rolling pass design and optimisation, their principles give a flavour of the nature of multi-pass problems in the work roll optimisation using thermal analysis and GA. However, these approaches are derivative based and require an initial guess which can influence the search and can get stuck in a sub-optimal solution. The techniques cannot identify multiple optimal solutions in a single run to multi-objective multi-pass problems while considering the relationship between passes. The multi-pass quantitative models are developed to represent a complex behaviour of a real life multi-pass work roll system in a simplified and controllable manner. The developed quantitative models represent the underlying characteristics of the multi-pass rolling problems issues being investigated. The characteristics are such as: rolling process, factors and parameters, as well as the influence of those factors on the roll thermal behaviour. The multi-pass problem design and optimisation has also needed to address the inherited problem characteristics from one pass to the next. For example, the speed of the roll increases from one pass to the next, while stock temperature decreases. The quantitative models developed for multi-pass should reflect these characteristics. The developed models are later used in the optimisation as fitness function for searching optimal design solution to the research problem. Chapter 7 presents detailed procedures of the modelling, model validation, and solution search in the optimisation, for the multi-pass work roll system design problem in presence of uncertainty.

3.3.7 Validations

The validation is vital for assuring the validity and accuracy of the work. The research carries out validation at the modelling stage and optimisation stage. Validation of the approximate model was carried out by comparing the experimental result with the properties of statistical simulation (regression) using a design of experiment. The optimisation stages are also validated taking in to account properties of the optimisation result obtained under different circumstances - for example, running the optimisation with varying or random generation and comparing the result for convergence, and once the convergence confirmed repeat (up to 10 times) under the same circumstances, so that the continuity of the convergence can be verified. The research also carried out an overall validation of the design and optimisation qualitatively, by taking on board experts from the sponsoring company and experts in the field from Cranfield University. Knowledge acquired from real life hot rolling practise is compared with the result from the optimisation. The validation, by experts, is supported by questionnaires. The methodology followed for validation and experts feedbacks for the questionnaires is given in Chapter 8. The validation achieves the following:

- Compare the modelling with real life rolling practice. It also verifies the theory, knowledge and understanding of work roll system optimisation using thermal analysis and GA.
- Evaluate the impact of uncertainty information integrated in the modelling and optimisation.
- Verify the methodology followed in the modelling and optimisation of work roll system thermal analysis and optimisation problem solution search. It also verifies design factors characteristics assumption made for modelling the single pass and multi-pass models.

Figure 3.2 presents an overview of the modelling, optimisation and the validation strategy and steps followed to develop the quantitative models through DoE, analysis of variance used to validate the model statistically and the regression. The modelling requirements such as employing efficient uncertainty propagation scheme and defining acceptable model error are also highlighted. The Figure also gives intuitive idea about constitute and steps of the optimisation framework development and validations.

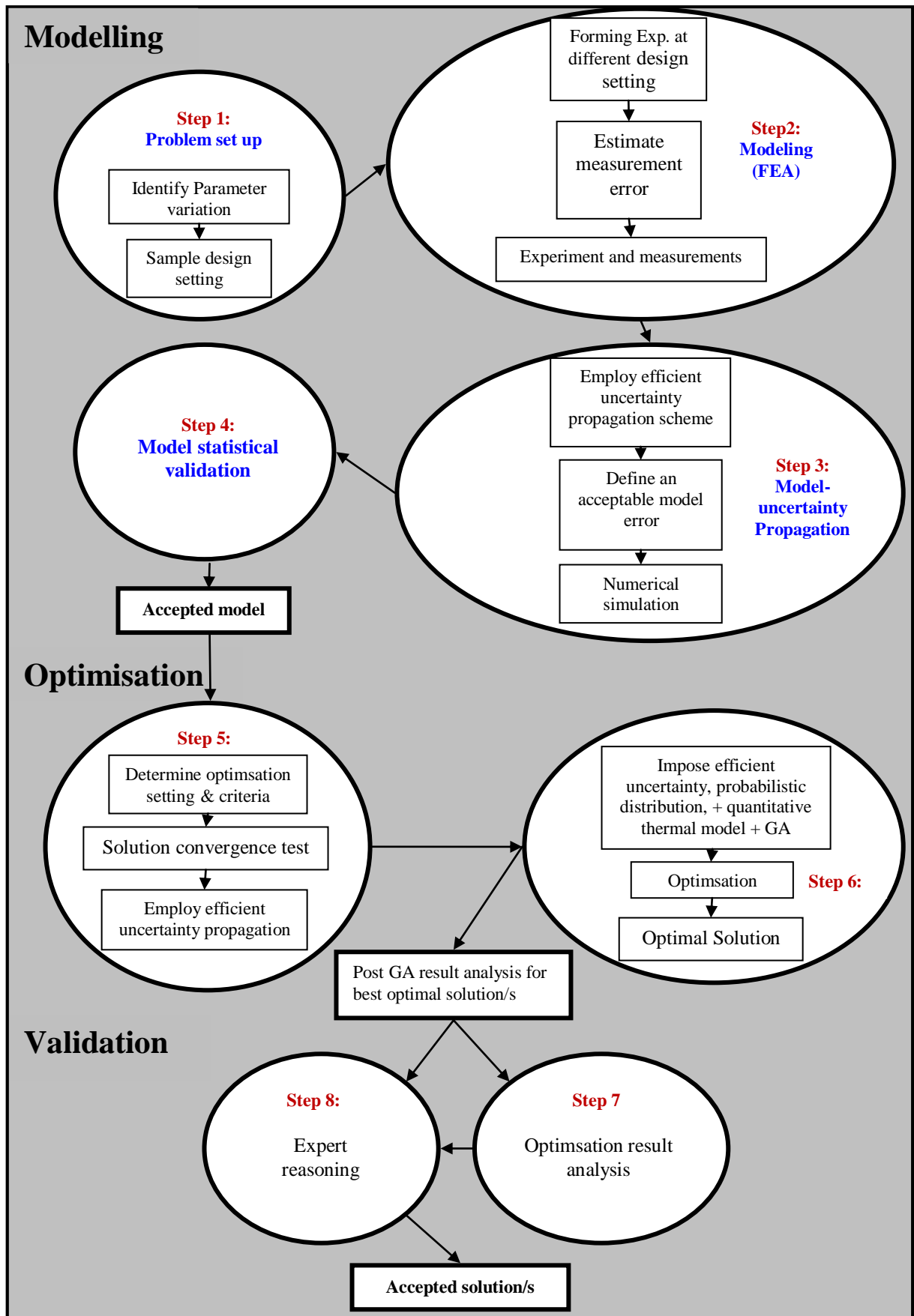


Figure 3.2. Single & Multi-pass Modelling, Optimisation & Validation Strategy

3.4 Chapters Summary

The chapter presents the aim and objective of the research. It also outlined the methodology that helps to achieve the objectives of the research. The chapter also gives brief descriptions of the procedures, used in the methodology, such as the knowledge elicitation exercise to capture requirements, literature review, the model building frameworks, optimisation frameworks and concluded with the validation. The next chapter describes details of the methodology followed for information gathering through real life rolling process observations and knowledge elicitation, in the research domain from experts in the sponsoring company and various other industries.

4 Current Practice Study

Improvement, or new process and product development, always start with the analysis of the existing one - AS-IS model. The main purpose of current practice study is to gather detailed information about the existing process, and decide where improvements are needed. Current practice study also gives a foundation for TO-BE modelling, which is a description of future desired processes. This chapter outlines the current practice study steps and procedures followed. The study, as part of the research requirement, will understand and document the activities and interaction between key process units. The result of this study is a representation of the current process, in terms of its inputs, outputs and mechanisms, as well as shortcomings of work roll system optimisation using thermal analysis within the rolling system design. Another key element of the study is to understand the process environment knowledge, such as uncertainty, including assumptions made by engineers in process design, and how this affects the current practice. A brief summary of the chapter is as follows. There are two main sections in the chapter: these are engineering design optimisation in industry and work roll system design using thermal analysis within steel manufacturing industry. Each section consists of a sub section detailing the technique used in knowledge elicitation, as well as the observations and understanding made from the study. The chapter is structured as follows: Section 4.1 describes the current practise study information gathering methodology; Section 4.2 presents engineering design optimisation in practise in industry Section 4.3 presents industry survey analysis and results; Section 4.4 knowledge elicitation exercise in the research problem domain; and the chapter concludes with the chapter summary in Section 4.5.

4.1 Information Gathering Methodology

The AS-IS study is wholly dependent on the process information gathered from available resources. Hence, for the best information to be found and maintained, a structured methodology is essential. This thesis focuses on thermal modelling, analysis and optimisation of work roll system in the rolling process. The topic was originally selected by the sponsoring company as the subject of interest; hence, the research problem in this thesis. Since there was very little work reported in the

literature regarding thermal analysis and optimisation within the work roll system design, the domain was considered an interesting area of research. Therefore, the information gathering has also focused on this process domain. Information gathering was conducted through interviews, supported by questionnaires. The objective of the interview is primarily for knowledge elicitation from experts in the research domain, particularly the rolling process, thermal modelling and optimisation in the sponsoring company, as well as current engineering design optimisation techniques in industry. Knowledge was elicited from experts by direct interviews, using a carefully prepared set of questions. Questionnaires were developed and made available to the participants in advance. This was to make experts aware of the specific areas of interest, and also to give them chance to comment on the structure of the elicitation process and the content of the questionnaire, so as to ensure that the required knowledge is elicited. Following the questionnaires, the interview was arranged to take place in the participants' location. The interview was supported by the introduction presentation, discussions and a review of the process after every session. Information gathering has taken place in two categories. These are the interview relating rolling system design involving the steel industry, and interviews relating engineering design optimisation and techniques survey in industry today. The latter involved companies associated with design and optimisation in their day to day activities. A wide variety of industries, such as automotive, aerospace and steel manufacturing, were considered. The current practice study was carried out in two categories - this is due to the particularity of the research topics and expertise required for knowledge elicitation. Detail procedures of the study of the current practise are discussed in the next sections.

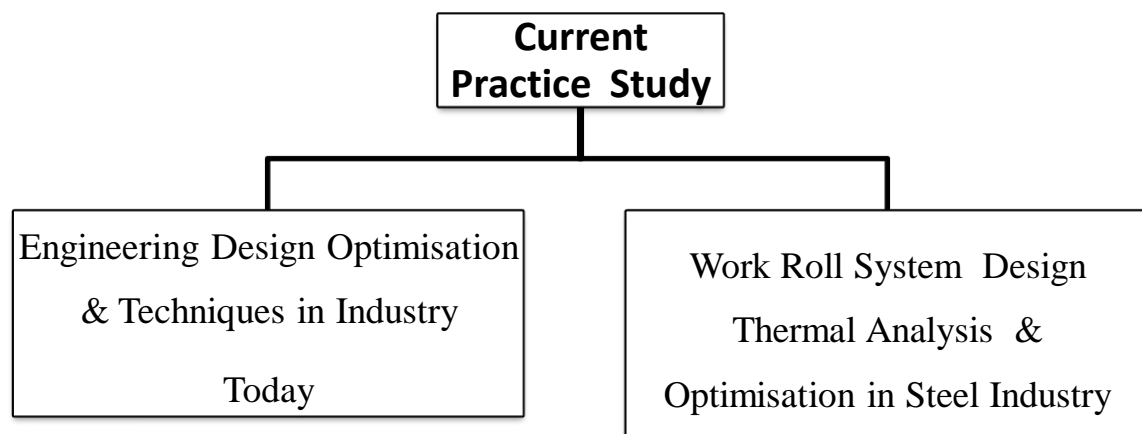


Figure 4.1 Current practice study categories

Since it is a specialised process, AS-IS study in the work roll system design, thermal analysis and optimisation is only carried out in the company where the research topic originated and the required information can be found. The details of the study of engineering design in industry today, the comparative study of optimisation techniques available, based on research papers published in the last decade and the work roll system design thermal analysis and optimisation in the steel industry, are presented in the next consecutive sections.

4.2 Engineering Design Optimisation & Techniques

Current Practice

This survey is carried out as part of the current practice study, to find out current design optimisation activities and techniques available in industry. The survey also can be seen as the supporting evidence for what has been learned in the review of literature, presented in Chapter 2. The knowledge acquired from the review was used as the initial background for the design of the survey and the questionnaire developed. The survey was carried out involving companies with significant experience of engineering design and optimisation. There are four companies that participated in the survey. One expert from the three most relevant departments, namely design, computing and manufacturing, and a total of twelve experts were selected. Expert information elicitation was carried out by having a one to one interview. Each interview lasted for two hours. In brief, the survey was designed to achieve the following objectives:

- To understand the practice and state of the art of design optimisation in industry today.
- To capture techniques and tools availability and popularity in industry.
- To identify GA based and Non GA based optimisation in industry.

Prior to the survey, the following important procedures were followed. The procedures are a guide to decide the objectives of the survey, preparation of the questionnaire and selection of relevant companies and people. Details of the procedure for guiding the survey are discussed as follows:

4.2.1 Selection of Companies

The current practise survey was initially motivated by the literature review conducted in the subject domain. The literature shows that the engineering design optimisation

techniques are a domain associated with wider disciplines across the industry. Although it seems that the application of techniques are mainly used in bigger scale companies like aerospace and automotives, it has been learned that it is also becoming interesting to small and medium enterprises (SME). With these realisations, therefore, to have the full sense of techniques' popularity and application in industry today, it is essential that the current practise survey includes all disciplines of all sizes across the industry. Achieving this to the full, of course, is constrained by time, resources and availability and willingness of participants. With this in mind, the survey was conducted with the involvement of various companies considered most familiar, with substantial expertise and willingness to participate in the survey. This includes Aeronautics, Automobile and Steel. Brief descriptions of the activities of the participant organizations presented as Company A, B, C and in Table 4.1 are described as follows:

Company A – is a steelmaking company. The company is Europe's second largest steel producer with main design & manufacturing operations in many European countries with major plants located in the UK, The Netherlands, Germany, France and Belgium. It is a leading supplier to many of the most demanding markets around the world including construction, automotive, packaging, mechanical and electrical engineering, metal goods, and oil & gas. The versatility of the products manufactured by the company is evident in the sheer number and diversity of their applications in engineering industries.

Company B - is a Europe based technical centre and part of globally well recognised, third largest car manufacturing company. The centre is a central player in company's global operations. In a sustained period of produce led growth and profitability the centre is pivotal in the development of next generation vehicles and the further enhancement of the car brand range which will take the company's market position to new levels. The company was founded in 1988 and originally based at Motor Manufacturing UK Ltd in Sunderland. In 1991, the centre moved to an ideal location on the Cranfield University Technology Park, one of Europe's largest academic centres for applied research. The centre in Cranfield is company's centre of excellence for the design and development of vehicles manufactured in their European plants.

Company C - The Company is a global and second largest defence and security company with approximately 100,000 employees worldwide. The company delivers a

full range of products and services for aerospace, land and naval forces, as well as advanced electronics, security, information technology solutions and support services. The company employed over 25,000 engineers across their global operations, delivering complex, challenging and diverse engineering solutions, providing customers with world class, highly innovative and affordable products and services.

Company D - The Company is a global business, with majority of the design, research and development centre is based in the UK, is providing integrated power systems for use on land, at sea and in the air. The group has a business portfolio with leading market positions, particularly in the civil aerospace, defence aerospace, marine and energy. The company, as a global group, conducts also research and technology programmers on behalf of governments, state and regional bodies around the world.

4.2.2 Departments Need to Participate within the Company

Design optimisation is a multidisciplinary engineering activity, involving different departments within an organization. The final solutions are the result of collaborative activity of these departments. Therefore, for accurate and realistic feedback to be found, the survey was required to include all relevant departments within the surveyed companies. To fulfil this, therefore, the survey first identified relevant departments involved in the optimisation and design process.

4.2.3 Selection of People/Experts

The quality of survey results are as good as the feedback obtained, and the feedback is as good as the people who participate in the survey. Therefore, the selection of people /experts is an important step of the process. The experience and number of participant is crucial. The experienced engineers will give an important insight and true nature of the subjective matter. If the number of participants is very limited in numbers and experience, it may have an impact on the survey feedback and results qualities. In consideration of all these therefore, a robust procedure has been followed in the selection of the participants. Table 4.1 and 4.2 are present the pre survey arrangements and survey participants' introductions.

Table 4.1. Pre survey arrangements

Companies	Affiliations	No of participants	Departments		
			Design	Computing	Manufacturing
A	Steel	3	1	1	1
B	Automotive	3	1	1	1
C	Aerospace	3	1	1	1
D	Aerospace & Automotive	3	1	1	1
Total	4	12	4	4	4

Table 4.2.A. Surveyed companies and participant expertise

Company A				
Department	Design	Computing	Manufacturing	Total
No. Of participants	1	1	1	3
Job title	Senior design engineer	Modelling and analysis expert	Senior research scientific fellow	
Years of relevant experience	10 years	40 years	15 years	

Table 4.2.B. Surveyed companies and participant expertise

Company B				
Department	Design	Computing	Manufacturing	Total
No. Of participants	1	1	1	3
Job title	Design & product development	Process improvement engineer	Senior Manufacturing engineer (Manager)	
Years of relevant experience	12 years	8 years	20 years	

Table 4.2.C. Surveyed companies and participant expertise

Company C				
Department	Design	Computing	Manufacturing	Total
No. Of participants	1	1	1	3
Job title	Senior design engineer	Senior programmer	Senior manufacturing engineer	
Years of relevant experience	6 years	9 years	15 years	

Table 4.2.D.Surveyed companies and participant expertise

Company D				
	Design	Computing	Manufacturing	Total
No. Of participants	1	1	1	3
Job title	Product design	Product development	Production engineer	
Years of relevant experience	11 years	8 years	19 years	

4.2.4 Questionnaire Development Procedures

A set of questions was developed to probe the required information of engineering design optimisation and techniques in industry today. Initially, the questionnaire was piloted, based on the knowledge acquired from literature, in one selected company before it was fully implemented and extended to other industries. The questionnaire was sent to engineers, accompanied by introductions and requirements - prior to that, a number of contacts had been made with participants to brief the purpose of the survey and for survey pre condition agreements. At the beginning, the questionnaire was developed with questions considered relevant and covering the survey subject matter through brainstorming. Next, from the brainstorm questions, a summarised, second form of questions were developed. The version contains fewer questions and eliminated any repetitions. The third and final version of the questionnaire is a result of a step by step evaluation of the initial brainstormed questions. The third and final version contains questions considered relevant to the survey and that can address the main objectives of the survey. Sample questions for design optimisation state of the art, industry survey are given in Table 4.3. The section also presents transcripts

(Transcript 1) of the expert responses to the questions. Details of survey questionnaires and engineer's response are given in Appendix (A).

Table 4.3. Sample questions, Survey, State of the Art Design Optimisation Techniques in Industry

Questions design to investigate the states of design & optimisations in industry

- Q1 Describe how you optimise the component design?
- Q2. Have you documented your design optimisation or design improvement process? (Could we have a copy please?).

Questions designed to investigate techniques, state of the art and level of applications

- Q1. Do you use any commercial software for the optimisation? Please describe why you use them. How long have you been using the software?
- Q2. Are the existing design optimisation techniques you are using algorithm based fully or partially?
- Q3 What advantages algorithm based design optimisation technique has in comparison to any other optimisation technique you know?

Questions design to investigate the Rationale in choosing techniques.

- Q1 What criteria you would like to use to evaluate commercial optimisation tools and software?

4.2.5 Implementation of Questionnaires

The section above, presents the development of the questionnaire and rationale of the questions. Primarily, the purpose of this questionnaire is used as a support during elicitation of knowledge from experts through direct interviews. The questionnaires were developed and issued to the interviewees prior to interview day. During the interview, the hard copy questionnaires were produced either completed by the interviewee in advance or with the option to be completed during the interview. The interview was conducted based on the questionnaire. Implementation followed the following procedures:

- Sent questionnaire in advance to participants.
- Made contact to arrange and agreed preconditions, date, time and place of interviews.

-
- Meet-up and conduct interview based on questionnaires. The interview began with a ten minutes presentation, followed by two to three hours of discussions. The discussion was driven by picking and reading question from the list - if the question was clearly understood as intended, then the interviewee give an answer to it orally before repeating it in writing. During this time, the interviewer was also taking notes.

The interview concluded with a ten minute summary discussion and closing remarks

4.3 Analysis and Presentation of Results

The knowledge elicitation exercise is a technique designed for identifying the likely areas within the evolutionary techniques appropriate for the design and optimisation and to confirm in particular, the suitability of techniques already identified in the review of literature. To identify and present the interview feedback, it is essential to process the feedback and define the expert assessment to the questions asked. This section discusses the steps followed to analyse the interview feedback and present the findings. The knowledge elicitation exercise conducted in this survey was wholly reliant on experts in the subject surveyed giving their own assessment of design, optimisation and techniques based on their experience. Hence, in some respects, the majority of answers given are subjective in nature, implying that feedback analysis required qualitative sorting. It has been observed from the feedback that there are similarities and differences in expert responses to questions. It was also observed that some answers are unique, depending on the industry and experts' experience, and some are different in expressions but similar in content. These realisations, therefore, lead to looking for an analysis technique that recognises these issues and, at the same time, extracting meaningful results out of the expert responses. The responses analysis followed the following procedures:

- First, list all responses together under the survey.
- Next, the response are categorised under similarities, uniqueness and Miscellaneous.
- Making decision

In each category, response feedback is summarised and presented. Unique answers, depending on their relevance, are taken as they are. Transcripts of the interview, questions and expert answers summery are presented in Appendix A.

4.3.1 Survey, State of the Art Design Optimisation Techniques in Industry

Survey Questions Themes and Aim

Table 4.4 and Table 4.5 present the survey questions themes and aim. The purpose is to assess the current status of design, optimisation and techniques in industry. Probe questions and aim of probes are given below.

Table 4.4. Questions themes and aim

Section 1 - Multiple Choices		
Qs	Questions Themes	Questions Aim
1	Participant personal responsibilities	To determine participants experience and knowledge to the survey questionnaires
2	Participant association within the company	To confirm the relevancy of the participant and dept. to the survey
3	How do you evaluate the design against criteria?	To search for what priority given to evaluate design
4	If you are using none algorithm based technique to improve a design, who much time required, relative to the total design cycle?	To gauge the importance of or otherwise, using none algorithm based techniques in the design process.
5	If you are using algorithm based technique to improve a design, how much time required, relative to the total design cycle?	To gauge the importance of or otherwise, using algorithm based techniques in the design process.

Table 4.5. Questions themes and aim

Section 2		
Qs	Questions Themes	Questions Aim
1	Describe how you optimise a component	To search for what factor determined the design optimisation
2	Have you documented your design optimisation or design improvement process?	To find out if there is a structured and reusable process exist
3	How much time (percentage) do you use to optimise one initial design?	To gauge the total time spent to improve a design
4	What criteria do you use to optimise your design?	To identify what derive the design optimisation

Qs	Questions Themes	Questions Aim
5	Do you have a process to develop a model?	If the modelling process is manual/iterative scientific?
6	How do you measure the efficiency of the design process?	To find out If there is a recognised way of measuring efficiency
7	How frequently would you use optimisation?	To find out the popularity and frequency of use of the optimisation process
8	Do you use any commercial software for the optimisation?	To gauge the dependency, if any and importance of commercial software.
9	What criteria you would like to use to evaluate commercial optimisation software?	To investigate if there is appetite for commercial software, if not why?
10	What are the draw backs in the current design optimisation process?	To gauge the efficiency of the current optimisation process
11	Are the current optimisation technique you are using are algorithm based fully or partially?	The gauge the state and popularity of algorithm based optimisation techniques
12	If using algorithm based techniques what are the drawbacks?	To gauge the efficiency of algorithm based optimisation techniques for real life application
13	What advantage algorithm based techniques have in comparison to any other techniques you may know?	To compare the algorithm based optimisation techniques in comparison to any other techniques
14	If your design improvement activities involve algorithm based techniques what particular tool/s you are using?	To identify if there is a particular algorithm based technique that is popular for real life application and why
15	If your design improvement activities is conventional based, what particular tool/s you are using?	To identify if there is a particular conventional technique/s that is popular for real life application and why
16	Is your design improvement techniques involves hybrid technique (conventional +algorithm based)	To gauge the popularity and advantages of hybrid techniques for real life optimisation process application
17	From your own experience what needs to be improved in the current optimisation technique you are using?	To identify the weakness of the current techniques for real life process applications
18	Please write if you have any general remarks and suggestions on algorithm based techniques	To gauge individuals understanding , strength and weakness of algorithm based techniques

4, 3.2 Observations

The section presents the engineering design and optimisation in industry and techniques availability survey. The section also discussed the survey methodology followed and knowledge elicitation approaches. The elicitation is based on interviews, questionnaires, observations, and discussions with experts in various engineering companies. The knowledge captured was analysed and the required information related to the research was identified. The required information includes: current engineering design optimisation in industries, shortcomings in the current techniques and what the industry needs to fulfil these shortcomings. Main points of the survey findings are the following:

- Design optimisation is carried out, either in conventional and in less extent, in evolutionary form. However the current design optimisation techniques are manual and mainly dependant on the designer's skills and experience.
- Although some of the industries have limited but growing evolutionary techniques application, mainly in research and development. The survey revealed that optimisation algorithms are not yet widely used in the engineering design process. There are several inhibiting factors identified as being responsible for this limited usage:
 - Lack of integration of existing optimisation tools
 - Limited optimisation skill among design engineers
 - The computational time and cost of simulation
 - The complexity of real life optimisation problems
 - Multinational companies, a need for a global lead in decision making to adopt new techniques.

However, experts in all surveyed companies universally agreed that, knowing the capacity of the algorithm based optimisation techniques in handling complex optimisation problems with minimum expert dependency, it would be beneficial to the business if have it in their organisation.

4.4 Knowledge Elicitation in the Research Problem Domain

Work roll system thermal analysis, design and optimisation are a specialised subject where the real life process understanding is essential to have a wider perspective and

to fill the issues influencing the process. Hence, in addition to the literature review, a real life current practise study is important. The current practise study in the rolling design and optimisation is carried out primarily to investigate the flow of information in the process, and through that, to understand, in particular, the thermal and its effect of the work roll. The study is carried out by eliciting rolling system process knowledge from suitable engineers identified from various relevant departments in the sponsoring company. The knowledge elicitation is also applied to map the process involved in the work roll system leading to the development of the process thermal model. This collaboration with the engineers for knowledge gathering also contributed towards identifying likely areas within the work roll system in the rolling process, and in particular, cause of roll thermal change. As reviewed in the literature, work roll system is a process characterised by high disturbance, taking place in extremely hot environments and with a potential that uncertainty can influence the product tool and the process. Therefore, the collaboration of experts in the elicitation exercise is very valuable, in a way that it provides knowledge in the form of qualitatively measured opinion, which would have been impossible to find otherwise. The literature review, conducted in the subject area at the initial stage of the research, also indicate the need to acquire more specialists' rolling design knowledge through participation with the experts, so that the real sense of the real life rolling and work roll system thermal analysis and optimisation problem could be realized. The information gathering was made in two ways:

- 1 Initially, the researcher spent time in the plant. The plant visit was for firsthand experience of the rolling process and the main factors involved in the process. During the stay, the real life process observations and informal discussion with various engineers in the shop floor were carried out. The time was also used to study software and the current activity in the area of modelling, design, analysis and optimisation within the company.
- 2 This was followed by formal interviews, workshops, company presentations, internal reports study and one-to-one training programs. The interaction and knowledge elicitation exercise with experts in the Tata, Steel Europe, Swinden Technology Centre (STC) has enhanced the knowledge acquired from the literature and been used for developing the research case adopted and identifying details of the work roll system thermal process design and optimisation problem. The current practice study particularly focused on

issues associated to the problems initially identified by the sponsoring company as a potential research topic. These are:

- Work roll system thermal modelling and optimisation.
- The modelling, analysis and optimisation techniques and capacity.
- Work roll system and system complexity.
- Rolling process and design factors uncertainty and constraints.

Pre Knowledge Elicitation Arrangements

Three engineers were particularly selected because of their many years of experience and also that they are currently actively involved in the work roll system thermal analysis and optimisation within the company. The three engineers, besides participating in the knowledge elicitation exercise at the start of the research, also remained in contact throughout the research programme. At the initial stage, intense knowledge elicitation, particularly on factors and factors parameters involved in the design and optimisation of work roll thermal analysis and optimisation, is carried out. This took a total of 25 hours (5 hours a day in 5 sessions). The three engineers are the most experienced and senior experts in the research domain; therefore, the elicitation exercise, particularly in the modelling and rolling thermal factors analysis, mainly relied on these experts. However, during the two weeks stay in the company, the researcher also has an informal discussion with engineers who are controlling the manufacturing process in the shop floor. Brief descriptions of the arrangements made for information gathering and achievements are presented in the table below. The arrangement consists of two parts:

- 1 Informal discussions with engineers in the shop floor and physical observation of roll damages due to thermal stress; learn from engineers the unforeseen or uncertainty in the rolling process that might influence the thermal behaviour of rolls; and brainstorming of rolling process factors determining rolls' thermal behaviour.
- 2 Two days training and practise on modelling and finite element analysis, using software widely used by the sponsoring company. Learn effects of design process factors on work roll thermal behaviour by creating different scenarios and simulating on ABAQUS.

Table 4.6. Initial arrangements for knowledge elicitation

Rolling experts	Years of relevant experience	Expertise
Expert 1	40 years	Mathematical modelling
Expert 2	15 years	Long product rolling, design, modelling and optimisation
Expert 3	10 years	Long product rolling modelling and FEA

The collaboration with the sponsoring company started with presentation by experts, who are involved in the research. The presentation by the experts gave the overall understanding of what is required. During the two weeks stay, the researcher learnt also that regarding the current design and optimisation techniques, even though there are approaches in place for the rolling system and pass design that are able to deal with multi-pass and multi-objective problems, the work roll thermal analysis and optimisation problems have not been integrated. It was also learnt that the optimisation techniques in place do not address the roll thermal problems with uncertainty. Although there is some work reported in the literature in this regard, in most cases it is only addressing single pass and single objective problems, and the works are mainly assumption based and lack real life case study. The collaboration of the author with the engineers contributed towards identifying likely areas within the work roll thermal analysis and design that are appropriate for evaluating the optimisation technique. In particular, the inclusion of uncertainty in the optimisation, identifying the process factors and parameters for single and multi-pass work roll system thermal analysis and design problems scenarios, the number of passes that need to be considered, and modelling and optimisation of multi-pass cases. It also helps to understand multi-pass rolling design factors functional relationships so that make realistic assumptions during quantitative modelling of the multi-pass problem. This thesis focuses on modelling and optimisation of work roll system optimisation using thermal analysis and GA. Hence, the survey for brainstorming and knowledge elicitation was carried out with engineers mainly focused in these particular domains. Elicitation exercise query topics and the rationale for the query are presented in Appendix B. Sample questions and the rationales behind the questions are given in Table 4.7. The section also presents scripts of engineer's interview feedbacks.

Table 4.7. Sample questions, Work roll system in rolling process

Qs	Survey Question	Survey Aim
Q1	What is the cost of rolls	To gauge the cost associated to rolls
Q2	What are roll design criteria	To fully understand rolls and key design criteria
Q3	What are the setup parameters, work roll thermal design parameters?	To identify the nature of the set-up, parameters involved and parameter interactions

4.4.1 Knowledge Elicitation Exercise, (Questionnaires and Experts Feedback Transcript

Transcript 2

This transcript reports on an interviewing session with two Tata-Europe engineers. The purpose is to assess the current status (general assessments) of work roll system design within the rolling process taking in account uncertainty and thermal effect. This is transcribed as follows:

Researcher: What is the cost of rolls and how do you and measuring the roll life?

Tata Steel-Europe: Single roll (Section roll) cost 8,000 pounds and Plate mill cost 70000 pounds. The roll life time measured by the amount (tons) of material rolled. For example under normal circumstances, cast steel roll estimated to roll up to 100 to 160 tons of material.

Researcher: What criteria you use to design roll?

Tata Steel-Europe: Roll design criteria is achieving the final shape in minimum number of passes within the constraints of the mill

Researcher: How do you measure rolls data?

Tata Steel-Europe: Roll data measurements are CNC /redressing data. Factors such as speed measured using decoder.

Researcher: How do you measure roll thermal profile?

Tata Steel. Europe: Roll thermal profile is not measured, only estimated from models

Researcher: What is the percentage of cost of rolls from the total production cost?

Tata Steel-Europe: Roughly rolling cost estimated to be 5% to 15% of the total production cost, higher portion of this goes to tooling costs.

Researcher: What are the main causes of work roll damage that trigger higher roll cost in hot rolling?

Tata Steel-Europe: Stress due to thermal force acting on the roll during rolling and cooling is the main cause of roll damage. The depth and degree of roll damage is influenced by process design factors. It is believed that the mechanical and process environments factors may also have influence roll damage.

Researcher: How do you maintain roll from damage?

Tata Steel-Europe: Roll thermal condition regulated by the roll cooling system. However redressing the roll (removing the upper shell of the roll by machining is the main form of renewal of the work roll.

Researcher: How do you design and optimise rod rolling does it include work roll thermal analysis and optimisation?

Tata Steel-Europe: We have innovative techniques for roll pass design and product quality and scheduling, that reduce our cost, reduce manpower, reduce change times. However these existing techniques do not incorporate work roll system thermal analysis and optimisation.

Researcher: What do expect or benefits will you be looking for from this research project?

Tata Steel Europe: Develop innovative techniques that give a range of design solutions. It got to reduce the conversion cost to increase the margin, Reduce our cost, reduce manpower, roll for longer period of time reduce energy cost, reduce change times, if we keep the same roll, we can have more stock and less down time.

Transcript 2.1

This transcript reports on a session held with two engineers. The purpose is to gather information about the rolling and work roll system thermal analysis, design and optimisations behaviours. This is transcribed as follows:

Researcher: What are the setup parameters, work roll thermal design parameters?

There is no work roll thermal design parameter as such, but rolling process parameters set from which the work roll system thermal design parameters can be found.

Researcher: What are the main outputs and input of the mill pass?

Tata Steel-Europe: The outputs are physical stock size, the speed, the torque develop in the drive spindle, roll separation force. The input are: collar gap, the draught and the speed, those are the basic input we put in. The other you input is the preceding pass output i.e. the incoming stock gap.

Researcher: What are the constraints & parameters that must hold to satisfy rolling thermal design & optimisation requirements?

Tata Steel-Europe: Stress and surface temperature of work roll should remain within the material allowable limit, beside you should look in to other process factors need to be considered for constraint, one example could be coolant temperature.

Researcher: Is the functional relationship between passes can define the real life process?

Tata Steel-Europe: One can calculate the multi-pass rolling set up by carefully worked out functional relationship, by considering known factors parameters of passes. This is relatively strait forward for continuous rolling pass set.

Researcher: Do you currently consider process uncertainty in the design & optimisation of the work roll thermal analysis?

Tata Steel-Europe: Work roll thermal design is part of the rolling process scheduling, work roll thermal analysis, design and optimisation is not rigorously explored, work roll cost due to thermal issues is still a problem. In the previous improvement process uncertainty was not considered.

Researcher: Do you have record of study made for process uncertainty relevant to rod rolling thermal analysis and optimisation?

Tata Steel-Europe: Not particularly related to work roll design and optimisation for work roll thermal analysis,

Researcher: Is there a specific conditions, factors/ parameters each pass experience during the rolling process?

Tata Steel-Europe: with few exceptions such as roll bulk temperature, process factors; each pass is experiencing isolated thermal, mechanical and thermo-mechanical conditions. Factor parameters are also pass specific however a compromised design can also be found that serve a rolling set involving number of passes.

Transcript 2.2

This transcript reports on a session (work shop) held with two Tata engineers. The purpose is to clarify the work roll system thermal analysis, design and optimisations problem to be addressed by the research. This is transcribed as follows:

Researcher: what do you look from the research?

Tata Steel - Europe: We need to look at is optimisation, involving single pass, multi-pass, multi-variable, multi-objective, uncertainty and constraint issues. Basically we

have to develop optimisation framework. The quantities we've considered optimising is the work roll thermal analysis and optimisation; we've picked the single pass of the rod schedule and multi-pass consisting of 5 passes for investigation. Also we need to look the mechanical, thermal and thermo-mechanical significance on the work roll thermal behaviour. We also want to look at the inter-pass relationships, taking in to account the output of one pass fed as input to the next pass. Temperature and stress have some sort of proportionality, so the first stage is to minimise the work roll temperature and at the same time looking in to the stress behaviour may occurred as a result of minimising work roll temperate.

Researcher: The context of approximate modelling and optimisation for the research.

Tata Steel-Europe (Expert 1): The main issue is methodology for optimisation.

Tata Steel-Europe (Expert 2): Your role is not to find the most accurate FE run. We can provide initial process model, your project is developing a method for pre-processing DoE, and post processing for optimisation.

Researcher: How about the uncertainty issues?

Tata Steel-Europe (Expert 1): Uncertainty is the main issues affecting life of work rolls that need to be addressed. Current practise cannot efficient to deal with the uncertainty issues, current technique lack robustness.

Tata Steel-Europe (Expert 2): The uncertainty can be used as additional information for the initial knowledge. In addition uncertainty can be included in the optimisation. Uncertainty and degree of uncertainty has not been considered in the current design and optimisation of work roll system, however based on research on the rolling system, closely related to work roll system thermal design and optimisation at least 95% design variables accuracy expected.

4.4.2 Observations

Following the industrial survey and collaboration with experts in the sponsoring company, the following important findings related to the research domain are identified:

- Work roll thermal analysis and optimisation is a process optimisation problem and influenced by various process factors that needs to be investigated.
- Real-world multi-pass work roll thermal analysis and optimisation problems involve many design factors, which increases their complexity and reduces the ability of engineers to easily reason about them. However studying the factors

complexity and functional relationship between design factors is a possible strategy help to understand the behaviour of multi-pass rolling arrangements.

- During hot rolling operation, the roll cooling system is to balance heat entering to the roll and leaving it; hence, keep the work roll from excessive temperature. However, due to the nature of the rolling environment and the presence of uncertainty, cause the cooling system from keeping the work roll in the required temperature range and protect it from damage.
- Although the work roll system thermal design is a vital part of the rolling process for keeping the work roll from thermal shock, its operation is conventional. These techniques are inefficient and unable to deliver if a robust and optimal solution is sought.
- Presence of uncertainty in the process is one main factor affecting the work roll system design, however currently the presence of uncertainty has not been considered in the design and optimisation.
- The Current practise study reveal that even though there are approaches in place for the rolling system and pass design that are able to deal with multi-pass and multi-objective problems, the work roll system and thermal analysis and optimisation problems have not been integrated. It was also learnt that the optimisation techniques in place do not address the roll thermal problems with uncertainty in the design space and fitness function. Although there are few work reported in the literature in this regard, in most cases it is only addressing single pass and single objective problems, and the works are mainly assumption based and lack real life case study.

The elicitation exercise was designed to explore the product development process in the sponsoring company within the technical centres, Rotherham office. The exercise helps to understand the work roll thermal analysis and optimisation problems and an overview of the process of rolling designing and optimisation. The elicitation exercise report, the current work roll thermal analysis and optimisation activity, and capacity to deal with it, identified critical areas requiring further analysis and the knowledge gaps in the current practise. These also led to identifying and setting the aim and objectives required to address and filling the gaps. These gaps define the main focus of this research. As mentioned in Chapter 3, this research attempts to develop GA based techniques for work roll thermal analysis and optimisation problems. The

chapter has given an overview of the rolling process and work roll system thermal analysis and optimisation problems, and existing techniques for handling the problems. It also identified the research gaps that form the focus of this thesis. This chapter re-evaluates and affirms the initial scope of the research, defined by the sponsoring company, and knowledge gained from the review of literature. The next section summarised the key issues and challenges.

4.4.3 Key Issues and Challenges

Based on the observation made in the real life rolling practise and as stated by engineers during the knowledge elicitation exercise, the following are main issues and challenges identified with regard to the research problem case studies.

- The features of real-life work roll system thermal design and optimisation problems, such as presence of multiple objectives, constraints, interaction among decision variables, quantitative and uncertainty create challenges for the design and optimisation techniques currently in use in industry. These are also an issue that discourages the industry from adopting algorithm based techniques.
- A process model that explains the behaviour of complex design problem is a pre-requisite of any optimisation process. It is needed by the optimisation algorithm to evaluate the goodness of the solution. The nature of the model influences the wider application of the optimisation algorithm. Realistic process models is a result of, not only based on quantitative formulations but also models based on perception based reasoning elicited from engineers.
- Understanding inter-stage dependency plays a crucial role in the search for realistic real life multi-pass process optimisation problems. The link between passes establishes communication that can be useful to ensure the information about the previous passes is taken into account when dealing with the next passes. This is useful in ensuring that the search at the current pass is consistent with passes before. As in the case of real life practise.
- The issue of high dimensionality is a common problem difficult to deal with in the current multi-pass work roll system thermal design and optimisation practise. The number of variables present in the design problem increases significantly with the number of passes. This has a significant impact on the feasibility of solutions obtainable by process optimisation algorithms. As the

problem size increases so does the complexity of the problem. The high dimensionality is also an issue for visualising the optimisation problem solutions (Pareto front).

4.5 Chapter Summary

This chapter described the part of the research methodology that has formed the basis of the research work carried out in this thesis. Since the research is an industry based case study, it is vital to acquire understanding of the real life process and operation in industry. This includes the knowledge elicitation exercise to capture requirements at the initial stage of the research. The knowledge elicitation exercise is an essential stage, helping to acquire more specialist rod rolling thermal analysis and optimisation knowledge through participation with experts in the design process. The primary objective of this exercise was to assess the current status of work roll system thermal design and optimisation within the organisation, and to verify the proposed aim of the research. The exercise was carried out through industrial visits, structured, semi-structured interviews supported by questionnaires.

Since the aim of the research is to develop an optimisation technique using thermal analysis and GA for work roll system design and optimisation, it is important and necessary to study the current state of GA based optimisation technique in industry and in research. The research also conducted a comparative study of techniques application in the last decade, shown in Chapter 2. The study explored the fundamentals of techniques and their applications, advantages and shortcomings. The survey and the comparative study outcome on the techniques are used as a prerequisite for the development of the optimisation technique for searching for a solution for the research problem. While this chapter discussed the current practise study in the research domain, such as the rolling process, work roll system thermal analysis and optimisation, as well as the process factors and parameters influencing the thermal behaviour of the work roll, the next chapter presents the development of the single pass work roll system quantitative approximate models for design optimisation.

5 Work Roll System Single Pass Thermal Model Development

Chapter 1 introduced the nature of the research problem, the complexity of real life work roll thermal process design, and hence, the need for an alternative, easy to use surrogate model. Chapter 2 explored in the literature, among other issues, the simulation techniques, and acquired knowledge for developing a model to represent the work roll thermal process design in a controllable manner. Chapter 3 presented the methodology adopted for modelling the thermal model. Chapter 4 discussed the current practise of the research area and explored the roll thermal modelling activity and shortcomings. This chapter presents the quantitative thermal model and the strategy used for the development of the thermal quantitative model. As presented in Chapter 2, thermal modelling approaches such as finite element analysis (FEA) are the most important techniques available in representing a complex real life process such as roll cooling system design. The collaboration with experts in the company is an important stage of the modelling process, and helped to identify the main problem area and possible contributory factors for the identified problems. The collaboration also helps to ensure that the surrogate model developed can approximate and represent the real world rolling process. The modelling also incorporates the uncertainty in the design input factor parameters. This is important for realistic representation of real life work roll thermal system design. The model is later used in the optimisation for searching for optimal design solutions for work roll system design problem. The mathematical modelling is based on the response surface of the FEA model supplied by the sponsoring company. Details of the FEA model, response surface simulation and the regression modelling are discussed in this chapter. The chapter is structured as follows:

Section 5.1 presents details of the FEA problem model supplied by the company. Section 5.2 presents the functional modelling (mathematical modelling) for work roll system thermal analysis and design problem. Section 5.3 presents the procedures for the design of experiment (DoE) for work roll system design thermal modelling. Section 5.4 concludes the chapter by summarising the key points of the modelling process.

5.1 Description of the FEA Model

The basic principle of approximation is to develop an alternative model that represents the underlying behaviour of the real life rolling process. The main objective of such a model is to be less complicated, less expensive, easier to use and able to achieve a reasonable trade-off between the expensive objective evaluations and the search problem. It is also simplifying the representation of a complex behaviour and speeding up the numerical solution process. As discussed in Chapter 3, the fundamental background information and research formulation is derived from literature review and knowledge elicitation from engineers. The information gathered was analysed and presented back to engineers, where the presentation describes, among other issues, the complexity of the rolling process and the need for an approximate modelling. In the presentation and subsequent discussion, it was agreed that the approximation should take place in two phases. These are problem and functional approximations. Problem approximation is recommended to replace the original problem by an approximate problem using FEA, and the functional approximation aims to construct an implicit model in place of an underlying behaviour by developing a Meta-model. However, since the case study of the research problem is part of a previously started wider process improvement project being carried out by the sponsoring company where various problem approximations (FEA model) are already in use, it has been decided that the first phase of approximation (FEA) model in this research be omitted, and instead provided by the client company. The specification of the approximate problem model and regression modelling are described in the following sub sections.

5.1.1 Problem Approximation (FEA Model) and Its Specifications

The sponsoring company provided a CAD model for the rolling simulation. The model can be used for FEA based thermal analysis. The 2D thermal model consists of the thermal, mechanical and thermo mechanical properties of the rolling system design, representing real life single pass rolling. However, during the development of the functional modelling, the single pass model process factors' functional relationships have been manipulated so that the 2D single pass approximate model can be extended and used to develop functional approximation for multi-pass work roll system problem. Details of the multi-pass functional modelling are discussed in

Chapter 7. Original problem approximation (FEA) 2D model specification is described as follows:

Specification of the problem approximation (FEA) model

The problem approximate FEA model, supplied by the sponsoring company, is made up of three main parts of the rolling process. These are: the roll, stock (represented by the static pressure in the roll stock contact) and a cooling system with 6 cooling sprays rotating nozzles. The model specification is generated from the given original FEA model, in which all the necessary predefined fields and properties of the model parts can be accessed. For functional Meta models, developed by the researcher, the responses of simulation matrix of 27 FEA simulation runs have been carried out by changing the predefined property, for example, material property; roll speed, heat transfer coefficients, and other relevant variables, according to requirements, to measure the effect of cooling on the roll, using a specified roll thermal profile measures or responses. The quadrant original problem approximate (FEA model) supplied by the sponsoring company is presented in Figure 5.1. The quadrant FEA model is chosen to save computational time and the size of simulation Output Data Base (ODB) unnecessarily during simulation. Therefore the inexpensive model with stationary roll/stock but with rotating cooling nozzles has been selected. The problem FEA model shown in Figure 5.1 represents the rolling thermal process design, without compromising the true nature of the process. Heat affects the roll most in the area of contact, lower part of the roll, and tense at the time of contact. The model presented here represent the roll lower part that have direct contact with hot stock and the surrounding area where the cooling applied to remove the excess heat from the roll. It has been learned during the interview, knowledge elicitation with rolling experts in the sponsoring company that, the part selected is determined the thermal profile of rolls most. The model represents two steps of single pass, long product rolling process. The two steps are the rolling and the delay time steps. The meshing and boundary conditions of the FEA problem model, developed using ABAQUS, are given in Figure 5.1 and Tables (5.1-5, 2).

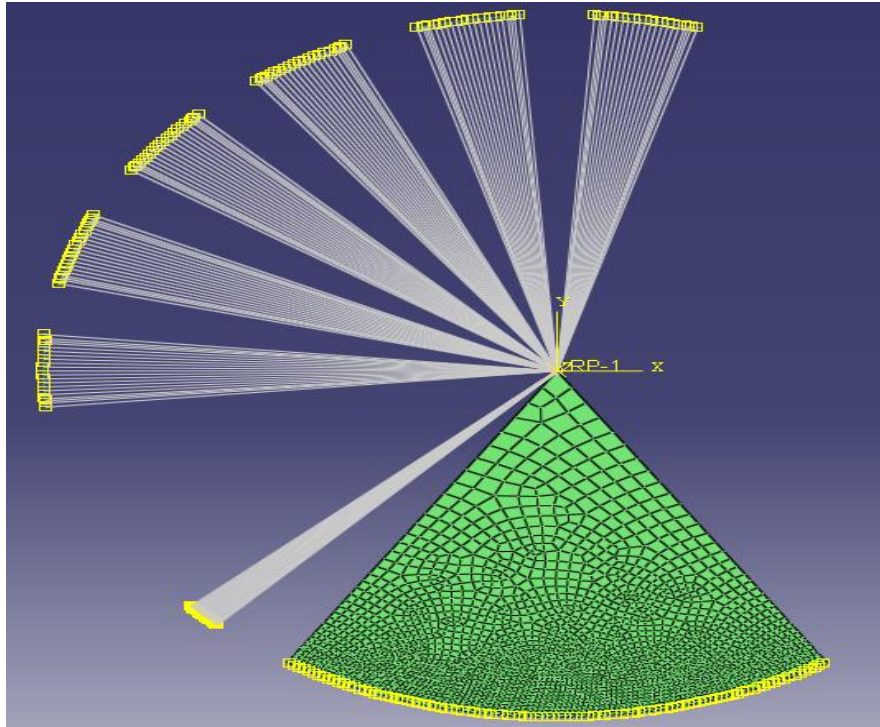


Figure 5.1. Original problem approximate (FEA) model (source the sponsoring company)

Table 5.1. FEA problem model meshing part boundary condition

Meshing Boundary Conditions (Material property)			
Roll Shell	Roll Core	Nozzles	Stock
Material, name=highcr_shell Conductivity (w/m.k) 18.4, 20.0 Density 7.5833e-09 (kg/m ³) Elasticity 215000, 0.3, 20.0 (MPa) Expansion 1.3e-05, 20.0 (mm) Inelastic Heat Fraction 0.9 Specific Heat 4.78e+08 (j/kg.k)	Material, name= sgac core Conductivity 48.58,20.0 (w/m.k) Density 7.172e-09 (kg/m ³) Elasticity 167000, 0.3,20.0 (MPa) Expansion 1.22e-05 (mm) Inelastic Heat-Fraction 0.9 Specific Heat 4.78e+08 (j/kg.k)	Material, name=nozzle Conductivity 55. 50.0 (w/m.k) Density 0.02075 (kg/m ³) Elasticity 812000,0.281,20. 0 (MPa) Specific Heat 5.86e+08 (j/kg.k)	Material Material=lead steel Stock truss, (Beam Orientation)

Table 5.2. FEA problem model part interaction property

Interaction Properties			
Surface Interaction name=INT-11 Friction, slip tolerance=0.0050.3 gap conductance (HTC roll/stock contact)	Surface Interaction name=nozzle - roll Friction 0. gap conductance (HTC cooling)	Nozz1Contact Pair interaction= nozzle-roll, type=surface to surface	roll stock- contact Pair- interaction (nt-1) type=surface to surface

5.1.2 Purpose of the Thermal Quantitative (Functional) Models

The thermal models developed are used as a substitute for real life work roll system design characteristics for physical experiment. The work roll system characteristics such as: heat / cooling system effect on rolls, rolling process factors and parameters, and their associated uncertainty. The purpose of the thermal model is aimed at addressing the following:

- To develop an alternative, mathematical model that represents the underlying behaviour of the research problem being investigated.
- Approximate Meta-Models are developed in most cases to simplify the representation of a complex behaviour, less complicated, less expensive, easier to use and speeding up the experimental work.
- To increase the integration of numerical information and the uncertainty in the work roll to be used in the optimisation; thus, better decision making.
- Since the model developed is based on response surface methodology, it makes it possible to capture the dependent and independent design variables (input / output) relationships. the measure indicate the roll thermal profile and the effect of the cooling on the roll for given input design set as observed in real life rolling process.

5.2 Approximate Modelling for Work Roll System Thermal Analysis and Design Problem

The purpose of approximate modelling, also known as functional approximation, is to develop an alternative mathematical model that represents the fundamental characteristics of a process being examined. The main objective of a functional approximation model is to develop a less expensive and easier to use model, and be

able to achieve a reasonable representation of the real life complex process, such as roll cooling system in rolling design. Other reasons to develop approximate models are to minimise time required for real life physical experiment, and speed up the numerical solution process, which otherwise would have been difficult, if not impossible. Meta-model is a typical example of functional approximation (Friedman, 1996). It is often referred to as the approximation of the simulation program's input/output transformation, also called response surface. Statistical meta-modelling techniques build approximate meta-models to output responses based on experimental or simulation data at carefully selected design points. Due to its simplicity in application and ability to emulate the complex real life process behaviour, the Meta modelling approach is becoming widely used in various engineering design disciplines. However, it has been established from the literature that there is still very little application reported, particularly in roll thermal modelling. Therefore, the research adopted a statistical meta-modelling technique for generating models for work roll system design problem. The design of experiment and the descriptions & development of the functional approximate models are presented in Section 5.3. The approximate models are developed based on the strategy shown in the flow chart presented in Figure 5.2.

The flow chart is the framework describing the steps and constitutes of each step, from problem realization, model development to the validation, of the approximate modelling process. The framework used for flow of information between steps and help to define requirements relevant to the intended model in advance.

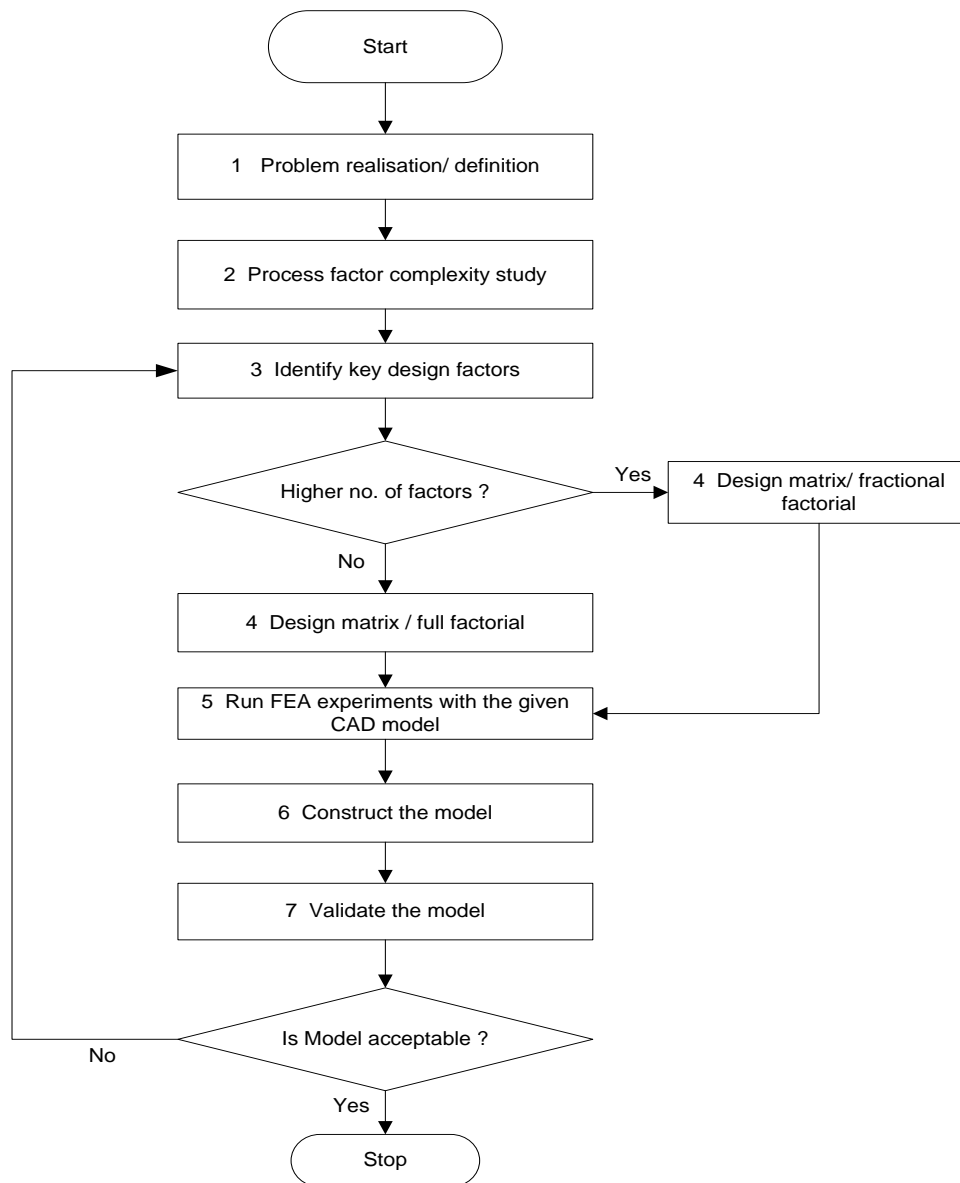


Figure 5.2. Meta-modelling flow chart for single pass rolling thermal process design

5.2.1 Rolling Process Factors Relevant to Roll Temperature Variations

This section discusses the issues concerning the work roll system thermal analysis and design problems and presents the rolling process variables relevant in the work roll system thermal analysis and design. The variables identified through literature review and brain storming session during knowledge elicitation exercise with rolling experts in the sponsoring company. The listing of variables leads to the identification of the most relevant process variables contributing to the roll thermal design problem. Most importantly, the complexity study and analysis is carried out among variables to determine process factors' relationships and dependency, if any, between variables to

determine process factors' relationships and dependency, if any, between variables to ensure that only independent fewer number of variables are selected for functional modelling. Identifying the most relevant process factors follows the steps shown at the end of this section: Figures 5.3 and 5.4, present rolling process factors determine rolls' thermal behaviour, and rolls thermal variation cause sources respectively.

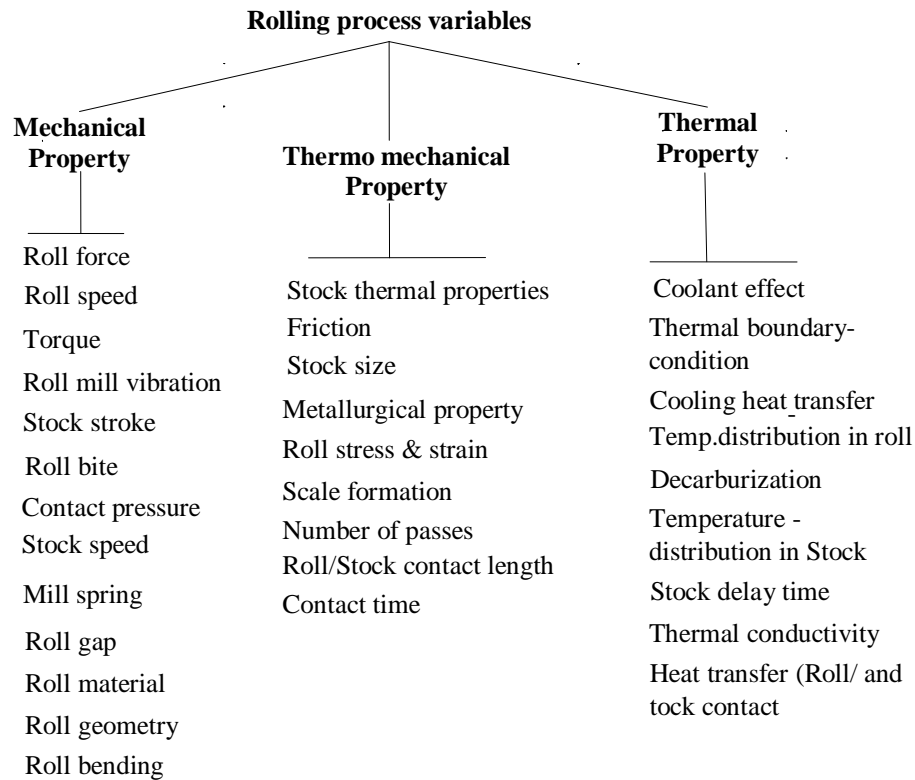


Figure 5.3. Rolling process factors features associated to roll thermal behaviours

Figure 5.3 lists the rolling process factors (mechanical, thermal and thermo mechanical) in the hot rolling process. The factors in the list are identified through rolling expert knowledge elicitation, presented in Chapter 4. The list helps to identify the particular factors from the three categories that influence the thermal behaviour of work roll in the rolling process design. Figure 5.4 shows a cause and effect diagram where the factors are categorised depending on their source. The categories are tool, product, process and other, such as environmental. The identified thermal factors are further analysed for factors complexity and relationships before the final independent most relevant work roll system thermal analysis and design factors are chosen. Descriptions of the steps followed for identifying input design factors used in the modelling are as follows:

- Identify list of process factors and parameters for work roll thermal analysis and design from literature review.
- Arrange meeting with engineers in the client company for further study and brainstorming of work roll system design factors, as well as identifying factors important for thermal design.
- Study and analyse factors complexity, if any, among factors identified as important for work roll system thermal design. Here also, the relevant and independent factors are determined. Sample factor complexity study is presented in Appendix D.
- Issue the selected, independent identified factors relevant for work roll system thermal analysis and design to expert in the client company for approval.
- Document the validated final list of factors, to be used in the functional modelling of work roll system thermal analysis and design problem.

The next section discusses the final, independent rolling process thermal design factors. The identified factors include the input design factors, as well as thermal measuring or dependent factors.

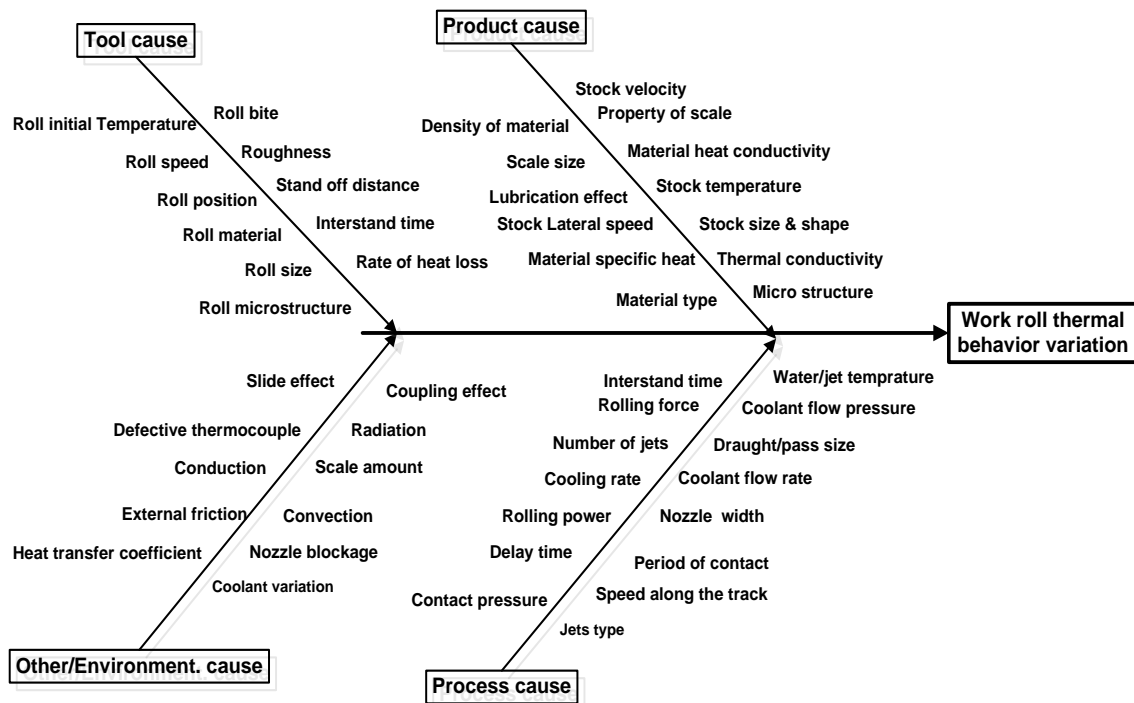


Figure 5.4. Causes of work roll thermal behaviour variations

5.2.2 Description of Final Independent Factor Relevant in Rolling Process Thermal Design

The aim is to understand the issues concerning the roll cooling problems and identify specific contributing factors to the identified problem. This step also lists the most important design variables from a large number of potentially important factors, presented in the previous section. The choice of design variables was driven by the need to mimic the real design problem experienced in the plant. This is achieved through a number of visits to the plant, for process real life operation physical observations, knowledge elicitations from rolling experts through interviews and questionnaires, as presented in Chapter 4. The literature review also helped to verify the rolling process factors relevant to work roll system thermal behaviours identified by rolling experts. Seven variables were identified and their operating range specified. The variable bounds are estimated for feasible design values. These are established after consultation with the rolling engineers. Table 5.3, shows the factors identified and factor levels recommended. Identifying the final seven design variables is based on the following steps:

1. Brainstorm and list large portion of design variables involved in the rolling process
2. Identify factors from step above, relevant to work roll thermal behaviour
3. Study the factors identified in step 2 for complexity/functional relationships. The study is important in determining the relationships between the final selected design factors affecting roll thermal behaviour so that assuring only independent variables are selected in the modelling. Sample complexity study is shown in Appendix D.
4. Select small number of independent factors from step 3, most relevant to work rolls thermal characteristics.

The selected variables and their parameters are then fed in to the problem CAD model for FEA simulation. The responses from the simulation (the selected dependent variables i.e. objective functions measuring the behaviour of roll thermal behaviour) are recorded and later used to develop the functional/ mathematical models. The functional models are the fitness function in the optimisation used for searching solutions for the design problem. As discussed in the previous section, there are a number of process and operating contributing factors to rolls' thermal fatigue.

However, those factors sometimes are difficult to quantify. Also, depending on the degree of their contribution, as well as the fact that the higher the number of factors the more complex the design of experiment will be, hence, priority should be given to those factors most important to the problem. Those less contributing factors and factors created during operation, such as roll stock contact during rolling and the cooling operation, are represented by one compensating factor called heat transfer coefficient (HTC). Here, the HTC 1 and HTC 2 are the heat transfer coefficient values given for cooling and roll/stock contacts, respectively. The design factors have been given a range of design space, called factor levels that lie between acceptable upper and lower boundaries; therefore, modelling problems caused by factor variability can be resolved. The boundaries are assigned based on information from real world rolling practices. Higher model accuracy is expected from higher number of levels in the design space. Therefore, a 3-level is allocated for each of the identified main factors. The number and level of factors selected determined the basis for how the design samples will be allocated in the experimental FEA simulations, particularly in terms of size and quality of the design. The choice of design samples, as well as being known as design matrix, is shown in Section 5.3.3.

Table 5.3. Work roll system independent design variables used in the model

Key: HTC = Heat Transfer Coefficient

	x1	x2	x3	x4	x5	x6	x7
Variables	(HTC Roll/stock contact) (kW/m ² K)	Stock temperature (°C)	Contact length (mm)	(HTC - Cooling) (kW/m ² K)	Roll speed (Rad/sec)	Roll Temperature (°C)	Delay time (sec)
Limits	5	950	10	15	0.14	40	20
	15	1250	30	50	1.256	80	100

Table 5.4. Design simulation 3 level matrix inputs

Design variables	x1	x2	x3	x4	x5	x6	x7
Levels	(HTC- Roll/stock contact) (kW/m ² K)	Stock temperature (°C)	Contact length (mm)	(HTC - Cooling) (kW/m ² K)	Roll speed (Rad/sec)	Roll Temperature (°C)	Delay time (sec)
1	5	950	10	15	0.14	40	20
2	10	1100	20	35.5	0.698	60	60
3	15	1250	30	50	1.256	80	100

Roll thermal behaviour during rolling is dictated by a combination of input and output factors of the rolling process. However, due to the nature of the process and the wider impact on work rolls, the output factors change in temperature on rolls, and roll radial stress are taken as the main fitness measures in the research problem. The responses (dependent) factors are a result of a wide range of design factors (thermal) of the process. In the literature review, it was discovered that the obvious known design factors influencing the thermal behaviour on the roll are contact between the hot work piece and the tool, the temperature of the material, as well as the speed of the rolls. Similarly, however, there are other important design factors in the rolling process, relevant to roll thermal behaviour change. The design variables are inputs that are used to develop the new system and/or adjust in order to modify the system in progress. The dependent variables are the response from the design or independent variables, and used to measure the thermal behaviour of rolls. With the state and operational variables, although they may not have a direct contribution in the design, the uncertainty may rise in them and could affect the final result. The sources are classified in to independent, dependent, operational and state variables. The variables in each source are the input and output response of the modelling process. The variables and their source categories, in the rolling process relevant for work roll system thermal analysis and design are presented as follows:

Independent design variables, these are the actual variables used in system as input to form the design. Here, the design variables used for system modelling are called input design factors. Following are the main factors in the rolling process that determine roll thermal characteristics.

Temperature, In metal forming, both plastic deformation and friction contribute to heat generation. Approximately 95 % of mechanical energy involved in the process is transformed in to heat. A part of the generated heat remains in the deformed material, and the other goes in to tooling. This temperature developed influences the cooling conditions and tool life as much as the properties of the final product. Since the heat generated can influence the maximum deformation speed set to produce a quality product without excessive tool damage, it can be said that temperature generated during plastic deformation is the major influencing factor in the forming process. The main rolling variables relevant in determining work roll system thermal characteristics are discussed in the following.

Stock Temperature - Rolling temperatures vary mainly between 950⁰C to 1250⁰C. The temperature is mainly from the hot stock coming out of the furnace. The roll surface is heated initially to approximately 650⁰C while it is in contact with the hot stock, and subsequently cooled by water to around 50⁰C during the same cycle. The flash temperature could in fact rise above 800⁰C due to the friction generated heat. The mechanical properties and dimensions of the rolled product have a strong influence on the rolling temperature and amount of heat that goes to the roll, and hence have a direct effect on roll life.

Roll Temperature - roll temperature is the initial or bulk temperature of the roll, before it comes in to contact with the hot stock. As observed in the production plant in the sponsoring company, the initial rolls temperature is normally is in the range between 40⁰C to 80⁰C. Roll temperature will go up to 650⁰C when it comes in contact with hot stock, but immediately cool down to normal temperature by the cooling system/ water spray. To maintain the working life of the roll, an adequate cooling system is a must - a system able to keep the roll in optimum temperature, regardless of the conditions of the working environment, such as uncertainty, variability and temperature variations arising in the process.

HTC (roll stock contact) - heat transfer coefficient is an important factor in determining the roll life and better product during hot rolling of metals. HTC is a way of treating heat transfer problems in the roll gaps during hot rolling. According to many researchers, HTC parameters selection during hot rolling is dependent on a number of factors - for example, the size of metal reduction from the stock, presence and size of oxide scale in the stock, section of rolling operation and the contact time. In the literature, it is reported that HTC (α) is in the range of 25-30 kW/m² K if the surfaces are free from oxides and 7-10 kW/m² K if a 0.01 mm thick oxide layer covers the surface (Raudensky and Horsky, 1992). However, other researchers argued that heat-transfer rate has to be dependent on the contact time and the thickness of the oxide scale, and rejected the simple heat-transfer coefficient and looked at the heat transfer in the roll gap as heat transfer through a one-layer wall of thickness α equal to the oxide scale thickness. Pawelski *et.al.* (1989) derived an upper- and a lower-bound value for the coefficient of heat conduction k, where the upper bound represents the heat transfer without scale and the lower bound the heat transfer when the scale is sufficiently thick to determine the entire heat transfer rate. They are also derived the

values. $K_{upper} = 8870 / \sqrt{t}$ for upper and $K_{lower} = 2360 / \sqrt{t}$, where t is roll / stock contact time. The simplest way researchers come up with to treat the heat-transfer problem in the roll gap is to use the heat-transfer coefficient α , and write the heat-transfer rate or the power of heat transfer. $P = \alpha A \Delta T$. Where: $A = wbL$, stock width, breadth and L length respectively. $L = \sqrt{Rt\Delta h}$, $\Delta h = h_o - h_i$, h_o and h_i are stock height entry and exit respectively. $\Delta T = T_s - T_r$, T_s and T_r are temperature of roll and temperature of stock respectively. In his work, he also discussed a quite simple method for the calculation of the coefficient of thermal conductance and of the thermal field in the rolls and rolled bar, as well as the total heat penetration depth and the boundary value, mathematically denoted as $\delta / 2 \sqrt{(dt)} \geq 3$ and $\delta \sqrt{(dt)}$, respectively where d is thermal diffusivity and t is roll / stock contact time.

HTC for roll-stock contact determined based on the following factors:

- Scale size
- Contact time
- Rolling process section
- Material specific property such as conductivity, heat capacity
- Reduction size

HTC (Cooling) - Another important heat transfer coefficient involved in hot rolling, and that has significance in determining roll wear and roll life, is the interface between cooling and rolling, as well as being known as Heat Transfer Coefficient (HTC) for cooling. This parameter controls the rate of heat transfer from the rolled metal to the work-roll. HTC for cooling is comprised of a number of sub factors that determine the transfer of heat. Those sub factors include water temperature, water pressure, coolant flow rate, velocity, jet distance from the roll and orifices diameter are just to mention a few. To derive the proper heat transfer coefficient, both the rolling program and the cooling layout have to be taken into account. According to experimental work by Ye and Samarasekara (1994) the heat transfer coefficient for the water spray zone has been derived from the following relations: $h_{ws} = 2900W^{0.85} (1 + 0.014T_w)$, where W is the water flow velocity, in m/s , and T_w is the water temperature, in $^{\circ}C$. It is also confirmed that HTC cooling depends on the section of the rolling process - for example roughing, intermediate and finishing, shown in Figure 1.6, Chapter 1. Generally, the contact time is higher and temperature of stock is higher in the roughing stage than the finishing stage. Thus, for this and a few other

reasons, flow stress behaviour and interfacial heat transfer coefficients differ between the roughing and finishing operations. In this research, however, to accommodate these variations, a parameter with range has been considered. Hadly *et al.* (1995) devised an empirical equation for HTC cooling, constituting the necessary factors that need to be addressed.

$$H_{con} = \lambda_{mean} / c1 (p_r / \sigma_s)^{1/7}$$

$$\lambda_{mean} = \frac{\lambda_r \lambda_s}{\lambda_r + \lambda_s}$$

The terms σ_s and p_r are the mean flow stress and the mean roll pressure, respectively, and $c1$ is a constant that varies depending on the material used, and λ_s and λ_r are slab work-roll thermal conductivity, respectively. The above relation shows that the interfacial heat transfer coefficient is a function of the rolling conditions, such as the rolling speed, the reduction in thickness, and the friction. All these parameters affect the rolling pressure. Therefore, changes in the rolling program can alter the roll pressure, as well as the interfacial heat transfer coefficient. For example, as the rolling speed is increased, the contact time is reduced, and thus, the quantity of thermal energy that is transferred into the work-rolls is reduced. In addition, as a result, the interface heat transfer coefficient will also change. Roll cooling heat transfer coefficient HTC sub components can be divided into two main sections. These are from cooling source and roll stock contact.

HTC for cooling determined based on the following factors:

- Stand-off distance
- Number of nozzles
- Flow rate [l/min]
- Flow pressure
- Roll speed [rad/sec]

HTC for roll-stock contact

- Scale size
- Contact time
- Rolling process section
- Material specific property
- Reduction size

Rolling loads and stress - Hot wear rate is directly proportional to the normal pressure on roll surface. Average rolling pressures can be considered to be in the range 100-300 MPa. The corresponding cyclic stresses, amplified by thermal cycles, in roll surfaces are estimated to amount to 500 MPa. The rolling pressure can be linked to the initial stock temperature and stock size. The higher stock size will result in higher roll pressure and stress, and the opposite is true for increased roll temperature where the stress could be minimal.

Roll speed/velocity - Roll speed is the most important factor in the rolling process, having the most influence on the thermal behaviour of rolls. Most other factors and factors behaviours are dependent on roll speed. The increase and decrease of the roll speed will have a direct impact on the heat transfer. For example, as the rolling speed increases, the contact time is reduced, and thus, the quantity of thermal energy transferred into the work-rolls is also reduced, and interface heat transfer coefficient will also change. There are various ways to derive velocity as a function from the rolling system. Most noted and relevant to the thermal characteristic of rolls is the speed as a function of inter-stand distance and time, i.e. (speed = inter-stand distance / time in [rad/sec]). Speed variation impacts all other factors relevant to roll thermal distribution and roll wear. For example, increasing the rolling speed lowers the temperature variations in work-rolls. This is due to the fact that the higher the speed the lower the contact time and heat transfer coefficient.

Roll stock contact time - Roll stock contact time is another equally important factor in the rolling process, determining the variation of temperature in the roll. In hot rolling, the transfer of heat from the stock is directly proportional to the time and length of contact. The more the contact, more heat in to the roll results. The impact from the relation can also be the cause for temperature imbalance in the roll, as well as stress, and hence, shorter roll life. Longer contact time after long delay of stock before coming in to contact with the roll can cause sudden shock to the roll that may lead to roll crack. The impact of the delay time is discussed next.

Stock delay time - Stock delay time refers to the time which the stock needs to reach to the roll gap. The stock experiences delay for various reasons - it may be the normal time the stock requires to reach to the roll gap, depending on pace and inter-stand distance, or it may be longer delay due to unspecified circumstances. A longer delay may result in a shock to the roll, unless it may be balanced by the scale amount on the stock formed because of the delay. However, a higher scale amount on the stock may

result in problems to the roll and quality issues to the rolled product. Therefore, the delay time is an important factor in the modelling and optimisation of the roll cooling system design.

Dependent variables are not directly assigned in the design, but values to be measured as an output of the input or independent design variables. The dependent variables, otherwise known as characteristics of design, are largely a function of the characteristics of the input design variables. In the work roll system design problem optimisation, the objective function elements such as temperature change and stress on the roll are values corresponding to the function characteristics of the design input variables. The literature review disclosed that the two variables are best describing the thermal condition of rolls during the hot rolling of metals.

Change in roll temperature (ΔT) is an important work roll system thermal design objective that expresses the effect of roll cooling system on rolls during hot rolling. It is a suitable measurement since it displays rolls' thermal behaviour (i.e. how well the current cooling design meets the requirements). The change in temperature is measured as the difference between roll temperature after rolling and subsequent cooling, measured over a cycle in quasi steady state heat exchange rolling conditions (T_1) and initial or bulk temperature state of rolls before rolling (T_0). Change in temperature is expressed as $\Delta T = T_1 - T_0$, measured in $^{\circ}\text{C}$.

Roll radial stress (S_{11}) Another equally important measure/objective in optimising work roll system is keeping the roll radial stress (S_{11}) at the roll surface as low as possible. Roll stress characteristics is a useful objective to consider since it has an inverse proportional effect with change in temperature in rolls. As the review of disclosed that roll thermal wear is highly influenced by stress. Roll surface passing under the water cooling and hot stock undergoes a cyclic state of tensile and compressive stress, respectively. This tensile stress is a contributory factor to thermal crack growth. The tensile state of rolls also has effect on roll loads. The deformation load is a function of roll wear, where excessive deformation load results in large roll wear. Therefore, it is desirable to reduce the rolling deformation load by reducing the tensile stress. There are various types of stress on the roll as a result of mechanical and thermal cycle during rolling, such as axial, surface or hoop stress maximum principal, radial stress (S_{11}) in the form of compressive and tensile stress. Although all have impact at a degree, radial stress (S_{11}) is the most recognised in determining the roll wear.

State variables are intermediate design variables between dependent and independent design variables, which have no direct contribution or effect on either independent or dependent variables and the design itself. State variables cannot directly be assigned values, but exist during simulation process - for example, computer speed, current, and other conditionality in setting the simulation state.

Operational variables are variables related to the environmental working condition of the design when in use. The environmental conditions are variables that can be changed by the operator on the ground to make the condition fit to the design. Factors such as coolant type coolant temperature, coolant pressure, spray distance from the roll as well as known as heat transfer coefficient (HTC) are examples of operational variables. These variables are also prone to uncertainty. Operational condition variables are conditions set for the system while in operation. Operational variables could be used, depending on the problem. In this work, the main focus is on independent and dependent variables of the process, as well as operational variables. The details of those variables application in the quantitative modelling are discussed in the next section.

5.3 The Design of Experiment (DoE) for Work Roll System Design Thermal Modelling

Following the identification of the important process factors in the rolling and the factors measuring rolls thermal characteristics, the research developed a mathematical model based on the finite element method, to predict the work-roll change of temperature during the hot rolling process and the associated stress induced in rolls. The model takes into account the effect of process parameters discussed above. The design of experiment is based on response surface, targeting dependent variables discussed in the previous section, i.e. the change in temperature and stress on the roll. The response data are collected at the roll surface and various depths below the surface. This helps to figure the response's effect on the roll surface and depth of penetration in rolls below the surface. The depth of roll temperature and stress effect is dependent on the working conditions and the cooling system applied to it. Design of experiment is a technique often used to approximate a process. The technique is adopted here in the thesis because of its ability to systematically and accurately sample the design space. The method is used to capture the all important relationship

between the above described dependent and independent variables with a reasonable number of experiments. However, DoE is, although it is efficient in collecting response data of FEA simulated design variables, difficult to conduct in the real life production process. Hence, the need for an approximate mathematical model is important. Approximation of the model is carried out using a statistical analysis using the response data from the FEA simulations. As described in the literature, there are a number of techniques in the design optimisation that are used for constructing the approximate mathematical model, but here, however, because of its simplicity, less cost and the fact that it is the most popular technique adopted by industries, response surface methodology RSM is used.

5.3.1 Response Surface Methodology

The aim of the statistical technique, the response surface methodology, is to generate smooth functions, typically linear or quadratic polynomials, of model system response. The fundamental properties of the techniques relevant to the qualitative model building include: the design of experiment which is used to form the response data, and the analysis of variance and the regression analysis used to form and analysis the mathematical model. The modelling is based on 2nd degree polynomial with the mathematical expression: 2nd degree polynomial consisting of main effect, interaction effect and quadratic effect, also known as quadratic model, expressed as:

$$ax + bx^2 + cxy + d + \varepsilon ; x \text{ and } y = 1 \dots k \quad \text{Equation 5.1}$$

Where a, b, c and d are the coefficients to be estimated, x and y are a vector of k system variables, ε is an error in most general cases and assumed to be zero. Here, in this work, due to the nature of the problem in the research domain, ε has a non zero value. Details of the uncertainty (design variables and model) are discussed in Chapter 6. The research adopted the quadratic model due to the nature of the problem and the fact that the quadratic model has the appeal of representing most forms of real life engineering problem behaviours, such as the main effect, interaction effect and quadratic effect of design variables.

5.3.2 Problem Definition

The problem definition is referring to the identification of change in thermal behaviours in rolls which occur during contact with hot stock and cooling. The change in behaviours is used to measure the quality of solution for achieving optimum roll

cooling system design. Here are also defined the roll wear influencing factors, as well as the dependency, if any, between factors. The effects of other important rolling process characteristics such as presence of uncertainty, constraints and high dimensionality on work roll determined. Knowledge elicitation exercise, carried out through a series of contacts with engineers, conducted through interviews supported by semi-structured questionnaires, as well as observation of real life rolling processes in the manufacturing plant presented in, Chapter 4 led to the identification of the problem and the objectives that need to be addressed. As presented in the literature review, Chapter 2, hot metal rolling is a large scale, complex process where thermal behaviour of rolls could be as result of one or a combination of sections of the system. Therefore, the roll thermal characteristics problem has to be seen as a process problem (Kleiber and Kulpa, 1995). Hence, process factors, as well as associated qualitative phenomenon such as uncertainty and variability needs to be taken in to account in the problem definition and solution search. Modelling of the work roll system is used to predict roll thermal behaviour, such as temperature change and roll tensile stress. These predictions are obtained using design variables related to the rolls, stock and operational variables relevant in determining the roll thermal characteristics.

5.3.3 Specify Design Matrix

The design matrix specifies how the design space is to be sampled. The basis of selection of the design matrix is fair representation of factors in the design space for simulation. Computational cost and time for the design of experiment, as well as resources available to run it, are also reasons that need to be taken in to account. In this study, the L-27 (7^{3-1}) matrix, shown in Table 5.5 is adopted. This design shows a three-level, 7 factor matrix. Each design variable is scaled such that it has a range of maximum, minimum and centre point values. ABAQUS FE simulations are performed, based on the selected matrix to generate the input values for the simulation runs. The first step in selecting the design matrix is to find the total degree of freedom. The total degree of freedom determines the minimum number of experiments required to accommodate all chosen factors, with acceptable representation in the design space. Here, the first degree of freedom is associated with the overall mean, regardless of the number of design variables to be studied, and the other degree of freedom is associated factors and their levels, and calculated as one less than the number of levels for each factor. This is because only one less than the

number of levels assigned for a variable are required for comparison. For example, in the case of 3 level design variables, only two comparisons are required. Thus, the total degree of freedom for the problem with 7 number design variables can be estimated as:

$$\begin{array}{rcl}
 \text{Overall mean} & & 1 \\
 \text{All variables} & 7 \times (3-1) = & 14 \\
 & \text{-----} & \\
 \text{Total} & & 15
 \end{array}$$

That is, at least 15 experiments (evaluations) are required to estimate the effect. However, reasonable increase in the design space will increase proportional representation of samples; hence, better design. Therefore, a design matrix with increased sample space is chosen.

Table 5.5. Design matrix for FEA simulation ($L-27 = 7^{3-1}$) (Taguchi, 1978).

x1 = HTC Roll/stock contact (kW/m²K), x2 = Stock temperature (°C), x3 = Contact length (mm), x4 = HTC - Cooling (kW/m²K), x5 = Roll speed (Rad/sec), x6 = Roll Temperature (°C), x7 = Delay time (sec)

No. Of runs	x1	x2	x3	x4	x5	x6	x7
1	1	1	1	1	1	1	1
2	1	1	1	1	2	2	2
3	1	1	1	1	3	3	3
4	1	2	2	2	1	1	1
5	1	2	2	2	2	2	2
6	1	2	2	2	3	3	3
7	1	3	3	3	1	1	1
8	1	3	3	3	2	2	2
9	1	3	3	3	3	3	3
10	1	1	2	3	1	2	3
11	2	1	2	3	2	3	1
12	2	1	2	3	3	1	2
13	2	2	3	1	1	2	3
14	2	2	3	1	2	3	1
15	2	2	3	1	3	1	2
16	2	3	1	2	1	2	3
17	2	3	1	2	2	3	1
18	2	3	1	2	3	1	2
19	3	1	3	2	1	3	2
20	3	1	3	2	2	1	3
21	3	1	3	2	3	2	1
22	3	2	1	3	1	3	2
23	3	2	1	3	2	1	3
24	3	2	1	3	3	2	1
25	3	3	2	1	1	3	2
26	3	3	2	1	2	1	3
27	3	3	2	1	3	2	1

Table 5.6. Input Setting for the FEA Simulation

x1 = HTC Roll/stock contact (kW/m²K), x2 = Stock temperature (⁰C), x3 = Contact length (mm), x4 = HTC - Cooling (kW/m²K), x5 = Roll speed (Rad/sec), x6 = Roll Temperature (⁰C), x7 = Delay time (sec).

No. Of runs	x1	x2	x3	x4	x5	x6	x7
1	5	950	10	15	0.14	40	20
2	5	950	10	15	0.698	60	60
3	5	950	10	15	1.256	80	100
4	5	1100	20	35.5	0.14	40	20
5	5	1100	20	35.5	0.698	60	60
6	5	1100	20	35.5	1.256	80	100
7	5	1250	30	50	0.14	40	20
8	5	1250	30	50	0.698	60	60
9	5	1250	30	50	1.256	80	100
10	5	950	20	50	0.14	60	100
11	10	950	20	50	0.698	80	20
12	10	950	20	50	1.256	40	60
13	10	1100	30	15	0.14	60	100
14	10	1100	30	15	0.698	80	20
15	10	1100	30	15	1.256	40	60
16	10	1250	10	35.5	0.14	60	100
17	10	1250	10	35.5	0.698	80	20
18	10	1250	10	35.5	1.256	40	60
19	15	950	30	35.5	0.14	80	60
20	15	950	30	35.5	0.698	40	100
21	15	950	30	35.5	1.256	60	20
22	15	1100	10	50	0.14	80	60
23	15	1100	10	50	0.698	40	100
24	15	1100	10	50	1.256	60	20
25	15	1250	20	15	0.14	80	60
26	15	1250	20	15	0.698	40	100
27	15	1250	20	15	1.256	60	20

5.3.4 The FEA Experiments

Here, it involves running experiments from the given set of input data and FEA model supplied by the sponsoring company. The experimental run is a carried out with fixed values for all its inputs and parameters, and is performed to obtain the output. The results/responses obtained from the experimental runs are used to estimate the parameter values of the meta-model. In the experimental simulations, a total of 27 runs were conducted using the data sampling matrix shown in the tables above. Values of the response variables, change in temperature and stress (S11) are recorded. The two responses are the main thermal characteristics identified that best describe the behaviour of rolls during hot rolling. Change in temperature is a result of temperature data collected from rolls after simulation minus original roll bulk temperature (T1 - T0). The experimental simulation was carried out for rolling,

consisting of two steps of the rolling process. The two steps are rolling and delay time shown in Figure 1.4, Chapter 1. The rolling step is the step where hot stocks pass through and have contact with rolls, while delay time is an occasional occurrence during rolling where no hot stocks pass or come in contact with the rolls. Delay can occur at any time in the process and results due to known or unknown reasons. For example, time from furnaces to the first pass and time for the stock to travel between passes, and also occasional occurrence of stock delay for unknown reasons. Generally, unsolicited delay time occurs at any time in the process and it is not certain to determined period and cause of the delay. Too short or too long delay can be a contributory factor for temperature variations on the roll, and hence, need to be considered in the design for safe operation to be achieved. The rolling and delay steps are more relevant for multi-pass process. The steps and responses expected are shown in Table 5.7. The design input factors properties and simulation initial conditions are also shown in Table 5.8 and Table 5.9.

Table 5.7. Expected responses from the FEA simulation

Expected Response (3 x 2) = 6
At roll surface, 9 mm and 15 mm depth below the surface
Change in temperature (ΔT)
Radial stress (S11)

Figure 5.5 shows the 3 sample data points where the expected 6 response are taken from the roll. The data points shown in the Figure are at the roll surface, 9 mm and 15 mm below the surface. In the experiment 9 mm is where the rate of change of temperature start to decline or at least steady state start and 15 mm is where all the experiment shows heat effect is minimal. There are also additional simulation runs and data collected at depth below the surface. The data are used to see the temperature trend patter along the heat affected area from surface towards the roll centre. The additional run is conducted with various materials type property and experimented by taking in to account the worst case scenario design input set, where heat from stock going in to the roll would be the maximum. Such scenario is where the design set includes the lowest roll speed; hence the longer contact between roll and stock, highest stock temperature parameters. The experiment is discussed in Section 5.3.8.

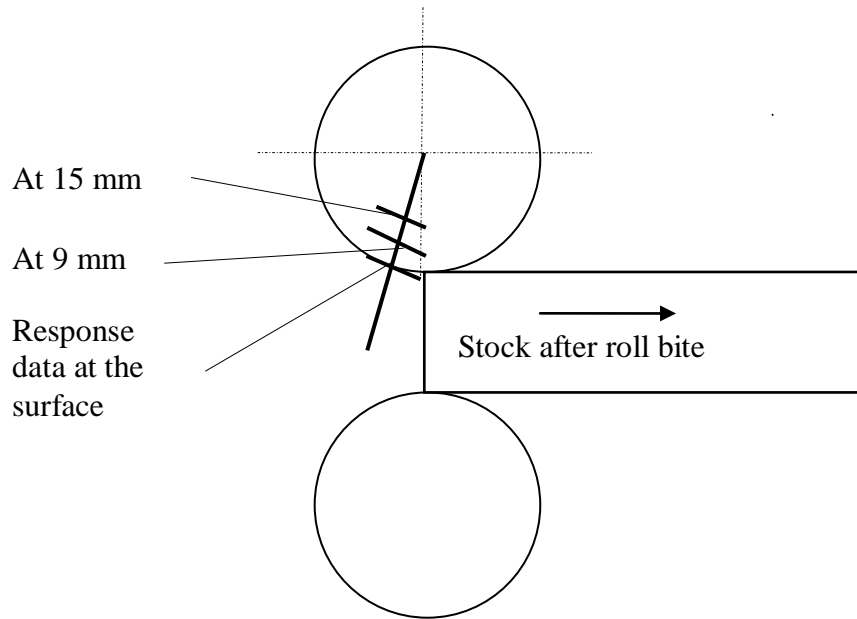


Figure 5.5. Simulation response data points from the roll, for functional modelling

Table 5.8. Independent design variables set used in the FEA simulations.

Process input variables		Process input variables
HTC 1 (for cooling & rolling)	HTC 2 (for roll & stock contact)	Stock temperature
HTC 1 & 2 are the 2 single entities of the design variables representing a number of sub factors discussed in Section 5.2.2.		Roll temperature
		Roll speed
		Delay time
		Roll-Stock contact length

Table 5.9. The experimental simulation initial conditions

Rolling simulation Initial conditions			
		Thermal diffusivity (α) = $\lambda / \rho C_p$	
Roll size	180 mm	Thermal conductivity (λ) = 48w/m.k	
Roll material	High chromium	Specific heat capacity (C_p) = 478j/kg.k	
		Density (ρ) = 7083kg/m3	
Thermal diffusivity expressed as a function of thermal conductivity density and heat capacity (ρC_p).			
t is stock and rolls contact time and expressed as a function of roll stock contact length, roll speed (omega) and roll radius, ($t = L / \Omega X r$)			

5.3.5 Experimental Set-Up

The experimental runs are performed in high power grid computing. The grid computing is selected due to the fact that the time required to run a job is quicker, so that makes a significant reduction in computational time. It is also that a number of simulation jobs can be run in parallel. The jobs are sent to grid from a PC in a batch with the return directory in the PC, so that when the run completes, the jobs go back to the pre prepared folder in the PC - from which the analysis for response extraction takes place. Sending jobs from PC to the grid and back follows the following line, (*CD.../ \$W/ Job-A2 Roll-A2 Run-A-2*), where CD corresponds to the researcher ID, \$W the directory where the input data is sent to GRID and FEA simulation response from GRID returned and stored, Job A-2, is a script that contains a description that links the input data with particular features in the GRID; for example: to send a particular job to particular grid node, to determine if the job is to run in parallel in a number of nodes at the same time, choice of 64 or 32 byte node. Roll-A2 is a folder containing the input file of the rolling simulation 2, and the Run-A2 is the file containing the data parameters and specifications of run2 (as well as known as design input data). Jobs run both in parallel and single depending on nodes availability. Parallel runs help to reduce the total computational time significantly. A total of 12 jobs run in parallel node out of the total of 27 simulation inputs. This is because there were only 6 nodes available for parallel runs at the time of simulation. Although there is no significant difference in using either 32 bite or 64 byte nodes, in relation to the size of the ODB of the runs, 64 byte nodes have been selected for all simulation runs in this research. The Graphical illustration of the log in, and sending and running of jobs in the GRID is shown in Figure 5.6 and 5.7. Also shown in Figure 5.8 is a typical example of the post analysis result from the GRID back to the PC.

```

home.central.cranfield.ac.uk - PuTTY
login as: c068471
-----+-----
| This system is for the use of authorized users only.      |
| Individuals using this computer system without authority, |
| or in excess of their authority, are subject to having all |
| of their activities on this system monitored and recorded   |
| by system personnel.                                     |
|                                                           |
| In the course of monitoring individuals improperly using   |
| this system, or in the course of system maintenance, the  |
| activities of authorized users may also be monitored.     |
|                                                           |
| Anyone using this system expressly consents to such       |
| monitoring and is advised that if such monitoring reveals  |
| possible evidence of criminal activity, system personnel  |
| may provide the evidence of such monitoring to law         |
| enforcement officials.                                     |
|                                                           |
+-----+-----

YOU ARE NOW LOGGED INTO GRID LOGIN SERVER:

victor

c068471@home's password: █

```

Figure 5.6. Log in to the GRID from the PC using personal ID

```

home.central.cranfield.ac.uk - PuTTY

4
c068471@victor [119] 12:54 AM [c068471] qsub Job-M10 Roll-M10 Run-M10
Your job 176425 ("Run-M10") has been submitted
c068471@victor [120] 12:55 AM [c068471] qstat
job-ID prior name user state submit/start at queue
slots ja-task-ID
-----+-----
176397 0.54261 threedextr c107227 r 09/23/2010 17:02:38 long@grid-comp
-01.central.cran 4
176410 0.53982 threedfine c107227 r 09/24/2010 08:45:30 long@grid-comp
-02.central.cran 4
176417 0.13638 lsdyna_R5 c092060 r 09/24/2010 18:06:43 extralong@grid
-comp-03.central 4
176261 0.19945 lsdyna_R5 c092060 r 09/20/2010 10:21:17 verylong@grid-
comp-04.central. 4
176418 0.13637 lsdyna_R5 c092060 r 09/24/2010 18:07:19 extralong@grid
-comp-05.central 4
176414 0.17857 mcmcdyna ah1756 r 09/24/2010 15:12:55 verylong@grid-
comp-06.central. 1
176424 0.17981 Run-M10 c068471 r 09/25/2010 00:54:19 verylong@grid-
comp-08.central. 4
176425 0.06374 Run-M10 c068471 r 09/25/2010 00:55:23 verylong@grid-
comp-09.central. 4
172626 1.18853 batch.sh c111269 qw 08/11/2010 10:08:04
1

```

Figure 5.7. Sending and running jobs on the GRID

Figure 5.6, shows the GRID display after log in, and Figure 5.7 displays the states of the job while it is in the GRID. For example, user ID, number of slots the job is using (4 in this case), Job ID, as well as job submission time and date. It also states whether the job is running or waiting in the queue. The upper section of Figure 5.6 indicates the job submission command, followed by the information about the success of the submissions. After successful completion of the simulation, the information, results and input data file are sent back to the pre set directory in the PC. The post simulation information is sent back in the form of files as shown in the following.

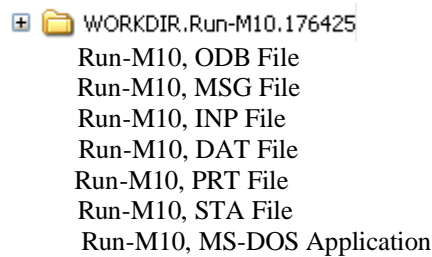


Figure 5.8. Showing post analysis results sent back to the PC by the GRID

In the post simulation results shown above, each file holds useful information of the FEA individual run. However it is only the ODB file is useful for taking data information from the simulation. The ODB file is where the responses output data are stored. From this file, the dependent/responses variables (Temperature on the roll and radial stress after simulation) will be collected and the result later used for developing the approximate functional models and eventually as fitness function in the optimisation for searching solution for the research problem. The Output Data Base (ODB) file contains up to 75% of the return data hence is the bigger size item in the file. Information from the other smaller files listed above is not used in the modelling or optimisation. The files mainly describe the states of the simulation run and result as shown in the following:

- DAT file report processing part instance and assembly information of the FEA model. It also display if there is a warning, error or successful completion of the simulation run. DAT also shows memory used and size of the result package.
- INP file present the input file used in the simulation.
- STA file presents summery of job information such as the number of iteration, frequency and steps taken in the simulation and data saving.

- PRT file gives numbers describing part and assembly meshing elements and nodes of the FEA model. MSG is a file contains a message stating detail description of the simulation run, constraints in the model, response and part assembly. It also presents, at each step the criteria fulfilled while simulation complete. Step is the size of time increment.

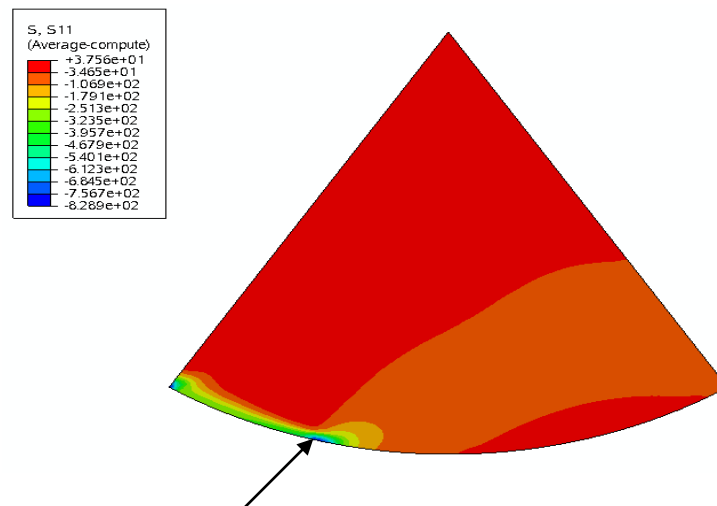
Running period/time and size of simulation job using GRID computing

Time required to complete a single job using GRID computing and size of simulation output, is dependent on various features of the input data and parameter specification set for the simulation run. Such data and specification includes: the number of responses/dependent factors ordered to be saved, and the frequency within the steps, in which the data is saved during simulation. Rolling process has two steps. These are a rolling step and delay step. The steps time is a time needed to complete a single step, either rolling or delay step in the process. Step time determined by and is a function of roll speed and roll radius, hence, these rolling features also have a direct effect on the overall run time needed for single simulation. Here in this experiment, all non relevant responses are omitted, and only 2 responses (measured roll thermal characteristics), namely Radial stress (S11) and roll surface temperature (NT11) are saved. This helps to reduce computational time and the size of the simulation **Output Data Base (ODB)**. The frequency in which the data needs to be saved is dependent on the period/step in which change occurs in the roll during simulation. Particular interest is the effect of heat and cooling on the roll; hence, the ODB is designed to save output that measures these effects. Taking in to account the input data parameters, such as the roll size and speed, a functional relationship is employed to decide interval time within the steps, which is the time period 1 full rolling will, takes place. The steps time refers to the cycle time in which the data expected to be saved. In this experiment, therefore, instead of saving every increment of the simulation, which is time consuming and increases the size of ODB, interval time and step time are determined, (calculated) and introduced in the FEA simulation input file. The functional relationship shown here is used to determine the interval time and step time. Interval Time in second = $\frac{2\pi}{\omega}$ where ω is the speed of the roll and, $\pi = 3.14$ and the step time is calculated as the interval time multiplied by cycle number. 3 cycle time has been chosen in the research hence the step time in second = $\frac{2\pi}{\omega} \times 3$. The function means that data to be saved

every 3 cycle of the roll. Response from simulations output, taken from the data saved from the cycles are then used in the simulation result analysis and subsequent model developments.

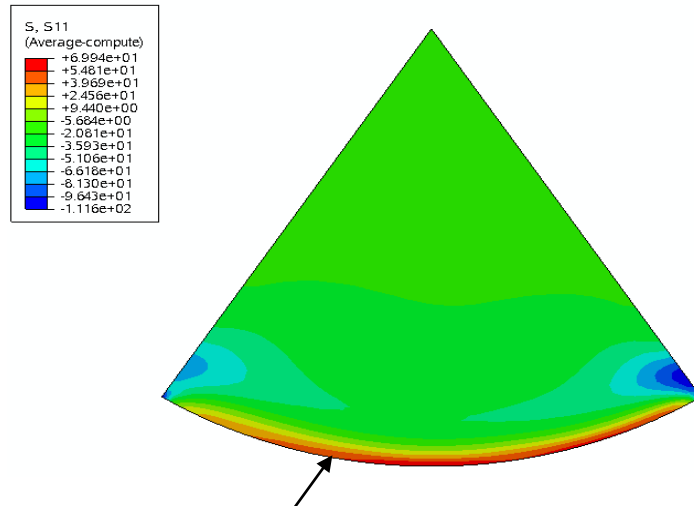
Responses from simulation outputs

As described in the previous section, the rolling process consists of two steps, the rolling steps and delay. The response data are collected from the step that comprised both steps, and by doing that, the effect of delay, delay from the furnace to the 1st roll, and rolling steps thermal effects on the roll can be realized. Data from calculated depth from roll surface, as well as data at various depths below the surface, are the response target. Hence, a total of six (change in temperature and radial stress) data are taken. Response data from ODB, however, required careful observation. This is because, as discussed above, the functional relationships among input data specification determined the area of interest from the simulation run for analysis; hence help to locate precisely. If this the area of interest is not precisely identified, the cooling effect and temperature and stress result may not be fully realized. Figure 5.9A illustrates a typical error which may happen that will give misleading results. The instance Figure 5.9A should be avoided when taking data from FEA simulation runs.



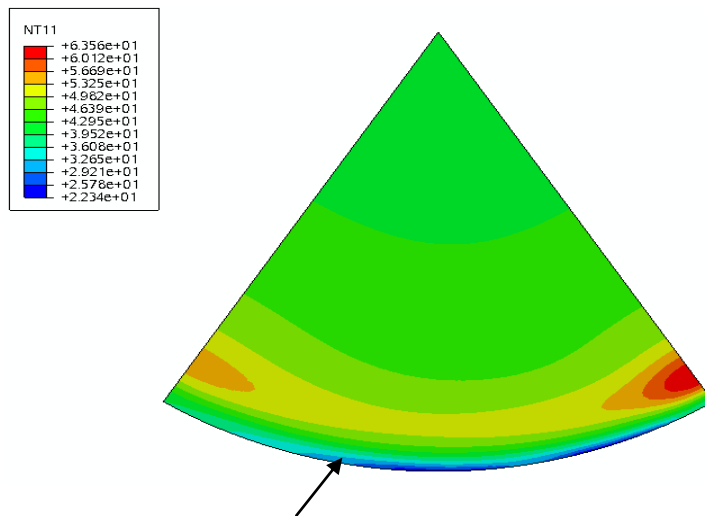
Stock is here at this moment, and compressive (hoop stress) due to stock presence. This instance analysis should not be taken, as the stock is mainly outside of the roll, on the left side of the roll. The roll is rotating counter clockwise hence after rolling the rolled metal will move to the right side of the roll. At that instance the effect of heat and cooling on the roll can be observed.

Figure 5.9A. Typical error which may happen that will give misleading results.



Now stock is away from the roll (moved to the right side of the roll) and the cooling has taken effect. As a result, the tensile hoop stress (S11) seen here is formed. The corresponding temperature feature is shown in Figure C. This instance is where data should be taken from the roll.

Figure 5.9B. Instance where data, Radial stress from the roll should be taken



After the stock/roll contact, the roll cooling starts to take effect and a temperature value is recorded. This instance is where data should be taken from the roll.

Figure 5.9C Instance where data, temperature from the roll should be taken after simulations run.

5.3.6 Response Data from Finite Element (FE) Simulation

The finite element runs were performed using ABAQUS standard version 6.7.1. The same loading and boundary conditions are applied in the simulations, so that the responses are measured under similar conditions. For each run, values of the six

response variables are recorded. Response values for change in temperature ΔT are collected from the roll at a depth, depending on the speed of rolls and roll /stock contact length, while stress is represented by the value directly measured from the roll below the surface. X-Y plot of the field output / Output Data Base (ODB) is used to determine the trend and exact value of the responses expected. The X-Y plot helps to accurately measure the depth at which temperature reaches, depending on roll speed and contact time, by interpolating the size of finite element on the roll. The calculated depth (r_i) indicates the maximum heat penetration in to the roll below the surface when in contact with the stock at a given roll speed. The functional relationship of these dependent factors determining temperature, and procedures followed to determine the depth calculation are the following:

$$\sqrt{6\alpha t} = \text{Depth of heat penetration} \quad \text{Equation 5.2}$$

Where α is thermal diffusivity of the roll material, expressed as a function of thermal conductivity (λ) and the product of density (ρ) and specific heat capacity (C_p), mathematically can be expressed as:

$$\alpha = \lambda / (\rho C_p) \quad \text{Equation 5.3}$$

ρ and C_p represent roll material density and specific heat capacity, respectively. The parameter t is the stock and rolls contact time and is expressed as a function of roll /stock projected contact length (L) divided by roll rotational speed (Ω) and roll radius (r). Mathematically it is expressed as the following:

$$t = L / (\Omega r) \quad \text{Equation 5.4}$$

Following the above functional expressions, the expected depth of heat penetration, and thus the data for temperature responses, are calculated (a total of 27 runs), as shown below. Based on the roll material considered for the simulation, the following values are allocated to calculate roll depth before the temperature extracted from the roll. The roll radius taken is 180mm, $\lambda = 48 \text{ w/m.k}$, $\rho = 7083 \text{ kg/m}^3$, $C_p = 478 \text{ j/kg.k}$ hence $\alpha = 48 \text{ w/mk} / 7083 \text{ kg/m}^3 \times 478 \text{ j/kg.k} = 0.000014$. This value used for the 27 runs depth calculation. t value varies depending on specific case and calculated based on functional relationships among factors shown in Table 5.10. Applying equation 5.2, the expected depths are calculated and presented as the following.

Table 5.10. Based on function given, expected heat penetration depth in to the roll

Runs	Procedure	Depth
1	Contact length = 10mm, Roll speed = 0.14r/s $t = 10\text{mm} / 0.14 \text{ r/sec} \times 180\text{mm} = 0.397\text{sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.397 \text{ sec}} = 0.0057\text{m} = 5.7\text{mm}$	5.7mm
2	Contact length = 20mm, Roll speed = 0.14r/s $t = 20 / 0.14 \times 180 = 0.7940 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.7940 \text{ sec}} = 0.0081\text{m} = 8.1\text{mm}$	8.1mm
3	Contact length = 30mm, Roll speed = 0.14r/sec $t = 30 / 0.14 \times 180 = 1.19 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 1.190 \text{ sec}} = 0.0099\text{m} = 9.9\text{mm}$	9.9mm
4	Contact length = 10mm, Roll speed = 0.698r/s $t = 10 / 0.698 \times 180 = 0.0795 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0795 \text{ sec}} = 0.00258\text{m} = 2.58\text{mm}$	2.5mm
5	Contact length = 20mm, Roll speed = 0.698r/s $t = 20 / 0.698 \times 180 = 0.1592 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1592 \text{ sec}} = 0.0036\text{m} = 3.6\text{mm}$	3.6mm
6	Contact length = 30mm, Roll speed = 0.698r/s $t = 30 / 0.698 \times 180 = 0.2388 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.2388 \text{ sec}} = 0.0044\text{m} = 4.4\text{mm}$	4.4mm
7	Contact length = 10mm, Roll speed = 1.256r/s $t = 10 / 1.256 \times 180 = 0.0442 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0442 \text{ sec}} = 0.0019\text{m} = 1.9\text{mm}$	1.9mm
8	Contact length = 20mm, Roll speed = 1.256r/s $t = 20 / 1.256 \times 180 = 0.0884 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0884 \text{ sec}} = 0.0027\text{m} = 2.7\text{mm}$	2.7mm
9	Contact length = 30mm, Roll speed = 1.256r/s $t = 30 / 1.256 \times 180 = 0.1327 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1327 \text{ sec}} = 0.0033\text{m} = 3.3\text{mm}$	3.3mm
10	Contact length = 20mm, Roll speed 0.698r/s $t = 20 / 0.698 \times 180 = 0.1592 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1592 \text{ sec}} = 0.0036\text{m} = 3.6\text{mm}$	3.6mm
11	Contact length = 30mm, Roll speed = 0.698r/s $t = 30 / 0.698 \times 180 = 0.2388 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.2388 \text{ sec}} = 0.0044\text{m} = 4.4\text{mm}$	4.4mm

Runs	Procedure	Depth
12	Contact length = 10mm, Roll speed = 0.698r/s $t = 10/0.698 \times 180 = 0.0795 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0795 \text{ sec}} = 0.00258 \text{ m} = 2.58 \text{ mm}$	2.5mm
13	Contact length = 20mm, Roll speed = 1.256r/s $t = 20 / 1.256 \times 180 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0884 \text{ sec}} = 0.0027 \text{ m} = 2.7 \text{ mm}$	2.7mm
14	Contact length = 30mm, Roll speed = 1.256r/s $t = 30/1.256 \times 180 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1327 \text{ sec}} = 0.0033 \text{ m} = 3.3 \text{ mm}$	3.3mm
15	Contact length = 10mm, Roll speed = 1.256r/s $t = 10/1.256 \times 180 = 0.0442 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0442 \text{ sec}} = 0.0019 \text{ m} = 1.9 \text{ mm}$	1.9mm
16	Contact length = 20mm, Roll speed = 0.14r/s $t = 20/0.14 \times 180 = 0.7940 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.7940 \text{ sec}} = 0.0081 \text{ m} = 8.1 \text{ mm}$	8.1mm
17	Contact length = 30mm, Roll speed = 0.14r/s $t = 30/0.14 \times 180 = 1.19 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 1.19 \text{ sec}} = 0.0099 \text{ m} = 9.9 \text{ mm}$	9.9mm
18	Contact length = 10mm, Roll speed = 0.14r/s $t = 10 / 0.14 \times 180 = 0.397 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.397 \text{ sec}} = 0.0057 \text{ m} = 5.7 \text{ mm}$	5.7mm
19	Contact length = 30mm, Roll speed = 1.256r/s $t = 30/1.256 \times 180 = 0.1327 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1327 \text{ sec}} = 3.3 \text{ mm}$	3.3mm
20	Contact length = 10mm, Roll speed = 1.256r/s $t = 10/1.256 \times 180 = 0.0442 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0442 \text{ sec}} = 0.0019 \text{ m} = 1.9 \text{ mm}$	1.9mm
21	Contact length = 20mm, Roll speed = 1.256r/s $t = 20/ 1.256 \times 180 = 0.0884 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.0884 \text{ sec}} = 0.0027 \text{ m} = 2.7 \text{ mm}$	2.7mm
22	Contact length = 30mm, Roll speed = 0.14r/s $t = 30/0.14 \times 180 = 1.19 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 1.19 \text{ sec}} = 0.0099 \text{ m} = 9.9 \text{ mm}$	9.9mm

Runs	Procedure	Depth
23	Contact length = 10mm, Roll speed = 0.14r/s $t = 10 / 0.14 \times 180 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.397 \text{ sec}} = 0.0057\text{m} = 5.7\text{mm}$	5.7mm
24	Contact length = 20mm, Roll speed = 0.14r/s $t = 20/0.14 \times 180 = 0.7940 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014\text{m}^2/\text{s} \times 0.7940\text{sec}} = 0.0081\text{m} = 8.1\text{mm}$	8.1mm
25	Contact length = 30mm, Roll speed = 0.698r/s $t = 30/ 0.698 \times 180 = 0.2388 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014\text{m}^2/\text{s} \times 0.2388 \text{ sec}} = 0.0044\text{m} = 4.4\text{mm}$	4.4mm
26	Contact length = 10mm, Roll speed = 0.698r/s $t = 10/0.698 \times 180 = 0.0795 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014\text{m}^2/\text{s} \times 0.0795 \text{ sec}} = 0.00258\text{m} = 2.58\text{mm}$	2.5mm
27	Contact length = 20mm, Roll speed = 0.698r/s $t = 20/0.698 \times 180 = 0.1592 \text{ sec}$ $\text{Depth} = \sqrt{6 \times 0.000014 \text{ m}^2/\text{s} \times 0.1592 \text{ sec}} = 0.0036\text{m} = 3.6\text{mm}$	3.6mm

5.3.7 Procedures for Response Data from Experimental Simulations

The results are taken when temperature reaches the steady state. The steady state is defined as the region where the temperature characteristics reach uniform. The steady states may vary depending on the speed of the roll, the size of the roll and the material property of rolls. Hence, the above depth calculation results indicate the depth at which the steady state is expected, taking in to account these factors. At steady state, the response values are collected by plotting an X-Y graph. Figures 5.12, 5.13, 5.14, show non dimensional FE results and steps followed to extract the response data. In the same way, each simulation response data results are recorded from a total of 27 x 6 points, and 162 results for single pass rolling. Respective data points, for temperature and stress are shown in Figure 5.10 and 5.11.

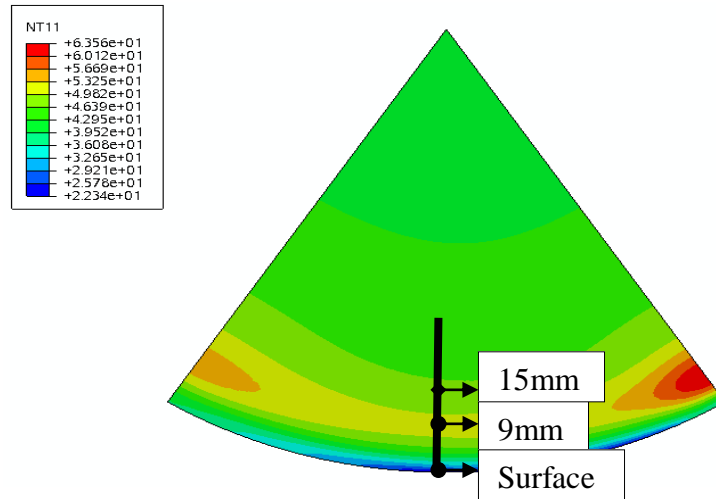


Figure 5.10. Finite element plots for roll profile temperature at the surface of the roll, 9mm and 15mm below the surface of the roll

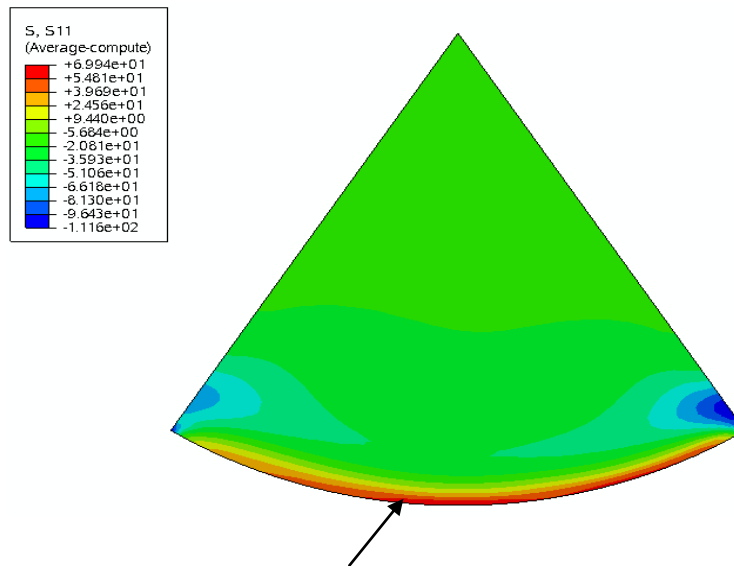


Figure 5.11. Finite element plots for roll profile radial stress at the surface

Procedure for response data from rolls (change in temperature ΔT)

- 1st - Select nodes at the bottom surface of the roll while the simulation output is on the NT11 (Temperature output states), Figure 5.10.
- 2nd - Plot the true distance along the line of heat penetration from the same surface node selected at step 1 towards the centre. (Line at the centre of the roll in Figure 5.10).
- 3rd - from true distance plotted at step 2, plot temperature / true distance graph. From the plot graph data collected at calculated depth and at various depths below the surface along the heat affect path. (Samples given in Figure 5.12 and Figure 5.13).

- Finally, values of the extracted temperature data are recorded. The difference between the recorded responses (T1) and the initial bulk temperature (T0) data in each simulation run are calculated. ($\Delta T = T1 - T0$).

The results are later used for the regression model. Here, the data at depth is considered more accurate, since it is the interpolation of the heat penetration along the path and convenient to pick the accurate values at the specified point or depth, as shown in Figure 5.13 Same setting and node locations are used to record the second response (radial stress), while the simulated roll is in the Stress (S11) state shown in Figure 5.11. Using a stress time graph values of the radial stress (S11) are recorded as shown in Figure 5.14. The values are later used to build the second regression model.

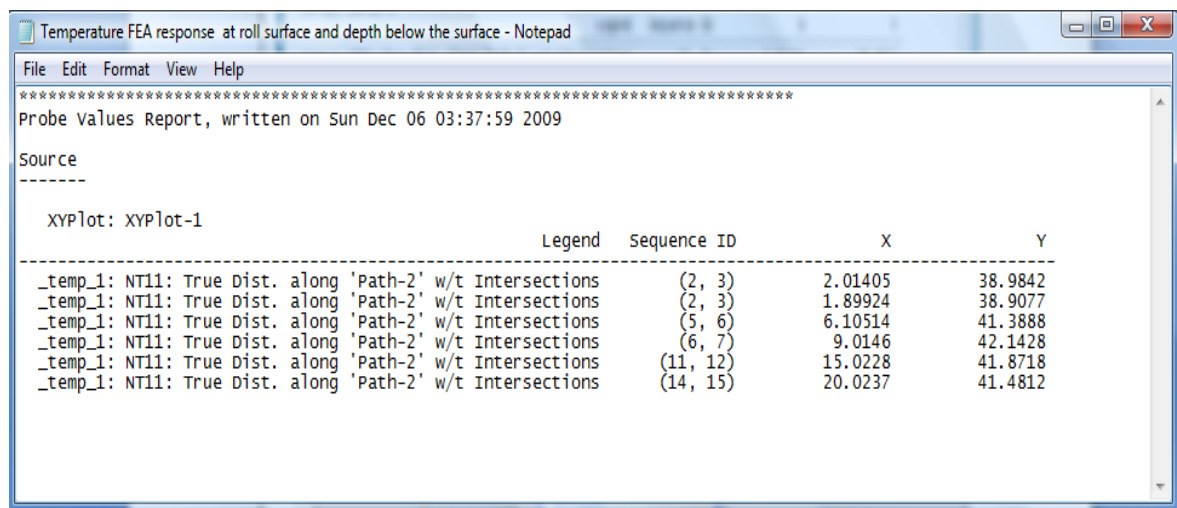


Figure 5.12. Probe value report temperature from FEA simulation run

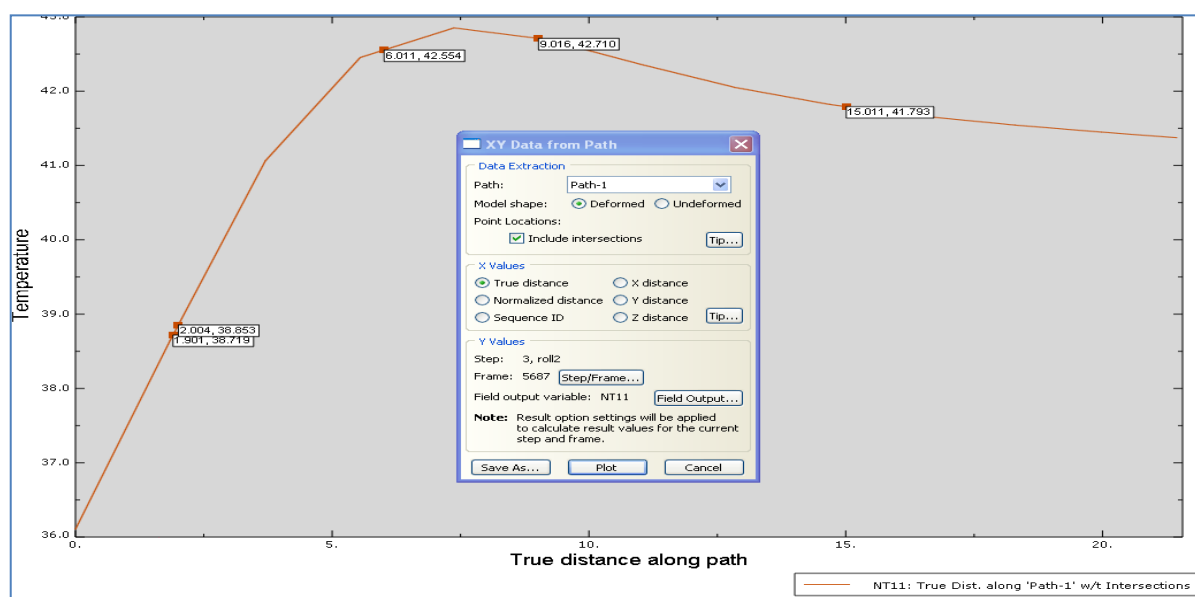


Figure 5.13 Temperatures response at calculated and various depth below the surface

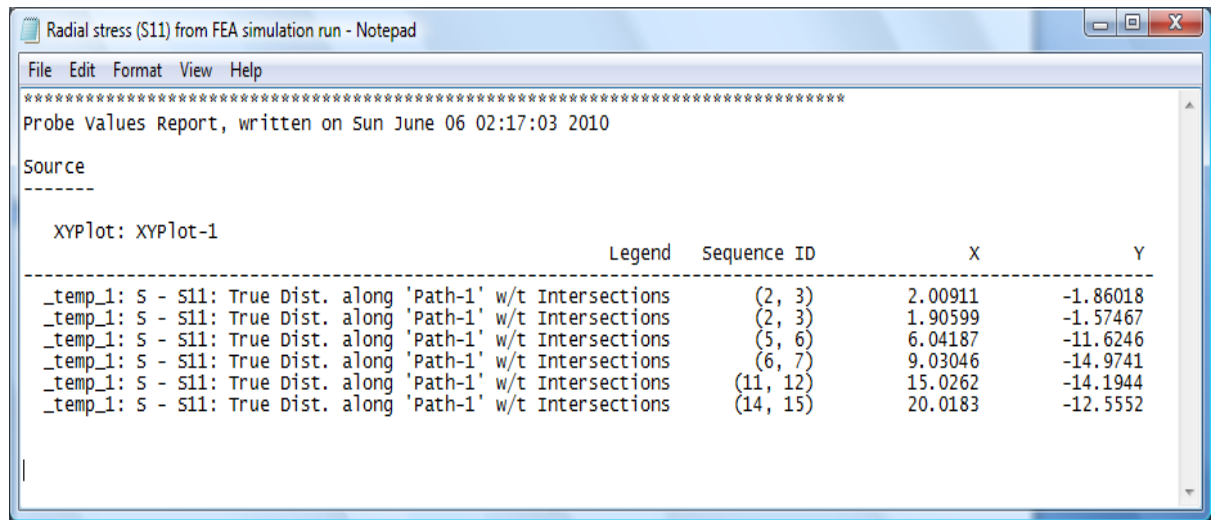


Figure 5.14. Probe value report Radial stress (S11) from FEA simulation run

Response data is collected from the simulation in two forms. The first is at the calculated depth. There are also data collected at various points below the surface at 9 and 15mm). The responses from the simulations are presented in Table 5.11.

Table 5.11. FEA simulation responses

Responses from FEA					
Ts (⁰ C)	S11s (MPa)	T9mm (⁰ C)	S119mm (MPa)	T15mm (⁰ C)	S1115mm (MPa)
49.9	47.8	49.9	-12.77	50.8	-22.15
86.6	45.6	86.8	-80.73	85.9	-103.84
114.9	75.9	114.6	-122.7	112.9	-159.27
43.4	13.6	45.8	-19.74	46.3	-22.75
92.9	-78.5	95.1	-163.4	89.9	-153.09
158.3	-127.	161.2	-305.7	152.5	-302.79
60	7.0	41.8	-14.97	41.8	-14.19
101.1	-124.	102.4	-193.7	91.9	-165.66
187.2	-250.	187.6	-406.4	162.2	-327.8
85.5	-1.5	91.4	-90.94	89.3	-92.72
54.5	46.5	57.4	-0.05	58.4	-3.52
42.4	54.1	57.2	19.96	59.4	17.78
137.6	-159.	139.286	-254.4	121.3	-239.91
105.8	-227.	104.3	-234.3	72.4	-242.37
90.7	-74.2	91.4	-90.69	85.5	-68.03
113.3	-145.8	113	-76.74	116	-114.58
94.9	124.1	94.5	-49.17	97.1	-76.77
65.5	97.0	66.4	-4.8	68.4	-17.69
93	3.6	98.4	-55.52	95.4	-48.49
53	70.7	60.4	40.65	60.4	41.04
48	65.7	53.4	25.8	56.4	26.12
60.1	37.1	62.2	31.52	59.2	22.09
106	177.1	105.9	-22.19	109.4	-53.44
66.1	127.1	66.5	31.52	69.4	22.1
239.1	-251.	238.9	-225	223.8	-204
106	-10.3	110.2	-87.87	108.1	-87.03
86.2	0.43	89.4	-56.18	87.7	-47.43

Table 5.12 presents the objectives, change in temperature which is the difference between response data after simulation and initial bulk roll temperature ($\Delta T = T1 - T0$) and the radial stress (S11) from surface and at depth below the surface, taken at the same nodules where the roll Temperature value have been taken.

Table 5.12. FEA results for Meta-model prediction.

No. Of runs	Calculated Depth (At roll surface.) (mm)	Results at surface and depths					
		At surface		At depths			
		ΔT_s ($^{\circ}\text{C}$)	S11 (MPa)	$\Delta T_{9\text{mm}}$ ($^{\circ}\text{C}$)	S11 _{9mm} (MPa)	$\Delta T_{15\text{mm}}$ ($^{\circ}\text{C}$)	S11 _{15mm} (MPa)
1	5.7	9.9	47.8	9.9	-12.7	10.8	-22.15
2	8.1	46.6	45.7	46.8	-80.7	47.9	-103.8
3	9.9	74.9	75.9	74.6	-122.7	75.9	-159.2
4	2.58	6.4	13.6	5.8	-19.74	3.3	-22.7
5	3.6	52.9	-78.5	55.1	-163.4	49.9	-153.0
6	4.4	118.	-127	114	-305.7	112	-302.7
7	1.9	1.8	7	1	-14.97	-1	-14.19
8	2.7	61.2	-124.7	62.4	-193.7	51.9	-165.66
9	3.3	147	-250.7	147	-406.4	122	-327.8
10	3.6	31.5	-1.5	29.4	-90.94	25.3	-92.72
11	4.4	-5.5	46.5	-2.6	-0.05	-1.6	-3.52
12	2.58	-17.6	54.1	-2.8	19.96	-0.6	17.78
13	2.7	191	-159	79.3	-254.4	61.3	-239.91
14	3.3	159.	-427.6	144.	-434.3	112.	-342.37
15	1.9	30.2	-74.2	31.4	-90.69	25.5	-68.03
16	8.1	53.3	145.8	53	-76.74	50	-114.58
17	9.9	34.9	124.1	34.5	-49.17	32.1	-76.77
18	5.7	5.5	96.	6.4	-4.8	8.4	-17.69
19	3.3	13	3.6	15.4	-55.52	19.4	-48.49
20	1.9	-27	70.7	-19.6	40.65	-19.6	41.04
21	2.7	-32	65.7	-26.6	25.8	-23.6	26.12
22	9.9	-11.6	37.1	-10.3	31.52	-7.5	22.09
23	5.7	26	7.1	25.9	-22.19	24.4	-53.44
24	8.1	-13.9	127.1	-13.5	31.52	-10.6	22.1
25	4.4	157	-251.6	158	-425	143	-404
26	2.58	26	-10.3	28.2	-87.87	30.1	-87.03
27	3.6	6.2	0.4	9.4	-56.18	7.7	-47.43

Temperature trend along the heat affected area, from the surface towards the centre of the roll

As explained in Chapter 2, under normal circumstances (optimum cooling conditions), the temperature is expected to remain at certain depth depending on roll speed and contact time, and then decrease going towards the centre. To verify this characteristics additional 9 runs has been simulated, with various roll material property but keeping the 7 design variables used in the modelling, shown in Table 5.15 fixed. The post simulation response data (at surface, 2mm, 6mm, 9mm and

15mm) collected are used to plot the temperature trend along the line towards the centre, and the trend used to verify the temperature condition of roll from the surface to depth below the surface. Table 5.13 -5.17 and Figure 5.16 illustrate the temperature trend verifications.

Table 5.13. Material property value ranges considered for the simulation

<u>Material property and value ranges</u>	
$\varepsilon = 11\text{e-}6 - 13\text{e-}6$	Expansion $\Delta L/L$
$E = 150 \text{ GPa} - 210 \text{ GPa}$	elasticity (Giga Pascal)
$\lambda \ 15 - 50 \text{ W/ mk}$	material conductivity (W/mK)
$C_p = 400 - 550 \text{ J/kg.K}$	specific heat (J / kg. $^{\circ}\text{C}$)

Table 5.14. Simulation matrix and material property values for the selected material types

<u>Properties of the 9 types of materials used in the simulation</u>			
λ	E	ε	c_p
15	150000	11e-06	4.00e+11j/kg. $^{\circ}\text{C}$
15	180000	13e-06	5.50e+11j/ kg. $^{\circ}\text{C}$
15	210000	12e-06	4.75e+11j/ kg. $^{\circ}\text{C}$
35.5	150000	13-e6	4.75e+11j/ kg. $^{\circ}\text{C}$
35.5	180000	12e-06	4.00e+11j/ kg. $^{\circ}\text{C}$
35.5	210000	11e-06	5.50e+11j/ kg. $^{\circ}\text{C}$
50	150000	12e-06	5.50e+11j/ kg. $^{\circ}\text{C}$
50	180000	11e-06	4.75e+11j/kg. $^{\circ}\text{C}$
50	210000	13-e06	4.00e+11j/kg. $^{\circ}\text{C}$

Table 5.15. Simulation run input factors

Variables	Roll/stock contact (HTC) (kW/m 2 K)	Stock temperature ($^{\circ}\text{C}$)	Contact length (mm)	Heat transfer coef. (HTC - Cooling) (kW/m 2)	Roll speed (Rad/sec)	Roll Temperature ($^{\circ}\text{C}$)	Delay time (Sec)
Design Input Values	x1	x2	x3	x4	x5	x6	x7
	15	1100	10	50	0.14	80	60

Table 5.15 presents the design input data parameters used in the experimental simulation carried out for verifying the temperature trend, under various material types, along the heat affected area from the roll surface towards the centre of the roll. The experiment is conducted based on the matrix, fractional factorial (3^{3-1}) shown in the Table 5.16 below. After simulation data are collected from the surface of the roll and various depths below the surface, at 2mm, 6mm, 9mm and 15mm, as shown in the Table 5.17. As discussed in section 5.3.8 data from the surface (calculated depth) are calculated based on functional relationship of relevant input factors parameters of individual runs. Taking in to account those factors relevant in determining the depth heat penetration, in this case 9.9 mm has calculated for depth of heat penetration, where heat expected to reaches steady state.

Table 5.16. FEA Simulation run matrix

Run	x1	x2	x3	x4	x5	x6	x7
1	0	0	0	0	0	0	1
2	0	1	1	1	1	1	2
3	0	2	2	2	1	1	2
4	1	0	1	2	2	0	2
5	1	1	2	0	2	0	2
6	1	2	0	1	1	2	0
7	2	0	2	1	1	0	1
8	2	1	0	2	2	1	0
9	2	2	1	0	1	0	1

Table 5.17. Responses (Temperature in $^{\circ}\text{C}$) from simulation with different roll material (M) types, at roll surface and various depths below the roll surface

Depth	2mm	6mm	9mm	9.9mm	15mm
M1	92.49	90.54	84.81	80.24	79.54
M2	112.47	91.09	91.84	87.23	85.33
M3	121.15	95.56	90.04	86.42	86.59
M4	81.46	81.05	78.58	78.79	76.16
M5	86.02	86.1	86	85.85	84.19
M6	78.58	69.19	69.07	60.11	59.58
M7	75.49	73.89	73.34	76.51	76.58
M8	86.64	77.05	77	68.67	68.76
M9	85.32	85.68	76.11	70.25	68.3
M0	80.6	80	62.2	60.1	59.2

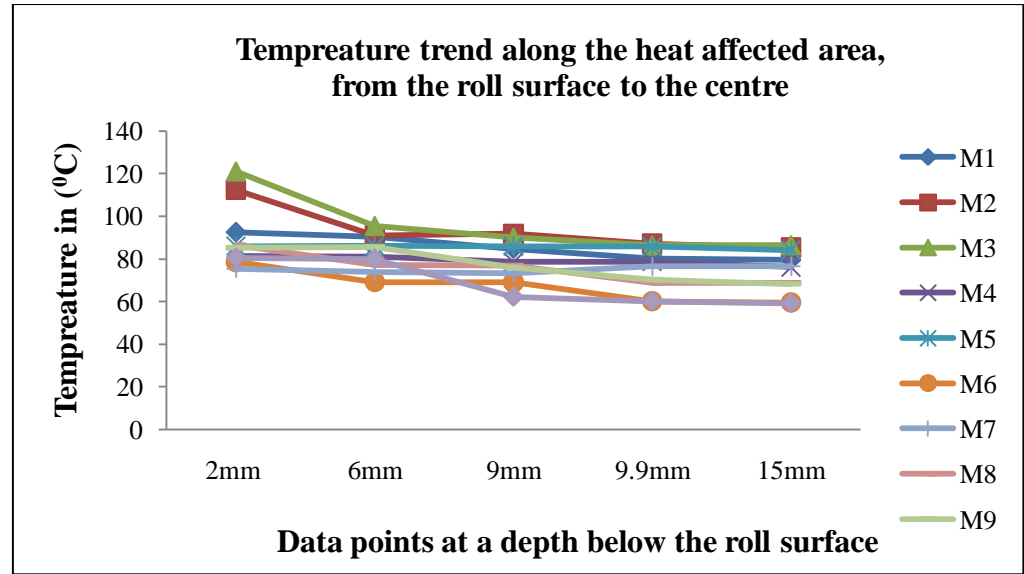


Figure 5.15. Temperature trend along the heat affected area, from the surface to the centre of the roll

The trend in Figure 5.16 indicate that as expected, the temperature is decreasing from the roll surface towards the centre and also the rate at which it is changing inside the roll (at 9, 9.9 and 15 mm) is slowing. This indicates the consistency of temperature profile decline depth below the surface of the roll. A material high chromium steel (M0) in the graph, due to its high wear resistance ability, selected for the modelling. In comparison with other materials, considering its less conductivity it possesses, it is considered a better choice. Chromium has better wear resistance. M0 to M9 in Figure 5.16 represents 9 type of materials used in the experiment.

5.3.8 Meta-Model Construction

The quantitative models, a total of 6 models, were generated by fitting a second degree polynomial, consisting of a main effect, quadratic effect and interaction effect. The modelling was carried out using STATISTICA, a tool selected due to its applicability and availability. It is also widely used by the sponsoring company. The process was then repeated in MATLAB tools to compare results accuracy and observe statistical uncertainty/errors, if any. The dependent factors as objectives, change in temperature and radial stress, are used to form the approximate meta-models. The regression models developed with the input variables x_1, x_2, \dots, x_3 , shown in Table 5.6. The models and the post regression analysis results are shown in the followings. (The brackets [] in the models, (Equations 5.5-5.10), are used to simplify the symbols, linear & quadratic, representing the variables).

Models fit for single pass work roll system problems

Change in temperature ΔT at roll surface

$$\Delta T-S = (-370.8659 + 3.92666667 * x[1] + 0.046222222 * x[1]^2 + 3.02845679 * x[2] - 0.00130938 * x[2]^2 + 0.0000001 * x[3] - 0.0000025 * x[3]^2 - 7.0603175 * x[4] + 0.085079365 * x[4]^2 + 26.9230797 * x[5] + 3.44362939 * x[5]^2 + 3.99055556 * x[6] - 0.04194444 * x[6]^2 - 0.801944 * x[7] + 0.004701389 * x[7]^2) \quad \text{Equation 5.5}$$

Stress (S11) at roll surface

$$S11-S = (140.63997 - 10.082111 * x[1] + 0.064200000 * x[1]^2 - 1.2915963 * x[2] + 0.002292222 * x[2]^2 + 0.0014444 * x[3] - 0.000003333 * x[3]^2 + 12.1149569 * x[4] - 0.21604354 * x[4]^2 - 387.34458 * x[5] + 145.751168 * x[5]^2 - 2.6677500 * x[6] + 0.0386875 * x[6]^2 - 1.4585556 * x[7] + 0.01198229 * x[7]^2) \quad \text{Equation 5.6}$$

Change in temperature ΔT at 9mm depth below the surface

$$\Delta T-9\text{mm} = (-819.98558 + 9.97380000 * x[1] - 0.31336444 * x[1]^2 + 1.43803309 * x[2] - 0.59030\text{E-}3 * x[2]^2 - 0.13506667 * x[3] + 0.095348889 * x[3]^2 - 5.1424209 * x[4] + 0.062201542 * x[4]^2 + 52.8477445 * x[5] - 23.073031 * x[5]^2 + 0.050088889 * x[6] - 0.00849611 * x[6]^2 - 0.22464444 * x[7] + 0.001426597 * x[7]^2) \quad \text{Equation 5.7}$$

Stress (S11) at 9mm depth below the surface

$$S11-9\text{mm} = (913.51841 - 18.435556 * x[1] + 0.508400000 * x[1]^2 - 5.0893000 * x[2] + 0.002138444 * x[2]^2 - 3.9332778 * x[3] - 0.13521667 * x[3]^2 + 14.6337279 * x[4] - 0.18028299 * x[4]^2 - 248.51971 * x[5] + 101.248057 * x[5]^2 + 0.1710833 * x[6] + 0.017137500 * x[6]^2 + 0.108888 * x[7] - 0.17812\text{E-}3 * x[7]^2) \quad \text{Equation 5.8}$$

Change in temperature ΔT at 15mm depth below the surface

$$\Delta T-15\text{mm} = (-553.55904 + 9.74111 * x[1] - 0.35888889 * x[1]^2 + 1.00235802 * x[2] - 0.40321\text{E-}3 * x[2]^2 - 0.51055556 * x[3] + 0.0949444 * x[3]^2 - 3.9777324 * x[4] + 0.04591383 * x[4]^2 + 51.7361959 * x[5] - 28.708807 * x[5]^2 - 1.0575000 * x[6] + 0.001652778 * x[6]^2 - 0.29222 * x[7] + 0.0022048 * x[7]^2) \quad \text{Equation 5.9}$$

Stress (S11) at 15mm depth below the surface

$$S11-15\text{mm} = (316.50677 - 19.781444 * x[1] + 0.553933333 * x[1]^2 - 4.0415037 * x[2] + 0.001683704 * x[2]^2 - 5.6866667 * x[3] - 0.07520000 * x[3]^2 + 11.4528209 * x[4] - 0.13340408 * x[4]^2 - 199.10688 * x[5] + 97.5171611 * x[5]^2 + 0.867388889 * x[6] + 0.009866667 * x[6]^2 + 0.738388889 * x[7] - 0.00434792 * x[7]^2) \quad \text{Equation 5.10}$$

5.3.9 Model Validations

This section gives justification for the acceptability of the models for representing the problem in question. Validation is based on post processing statistical features from the regression. Post processing statistical results helps to determine the relevance of the independent input factors in the model building, as well as measure the ability of the model to predict the system response over the search space. The criteria of the performance are based on four measures: Pareto chart of p- values for coefficient, sum of squares error, R^2 and R. R^2 & R are measures of the amount of variation experienced by the model. R^2 equals 1 indicates a perfect fit. The higher R^2 implies the lower variation between observed and predicted values; therefore, a better model. The corresponding R^2 and R for each model are given in Table 5.18. During model generation, a relatively high value of R^2 & R has been recorded. It is, therefore, likely that these models would give good predictions when used in the optimisation. Other important model summaries, such as Pareto chart of p-values for coefficients, are used. The p-values for coefficient are used to determine the confidence of those factors' relevancies to the model. A p-value less than 0.005 is considered acceptable.

Table 5.18. Model validation summary, p-values, sum of square errors (R) and (R^2)

Single-pass R , R^2 & p values				
		R	R^2	p-values
At roll Surface	Change in temperature	0.908590	0.897465	0.001615
	Radial stress	0.937748	0.879371	0.001485
At 9mm Depth	Change in temperature	0.920435	0.897200	0.005103
	Radial stress	0.907458	0.853481	0.001555
At 15 mm depth	Change in temperature	0.929199	0.903411	0.002859
	Radial stress	0.921993	0.870071	0.004630

Model validations for genera ability

The model is further validated for general ability by taking 9 randomly selected data points within the design space. The experimental responses from those data points are then collected and recorded. The same procedure that was used for the main simulation runs is applied. The input factor parameters and the simulation response values from the validation runs are presented in Table 5.19 and Table 5.21 respectively.

Table 5.19. Validation runs input data set (factors and factors parameters)

(HTC Roll/stock contact) (kW/m ² K)	Stock temperature (°C)	Contact length (mm)	(HTC - Cooling) (kW/m ² K)	Roll speed (Rad/sec)	Roll Temperature (°C)	Delay time (Sec)
6	12	1000	20	0.18	43	30
6	12	1210	40	1.25	43	30
9	19	1105	30	0.715	43	62.5
6	19	1000	30	1.25	65	95
6	19	1210	20	0.715	65	95
12	26	1000	20	0.18	43	95
6	26	1000	40	0.715	55	62.5
9	26	1105	40	0.18	65	30
12	26	1210	30	0.18	55	30

The validation simulation run carried out using the input data set shown in Table 5.19. The results are taken when temperature reaches the steady state. As discussed in the Section 5.3.6 the steady states may vary depending on the speed of the roll and the size of the roll therefore to determined the expected steady state the temperature reach at depth, depending on those relevant factors a functional relationship have employed. The functional relationships and result obtained for the 9 validation runs are given in Table 5.20. Data for temperature and stress are shown in Table 5.21.

Table 5.20. Calculated depth at the roll surface, for data taking

Run	Procedure	Depth
1	contact length 10mm and r 0.18r/s $t = 10 / 0.18 \times 180 = 0.3086$ Depth = $d = \sqrt{6 \times 0.000014 \times 0.3086} = 0.0050\text{m} \times 1000 =$	5.0mm
2	contact length 10mm and r 1.250r/s $t = 10/1.250 \times 180 = 0.0444$ Depth = $d = \sqrt{6 \times 0.000014 \times 0.0444} = 0.0019\text{m} \times 1000 =$	1.9mm
3	contact length 10mm and r 1.250r/s $t = 10/1.250 \times 180 = 0.0444$ Depth = $d = \sqrt{6 \times 0.000014 \times 0.0444} = 0.0019\text{m} \times 1000 =$	1.9mm
4	contact length 20mm and r 0.715r/s $t = 20/ 0.715 \times 180 = 0.1554$ Depth = $d = \sqrt{6 \times 0.000014 \times 0.1554} = 0.0036\text{m} \times 1000 =$	3.6mm

Run	Procedure	Depth
5	contact length 20mm and r 1.250r/s $t = 20/1.250 \times 180 = 0.0889$ $\text{Depth} = d = \sqrt{6 \times 0.000014 \text{m}^2/\text{s} \times 0.0889} = 0.0027\text{m} \times 1000 =$	2.7mm
6	contact length 20mm and r 0.715r/s $t = 20 / 0.715 \times 180 = 0.1554$ $\text{Depth} = d = \sqrt{6 \times 0.000014 \times 0.1554} = 0.0036\text{m} \times 1000 =$	3.6mm
7	contact length 30mm and r 0.18r/s $t = 30/0.18 \times 180 = 0.9259$ $\text{Depth} = d = \sqrt{6 \times 0.000014 \text{m}^2/\text{s} \times 0.9259} = 0.0088\text{m} \times 1000 =$	8.8mm
8	contact length 30mm and r 0.715r/s $t = 30/ 0.715 \times 180 = 0.2331$ $\text{Depth} = d = \sqrt{6 \times 0.000014 \text{m}^2/\text{s} \times 0.2331} = 0.0044\text{m} \times 1000 =$	4.4mm
9	contact length 30mm and r 0.18r/s $t = 30/0.18 \times 180 = 0.9259$ $\text{Depth} = d = \sqrt{6 \times 0.000014 \text{m}^2 / \text{s} \times 0.9259} = 0.0088\text{m} \times 1000 =$	8.8mm

Table 5.21. Validation FEA simulation run Response (Change in temperature in rolls after rolling (T1) and before rolling (T0) and the corresponding radial stress (S11)

No. of runs	T1 (°C)	T0 (°C)	ΔT (°C) (T1-T0)	S11 (MPa)
1	51.49	(43)	8.49	53.92
2	102.14	(43)	39.14	44.398
3	107.68	(43)	64.68	86.27
4	66.06	(65)	1.06	13.9
5	111.55	(65)	44.55	- 52
6	114.04	(43)	79.04	- 139.76
7	72.91	(55)	17.91	6.96
8	86.72	(65)	41.72	- 139.1
9	130.05	(55)	75.05	- 142.07

The individual FEA response from the 9 runs shown in Table 5.21, then compared with the result from the validation input data set fed in to the mathematical model for error. The error evaluates the probability error in percentage terms that the validation runs will have in relation to the Meta model, i.e. compares the FEA results against the Meta model results. The aim of validation is to determine whether the conceptual simulation model closely represents the system under study generically.

Table 5.22. validation results

Radial stress (S11 in MPa) at roll surface				Change in temperature (ΔT in $^{\circ}\text{C}$) at roll surface		
	Predicted	Observed	Absolute error	Predicted	Observed	Absolute error
1	51.03	53.92	2.89	8.76	8.49	0.27
2	45.09	44.39	0.69	51.15	59.14	7.99
3	87.44	86.27	1.17	67.13	64.68	2.45
4	14.37	13.9	0.47	1.30	1.06	0.24
5	-50.51	-52	1.49	48.70	46.55	2.15
6	-143.19	-139.76	3.43	73.65	71.04	2.61
7	5.82	6.96	1.14	17.99	17.91	0.08
8	-36.64	-39.1	2.46	21.30	21.72	0.42
9	-146.43	-142.07	4.36	73.06	75.05	1.99

The statistically universally accepted maximum percentage error allowable is 5%. As shown in the table above, the absolute errors values are negligible and assumed to be below 5 %. Therefore the result proves that the model, second degree polynomial, is expected to generate good predictions when used in the optimisation. As discussed in Chapter 6, multi-pass models are developed based on the single pass model developed from data taken at the roll surface and generate other pass models by taking in to account functional relationships between passes. Hence the validation of the single pass model presented here also gives an indication the possibility of using the model for multi-pass process modelling.

5.4 Chapter Summary

The chapter has developed a framework for quantitative models. The quantitative models are designed to represent and evaluate the work roll system thermal design in the rolling process. Several work roll system thermal models are developed, each representing the thermal behaviour of rolls at the surface and various depths below the surface. In summary, the chapter achieved the following:

- Studied the rolling process, identified the fundamental issues of the work roll system design problems and their effect on the thermal behaviour of rolls.
- Suggested a generic methodology to represent and evaluate the work roll system design problems quantitatively.
- Presented a mathematical concept to detect heat effected zone on rolls (depth of penetration), depending on the rolling process initial conditions.

-
- Presented Meta-modelling framework, and detailed descriptions of steps used to develop the qualitative model for work roll system thermal design and
 - Validated the developed quantitative model.

The next chapter discuss, the optimisation of the work roll system design problems with uncertainty, using the developed quantitative models as fitness functions.

6 Single Pass Work Roll System Optimisation, in presence of Uncertainty and Constraints using Thermal Analysis and GA

Chapter 2 discussed the importance of acquiring optimal work roll system design for effective and longer roll life. As stated in the previous chapter, it is also equally important to acquire a suitable simulation quantitative model to capture the real life work roll process design and quantify the formulation of an optimisation problem. It is also learned in the literature review that in practice, the properties of the design solution may be subject to a certain amount of variation because its implementation cannot be realized with arbitrary precision. Hence, optimisation without taking uncertainty/variability in to consideration, would result in a solution that is risky, since they are likely to perform differently when put in to practice. Literature revealed that there are a number of GA based techniques available to deal with current complex engineering design problems, allowing finding an entire set of Pareto optimal solutions in a single run, instead of having to perform series of separate runs, as in the case of the traditional technique. However, having considered the overall capacity and flexibility in dealing with today's engineering design problems complexity, such as handling uncertainty and constraints, the current techniques lack maturity. The developed framework is designed to address these limitations. This chapter presents a multi-objective optimisation technique and steps followed to develop the technique. The robust evolutionary multi-objective evaluation technique is applied to the constrained optimisation problems with real life uncertainty. The approach handles uncertainties associated both with the design variables and the mathematical Meta models used as fitness functions in the optimisation. The real life uncertainty includes:

- Uncertainty associated with the inherent *variation* in the physical system or environment that is under consideration. For example, tooling setup, process setup, and operating environment.

-
- Uncertainty associated with *deficiency* in any phase or activity of the simulation process that originates in lack of system knowledge. For example, uncertainty associated with the lack of knowledge in the laws describing the behaviour of the system under various conditions.
 - Uncertainty associated with the limitations of numerical methods used to construct simulation models. When providing the stochastic assessment of model validity. This real life process design behaviours motivates that the technique developed to deal with the optimisation problem also need to take in to account these types of uncertainties.

Constraints violation within the neighbourhood of a design is considered as part of a measurement for degree of feasibility and robustness of a solution. Two optimisation approaches are introduced. The first is robust non dominance criteria based optimisation technique, to deal with two objectives, single pass problems and the second is application of the technique, for dealing many (m) objectives problems. The second technique developed to address the issues the first technique experienced in searching solution for high dimensional, many objective problems. The techniques' ability in dealing with the work roll thermal analysis and optimisation problem in presence of uncertainty and constraints, addressing multi objectives single pass work roll design problems is analysed and their advantages and shortcomings are highlighted. The first technique is used to satisfy the initial target of the research i.e. searching optimal design solution for single pass optimisation problem with uncertainty and constraints involving two objectives at the surface of the roll. One of the main challenges these approaches pose to optimisation algorithms is scalability and high dimensionality. This refers to the increase of the complexity of the problem as the number of objectives and number of passes increase. To overcome these challenges the second technique is developed. The second technique is designed to deal with single pass rolling arrangements for increased search space problem (surface and two random points at depth below the surface) and the multi-pass problem, to deal with high dimensional, many objectives problem discussed in Chapter 7. The chapter consists of the following: It begins with Section 6.1, giving a brief introduction of the robust non dominance criteria technique and R environment based non sorting GA technique. Section 6.2 introduces the case study, two-objective single pass work roll system thermal analysis and optimisation problems with uncertainty and constraints.

Section 6.3 evaluating criticality of constraints to optimum designs solution point. Section 6.4 demonstrates the application of the non dominance technique, in R environment to many-objective optimisation, for single pass, 6 objectives work roll system optimisation problem with uncertainty. The section also presents the application of the proposed post optimisation result analysis for identifying the final best, optimal design solution for the high dimensional problems. Section 6.5 concludes the chapter with a summary of the main points.

6.1 Robust Non Dominance Criteria Technique for Optimisation Problem with Uncertainty

Review of literature shows that although evolutionary computing has proven to be an efficient and powerful problem-solving strategy, they are not problem free techniques. The majority of EC techniques do have certain limitations, particularly in the following areas:

- The first, and most important, consideration in creating a genetic algorithm is defining a representation for the problem. The language used to specify candidate solutions must be robust; i.e., it must be able to tolerate random changes such as noise and uncertainty, as well as constraints. These are the most common characteristics of real world engineering design problems such as rolling thermal analysis and optimisation.
- In a complex and uncertain engineering process environment a mathematical simulation is often required as the empirical study is very difficult. However, the mathematical model is a numerical representation which is prone to forced accuracy compromises which leads to model uncertainty.

These limitations have to be taken in to account in the optimisation for the required solution to be found. To address these issues, therefore, the current multi-objective optimisation techniques need to be reviewed for capability in handling the problems' complexity. The techniques proposed in this thesis is called robust non dominance criteria technique, implemented in MATLAB and R environment, for searching design solution for two objective and many objectives problems respectively. Primarily, the techniques are adopted due to their adaptability, access and easy to use nature - this nature makes it possible to include (incorporate) the uncertainty and constraint criticality in the technique, and hence, be able to search for solutions for the

optimisation problem of the thesis case study, regardless of the limitations listed above. The description of the techniques' application is presented as follows:

The robust dominance criterion is a technique, designed to utilize the new robust multi-objective evaluation technique to generate robust best compromise solutions for problems with noise and uncertainty (Parmee, 2001; Chen, *et al.*, 1996; Mehnen and Trautmann, 2008). The technique was developed and initially used by Mehnen and Trautmann (2008) in robust multi-objective optimisation of weld bead geometry for Additive manufacturing. In his work, the technique was used to search for solutions for two objective problems with uncertainty in the objective space. The technique is easy to use, adaptive, computationally inexpensive and flexible, so that it can be extended to be used for other engineering problems, such as uncertainty in the objective and decision space. Inspired by these qualities, hence, this research adopted the technique and extended it to include high dimensional problems with uncertainty, both in the objective and decision space. A brief overview of the technique and its initial application, supported by graphical illustrations is presented as follows.

In the case of uncertain fitness functions (f_1 and f_2), Figure 6.1, the conventional Pareto criterion is not able to decide whether a point x is dominating another point x^* because it can only compare two discrete solutions at a time. The robust dominance criterion takes uncertainty of the fitness function values into account by calculating median estimates and the convex hull around a solution in the objective space (Mehnen and Trautmann, 2008). The convex hull represents the area of uncertainty of a solution. To calculate the Pareto-non dominance properties of any two solutions x and x^* , one calculates the median of all noisy fitness values. A solution x of the multi-objective optimisation problem dominates a solution x^* iff:

$$\begin{aligned} \text{med}(f_{ik}|x, \varepsilon) + \text{mean}(dMCH_i|x, \varepsilon) &< (\text{med}(f_{ik}|x^*, \varepsilon) - \text{mean}(dMCH_i|x^*, \varepsilon)), i \in \{1, \dots, m\} \\ (\text{med}(f_{jk}|x, \varepsilon) + \text{mean}(dMCH_j|x, \varepsilon)) &\leq (\text{med}(f_j|x^*, \varepsilon) - \text{mean}(dMCH_j|x^*, \varepsilon)), j = 1, \dots, m, j \neq i \end{aligned}$$

Equation 6.1

Where $dMCH_i$ is an uncertain vector that holds the absolute distance of each point in the convex hull to x so it defines the bounds of the uncertain space around the solution. This approach using the convex hull, Figure 6.1, is considered more reliable because it takes always the worst case scenario. In the equation the arithmetic mean of the sample solutions is theoretically unbiased estimator of the true front (for $k \rightarrow \infty$). However, the median is a statistically robust estimate of the noisy fitness values.

Therefore, the median is used in the case study. The problem at hand is then to estimate the true Pareto front from a set of k noisy samples $(f_{ik}|x, q)$, $i = 1 \dots m$ which cover true Pareto front. In order to introduce a dimension of the point clouds (due to noise) in the objective space, the mean distances of all points on the convex hull from the median representatives are calculated as in Figure 6.1 below. Then, the measure of uncertainty of a solution in m -dimensional objective space can be introduced by taking say $P := \text{med}(f_k)$ as a robust estimate of a solution, and the Convex Hull $\text{CHP}(P)$ of all k sample points around P describes a worst case representative of solution P containing all k samples. The absolute distances in each dimension of all points in $\text{CHP}(P)$ to P can be used to define the uncertainty vector. Given the uncertainty vectors around a solution P , all points within the box formed by uncertainty vectors are represented by P . This implies that the conventional Pareto-dominance definition may not hold any more if any two points, P and say Q , are inside the uncertainty vicinity of each other. Although these points may dominate each other in a noise-free case, in the case with noise it is impossible to tell which point dominates the other, as shown in Figure 6.1. Therefore, in this case, both points are considered as potential solutions (Pareto set). The set of non-dominated solutions are called the (expected) Pareto set. The median representatives are the elements of the (expected) Pareto front.

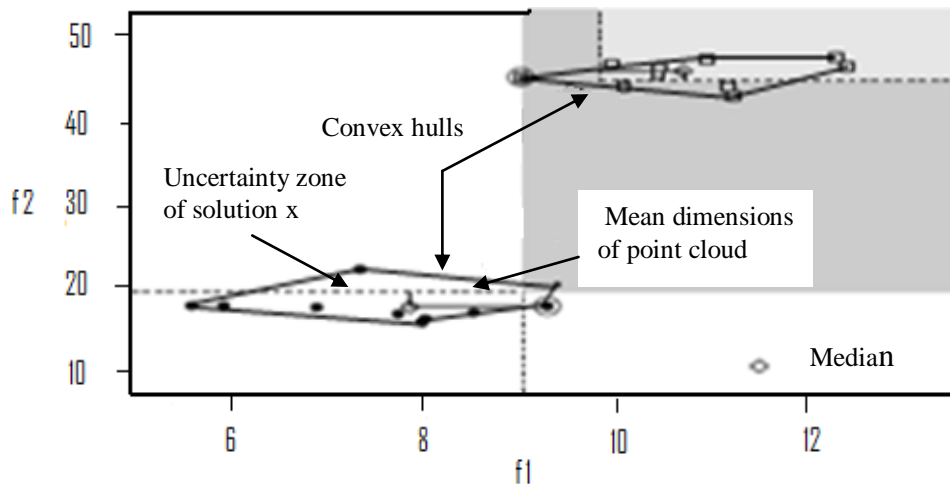


Figure 6.1. Concepts of robust dominance criterion with noisy fitness functions
(Mehnen and Trautmann, 2008)

Figure 6.1 illustrates the major concepts in identifying dominance of one point over another. The small diamonds in the middle of the convex hull indicate the median estimates of $f(x) + \varepsilon$ and $f(x^*) + \varepsilon$, respectively. The mean dimensions of the point

cloud distributions are also shown as small horizontal and vertical lines extending from the diamonds. They indicate the uncertainty zones around the solutions in the objective space. The dark grey area indicates the region which is dominated by the solution in the lower left part of Figure 6.1 while the light grey area shows the dominated area of the upper right solution. In the Figure, the lower left solution dominates the upper right solution because the light grey area completely fits inside the dark grey area. In case either of the areas overlap or one area does not fit within the other area, the corresponding solutions do not dominate each other. In this case, the non dominance criteria state that both solutions are best, and hence should be considered as an optimal solution for the problem. Figure 6.2 additionally shows the effect of the uncertainty zone in making the decision of dominance. In the figure, if the problem were to rely on the traditional approaches, which is only using expectation (median), it would have yielded the decision that solution x (median of the round points) dominates solution x* (median of the squares). In the proposed approach, however, it becomes obvious that this decision is too uncertain – hence, both solutions remain non-dominated.

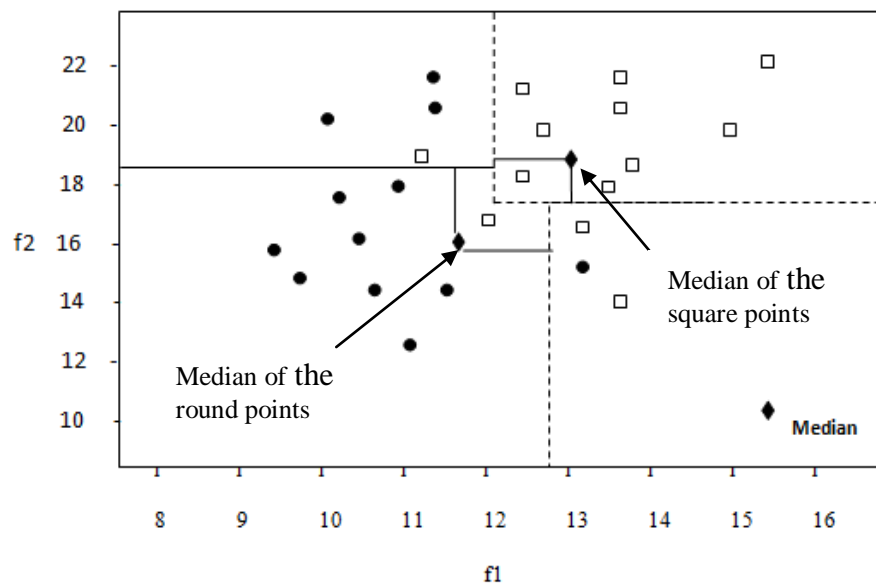


Figure 6.2. Concepts of robust dominance criterion with noisy fitness functions

6.1.1 Application of the Technique in the Work Roll System Design Problem in presence of Uncertainty

The technique has been implemented in the work roll thermal analysis and optimisation problem to help identify optimum designs in presence of uncertainties

and constraints. A predecessor of this algorithm, applied in problem with uncertainty in the fitness functions, is described in the previous section. Here, the new technique, in conjunction with central limit theorem, is applied in the case of real life many objective problem with uncertainty in the design variables and in the fitness functions. The Central Limit Theorem, discussed in Section 6.2.1.3 is adopted since the application of the robust non dominance criteria technique in the problem with uncertainty in the decision space proved unsatisfactory i.e. unable to satisfy the solution requirements as expected. Although the technique is able to find the Pareto front, it is discontinuous and scattered. This indicate that how small uncertainty presence in the decision variables have a bigger impact on the design solution. The problem is unique only for uncertainty in the decision space; various approaches are explored to be used with the robust dominance criteria so that the problem occurred can be understood and rectified. One of the approaches is the application of central limit theorem CLT. CLT is used to control the sample size or iteration in a sequence of n independent and identical distributed random variables, where each having finite values of expectations. The theorem says that as the sample size n increases, the distribution of the sample average of these random variables approaches the normal distribution. In the optimisation the theorem applied to control the sampling size. The sample size, depending on the problem and uncertainty in the problem is determined through experimental trial. Degree of uncertainty in the research problem, as discussed in chapter 4, is assessed through expert opinion and real life process practice observations. The experimental trial for determining the sample size and the sample size identified to be used in the research problem is discussed in the section 6.2.1.3. Problem solution search strategy using the robust dominance criteria technique and CLT, for the multi objective optimisation problem with uncertainty in the design space and fitness function is presented in Figure 6.3.

Solution search Strategy

Pseudo-code for the uncertainty representation in the design variables and fitness function evaluation for the multi-objectives single pass problem

Step 1: Initialise population pool at $t = 0$. For every member of the population i , generate random value x_j in its range as well as ranges of uncertainty. This random value aids the exploration of the entire search space.

1.1: Evaluate decision space and uncertainty in the design variables

Evaluate $X_i = \{ (x_1 + \varepsilon), \dots, (x_n + \varepsilon_n) \}$

Step 2: Evaluate the individuals in terms of quantitative model and model uncertainty. The individual chromosomes in terms of local and global QT objective functions values, for all selected points on the roll, (at surface and depth below the surface at 9 mm & 15 mm), then aggregate (sum) these objective function values as the global objective and use the aggregated value as the fitness function value for the chromosome.

2.1: Evaluate fitness functions and uncertainty in the fitness functions

Evaluate $(\bar{F}_i(\bar{x}) + \varepsilon = \sum_{j=1} f_{ij}(\bar{x}) + \varepsilon \mid i = 1, 2, \dots, k) + \varepsilon$; // assign a fitness value to

each GA individual based quantitative model

Step 3: Assign fitness to every member of the population based on dominance-ranking criteria of NSGA-II and Central Limit Theorem. The quantitative value is used for the quantitative objective value.

Step 4: Termination If current generation satisfy the conditions, else return to step2

Step 5: Create offspring population using binary tournament selection, crossover, and mutation operators

$t = t + 1$, go to step 2.h

Figure 6.3. Solution search strategy for multi-objective problems with uncertainty

The work started with the assumption that a general multi-objective optimisation problem seeks to simultaneously minimise f objectives: $f_d(x)$, $d = 1, \dots, i$ where each objective depends on a vector $x = x_1, \dots, x_n$ of n design variables. The research problems, with the problem in which both the fitness functions and the decision variables are uncertain, are expressed as shown below. Uncertainty is denoted by $\varepsilon_1, \varepsilon_2, \varepsilon \sim F$, F is some distribution:

$$y = (x + \varepsilon_1) + \varepsilon_2, \quad \text{Equation.6.2}$$

The parameters are subject to the j constraints:

$$g_j(x) \leq 0, j = 1; \dots; k \quad \text{Equation 6.3}$$

The multi-objective optimisation problem may thus be expressed as:

$$\text{Minimise } f(x) = (f_1(x), \dots, f_n(x)), \quad \text{Equation 6.4}$$

Subject to the constraints:

$$g_j(x) \leq 0, j = 1, \dots, k. \quad \text{Equation 6.5}$$

Equation 6.2 can also be written in a real value vector (problem with uncertainty in the design variables and fitness function) as shown in Equation 6.6:

$$\vec{Y} = \vec{f}(\vec{x} + N(\vec{\mu}, \vec{\sigma})) + N(\vec{\mu}, \vec{\sigma}) \quad \text{Equations 6.6}$$

$$\vec{x} \in \mathbb{R}^n \quad n = \text{dimension}$$

The procedure and application of the technique, searching for solution for the intended single pass two objectives and many objectives problem case study are discussed in Section 6.2 and 6.4 respectively.

6.2 Application of the Technique in the Single Pass Work Roll System Design Optimisation Problems in Presence of Uncertainty and Constraints

This section and subsections gives details of the optimisation algorithm of the quantitative search space of multi-objective single pass, work roll system optimisation problems in the presence of uncertainty and constraints using thermal analysis and the GA based techniques proposed. The study introduces the concepts of conflicting behaviour between multiple objectives problems, on the proposed robust dominance criteria technique in collaboration with CLT. The optimisation carried out in two forms: the first application of the technique in two objective problems in MATLAB environment and application of the technique in many objective problems in R environment. The models (1 to 6) presented in Section 5.3.9, for single pass work roll system are used in the optimisation. The models are for work roll system thermal analysis at roll surface and at a depth below the surface of 9mm and 15mm. These equations are formulated as roll design optimisation problems, where the goal is to optimise/minimise temperature change (ΔT) and radial stress (S11) functions at the roll surface, as well as at depth, Details of the application of the technique in the optimisation problem is presented in the sections in the following sub sections.

6.2.1 The Single Pass Problem

The main objective of single pass optimisation is keeping the temperature of rolls at the surface at a minimum, while at the same time, minimising the tensile stress on the surface created by the effect of cooling applied on the roll to cool it. Depending on the design input factors parameters, such as speed and contact length, heat steady state in rolls can reach up to certain depth when hot stock comes in contact with the rolls. As discussed in Section 5.3.7 and presented in Table 5.9, the expected depth of heat penetration and effect of stress on rolls are calculated. The objective function is then

formulated using the data taken. However, rolling is an iterative process where the hot stock comes in contact with the roll repeatedly. During rolling, although the heat is removed constantly from the roll by the cooling system, there is still a possibility that heat remaining will pass beyond the specified depth and build up at the core. The heat accumulated at the core has a potential to trigger thermal shock. The shock then leads to roll outward crack. The overall aim of optimisation at the surface is to prohibit the temperature from reaching and accumulating at the roll core. This problem is a two objectives design optimisation problem, given in Equation 6.7 & 6.8. The optimisation assumes the design input parameters presented in Table 5.7 and 5.8 in Chapter 5. The case study has also addressed the constraint criticalities to the design solution obtained and ranking of the criticality. The application of robust dominance criteria technique, in collaboration with the central limit theorem (CLT) on the work roll system optimisation problem with uncertainty in the decision and objective space is discussed in Section 6.2.2.

6.2.1.1 Objective Functions

This work focuses on optimising roll temperature change (ΔT) and radial stress (S11) for work roll thermal analysis and optimisation - since numerous design variables influence the optimisation problem, and it is difficult and complex to include all the possible variables. The problem formulation adopted in this work focuses on relevant process variables identified in the literature, and interviews with the roll and rolling system designers. Details of the objectives and design variables identified are presented in Chapter 2.

Change in roll surface temperature (ΔT): is an important rolling thermal analysis objective that expresses the thermal condition of rolls during hot rolling. The change in temperature is measured as the difference between final surface temperature (T1), after rolling and cooling, and the initial bulk temperature (T0), before roll/stock contact. T1 values are taken over a cycle in Quasi-steady state heat exchange rolling conditions. ΔT is formulated as follows:

$$\text{Change in temperature} \quad \Delta T(\mathbf{x}) = T1 - T0 \quad \text{measured in } ^\circ\text{C}. \quad \text{Equation 6.7}$$

Roll radial stress (S11): Another equally important measure/objective in the optimising problem is keeping the roll radial stress at the roll surface as low as possible, but within rolls material allowable value. Minimising the roll temperature may trigger maximising the roll radial tensile stress and cause roll breakage.

Therefore, to normalise / (minimise) it, it is essential that the stress is also included in the optimisation.

Radial stress $S11(\mathbf{x}) = S11$ Equation 6.8

6.2.1.2 Constraints

The industrial application imposes the introduction of some constraints, relevant to the work roll system thermal design; these constraints can be classified into mechanical and/or thermal design constraints and variables constraints. The variable constraints are the upper and lower limits of the design variables used in the work roll system thermal modelling and optimisation. Here, the thermal design constraint is applied to limit the allowable tensile stress value to the roll material type used in the rolling. Based on information from real life engineering practice, the minimisation of the change in temperature will also have a negative effect on the roll. This is because minimising temperature will increase the tensile stress on the roll. If the tensile stress is beyond the limit of the allowable value of the material, it could cause fire cracking and thermal fatigue to the roll. Hence to protect the roll from fatigue the stress value has to be constrained to the allowable stress value of material type used in the rolling. The thermal constraint of the problem optimisation is formulated as follows:

Allowable radial stress $g_1(\mathbf{x}) \equiv S11_i \leq S11_{allowable}$ Equation 6.9

For the optimisation task, a real-coded multi-objective Genetic Algorithm (GA) (MATLAB version) was chosen and revised in such a way that it can deal with the uncertainty in the problem. The robust dominance criterion-based technique is designed to find robust optimal solutions for design problems with uncertainty. In this research, in consideration of the wider nature of design problems, the technique is extended to multi-objective problems with uncertain design space, uncertain objective space and problems with uncertainty in both spaces. However, in the application of the technique to problems with uncertainty in the decision space, it has been observed that the Pareto front is inconsistent, clustered and scattered. This implies that the robust non dominance criteria techniques can not deal with the uncertainty in the decision space by itself. To address these issues and improve the solution, the research proposed the introduction of the Central Limit Theorem (CLT) technique to be used in conjunction with robust dominance criterion, so that the technique can be applicable in complex multi-objective problems with uncertainty in the decision space. The

following sections discuss the central limit theorem and application steps followed to find solution for problems with uncertainty in the decision space.

6.2.1.3 Principle of Central Limit Theorem (CLT) to deal with Uncertainty in the Problem

This section introduces a method called central limit theorem. The central limit theorem is also known as the second fundamental theorem of probability, and states the following. Let $X_1, X_2, X_3, \dots, X_n$ be a sequence of n independent and identically distributed random variables, each having finite values of expectation μ and variance $\sigma^2 > 0$. As the sample size n increases, the distribution of the sample average of these random variables approaches the normal distribution, with a mean μ and variance σ^2 / n , irrespective of the shape of the original distribution (empirical mean value reaching to the true mean value) (Dean and Illowsky, 2008). The theorem is mathematically expressed as follows: Let the sum of n random variables be S_n , given by: $S_n = X_1 + \dots + X_n$. Then, defining a new random variable:

$$Z_n = \frac{S_n - n\mu}{\sigma\sqrt{n}} \quad \text{Equation 6.10}$$

The distribution of Z_n converges towards the standard normal distribution $N(0, 1)$ as n approaches ∞ (this is convergence in distribution. This is often written as:

$$\sqrt{n}(X_n - \mu) \xrightarrow{D} N(0, \sigma^2) \quad \text{Equation 6.11}$$

Where the samples mean is:

$$\bar{X}_n = S_n / n = (X_1 + \dots + X_n) / n \quad \text{Equation 6.12}$$

In an uncertainty environment, a point assumed to be in a particular location could have a chance to be at any other location within a specific radius due to presence of uncertainty in the decision variables $(x + \varepsilon)$, where x is a variable and ε is uncertainty in x . The technique adopted here is to find a random variable following a normal distribution with n samples. The sample taken, n times, is then used to calculate the estimate. The estimate is calculated using the arithmetic mean. This result is going to be the representative of the original point cloud assumed, and is then used in the optimisation. Here, a normal distribution was considered (it has to be noted that the technique can also be used regardless of the type of distribution). To determine the sample size n to be used in central limit theorem, a number of experiments have been conducted. The experiments are conducted by increasing the sampling ' n ', step by step, until a better estimate can be found. Criteria set for the experiment are as

follows: A number of experiments have conducted for different sampling ‘ n ’, starting from lower number until better sampling n is found. The samples sizes 30, 50, 70, 90, have been experimented with. Each sample size experiments are repeated 10 times, so that the consistency of the result obtained can be verified. Since there is no improvement detected the 10th runs has selected in all cases, Figures 6.4 – 6.7. Sample size $n = 70$ was considered acceptable to be used in the optimisation since no significant improvement was detected in the experiment after the sample size $n = 70$. The higher the sampling size n is the higher the computational time. Therefore, careful consideration is required during the sampling experiment not to pick the n value larger than required. The n value = 70 is based on 5% uncertainty due to noise level in the decision space. The 5% is taken as a result of experimental and real life observation of design input factor uncertainty incurred. If the uncertainty level had been more than 5%, then the sampling n would have been higher too. The results from the experiment with various samples size is presented in Figures (6.4-6.7). Limits and simulation run initial conditions presented in section 6.2.2.1 are used in the experiment.

Experiment with sample size $n = 30$

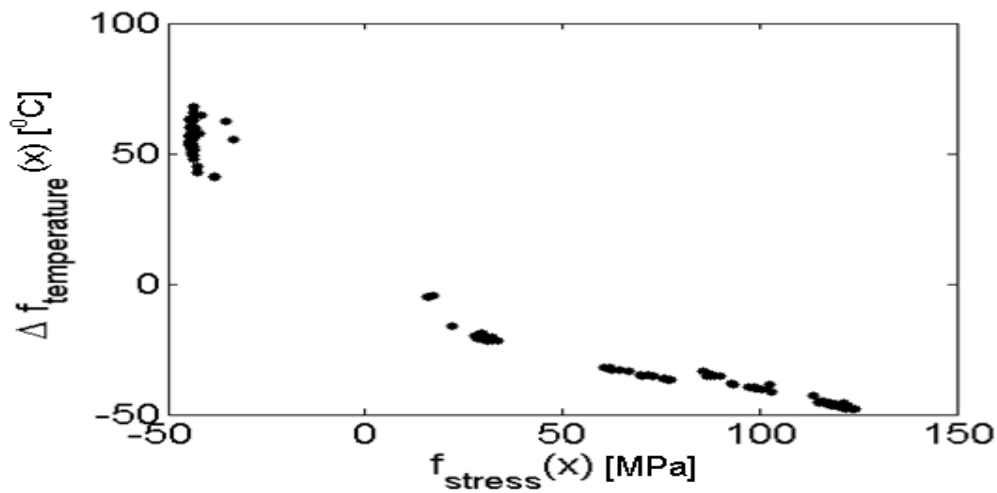


Figure 6.4. Simulation run with sample size $n = 30$

Figure 6.4 illustrates the optimisation simulation experiment run conducted for determining the CLT iteration sample size **30**. The result shows that the sample size (number of iteration before convergence) 30 is inadequate. The Pareto front is scattered, discontinuous and not distributed evenly. The sample size $n = 30$ is taken as initial in the experiment and the experiment repeated with increased n value until better result, hence Pareto front is found.

Experiment with sample size $n = 50$.

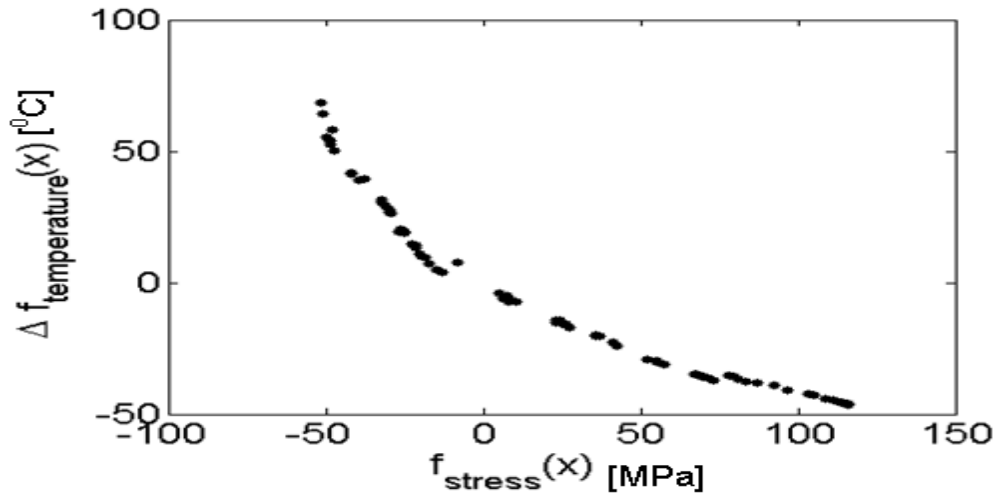


Figure 6.5. Simulation run with sample size $n = 50$

Figure 6.5 illustrate the optimisation simulation experiment run with sample size $n = 50$. The result shows that the sample size $n = 50$ gives a better Pareto front, distributed fairly evenly and convex in shape in comparison to $n = 30$ result shown in Figure 6.4. However there is still discontinuity observed in the Pareto front as shown in the Figure 6.5 hence n size higher than 50 needs to be tested. The experimental result with $n = 70$ is given in Figure 6.6.

Experiment with sample size $n = 70$

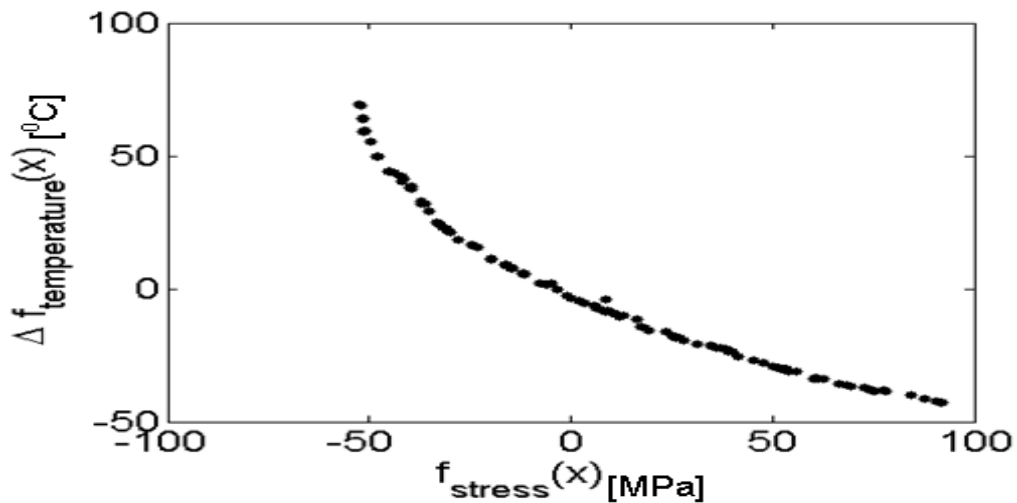


Figure 6.6. Simulation run with sample size $n = 70$

Figure 6.6 illustrate the optimisation simulation run with sample size $n = 70$. The result shows that the sample size $n = 70$ gives a better Pareto front, distributed fairly evenly and convex in shape. The higher the size of n resulted in the higher the

computational time, hence to minimise the computational time the sample size $n = 70$ can be considered as the final iteration size and used in the optimisation, if no significant improvement observed in the Pareto front in the consecutive experimental runs conducted with higher sample sizes.

Experiment with sample size $n = 90$

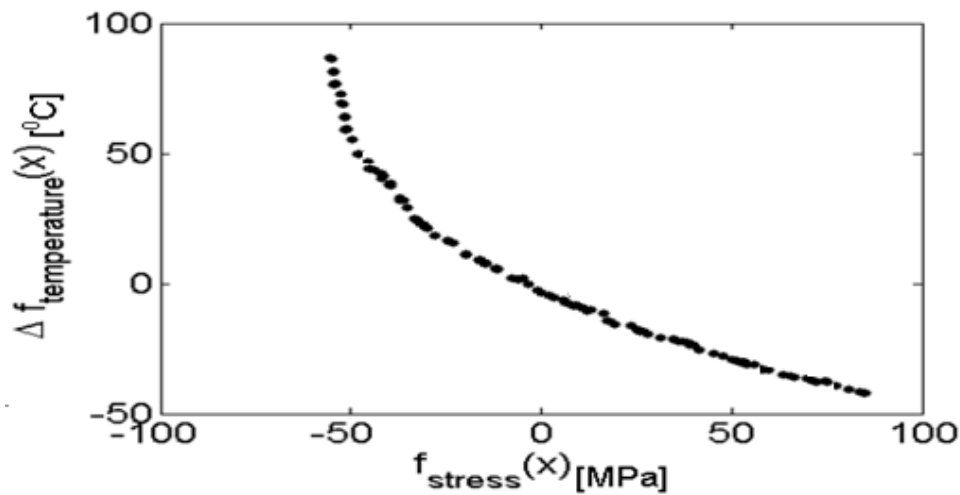


Figure 6.7. Simulations run with sample size $n = 90$

Figure 6.7 illustrate the optimisation simulation run with sample size $n = 90$. The results show that there is no significant improvements in the Pareto front in the experiment after sample size $n = 70$. There are also experiments carried out with higher sample sizes. In all cases the result show that there is no significant improvement observed in the higher sample size after $n = 70$. Therefore the sample size $= 70$ is selected and applied in the CLT. The technique CLT with sample size $n = 70$ is later used in the optimisation for searching design solution for problem with presence of uncertainty in the design variables. The next section presents the application and the experimental result of robust non dominance criteria and CLT techniques in the optimisation.

6.2.2 Application of the Techniques to Two Objective, Single Pass Design Optimisation Problems with presence Uncertainties

This section presents the application of robust non dominance criteria and the central limit theorem for the optimisation problem. The technique is applied in two objectives, work roll surface optimisation of the single pass problem, where both the fitness functions and design variables are uncertain. The performances of the solution

are based on quantitative models and uncertainty values introduced in the problem in the form of perturbation where the perturbation represented by normal distribution with sigma (σ) values. The sigma is the value in the design space calculated as a percentage of decision space of each decision variables used in the modelling shown in Table 6.1. The calculated values, representing the level of uncertainty in the design space and fitness function are then introduced in the optimisation programme code used for searching robust design solution to the problem with presence of uncertainty. Examples of calculated value in percentage, representing level of uncertainty given in Table 6.2 of the design variables used in the optimisation are given in Table 6.3. Similar approach has followed for fitness function uncertainty representation. The case study solution strategy flowchart is given in Figure 6.3. After the application of the technique, set of optimum designs (Pareto solutions) is identified and then they are evaluated for constraint violations and constraint criticality in the neighbourhood of each design solution. Evaluating for constraint criticality is presented in Section 6.3.

Experimental Detail

The proposed Algorithm based optimisation technique is used to locate good solutions for the optimisation problem, formulated in Equation 6.13, by evaluating each member of the population using the quantitative models shown in Equation 6.14 and 6.15.

Design optimisation formulation Equation 6.13

Minimise	Change in Temp at roll surface	$f_1(x) = \Delta T_S(x)$
Minimise	Radial stress at the roll surfaces	$f_2(x) = SII_S(x)$

Change in temperature ΔT at roll surface

$$\Delta T-S = (-370.8659 + 3.92666667 * x[1] + 0.0462222 * x[1]^2 + 3.02845679 * x[2] - 0.00130938 * x[2]^2 + 0.0000001 * x[3] - 0.00000.02 * x[3]^2 - 7.0603175 * x[4] + 0.085079365 * x[4]^2 + 26.9230797 * x[5] + 3.44362939 * x[5]^2 + 3.99055556 * x[6] - 0.041944 * x[6]^2 - 0.801944 * x[7] + 0.004701389 * x[7]^2) \quad \text{Equation 6.14}$$

Stress (S11) at roll surface

$$S11-S = (140.63997 - 10.082111 * x[1] + 0.0642000 * x[1]^2 - 1.2915963 * x[2] + 0.002292 * x[2]^2 + 0.001444 * x[3] - 0.00000033 * x[3]^2 + 12.11495 * x[4] - 0.21604354 * x[4]^2 - 387.34458 * x[5] + 145.751168 * x[5]^2 - 2.66775 * x[6] + 0.0386875 * x[6]^2 - 1.45855567 * x[7] + 0.0119829 * x[7]^2) \quad \text{Equation 6.15}$$

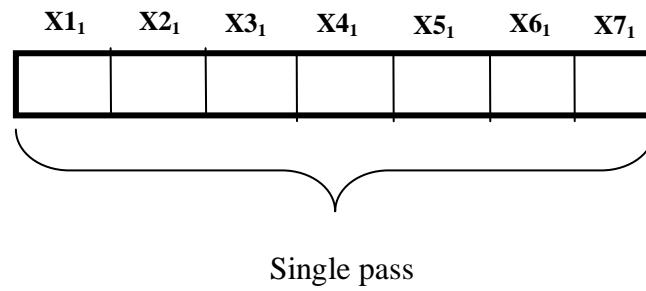


Figure 6.8. Design variables representation sequence in the optimisation of single pass 2 objective problem

Table 6.1 Design details of single pass work roll design problem

Design Variable	Design Variable Bounds	Outputs
Roll / Stock contact HTC (x1)	$5 \leq x1 \leq 15$	Change in Temp at roll surface Radial stress at the roll surfaces
Stock temperature (x2)	$950 \leq x2 \leq 1250$	
Roll /Stock Contact length (x3)	$15 \leq x3 \leq 50$	
Cooling HTC (x4)	$10 \leq x4 \leq 30$	
Roll speed (x5)	$0.14 \leq x5 \leq 1.256$	
Roll temperature (x6)	$40 \leq x6 \leq 80$	
Delay time (x7)	$20 \leq x7 \leq 100$	

Table 6.2. Level of uncertainties, (Where, FF = Fitness Function (two objective functions), DS = Decision Space (7 variables), CLT = Central Limit Theorem)

Opt. with no uncertainty in DS and FF	Error %
DS with noise and no CLT	5%
DS with noise and CLT	5%
DS with noise and CLT	10%
FF with noise, No CLT	5%
FF with noise and NO CLT	10%
(DS+FF) with noise no CLT	5%
(DS+FF) with noise, CLT	5%
(DS+FF) with noise and CLT	10%

Table 6.3. – 5% error values for design input factor parameters, shown in Table 6.1

$$\begin{aligned}x1_sigma &= 0.5; & x2_sigma &= 15.0; & x3_sigma &= 1.0; \\x4_sigma &= 1.7; & x5_sigma &= 0.0558; & x6_sigma &= 2.0; & x7_sigma &= 4.0;\end{aligned}$$

The 5% errors assumed above, are based on literature review, and knowledge from rolling engineers stating that in the real life rolling practise, normally 95 % accuracy is expected. The fitness function is an approximation of the real life scenario and forced accuracy compromises are inevitable. The sigma values in the fitness function represent these compromises.

6.2.2.1 The Optimisation Initial Conditions

The design optimisation approach was applied on the research problem to identify optimum design solutions in the presence of uncertainties. A crossover probability (p_c) of 0.9 and mutation probability (p_m) = $1/n$ are used for the design optimisation with NSGA II, where n is the number of decision variables. The distribution indices for cross over and mutation operators are $v_c = 20$ and $v_m = 20$, respectively. A population size of $pop = 400$ resulted in sufficient spread of the solutions along the Pareto front (Pareto convergence), and all the optimisations have been performed with $gen=1000$ generations. The size of population and generation are determined through experiment. The experiment was conducted using different sizes of generation and running each experiment 10 times i.e. 10 different generations' experiments and 10 runs at each generation; hence, a total of 100 experiments are carried out. Based on results quality and reasonable computational time, the generation = 1000 and population = 400 are selected, to be used in the final optimisation. Prior to searching for solutions for the research optimisation problems with uncertainty and constraint, an exhaustive grid exploration is conducted. This is vital to make sure that the optimisation framework is fit for the intended problem. The result obtained from the classical search compared with the solution from the proposed GA based optimisation techniques applied on the problem with no uncertainty. Before comparing the results however, a total 10 experiment run have been conducted, so that result obtained can be verified for consistency. The final test result is presented in the Figure 6.9. As shown in the Figure, comparisons of the random search points with the standard NSGA-II results confirm the likely convergence to the Pareto front. The Figure shows the result of an exhaustive enumeration of the seven-dimensional decision space using

grid, and the Pareto front from the normal NSGA-II search. The Pareto front is the highlighted line below (at lower end) of the grid search. The dim dots cloud above the Pareto front is the map generated by the exhaustive grid exploration of the decision and objective space. Furthermore, the Pareto front of this problem is convex and continuous in nature. Since the search space is not known in absolute terms, it is likely that the result obtained in Figure 6.9 has converged to the near optimal Pareto front with a good spread of multiple optimal solutions for the problem, i.e. minimisation of radial stress and change in temperature at roll surface. Design solution at three random points along the true Pareto front is given in Table 6.4. The Pareto front obtained here also used to as a reference to verify the goodness of solution from the experiment carried out for the optimisation problem with presence of uncertainty. Next sub sections present the experimental result of the design problem with presence of uncertainty.

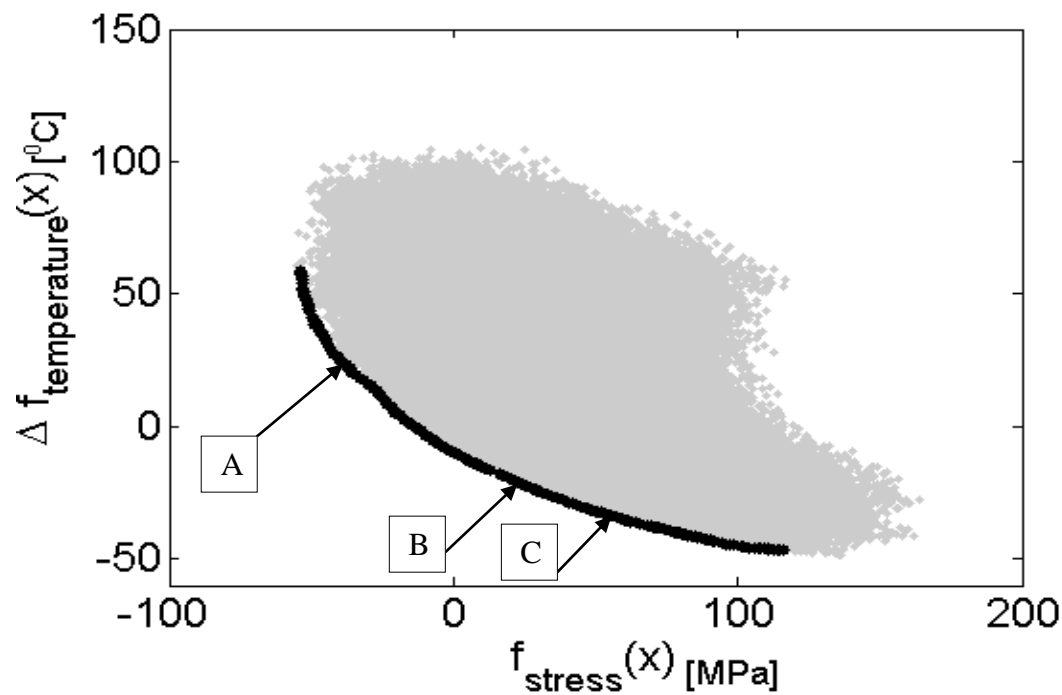


Figure 6.9. Map generated by an exhaustive grid exploration of the decision and objective space

Table 6.4 below presents array (sample design solution) at randomly selected points from the Pareto front given in Figure 6.9. Similarly array also taken from the optimisation run carried out with problem in presence of uncertainty in the design space and fitness functions presented in Section 6.2.2.8., Figure 6.16. The arrays are presented in Table 6.5.

Table 6.4. Design solution at three random points (A, B and C), along the true Pareto front shown in Figure 6.9 representing High ΔT Low S, ΔT & S close to 0 and Low ΔT High S respectively.

High ΔT Low S	ΔT & S close to 0	Low ΔT High S
4.4149739e+001 x1	5.6765971e+001 x1	7.1391190e+001 x1
1.2492034e+003 x2	1.2489702e+003 x2	1.2500000e+003 x2
5.9746937e-001 x3	2.0334979e-001 x3	1.4795820e-001 x3
1.7674119e+001 x4	3.3330531e+001 x4	3.9230013e+001 x4
3.2921554e+001 x5	3.2404193e+001 x5	3.0991533e+001 x5
1.0122106e+001 x6	1.0193128e+001 x6	1.3010299e+001 x6
9.3709086e+000 x7	8.4452076e+000 x7	8.2915558e+000 x7
-4.0674706e+001 f1	2.2327721e+001 f1	6.1169170e+001 f1
2.1351676e+001 f2	-2.0709819e+001 f2	-3.5910205e+001 f2

Application of Techniques in the Problems with presence of Uncertainty

Here presented the experimental results of the optimisation problem with presence of uncertainty carried out based on the experimental set shown in Table 6.1. Based on information from real world rolling practice the maximum level of inherent noise expected in the design, 5% for each design factors in the decision space and 5% for the fitness functions are allocated for uncertainty. However to investigate the impact of higher level of uncertainty (worst case scenario) additional runs with 10% uncertainty in the design space and fitness function are also experimented. The experimental results and discussion of results are presented in the following sections.

6.2.2.2 Uncertainty in the Decision Space without the Application of CLT

Here is presented the application of the robust non dominance criterion technique, without CLT, on the work roll optimisation problems with uncertainty in the decision space. As the results indicate, the multi-objective optimisation technique adopted for searching for solutions for the case study problem with uncertainty in the decision space, is not be able to find the solution as intended. The result proved that the presence of uncertainty in the decision space, have impact in the solution. The spread of the Pareto front is clustered and scattered, as shown in Figure 6.10. Similar experiment has also been carried out, but this time with the application of CLT to the problem. The corresponding result and comparison analysis is given in Figure 6.11.

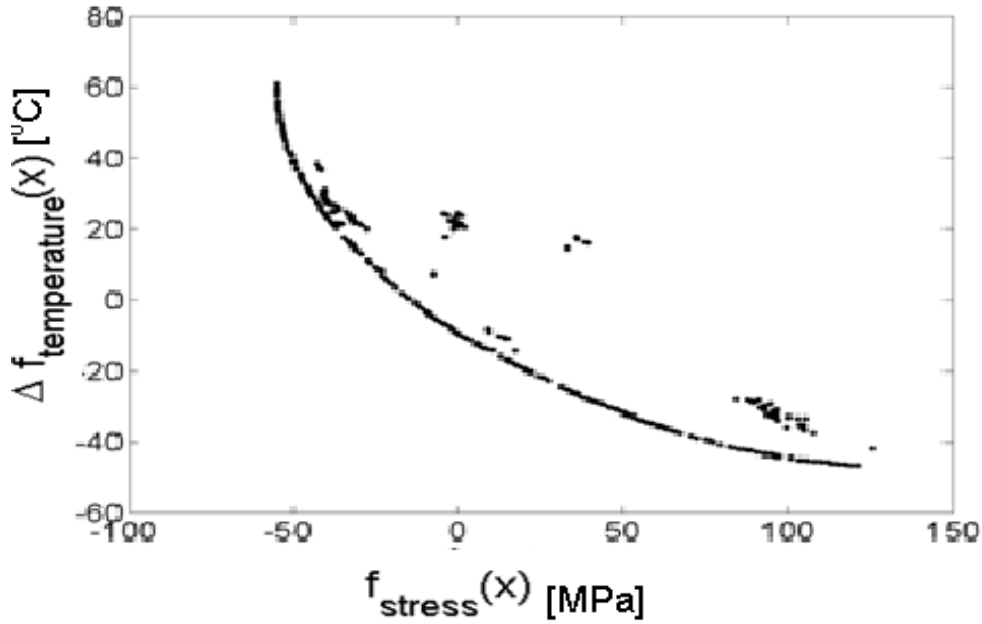


Figure 6.10. Optimisation of the problems with uncertainty in the decision space, and no application of CLT

This is, in fact, an expected feature of solutions according to the Pareto dominance in an uncertain environment. However, unlike results of other experiments presented in the next sections for uncertainty in the fitness function, this property is uniquely observed more in the case of problems in the decision space. Nevertheless, the all over spread of the solution lies around/behind the true Pareto front. To overcome the clustered behaviour and improve the solution, in this particular case, the technique CLT has been adopted and successfully incorporated with the robust dominance criterion techniques and is able to search for an evenly spread optimal solution for the problem. The result is presented in Figure 6.11.

6.2.2.3 Uncertainty in the Decision Space & Application of CLT (5% Sigma)

This section presents the application of the robust non dominance criterion technique and the CLT on work roll system optimisation problem with uncertainty in the decision space. Figure 6.11 shows the optimisation result of the problem, based on the CLT emphasising on the arithmetic mean. Runs are conducted with the sampling size $n = 70$. The result shown in Figure 6.11 is the representative out of the 10 runs conducted under the same initial optimisation conditions and problem circumstances. The experimental result and result descriptions are presented as follows.

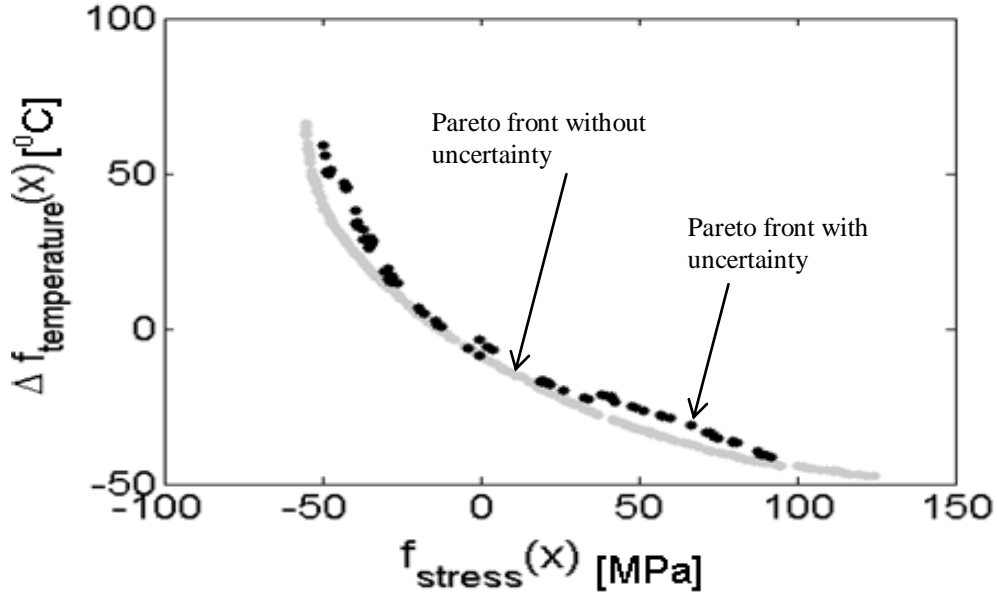


Figure 6.11. Optimisation of the problems with uncertainty in the decision space,

$$\sigma = 5\%$$

As shown in the Figure 6.11, the results are conclusive. The optimisation results with uncertainty (dot line) lie very close to the true Pareto front (continuous line). From the result, it can be concluded that the optimisation framework proposed (robust non dominance criteria and CLT for problems with uncertainty in the decision space) manages to search and find a solution to the problem, regardless of the presence of uncertainty. The values in Figure 6.11, the radial stress axis, the negative and positive, indicate the respective compressive and tensile behaviour on the roll as a result of cooling. Tensile stress is the internal reaction of the roll due to the external force applied to it - application of cooling in this case. Generally, the lower roll temperature is, the better; however, excess cooling can lead to higher tensile stress, but if the tensile stress goes beyond the allowable, depending on material property, this could lead to crack on the roll. Hence, to avoid this happening, constraint needs to be imposed in the design optimisation. Section 6.3 presents constraints and their criticality to the design solutions.

6.2.2.4 Uncertainty in the Decision Space, & Application of CLT, (10% Sigma)

Here presented the optimisation problem with presence of high level of uncertainty in the decision space. Sigma value ($\sigma = 10\%$) for uncertainty introduced to the design variables and the robust dominance criteria technique with CLT has applied for searching optimal design solutions to the problem. As the Pareto front in Figure 6.12

indicates the presence of high level of uncertainty in the design space shows higher impact in the solution in the objective space. The result shows a slight scattering behaviour, few design points and a slight shift away from the true Pareto front. The result from the experiment is given in Figure 6.12.

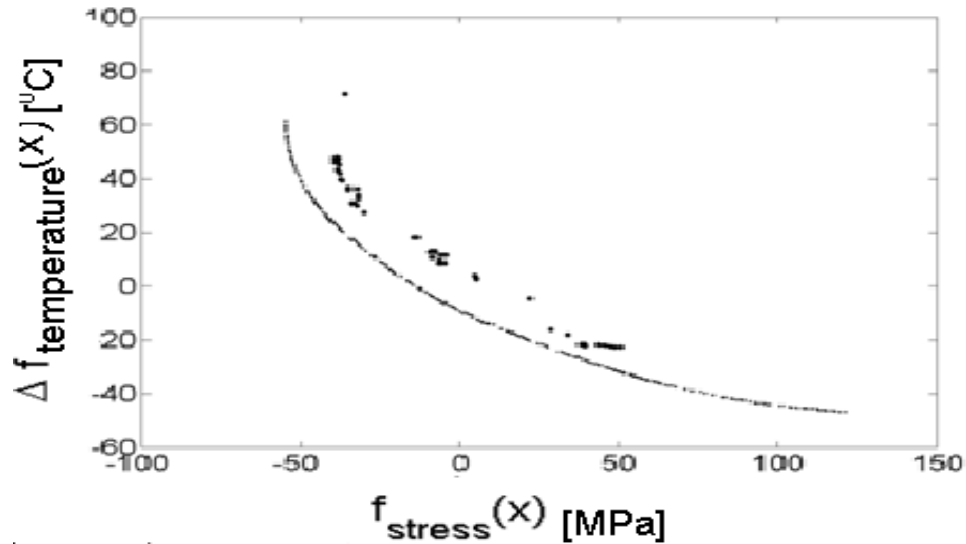


Figure 6.12. Optimisation of the problems with uncertainty in the decision space,

$$\sigma = 10\%$$

6.2.2.5 Uncertainty in the Fitness Function, No Application of CLT, (5% Sigma)

The section gives the application of the robust non dominance criterion technique on work roll optimisation problems with uncertainty in the fitness function. The uncertainty is introduced in the fitness functions Δf (change in temperature) and S11 (Radial stress). As shown in Figure 6.13, Unlike the result observed in the above section, here the solutions for the problem with uncertainty (dark dotted line) are evenly spread and close to the true Pareto front (light continuous line). The Pareto, here, is the result of robust dominance criteria without the application of CLT for reasons discussed in Section 6.1.1. The result indicates that the uncertainty in the fitness function can be dealt with in the optimisation using the robust non dominated criterion technique. The experiment repeated with the same setting but with higher level of uncertainty, $\sigma = 10\%$, Figure 6.14. As shown in the Figure the presence of high level of uncertainty in the fitness function cause the result display slightly discontinuous and fewer number of design points in the final solutions. However despite the increase level of uncertainty in the problem, the technique searches and found robust optimal design solution to the problem.

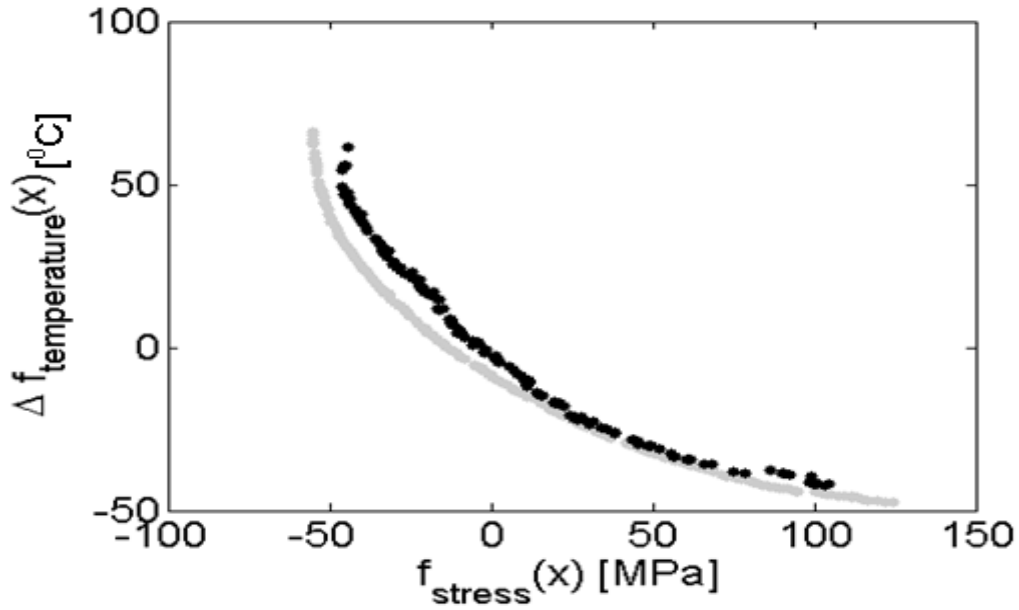


Figure 6.13. Optimisation of the problems with uncertainty in the fitness functions,
 $\sigma = 5\%$.

6.2.2.6 Uncertainty in the Fitness Function, No Application of CLT, (10 % Sigma)

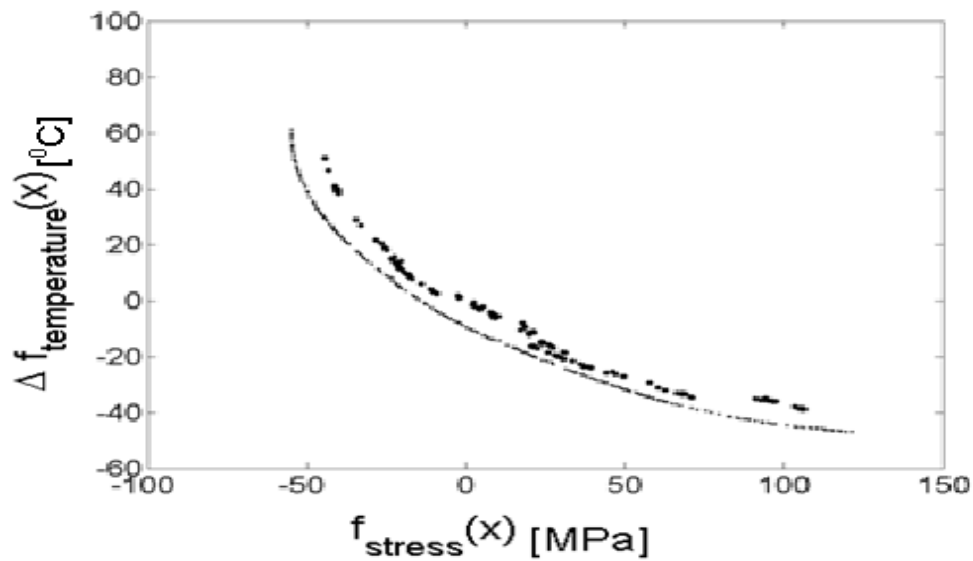


Figure 6.14. Optimisation problems with uncertainty in the fitness functions = 10%.

6.2.2.7 Uncertainty in the Decision Space and Fitness Function, No Application of CLT, (5% Sigma)

This deals with the experiment carried out for the optimisation problems with uncertainty in the decision space and in the fitness functions. As presented above, the two cases have been experimented separately, and each resulted in a Pareto of unique

characteristics. Here, the result shows that the Pareto dominance criteria technique (without CLT) finds solution very close to the true Pareto, but with few design solution points in comparison with results presented in the previous sections. This may be due to higher overall uncertainty level, and particularly, the presence of uncertain in the design variables in the problem, Figure 6.15. Nevertheless, the results suggest that the uncertainty in the decision space and the fitness function can be dealt with in the optimisation using the robust non dominated criterion. For comparison, the same problem is experimented, this time with the application of robust non dominance criterion technique and CLT. The result indicates that the algorithm is able to find evenly spread and improved design solutions, regardless of the presence of uncertainty in both the fitness function and design space. Figure 6.16 shows the improved Pareto front as a result of application of the robust dominance and CLT techniques to the problem. A further experimental work has been carried out but this time with higher level of uncertainty in both design variable and fitness function. This is an important step help to realize the impact of presence higher level of uncertainty in the design space and fitness function, to the design solution and also to verify the robustness of the optimisation techniques for searching optimal design solutions to the problem in such circumstances. The Pareto front from the experiment is presented in Figure 6.17.

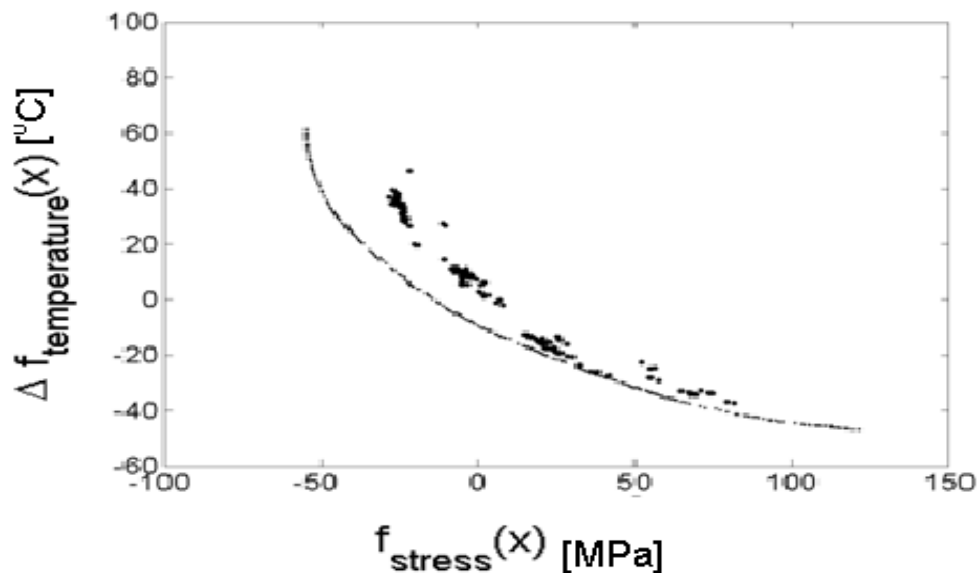


Figure 6.15. Optimisation of problems with uncertainty in the decision space and in the fitness function, with no CLT, $\sigma = 5\%$ and 5% respectively.

6.2.2.8 Uncertainty in the Decision Space and Fitness Function, with Application of CLT, (5% Sigma)

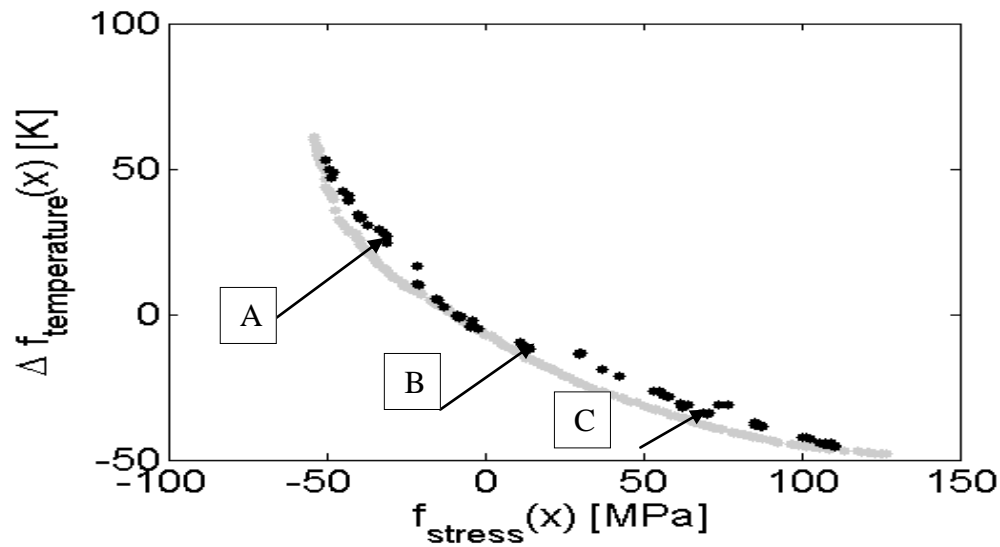


Figure 6.16. Optimisation of problems with uncertainty in the decision space and in the fitness function, with application of CLT, $\sigma = 5\%$ and 5% respectively.

Table 6.5. Design solution at three random points, (A, B and C), along the true Pareto front shown in Figure 6.16 representing High ΔT Low S, ΔT & S close to 0 and Low ΔT High S respectively.

High ΔT Low S	ΔT & S close to 0	Low ΔT High S
4.0139094e+001 x1	6.0196157e+001 x1	7.4398069e+001 x1
1.2487495e+003 x2	1.2499999e+003 x2	1.2489977e+003 x2
8.3606704e-001 x3	2.6679263e-001 x3	1.4000000e-001 x3
1.9082500e+001 x4	3.3725270e+001 x4	3.8086032e+001 x4
5.1083302e+001 x5	3.1266764e+001 x5	3.0876395e+001 x5
2.4113177e+001 x6	1.2304552e+001 x6	1.2630920e+001 x6
6.3303832e+000 x7	8.2982104e+000 x7	8.3185788e+000 x7
-3.9041450e+001 f1	2.4005838e+001 f1	6.9236896e+001 f1
2.2635540e+001 f2	-1.4045620e+001 f2	-2.946610e+001 f2

6.2.2.9 Uncertainty in the Decision Space and Fitness Function, with Application of CLT, (10% Sigma)

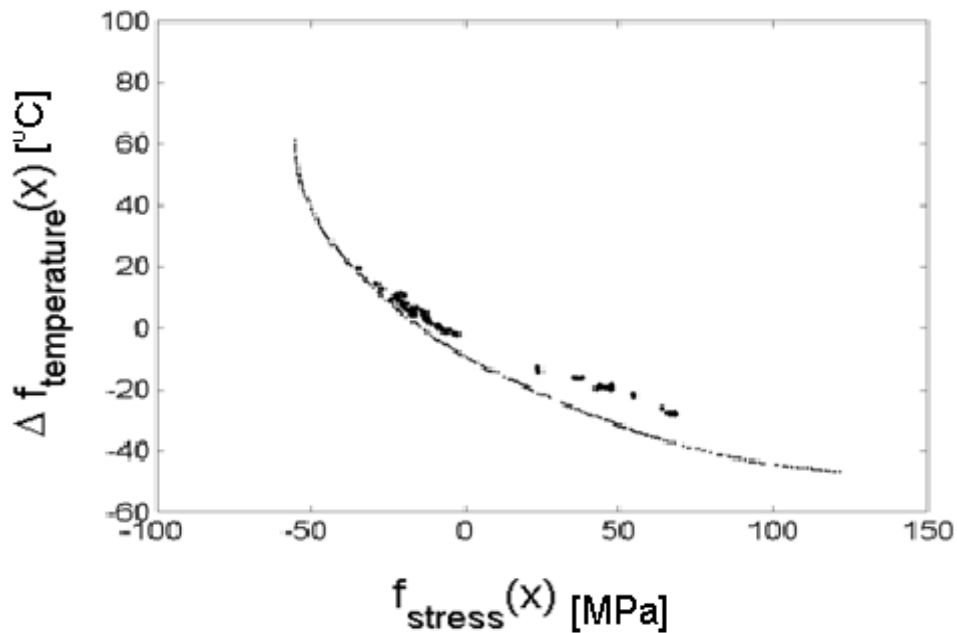


Figure 6.17. Optimisation of problems with uncertainty in the decision space and in the fitness function, with application of CLT, $\sigma = 10\%$ and 10% respectively.

The result in Figure 6.17, the design solution, Pareto front for problem with 10% sigma level of uncertainty shows that even though the techniques, robust non dominance criteria and CLT have applied in comparison the front has fewer number of design points an even and slightly away from the true Pareto front. 10% sigma values are the worst case scenarios which are beyond the expected level of uncertainty in the real life work roll system design.

Result Summary and Observations

The section presents the application of robust non dominance criteria techniques and CLT on work roll system design optimisation problem in the presence of uncertainty and constraints. Various scenarios have been experimented, such as uncertain design space problems, uncertain fitness function and where both design space and fitness functions are uncertain. There are also additional experiment for cases where no uncertainties in the problem. The result from the scenarios are analysed and the results are presented. The optimised result shown in Figure 6.9 identifies the true Pareto front in comparison with the exhaustive grid exploration for work roll system thermal analysis and optimisation problem. Since the search space is not known in absolute

terms, it is likely the result reported in Figure 6.9, has converged to the true Pareto front, locating a reasonable spread of multiple optimal solutions. It is clear from the result that the solutions obtained by the GA based technique are superior to the grid search; an indication of the proposed GA based optimisation technique's acceptability for solving the research problem. The presence of a Pareto front also confirms the conflicting relationship between change in temperature and radial stress. Having continuous, convex and uniform Pareto, as this is the case in the result shown in Figure 6.9, it is fair to say that the Pareto maintain diversity. Results obtained from the proposed approach not only identify good solutions, but also provide insight into the complex behaviour of the design problem, such as the presence of uncertainty in the design space and its effect on solutions obtained. As the results indicate, particularly in Figures (6.11, 6.13, 6.14 and 6.16), the well spread Pareto front is close to the true Pareto, implying that the proposed approach and introduction of CLT is capable of identifying good solutions, regardless of the presence of uncertainty. The results also proved that the presence of uncertainty has impact on the ability of the algorithm to search for optimal global solution. Figure 6.10 and 6.15, particularly show that the result obtained lack diversity and cannot be said that the Pareto converged to global optima. In the next section, the obtained design solutions are evaluated for constraint violations in the neighbourhood of each solution.

6.3 Evaluating Criticality of Constraints to Optimum Designs Solution Point

This section presents a constraint handling approach of the design solution obtained and the constraint criticality relative to the design solution. As mentioned above in Section 6.2.1.1 fulfilling the objectives of the optimisation problems may come at a price. For example, in the problem, one of the objectives is minimising the change in temperature on the roll. However, minimising temperature has an inverse effect on stress, particularly tensile stress. If the tensile stress reaches beyond the allowable stress limit, it has a potential to cause thermal shock, leading to cracks on work rolls. In real life practise, the stress limit can also be dependent on other factors involved in the process and process condition. Process factors such as speed and cooling conditions, have greater effect on the roll stress. Therefore, to give engineers a chance to choose the design depending on constraints criticality, the research adopted a

technique to analyse the obtained result criticality relative to roll materials allowable stress. The constraint sensitivity is described in the form of their criticality in the neighbourhood of a design solution (Sundaresan, 1993; Roy, 1997 and Roy, *et al.*, 1997). Categorisation is based on tolerance space (TS) around a design solution with a set of points where each point represents a possible combination of the design variable with tolerance associated to them. The criticality is given a rank '1 to 5', where 1 is less critical and 5 very critical. Each design variable of a solution can have an upper and lower value defined by its tolerance. Thus, the three levels of each variable can be expressed as the variable value (g), the upper value (g_u), i.e. $g + \text{tolerance}$, and the lower level (g_l) that is $g - \text{tolerance}$, Figure 6.18. In the Figure, the rectangle represents the tolerance space and five possible constraint criticalities in relation to the design solution shown in the circle at the centre of the rectangle. The thermal fatigue stress (material allowable stress limit) is used as the single constraint for the case study.

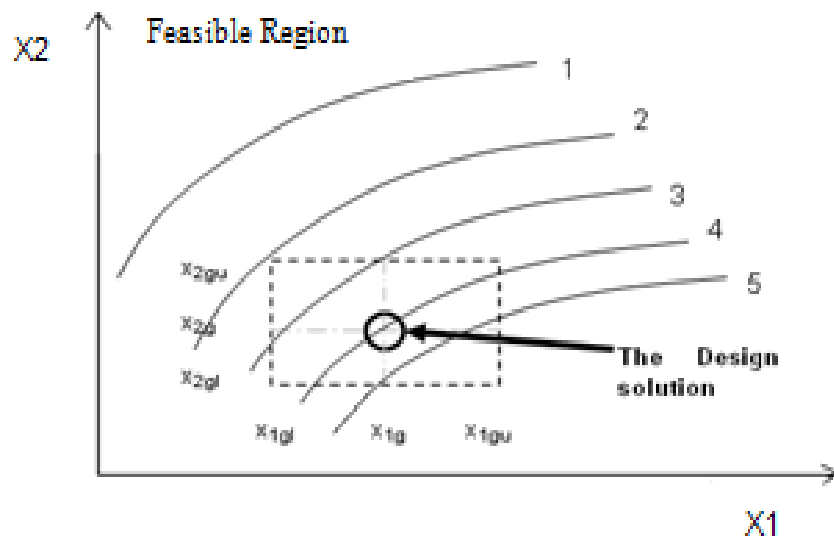


Figure 6.18. Criticality of constraint in the design space (Roy *et al.*, 2009)

Criticalities, number 1 to 5, shown above, are identified based on design solution sensitivity towards the constraints. Constraints are assumed to be monotonic with respect to all design variables in the tolerance space - this leads to the assumption that the maximum constraint value will occur at one of the corner points. Based on this assumption, the criticality of constraints is categorised as constraint satisfied (1), statistically active constraint (2), Quasi active constraint (3), peak active constraints (4) and constraint not satisfied (5) (Roy *et al.*, 2009). The criticalities can be given colour coded or, as in the case of this research, symbolic identities so that they can be traced and identified after the optimisation.

6.3.1 Application of the Constraint Criticality Analysis Technique to the Work Roll System design Problems

The sensitivity analysis is applied to good designs already identified by the GA in the case study of work roll system optimisation problem with uncertainties and constraints. The technique is applied as a method of obtaining sensitivity of the design to constraints, based on criticality described above. The sensitivity is calculated within the neighbourhood of the design by focusing on the edges of the seven dimensional neighbourhoods, as shown in Figure 6.18. The Pareto optimum design solutions that are of ‘constraint satisfied’ type are preferred over ‘statistically active constraint’ or ‘quasi active constraint’. Constraint not satisfied, although not preferred as a solution, would give information to engineers about the design limit. Except constraint not satisfied, other none automatically preferred constraints solution may also be selected by engineers in some circumstances, depending the design requirements and priorities.

6.3.2 Sensitivity Analysis Result and Discussions

Information of how sensitive the design optimisation solution to constraints, the roll allowable stress in this case study, is important information to help engineers in making design decision - although it has been common in engineering design that penalising constraints is the best approach for the safety of the design. In this research, however, instead of penalising the degree of criticality of the constraints to the design has been ranked. The ranking then would give engineers flexibility in making a design decision that is best, depending on requirements. In Figures 6.19 and 6.20, constraint criticality is presented with symbols, such as ‘*’ represents constraint not satisfied, sign ‘Δ’ for statistically active constraint, black dot for constraint satisfied, ■ for quasi active and ● for pick active constraints. The last two, namely quasi active constraint and peak active constraints, are not shown during the evaluation. The solution marked with ‘Δ’ in the Pareto set is the statistically active but critical, next to the non feasible segment marked with ‘*’ at the bottom right hand side in Figure 6.19. ‘Statistically active constraint’ type design solutions could be selected if there are other advantages, depending on the operations type, design requirements and factors involved in the operation. The Figures 6.19 and 6.20, show the constraint and criticality of the constraints to the design solution obtained.

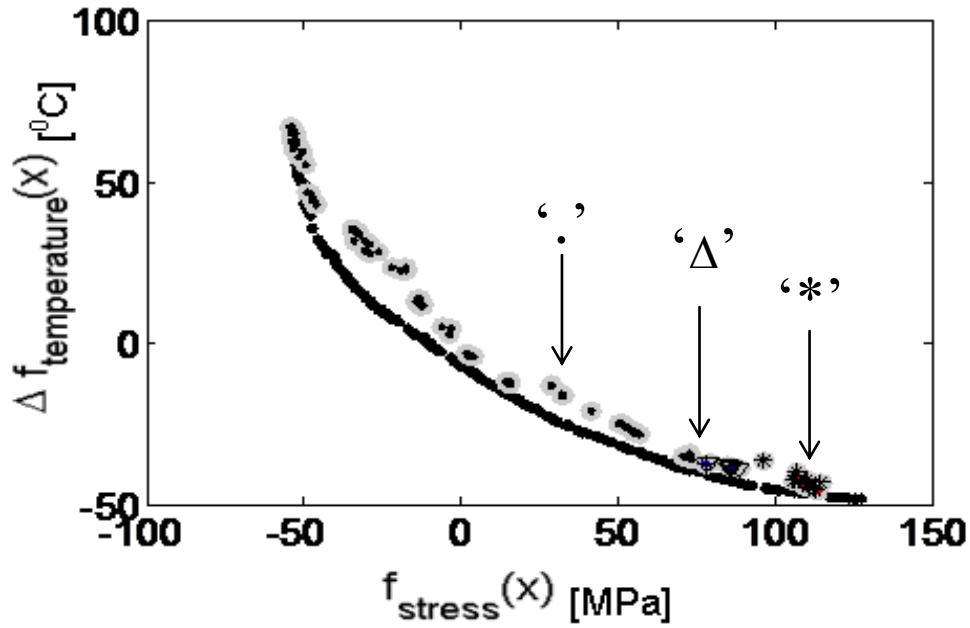


Figure 6.19. The optimisation problem with uncertainty and constraints in the decision space and fitness function

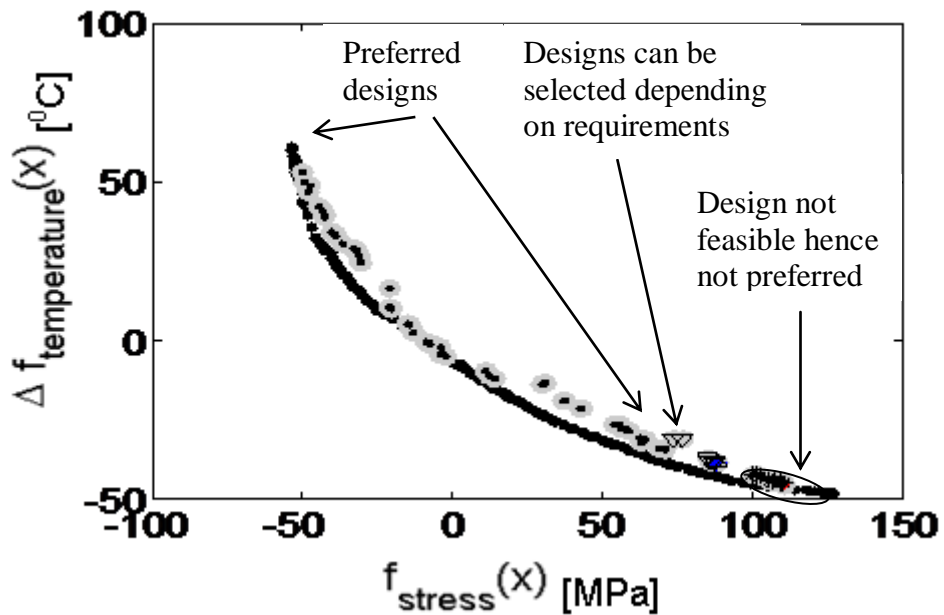


Figure 6.20. The optimisation problem with uncertainty and constraints in the decision space and fitness function

6.3.3. Section Summary, Two Objectives Problem Optimisation in presence of Uncertainty and Constraints

In the above sections, the optimisation technique, the robust dominance criterion with the collaboration of CLT, and constraint criticality to the design solution are presented. The framework developed is applied in two objective work roll surface

thermal analysis and optimisation problems with uncertainty and constraints. The study introduced the concepts of conflicting behaviour between multiple objectives and presence of uncertainty, and showed how this can be resolved using GA based techniques to identify Pareto based solutions. A number of optimisation experiments have been conducted using the Mathematical models as fitness function and proved that the research problem, with uncertainty in the decision space and fitness function can be addressed using the robust non dominated criterion and CLT technique. The technique converges to a set of solutions that gives good nominal performance while exerting maximum robustness, giving an important work roll design parameter set. The step is also used to analyse the effect of uncertainty and constraint in the work roll surface optimisation problem in a simplified manner, by comparing the problem with uncertainty and without uncertainty. The results also considered important in order to show how the various algorithmic development stages led to the development of optimisation frameworks for handling the quantitative and uncertainty search space for more than two objectives (high dimensional problem), where the result cannot be visualised or observed with the help of a Pareto front. The approach then extended for many objective (more than 2) problems with presence of uncertainty. The framework for handling many objectives, single pass problems is discussed in the next section.

6.4 Application of the Technique to the Many Objective, Single Pass Work Roll System Design Optimisation Problems with presence of Uncertainty

Work roll damage due to heat is severe at the roll surface hence searching for an optimal design overcome this problem is essential. Keeping the roll surface temperature at optimum is also help to minimise the effect of heat on the roll beyond the surface. The previous section demonstrates the optimisation procedure to search for a design that can solve these issues. As presented in the literature review, Chapter 2, however the severity and penetration of heat beyond the point of contact (roll and stock), is depends on the type of operation and design factors - such as the radius of rolls, speed of roll, time of contact and stock temperature, involved in the process. The cooling conditions also have an impact on depth in which the heat can reach in to the roll below the surface. It was also learnt that after repeated rolling operation, heat may pass beyond the surface and be accumulated at a depth, and if this heat is not

controlled and dealt with on time, eventually it will reach to the core. When cooling applied on the roll thermal shock and roll crack emerged at the interface between the hot core and cold surface. The research conducted a number of experiments trying to establish the average depth the heat, under different operation circumstances, will penetrate in to the roll during hot rolling. The technique, developed in R environment, is designed to recognise these temperature variations at depth and deliver a solution that is optimal (robust), regardless of these variations. To achieve these depth parameters, taking the maximum depth the heat can reach under normal circumstances has been established. Based on experimental trial the depths 9 and 15mm below the surface have been considered. Therefore, at these depths, FEA response data are collected and a regression model developed. To increase the search space and so that a robust solution can be found, the regression model is used as fitness in the optimisation, treating the problem as 6 objectives problems. The 6 objectives, change in temperature and radial stress at roll surface, at 9 mm and 15mm, are presented in Section 5.3.8. Adopting the optimisation strategy is based on the following considerations:

- A multi-objective GA is applied for solving the quantitative problems where the objectives are comprised of two or more search spaces.
- This problem is such that the nature of this relationship exhibits a conflict. The conflicting nature is that the value of any one of the solutions cannot be improved without deteriorating at least one of the others.

As discussed in the literature review, the presence of multiple objectives in a problem, in principle, gives rise to a set of optimal solutions (largely known as Pareto-optimal solutions), instead of a single optimal solution. The adoption of the GA based optimisation technique primarily is due to its ability to search for these solutions for multi-objective problems. However, in the research, due to the fact that uncertainty and constraints are also part of the problem, the AS-IS GA cannot be used on its own. Hence, the basic GA based technique is enhanced so that it is able to handle the problem complexity. The R language and software environment was chosen to develop the code for the research single pass many objective problem, because of its accessibility and flexibility, as well as the fact that it is powerful software capable of handling the research case study, regardless of problem complexity and number of objectives. R is designed in such a way that it allows users to add additional

functionality by defining new functions. This characteristic makes it possible for users to extend the optimisation components, such as NSGA-II, to accommodate additional features of the optimisation problems, such as uncertainty. Other features of R include the option that any code written in other languages can be linked and called at run time. Another important feature is that R can be extended easily via packages supplied with the R distribution, and many more are available through the CRAN family of Internet sites, covering a very wide range of modern statistics (Ihaka, *et.al.*, 1996). Details of the application of the optimisation technique, programmed in R environment, to the research many objectives problem case study is discussed in Section 6.4.1. The technique has followed a similar, but with added features, procedure presented in 6.1 and 6.2 for two objective case study. Here, the technique is for solving the optimisation problems with uncertainty in high dimensional problem, i.e. regardless of the number of objectives and number of design variables. In high dimensional optimisation problem identifying the best optimal final design from the solution found by the optimisation techniques is an important feature of the design solution search process. The steps helps designer save time and obtain the best few or single compromised design instead of having the population of design solutions to choose from. The many objectives technique is applied to problems of more than 2 objectives, and hence, the compromised solution Pareto front cannot be seen graphically. Therefore, here, compromised solutions between the conflicting objectives are found through alternative means. The research proposes a search space reduction technique for searching the final design solution from the Post GA result, where the result population goes through an iterative search space reduction steps before reaching the final best compromised design solution/s. In this case study, a weight vector methods solution search technique consisting of weight, average weight and step by step percentage reduction of the search space based on average weight, is proposed and used as post processing/filtering of the initial potential solutions obtained by the GA. The weight calculation is carried out using the pseudo weight vector approach presented in Section 6.4.3. In order to make the filtering possible and arrive at the last best design solution, a percentage search space reduction of the potential solution obtained by the GA is proposed. The percentage (%) is determined through trial and error experiment. The percentage reduction filters the less weighted objectives, step by step, until the best compromised solutions, good for all, can be found. The sequential reduction helps to arrive at the final solution in the objective

space, and subsequent corresponding best design solutions in the decision space. Other strategies such as utility functions and the advantages and disadvantages in relation to this problem are also studied. However the parentage reduction technique is chosen because of its simplicity and the fact that no compromise of solution, involved for searching the final robust design solution. The next sections present the optimisation procedure, Pseudo code for solution search strategy and the section that follows presents real-life case studies illustrating the optimisation concepts and solution results.

The single pass many-objective optimisation process consists of two main steps: the first step is the application of the GA for locating the area of interest / identifying the population of good solutions and the second step is the post GA result analysis for identifying the final best optimal design solution. The programme codes for the two steps shown in the schematic view below are presented in Appendix E and G respectively.

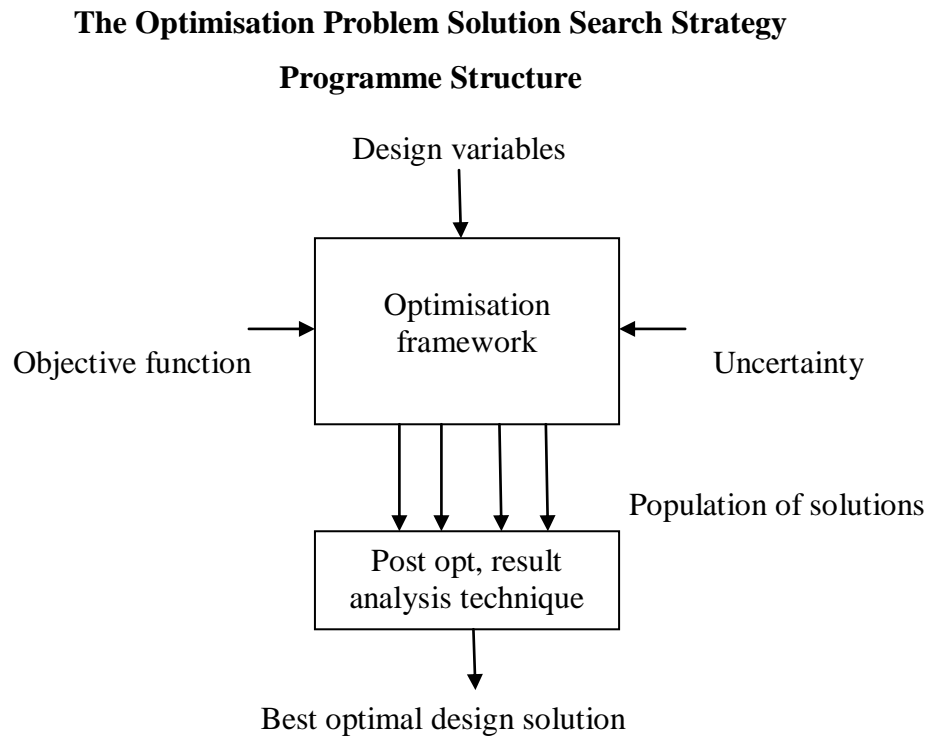


Figure 21. Design solution search strategy

6.4.1 Experimental Details

The quantitative evaluation with uncertainty in the design variables and in the fitness function of individual members of the population is carried out as the following. First is the evaluation of the design variables and uncertainty, and second is the evaluation

of the fitness function with uncertainty. This represents the global objective functions values evaluation for the single pass work roll thermal analysis and optimisation problem. The objective function value of the global evaluation represents the fitness of the chromosome. The global evaluation is given by a real value vector, as in Equation 6.17. The optimisation strategy is presented in Figure 6.3.

$$X_i = \{ (x_i + \epsilon), \dots, (x_n + \epsilon_n) \} \quad \text{Equation 6.16}$$

$$\vec{F}_j(\vec{x}) = \sum_{m=1} \vec{f}_j(\vec{x}) \mid j = 1, 2 \dots k \mid \quad \text{Equation 6.17}$$

Where i is the i th design variables, n is the number of design variables, j is the j th objective and k is the number of objectives.

The optimisation is carried out with the proposed GA based algorithm, to find a solution for a design optimisation problem with uncertainty, minimising change in temperature (ΔT) and radial stress (S_{11}) at work roll surface, and depth below the surface at 9 mm and 15mm. Ten independent GA runs, with varying populations and generations size have been carried out. In each case, 10 repeated runs are experimented. Hence, a total of 100 experiments have been conducted before selecting the size of population and generation. The final optimisation is carried out with population size 400 and 1000 generations. The set selected is the representative of 10 runs carried out. The final population and generation set is selected since there is no improvement observed after 10 runs. All runs are performed with the following standard parameters: crossover probability (c_p) of 0.7 and mutation probability (m_p) 0.2. This case study deals with six quantitative based objectives and aims to show how the proposed algorithm can deal with many objectives rolling system thermal design problem with uncertainty. The case study is 6 quantitative objectives formulated in Equation 6.18, and used the design factors bounds given in Table 6.6. The design variable representation sequence in the optimisation is presented in Figure 6.22. The variable bounds are estimated for feasible design values. These are established after consultation with the rolling experts during the knowledge elicitation exercise. The representing design variables are linked together as a chain to form the chromosome. The proposed technique was used to locate good solutions for the optimisation problem formulated in Equation 6.18, by evaluating each member of the population using the quantitative models shown in Section 5.3.8 in Chapter 5.

Optimisation formulations, Equation 6.18

Minimise	Change in Temp at roll surface	$f_1(x) = \Delta T_s(x)$
Minimise	Radial stress at the roll surfaces	$f_2(x) = SII_s(x)$
Minimise	Change in Temp at 9mm depth	$f_3(x) = \Delta T_{9d}(x)$
Minimise	Radial stress at 9mm depth	$f_4(x) = SII_{9d}(x)$
Minimise	Change in Temp at 15mm depth	$f_5(x) = \Delta T_{15d}(x)$
Minimise	Radial stress at 15mm depth	$f_6(x) = SII_{15d}(x)$

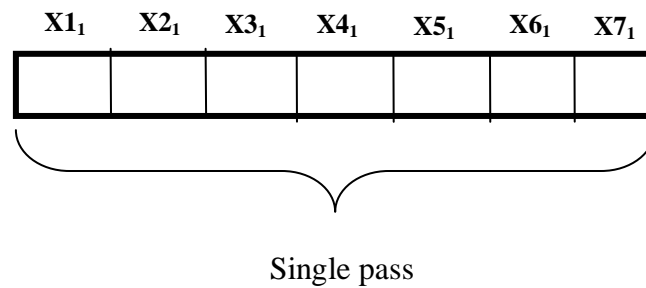


Figure 6.22. Design variables representation sequence in the optimisation of single pass 6 objective problem

Table 6.6. Design details of single pass work roll design problem

Design Variable	Design Variable Bounds	Outputs
Roll / Stock contact HTC (x1)	$5 \leq x_1 \leq 15$	Change in Temp at roll surface, 9mm and 15mm depth Radial stress at the roll surfaces, 9mm and 15mm depth
Stock temperature (x2)	$950 \leq x_2 \leq 1250$	
Roll /Stock Contact length (x3)	$15 \leq x_3 \leq 50$	
Cooling HTC (x4)	$10 \leq x_4 \leq 30$	
Roll speed (x5)	$0.14 \leq x_5 \leq 1.256$	
Roll temperature (x6)	$40 \leq x_6 \leq 80$	
Delay time (x7)	$20 \leq x_7 \leq 100$	

Introducing Uncertainty in the Optimisation

The uncertainty is introduced and applied in the optimisation by altering the design fitness randomly with a noise factor, represented by sigma (σ) values. The sigma is the value in the design space calculated as a percentage of decision space of each decision variable given in Table 6.6. The sigma values calculated are the following.

$$x1_sigma = 0.5; x2_sigma = 15.0; x3_sigma = 1.0; x4_sigma = 1.7; x5_sigma = 0.0558; x6_sigma = 2.0; x7_sigma = 4.0;$$

The sigma values are based on 5% error in the work roll system design factors, The 5% errors assumed above, are based on literature review, and knowledge from rolling engineers stating that in the real life rolling practise, normally 95 % accuracy is expected. The 5% error also applied for the fitness function. The fitness function is an approximation of the real life scenario and forced accuracy compromises are inevitable. The sigma values in the fitness function represent these compromises.

6.4.2 GA Results

The optimisation run with parameters outlined in the previous section, has produced the initial solutions. The NSGA-II based optimisation identified the solutions (Pareto set) that are optimal, best compromised between the change in temperature and radial stress at the roll surface, 9mm and 15mm below the surface. The problem is many dimensional in nature; hence, it is not possible to visualise the Pareto front. The post GA results search space reductions strategy, based on weight vector average, discussed in Section 6.4.3 is proposed to identify the final best optimum solution/s from the population of solutions set identified by the GA. 7 selected sample results (array) out of 400 population of solution identified by the GA are shown in Table 6.7 and Table 6.8. Table 6.7 presents' objectives results, in the objective space, corresponding to change in temperature at the surface of the roll, at 9mm and 15mm below the surface as well as radial stress at the surface of the roll, at 9mm and 15mm below the surface of roll. Results in Table 6.8 are optimal design solutions set in the design space, giving the values for the design variables that guarantee minimal thermal effect on the work roll during hot rolling. As indicated above, the results in the Tables are samples (6 objectives and 7 design variables arrays) from the population of solution found by the GA.

Table 6.7. Sample array from good solutions found by the GA, (Objective space),

Change in tempreature (ΔT) in $^{\circ}\text{C}$ and Radial stress (S11) in MPa

ΔT -Surface Objective 1	S11-Surface Objective 2	ΔT -9mm Objective 3	S11-9mm Objective 4	ΔT -15mm Objective 5	S11-15mm Objective 6
36.2	9.2	31.2	-96.9	28.1	-97.7
18.1	-92.3	12.6	-82.7	6.9	-55.5
14.2	-85.2	18.0	-88.8	8.4	-61.1
33.9	-54.7	18.9	-82.0	10.4	-62.6
-85.9	153.2	-64.3	147.9	-53.3	131.3
21.5	-43.8	36.4	-126.7	33.3	-110.9
-71.3	107.4	-41.0	105.0	-32.9	91.8

Table 6.8. Sample arrays from good design solutions found by the GA,
(Design space)

HTC R/S contact (kW/m ² K)	Stock Temp. (°C)	Contact Length (mm)	HTC Cooling (kW/m ² K)	Roll Speed (Rad/sec)	Roll Temp. (°C).	Delay Time (Sec)
5.1	1216.2	22.8	17.8	0.31	78.4	36.7
14.1	1099.5	26.2	15.3	1.04	40.0	26.0
5.0	967.0	13.1	40.3	0.60	76.1	83.9
5.1	1197.1	12.5	40.6	1.24	41.4	21.8
5.0	967.0	13.1	40.3	0.60	76.1	79.8
5.4	1178.5	28.3	43.7	0.73	79.6	73.8
5.2	957.6	10.2	43.0	0.54	41.4	73.9

6.4.3 Post GA Result and Analysis

The post processing or search space reductions are independent steps designed to process the obtained solution of the objective space, as well as the corresponding design space. An important step of the solution strategy begins by calculating the weight vector of results in the objective space, found by the GA. Programme code and the procedure adopted for finding the final optimum set of design solutions is presented in Section 6.4.4. The programme code, developed in MATLAB, is to represent the mathematical formula used to calculate weights vector of the objectives result from the GA and the follow-up search space reduction steps for identifying the final optimal design. The formula, called Pseudo-Weight Vector Approach is designed to compute the weight W_i for the i -th objective function, and calculate the relative distance of the solution from the worst (max) value in each objective function; thus, the best solution for the i -th objectives, the weight W_i is the maximum. The mathematical formulation of the Pseudo-Weight Vector Approach is given in Equation 6.19.

Pseudo-Weight Vector calculation (Deb, 2001)

$$w_i = \frac{f_i \max - f_i(x) / (f_i \max - f_i \min)}{\sum_{m=i}^M (f_m \max - f_m(x)) / (f_m \max - f_m \min)} \quad \text{Equation 6.19}$$

Where $f_{i\min}$ and $f_{i\max}$ are values of each objective functions i from the obtained set of solutions from GA. $f_i(x)$ is the result from the GA population, 400 in this case. In the equation above, the characters on the left side of the numerator always ensure a value between 0 and 1 (normalise). Hence, after the application of the weight vector approach, the sum total of all the weight/objectives should add up to 1. Once the weights have been calculated, the next step is the prioritising of the weights, based on their weights average values. Prioritising is carried out as follows: first, take the average weight of all the populations of each objective individually; second, rearrange the average weight in descending order; third, taking the higher weight average value as high priority, hence considered the most important (rank 1) objective, place all the weights vectors according to their importance, such as the second highest weight average second most important, and so on, until all the m ($m = 6$ in this case) objectives arrangements are completed. The arrangement provides a condition for each design factor solution in the decision space to satisfy the criteria, and hence preserve itself, and eventually be selected as best. As stated above, the 1st ranking weight is considered as a good solution for all objectives. Taking the 1st ranking weight vector as reference, carry out filtering (search space reductions) of the objective space. The filtering is an iterative process, leading to the identification of the final design solution. Details of filtering steps are described as follows:

6.4.4 Post GA Result Analysis, Search Space Reduction for Final Optimal Design Solution/s

Introduction of the refining technique, for search space reduction in the objective space and the corresponding decision space, helps to locate the area of interest considered to be the most preferred design solution. The post GA result processing, (search space reduction) steps for identifying the final optimal design solution, are summarised as follows:

- Run GA to identify optimal solutions for the intended problem.
- Programmed in MATLAB, calculate the weight vector for the objective functions space results obtained by the GA.
- Calculate the average weights for the population of results of each column/objectives in the space.

-
- Prioritise the objectives according to their average weight, giving the highest priority for the highest average weight and assign rank 1 to it, indicating that it contains the most desired solutions, good for all objectives. In the same way, rank 2, 3..., to all the remaining objectives, respectively.
 - Rearrange the objective functions positions according to importance or rank in descending order.
 - Rearrange the most important (1st ranked) objective population of solutions in descending order so that elitist weighted vectors are identified. The aim is to filter out the least weight values and preserve the top n number of higher weights vectors (as discussed in Section 6.4.3, the higher the weight gives the better or, as in the case of this case study minimised solution).
 - Taking the 1st column or most important objectives as a reference, gradually filtering or reducing the search space so that a single best design solution, that is shared by all objectives can be found. The filtering is conducted by assigning a percentage (%). The reduction started from the original solution obtained by the GA (400 populations) to the least ranked objective (the 6th objective in this case). Next, starting from the 1st ranking objectives applied the percentage reduction. The percentage is determined through experimental trial, and in this case, 30 % for 6 objectives problem has been considered. The percentage reduction will preserve 30 % of the top n number of the highest weight vectors of the rank 1 objective. For population of solution 400, the 30% reduction will give $30\% \times 400 = 120$ population. This means that only top 120 (higher weight vector) or better population of solution remains.
 - Taking the selected 30% of the 1st ranking objectives as reference, proceeds to find 30 % of the corresponding good solutions from the 2nd ranking objective. The same procedure continued to all objectives until the final best optimal design solution/s shared by all objectives is obtained.
 - Following the search space reduction in the objective space, and locating the final best optimal design solutions, as described above, the corresponding design factors in the decision space are identified. The percentage reduction is a step used to determine the best set of design parameters, giving the best optimal design solution for the work roll system thermal design problem.

Table 6.9 illustrates the percentage reduction procedures shown above. The graph shows the steps in the search space reduction and remaining good population of solutions, in the objective space.

Table 6.9. Post GA percentage reduction, within the objective space for final design solution

Initial solutions obtained by the GA		Search Space Reduction				
400 pop	400 x 30 %	120x 30 %	36x 30 %	11x 30%	4x 30%	2x 30%
	120	36	11	4	2	1

The Figures (6.23-6.30) give graphical illustrations of the post GA results search space reductions steps provided in Table 6.9. Figure 6.23 presents the original good solution population from GA (400 population), and Figures (6.24-6.29) are the reduced size of solution at each step. In the Figures, the x-axis indicates the search space and the y-axis are the individual's weight. The step by step reduction aims to identify the best optimal design from the initial solution population obtained by GA, and ensure that the identified solution is also good for all objectives within the space.

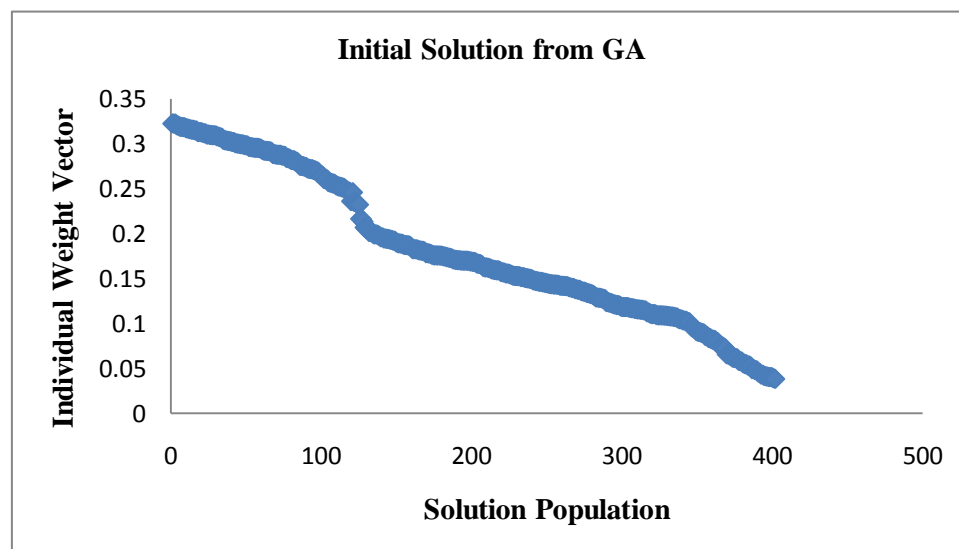


Figure 6.23. Initial solution from GA (400 population)

The result in Figure 6.24 presents the reduced number, by 30% from the initial 400 population of solutions given in Figure 6.23. As discussed in Section 6.4.4, the population of solutions found in Figure 6.24 are the top n numbers of, highest weight average within the space hence are the most important or most preferred solutions. However to search for the best optimal preferably single solution that is commonly shared by all objectives in the space, the same procedure and percentage is applied to other subsequent objectives in the space. The followings are the reduction steps and the final result obtained.

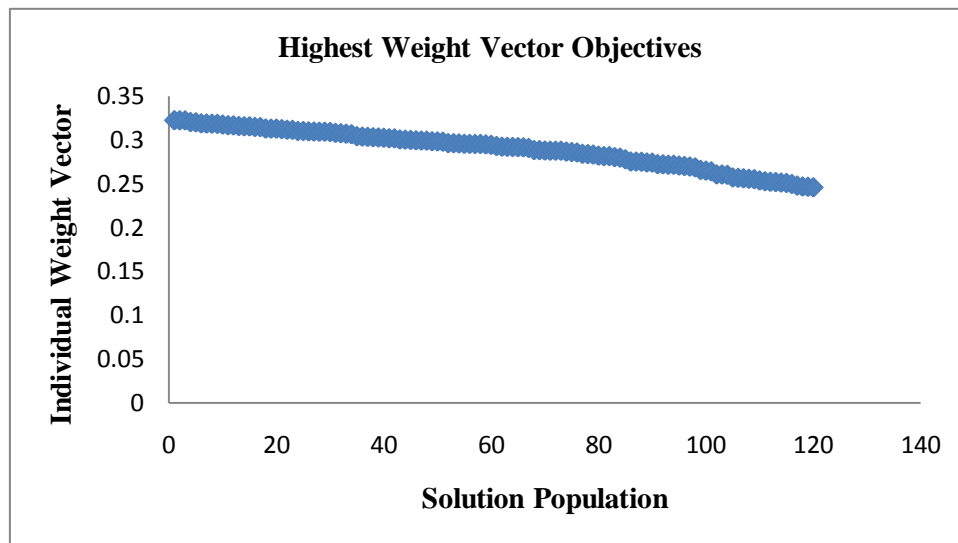


Figure 6.24. The highest weight vector average solutions (121 populations)

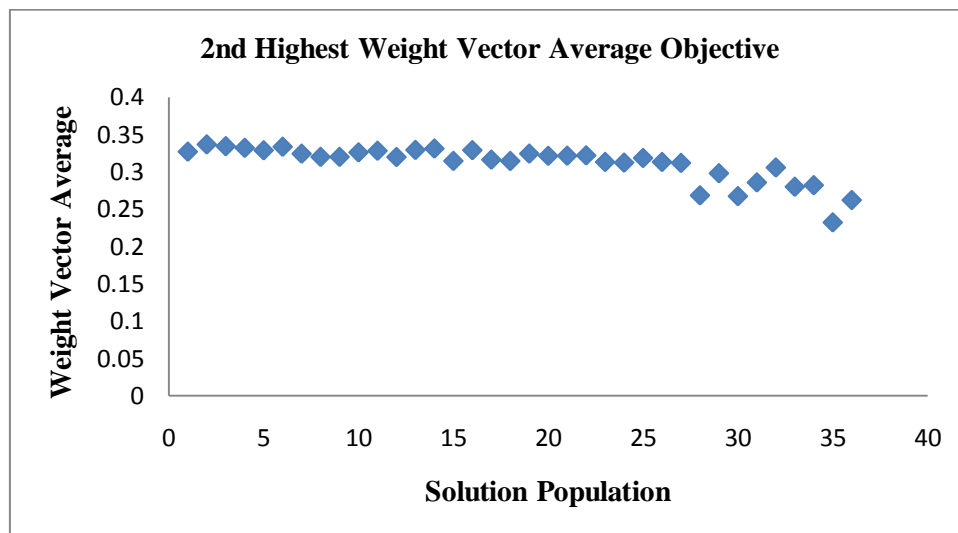


Figure 6.25. The 2nd highest weight vector average solutions (36 populations)

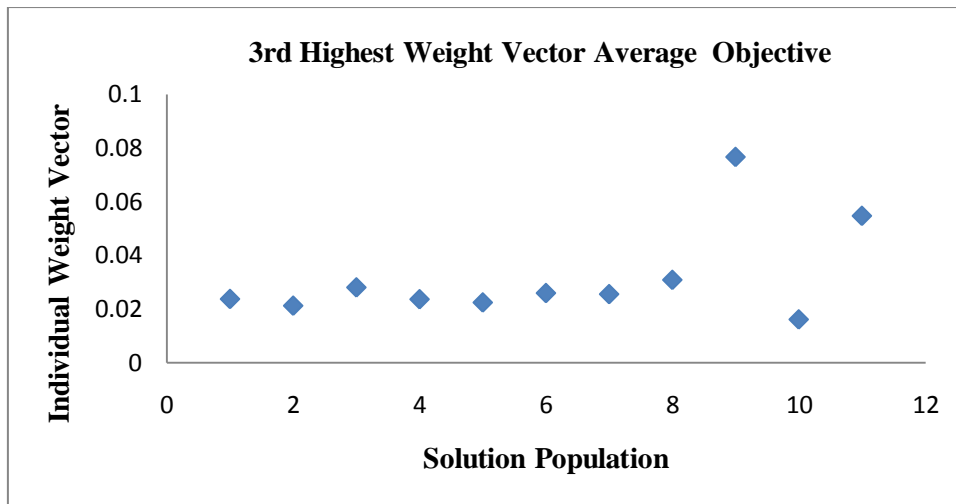


Figure 6.26. The 3rd highest weight vector average solutions (11 populations)

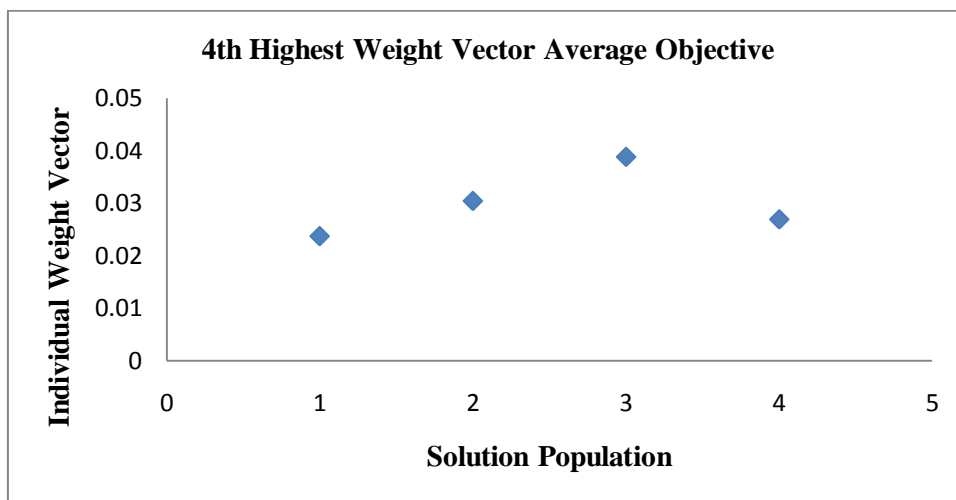


Figure 6.27. The 4th highest weight vector average solutions (4 populations)

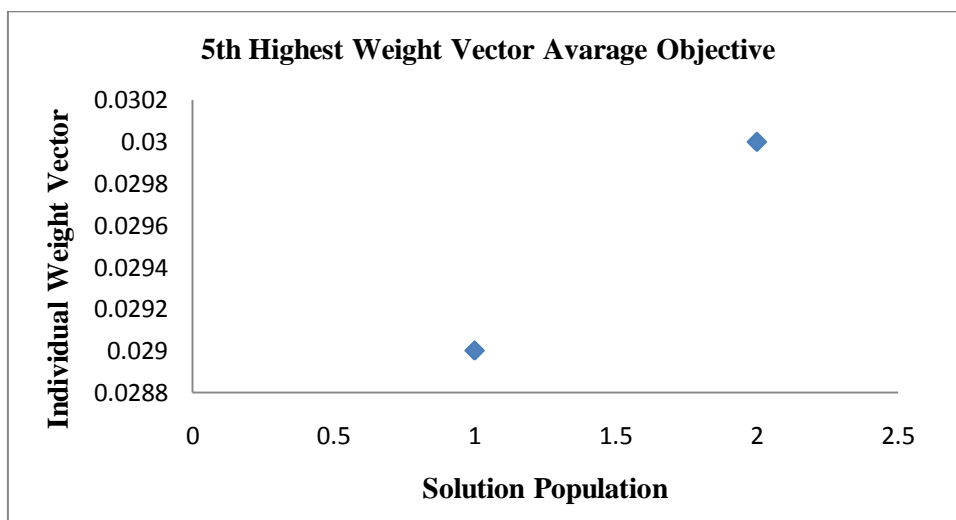


Figure 6.28. The 5th highest weight vector average solutions (2 populations)

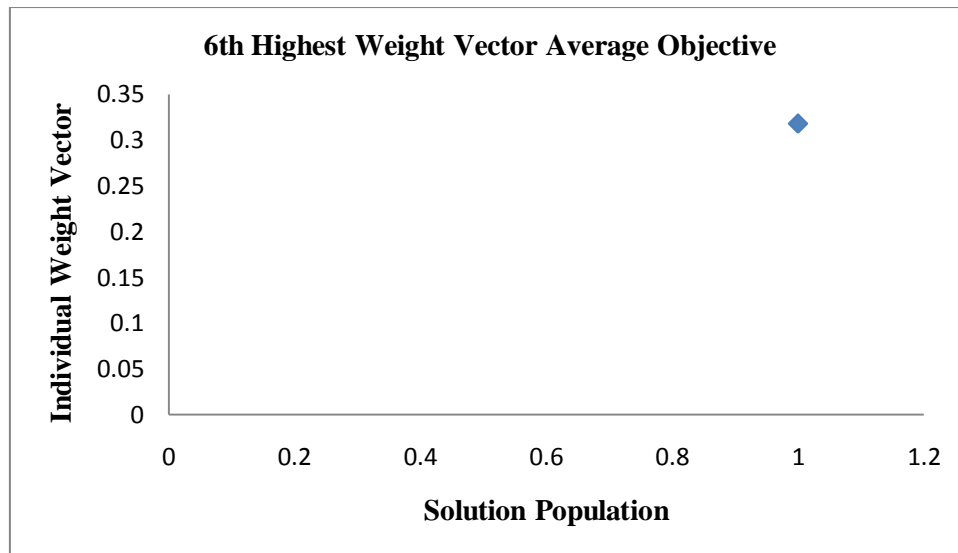


Figure 6.29. The 6th highest weight vector average solutions (1 individual)

Figure 6.30 and Table 6.10 present optimal solutions in the objective space and the corresponding best, optimal design variables and parameters in the decision space, corresponding to the result, shown in the Figure 6.29 for single pass, work roll system thermal analysis and optimisation problems, identified through the search space reduction procedures discussed above. The percentage search space reduction technique is filters out the search space and arrives at the final optimal best design solution.

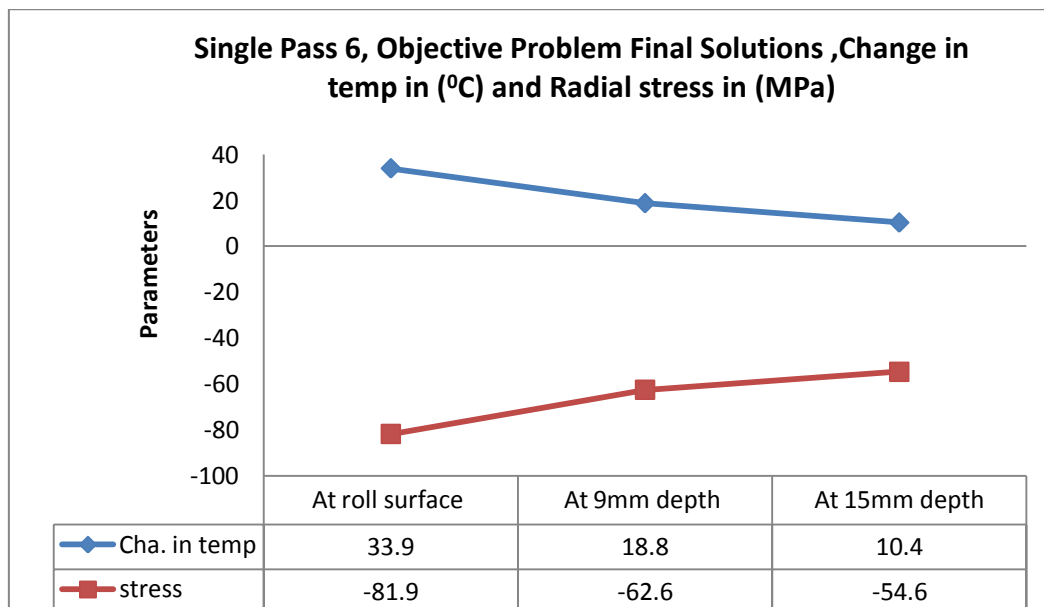


Figure 6.30. Single pass 6 objective problem solutions in the objective space

Table 6.10. Best optimum design variables and parameters in the design space

Design input factors	Optimised design parameters
Roll stock contact HTC	5.09 (kW/m ² K)
Stock temperature	1197 (°C)
Contact length	12.5 (mm)
Cooling HTC	40 (kW/m ² K)
Roll speed	1.24 (rad/sec)
Roll temperature	41.4 (°C)
Delay time	21.8 (mm)

6.4.5 Observations

This section presents the observation made on the final result obtained in the optimisation and subsequent search space reduction for identifying the final best optimal design solution to the problem presented in the Figure 6.30 and Table 6.10. Referring to Figure 6.30, the result obtained from the optimisation shows that the surface temperature trend decreased steadily going to the centre of the roll as expected. The rate of change of temperature, at depth between 9mm and 15mm is slowing, implying that heat effect below the surface is minimal. At the same time, the stress trend, as expected, contradicts with temperature behaviour. The stress at the surface decreased steadily, and rate of change from 9mm towards the centre is slowing, indicating that the stress level (particularly tensile stress) is minimal. Another important piece of information observed from the result, is the total roll temperature trend i.e. the sum total of the surface temperature and initial (bulk) roll temperature values. The result is plausible - as shown in Figure 6.31 the total temperature trend is decreasing and the rate of change of temperature towards the centre of the roll is believable. The result is in line with what has been learned in the review of literature and knowledge elicitation from rolling expert. It has been learned in the knowledge elicitation exercise that for longer utilization of rolls, the temperature on the surface of the roll preferred to be in the range of 40 °C to 80 °C and expected to decrease at depth below the surface towards the centre of the roll.

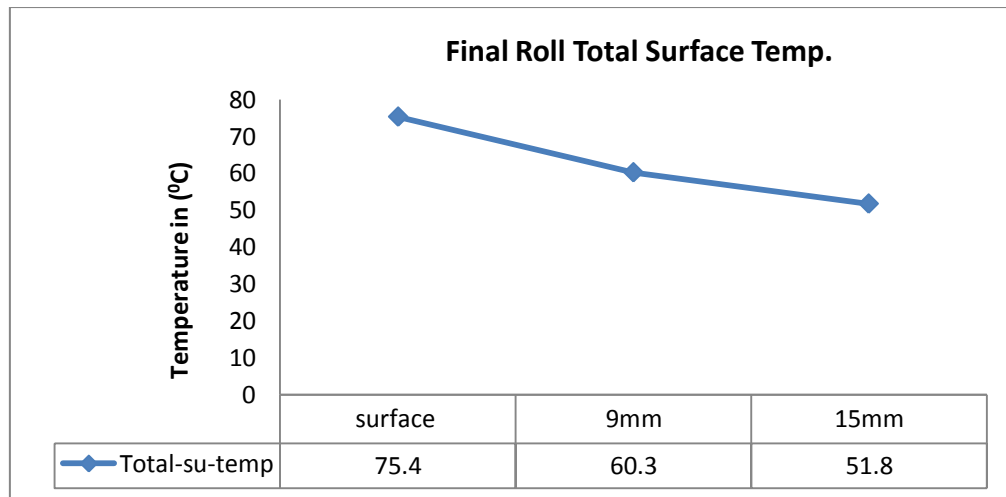


Figure 6.31. Roll total temp. (Change in temp. + Bulk initial roll temp. in [$^{\circ}\text{C}$])

Solutions obtained, following the above proceedings demonstrate that the proposed methodology works for solving the intended multiple objective, single pass optimisation problems with uncertainty in the design space and fitness function. The results obtained reflect the fundamentals of the rolling process roll thermal characteristics observed in the real life practise; for example, the temperature condition in rolls varies from surface to depth, and the variation ought to be decreasing from the surface towards the centre of the roll. In this regard, the analysis of the results presented above, confirms that the optimal solutions obtained, from the proposed algorithm and search space reduction technique, behave as expected. This confirms that the solution search strategy is able to find good optimal solution for quantitative, multi-objective problem with uncertainty. The result further validated, shown in Chapter 8, with experts from the sponsoring company and academic from Cranfield University. The results are presented to the experts, supported by questionnaires asking to verify the result findings based on their real life experience.

6.5 Chapter Summary

The chapter study the optimisation problem of a real-life process concerning the design of a single-pass, multi-objective work roll system problem with uncertainty and constraints. The problem consists in defining a set of parameters able to guarantee the efficiency of the process in term of time, cost, and final quality. The overall process is made of single pass, and it is affected by a set of real factors characterised by uncertainty and constraints. To face the problem the chapter developed and introduce a novel thermal analysis and GA based optimisation framework so that the

unique challenges identified in relation to the problem can be addressed. Those challenges such as multiple objective, uncertainty in the design variables, and uncertainty in the models developed to represent the real life process and effect of real life process constraints. The chapter particularly contribute to the thesis by developing an optimisation framework to address those challenges. Particular achievements of the chapter are summarised as follows:

This chapter has demonstrated the successful application of a proposed optimisation framework for handling the work roll design problems with uncertainty and constraints using thermal analysis and GA. Two optimisation frameworks have been developed. The first framework is two objective optimisation frameworks, designed to verify the ability of the mathematical model to represent the intended problems, search for solution for work roll surface optimisation problem with uncertainty using thermal analysis and GA. And also gives an assurance, in a simplified manner that consideration of constraint criticality to the design solution can be dealt with using GA based optimisation technique. The second framework is an optimisation technique for searching solutions to the design problem, regardless of the number of objectives and problem dimension. A single pass work roll system thermal design problems consisting of six-objective minimisation (fitness function) problems, representing the objectives, change in temperature and radial stress at roll surface, as well as at 9 mm and 15 mm depth below the roll surface considered in the case study. The chapter also develop and applied a post GA result analysis technique iteratively reduce the search space to identify the best optimal design solution from the population of solution found by the GA. The procedure identifying the final optimum design solution and the result obtained are given in the chapter. Summary of The chapter achievements are the following:

- Developed a noble, thermal analysis and GA based solution strategy for handling multi-objective, quantitative, constraint and uncertainty information based optimisation framework for work roll system design problem.
- Presented experimental results obtained for the work roll system thermal analysis and optimisation problems, using the proposed framework.
- Developed a methodology for dealing with criticality of process constraint to the design solution obtained, hence engineers be able to choose a design depending on to its criticality in relation to requirements.

-
- Developed a strategy for post GA results search space reduction and analysis for many objective high dimensional optimisation problems. The post GA processing (search space reduction) technique is used for identifying the final best optimal design solution for the problem, the obtained solution was analysed and graphical illustrations have been presented.

While this chapter has satisfied key research objectives for the single pass work roll system design optimisation problems in presence of uncertainty and constraints, the next chapter presents the optimisation approaches for multi-pass work roll system design problems in presence of uncertainty.

7 Multi-Pass Model Development and Optimisation

Chapter 6 presents the optimisation of the single pass, carried out for searching solution for work roll system design problem; in presence of uncertainty and constraints using the proposed novel thermal analysis and GA based optimisation technique. The case study in the chapter particularly helps to understand the effect of heat at the surface of the roll and at depth below the surface. It also give insight to how presence of uncertainty in the fitness function and design variables can influence thermal behaviour of rolls. The case study highlights the sensitivity of designs to constraints and provides information about criticality of constraints and choice of design depending on requirements in presence of constraints. In real life however work roll system in hot rolling is a multi-stage process, involving several passes. Hence a real life work roll system design is a multi-pass case requires a multi-pass process optimisation. This chapter designed to address the multi-pass work roll system design problems and introduce a solution search strategy to deal with the problem.

The multi-pass rolling is an ordered, multi-stage process, involving several stands arrangement. The arrangement introduced in Figure 7.1 allows the product to pass from one stand to the next sequentially, where the output of one pass is an input in to the next pass. Therefore to seek a realistic design solution that address the real life work roll system design and optimisation problem in the rolling process this process behaviour has to be taken in to account. Due to these characteristics however and the fact that multi-pass rolling operations sequentially interlink, solving multi-pass optimisation problems will increase the complexity and size of the problem, i.e. number of design factors, number of objectives involved in the process. As the problem size increases, so does the level of uncertainty - since the rolling process is a sequential process where product, tool and process characteristics in one pass are directly associated to the pass before. For these reasons, therefore, the multi-pass study and design optimisation discussed in this chapter, has been developed. As stated above, multi-pass rolling involves a large number of variables and uncertainty associated to them; hence, finding good design solutions within the multi-pass environment is a very complex problem. Although manual based design has been tried

and been successful in optimising work roll thermal analysis and optimisation problems, it is mainly with experts who have prior knowledge about the design. However, the manual approach can be very time consuming and tedious. This is mainly as a result of lack of knowledge about the process behaviour and due to the relationship among individual passes, leading to problem inheritance such as design factors relationship and uncertainty. This complexity means that the manual and classical way is not a recommended approach to deal with multi-pass problems. To address these problem complexities, a need for an intelligent, flexible and adaptive approach, such as evolutionary based algorithm optimisation solution search is essential. Literature review shows that there are a number of algorithm based techniques available to deal with multi-objective optimisation problems. For example in Oduguwa (2003) work although the technique was developed and applied in the roll pass design and optimisation problems but not include the work system design, the principles give a flavour of the complexity of the nature of multi-pass work roll system design problems. It also gives prior knowledge about the problem faced in the solution search process. There are various approaches reported in the literature review for searching for solutions of problems in the multi-pass rolling process, either aiming to provide optimal design solutions for individual passes or provide design solution for the system as a whole, by aggregating, sum or forming a total score for pass involved (Oduguwa, 2003). However, not much is reported in the literature, or learnt in the knowledge elicitation exercise from the rolling experts in the sponsoring company, to suggest that GA based techniques have been developed and used for multi-pass multi-objective work roll system thermal analysis and optimisation problems with uncertainty. Presence of uncertainty in the problem could be in the design variables and/or the mathematical model developed to represent the real life process. Due to the significant lack of research in the many objective multi-pass thermal design and optimisation environment, particularly addressing presence of uncertainty both in the design variables and fitness function, this chapter aims to develop a thermal analysis and GA based optimisation frameworks to fill the research gap. Since the real life process of the multi-pass rolling is a complex and uncertain activity, use of a mathematical model is often required as the empirical study is very difficult. Therefore the chapter also develop a methodology to generate multi-pass mathematical models from FEA responses that consider inter-pass relationship. The developed work roll system thermal analysis and optimisation problem models are

used as fitness functions in the optimisation for searching optimal design solution to the problem. The chapter expected contribution is defining a set of parameters able to guarantee the efficiency of the work roll system in the rolling process in term of time, cost, and final quality. The overall process is made of several passes, and it is affected by a set of uncertain real factors. The thermal analysis and the GA based optimisation framework and the mathematical model are designed to overcome these problems. The chapter consists of two main parts. These are the strategy for multi-pass work roll system thermal design process modelling and the development of the optimisation framework. The first part investigates the multi-pass rolling process, factors that have impact in the multi-pass work rolls thermal characteristics, and develop the quantitative model. It also addresses design factors relationships and complexities among passes. The second part presents the optimisation framework development, the optimisation experiment and post optimisation solution search analysis strategy for identifying the final best optimal design. The chapter is organised as follows: Section 7.1 presents the multi-pass quantitative model development and the background review used for the modelling. Section 7.2 presents the optimisation solution search strategy for multi-pass work roll thermal analysis and design problem. Section 7.3 concludes the chapter by summarising the key points.

7.1 Quantitative Modelling for Multi-Pass Work Roll System Design Optimisation Problem

The multi-pass quantitative model is developed to represent the complex behaviour of a real life multi-pass rolling process in a simplified and controllable manner. The developed alternative/surrogate model represents the underlying characteristics of the multi-pass roll thermal design and uncertainty issues. Unlike the single pass, the multi-pass problem design and optimisation needs to address inherited phenomena, such as uncertainty from one pass to the next. There are also rolling system design factor dependencies among passes, and their dynamic behaviour from one pass to the next, that needs to be addressed in the design. The dynamic nature of the process factors such as the inter-pass distance and the delay time between passes, are the fundamental rolling behaviours that are used to interlink between passes in the modelling of the multi-pass cases. The inter-pass distance, delay time and contact time have a direct effect on the temperature conditions of rolls and stocks. For example, the longer inter-passes distance and delay give time for the roll and stock to

cool naturally, and due to the application of coolant, as a consequence, the roll thermal condition will change. Roll speed is another main roll thermal behaviour determining factor. It was learnt in the literature that, under normal circumstances, speed of roll increases from one pass to the next, while stock temperature decreases. Roll speed has a direct operational relationship with other important design factors, such as roll stock contact time, heat transfer coefficient, delay time, as well as contact length. Recognising these important operational relationships among factors in sub passes and all passes as a system, is vital to address the multi-pass work roll thermal analysis and optimisation problems. Figure 7.1 shows stock reduction during rolling, delay time and inter pass distance.

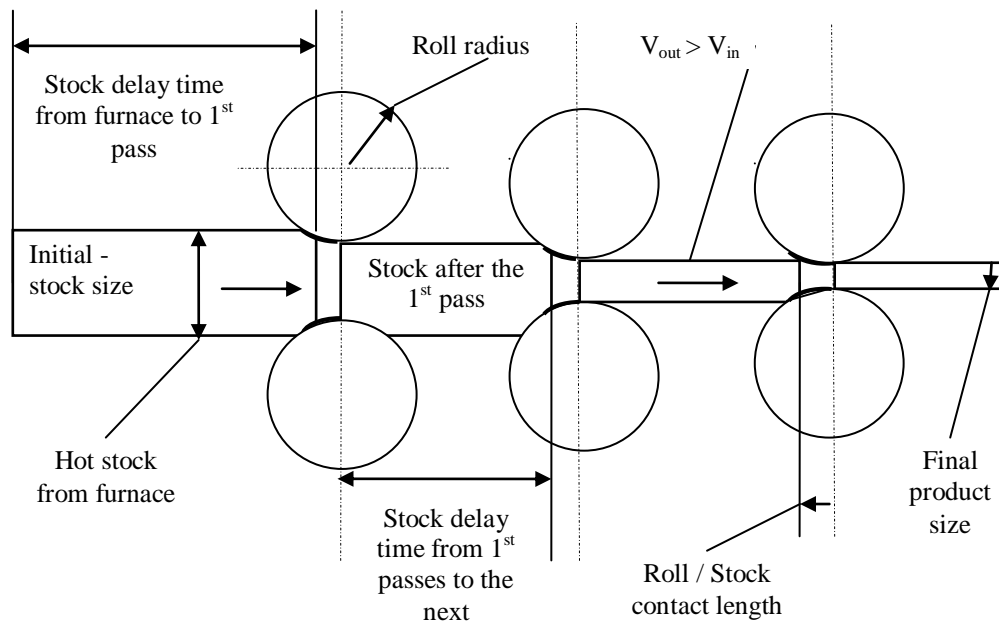


Figure 7.1. Multi-pass rolling arrangements involving three passes showing inter pass distance and stock reduction after roll stock contact

The quantitative model developed for multi-pass is required to reflect these facts for effectively representing the real life process behaviour. The framework for model development, for the multi-pass problem is fundamentally dependant on two main process features. These are the inter-dependency between stages and the search space dimensionality. The features are briefly described as follows:

- Inter-stage dependency between passes is the main feature discovered that plays a crucial role in developing the multi-pass model. The link between stages establishes communication between stages that can be useful to ensure

the inter-pass information is taken in to account. This link can be useful in ensuring the search at the current stage (i) considers information of the previous stage ($i-1$).

- High dimensionality is inevitable in the optimisation of multi-pass. The number of variables present in the design increases significantly with the increase in number of passes. This has a significant impact on the feasibility of solutions obtainable by process optimisation algorithms. The dimensionality has also a greater impact on computational time. Other important characteristics of multi pass rolling are the number of objectives involved. Just like the design variables dimensionality, as the number of passes increased, so do the number of objectives and uncertainty associated to them. Therefore, the optimisation framework development is required to be efficient in addressing these issues. This implies the need for finding algorithms and analysis of result from the algorithm to suit the specific features of the problems. It also requires knowing how to process the search result obtained by the GA. Since the conflicting objectives are many in numbers (high dimensional) identifying the final optimal design solution may require additional steps to reduce the search space and filter out the final optimal design solution/s.

7.1.1 Multi-Pass Work Roll System and Modelling Characteristics

The modelling of multi-pass problem is the continuation of the procedure followed for single pass approximate modelling, discussed in Chapter 5. The original FEA model shown in Figure 5.1 is the basis for developing the multi-pass model. The rolling process factor study and the expert knowledge elicitation exercise, carried out in the sponsoring company, presented in Chapter 4, and in Appendix D are served as information source for the multi-pass modelling and optimisation problems study. The multi-pass case is unique in itself, due to the fact that the modelling and optimisation process is dependent on the inter-pass factor relationships and uncertainty associated to them. As discussed in Section 7.1, the process factors involved between passes are interlinked, i.e. the output from one pass is the input to the next. This implies that the fundamental processing input design factors, in each pass, remains the same. The only exception is the differences in the design factors characteristics and parameters, depending on the pass position - for example, roughing pass, intermediate or finishing pass. These important process factors behaviours are manipulated and used as the

main drivers for building the multi-pass model. The modelling procedures and the mathematical model developed based on FE response data taken from the FEA problem model supplied by the sponsoring company. The response data taken at the roll surface is used to develop the first pass and all the other subsequent pass models (a total of 5 passes) developed by taking in to account the inter-pass factors relationships. The model development based on inter-pass factors relationship is discussed in the following.

During the review of literature and knowledge elicitation from expert in the sponsoring company, it was learnt that although some design factors in the design space remain constant, there are also factors that are changing from one pass to the next. Making use of the factors' changing behaviour from one pass to the next makes the existence of interdependency between passes. For example, the speed of rolls increases along the path from one pass to the next. The increase in roll speed is directly related to decrease in size of stocks – thus, the roll is able to rotate faster. At the same time, stock temperature decreases along the line from pass to pass. The stock temperature starts losing heat immediately after coming out of the furnace. However, the higher heat losses start after the stock comes in contact with the first pass and the follow up cooling process. It is understood that in practise, based on expert knowledge elicitation in the sponsoring company, that the stock temperature decreases by an average of 75⁰c after the first contact with the roll, and the roll speed increases by an average of 1.65rpm from pass to the next. One of the characteristics of multi-pass design is the presence of delay or stock travel time between passes. Under normal circumstances, the delay time is the time taken by the stock to cover the distance between consecutive passes, which is normally about 1.5m. However, depending on the condition of the process, as well as the nature of design factors, such as speed at section of the process (roughing, intermediate and finishing), the delay time is expected to vary. It is also observed that there are occasions in which delay time varies due to uncertainty or unforeseen circumstances in the process. The uncertainty that causes the delay time variations (small or too long delay time) will have an impact on work rolls thermal behaviour (the details are discussed in the literature review). The research makes use of these important characteristics for the mathematical modelling and optimisation of the multi-pass work roll thermal analysis and optimisation problems. The parameters are determined through real life process study and it reflects the functional relationship of the process as presented in the

Figure 7.1. These factors although they are pass specific in their characteristics they are also interdependent to each other, hence used as a link between passes during Meta modelling. Based on real life study the main factors identified that uniquely interlink one pass to the next are stock temperature, roll speed and delay time. The factors parameter variation from one pass to the next is presented in Table 7.1. The other design factors identified in the factors study made in Chapter 5, relevant to the thermal behaviour of rolls and whose parameter range given in Table 5.1, called the ‘free variables’ are generic to all passes, hence used in all passes during multi-pass process modelling.

Table 7.1. Inter-pass factor relationships for modelling multi-pass model

Stock temperature decrease by up to 75 °C from one pass to the next
Roll speed increase by average 1.65m/s from one pass to the next
Delay time calculated depending on pass velocity and 1.5m inter-passes distance (Delay time = distance between passes / roll velocity (RPM) at specified pass)

Modelling for a multi-pass problem take the 7 design input factors and parameters discussed in Section 5.2.2, Table 5.1 in Chapter 5. The interdependency nature of the three factors (i.e. rolls speed, delay time and roll temperature) and the functional relationship along the passes (parameters) are calculated and presented in Table 7.2, 7.3 and 7.4. The functional relationships are calculated based on information gathered in the literature review in Chapter 2 and knowledge elicited from rolling experts in the research sponsoring company, presented in Chapter 4.

Roll Speed

Speed is increased by average of 1.65m/s from one pass to the next

Table 7.2. Inter-pass speed in multi-pass rolling

0.14 m / s (pass1)
0.14 m/s x 1.65 = 0.23m/s (pass 2)
0.23 m/s x 1.65 = 0.38 m/s (pass 3)
0.38 m/s x 1.65 = 0.63 m/s (pass 4)
0.63 m/s x 1.65 = 1.04 m/s (pass 5)

The initial roll speed 0.14m/s is the speed considered in pass 1 determined through real life process scenarios and expert opinion. All other pass speeds are calculated,

taking in to account the functional relationship among passes and the result is shown in the Table, Table 7.2. The same procedure followed for other factors presented in Table 7.3 and 7.4.

Delay Time

Time = inter-pass distance (IPD) / roll speed (Rotational speed)

Table 7.3. Inter-pass delay time under normal circumstances

	Total delay Time
From furnace to 1 st pass ~ 100 s	75 s
1.5m / 0.14m/s = 10.75 s (pass1 – pass 2)	85.75 s
1.5m / 0.23m/s = 6.5s (pass 2 – pass 3)	92.25 s
1.5m/ 0.38m/s = 3.95s (pass 3 – pass 4)	96.20. s
1.5m/ 0.63 m/s = 2.38s (pass 4 – pass 5)	99.58 s

The total delay time at each pass is the summation of time from furnace and the time the stock take to reach to the current pass from the pass before. The maximum delay time is at pass 5. The delay time at pass 5 is the sum of total delay time of all 4 passes before, and the time for stock to travel from furnace to first pass.

Stock Temperature

Temperature decreased by average of 75⁰c from one pass to the next

Table 7.4. Inter-pass stock temperature in multi-pass rolling

1250 ⁰ c (pass1)
1250 ⁰ c – 75 ⁰ c = 1175 ⁰ c (pass 2)
1175 ⁰ c – 75 ⁰ c = 1100 ⁰ c (pass 3)
1100 ⁰ c – 75 ⁰ c = 1025 ⁰ c (pass 4)
1025 ⁰ c – 75 ⁰ c = 950 ⁰ c (pass 5)

Based on functional relationship among passes as shown above the three pass-independent variables are calculated and there parameters range are determined. The number of passes considered in the multi-pass case is 5, where each pass consists of 2 objectives and 7 input design factors per pass. Hence, the total number of variables (3 pass dependent and 4 free variables), (7 X 5) = 35 and objectives are (2 x5) = 10.The

Independent design factors parameter set used for the modelling and the dependent factors (objectives) for multi-pass problem are given in Table 7.5 and Table 7.6, respectively.

Table 7.5. Design variables of multi-pass problems (5 passes)

	x1	x2	x3	x4	x5	x6	x7
Factors	Roll/stock contact(HTC) (kW/m ² K)	Stock temperature (⁰ C)	Contact length (m)	(HTC- Cooling) (kW/m ² K)	Roll speed (m /s)	Roll Temperature (⁰ C)	Delay time (s)
Limits	Pass 1						
Lower	5	1230	10	15	0.14	40	65
upper	15	1250	30	50	0.2	80	75
	Pass 2						
Lower	5	1155	10	15	0.17	40	75.75
upper	15	1195	30	50	0.29	80	85..75
	Pass 3						
Lower	5	1080	10	15	0.32	40	82.25.
upper	15	1120	30	50	0.44	80	92.25.
	Pass 4						
Lower	5	1005	10	15	0.57	40	86.20
upper	15	1045	30	50	0.69	80	96.20.
	Pass 5						
Lower	5	950	10	15	0.98	40	88.58
upper	15	970	30	50	1.1	80	98.58

Table 7.6 objective for multi-pass problems

No. of Passes	Pass1	Pass 2	Pass 3	Pass 4	Pass 5
No. of Objectives (2 x 5) = 10	2	2	2	2	2
Objectives	Change in Temperature (ΔT in ⁰ C), at the surface of the roll				
	Radial Stress (S11 in MPa)) at the surface of the roll				

The number of variables present in the design problem increases significantly with the increase in the number of passes. As the number of passes increases, so does the size of the search space. The aim of this chapter is to develop a quantitative model representing thermal characteristics of multi-pass rolling process design, and to develop an optimisation framework for searching optimum design solution to the

multi-pass problem with uncertainty, regardless the size of the search space. Uncertainties in the problem are both in the design space and/or in the fitness functions. The following section discusses the quantitative modelling for the Multi-pass problem.

7.1.2 Multi-Pass Regression Model

The modelling of the multi-pass is based on a follow-up of procedures shown in Chapter 5, for single pass design and optimisation. The work here focuses on optimising change in temperature and radial stress on the surface of the roll in 5 pass rolling process; the response models for the passes are developed from response data taken from FEA process model supplied by the sponsoring company. However, it has been learnt from discussion with experts in the industry, that it is a common practise that the FEA simulation response data used to develop the single pass mathematical model can also be used to develop other subsequent models in multi-pass cases, provided the design input design factors of the passes are known and the relationship between passes are known. Depending on the size of the range of factors parameters in the initial single pass model, the subsequent n number of new models can be developed by taking in to account the inter-pass factors relationships discussed in Section 7.1.1. The previous section discussed the inter-pass factor relationship and the factors parameter in each pass. Based on the discussion, the independent factors and factors parameter ranges at each pass, shown in Table 7.5, are identified. Taking the dependent factors, change in temperature and radial stress at the surface of the roll as objectives, the mathematical models shown below are developed. Based on the FE simulation run procedure and the steps followed for taking response data from ODB after simulation, presented in Section 5.3.6 and Section 5.3.7 in Chapter 5, the response (dependent variables) values shown in Table 7.7 and objectives data values used for generating mathematical models shown in Table 7.8 are recorded. Using the objective values obtained the quantitative models, a total of 10 models, were generated by fitting a second degree polynomial consisting of a main effect, quadratic effect and interaction effect. The input data matrix specified for each passes for generating the models are given in Appendix H. The modelling was carried out using STATISTICA, a tool selected due to its applicability and availability. It is also widely used by the sponsoring company. The following present the response data from simulations and the 5 pass regression models.

Table 7.7. Respons datas values from FEA simulation (Ts) = tempreature at roll surface and (S11) = Radial stress at roll surface

Responses from FEA	
Ts (⁰ C)	S11s (MPa)
49.9	47.8
86.6	45.6
114.9	75.9
43.4	13.6
92.9	-78.5
158.3	-127.
60	7.0
101.1	-124.
187.2	-250.
85.5	-1.5
54.5	46.5
42.4	54.1
137.6	-159.
105.8	-227.
90.7	-74.2
113.3	-145.8
94.9	124.1
65.5	97.0
93	3.6
53	70.7
48	65.7
60.1	37.1
106	177.1
66.1	127.1
239.1	-251.
106	-10.3
86.2	0.43

Table 7.8. Response data values used for generating the multi-pass models, (ΔT_s) = Change in temperature at roll surface and (S11) = Radial stress at roll surface;

$$(\Delta T_s = T_1 - T_0)$$

No. Of runs	Calculated Depth at roll surface. (mm)	At surface	
		ΔT_s ($^{\circ}\text{C}$)	S11 (MPa)
1	5.7	9.9	47.8
2	8.1	46.6	45.7
3	9.9	74.9	75.9
4	2.58	6.4	13.6
5	3.6	52.9	-78.5
6	4.4	118.	-127
7	1.9	1.8	7
8	2.7	61.2	-124.7
9	3.3	147	-250.7
10	3.6	31.5	-1.5
11	4.4	-5.5	46.5
12	2.58	-17.6	54.1
13	2.7	191	-159
14	3.3	159.	-427.6
15	1.9	30.2	-74.2
16	8.1	53.3	145.8
17	9.9	34.9	124.1
18	5.7	5.5	96.
19	3.3	13	3.6
20	1.9	-27	70.7
21	2.7	-32	65.7
22	9.9	-11.6	37.1
23	5.7	26	7.1
24	8.1	-13.9	127.1
25	4.4	157	-251.6
26	2.58	26	-10.3
27	3.6	6.2	0.4

x_1, \dots, x_7 in the model shown in Equations (7.1 – 7.10) are symbols used to represent the design variables, given in Table 7.5. (The brackets [] in the models are used to simplify the symbols, linear & quadratic, representing the variables).

Change in temperature at roll surface for passes 1 to 5

Pass-1 $(-3078.7483 + 3.92666667 * x[1] + 0.046222222 * x[1]^2 + 2.39944444 * x[2] + 0.00000000 * x[2]^2 + 4.90000000 * x[3] - 0.02511111 * x[3]^2 - 7.0603175 * x[4] + 0.085079365 * x[4]^2 + 433.703704 * x[5] + 0.00000000 * x[5]^2 + 3.99055556 * x[6] - 0.04194444 * x[6]^2 - 0.80194444 * x[7] + 0.004701389 * x[7]^2)$. Equation 7.1

Pass-2 $(-74017.666 + 3.92666667 * x[8] + 0.046222222 * x[8]^2 + 124.916389 * x[9] - 0.05286111 * x[9]^2 + 4.90000000 * x[10] - 0.02511111 * x[10]^2 - 9.3007256 * x[11] + 0.112235828 * x[11]^2 + 2560.67901 * x[12] - 4322.5309 * x[12]^2 + 1.07972222 * x[13] - 0.02115278 * x[13]^2 - 0.90302431 * x[14] + 0.004701389 * x[14]^2)$, Equation 7.2

Pass-3 $(-90392.107 + 3.92666667 * x[15] + 0.046222222 * x[15]^2 + 163.144722 * x[16] - 0.07365278 * x[16]^2 + 4.90000000 * x[17] - 0.02511111 * x[17]^2 - 7.0603175 * x[18] + 0.085079365 * x[18]^2 + 68.7345679 * x[19] + 297.839506 * x[19]^2 + 3.99055556 * x[20] - 0.04194444 * x[20]^2 - 0.95991111 * x[21] + 0.004701389 * x[21]^2)$ Equation 7.3

Pass-4 $(-78565.254 + 3.92666667 * x[22] + 0.046222222 * x[22]^2 + 152.096806 * x[23] - 0.07365278 * x[23]^2 + 4.90000000 * x[24] - 0.02511111 * x[24]^2 - 7.0603175 * x[25] + 0.085079365 * x[25]^2 - 80.185185 * x[26] + 297.839506 * x[26]^2 + 3.99055556 * x[27] - 0.04194444 * x[27]^2 - 0.99705208 * x[28] + 0.004701389 * x[28]^2)$ Equation 7.4

Pass-5 $(-868.02142 + 3.92666667 * x[29] + 0.046222222 * x[29]^2 + 0.926388889 * x[30] + 0.00000000 * x[30]^2 + 4.90000000 * x[31] - 0.02511111 * x[31]^2 - 7.0603175 * x[32] + 0.085079365 * x[32]^2 - 324.41358 * x[33] + 297.839506 * x[33]^2 + 3.99055556 * x[34] - 0.0419333 * x[34]^2 - 1.0194307 * x[35] + 0.004701389 * x[35]^2)$ Equation 7.5

Radial Stress (S11 models) at roll surface pass 1 to 5 =

Pass-1 $(5551.59887 - 9.7710000 * x[1] + 0.419755556 * x[1]^2 - 4.1428889 * x[2] + 0.00000000 * x[2]^2 + 1.91477778 * x[3] - 0.18294444 * x[3]^2 + 17.2142766 * x[4] - 0.21967166 * x[4]^2 - 2961.7685 * x[5] + 0.00000000 * x[5]^2 - 3.3344167 * x[6] + 0.044243056 * x[6]^2 - 1.6252222 * x[7] + 0.013371181 * x[7]^2)$ Equation 7.6

Pass-2 $(-69381.097 - 9.7710000 * x[8] + 0.419755556 * x[8]^2 + 120.479931 * x[9] - 0.05048750 * x[9]^2 + 1.91477778 * x[10] - 0.18294444 * x[10]^2 + 37.1468753 * x[11] - 0.46127891 * x[11]^2 - 28760.889 * x[12] + 53404.1667 * x[12]^2 + 22.5628611 * x[13] - 0.14073750 * x[13]^2 - 1.9127026 * x[14] + 0.013371181 * x[14]^2)$ Equation 7.7

Pass-3 $(167054.217 - 9.7710000 * x[15] + 0.419755556 * x[15]^2 - 297.75003 * x[16] + 0.134493056 * x[16]^2 + 1.91477778 * x[17] - 0.18294444 * x[17]^2 + 17.2142766 * x[18] - 0.21967166 * x[18]^2 - 11074.571 * x[19] + 12297.3765 * x[19]^2 - 3.3344167 * x[20] + 0.044243056 * x[20]^2 - 2.0744939 * x[21] + 0.013371181 * x[21]^2)$ Equation 7.8

Pass-4 $(149025.120 - 9.7710000 * x[22] + 0.419755556 * x[22]^2 - 277.57607 * x[23] + 0.134493056 * x[23]^2 + 1.91477778 * x[24] - 0.18294444 * x[24]^2 + 17.2142766 * x[25] - 0.21967166 * x[25]^2 - 17223.259 * x[26] + 12297.3765 * x[26]^2 - 3.3344167 * x[27] + 0.044243056 * x[27]^2 - 2.1801262 * x[28] + 0.013371181 * x[28]^2)$ Equation 7.9

Pass-5 $(16371.3330 - 9.7710000 * x[29] + 0.419755556 * x[29]^2 - 1.4530278 * x[30] + 0.00000000 * x[30]^2 + 1.91477778 * x[31] - 0.18294444 * x[31]^2 + 17.2142766 * x[32] - 0.21967166 * x[32]^2 - 27307.108 * x[33] + 12297.3765 * x[33]^2 - 3.3344167 * x[34] + 0.044243056 * x[34]^2 - 2.2437730 * x[35] + 0.013371181 * x[35]^2)$ Equation 7.10

7.1.3 Multi-Pass Model Validation

As noted in the previous sections, the mathematical representation of the multi-pass work roll thermal analysis and optimisation presented in this chapter is developed using several sources from the review of literature presented in chapter 2. Information from expert knowledge elicitation discussed in chapter 4, as well as manufacturing shop floor observations made during the visits to the sponsoring company has also contributed significantly. However, some of the information gathered, particularly during the knowledge elicitation exercise, is subjective in nature. Therefore, in order to make sure that the knowledge gathered is well understood and applied in the model building and optimisation as expected, it is vital to carry out a verification exercise. The verification is made based on the post optimisation results, studying the trends of the obtained final design factors along the passes of the multi-pass rolling arrangements. This section presents the research strategy followed for validating the model and the optimisation results. The validation has two parts. These are:

- The statistical post regression analysis for model validation and
- Validation based on experts' opinion, of the optimisation results and design factors result trends. Result factor trends are used to verify the assumption made of factors in the modelling and factors trends relevance in relation to real life rolling process factors behaviour. The validation based on expert opinion is presented in Chapter 8, the research validation chapter.

Statistical Validation

The post regression model characteristics of the 5 passes have been analysed to see if the model is statistically acceptable based on statistical model acceptance criteria reviewed in the literature. The criteria of the performance of the multi-pass models are based on three measures: Pareto chart of p-values for coefficient, R^2 and R. R^2 & R are measures of the amount of variation experienced by the model. R^2 equals 1 indicates a perfect fit. The higher R^2 implies the lower variation between observed and predicted values, and therefore, a better model. The corresponding R^2 and R for each model are given in Table 7.7. During model generation, a relatively high value of R^2 & R has been recorded. It is, therefore, likely that these models would give good predictions when used in the optimisation. Other important model summaries, such as Pareto chart of p-values for coefficients, are used. The p-values for coefficient are

used to determine the confidence of those factors' relevancies to the model. A p-value less than 0.05 is considered acceptable. P-values are also indicating that either the factor relationship with the model is linear or quadratic.

Table 7.9. Multi-pass models statistical validation

Multi-pass regression R, R² & p values				
		R	R²	P-values
Pass-1	Temperature	0.927754	0.860728	0.000422
	Stress	0.967115	0.869330	0.009010
Pass-2	Temperature	0.937748	0.879371	0.001485
	Stress	0.895968	0.802758	0.018153
Pass-3	Temperature	0.939948	0.880071	0.002485
	Stress	0.899968	0.822758	0.019153
Pass-4	Temperature	0.932448	0.882390	0.001995
	Stress	0.895968	0.802758	0.018153
Pass-5	Temperature	0.869986	0.806875	0.025060
	Stress	0.864313	0.809851	0.012353

The post regression validation data shown in Table 7.9 indicates that the models are statistically within the recommended acceptance criteria. For reasons explained in Chapter 4, the validation criteria are considered best to describe the model to represent the real life process. The R and R² values are relatively high (above 80) and the p-values are within the recommended range, implying that the models are statistically acceptable to represent the intended problem. However, the regression is only modelled with the given data – therefore, the generality and consistency of the model needs to be checked. Hence the validation based on expert opinion has been proposed.

The Need for Expert Opinion

Although multi-pass mathematical models offer a fast simulation alternative for real life process, since the models are based on fundamental rolling theories and these theories have been originally formulated with many assumptions, such as inter pass factor parameters relationships, that influence the quality of the simulated behaviour, the models may lack completeness. On the other hand, such models offer several benefits. They are capable of predicting system behaviour. They can be used to gain an insight into the structure of the problem. Since the model building process focuses on interrelationships of design variables rather than individual variables, the model building process allows the increased visibility of how the design variables influence

each other. This helps to improve an understanding of the underlying multi-pass behaviour (Tiwari *et al.*, 2008). However, the regression is only modelled with the given data and assumptions made for the modelling; hence, the accuracy and consistency of the assumption need to be verified and validated. To fulfil that, the chapter proposes a verification strategy involving rolling experts from the sponsoring company who also participated in the initial knowledge elicitation exercise. A questionnaire was developed based on results of the optimisation experiment made using the developed multi-pass models. The verification was carried out to determine if the assumptions made previously, of design input factor inter-pass relationship and factor trends along passes in real life, is reflected in the optimisation experiment results found using the developed models, hence, the model is representing the intended problem. Details of the optimisation result validation and verification of assumptions made during the modelling of the multi-pass continuous rolling, work roll system problem is discussed in Chapter 8.

7.2 Optimisation Solution Search Strategy for Multi-Pass Work Roll Thermal Analysis and Design Problem

This section proposes the solution search strategy for the multi-pass work roll thermal analysis and optimisation problem with uncertainty. The main solution strategy adopted is GA. The algorithm's coding and optimisation strategy of the multi-pass problems is similar to the single pass, 6 objectives optimisation, discussed in Section 6.4, Chapter 6. This section gives only the description of the quantitative evaluation and the coding scheme adopted for the multi-pass problem and other features already discussed in Sections 6.4, are omitted to avoid repetition. As discussed in Section 7.1.1, the multi-pass problem has 10 objectives and 35 design variables, as well as uncertainty associated to them. The optimisation used the design factors parameter ranges presented in Table 7.5 and the models given in Section 7.1.2. Equation 7.2, real value vector gives a formal definition of the multi-objective optimisation problem that aims to minimise the change in temperature at roll surface and minimise the radial stress at the surface, which is increased due to the application of cooling to reduced temperature. Both objectives are assumed conflicting in nature, since the decrease in temperature on rolls increases the radial tensile stress, and vice versa. As stated in Section 6.4, Chapter 6, the optimisation of a high dimensional, many

objective problem in R environment consists of two parts. These are the solution search using GA, and the post GA search space reduction for identifying the final best optimal solution/s. The first part, searching for a solution using GA, is discussed in the next section. The Pseudo code for searching for the design solution for the multi-pass problem is presented in Figure 7.2 and the programme code for the optimisation is given in Appendix I.

Pseudo-code for the quantitative and the uncertainty in the design variables and fitness function evaluation for many objective, multi-pass problems

Step 1: Initialise population pool at $t = 0$. For every member of the population i , generate random value x_j in its range as well as ranges of uncertainty. This random value aids the exploration of the entire search space.

1.1: Evaluate decision space and the uncertainty in the design variables
Evaluate $X_i = \{ (x_1 + \varepsilon), \dots, (x_n + \varepsilon_n) \}$

Step 2: Evaluate the individuals in terms of quantitative model and model uncertainty.

2.1: Evaluate fitness functions and the uncertainty in the fitness function
Evaluate $(\vec{F}j(\vec{x}) = \sum_{m=1} \vec{f}j(\vec{x}) \mid i = 1, 2 \dots k \mid + \varepsilon; \quad // \text{assign a fitness value to each GA}$
individual based quantitative model

Step 3: Assign fitness to every member of the population based on dominance-ranking criteria of NSGA-II. The quantitative value is used for the quantitative objective value.

Step 4: Termination If current generation satisfy the conditions, else return to step2

Step 5: Create offspring population using binary tournament selection, crossover, and mutation operators
 $t = t + 1$, go to step 2.h

Figure 7.2. Solution search strategy for multi-pass problems with uncertainty

7.2.1 Experimental Details

The proposed many objective GA is used to locate good solutions for the optimisation problem formulated in Equation 7.3 by evaluating each member of the population using the multi-pass quantitative models given in Section 7.1.1. The quantitative evaluation with uncertainty in the design variables and in the fitness function of individual members of the population is carried out, based on the solution search strategy shown above, as the following. First is the evaluation of the design variables of the five passes and uncertainty, followed by the evaluation of the fitness function of the five passes with uncertainty. This represents the global objective functions values evaluation for the multi-pass work roll thermal analysis and optimisation problem. The objective function value of the global evaluation represents the fitness of the chromosome. The respective mathematical evaluation formulations are given in Equation 7.1 and Equation 7.2.

$$X_i = \{ (x_i + \epsilon), \dots, (x_n + \epsilon_n) \} \quad \text{Equation 7.1}$$

$$\vec{F}j(\vec{x}) = \sum_{m=1} \vec{f}j(\vec{x}) \mid j = 1, 2, \dots, k \mid + \epsilon \quad \text{Equation 7.2}$$

Where i is the i th design variables, n is the number of design variables, j is the j th objective and k is the number of objectives.

Prior to the optimisation run for solution search to the design problem, an experiment conducted to determine the size of population and generation. Ten independent runs, with random generation, are carried out. Each run have been repeated 10 times in the experimented. Hence, a total of 100 experiments have been conducted before selecting the size of the population and generation. This is essential for assuring the diversity and convergence of the solutions. The final optimisation is carried out with population size 400 and 1000 generations. All runs are performed with the following standard parameters: crossover probability (c_p) of 0.7 and mutation probability (m_p) 0.2. This research problem deals with qualitative based objectives and aims to show how the proposed algorithm can deal with many objectives work roll system optimisation problem with uncertainty using thermal analysis and GA. The case study is aimed at finding a solution for a design optimisation problem with uncertainty, minimising change in temperature (ΔT in $^{\circ}\text{C}$) and radial stress (S11 in MPa) at work roll surface (s_1, s_2, \dots, s_5) for 5 consecutive passes.

Ten Objectives, Multi-pass Optimisation Problem

Equation 7.3 Optimisation formulation for multi-pass problem

Minimise	Change in Temp pass-1	$f_1(x) = \Delta T_{s1}(x)$
Minimise	Stress (S11) -1	$f_2(x) = SII_{s1}(x)$
Minimise	Change in Temp pass-2	$f_3(x) = \Delta T_{s2}(x)$
Minimise	Stress (S11) pass-2	$f_4(x) = SII_{s2}(x)$
Minimise	Change in Temp pass-3	$f_5(x) = \Delta T_{s3}(x)$
Minimise	Stress (S11) pass-3	$f_6(x) = SII_{s3}(x)$
Minimise	Change in Temp pass-4	$f_7(x) = \Delta T_{s4}(x)$
Minimise	Stress (S11) pass-4	$f_8(x) = SII_{s4}(x)$
Minimise	Change in Temp pass-5	$f_9(x) = \Delta T_{s5}(x)$
Minimise	Stress (S11) pass-5	$f_{10}(x) = SII_{s5}(x)$

The sequence in representing the design variables in the optimisation of the multi-pass problem is shown in Figure 7.3. Pass are represented by the string. A string is made

up of sub-strings representing the number of passes; each of the sub-strings consists of product and process variables. Random values are chosen for these variables within the allowable range for each of the passes, based on discussion given in Section 7.2.1.

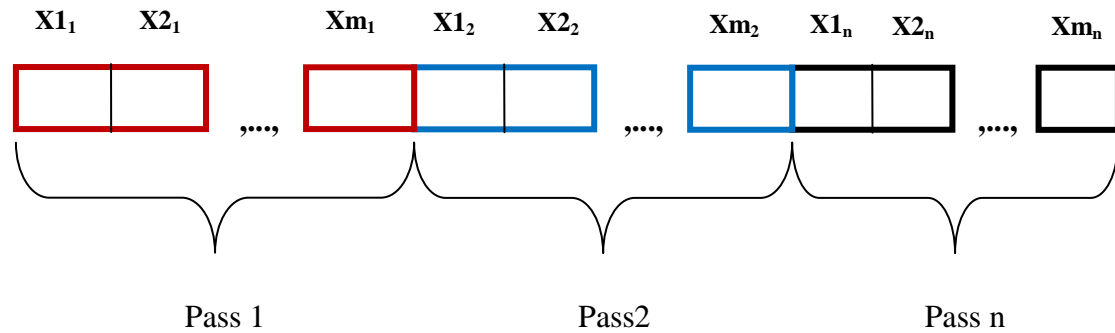


Figure 7.3. Design variables representation sequence in the optimisation

Introducing Uncertainty in the Optimisation

The uncertainty is introduced and applied in the optimisation by altering the design fitness randomly with a noise factor, represented by sigma (σ) values. The sigma is the value in the design space calculated as a percentage of decision space of each decision variable given in Table 7.5. In the case study the following sigma values are assigned. x1 to x35 represent the design variables given in Table 7.5.

x1_sigma = 0.5; x2_sigma = 1.0; x3_sigma = 0.5; x4_sigma = 1.7; x5_sigma = 0.003;
x6_sigma = 2.0; x7_sigma = 0.5; x8_sigma = 0.5; x9_sigma = 2.0; x10_sigma = 1.0;
x11_sigma = 1.7; x12_sigma = 0.006; x13_sigma = 2.0; x14_sigma = 0.5;
x15_sigma = 0.5; x16_sigma = 2.0; x17_sigma = 1.0; x18_sigma = 1.7; x19_sigma =
0.06; x20_sigma = 2.0; x21_sigma = 0.5; x22_sigma = 0.5; x23_sigma = 2.0;
x24_sigma = 1.0; x25_sigma = 1.7; x26_sigma = 0.006; x27_sigma = 2.0; x28_sigma
= 0.5; x29_sigma = 0.5; x30_sigma = 1.0; x31_sigma = 1.0; x32_sigma = 1.7;
x33_sigma = 0.006; x34_sigma = 2.0; x35_sigma = 0.5;

The sigma values are based on 5% error in the process. The 5% errors assumed above, are based on literature review, and knowledge from rolling engineers stating that in the real life rolling practise, normally 95 % accuracy is expected. The 5% error also applied for the fitness function.

7.2.2 GA Results

The optimisation run, with parameters outlined in the previous section and the models shown in Section 7.1.2, has produced the result. The optimisation identified the

solutions (Pareto set) that are, good compromised between the change in temperature and radial stress at the roll surface of the 5 passes. Experiments were carried out using the proposed optimisation algorithm framework for the 10 objectives, to illustrate how the algorithm deals with the multi-objective multi-pass problem with uncertainty. 10 runs have been carried out with the selected final generation and population sizes before the final result selected. The purpose of the run is to measure the consistency of results from the GA runs. The result selected as final is the representative from the ten GA runs, (the tenth run in this case). The tenth run is selected as final because there is no significant change observed in all the 10 runs. Sample results (array) of 10 objectives and 35 design variables from the 400 good populations of solutions found by the GA are presented in Table 7.10 and 7.11.

The problem is high dimensional in nature; hence, it is not possible to visualise the Pareto front. The post GA search space reductions strategy, based on weight vector average discussed, in detail in Section 6.4.4. Chapter 6 and summarised in Section 7.2.3, is used to search for the final best optimum design solution/s from the population of good solutions identified by the GA. The search space reduction procedure programme code is given in Appendix G. The strategy for searching the final best optimal design solution and discussion of the results are presented in Section 7.2.3 and Section 7.2.4.

Table 7.10. Sample array from good solutions found by the GA,

Objective space (Obj-1 - Obj-10)

Obj-1	Obj-2	Obj-3	Obj-4	Obj-5	Obj-6	Obj-7	Obj-8	Obj-9	Obj-10
115.2	-160.1	-14.7	186.3	28.1	-102.7	56.8	-136.3	64.1	-184.0
-19.3	141.2	-92.1	196.7	-80.8	116.4	-84.8	104.0	-16.5	193.2
8.0	115.0	6.3	144.5	30.1	-181.2	2.2	-37.7	-29.8	198.6
42.2	-60.9	171.7	-421.2	113.6	-108.4	38.0	-105.4	38.2	-50.2
55.6	-44.9	-115.0	266.4	-101.0	235.2	-3.1	160.6	60.6	-144.0

Table 7.11. Sample arrays from good design solutions found by the GA,
(Design space)

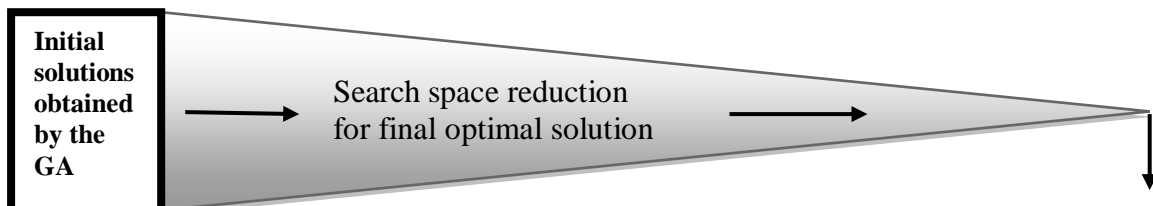
HTC R/S contact (kW/m ² K)	Stock Temp. (°C)	Contact Length (mm)	HTC Cooling (kW/m ² K)	Roll Speed (Rad/sec)	Roll Temp (°C).	Delay Time (Sec)
7.0	1245.2	26.5	17.4	0.2	47.4	85.6
5.1	1230.2	10.4	35.5	0.1	79.7	90.8
14.5	1247.5	12.5	39.8	0.2	59.9	24.2
5.0	1230.1	13.3	43.1	0.2	78.0	64.4
5.0	1231.1	10.4	38.7	0.1	79.3	94.6
11.1	1155.2	30.0	15.6	0.3	40.2	77.5
10.5	1182.8	10.4	15.4	0.2	42.3	48.4
13.5	1181.1	14.2	40.6	0.2	79.6	38.8
14.6	1160.5	29.7	17.0	0.3	41.7	57.1
9.2	1157.4	10.2	15.3	0.2	46.7	40.9
12.2	1115.3	27.3	19.3	0.4	44.8	77.8
13.4	1109.6	27.2	16.2	0.4	77.6	113.7
5.3	1100.6	13.2	16.3	0.4	44.0	69.5
12.6	1112.2	28.6	15.3	0.4	76.3	69.3
13.0	1109.6	27.4	22.6	0.4	45.7	70.4
6.0	1031.9	12.3	34.5	0.6	61.1	50.2
6.4	1031.7	11.6	35.5	0.6	58.2	40.9
7.4	1011.8	12.7	43.2	0.7	40.3	80.3
14.9	1025.4	29.5	16.9	0.7	48.1	58.4
7.4	1035.2	15.0	16.4	0.7	57.7	41.4
12.3	965.4	26.4	16.4	1.1	61.8	56.0
11.7	967.7	29.9	16.1	1.1	49.2	63.4
7.7	967.3	11.0	36.4	1.0	70.2	100.8
13.4	969.5	28.4	15.7	1.1	78.3	73.2
13.5	969.8	28.7	20.2	1.1	45.6	54.4

7.2.3 Post GA Result and Analysis

The result in the previous section gives the final design solutions (preferred design set) identified by the GA. This section presents a strategy for identifying the final optimal best design solution/s, from the obtained population of solutions by the GA. The filtering/search space reduction strategy (based on percentile), as discussed in Section 6.4.3 and 6.4.4, Chapter 6, is adopted for identifying the final optimal roll design solution. Detail descriptions of the technique is omitted here to avoid repetition. Here only techniques application to the multi-pass, multi-objective problem is explained. The technique is adopted due to its simplicity and flexibility in application. As explained in Section 6.4.4, the aim of percentage reduction is to step

by step reduce the search space and preserve **n** number of good design solutions within the space. The technique make it possible for a single best optimal design solution, best for all objectives can be identified from the remaining preserved few **n** number of good solutions, (Percentage taken is depending on the size of original population of solutions from GA). The percentage is determined through experimental trial - in this case, 55 % has been identified. Table 7.12 gives brief descriptions of the steps taken for search space reduction, as well as the remaining good **n** number of population of solutions within the space. The example demonstrates how the procedure gradually searching for optimal design solutions before identifying the design solution that is best for all passes as a system, (out of 400 population found by the GA to the final 2 population best optimal solutions giving the design variables set good for all objectives in all passes).

Table 7.12. Post GA percentage reduction, within the objective space for final design solution



The diagram illustrates the search space reduction process. It starts with a box labeled 'Initial solutions obtained by the GA' containing '400 pop'. An arrow points to a large, light-gray wedge that tapers from left to right. Inside the wedge, the text 'Search space reduction for final optimal solution' is written. Another arrow points from the wedge to a final point on the right, which is connected to a downward-pointing arrow. Below the diagram is a table showing the population size at each step of the reduction process.

400 pop	400 x 55 %	220 x 55 %	121x 55 %	67x 55 %	37x 55 %	21x 55 %	12x 55%	7x 55%	4x 55%	3x 55%
	220	121	67	37	21	12	7	4	3	2

Figures (7.4-7.14), give graphical illustrations of the post GA results search space reductions provided in Table 7.12. Figure 7.4 presents the original good solution population from GA (400 pop), and Figures (7.5-7.14) are steps showing the reduced number of population at each step after the application of the reduction strategy on the solution found by the GA. In Figures (7.4-7.14), the x-axis indicates the search space and the y-axis is for the individuals (weight). The step by step reduction aims to identify the best optimal design from the initial solution population obtained by the GA, and ensure that the identified solution is also commonly share by all objectives in the search space.

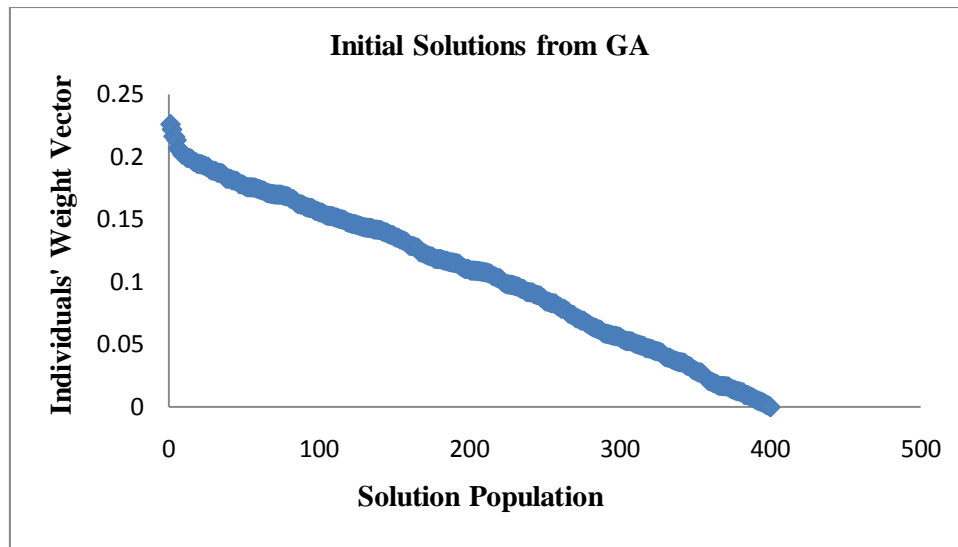


Figure 7.4. Initial solutions from GA (400 population)

The result in Figure 7.5 presents the reduced population of solutions, by 55% from the initial 400 population of solutions found by the GA, given in Figure 7.4. As discussed in Section 6.4.4, Chapter 6, the population of solutions found, shown in Figure 7.5 are selected **n** number of weights with the heights average within the space, hence are the most important or most preferred solutions, good for all objectives in the space. However the same procedure and percentage is continuously applied on the results in Figure 7.5 and subsequent results shown in Figures (7.6-7.14), to identify the best (preferably single) optimal design solution that is shared by all the objectives in the space. As expected the techniques is able to successfully identify the final best design solution (a single solution out the 400 good solutions from GA). The following presents the reduction steps and the remaining populations in each step.

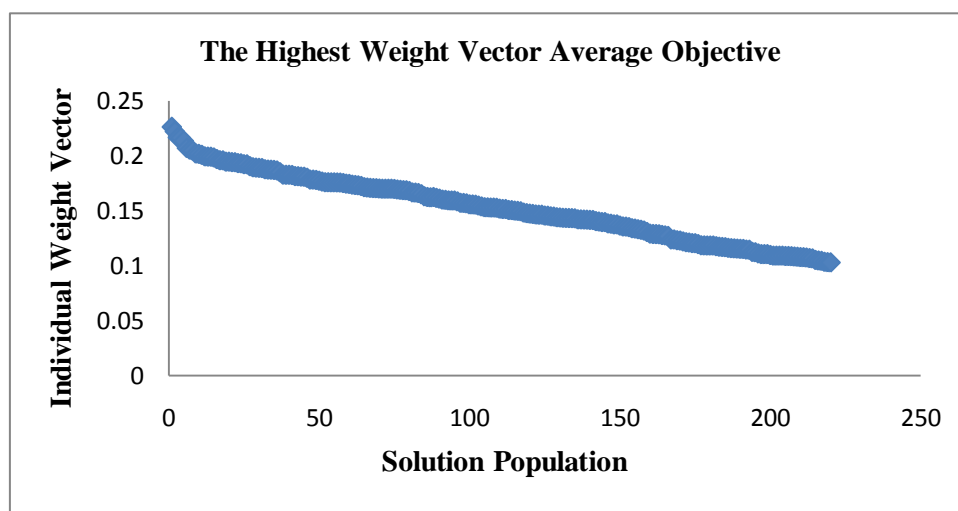


Figure 7.5. The highest weight vector average solutions (220 populations)

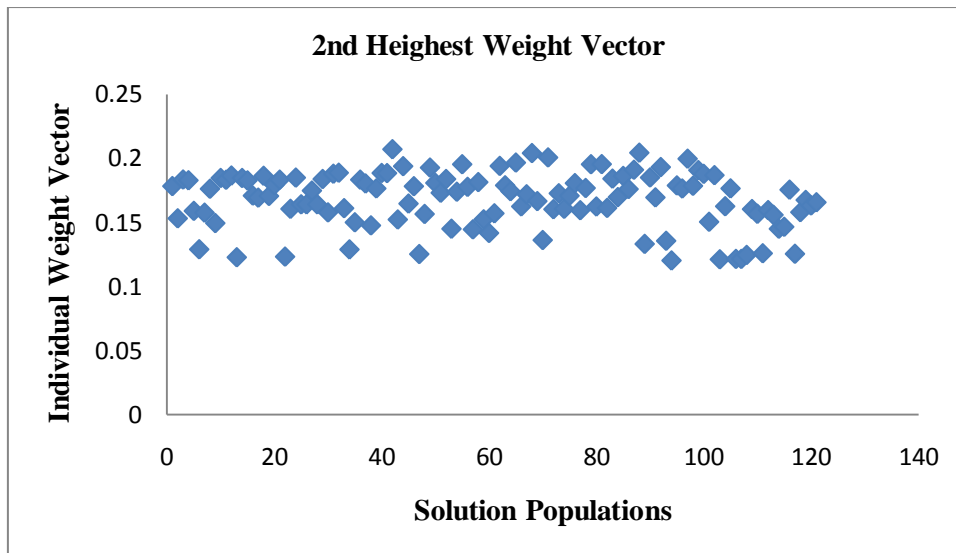


Figure 7.6. The 2nd highest weight vector average solutions (121 populations)

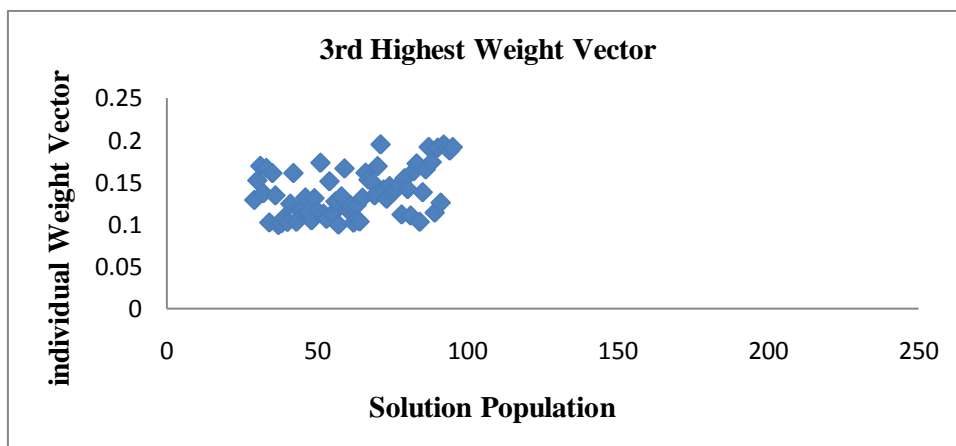


Figure 7.7. The 3rd highest weight vector average solutions (67 populations)

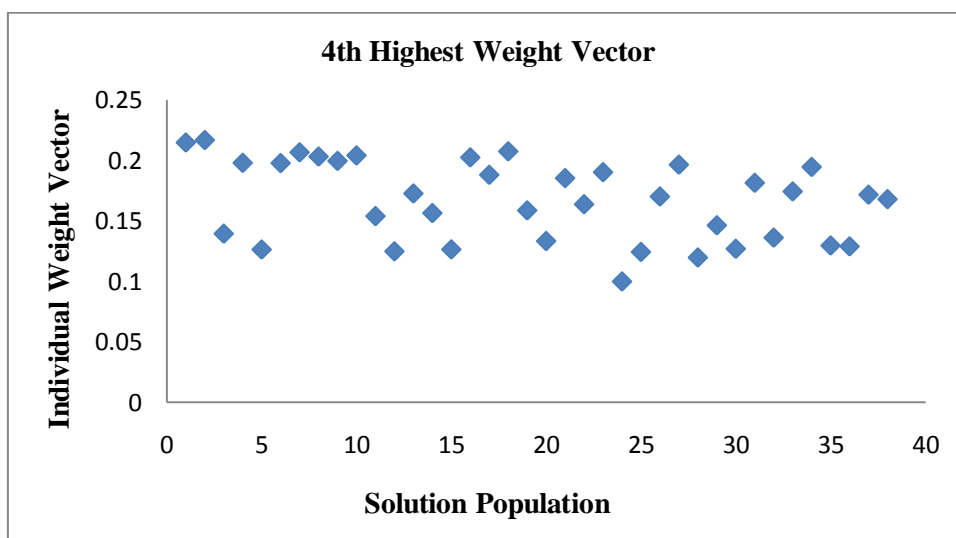


Figure 7.8. The 4th highest weight vector average solutions (37 populations)

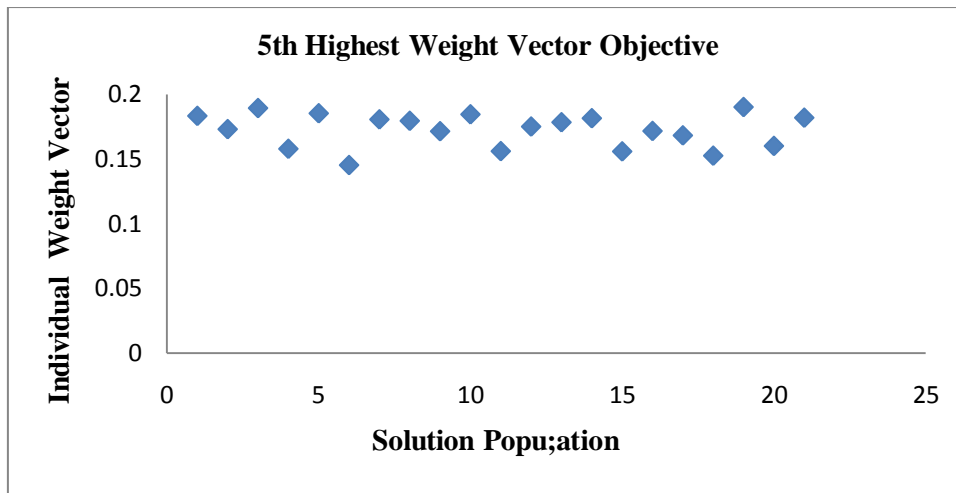


Figure 7.9. The 5th highest weight vector average solutions (21 populations)

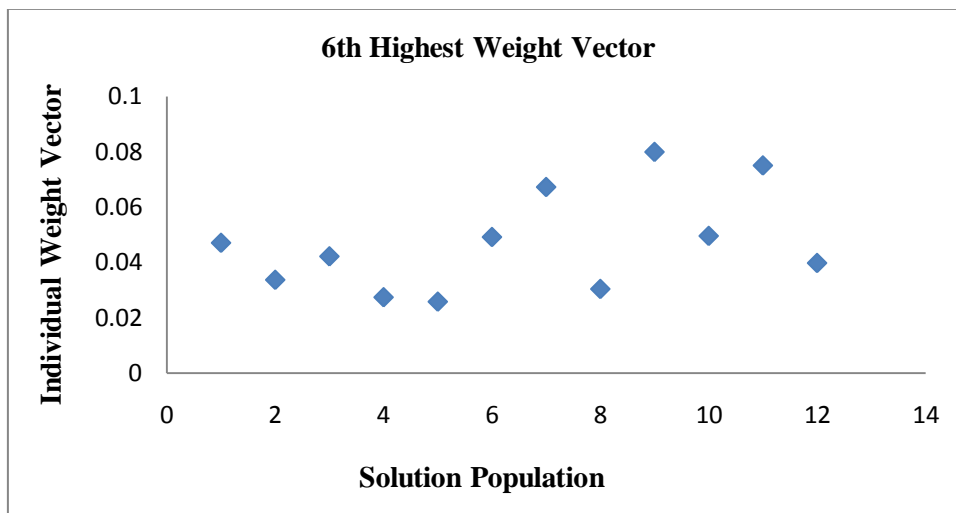


Figure 7.10. The 6th highest weight vector average solutions (12 populations)

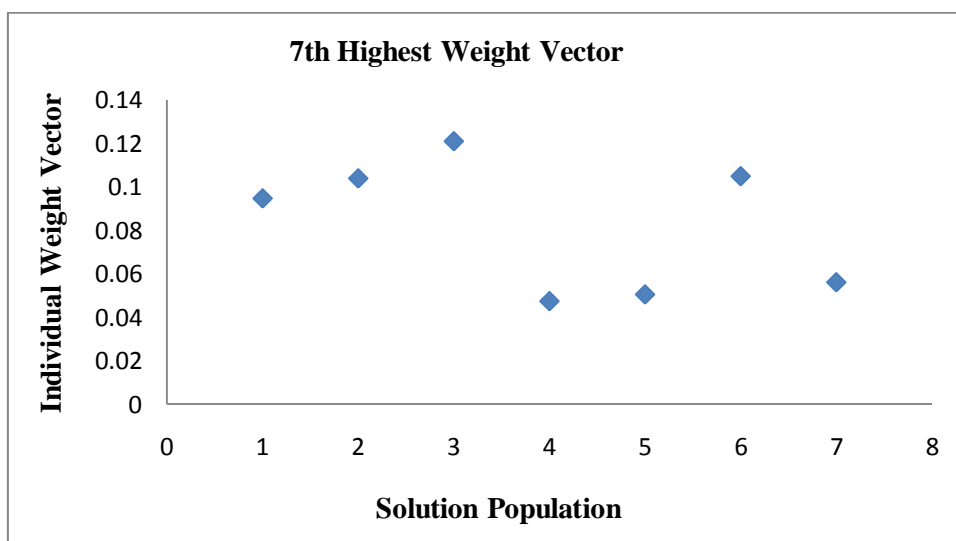


Figure 7.11. The 7th highest weight vector average solutions (7 populations)

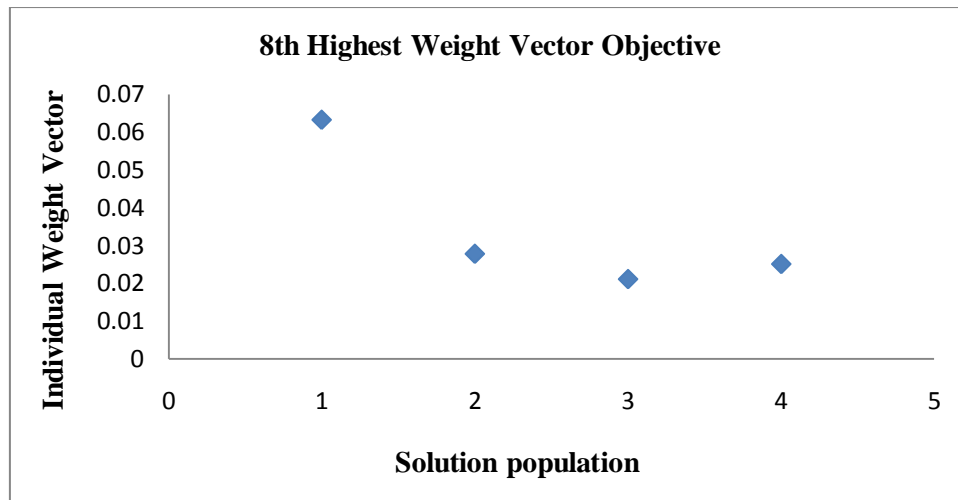


Figure 7.12. The 8th highest weight vector average solutions (4 populations)

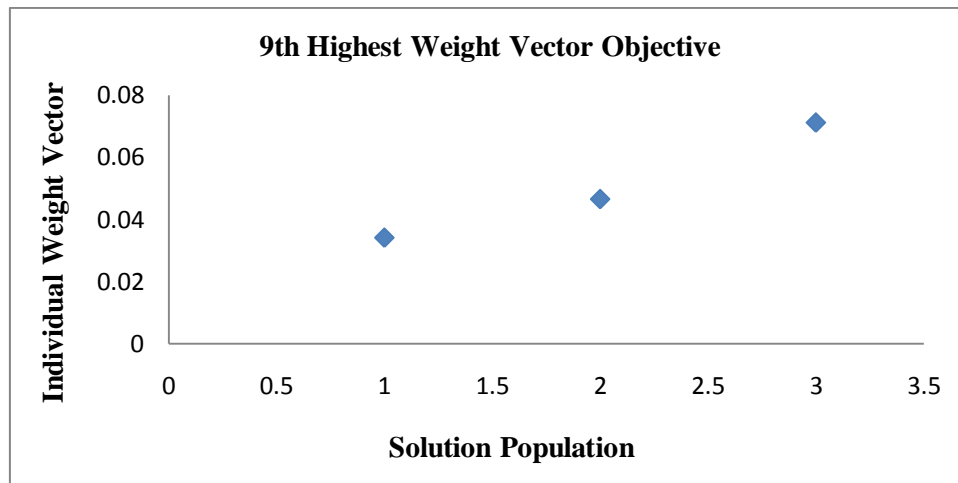


Figure 7.13. The 9th highest weight vector average solutions (3 populations)

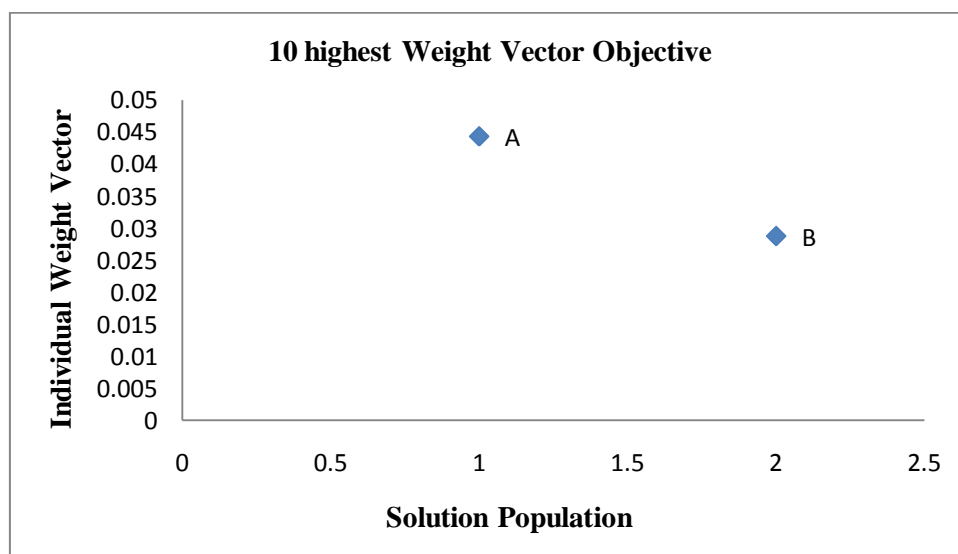


Figure 7.14. The 10th highest weight vector average solutions (2 populations)

Figure 7.14 shows the final best optimal design labelled A and B identified by the technique, from the population of solutions obtained by the GA in the optimisation. Table 7.13 shows an example of the objectives vectors (out of 400 population of solutions) arranged in descending order based on average weight vector and the reduction strategy taking effect in the space to identify the best optimal solution good for all objectives. Table 7.13 also shows the preferred (best optimal) solution at each column identified by the post GA result processing technique. Design shown in red are preferred solutions while the not preferred ones are in black. The example in the Table demonstrate how the technique gradually filtered out the search space and arrived at the final optimal design solution best for all objectives. The bold red numbers in the middle of the Table are the final solution identified, where the corresponding factors in the design space are taken as final best optimal design solution factor parameters for the design problem. The weight vector shown in the Table (Obj-10) identified as the final individual in the row confirming that the final best optimal solution lies in that particular row in the space. The individual solution with the weight (0.0443) in Obj-10 in Table 7.15 represents the point labelled B in Figure 7.14. Following the identification of the preferred weight vectors as shown in Table 7.13, the corresponding actual solution array traced back in to the population of solution from GA, where the actual solution in the objective space and the design parameter set in the decision space can be identified. The solution identified and the descriptions of the solutions are discussed in the result and analysis section, Section 7.2.4.

Table 7.13. Objective (Obj) weight vectors samples showing population reduction before identifying best optimal solution good for all objectives in the search space

Obj 1	Obj 2	Obj 3	Obj 4	Obj 5	Obj 6	Obj 7	Obj 8	Obj 9	Obj 10
0.1732	0.207	0.1189	0.1726	0.1182	0.0496	0.0488	0.0434	0.0367	0.0316
0.1729	0.1523	0.1319	0.1564	0.1853	0.0337	0.0947	0.0137	0.0174	0.0417
0.1723	0.1938	0.1161	0.0448	0.1652	0.1663	0.0528	0.0324	0.0266	0.0297
0.1712	0.1018	0.1251	0.1939	0.1958	0.01	0.0548	0.0228	0.0404	0.0843
0.1709	0.1647	0.1047	0.1264	0.1455	0.0422	0.1039	0.0633	0.0342	0.0443
0.1706	0.1782	0.0035	0.1781	0.1622	0.0182	0.1884	0.0429	0.0333	0.0247
0.1704	0.1254	0.0489	0.1826	0.1683	0.0076	0.1562	0.021	0.0287	0.0909
0.1703	0.0655	0.0896	0.1429	0.17	0.0926	0.1192	0.0222	0.0231	0.1046
0.17	0.1566	0.1311	0.2024	0.1806	0.0085	0.047	0.0247	0.0255	0.0536
0.1698	0.0405	0.0594	0.1526	0.1488	0.0768	0.15	0.0645	0.0294	0.1082

Figure 7.14 presents the final most preferred two solutions, best optimal, for all objectives identified by the search space reduction procedure applied above. The two identified solutions labelled A and B in the Figure 7.14 are equally good and are the final best from which user can choose one depending on particular design requirements. Here in the thesis however, result discussions presented are referring to the solution labelled B in Figure 7.14.

7.2.4 Results and Analysis

Section 7.2.2 discusses the GA based algorithm solving a multi-pass, 5 pass arrangement of continuous rolling, work roll system design optimisation problem, minimising the change in temperature and radial stress at the surface of the roll. Section 7.2.3, presents the strategy for identifying the optimal solution from the results obtained by the GA shown in Section 7.2.2. This section presents and discusses the details of the final optimal design solution identified. The final optimal design solution discussed here includes solutions characteristics, such as the result in the objective space, Table 7.14.A the design factors and factors trends along the passes presented in Figures (7.17-7.23), Section 7.2.4.2. Also presented are the total temperature, (Table 7.14.C) which is the sum total of surface temperature and the roll initial / bulk temperature. The roll bulk temperature is the roll initial temperature before it comes in contact with the hot stock. The roll surface temperature is the additional temperature absorbed mainly at the surface of the roll when the roll comes in contact with the hot stock. Under optimum design rolling operation the additional temperature absorbed by the roll expected to be removed by the cooling system and roll temperature should remain around the initial/ bulk temperature range. The result presented in Table 7.14.C and the respective Figure 7.16 verifies this assessment. The details of the results and analysis are presented as follows.

7.2.4.1. Results

Table 7.14. Roll change in temperature (surface temperature) and total roll temperature after the optimisation (Objective space)

.	No. of passes	1	2	3	4	5
A	Change in Temperature (ΔT in $^{\circ}\text{C}$) (surface temperature)	7.99	6.34	30.1	2.15	-30.0
B	Optimal (initial) roll bulk temperature in $^{\circ}\text{C}$,	59.89	79.60	43.98	40.3	70.2
C	Total Temperature ($(\Delta T + \text{Bulk})$, $^{\circ}\text{C}$	67.88	85.94	74.08	42.45	40.2

Figures 7.15 and 7.16, show graphical representation of the change in temperature (roll surface temperature) and the roll total temperature trend, respectively, along the 5 passes occurred after roll stock contact. The Figures are illustrating the final best optimal design solutions, shown in Table 7.14, obtained in the optimisation. Expected behaviours of the temperature change and total temperature on the roll and analysis of factors behaviours along the passes are discussed in Section 7.2.4.2.

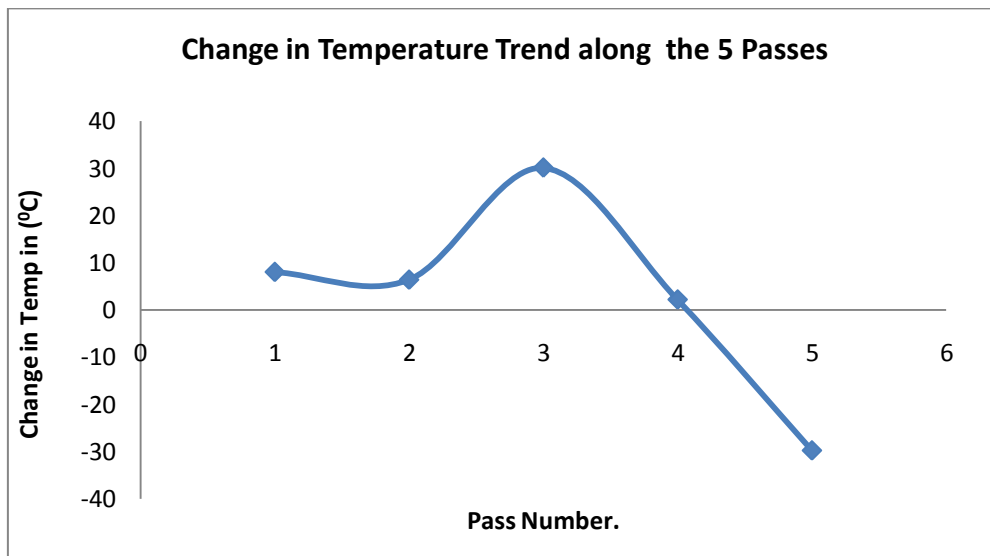


Figure 7.15. Temperature change in rolls along the 5 passes

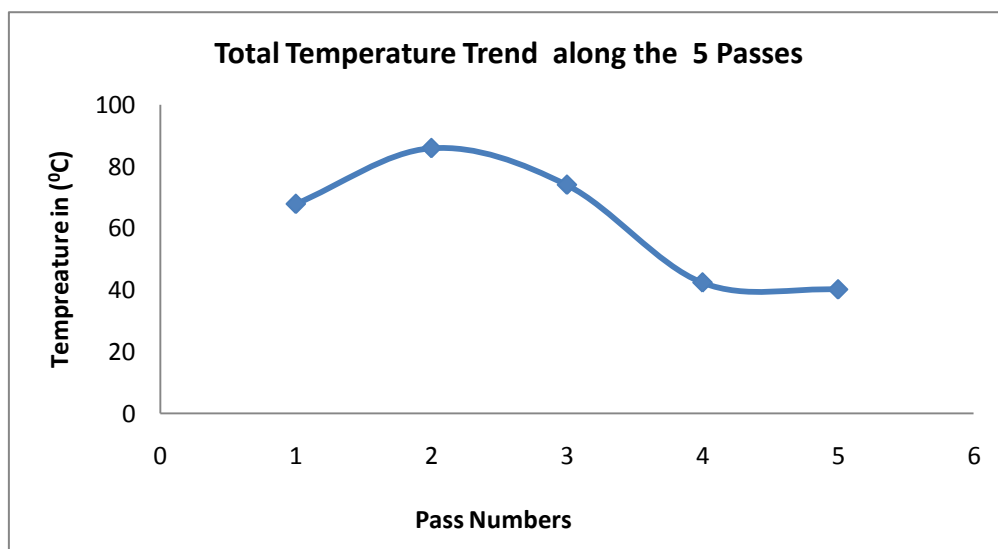


Figure 7.16. Total temperature in rolls along the 5 passes

Table 7.15 shows the optimal design parameters, in each passes corresponding to the objective space results (change in temperature (ΔT) presented in Figure 7.15.

Table 7.15. Best optimum design factors in design space corresponding to solutions in Table 7.14.A in objective space

Design input factors		Optimised parameters
Roll stock contact HTC		14.52 (kW/m ² K)
Stock temperature		1247.51 (°C)
Contact length		22.54 (mm)
Cooling HTC		39.84 (kW/m ² K)
Roll speed		0.15 (rad/sec)
Roll temperature		59.89 (°C)
Delay time		24.24. (mm)
Roll stock contact HTC		13.51 (kW/m ² K)
Stock temperature		1181.09 (0C)
Contact length		14.16 (mm)
Cooling HTC		40.59 (kW/m ² K)
Roll speed		0.19 (rad/sec)
Roll temperature		79.60 (0C)
Delay time		38.79 (mm)
Roll stock contact HTC		8.30 (kW/m ² K)
Stock temperature		1100.60 (0C)
Contact length		14.19 (mm)
Cooling HTC		16.30 (kW/m ² K)
Roll speed		0.41 (rad/sec)
Roll temperature		43.98 (0C)
Delay time		69.45(mm)
Roll stock contact HTC		7.44 (kW/m ² K)
Stock temperature		1011.77 (0C)
Contact length		12.71 (mm)
Cooling HTC		33.17 (kW/m ² K)
Roll speed		0.69(rad/sec)
Roll temperature		40.26 (0C)
Delay time		80.31 (mm)
Roll stock contact HTC		7.69 (kW/m ² K)
Stock temperature		967.34 (0C)
Contact length		10.98(mm)
Cooling HTC		34.40 (kW/m ² K)
Roll speed		0.98 (rad/sec)
Roll temperature		70.17 (0C)
Delay time		100.83 (mm)

7.2.4.2 Discussion of the Results

The research aim is to minimise or keep the roll change in temperature, i.e. temperature increased at the surface when the roll comes in contact with hot stock, within the initial/ bulk temperature parameters (parameter the roll hold before in

contact with hot stock). The optimisation framework developed designed to achieve this by searching for optimal design factor parameters set for the multi-pass rolling process hence guarantee the system operation with minimised roll damage due to thermal effect. The results obtained and presented above, reflect the fundamental of the optimal work roll system thermal design characteristics of a continuous mill. The factors trend also verifies the design factors assumption made initially for designing the continuous mill work roll system optimisation problem. The justifications for optimality, based on the results obtained, can be summarised as follows:

As observed in the review of literature, the temperature condition on rolls varies depending on section of rolling. This is due to the fact that different sections of rolling have different design factors characteristics. At the start of the rolling or the roughing section, particularly in pass 2 and 3, for example, the roll temperature is expected to rise to the highest because of contact with the stock with highest temperature. Normally, the first pass is immune from this because of the build up of scales on the stock due to the delay time of the stock from furnace to the first pass and the application of water to cool it. At the roughing stage, the stock size is relatively higher and roll speed is lower; hence, the contact between roll and stock is also higher. The condition allows the roll to absorb more heat from the stock. As a consequence of these conditions, the cooling heat transfer coefficient and roll bite heat transfer coefficient to go relatively higher as well. However, in the intermediate and finishing stage, the design process factors' behaviours change. As observed in real life practise, the change in factors' behaviours starts at pass 3. This is the stage where the decrease in size of stock, and thus the increase in roll speed starts. The increase in roll speed is a major driving force for other process factors' behaviour change - factors such as contact time and heat transfer coefficient. The sudden drop of these factors can be felt in pass 3 before regaining normality in the subsequent passes. The result obtained using the optimisation strategies developed in the thesis, reflects these facts. For example, change of temperature is expected to lower along the pass, and if the design solution set is optimal, the total temperature, (roll surface and bulk temperature) is expected to be around the roll bulk temperature (temperature before contact with hot stock), Figures 7.15 and 7.16, change in temperature and the total temperature along the passes after optimisation, indicate these facts. As expected, the temperature change trend is descending along the passes, with the exception of pass 3, as shown in

Figure 7.15. Pass 3 shows a comparatively higher temperature value. As stated above, the change in temperature trend is dictated by the roll thermal design factors, such as roll speed, roll bite, heat transfer coefficient, contact length, delay time and cooling heat transfer coefficient parameter behaviours. As presented in Figures (7.17 to 7.23), some of these design factors' behaviour, shows a trend that causes relatively higher change in temperature at pass 3. For example, during continuous rolling, roll/stock contact is lower after the roughing stage, mainly after the second pass. This is due to the fact that from pass 2, the speed and rate of change of speed increase continuously. Ascending speed, delay time and the descending stock temperature are typical characteristics of the continuous rolling process. The decrease in roll stock contact also triggers a sudden drop in roll bite heat transfer coefficient, as shown in Figure 7.21. Usually, the drop regains normality in the next pass. The drop in contact length, (Figure 7.20) and roll bite heat transfer coefficient, as well as the slight increase in delay time between pass 2 and 3, (Figure 7.19) cause relatively lower cooling heat transfer coefficient at pass 3. The drop in cooling heat transfer coefficient, shown in Figure 7.22, has a direct effect on the change in temperature to increase at pass 3, shown in Figure 7.15. However, although these conditions cause the change in temperature trend to be higher at pass 3, the overall trend remains consistently descending along the passes. The final total roll temperature, i.e. the sum of the roll bulk temperature and the change in temperature or roll surface temperature, shows a decreasing trend along the passes as expected. The results also remain within and around the bulk roll temperature parameter considered realistic in real life rolling practise, based on knowledge elicited from expert in the sponsoring company. These indicate that the obtained designs parameter set is a solution that is best optimal for the intended work roll system thermal design problems. The results also demonstrate that the proposed optimisation methodology is able to search solution for the intended multi-pass, multi objective optimisation problems with presence of uncertainty. Figures (7.17 to 23) show optimisation result design factor parameters trend along the 5 passes.

Design Factors trends along the 5 passes

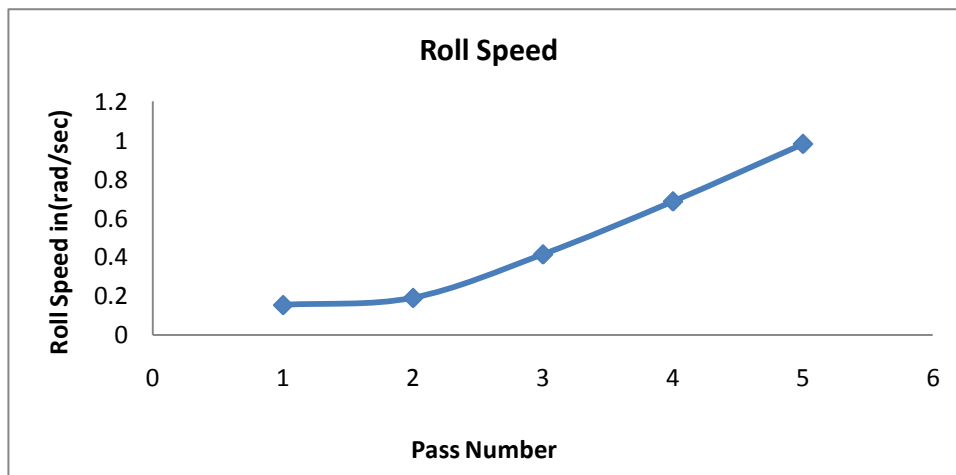


Figure 7.17. Roll speed trend in 5 passes

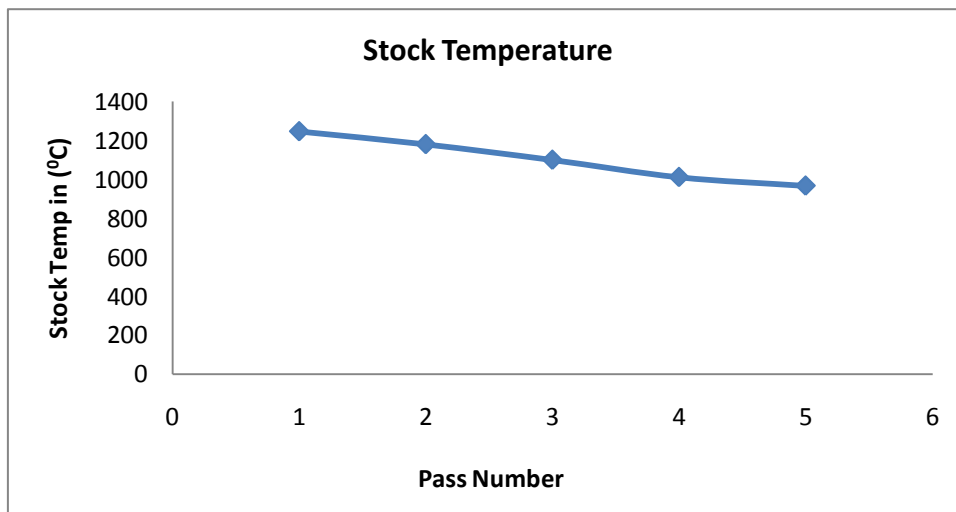


Figure 7.18. Stock temperature trend in 5 passes

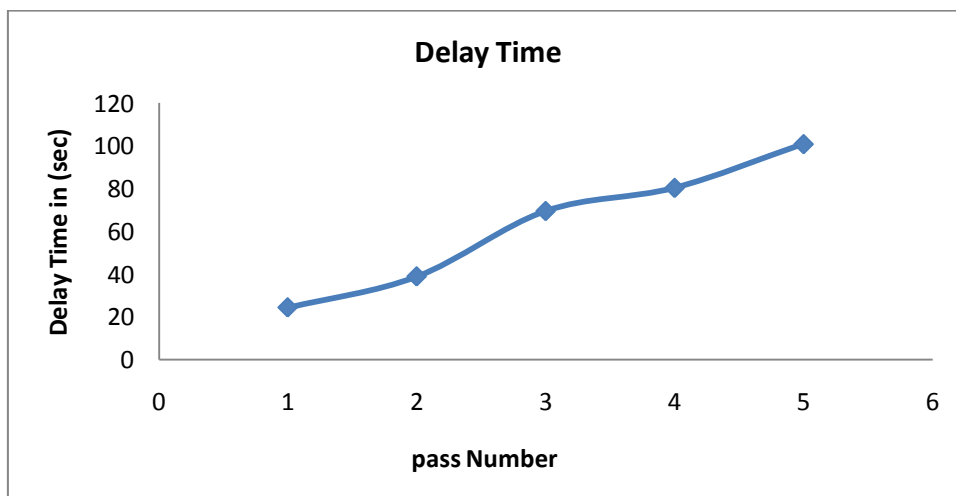


Figure 7.19. Delay time trend in 5 passes

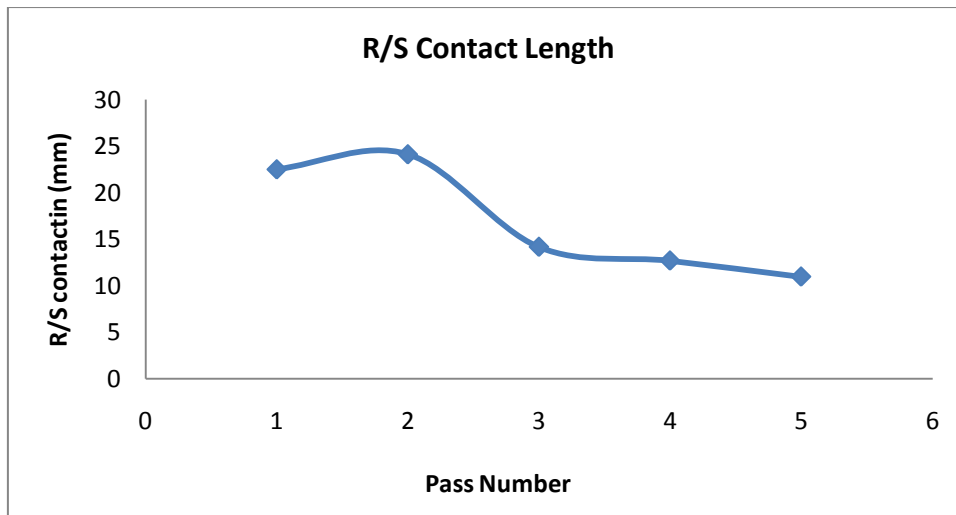


Figure 7.20. Roll / stock contact trend in 5 passes

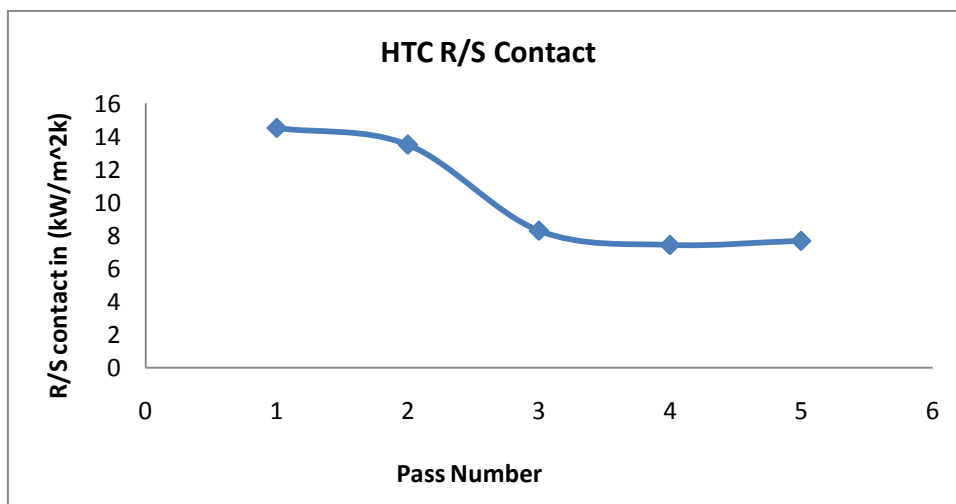


Figure 7.21. Roll / stock contact HTC trend in 5 passes

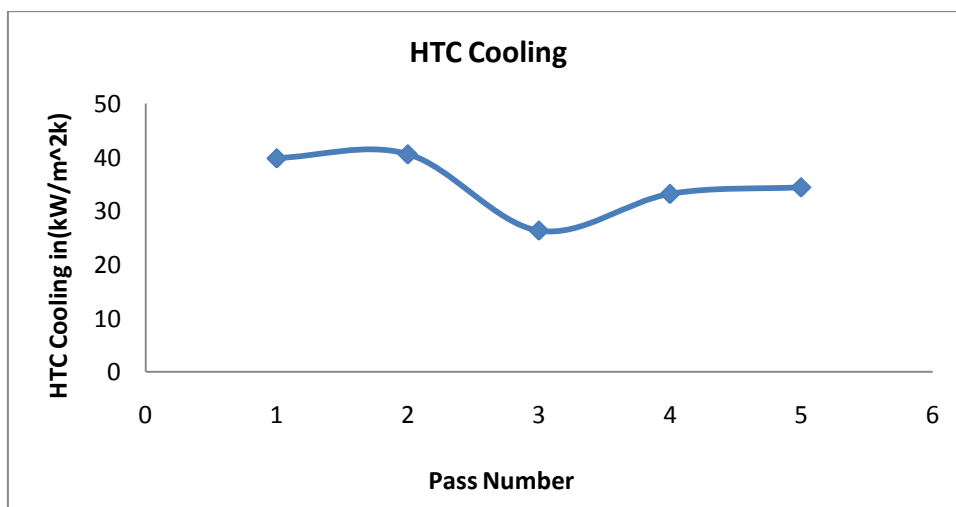


Figure 7.22. HTC cooling trend in 5 passes

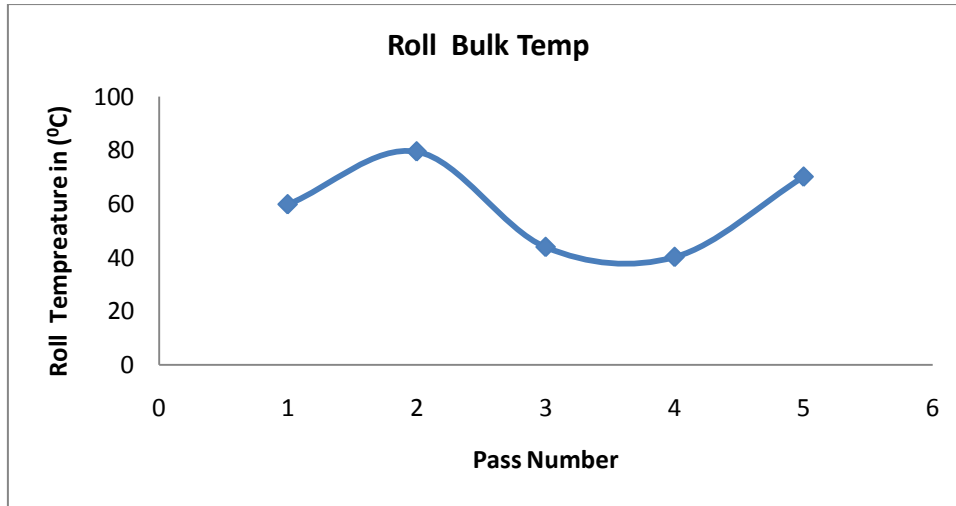


Figure 7.23. Roll bulk temperature in 5 passes

7.3 Chapter Summary

This chapter has demonstrated the successful application of proposed optimisation framework for handling multi-pass work roll system thermal analysis and optimisation problems with uncertainty in the design variables and fitness function. A multi-pass rolling system models have been developed from several sources reported in the literature and information from rolling experts. A 10-objective, multi-pass problem for minimising change in temperature (ΔT) and radial stress (S11) on the rolls' surface has been solved using the proposed GA based optimisation framework and the post GA result analysis strategy. The post GA strategy is used to reduce the search space of the solution obtained by the GA, and arrive at the final optimal design solution/s for the research case study; multi-pass, many objective problems with presence of uncertainty.

As presented in the chapter, the results achieved from the algorithm confirm that the optimisation framework and the post optimisation result analysis developed have been able to search and identify the solution for the research multi-pass problem case study. Furthermore, the results factors trends along passes behave in a consistent manner with what has been observed in the real life work roll system of continuous rolling, confirming the successful application of the solution search strategy. The chapter has achieved the followings:

- Identified issues concerning multi-pass work roll system design, thermal analysis and optimisation problems.

-
- Studied factors and factor parameters involved in the rod rolling process relevant to work roll system thermal analysis and optimisation problem, and identified factors most relevant to the problem.
 - Studied inter-pass design factors relationships as well as uncertainty associated to them.
 - Developed a work roll system thermal models, represent multi-pass rolling real life practise.
 - Applied the developed novel GA based optimisation framework for searching solution for the multi-pass, many objective work roll system design problems in presence of uncertainty.
 - Developed a post GA solution search strategy for (high dimensional) many-objective, multi-pass optimisation problems to identify the final optimal design solution from the population of solution obtained by the GA.
 - Presented the experimental results and the analysis for the multi-pass work roll system optimisation problem obtained using the proposed optimisation framework and post optimisation result analysis strategy.

While this chapter deals with the development of the multi-pass problem models and the solution search strategy to the multi-pass design optimisation problem in presence of uncertainty, the next chapter presents the validation and verification of results.

8 Validation of Results

Chapter 8 presents result validation and the methodology followed to validate the optimisation result consistency in relation to the real life process practise. It also validates the ability of the optimisation framework in dealing with the research problem. The validation was conducted through questionnaires and involves experienced rolling experts and academics. The multi-pass rolling process model was initially generated to capture the real life performance of the work roll system thermal analysis and optimisation problem in presence of uncertainty. The validation process is designed to enquire about the optimisation results and design factors behaviour in relation to work roll system design real life practise hence verifies if the results obtained from the optimisation reflect the real life performance initially captured. The questionnaires are used to gather expert judgement on the results, asking to study result obtained and verify the acceptability of results based on their real life rolling practice experience. The process mathematical models have been validated statistically and the results are presented in Chapter 5, for single pass model and in Chapter 7 for multi-pass models. Therefore this chapter is an additional validation and mainly focused on the validation of optimisation result, based on expert knowledge for single and multi-pass problems. However the chapter also gives brief summary of the validation, based on statistical and experimental trial, used to validate the process models and the optimisation solution convergence. The validation chapter consists of the following sections: Section 8.1 gives brief summary of models and Pareto convergence validations for single and multi-pass cases study. Section 8.2 presents validation of the optimisation results and the performance of the optimisation framework, based on expert opinion. The section discusses also the methodology used for the validation, questionnaire development and presents the extracts of questions and response from experts. Section 8.3 gives chapter conclusions.

8.1 Summary of the Statistical and Experimental Validation

The research applied single pass process model to analyse and validate the performance of the optimisation framework. The validity test with the process model shown in Chapter 6, Figure 6.8 (comparing results from grid search and result from

the proposed GA based optimisation framework) indicates a satisfactory consistency with the underlying work roll system domain. This gives some confidence that provided the optimisation algorithm can find the set of near optimal solutions to the problem in presence of uncertainty; it is likely that the process models are suitable for the optimisation purpose. The presence of the conflicting behaviour of the objectives functions that are used to measure the underlying characteristics of the work rolls system thermal analysis and optimisation problems in the search result is also give confirmation that the models and the framework proposed are suitable for the intended problem. The size of population and generation are determined through experiment. The experiment was conducted using different sizes of generation and running each experiment 10 times i.e. 10 different generations experiments and 10 runs at each generation; hence, a total of 100 experiments are carried out before choosing the population size and generation required for the optimisation. All other subsequent experimental optimisation runs are also repeated so that the consistency of result can be verified before the final optimal design solution recorded.

The single pass and multi-pass models are validated statistically based on post regression analysis and the results are presented in Chapter 5 and 7 respectively. The original mathematical models are also validated for general ability. This is done by conducting 9 FEA runs with the input design variable values selected randomly from the design space. The selected random factors parameters are also fed in to the mathematical model and the results for the 9 selected runs are obtained. The two results, the observed (FEA runs) and predicted (results from the mathematical model) are compared and the error values are calculated. The results, shown in Chapter 5, indicate that the absolute errors are insignificant and below the universally accepted 5 percentage. The result indicate the generic nature of the models, hence applicability for the intend problem.

While this section summarised the statistical and experimental validation carried out for the models and in the optimisation, the next section presents validation, based on expert opinion on the final result from the optimisation. The next section also presents extracts of questions and response from experts verifying the results obtained from the optimisation. To facilitate the validation, questionnaire was developed. The questionnaire is consists of two main parts: the first is to validate the optimisation result of the single pass and multi-pass problem and probe their relevance in relation to real life practise. The second part asks engineers to verify response variables

characteristics (trend) across the five passes. This is vital for determining the integrity and consistency of the multi-pass process models, generated based on factors functional relationships assumption made initially during the knowledge elicitation sessions. Validation of the results, based on experts and the methodology followed for the validation are presented in the following section.

8.2 Optimisation Result Validation based on Expert Opinion

As learnt in the current practise study in Chapter 4, work roll system thermal analysis, design and optimisation is a specialised subject where the knowledge in the domain can only be acquired from specialist with many years experience. Real life process understanding is essential since it gives a wider perspective about the issues concerning the research problem. Hence, in addition to the literature review, a real life current practise study and knowledge elicitation in the research domain was carried out in collaboration with engineers selected from various departments in the sponsoring company. As discussed in the current practise study, Chapter 4, the knowledge from the elicitation serve as the main source for mapping the rolling process factors influencing the work roll system thermal characteristics. This collaboration with the engineers for knowledge gathering also contributed towards identifying the likely areas within the rolling process, cause the roll thermal characteristics change and process factors characteristics along passes, in the multi-pass rolling. As reviewed in the literature, work roll system is a complex process, characterised by high disturbance taking place in extremely hot environments and with a potential that uncertainty can influence the product, tool and the process. Therefore, the collaboration of experts in the elicitation exercise is very valuable in a way that it provides knowledge in the form of qualitatively measured opinion about this complexity, which would have been impossible to find otherwise. The information gathered is the main prerequisite for developing the quantitative models that are generated for representing the real life work roll system problems. Consideration of this knowledge from expert and the quantitative knowledge influence the modelling and the optimisation. The assumption made in determining the design factors, factors parameters and the relation between factors within passes, in the multi pass problem are also influenced by it. The validation of the final result,

based on expert opinion is necessary so that effect of the real life process knowledge elicited and applied in the modelling and optimisation can be evaluated. The verification/ validation must prove the consistency of results in relation to the intended real life work roll system thermal behaviour, as recognised by the domain experts. It also verifies process factors trend consistency in passes in relation to assumed continuous multi-pass real life rolling process behaviours. Section 8.2.1 discusses the methodology followed in the verification/validation.

8.2.1 Methodology for Result Validation

The section present the methodology (structured procedure) used to guide through the validation process, establishing a link between steps within the validation process. The validation involves experts in the research domain who are involved in the initial knowledge elicitation exercise from the sponsoring company and academics who are expert with many years experience in design and algorithm based optimisation techniques. The verification/validation is carried out using questionnaire requesting experts to compare and comment on the process behaviour exhibited by the design solution result from the optimisation to what is perceived normal according to their real life experience. The methodology consists of the following steps:

- Establish what needs to be validated,
- Extract relevant validation information from the optimisation solution (objectives and design space),
- Manage requirements for validations such as developing questionnaire and selecting participants,
- Held validation session with experts, supported by questionnaire,
- Questionnaires feedback analysis and measuring results in relation to what needs to be validated

Schematic view of the procedure followed is shown below.

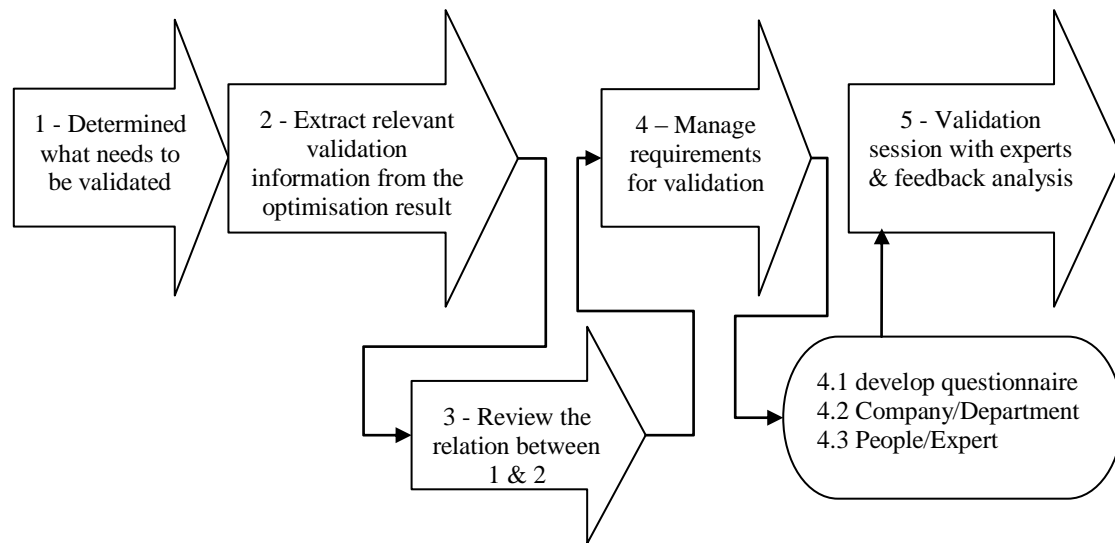


Figure 8.1. Procedure followed for result validation.

Each of the steps in the procedure shown in Figure 8.1 is described as follows:

8.2.1.1 Establishing what needs to be validated

The step identifies the main concern and issues raised during the knowledge elicitation exercise, particularly information related to design factors and factors relationship between passes, in multi-pass modelling and optimisation. As discussed in Chapter 4, rolling is a specialised subject where during the case study the real life process realisation is mainly based on expert's assumptions. The assumption is based on real life practise and made by experienced engineers with many years relevant experience. However the assumption made and used in the modelling and optimisation needs to be verified for consistency, if reflected in the design solution result found by the GA.

8.2.1.2. Extract Data from the Optimisation Results for Validation

Identify the information from the optimisation result relevant to the validation that can verify the issues and concern raised and needs to be validated. The information extracted from the optimisation results (data and Figures) are the prerequisite for the questionnaire development that are used by the experts to express their views of the result found, based on their experience in the real life practise.

8.2.1.3 Manage Requirements for Validation

The section discusses the requirements necessary to carry out the validation. This includes development and implementations of questionnaires, selection of company

and experts/people. The steps followed in the development and implementation of questionnaire, identifying and selecting of company and people are presented shown as follows.

Questionnaire development procedure

A set of questions was developed to describe selected results and factors behaviours from the optimisation. Initially, the questionnaire was piloted with one selected company and expert before it was fully implemented and extended to other establishments and experts. At the beginning, the questionnaire was developed with questions considered relevant and covering the, what needs to be validated. Next, from the wider questions recorded in the initial list of questions, a summarised, second form of questions were developed. The second version contains fewer questions and eliminated any repetitions. The third and final version of the questionnaire also developed through step by step evaluation of the initial list of questions. The third and final version contains questions considered most relevant to the purpose and probe the concern as expected. Here the questions are reviewed and some of the questions rewritten so that questions with similar themes can be avoided. The questionnaire was then sent to experts, accompanied by introductions and requirements - prior to that, contacts had been made to brief participant the purpose of the questionnaire and pre condition agreements. Questions themes and rational behind the questions are shown in Table 8.1A for single pass problem and Table 8.1.B for multi-pass problem.

Table 8.1A. Validation questionnaire theme and aim

No.	Validation themes	Probe aim
Single pass validation		
1	Review solutions and factors trend presented and comment if in line with real life single pass optimal design knowledge?	To verify & confirm the acceptability of the final design solution obtained from the optimisation; hence validate the optimisation framework developed for solution search to the single pass design problem.

Table 8.1B Validation questionnaire theme and aim

No.	Validation themes	Probe aim
Multi-pass validation		
1	Review solutions and factors trend presented and comment if in line with real life multi pass optimal design knowledge?	To verify & confirm the acceptability of the final design solution obtained from the optimisation; hence validate the optimisation framework developed for solution search to the single pass design problem
2	Is the design factors trends & relationships between passes, as found by the GA relevant to the intended problem?	To verify the assumption made during the multi-pass modelling and optimisation. This is done by analysing the design factors in the single pass and factors in each passes and trends between consecutive passes in multi-pass cases.

Selection of organisation and experts/people

The literature shows that the engineering design optimisation techniques are a domain associated with wider disciplines across the industry, mainly with high scale companies such as aerospace and automotives, Therefore, to have the wider perspective of the research problem and techniques available to solve the problem, the current practise study in the research domain was conducted with the involvement of various companies considered most relevant to the research domain, with substantial expertise and willingness to participate in the study. This includes Aeronautics, Automobile and Steel. Hence it would be useful if the validation revisited all those companies and people involved in the initial knowledge elicitation exercise and current practise study. However achieving this was a challenge due to time constrained, resources and experts availability and willingness to participate in the validation process. Due to these constraints therefore it was necessary to limit organisations, expert with relevant experience and have better association with the research. Two organisations found to be fulfilling these requirements and selected for validation. These are: Tata-Steel Europe and Cranfield University. The quality of the validation results are as good as the feedback obtained, and the feedback is as good as the people who participate in the validation. Therefore, the selection of people

/experts is an important step of the process. The experience of participant is crucial. The experienced engineers will give an important insight and true nature of the result obtained and its relevance to real life scenarios. For this reason therefore, a careful consideration has been made in the selection of participants. Table 8.2 and 8.3 are present the pre survey arrangements and survey participants' introductions.

Table 8.2. Pre survey arrangements for validation (People and establishments)

Company A

Rolling expert	Years of relevant experience	Expertise
Expert 1	15 years relevant experience	Long product rolling, design, modelling and optimisation (Tata-Steel Europe)

Table 8.3. Pre survey arrangements for validation (People and establishments)

Company B

Academics	Years of relevant experience	Expertise
Expert 2	10 years	Design, optimisation and soft computing (Cranfield University)
Expert 3	8 years	Modelling and optimisation (Cranfield University)

One expert from the sponsoring company was particularly selected because of his many years of experience and for the reason that he is currently actively involved in the work rolls system thermal analysis and optimisation, within the company. Besides he is the only highly experienced engineers in the field, he is also participating in the knowledge elicitation exercise at the start of the research. Due to his association to the research and the fact that he is well aware of the real life practise problems, he is considered effective and important participant of the validation process. There are two academics with relevant experience, shown in Table 8.3 are also selected. There are

experts in design, optimisation and evolutionary computing. The two academics are particularly useful in verifying the GA based optimisation techniques consistency and ability in dealing with the intended real life design problem.

8.2.1.4 Implementation of Questionnaires

The section above, presents the development of the questionnaire and rationale behind the questions. This section highlights the procedure followed in the implementation. The questionnaires were developed and issued to the interviewees prior to interview day. The interview was conducted based on the questionnaire, and the copy was completed during the interview. Implementation followed the following procedures:

- Sent questionnaire in advance to participants.
- Made contact to arrange and agreed preconditions, date, time and place for the validation.
- Meet-up and conduct interview based on questionnaires. The validation began with a ten minutes introduction, followed by two to three hours session. The discussion was driven by picking and reading question from the list - if the question was clearly understood as intended, then the interviewee gave an answer to it orally and in writing. During this time, the interviewer was also taking notes so that the consistency of the answers given by experts can be verified later during the feedback analysis. The interview concluded with a ten minute summary and closing remarks.

8.2.2 Overview of the Result from the Optimisation and the Result Validation

This section presents overview of the result from the optimisation; the summary of the issues needs to be validated and gives extracts of questions and validation feedback from experts. The questionnaire gives the design factors and their behaviour across the five passes. The selected factors (process factors) shown in Table 8.4 and 8.5 are believed to be an important measures, taken from the results found by the GA in the optimisation, that can describe the real life continuous rolling work roll thermal behaviours. It also verifies the consistency of the design factors and factors relationships assumption made for thermal process modelling and optimisation of multi-pass rolling, in relation to the real life practise as elicited from experts and observed in real life rolling process in the industry. The section also gives brief

overview of the design solution obtained ability in keeping the change in temperature on the roll as intended (minimal). The section has two parts. The first part (Part A) is for single-pass validation and the second part is the validation for multi-pass problem case (Part B and C). The work roll process factors selected for result validation are shown in Tables (8.4 and 8.5).

Table 8.4. Multi-pass factors chosen for verification

Design factors in i (i = Pass number, where $i = 1...5$
<ul style="list-style-type: none"> • Roll speed trend along passes • Stock delay time trend along passes • Stock temperature trend along passes • Heat Transfer Coefficient (HTC- Cooling) along passes • Roll / Stock contact length • Roll/Stock contact HTC

Table 8.5. Optimisation results selected for validation

Results in single and multi-pass cases
<ul style="list-style-type: none"> • Change in temperature in the single pass problem • Change in temperature of rolls at each pass and along the passes

The optimisation result shown in Table 8.4 and 8.5 reflects the fundamentals of work roll system thermal design characteristics. The results graphical illustrations are given in Section 8.2.2.1 (A, B and C). Based on the result the fundamentals of the work roll system thermal design characteristics can be summarised as follows:

As demonstrated in the results (A, B and C) rolls temperature and stress conditions vary depending on the process sections and pass positions. Other important characteristics such as speed of rolls and stock temperature have also follows real life rolling process characteristics. The speed of rolls increases along the path from one pass to the next, (Figure 8.6). At the same time temperature decreases along the line from pass to pass, (Figure 8.7). The most important finding is the roll temperature profile. As shown in Figure 8.5 the roll total temperature, (bulk + surface temperature) remain within the minimum range (40°C - 80°C) usually considered in real life rolling practise and as expected higher roughing stage (pass1 & 2). This is because of the high intensity of stock temperature at that stage. However it is also observed in the result that the total temperature and the change in temperature at pass 3 is higher. However this occurrence is possible and expected provided the following

justifications met. As observed in the review of literature, the temperature condition on rolls varies depending on section of rolling. This is due to the fact that different sections of rolling have different design factors and parameter characteristics. At the start of the rolling or the roughing section, particularly in pass 2 and 3, for example, the roll is expected to have the stock with highest temperature - normally, the first pass is immune from this because of the build up of scales on the stock, due to the delay time of the stock from furnace to the first pass, and water spray to cool it. At the roughing stage, the stock size is relatively higher and roll speed is lower; hence, the contact between roll and stock is also higher. The condition allows the roll to absorb more heat from the stock. As a consequence of these conditions, the cooling heat transfer coefficient and roll bite heat transfer coefficient to go relatively higher. However, in the intermediate and finishing stage, the design process factors' behaviours change. As observed in real life practice, the change in factors' behaviours starts at pass 3. This is the stage where the decrease in size of stock, and thus the increase in roll speed starts. The increase in roll speed is a major driving force for other process factors' behaviour change - factors such as contact time and heat transfer coefficient. The sudden drop of these factors can be felt in pass 3 before regaining normality in the subsequent passes. The result obtained using the optimisation strategies developed in the thesis, reflects these facts. For example, change of temperature is expected to lower along the pass, and if the design solution set is optimal, the total temperature, (roll surface and bulk temperature) is expected to be around the bulk (temperature before contact with hot stock) roll temperature. Figures 8.4 and 8.5, change in temperature and the total temperature along the passes after optimisation indicate these facts. As expected, the temperature change trend is descending along the passes, with the exception of pass 3. Pass 3 shows a comparatively higher temperature value. As stated above, the change in temperature trend is dictated by the roll thermal design factors, such as roll speed, roll bite heat transfer coefficient, contact length, delay time and cooling heat transfer coefficient parameter behaviours. As presented in Figures 8.6 to Figure 8.11, some of these design factors' behaviour, particularly at pass 3, shows a trend that causes the change in temperature at pass 3 to be different. For example, during continuous rolling, roll/stock contact, (Figure 8.9) is lower after the roughing stage of rolling, mainly after the second pass. This is due to the fact that from pass 2, the speed and rate of change of speed, as shown in Figure 8.6, start to increase. The higher the speed is the

lower the roll/stock contact time. The decrease in roll stock contact also triggers a sudden drop in roll bite heat transfer coefficient, as shown in Figure 8.10. Usually, the drop regains normality in the next pass (pass-3). The drop in contact length and roll bite heat transfer coefficient, as well as the slight increase in delay time between pass 2 and 3, shown in Figure 8.8, cause relatively lower cooling heat transfer coefficient at pass 3, Figure 8.11. The drop in the cooling transfer coefficient has a direct effect for the change in temperature to increase at pass 3. However, although these conditions cause the change in temperature trend to be higher at pass 3, the overall trend remains consistently descending along the passes. The optimisation results, as illustrated in Section 8.2.2.1, (A, B and C) are also showing these characteristics. The single and multi-pass optimisation results discussed in this section and the graphical illustrations given are the information used in the verification of results and validity of the optimisation technique developed to search for optimal solutions to the research problem. Expert express their opinion based on these evidence provided. The extract of the questionnaire and expert answers are presented next.

8.2.2.1 Extract of Validation Questions and Experts Responses

Extracts of questionnaires and responses from experts are presented in three parts. The first part (Part A) gives the validation for single pass problems. Part B and C are the validation for the Multi-pass problem, showing objectives results and factor relationship trends between passes respectively.

A Single Pass problem Validation

Figure 8.2 and Figure 8.3 present the solutions obtained for single pass optimisation problems with uncertainty. The results are temperature condition in rolls at the surface as well as depth, 9mm and 15mm below the surface of the roll. And another important information observed from the result is the roll total temperature trend, i.e. the surface temperature + initial/bulk roll temperature), (Figure 8.3). The question shown in Table 8.6, supported by graphical illustration of the optimisation result obtained are presented to experts to comment and verify if the result obtained is matching with what they know in the real life practice. Results, with the corresponding questions and expert responses are presented in Figures 8.2- 8.3 and Table 8.6 respectively.

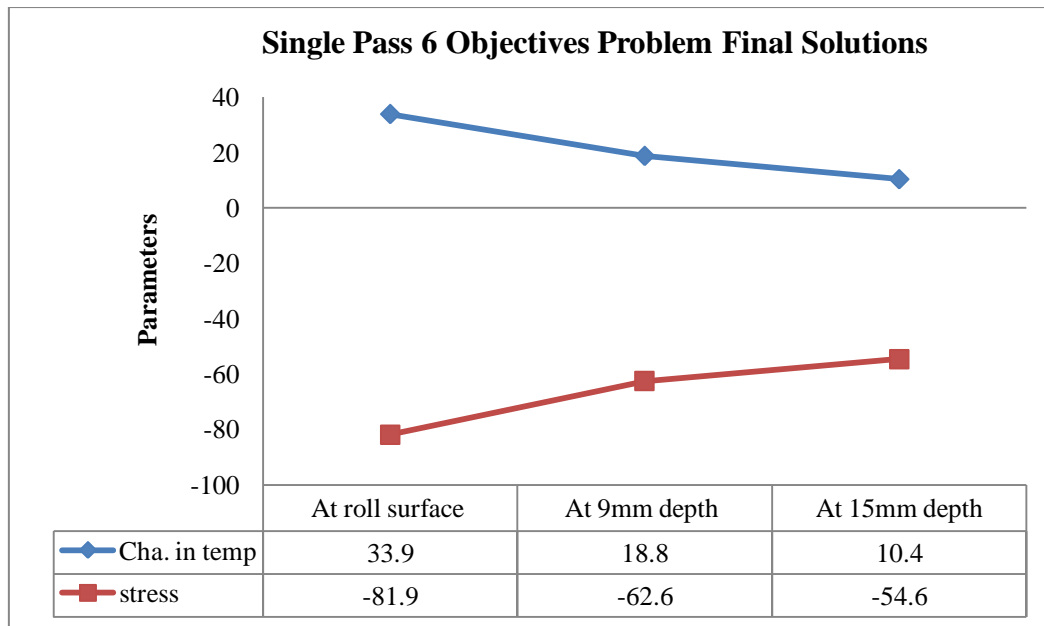


Figure 8.2. Single pass results for change in temperature in ($^{\circ}\text{C}$) and radial stress in (MPa) at roll surface and depth below the surface

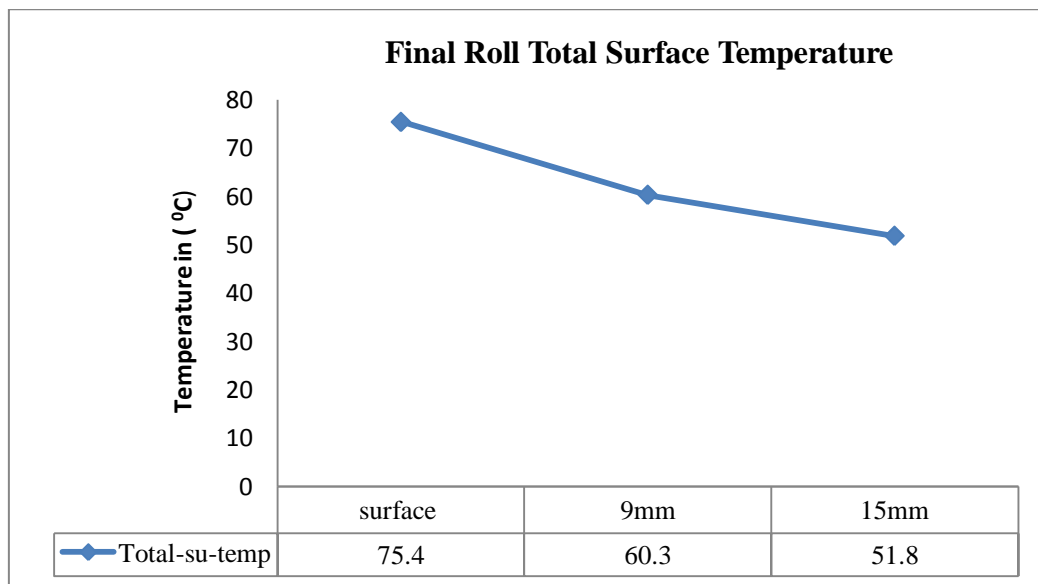


Figure 8.3. Final Roll temp profile (surface + bulk initial roll Temp in [$^{\circ}\text{C}$])

Table 8.6. Questionnaire 1. Single pass rolling design optimisation main objective
(change in temperature)

	Yes	No
Is the trend in Figure 8.2 and 8.3 going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results above, please comment if any inconsistencies or observations you may have,	Comments	
	The trend is plausible. As expected the total temperature trend decreased steadily going to the centre of the roll. The rate of change at depth between 9mm and 15mm is slowing, implying that heat effect below the surface is minimal.	

B Validation Questionnaire and Results for Multi-Pass

This section presents questions and responses from experts, shown in Table 8.7, validating the solution obtained by the GA in the optimisation. Figure 8.4 and Figure 8.5 are the selected solution for verification, change in temperature at roll surface and rolls total temperature at each pass of the multi-pass of the five passes.

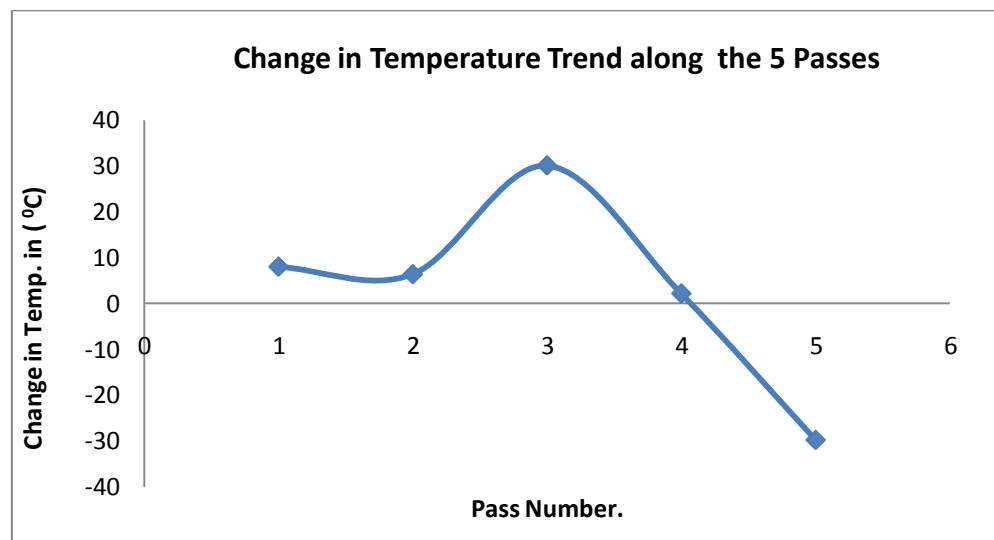


Figure 8.4. Temperature change result

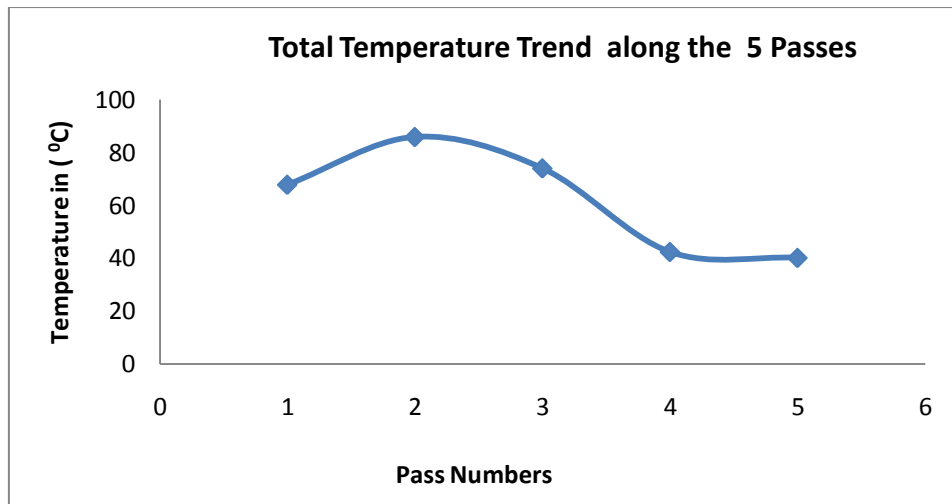


Figure 8.5 Total temperature profile of rolls at each pass

Table 8.7. Questionnaire 2. Multi-pass change in temperature in rolls, result trends along the 5 passes

		Yes	No
Is the change in temperature and total temperature trend along the passes going in the direction that agrees with real life rolling process knowledge?		Yes	
Based on the results in Figure 8.4 and 8.5, Please comment if noticed any inconsistencies or observations you may have.	Comments		
	The trend is plausible. As expected the total temperature decreased steadily from pass 1 to 5, and within the roll initial imposed bulk temperature range (adding the change in temperature and the initial imposed bulk temperature). This implies that the design solution obtained does control the temperature at the roll surface bite, However there is a slight increase in pass 3. As suggested this may well be that HTC cooling is slightly lower at pass 3, also related to other process factors behaviour presented.		

C Inter-Pass Verification

This section presents summary of questions and responses from experts presented in Tables (8.8-8.13), verifying the characteristics of response variables across the five passes. This is necessary to verify the consistency of the design factors that are used in the modelling and optimisation of the continuous mill. The verification begins by analysing the roll exit speed, which is the most important factor in the process where its characteristics influence other process factors, associated to the work roll thermal characteristics. Figure 8.6 and Table 8.8 gives the work roll exit speed profile and the corresponding questions feedbacks form experts respectively. The section also presents extracts of questions and expert feedbacks for other design factors validation.

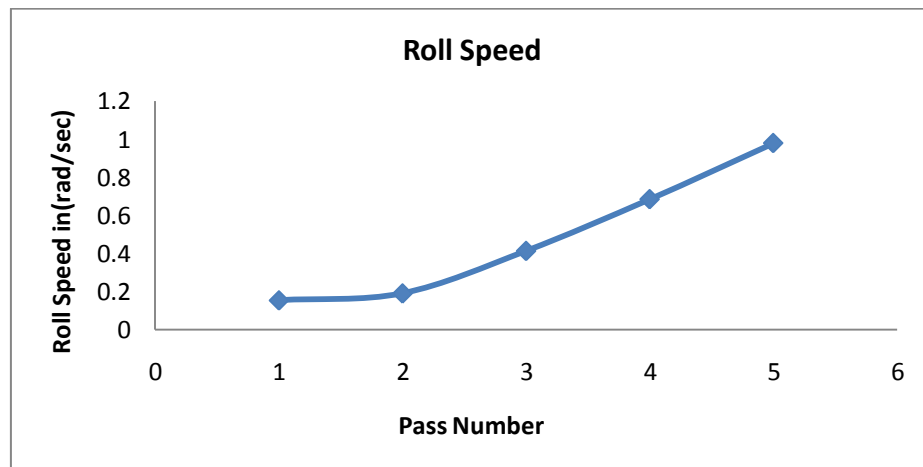


Figure 8.6. Roll speed profile

Table 8.8. Questionnaire 3. Multi-pass exit speed design factor result trends along the 5 passes

	Yes	No
Is the exit speed trend along the passes going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results in Figure 8.6, Please comment if any inconsistencies or observations you may have you may have	Comments	
	The exit speed remain consistently ascending from 1 st pass to the last, as this should be the case for continuous mill.	

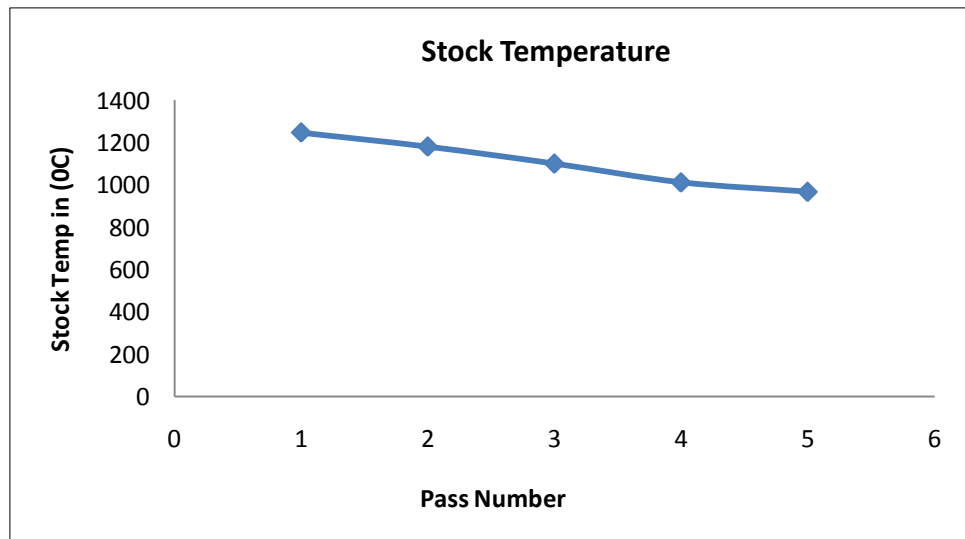


Figure 8.7. Stock temperature profile

Table 8.9. Questionnaire 4. Multi-pass stock temperature trends along the passes

	Yes	No
Is the stock temperature trend along the passes going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results in Figure 8.7, please comment if any inconsistencies or observations you may have.	Comments	
	The trend remain constant from 1 st pass to the last, as should be the case for continuous mill	

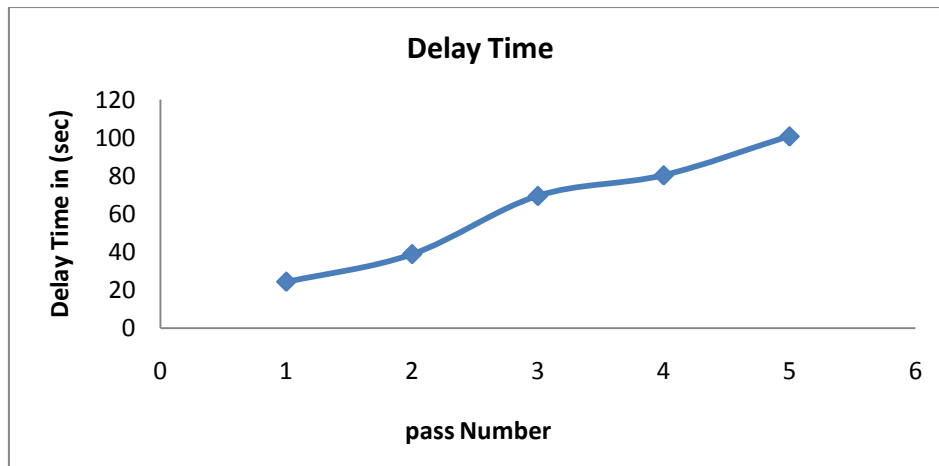


Figure 8.8. Delay time between passes profile

Table 8.10. Questionnaire 5. Multi-pass delay time design factor result trends along the 5 passes.

	Yes	No
Is the delay time trend along the passes going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results in Figure 8.8, Please comment if noticed any inconsistencies or observations you may have.	Comments	
	This is expected in continuous mill. If the graph trend was different, the initial assumption having a continuous mill would have been lost.	

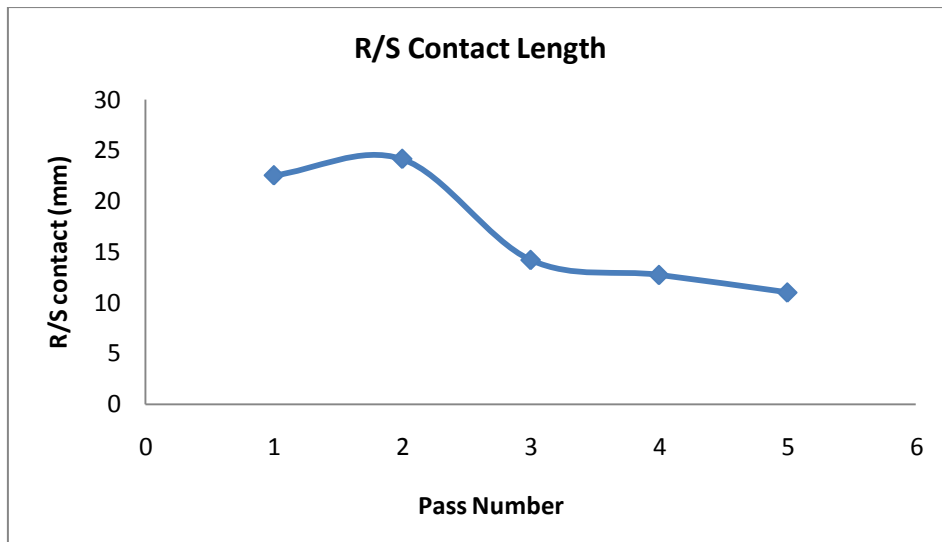


Figure 8.9. Roll / stock contact profile

Table 8.11. Questionnaire 6.Multi-pass contact length design factor result trends along the 5 passes

	Yes	No
Is the contact length trend along the passes going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results in Figure 8.9, Please comment if any inconsistencies or observations you may have.	Comments	
	The contact time followed roll exit speed. Trend as expected. Although this factor is now a free variable, it can be used as constraint, depending on the rolling schedule.	

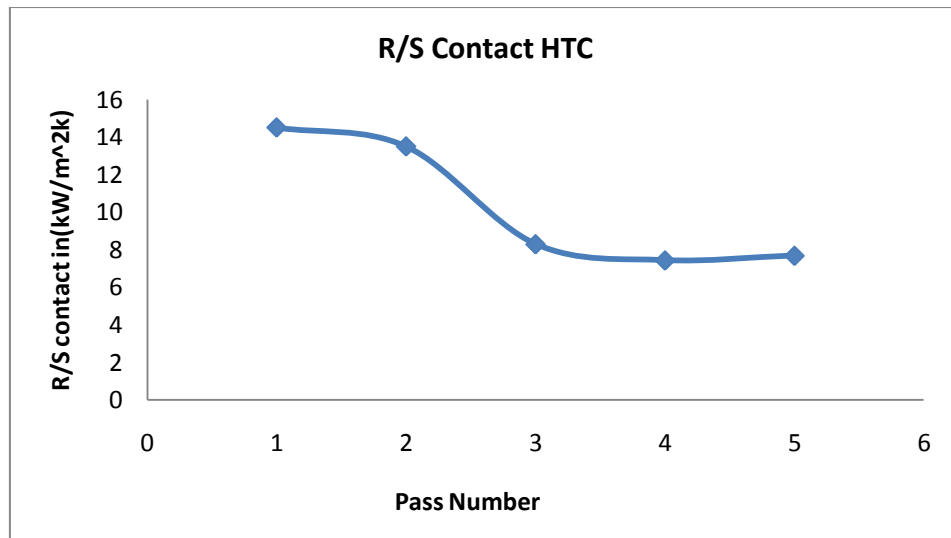


Figure 8.10. Roll / stock contact HTC profile

Table 8.12. Questionnaire 7. Roll/Stock contact HTC design factor result trends along the 5 passes

	Yes	No
Is the roll/stock contact HTC trend along the passes going in the direction that agrees with real life rolling process knowledge?	Yes	
Based on the results in Figure 8.10 Please comment if any inconsistencies or observations you may have.	Comments	
	The trend is consistent HTC contact expected to decrease along the passes following the decrease in contact length and the roll speed.	

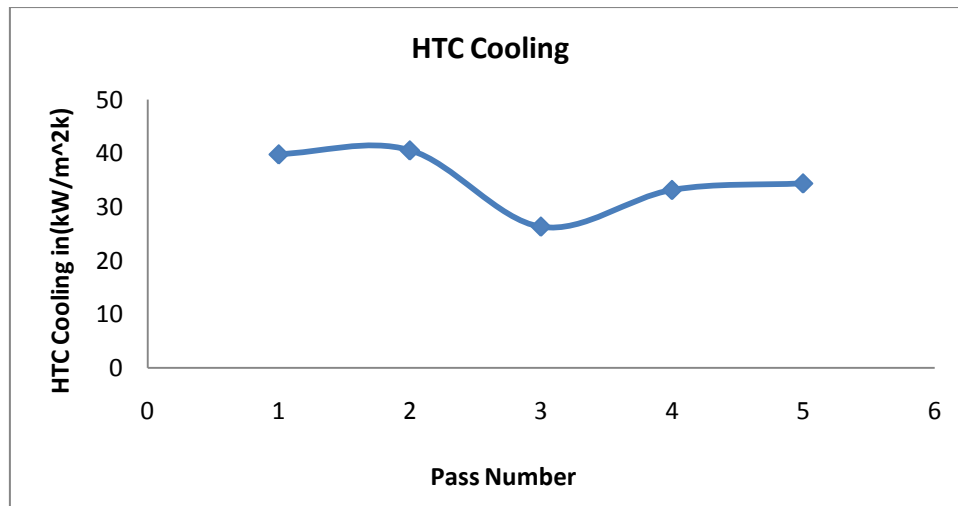


Figure 8.11. HTC cooling profile

Table 8.13. Questionnaire 8. HTC-Cooling trends along the passes

	Yes	No
Is the overall HTC-Cooling trend along the passes going in the direction that agrees with real life rolling process knowledge?	Ok	
Based on the results in Figure 8.11 Please comment if any inconsistencies or observations you may have.	Comments	
	<p>Relatively slight drops in HTC- cooling at pass 3. This could be, depending on HTC in roll bite and contact length.</p> <p>(A sudden drop in HTC roll bite could cause a drop in HTC cooling and then regain normality in the next passes)</p>	

Validation Result Observations

Analysis of the results presented in the sections confirms that the optimal solutions obtained from the proposed algorithm behave in a consistent manner with the results obtained from validation. For example, the exit speed at each pass increases as the pass progresses, and the roll/stock contact time correlates with that (as seen in Figure 8.6 and Figure 8.9,). Also observed is the decrease in stock temperature and steady

increase in delay time along the pass as shown in Figure 8.7 and Figure 8.8. These are typical features of a continuous mill rolling, as it is the case in this research. The results, as confirmed by the domain experts are good optimal design solution for the intended, continuous mill arrangement, single and multi-pass work roll system problems, with presence of uncertainty in the design variables and the mathematical models. The result from the validation can confirm also the ability of the developed optimisation framework for searching solution to the intended design optimisation problem.

8.3 Chapter Summary

This chapter has demonstrated the successful application of the validation procedure used to verify the result obtained and the applicability of the proposed optimisation framework for handling the intended work roll system thermal analysis and optimisation problems with presence of uncertainty in the design variables and fitness function. Work roll system thermal analysis and optimisation problem models have been developed from several sources reported in the literature and information from rolling experts. Single and multi pass many objective, problem for minimising change in temperature (ΔT) and radial stress (S_{11}) on the rolls have been solved using the proposed GA based optimisation framework and post GA result analysis strategy. The post GA strategy is used to reduce the search space of the solution obtained by the GA, and arrive at the final optimal design solution/s for the research high dimensional many objective problems using the search space reduction techniques applied on the population of solutions found by The GA. Questionnaire are developed based on information from the obtained final results and presented to experts. Experts are asked if they agree or disagree with the result and comment if they see any inconsistency in the result in comparison with what is perceived normal in the real life practise. The questionnaires are prepared to verify the goodness and acceptability of design solutions obtained. It is also verify the assumption (factor inter-pass relationship) taken during the multi-pass system modelling and optimisation. A numerical representation (modelling) of hot work roll system thermal analysis and optimisation problem was developed using sources from expert and real life process observations. Following the knowledge from expert's the design input factors and parameters are identified. The knowledge acquired helps particularly for making assumption for inter-pass factor relationship used in the multi-pass cases modelling. The models later

used as a fitness function in the optimisation for searching optimal good design solutions for the research multi-pass problem. This verification is vital for assuring the validity and realistic assumptions made in the modelling and optimisation process that reflect the real life work roll system knowledge. As the responses from the experts indicate, the optimisation successfully search and found the design solution for the research problem as intended. The response from expert's shows also that they are satisfied that based on the information provided the design factors behaviour is in line with what is perceived normal in the real life practise hence the results obtained from the proposed approach not only identify good solutions, but also provide insight into the complex behaviour of the design factors relationships.

While this chapter has demonstrated the successful application of the validation/verification of the optimisation results, the next chapter gives discussions of results and conclusion of the thesis.

9 Discussions and Conclusions

This chapter concludes the thesis with a summary of the findings of the research with respect to the aim and objectives set in chapters 3. The chapter is organised as follows. Section 9.1 summarises the key research findings and observations. The research contributions and achievement outlined in sections 9.2. Section 9.3 discussed the research business benefits. Section 9.4 highlights the limitations of the research followed by future work in section 9.5. Finally, section 9.6 concludes the research by highlighting the success in relation to the research objectives outlined in Chapter 3.

9.1 Research Findings and Observations

Roll consumption represents a major part of rolling cost. Many researches in the field conclude that thermal deterioration of the rolls is more severe than other wear mechanisms. Even though some materials such as cemented-carbide rolls are good enough to withstand thermal stresses due to their excellent heat conduction property, the cooling problem however is much more severe, since more heat is conducted into the roll body and when coolant applied to it. it will experience thermal shock. The thermal conditions at the interface between work rolls and the stock have been studied by a number of researchers and all universally accepted that rolling temperature is an important factor in determining roll wear and roll life. If the temperature concentration in the outer layer of the roll is not timely controlled with optimal cooling it can lead fatigue hence shorter roll life. The most noticeable roll wear due to heat is the thermal fatigue. It is observed that the existing solution strategies for work roll system thermal analysis and optimisation within the rolling process are not capable of delivering timely, high quality design solutions to the problem. The work roll system thermal design and analysis is mainly manual and not integrated with the existing rolling system design. These gaps coupled with the complexity of the rod rolling thermal analysis and optimisation problems, such as presence of uncertainty and constraints have motivate for developing more structured and scientific technique to search design solution that overcome these problems.

This research aims to explore the fields of GA for developing techniques that are capable of searching solutions for the work roll system thermal analysis and

optimisation problems, characterised by constraints, uncertainty and high dimensionality. The key observations of this research are summarised as follows:

9.1.1 Understanding the Research Problem

The review (industrial and literature) presented in the thesis has identified features of process optimisation problems and justified the work roll system thermal analysis and optimisation as a process optimisation problem qualified for the research case to be investigated. The review carried out on the existing technique in relation to process quantitative modelling; GA based optimisation approaches, quantitative, uncertainty and constraint search space, multi and single pass rod rolling thermal analysis and optimisation. The review identified gaps in these areas which motivates the proposition of this research.

Rolling takes place in high disturbance and extremely hot environment where live experimental work to improve process can be highly compromised. Although there are classical techniques that have been used to solve the design problem, they are limited in efficiency in terms of application, such as FE based computational techniques. The FE method although provides various detailed information it can be difficult to analyse and incur expensive computational cost. Literature review revealed that although there have been attempt to embed finite element analysis with optimisation algorithm so that improve the search (as well as known as online optimisation) it was proved that the computational cost and solution quality is still a problem. It is also that the complexity of the problem due to presence of uncertainty, which needs to be studied qualitatively, based on expert reasoning, makes this type of application difficult. For these reasons and the fact that due to the high dimensionality and multi objective nature of the problem the online optimisation is not a preferred way forward for solving such problem. Due to the significant modelling potential in representing a real life process however the finite element method is an integral part of the problem solving process. The finite element methods although it is a powerful technique for modelling and analysing, it cannot be used for identifying optimal solutions since they are not capable of an algorithmic search. Hence this led to the study and development of GA based optimisation techniques. The optimisation aims to find an optimal design solution for single and multi-pass work roll system design problem with uncertainty and constraint using thermal analysis and GA based optimisation technique. The real life optimisation problem is represented by a finite

element based quantitative model. A review of literature revealed that the current methods of optimising the work roll system thermal analysis and optimisation problem is not intelligent based. The few reported evolutionary based techniques are not capable of dealing with real life problem complexity such as uncertainty, high dimensionality and constraints. In addition, none of the reported existing techniques for rolling system design optimisation incorporate the work roll system thermal analysis and optimisation problem addressing, multi objectives, multi pass with presence of uncertainty in the design factors and fitness functions. To address these issues the research reviewed the existing techniques and strategies to realize the knowledge gaps. The knowledge obtained from review of literature,, industry real life process observations and knowledge elicitation help to understand the problem domain, develop a solution search technique, devise uncertainty handling techniques and a post optimisation result analysis strategy for searching optimal good solution from the populations of solutions obtained by the GA based optimisation technique. Review findings relevant to the research problem are summarised as follows:

- Lack of suitable single pass process quantitative model for work roll system thermal analysis and optimisation problem.
- Understanding uncertainty and sources of uncertainty in the rolling process relevant to the work roll system design thermal analysis and optimisation.
- Lack of Multi-pass work rolls system thermal analysis and optimisation quantitative process model that address inter-pass relationship.
- Lack of single pass optimisation framework for searching optimal design solution for work roll system thermal analysis and optimisation problem in presence of uncertainty and constraints. (Uncertainty both in the design variable and fitness function).
- Multi-pass, many-objective (high dimensional) optimisation approach for the work roll system thermal analysis and optimisation problem with presence of uncertainty, in the design variables and fitness function.
- The need for Post optimisation result analysis strategy for identifying optimal best design solution to the high dimensional many objective problems.
- Although there are few techniques reported in the literature to deal with uncertainty in the design problems, they are limited to single objectives and lack real life case study application. None of the reported techniques able to

deal with the many objective, real life work problem system design problem with uncertain design variables and fitness functions

The following section presents concluding remarks on the strategy and development carried out to address the problems in those areas.

9.1.2 Quantitative Model Development

This section discusses the approximate model-building frameworks for both single pass and multi-pass work roll system thermal analysis and optimisation problem. The modelling takes mechanical, thermal and thermo mechanical process information so that it can replicate the real life process. The main idea of developing the approximate quantitative model is to reduce the complexity of the design problem and time. Due to the nature of the process, such as disturbance and uncertainty, real world problems such as rolling system are very complex for carrying out real life physical experiment. To overcome this inconvenience the research proposes and used a quantitative modelling framework. The proposed framework is based on statistical design of experiments and response surface methodology. Both of these approaches are widely accepted in industry for generating approximate models representing the underlying behaviour of the process. The fundamental advantages of the approximate model can be summarised as follows:

- It provides the important correlation between the input design variables and output response variables.
- It facilitates, as the 1st step, the information to be used for wider application such as high dimensional and multi-objective complex optimisation problems.
- Reduce time and cost by providing fast information analysis capability otherwise would have been difficult in online (in a real life) process optimisation.

9.1.3 Uncertainty Information in Design Optimisation

Literature review shows that uncertainty is a major part of most process design problems such as work roll system thermal analysis and optimisation. For realistic optimal design to be found, the uncertainty information needs to be considered in the optimisation. In specific design optimisation problems, uncertainty information in the form of qualitative reasoning is mainly available from experts with many years experience. Expert use their qualitative knowledge to solve design problem, mainly in

unstructured, manual trial and error form. This information however is in its basic form; it's discrete and not generic in application. It is also that when used it require an extensive amount of rules to capture the system behaviour and only possible for individual experts with many years experience. In a scientific approach this information can be quantified and incorporated in the optimisation so that a better design can be found with less time and cost. In addressing this issue the research proposed an uncertainty information use, by incorporating with the quantitative model in the algorithm based optimisation technique, so that a reliable optimal design solution can be found. Uncertainty in engineering design can be also from the approximate model. As discussed in Chapter 2, the quantitative model is an approximation of a real life process; hence there is a degree of incompleteness in accuracy. These are may be due to statistical error such as rounding of numbers, inherited errors from the system. The developed optimisation technique is designed to address this problem too when searching for optimal design solution for the work roll system thermal analysis and optimisation problem.

9.1.4 Validation of the Quantitative Model

The research has validated and tested the developed quantitative models using statistical measures and expert opinion. The statistical validation used to measure the deviation of the response model from the true simulation model. As shown in section 5.3.10 and section 7.1.3 in all cases the models predict well. All of the models have high R^2 and R values. The p-values are also, as expected in all cases are below 5%. In summary it appears that these models predict well and are therefore considered suitable for approximating the intended process and hence used in the optimisation for searching optimal design solution for the research problem. The models are further validated by experts (academic industrial) who are involved in the initial knowledge elicitation exercise.

9.1.5 Quantitative and Uncertainty Information in Work Roll Thermal Analysis and Optimisation

The section discusses the observations made when addressing the optimisation problem using the process quantitative model and uncertainty information. The research is designed to search optimum design solution for single and multi-pass problems. However in both cases dealing with a multi or nowadays called many

objective optimisations problems. As a result, the optimisation frameworks developed in this research are based on multi-objective optimisation principles. The following sections presents the multi-objective optimisation technique for searching a design solution for the work roll system thermal analysis and optimisation problem with uncertainty in the design factor and fitness function, using the quantitative model as fitness function.

9.1.5.1 Single-Pass, Multi-objective Optimisation using Quantitative and Uncertainty Information for Work Roll System Thermal Analysis and Optimisation Problems.

In engineering and process optimisation, it is universally accepted that it is desirable to find the best set of compromise solutions to multiple objective problems. As it is a compromised solution however the results do not always give the desired solutions but optimal solution. The thesis has adopted a GA based technique to search best balanced solution for design and optimisation of work roll thermal design problem. The thesis proposed the GA based technique for addressing the multi-objective problems with uncertainty. The review of literature disclosed that GA based techniques are robust and offer the potential for achieving a good diverse set of near optimal solutions when applied to real world problems. This led to the adoption of the technique in this research. However the AS_IS GA based techniques are not able to address complex problems hence required to be made available in such a way that it is fit to the problem specific requirements, the problem requirements such as dealing with uncertainty and constraints. The GA based technique called NSGA-II optimisation techniques proposed, in this research, is designed to accommodate these requirements. The quantitative models discussed above were adopted as a fitness function in the multi-objective optimisation framework. The research applied the developed fitness function model to analyse the performance of an individual design. Previously explained validation of the quantitative model indicates a satisfactory consistency with the underlying characteristics of designing the real life work roll system thermal analysis and optimisation. This gives assurance that, provided the optimisation algorithm could find the set of near optimal solutions, it is likely that the model developed will be suitable for optimisation purposes. The optimisation framework has also validated for its convergence and diversity hence ability for searching solution for the intended multi-objective and complex optimisation

problem. The validation is performed based on observation made on result from the Grid (exhaustive) search and the developed algorithm search. As indicated in Chapter 6, Figure 6.9 the comparison of the result of the random search and the result achieved from the algorithm confirms that the solution algorithm has been able to converge to the near Pareto front with a good spread of solutions. This shows that the optimisation algorithm is capable of finding a near optimal solution, confirming its ability for dealing with the intended multi-objective optimisation problem. The algorithm further validated by repeating the same procedure but this time comparing the results from random search from the algorithm (problem with no uncertainty) and result from algorithm with presence of uncertainty. The results are conclusive, showing that the Pareto front of the search algorithm with presence of uncertainty lying close to the true Pareto front with good spread of solutions, This suggest that the proposed algorithm is capable for searching the design solution for the problem with uncertainty. Presence of uncertainty in the decision space, uncertainty in the fitness function and uncertainty both in the decision and fitness function have been experimented. In all cases the algorithms able to find optimal solution as expected. Conclusion of research overall validation is presented in Section 9.1.6.

9.1.5.2 Multi-Pass, Many-objective Optimisation using Quantitative and Uncertainty Information for work roll system Thermal Analysis and Optimisation Problems

The many objectives (more than two objectives) GA based optimisation framework is a technique designed to deal with high dimensional (many objective) problems with uncertainty. The multi-objective optimisation technique discussed in section 6.1 selected due to its flexibility and adaptability so that can be tailored to fit to the nature of the research problems. The technique is used for solving the optimisation problems with uncertainty in the design variables and fitness functions, regardless of the problem dimensionality such as number of objectives and number of design variables. It has been applied for searching solution for single pass rolling using quantitative models developed from data taken at roll surface and at various depths below the surface before extended to search design solution for multi-pass problem. In the single pass problem case the technique aim to increase the search space so that robust design solution, tolerate the effect of temperature from roll surface to depth below the surface, can be found. In principle under normal circumstances, if right type of roll

selected for specific type of rolling process and other associated rolling conditions, such as cooling, the temperature of rolls remain in the outer layer of radius (R_i) of the roll. Temperature below the surface at radius (r_i) should remain insignificant. The term (r_i) is the corresponding radius of the work-roll below which transient temperature variations during rolling can be considered insignificant. Thus, it is assumed that only the outer layer of thickness of the roll experiences thermal cycling. As shown in the research, there are various contributing factors determining the depth of the heat affected area R_i . If the heat penetration zone reach beyond the radius R_i , and accumulated to the r_i and beyond, it will cause rapid damage to the roll. Depth of heat penetration zone can be determined experimentally and also as used in this research using mathematical relationships of thermal, mechanical and process factors of the rolling process.

The developed framework for single-pass work roll system thermal analysis and optimisation problem with uncertainty then extended to include the multi-pass problem with uncertainty in the design variables and fitness function. The multi-pass quantitative model is developed to represent a complex behaviour of a real life multi-pass rolling process in a simplified and controllable manner. Unlike the single pass the multi-pass problem design and optimisation needs to address the important inter-pass relationship so that the continuous multi-pass rolling mill characteristics can be addressed. The important characteristics such as rolling system design factor dependencies among passes and their dynamic behaviour from one pass to the next. Those multi-pass rolling behaviours are accommodated in the multi-pass models before used in the optimisation as a fitness functions. Optimisation with high dimensional problem, with many objective search spaces has the obvious shortcomings. This is the inability to visualise the Pareto front. Here the GA based optimisation technique gives the users only a population of solutions to choose from but not the most desired design point. To overcome this problem the research proposed a search space reduction techniques that help to gradually filter the search space of the population of solutions found by the algorithm and arrived at the desired best optimal design solution or solutions. The post optimisation technique applied for identifying the best optimal design solution for the intended many objectives research problem from the population of solutions obtained by the GA. Concluding remark about the proposed post GA result analysis for searching the final best optimal design solution is presented in the following section.

9.1.5.3 Post GA Result Analysis for Identifying Optimal Design Solution

The optimisation run discussed above have produced the design solution for the single and multi-pass problems. The GA based optimisation search solutions (Pareto set) that are good, compromised between all the objectives in the problem. The post GA results search space reductions strategy discussed in section 6.4.3 and 7.2.3 is proposed to identify the final best optimum solution/s from the population of solutions set identified by the GA. The strategy for searching the final optimal design solution applied in the single and multi-pass many objective optimisations problem. The post process strategy is based on applying weight vector in the objective space. Later the weight vector average are calculated and based on the average the objectives are prioritised within the space. The highest weight average given the highest priority hence recognised as the most important weight vectors. In the same way all other weight average are also ranked. According to weight average priority, the weight vectors are then rearranged within the space in descending order. Next is the application of search space reduction of the rearranged weight vectors in the objective space. The reduction is based on a percentile. The percentile is determined through experiment. Applications of percentile to individual ranking weight vector gradually reduce the search space and arrived at the final best optimal design solution to the problem. Post GA result analysis is an important step of the design solution search process. In real life engineering design and optimisation problems such as work roll system thermal analysis and optimisation, identifying the final best optimal design solution has an advantage, particularly saving time. Engineers can use the identified best design solution in the process directly instead of having a population of potential design solutions to choose from.

Summary of the post GA result analysis strategy are as follows:

- Convert (the result from GA) in the objective search space in to weight vectors; hence all the values are normalized by giving them values range between 0 and 1. The weight indicates how important the vector is with respect to the other vectors in the same row. The higher the weight is the better with respect to the formulation of the problem. In this research a minimisation problem formulation sought hence a vector with high weight indicates a better solution.

-
- Calculate the average weights of vectors that are in the same column within the search space. This is an important step in the process because it helps to find a common ground for the various weights vectors in the columns. The calculated average weights of vectors make it easier to make comparisons with other vectors in columns within the search space.
 - The vectors weight averages are compared and the weight with higher average is given the highest priority/rank. The highest vector average is most important with respect to the problem formulation. The highest weight average considered superior to all other objectives in the search space. The vectors of this average are then arranged in descending order. The superior average weight vectors found are the best solution set found in the objective space.
 - The vector weight are then arranged within the search space in descending order, with the highest weight vector average found above is 1st. This is an extra step designed to reduce the search space so that the final best optimal design solution can be filtered out. The search space reduction carried out using a percentage. A repeated application of percentage in the search space (through all weight vectors) leads to the identification of the final best optimal design solutions.

The identified best design solutions then projected back in to the original design solution results from GA for locating the actual results parameters in the objective space and the corresponding design solutions factors parameters in the decision space.

9.1.6 Research Validations

There are a number of steps taken to measure the convergence of the results in the optimisation and also the validity of the final solutions with respect to the intended research problem. Results were obtained using the developed process model, which had its own statistical and expert opinion based validation process. The validation of procedure in the research summarised as follows:

Pareto Convergence Test

As observed in all algorithm based optimisation research work reviewed in the literature, none of them are proposed mechanisms that help to determine or predict in advance the convergence of solutions in the optimisation. In majority of the cases convergence criteria test are based on trial and error. In this research a similar

technique has been adopted for testing convergence. The experiment aimed to determine the size of population and generation needed to guarantee convergence with minimal computational time. The experiment conducted as the following:

Before deciding the population and generation in the optimisation, there are 10 independent GA runs (with varying generation and population size) have been performed. Each run repeated 10 times, but with similar generations. A total of 100 runs are performed. After the experiment the population 400 and generation 1000 has been selected. These results is from the typical population and generation set obtained from 10 runs giving smooth ,continuous and convex Pareto front. In almost all cases examined, the runs give similar results, i.e. no improvement recorded hence the set from the final run (10th run) taken as final.

Random Grid Search

A random grid search also conducted in order to get an indication of the search space and also used to identify the likely presence of a Pareto front in the design problem. The result from grid then compared with random solution from proposed GA based optimisation technique. The comparison indicates a clear convergence. The result is converged to the near optimal Pareto front locating a reasonable spread of multiple optimal solutions. The result indicates the ability of the GA finding the best optimal design solution to the problem. The presence of a Pareto front also confirms the conflicting relationship between the objectives, change in temperature and radial stress on the roll.

Result Validation Qualitatively (Expert Opinion)

Later the results are verified with the rolling experts and academics for validity. Experts asked to verify if the design solutions and design factors behaviours (trend) are matched with what is perceived realistic in real life process. This is an important part of the validation since it represent expert judgements of the result obtained from the optimisation and its relevance to real life work roll system thermal analysis and optimisation problem. The verification must prove that the result obtained represents the intended behaviour as recognised by the domain experts. The verification is carried out supported by questionnaires asking engineers to compare the results and design factors behaviour exhibited by the optimisation to what is the perceived normal according to their experience in real life practise. As presented in Chapter 8, analysis

of feedback from questionnaires indicate that experts are satisfied that the algorithm find solutions for the work roll system thermal analysis and optimisation problem. Academics asked to assess the optimisation technique solution searching activity, solution obtained and its relevance to the case study problem. Section 9.2 presents the overall achievements and contribution of the research.

9.2 Research Achievement and Contribution

This research has made a significant contribution to the understanding and handling of uncertainty, quantitative information and high dimensional many-objective multi and single pass work roll system thermal analysis and optimisation. The research has provided a framework for modelling quantitative and uncertainty information from the finite element data, suitable for simulating process problems. The research has also proposed two optimisation frameworks for handling many-objective and high dimensional constrained design problem with presence of uncertainty in the design space and fitness function. A percentage reduction method introduced to identify the final best optimal design solution from the population of solutions found by the optimisation framework. The contributions to knowledge made from the research work presented in the thesis are outlined as the followings:

- The research carried out a literature review to explore the capabilities of existing techniques for optimisation and addressing the quantitative, uncertainty and constraint information in single and multi-pass rolling process, for searching optimal robust design solution for work roll system thermal analysis and optimisation problem. The findings from the literature review disclose the need for suitable techniques to address these issues. The need has led to the development of the frameworks presented in the thesis.
- Development of a modelling framework for building a process models for a single pass work roll system thermal analysis and optimisation. The proposed methodology used for generating process models from numeric finite element data. The developed (6 quantitative) models are used later in the optimisation as fitness function for solution search for the design problems.
- Developed a quantitative work roll system thermal analysis models to replicate many objectives, multiple passes showing relationship between the passes.

-
- The research has developed multi-objective framework for searching optimal design solution for work roll system thermal analysis and optimisation for single pass rolling, presenting a novel technique for addressing quantitative information and uncertainty in the design variables and fitness function.
 - Demonstrate the application of constraint criticality of design solutions and rank criticality so that give users options to choose a design based on the constraint criticality to the design and its relevance in relation to requirements.
 - Developed many objective work roll system thermal analysis and optimisation framework for addressing multi-pass optimisation problems with uncertainty in the design space and fitness function.
 - Introduce a technique for post optimisation result analysis for identifying best optimal solution for the high dimensional design problem, from the population of solution found by the algorithms.

9.3 Business Benefit

The ultimate goal of researches is to add value to business and the value is measured by the benefit the business will attain from the research. Some of the main business benefit of this research are summarised as follows:

- Knowledge sharing and improve information efficiency
- Knowledge capture and reuse
- Minimised process and production cost
- Minimised tool changing time, repair time and production down time due to tool change over.

The business, in which the research associated to, such as new product development benefit from the modelling and optimisation developed in this research. Rolling cost estimated to be 5% to 15% of the overall steel production hence establishing an optimal roll thermal design is vital to prolong rolls working life. Longer roll working life reduce time required for maintenance such as roll dressing and cost of ordering of new rolls. The optimisation frameworks have also a greater impact on the business in the form of knowledge sharing, knowledge capture and reuse, as well as time and cost saving. The source of those impacts to the business can be summarised as follows:

As stated in the thesis the developed optimisation framework is able to generate multiple optimal solutions in a single run for the given work roll system thermal

analysis and optimisation problem. This means that a set of good optimal design solutions for many objectives, constraints problem with uncertainty is found in less time and cost i.e. the more costly and time consuming, iteration, trial and error of manual technique will be avoided. More over it also improve the quality of the solution since the techniques has the ability to explore large design space in short period of time giving good quality solution. For example the technique searches a design space to find optimal solution for work roll system thermal analyses and optimisation problem at roll surface and at depth below the surface in a single run. Similarly design solution for multi-pass arrangement process problem found in a single run. The technique also able to accommodate the ever increasing concern of rolling engineers, i.e. the complex characteristics of the rolling thermal analysis and optimisation problems such as uncertainty, constraint, high dimensionality and inter-pass relationship in the multi-pass rolling process. The modelling and optimisation framework was developed taking initially quantitative and qualitative information from various experts from the problem domain. Knowledge captured from experts is an integral part of the modelling and optimisation process. Since the rolling thermal analysis and optimisation problems behaviour is a specialised subject, it can only be fully understood by engineers with many years experience. Most of the true nature of the process characteristics is in the engineers mind. Capturing this knowledge and incorporate it in the modelling and optimisation make that knowledge to be reused and available to wider users. The wider users can use this stored knowledge in timely bases when required. Another most valuable aspect of the knowledge capture and reuse is that it provides opportunities to address problems that could not be solved with quantitative information. In this research incorporating design variables and fitness function uncertainty in to the optimisation for searching design solution to the problem is one of the objectives. Uncertainty information is mainly qualitative in nature. Knowledge elicited from expert is the main source used to understand and quantify the uncertainty. The knowledge captured and incorporated in to the optimisation help to improve the framework in the following way.

- Improve information efficiency so that a more realistic problem solution can be found.
- The uncertainty knowledge captured and incorporated in to the framework can be reused repeatedly.

-
- Helps to make better and reliable decision making.

These have a valuable reflection on the business and contribute to engineers work satisfaction. These achievements and its business benefit presented in the sections above confirm that this research has fulfilled the anticipated research objectives outlined in Chapter 3. The achievement expected to enhance process to the business section associated to the research domain in particular, and in the wider context add value to the company.

9.4 Limitations

The research achieves the aim and objectives set out at the start of the research. The section above presented also the business benefits from the research achievements to the company. The research was conducted within the parameters of certain conditions that are directly relevant to the research problem. Besides due to cost and time there was a need to prioritise and limit the conditions of the research. This section outlines the limitations in the approximate modelling and optimisation.

9.4.1 The Approximate Model for Work Roll System Thermal Analysis and Optimisation (Single-Pass)

The approximate model developed is validated and successfully applied in the optimisation as fitness function for searching optimal solution to the design problem as intended. In future work however the modelling can be improved to address the limitation in the following areas:

- The approximate model is developed to replicate the rolling process thermal, mechanical and thermo-mechanical behaviours and design factors associated to them. In the modelling however only few most relevant factor among the large number of potentially important design factors are selected. This is due to the fact that accommodating large number of factors will have a greater impact on computational cost.
- This research incorporates the uncertainty (data accuracy compromises) that may occur during data transfer between tools, in this case for example data from finite element analysis and statistical tools. Although the possible loss of data accuracy has compensated in the fitness function during the optimisation, the data collecting and handling is manual work, it is time consuming and requires considerable space for data storage.

9.4.2 The Approximate Model for Work Roll System Thermal Analysis and Optimisation (Multi-Pass)

In addition to the general limitation of the approximate model behaviours outlined in Section 9.4.1, the multi-pass approximate models have the following limitations:

- The approximate process models are representing the fundamental rolling theories. In most cases the modelling of multi-pass process is formulated with many assumptions. These assumptions may influence the quality of the models in capturing the real life process behaviour. They are prone to lack of absolute completeness and over-simplification.
- The approximate process models are suitable for continuous forward rolling process where the design variables from one pass influence the performance of the subsequent pass. Hence is not suitable for other type rolling arrangements known as an unordered multi-pass problem such as backwards and forwards process.

9.4.3 The Optimisation Framework for Single and Multi-Pass Problem

Limitation of the framework for handling the many objectives single and multi-pass optimisation problem is highlighted as follows.

- The framework developed for handling the optimisation problem characterised by design factor uncertainty where a repeated evaluation of design points required before selecting samples of estimation used in the optimisation. The repeated action will increase the computational time. This problem is more noticeable when the dimensions of the design factors in the process increased.
- In the case study the multi-pass optimisation framework uses fitness functions of a multi-pass continuous forward rolling process. It is important to consider optimisation problem regardless of the process type, for example to include such as unordered process and back and forth type process.

9.5 Recommended Future Work

This research has fulfilled its objectives, outlined in Chapter 3. However as any other researches this thesis also constrained with time, resource, and it is designed to focus on a specific issues that needs to be studied. For this reason therefore the research

cannot cover issues considered less relevant but may have some influence surrounding the research topic. Those issues not covered in this research could be an interesting topic to consider, thus recommended for further development. The recommended future work can be summarised as follows:

- Multi-pass modelling is an approximation of real life process problem; the approximation is based on assumption made on the nature of the process. The assumption has impact on the optimisation framework developed. It is also known that the modelling is the result of the design factors selected out of the large number of potentially important process factors. These may influence the design solution of the intended problem and may not always be the best in searching a realistic solution. Further study could consider a single process framework for modelling and optimisation with large number of input design variables with integrated problem behaviour such as uncertainty. This could be done by developing improved algorithm that addresses such information.
- The developed modelling framework is for work roll system thermal analysis and optimisation problems, specifically concerning a forward continuous rolling process. For this reason some of the rolling characteristics not directly relevant to the forward and continuous work roll system process are not included. Therefore the future work could be to develop a generic modelling framework addressing multi-pass optimisation problem incorporating rolling characteristics regardless the type of the process. Considering pass relationship ordered or unordered mill arrangements.
- Rolling process has inherent features, where the behaviour on one pass will determine the behaviour of the next. For example design factors relationship among passes. In this optimisation framework, these unique inherent relationships considered as predictable. It would be very interesting and innovative see those pass relationships as unpredictable and dynamic in nature.

9.6 Conclusions

This section gives the thesis conclusion, and summarised what is achieved with respect to the aim and objectives stated in Chapter 3. The section outlines the conclusion of each of the research objectives as follows:

-
- The thesis presented a critical review of the literature on rolling thermal process, design optimisation and GA based techniques in relation to multi-objective constraint, quantitative and uncertainty search space in single and multi-pass optimisation environments. The review reveals that although there are techniques for addressing single objectives single pass problems, there is a lack in recognising presence of uncertainty information in the optimisation. There is also a research gap in addressing constraint problem in presence of uncertainty in the design variables and fitness function. The review also reveals that multi-pass work roll system thermal analysis and optimisation is not fully explored, although there are few study have been carried out they lacks addressing relationships between passes and uncertainty associated to them.
 - This research has demonstrates that approximate quantitative models of single pass work roll system thermal analysis and optimisation can be developed using low cost experimental design principles and finite element analysis.
 - The novel GA based multi-objective framework, developed proves that the quantitative and process uncertainty information can be used in work roll system thermal analysis and optimisation to obtain multiple good design solutions. The framework proved that the application of central limit theorem in collaboration with the robust non dominance criteria optimisation technique proposed can successfully deal with the optimisation problem with uncertainty in the design variables and fitness functions.
 - The research demonstrates the importance of the application of constraint criticality in the design solutions. The principle gives designers an option to choose a design depending on its constraint criticality and its relative importance to requirements.
 - The research has proved that multi-pass work roll system thermal analysis and optimisation model can be developed based on process factors functional relationship between passes.
 - The multi-pass work roll system thermal analysis and optimisation framework developed proves that high dimensional, multi-pass design problem with uncertainty can be addressed using the GA based many-objective optimisation

technique and the fitness function models developed based on inter-pass factors functional relationships.

- The research introduce post optimisation result analysis; search space reduction based on percentage, for the research many objectives, high dimensional problem, and proves that best optimal design solution can be identified from the population of solutions obtained by the GA based optimisation technique.

The points outlined above conclude that this research has successfully proposed approximate modelling frameworks to develop meta-models. Based on the proposed framework a number of work roll system thermal analysis and optimisation models have been generated. The models are validated to evaluate their performance before used in the optimisation as a fitness functions. The research developed an optimisation framework to address work roll system thermal analysis and optimisation problem with constraint and presence of uncertainty in the design variables and fitness function. It also shows the development of the multi-pass work roll system thermal analysis and optimisation model based on design factors functional relationship between passes. The models are used as fitness function in many-objectives, multi-pass optimisation framework for searching optimal good design solutions.

The optimal design solutions obtained, using the approximate process models as fitness functions and the optimisation framework indicate that the GA based optimisation's capacity for addressing the intended complex work roll system thermal analysis and optimisation problems.

References

- Agarwal, H. Renaud, J. E. Preston, E.L. and Padmanabhan, D. Uncertainty Quantification using Evidence Theory in Multidisciplinary Design Optimisation. *Reliability Engineering & System Safety*, 85(1-3), 2004, p. 281-294.
- Apostolakis, G. "Model Uncertainty: Its Characterization and Quantification." A Commentary on Model Uncertainty, editors: Mosleh, A, Siu, N, Smidts, C. and Lui, C, NUREG/CP-0138, U.S. *Nuclear Regulatory Commission*, 1994.
- Aretz, H. *et.al.* "Integration of Physically Based Models into FEM and Application in Simulation of Metal Forming Processes." *Modelling Simulation Material Science Engineering*, 2000, p. 881-891.
- Arif, A. F. M. Kham, O. Zubair, S. M. "Prediction of Roll Temperature with a Non-Uniform Heat Flux at Tool and Work-piece Interface." *Heat Mass Transfer*, 41, 2004, p. 75-94.
- Avitzur, B. *Metal Forming Processes and Analysis*. (Book), Original Edition, McGraw-Hill, 1968, p. 500. Reprint with revisions and corrections, Robert E. Krieger Publishing Inc, NY, 1979, p. 498.
- Barber, C. B. Dobkin, D. P. Huhdanpaa, H. T. "The Quick hull Algorithm for Convex Hulls." *ACM Transactions on Mathematical Software*, 22(4), 1996, p. 469-483.
- Ben-H, Y. *Robust Reliability in Mechanical Sciences*, Springer-Verlag: Berlin, 1996.
- Ben-Haim, Y. "Uncertainty, probability and information-gaps," *Reliability Engineering and System Safety*, 85, 2004, p. 249-266.
- Beyer, H. and Sendhoff, B. Robust Optimisation - A Comprehensive Survey. *Computer Methods in Applied Mechanics and Engineering*, 196 (33-34), 2007, p. 3190-3218.
- Brintrup, A. M. Ramsden, J. and Tiwari, A. An Interactive Genetic Algorithm-based Framework for Handling Qualitative Criteria in Design Optimisation, *Computers in Industry*, 58 (3), 2007, p. 279-91.

Carlos, M., Fonseca, P. and Fleming, J. Genetic Algorithms for Multi-objective Optimisation: Stephanie F. editor, *Proceedings of the Fifth Int. Conference on Genetic Algorithms*, SAN MATRO, California, 1993, p. 416-423.

Castro, C. F. Antonio, C. A. C. Sousa, L. C. "Optimisation of Shape and Process Parameters in Metal Forming using Genetic Algorithms." *Journal of Materials Processing Technology*, 146, 2004, p. 356-364.

Chen, B. K. Thomson, P. F. Choi, S. K. "Temperature Distribution in the Roll-Gap during Hot Flat Rolling." *Journal of Materials Processing Technology*, 30, 1992, p.115-130.

Chen, J. S. *et.al.* "Analysis of Metal Forming Process Based on Mesh-less Method." *Journal of Materials Processing Technology*, (80-81), 1998, p. 642-646.

Chen, J. S. Roque, C. L. Pan, C. Button, S. T. "Analysis of metal forming process based on mesh less method." *Journal of Materials Processing Technology*, 81, 1998, p. 642-646.

Chen, W. Allen, J. Tsui, K. and Mistree, F. "A Procedure for Robust Design: Minimizing Variations Caused by Noise Factors and Control Factors." *ASME, Mechanical Design*, 118, 1996, p. 478-485.

Chen, W. Analytical Uncertainty Propagation via Meta-Models in Simulation-Based Design under Uncertainty. *10th AIAA/ISSMO Multidisciplinary Analysis and Optimisation Conference*, Albany, New York, 2004, p.43-56.

Chinyere, O. O. *Introduction to Engineering Design Optimisation*, Prentice hall, Upper Saddle River, NJ 07458, 2000.

Choi, K. K. And Youn, B. D. Hybrid analysis method for reliability-based design optimisation. *27th ASME Design Automation Conference, DETC2001/DAC-21044*, Pittsburgh, PA, 2001.

Coello, C. A. C. Theoretical and Numerical Constraint-Handling Techniques used with Evolutionary Algorithms: a Survey of the State of the Art. *Computer Methods in Applied Mechanics and Engineering*, 191 (11-12), 2002, p. 1245-87.

Corne, D. W. and Knowles, J. D. Techniques for Highly Multi-objective Optimisation: Some Non Dominated Points are better than others. *9th Annual Genetic and Evolutionary Computation Conference, GECCO, Jul 7-11 2007, Association for Computing Machinery, New York, NY 10036-5701, United States, 2007, p. 773-780.*

Davis, W. T. Cost and Quality Improvements Through the Use of High Chrome Work Rolls in a Hot-Strip Mill. *Mechanical Working and Steel Processing, XVIII AIME, 1981, p. 231-337.*

Dean, S. and Illowsky, B. "Central Limit Theorem: *Teacher's Guide*." Version 1.8: 2008.

Deb, K. Evolutionary Algorithm for Multi-Criterion Optimisation in Engineering Design. *Evolutionary algorithms in engineering and computer science*, UK, John Wiley & Sons, Ltd, 1999.

Deb, K. Multi-Objective Optimisation using Evolutionary Algorithms, England, UK: John Wiley & Sons Ltd, 2001.

Deb, K. Pratap, A. Agarwal, S. and Meyarivan, T. "A Fast and Elitist Multi objective Genetic Algorithm: NSGA-II." *IEEE Transactions on Evolutionary Computation*, 6, 2002, p.182-197.

Devadas, C. Samarasekara, I. V. Heat Transfer during Hot Rolling of Steel Strip *Iron Making and Steel Making*, 13, 1986, p. 311-321.

Du, X. and Chen, W. "An Efficient Approach to Probabilistic Uncertainty Analysis in Simulation-Based Multidisciplinary Design." *The 38th AIAA Aerospace Sciences Meeting, Paper No. AIAA 2000-0423*, 2000.

Du, X. and Chen, W. "Towards a Better Understanding of Modelling Feasibility Robustness in Engineering." *ASME Journal of Mechanical Design*, 122(4), 2000, p. 357-583.

Dudy Lim, Yew-Soon, O. and Yaochu, J. Inverse multi-objective robust evolutionary design (IMOR), *Springer Science*, 7, 2006, p. 383-404, DOI 10.1007/s10710-006-9013-7.

Fiacco, A. V. Introduction to Sensitivity and Stability Analysis in Nonlinear Programming, in Mathematics. In: *Science and Engineering*, Academic Press, New York, 165, 1983.

Friedman, L. W. *The Simulation Meta-model*. Dordrecht, Netherlands, Kluwer Academic publishers, 1996.

Fujita, K., Hirokawa, N. and Tachikawa, T. "Voronoi Diagram Based Cumulative Approximation for Engineering Optimisation. *Proceedings of 8th AIAA/USAF/NASA/ISSMO Symposium on Multi-Disciplinary Analysis and Optimisation*, 2000, Paper Number AIAA-2000-4919.

Grefenstette, J. J. GENESIS: A System for using Genetic Search Procedures. In: *Proceedings of the 1984 Conference on Intelligent Systems and Machines*, 1984, p.161-165.

Gunawan, S. Azarm, S. Non-Gradient Based Parameter Sensitivity Estimation for Single Objective Robust Design Optimisation. *Journal of Mechanical Design, ASME*, 126, 2004, p. 395, DOI: 10.1115/1.1711821.

Hadly, C. O. Brimacombe, J. K. Samarasekara, I. V. Hawbolt, E. B. Heat Transfer in the Hot Rolling of Metals, *Metal. Mat. Trans. B* 26, 1995, p. 1019-1027.

Han, C. S. Grandhi, R. V. and Srinivasan, R. "Optimum Design of Forging Die Shapes Using Nonlinear Finite Element Analysis." *AIAA Journal*, 31, 1993, p.774-781.

Hazelrigg, G. A. "On the Role and Use of Mathematical Models in Engineering Design." *Transactions of ASME, Journal of Mechanical Design*, 121(3), 1999, p 336-341.

Helton, J. C. "Uncertainty and Sensitivity Analysis in the Presence of Stochastic and Subjective uncertainty." *Journal Statistical Computation and Simulation*, 57, 1997, p. 3-76.

Hickley, R. H. Porthouse, D. "General Review of Rolls as Applied to Different Metals and Mills." *Metal Technology*, 1975, p.469-475.

Hill, D. R. and Gray, L. E. Cooling of Work Rolls in Hot Rolling Mills, *Iron Steel Engineering*, 58, 1981, p. 57-62.

Hitchcock, J. H. "Roll-neck bearings." *ASME research publications*, 1935.

Holland, J. H. "Outline of a Logical Theory of Adaptive Systems." *JACM*, 9, 1962, p. 297-314.

Holland, J. H. *Adaptation in Natural and Artificial Systems*. Ann Arbor, MI, University of Michigan Press, 1975.

Horn, J. and Nafpliotis, N. Multi-objective Optimisation using the Niche Pareto Genetic Algorithm. Technical Report, University of Illinois, Urbana, Illinois, USA, 1993.

Huang, M. Leu, D-K. "An Elasto-Plastic Finite Element Analysis of Sheet Metal U-Bending Process." *Journal of Materials Processing Technology*, 48, 1995, p. 151-157.

Huang, Y-P. Chen, Du, R. X. "A New Approach to Solve Key Issues in Multi-Step Inverse Finite-Element Method in Sheet Metal Stamping." *International Journal of Mechanical Sciences*, 48, 2006, p. 591-600.

Ihaka, R. Gentleman, R. R. A Language for Data Analysis and Graphics. *Journal of Computer Graphics and Statistics*, 3, 1996, p. 299-314.

Jeong, D. J. Kim, J. H. Kim, B. M. Dean, T. A. "Effects of Surface Treatments and Lubricants for Warm Forging Tool Life." *Journal of Materials Processing Technology*, 113, 2001, p. 544-550.

Jin, R. Du, X. and Chen, W. The Use of Meta Modelling Techniques for Optimisation under Uncertainty. *Structural and Multidisciplinary Optimisation*, 25(2), 2003, p. 99-116.

Jin, Y. Aloof, M. and Send-off, B. "A framework for evolutionary optimisation with approximate fitness functions." *IEEE Transaction*, 6(5), (2002), p. 481-494.

Jin, Y. and Branke, J. "Evolutionary optimisation in uncertain environment- A survey." *IEEE Transactions on Evolutionary Computation*, 9, 2005, p. 303-317.

Jung, D. W. "Static-Explicit Finite Element Method and Its Application to Draw Bead Process with Spring-Back." *Journal of Materials Processing Technology*, 128, 2002, p. 292-301.

Keller, J. D. 'A Study of Failures in Iron Work Rolls.' *Iron and Steel Engineer Year Book*, 1955, p. 567.

Kihara, J. *et al.* "Roll Wear in Hot Strip Mill." *Iron and Steel*, 7, 1983, p. 62-69.

Kleiber, M. Kulpa, Z. "Computer-Assisted Hybrid Reasoning in Simulation and Analysis of Physical Systems." *Computer Assisted Mechanics and Engineering Sciences*, 2, 1995, p. 165-186.

Knowles, J. D. Watson, R.A. and Corne, D. W. "Approximating the non-dominated front using the Pareto archived evolution strategy." *Evolutionary Computation Journal*, 8(2), 2000, p. 149-172.

Knowles, J. D. and Corne, D. W. Bounded Pareto archiving: theory and practice. Metaheuristics for Multi-objective Optimisation. Notes in Economics and Mathematical Systems, Springer, 535, 2004, p. 39-64.

Knowles, J. D. and Corne, D. W. Properties of an adaptive archiving algorithm for storing non-dominated vectors. *IEEE Transactions on Evolutionary Computation*, 7(2), 2003, p. 100-116.

Koch, P. N. Simpson, T. W. Allen, J. K. and Mistree, F. Statistical Approximations for Multidisciplinary Design Optimisation: The Problem of Size. *Journal of Aircraft*, 36(1), 1999, p.275-286.

Komori, K. "Simulation of Deformation and Temperature in Multi-Pass Three-Roll Rolling." *Journal of Materials Processing Technology*, (92-93), 1999, p. 450-457.

Komori, S. M. "Simulation of Deformation and Temperature in Work Roll." *Journal of Materials Processing Technology*, 169, 2005, p. 249-257.

Kuhn, H. A. and Weinstein, A. S. "Lateral Distribution of Pressure in Thin Strip Rolling." *Journal of Engineering for Industry, ASME*, 1970, p. 453-456.

Landa, B. R. and Coello, C. A. C. Cultured Differential Evolution for Constrained Optimisation. *Computer Methods in Applied Mechanics and Engineering*, 195(33-36), 2006, p. 4303-4322.

Leisten, B. Luce, R. Kopp, R. "Determination of Boundary Values for the Numerical Simulation of Metal Forming Processes using Fuzzy Control." *Institute of Bildsame Formgebung, Steel Research*, 70(10), 2001, p. 394-401.

Linhart, J. W. "Differential Heat Treatment of Rolls to Improve Life and Performance." *Iron and Steel Engineer Year Book*, 1972, p. 662-668.

Makinouchi, A. "Sheet Metal Forming Simulation in Industry." *Journal of Materials Processing Technology*, 60, 1996, p. 19-26.

Marquardt, D. "An algorithm for least squares estimation of nonlinear parameters." *SIAM Journal of Applied Mathematics*, 11(2), 1963), p. 431-441.

McManus, J. M. 'Roll Makers Keep Trying to Roll with Changes in the Market Place.' *Iron Age*, 1980, p. 7-13.

Mehnen, J. Trautmann, H. 'Robust Multi-objective Optimisation of Weld Bead Geometry for Additive Manufacturing.' *ICME 2008, Intelligent Computation in Manufacturing Engineering*, 2008.

Michele, M. Arthur C. Perry A. Lawrence L. "Approach for Input Uncertainty Propagation and Robust Design in CFD Using Sensitivity Derivatives." *ASME*, 124 (2002), p.60-69.

Muller, H. 'Application of Roll Ragging' *Iron and Steel Engineer Year Book*, 1959, p. 379-390.

Muller, H. E. 'HI-CR Work Rolls in the Hot-Strip Mill,' *Iron and Steel Engineer Year Book*, 1975, p. 355-362.

Oakley, D. R. Sues, R. H. Rhodes, G. S. "Performance Optimisation of Multidisciplinary Mechanical Systems Subject to Uncertainties." *Probabilistic Engineering Mechanics*, 13(1), 1998, p. 15-26.

Oduguwa, V. "Rolling System Design Optimisation using Soft Computing Techniques" EngD Thesis, SIMS, Cranfield University, Cranfield, UK, 2003.

Oduguwa, V. Roy, R. and Farrugia, D. Development of a Soft Computing-Based Framework for Engineering Design Optimisation with Quantitative and Qualitative Search Spaces. *Applied Soft Computing*, 7(1), 2007, p. 166-188.

Oduguwa, V. Roy, R. And Tiwari, A. "Evolutionary Computing in Manufacturing Industry: An Overview of Recent Applications." *Journal of Applied Soft Computing*, 2003a.

Ong, Y. S. Max-Min Surrogate-Assisted Evolutionary Algorithm for Robust Design, *IEEE, ASME Journal of Mechanisms, Transmissions, and Automation in Design*, 2004.

Pallone, G. T. Transient Temperature Distribution in Work Rolls during Hot Rolling of Steel Strip, *Iron and Steel Engineering*, 60, 1983, p. 21-26.

Park, J. J. *et.al.* "A new Approach to Perform Design in Metal Forming with the Finite Element Method." *International Journal of Machine and Tool Design*, 23(1), 1983, p. 71-79.

Parke D. M. Baker, L. L. Temperature Effects of Cooling Work Rolls Iron Steel Engineering, 211(8), 1972, p. 3-9.

Parkinson, A. Sorensen, C. and Pourhassan, N. "A General Approach for Robust Optimal Design." *Transactions of the ASME*, 115, 1993, p. 74-80.

Parmee, I. C. *Evolutionary and Adaptive Computing in Engineering Design*, Springer-Verlag, London, ISBN: 1-85233-029-5, 2001.

Pawelski, O. Rasp, W. Hoerster, C. The Ring Compression Test as Simulation Test for the Investigation of Friction in Hot Metal Forming, *Steel Research*, 60(9), 1989, p. 395-402.

Pawelski, O. Rasp, W. and Hoerster, C. Influence of Friction and Lubrication on Material Flow in Hot Strip Rolling and Ring Compression, *Proceeding of. 3rd ICTP*, 1990, p. 809-814.

Peng, W. Zhang, Q. Li, H. Comparison between MOEA/D and NSGA-II on the Multi-Objective Travelling Salesman Problem,. Technical report, Department of Computing and Electronic System, UK, 2007.

Gentleman, R, *et.al.* R: A language and environment for statistical computing, 2004, ISBN 3-900051-00-3.

Raudensky, Horsky, J. “Thermal Model of Rolls and Sheets Improvement by Experimental Study Cooling.” *Journal of Materials Processing Technology*, 34, 1992, p. 247-253.

Robson, C. Real World Research, (Quantitative & Qualitative), Blackwell Publishing, 2002.

Rosochowska, M. Chodnikiewicz, K. Balendra, R. “A New Method of Measuring Thermal Contact Conductance.” *Journal of Materials Processing Technology*, 145, 2004, p.207-213.

Roy, R. Adaptive Search and the Preliminary Design of Gas Turbine Blade Cooling System. PhD Thesis, University of Plymouth, 1997.

Roy, R. Teti, R. And Hinduja, S. “Recent Advances in Engineering Design Optimisation: Challenges and Future Trends” *CIRP Annals-Manufacturing Technology*, 57(2), 2008 p. 697-715.

Roy, R. Tiwari, A. and Corbett, J. ‘Designing a Turbine Blade Cooling System using a Generalised Regression Genetic Algorithm.’ *CIRP Annals, CIRP*, 52(1), 2003, p. 415-418.

Samuel, M. “Numerical and Experimental Investigations of Forming Limit Diagrams in Metal Sheets.” *Journal of Materials Processing Technology*, (153-154), 2004, p. 424-431.

Schaffer, J. D. Multiple Objective Optimisations with Vector Evaluated Genetic Algorithms. In: *Genetic Algorithms and their Applications: Proceedings of the First Int. Conference on Genetic Algorithms*, Lawrence Erlbaum, 1985, p. 93-100.

Schütz, M. Schwefel, H. Evolutionary Approaches to solve Three Challenging Engineering Tasks. *Computer Methods in Applied Mechanics and Engineering*, 186 (2-4), 2000, p.141-170.

Serajzadeh, S. and Mucciardi, F. "Modelling the Work-Roll Temperature Variation at Unsteady State Condition." *Journal of Modelling and Simulation in Materials Science Engineering, MSMSE*, 11, 2003, p 179-194.

Shkvar, E. A. Mathematical Modelling of Turbulent Flow Control by using Wall Jets and Polymer Additives Poster Paper, 2001, *American Society of Mechanical Engineers*, New York, NY 10016-5990, United States, 2001, p. 277-283.

Sluzalec, A. jr. A Preliminary Analysis of Temperatures within Roll-Forging Dies, using a Finite Element Method. *International Journal of Machine Tools Design and Research*, 24, 1984, p. 171-179.

Sousa, C. & Antonio, C. "Optimal Design of V & U Bending Processes using Genetic Algorithms." *Journal of Materials Processing Technology*, 172, 2006, p. 35-41

Spendley, W. Hext, G. R. Himsworth, F. R. "Sequential Application of Simplex Designs in Optimisation and Evolutionary Operation." *Technometrics*, 4, 1962, p. 441.

Srinivas, N. and Deb, D. "Multiple objective optimisations using non-dominated sorting in genetic algorithms." *Evolutionary Computation*, 2, 1994 p. 221-248.

Stephen, M. B. John E. R. Xiaoyu, Gu. "Modelling and Simulation Uncertainty in Multidisciplinary Design Optimisation," *AIAA Journal*, 122(6), 2000, p. 4803-4814.

Sundaresan, S. Ishii, K. Houser, D. "A Robust Optimisation Procedure with Variation on Design Variables and Constraints." *ASME, Advance in Design Automation*, 1, 1993, p. 379-386.

Taguchi, G. "Performance Analysis Design." *International Journal of Production Research*, 16, 1978, p. 521-530.

Tang, J. W. Wu, T. Wu, Walters, J. "Recent Development and Applications of Finite Element Method in Metal Forming." *Journal of Materials Processing Technology*, 46, 1994, p. 117-126.

Tekkaya, A. E. State-of-the-Art of Simulation of Sheet Metal Forming. *Journal of Materials Processing Technology*, 103(1), 2000, 1, p.15-23.

Terceelj, M. Turk, R. Knap, M. "Assessment of Temperature on the Roll Surface in Laboratory Hot Metal Forming." *Applied Thermal Engineering*, 23, 2003, p. 113-125.

Teseng, A. *et.al*. Thermal Behaviour of Roll and Strip in Steel Rolling with Non-Conventional Roll Design, Thermo-Mechanical Aspects of Manufacturing and Material Processing, New York, Hemisphere Publishing Corporation, 1992, p.217-232.

Teseng, A. A. Thermal modelling of rolls and strip interface in rolling processes, *Simulation and Num. Heat Transfer*, 35, 1999, p. 135-155.

Teseng, A. A. Lin, F. H. Gunderia A. S. Ni, D. S. Roll Cooling and its Relationship to Roll Life, *Metall. Trans*, A 20, 1990, p. 2305-2320.

Thieme, J. C. Ammareller, S. "Which Roll for Which Purpose" Part I Magazine, 33,1966, p. 73-81.

Tiwari, A. Evolutionary Computing Techniques for Handling Variable Interaction in Engineering Design Optimisation, PhD. Thesis, SIMS, Cranfield University, Cranfield, UK, 2001.

Tiwari, A. Oduguwa, V. Roy, R. Rolling System Design Using Evolutionary Sequential Process Optimisation. *IEEE Trans. Evolutionary Computation*, 12(2), 2008, p. 196-202.

Tiwari, A., Roy, R., Jared, G. and Munaux, O."Interaction and Multi-objective Optimisation." *Proceedings of the Genetic and Evolutionary Computation Conference, GECCO-2001*, Morgan Kaufmann Publishers, San Francisco, USA, 2001, p. 671-678.

Troeder, C. Spielvogel, A. Xu, J. W. Temperature and Thermal Stress in Work Rolls during the Hot Rolling of Strip, *Steel Research*, 56(7), 1985, p. 379-384.

Trucano, T. G. "Prediction and Uncertainty in Computational Modelling of Complex Phenomena." A Whitepaper, Sandia report, SAND, 98-2776, 1998.

Tseng, A. A. Gunderia, A. S. Sun, P. F. Cooling of Roll and Strip in Steel Rolling, *Steel Research*, 62(5), 1991, p. 207-215.

Tsutsui, S. Ghosh, A. Corne, D. and Fujimoto, Y. A. Real Coded Genetic Algorithm with an Explorer and an Exploiter Population. ICGA, 1997, p. 238-245.

Ullman, D. G. D'Ambrosio, B. "Taxonomy for Classifying Engineering Decision Problems and Support Systems." *Artificial Intelligence for Engineering Design, Analysis and Manufacturing, AIEDAM*, 9(5), 1995, p. 427-438.

Williams, R. V. Boxall, G. M. "Roll Surface Deterioration in Roll-Strip Mills." *Journal of the Iron and Steel Institute*, 1963, p. 369-377.

Wood, K. L. A Method for Representing and Manipulating Uncertainties in Preliminary Engineering Design. PhD Thesis, California Institute of Technology, Pasadena, CA, 1989.

Wusatowski, Z. Fundamentals of Rolling, Pergamon publishing, 1969.

Xing, H. L. Makinouchi, A. "FE Modelling of Thermo-Elasto-Plastic Finite Deformation and Its Application in Sheet Warm Forming." The Institute of Physical and Chemical Research, Saitama, Japan, 19(4), 2002, p. 392-407.

Yang, D. Y. *et.al.* "Comparative Investigation into Implicit, Explicit and Iterative Implicit/Explicit Schemes for the Simulation of Sheet-Metal Forming Processes." *Journal of Materials Processing Technology*, 50, 1995, p. 39-53.

Yang, S. Nezu, K. "Application of an Inverse FE Approach in the Concurrent Design of Sheet Stamping." *Journal of Materials Processing Technology*, 79, 1998, p. 86-93.

Yang, S. Ong, Y. and Jjin, Y. Evolutionary Computation in Dynamic and Uncertain Environments. 1st edn. Springer, 2007.

Ye, X. Samarasekara, I. V. "The Role of Spray Cooling on Thermal and Crown Development in Hot-Strip Mill" *Work-Rolls Iron and Steelmaker*, 21, 1994, p. 49-59.

Zaeh, M. F. Oertli, T. and Milberg, J. Finite Element Modelling of Ball Screw Feed Drive Systems. *CIRP Annals - Manufacturing Technology*, 53(1), 2004, p. 289-292.

Ziehenberger, K. H. Windhager, M. “Recent Developments in HSM Rougher Rolls-Risks and Chances.” *Iron & Steel Technology*, 2006, pp. 38-41, AIST- Association for Iron & Steel Technology, PA, USA.

Zitzler, E. Thiele, L. An Evolutionary Algorithm for Multi-objective Optimisation. The Strength Pareto Approach. Technical Report 43, Computer Engineering and Communication Networks Lab, Zurich, Switzerland, 1998.

Appendix-A

Industry Survey, Current Practise Questionnaires & Example Transcript

Design Optimisation Techniques in Industry

A Survey of Techniques Current States
The survey, as part of PhD research, is sponsored by: EPSRC and CORUS

Yoseph Tafesse Azene, Rajkumar Roy
Cranfield University

Organisation:

Address:

Name:

Job Title:

Role in the Organisation:

Years of Experience in Design:

Telephone Number:

Fax Number:

E-mail:

The information provided will only be used for academic and research purposes. If you agree please

Tick the box: ☐

Interview conducted by:

Date:.....

Time:.....

Venue:.....

Purpose of Questionnaire:

The purpose of this study is to understand state of the art practice in design optimisation across the new product development life cycle. The major focus is in the area of algorithm based optimisation. The questionnaire provides a structured requirement capture and consists of three sections. A multiple choice sections, section to answer in your own words and a self assessment section (optional)

Contact address: Cranfield University, Cranfield, Bedfordshire, MK430AL, UK

Tel: +44 (0) 1234754086, Fax: +44 (0) 1234750852

E-mail: R.roy@cranfield.ac.uk, Y.tafesseazene@cranfield.ac.uk

Section A.I. - Multiple choices

This section of the questionnaire is designed to understand the general design and design optimisation practice involved in your company and your involvement in those activities.

- Q1.** Describe the component you are involved in designing now or in the recent past.
- A. Name
 - B. Usage.....
 - C. Complexity.....
 - D. Size.....
- Q2.** Select the stage of the design process you are involved in:
- A. Feasibility stage
 - B. Styling stage
 - C. Other, please specify
- Q3.** How do you evaluate a design against the criteria?
- A. Manually, using experience
 - B. Using CAE tools ,such as FEA, CFD
 - C. Using analytical models, developed internally
 - D. Others, please specify
- Q4.** If you are using non algorithm technique to improve/optimize your design, how much time do you spend relative to the total design cycle?
- A. Below 25%
 - B. 25 to 50%
 - C. 50 to 75%
 - D. above 75%
- Q5.** If you are using algorithm based technique to improve/optimize your design, how much time do you spend relative to the total design cycle?
- A. below 25%
 - B. 25 to 50%
 - C. 50 to 75%
 - D. above 75%

Section A.2.

The aim of this section is to capture experts experience and thought as well as industry requirements on existing optimisation technique. The section also allows experts to outline the limitations in the algorithm based optimisation technique and inhibitors the industry has to use algorithm approach in the optimisation.

- Q1.** Describe how you optimize the component design?
- Q2.** Have you documented your design optimisation or design improvement process? (Could we have a copy please?)
- Q3.** How much time do you spend (% of your time) in improving or optimizing one initial design?
- Q4.** What criteria do you use to optimize your design?
- Q5.** Do you have a process to develop a model?
- Q6.** How do you measure the efficiency of the design process?
- Q7.** Are you trying to achieve the best design or an improved design? How frequently would you use optimisation?
- Q8.** Do you use any commercial software (e.g. I sight) for the optimisation? Please describe why you use them. How long have you been using the software?
- Q9.** What criteria you would like to use to evaluate commercial optimisation software?
- Q10.** What are the drawbacks and limitations in the current design optimisation process? How they could be improved?
- Q11.** Are the existing design optimisation techniques you are using algorithm based? Fully or partially
- Q12.** If you are using algorithm based design optimisation techniques, what are the draw backs and limitations the technique has? How they could be improved?
- Q13.** What advantages algorithm based design optimisation technique has in comparison to any other optimisation technique you know?
- Q14.** If your design improvement activities involve algorithm based technique, what particular tool/tools you are using?
- Q15.** If your design improvement activity involves conventional/traditional based technique, what particular tool/tools you are using?
- Q16.** Could you specify please if your design improvement activity involves a combination of both conventional and algorithm based, hybrid, technique?

-
- Q17.** From your own experience what do you think needs to be improved in the current design improvement/optimisation technique you are using?
- Q18.** Please write any general remarks you wish to make on GA based design optimisation, and mention if you have any other suggestions.

Section A.3. Self assessment section (optional)

The section is designed for evaluation purpose only, and to make sure your answers in the questionnaire is evaluated in the right prospective. If you are happy to answer please circle one of the numbers below.

If 1 is the best and 5 for worst, where can you put yourself in terms of?

Engineering design:

A.	Knowledge	1	2	3	4	5
A.	Experience	1	2	3	4	5

Design optimisation

A.	knowledge	1	2	3	4	5
B.	Experience	1	2	3	4	5

Optimisation algorithms

A.	Knowledge	1	2	3	4	5
B.	Experience	1	2	3	4	5

Transcript – A

The transcript reports interviewing session made with engineers in 4 companies, ladled company A, B, C and D. The purpose is to assess the current status of design, optimisation and techniques in industry. The descriptions below are answers given by the majority of the participants for same question ask. In some cases unique answers, given by specific companies are also included. The interview was supported by questionnaires. The questionnaire has two sections. The transcripts from the two sections are given below:

Section A.1. - Multiple Choices

- Q1 & Q2** are questions related to participant personal responsibility and associations?
- Q3.** How do you evaluation the design against the criteria?

Answer (summery from 4 companies)

About 65% are depend on manual /expert experience

About 20 % are depend on CAE tools

10 % CFB, customer feed back

Q4: If you are using non algorithm technique to improve/optmise your design, how much time do you spend relative to the total design cycle?

Answer

Existing technique is iterative and takes 25% to 50 % of the total design cycle

Q5: If you are using algorithm based technique to improve/optmise your design, how much time do you spend relative to the total design cycle?

Answer

GA based optimisation technique is not applicable

Section A.2.

The aim of this section is to capture experts experience and thought as well as industry requirements on existing optimisation technique. The section also allows experts to outline the limitations in the algorithm based optimisation technique and inhibitors the industry has from to using algorithm approach in the optimisation.

Q1: Describe how you optimise the component design?

Answer

Cost reduction is a major factor in the optimisation 65%

Quality and criteria 35%

Q2: Have you documented your design optimisation or design improvement process?
(Could we have a copy please?)

Answer

No formal documentation / some sections in the departments may have some form of documentations but not mandatory

Q3: How much time do you spend (% of your time) in improving or optimising one initial design?

Answer

Time spent to improve one initial design will take 40 % to 50%,

Q4: What criteria do you use to optimise your design?

Answer

Cost is the main criteria used to optimise design, but used a method called QFD to define relative importance. (The main drive is maximising profit)

Q5: Do you have a process to develop a model?

Answer

Not a process but steps to follow, mainly manual and iterative

Q6: How do you measure the efficiency of the design process?

Answer

There is no recognised way for measuring efficiency, but other manual ways like:

- Performance against target
- Output / cost
- Company C also say compare man hour spent with other design centres within the organization.

Q7: Are you trying to achieve the best design or an improved design? How frequently would you use optimisation?

Answer

In mass production priority given to achieve a design with balanced cost, quality and timing, the design may not be the best design,

Q8: Do you use any commercial software (e.g. I sight) for the optimisation? Please describe why you use them. How long have you been using the software?

Answer

Most participant answer NO,

Company A & B says there is limited availability, mostly in the R&D.

Q9: What criteria you would like to use to evaluate commercial optimisation software?

Answer

- Re- usability of results, optimisation time, generic nature,
- Show efficiency improvement needs, return on invested capital

Q10: What are the drawbacks and limitations in the current design optimisation process? How they could be improved?

Answer

- Inefficient, lack of rigor in documenting progress, not have access to all tools.
- late Time to get test feedback, late changes of spec by market requirement
- Not supported by system, impact on changes on spec. are not clear until requested of design.

Q11: Are the existing design optimisation techniques you are using algorithm based? Fully or partially

Answer

- Company A, B and C say they are currently using GA based technique in design but very limited,
- Company D say not using GA based optimisation technique in their design process

Q12: If you are using algorithm based design optimisation techniques, what are the drawbacks and limitations the technique has? How they could be improved?

Answer

Not in a position to give full comparison or assailment,

Company A says computational speed may be one that needs improvement in the GA based techniques

Q13: What advantages algorithm based design optimisation technique has in comparison to any other optimisation technique you know?

Answer

- Re-usability and standardization,
- Would improve management of change
- In comparison to the manual technique we have, algorithm based technique is faster.

Q14: If your design improvement activities involve algorithm based technique, what particular tool/tools you are using?

Answer

Design improvement activities are mainly based on traditional approach.

Q15: If your design improvement activity involves conventional/traditional based technique, what particular tool/tools you are using?

Answer

The following are most commonly used approaches and techniques

- Common mathematical calculations, mainly in excel and I-DEAS
- Kepner trago KT, OFD, FMEA, FTA, FEA, FMEA

Q16: Could you specify please if your design improvement activity involves a combination of both conventional and algorithm based, hybrid, technique?

Answer

Company B, C and D says used conventional

Company A says currently using limited combination form.

Q17: From your own experience what do you think needs to be improved in the current design improvement/optimisation technique you are using?

Answer

- Not standardized, no recognized process that reflects the most appropriate optimisation technique
- Be able to capture /document process, current method, lack for global strategy.
- Speeding up communication whilst identifying the risk and often changes.

Q18: Please write any general remarks you wish to make on GA based design optimisation, and mention if you have any other suggestions.

Answer

Companies are universally expressed that

- Company C say based on information about GA based technique they have, it would be beneficial to have the technique and use it but a restriction due to the need for a global lead direction and complex global nature of the company.
- Company A, B and D says, the need for integrated, robust and efficient process based design optimisation is necessary, may be GA will fill that gap in the future.

Appendix-B

Industry Survey, Work roll System Current Practise Questionnaire Themes & Probe Aim

Work Roll System & Problems, knowledge Elicitation Questionnaire Themes

Table B.1. Work roll system in rolling, current practice questions

Qs	Survey Question	Survey Aim
Q1	What is the cost of rolls	To gauge the cost associated to rolls
Q2	What are roll design criteria	To fully understand rolls and key design criteria
Q3	How do you measure rolls data	To find out the measurement standard and accuracy, presence of uncertainty
Q4	How do you measure roll thermal profile	To understand measuring and analysis of thermal issues in the roll, accuracy and uncertainty in measurements
Q5	What is the percentage of cost of rolls from the total production cost?	To understand depth of the problem and justify the merit of the research domain for study
Q6	What are the main causes of roll damage that trigger higher roll cost?	To identify the cause and source of the problem,
Q7	How do you maintain roll from damage?	To understand if there is a scientific procedure in place or it is a manual approach
Q8	How do you design and optimise rod rolling?	To understand the current activity of the design and optimisation process for rod rolling thermal analysis
Q9	Is the design and optimisation of the rolling process includes thermal analysis?	To realize for the extent the rod rolling thermal analysis and optimisation integrated to the existing techniques
Q10	What do expect or benefits will you be looking for from this research project?	To gauge the overall research outcome expectation

Table B.2. Work roll system Thermal Analysis and optimisation Questions

Qs	Survey Question	Survey Aim
Q1	What are the setup parameters, work roll thermal design parameters?	To identify the nature of the set-up, parameters involved and parameter interactions
	What are the constraints & parameters that must hold to satisfy rolling thermal design & optimisation requirements	To understand constraints and limits in the real life rod rolling thermal analysis and optimisation
Q4	Is the functional relationship between passes can define the real life process?	To understand input / output relationship among passes and also visualize if process modelling is possible using factors functional relationship
Q5	Do you currently consider process uncertainty in the design & optimisation in the rod rolling thermal analysis	To divulge level of the work roll system thermal analysis and optimisation process
Q6	Do you have record of study made for process uncertainty relevant to rod rolling thermal analysis and optimisation	To understand the uncertainty and source of uncertainty relevant to the rod rolling thermal analysis and optimisation
Q7	What are the conditions, factors/ parameters each pass experience during the rolling process	To identify the nature of the interface of inputs relationship among passes and to reveal specific or generic nature of factors and parameters.

Appendix-C

FEA Model Specifications

Model assembly specification

Table C.1. FEA problem model meshing part boundary condition

Material, name=highcr_shell	Material, name=sgac core	Material, name=nozzle	Material Material=leadsteel stock_truss (Beam Orientation)
Conductivity 18.4,20. Density 7.5833e-09, Elasticity 215000., 0.3, 20. Expansion 1.3e-05, 20. Inelastic Heat Fraction0.9, Specific Heat 4.78e+08	Conductivity 48.58,20. Density 7.172e-09, Elasticity 167000.,0.3,20. Expansion 1.22e-05, Inelastic Heat Fraction0.9, Specific Heat 4.78e+08,	Conductivity 55,50. Density 0.02075, Elasticity 812000. 0.281,20. Specific Heat 5.86e+08	

Table C.2. FEA problem model part interaction property

Interaction Properties			
Surface Interaction name=INT-11 Friction, slip tolerance=0.0050.3 gap conductance (HTC roll/stock contact)	Surface Interaction name=nozzle - roll Friction 0. gap conductance (HTC cooling)	Nozz1Contact Pair interaction= nozzle-roll, type=surface to surface	roll stock- contact Pair- interaction (nt-1) type=surface to surface

Table C.3. Output request from FEA simulation

OUTPUT REQUESTS
**
**Restart, write, frequency=0
**
** FIELD OUTPUT: F-Output-5
*Output, field, number interval=50
*Node Output
** FIELD OUTPUT: F-Output-6
**
*Element Output, directions=YES
*Output, history, frequency=0
*End Step

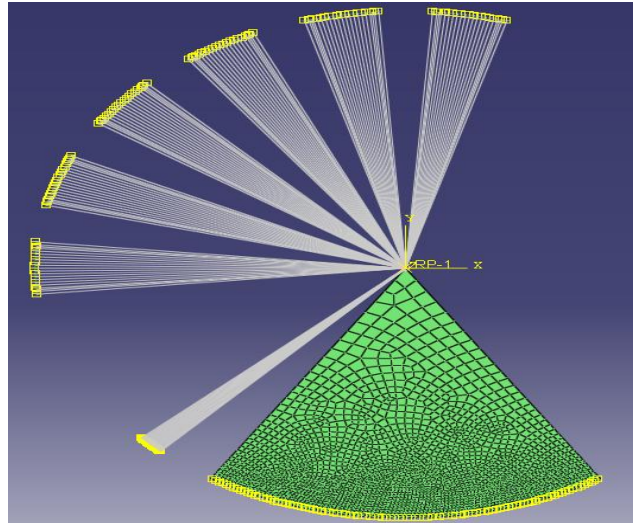


Figure C.1. Original problem approximate (FEA) model (source: the sponsoring company)

Table C.4. Process parameters/simulation initial conditions

Rolling Simulation Initial conditions		
Roll size Roll material	180 mm High chromium	Thermal diffusivity (α) = $\lambda / \rho C_p$
		Thermal conductivity (λ) = 48w/m.k
		Specific heat capacity (C_p) = 478j/kg.k
		Density (ρ) = 7083kg/m3
		Expansion (ϵ) = 12e-6
		Elasticity (E) = 180 GPa

The FEA model is the assembly of 6 nozzles, one simplified version of the feedstock rotate around the roll and 180 mm radiuses chromium steel roll.

The assembly boundary conditions inside the model are presented in the previous page. Tables C.4 and Table C.5 give the model specifications and process parameters.

Table C.5. Targeted independent design factors of the experiment

Process Parameters		Process Parameters
HTC 1 (for cooling & rolling)	HTC 2 (for roll & stock contact)	
HTC 1 & 2 are the 2 single entities of the design variables representing a number of sub factors discussed in section 5.2.2		Stock temperature
		Roll temperature
		Roll speed
		Delay time
		Roll-Stock contact length

Appendix - D

Work Roll System Design Factors Functional Relationships display

This section presents extracts of functional relationship study of factors that determine the work roll system thermal behavior. The Tables presented below show the few selected factors considered most relevant to the problem and their mathematical definitions so that the relationship, if any between factors can be identified. The functional relationships study is the follow-up of factors reduction process shown in Section 5.2.1, Figures 5.3 and 5.4. The dependency or independency of the factors studied by defining the factors identified mathematically and compare the factors definition to look for any relationship. Based on the study the final 7 design factors shown in Section 5.2.2, Table 5.3 in Chapter 5. Factor relationship is presented in Table D.1 below.

Table D.1. Work roll thermal design factors functional relationship

System				
REHEATING	FURNACE	Furnace	tunnel	[~2m]
Subsystem denomination				
Variable 1				
inter-stand time	(depends on	mill	pace	(ie, roll speed)
inter-stand time		1 =	1.4m	/ velocity 1 [m/s]
Variable 2				
roll stock contact length can be expressed as a function of rolling load and length				
$p_s = P / b_m L$ and length $L = \sqrt{R(h_1 - h_2) - h_1 - h_2}^2 / 4$ P_s specific mean roll pressure,				
P = rolling load, b_m = mean breadth of material, h_1 and h_2 = height at the entry and exit of the roll				
Variable 3				
rolling force expressed as a function of change in temperature				
$FL / WR = \Delta T$ f = is rolling force, L & W length and width of the rolled product, R = roll radius				
Variable 4				
contact time for given size of roll diameter				
time $t_1 = \text{asin}(\sqrt{\text{draught}_1 / R_1}) / \omega_1$				
for consecutive stands				
inter-stand time		2 =	1.5m	/ velocity 2 [m/s]
Stand	O2	(roll diam=628	mm)	
time $t_2 = \text{asin}(\sqrt{\text{draught}_2 / R_2}) / \omega_2$				
inter-stand time		3 =	1.5m	/ velocity 3 [m/s]
Stand	O3	(roll diam=630	mm)	
time $t_3 = \text{asin}(\sqrt{\text{draught}_3 / R_3}) / \omega_3$				
inter-stand time		4 =	1.5m	/ velocity 4 [m/s]
Stand	O4	(roll diam=585	mm)	
time $t_4 = \text{asin}(\sqrt{\text{draught}_4 / R_4}) / \omega_4$				
inter-stand time		5 =	1.5m	/ velocity 5 [m/s]
Stand	O5	(roll diam=665	mm)	
time $t_5 = \text{asin}(\sqrt{\text{draught}_5 / R_5}) / \omega_5$				

Table D.2. Work roll thermal design factors functional relationship

Variable	5					
roll speed	[rad/s]	(min	1.4 rad/s	max10.4	rad/s)	recommended
velocity	inter-stand distance / time [rad/sec]					
for consecutive stands based on recommended min max range						
velocity	1 (minimum	0.14 rad/s	max10.4	rad/s)		
velocity	2 velocity 1	X	1.68			
velocity	3 velocity 2	X	1.68			
velocity	4 velocity 3	X	1.68			
velocity	5 velocity	X	1.68			
Variable	6					
draught	per	pass	(i.e.,	reduction)	[mm]	draught = max 25%
redaction	time X roll diameter / roll velocity at a given pass					
Variable	7					
stock temperature	Tinit=950...1deg^c		range from stand 1 to 5			
Variable	8					
oxide	scale	thickness: ~0.8...2	mm	depending on distance from furnace and descaling spray		
Variable	9					
Stock	size:	varies between		180x180	mm/210x2	

Table D.3. Work roll thermal design factors functional relationship

Variable	10		
initial temp /pass			
T init - heat loss at each stage of the process (pass) + heat loss while the stock at delay time			
for consecutive passes the initial temp calculated as the following			
Tinit-heatLoss	(heatLoss=~1:deg C)		
Tinit1 - heat Loss at dT1 (from furnace to the 1st stand)			
secondary	oxide	scale=~5...40microm	
reduced	stock	size	1
Tinit2-heatLossR1 - dT1 - dT2			
secondary	oxide	scale=~5...40microm	
reduced	stock	size	2
Tinit3 - heatLossR2-dT1-dT2-dT3			
secondary	oxide	scale=~5...40microm	
reduced	stock	size	3
Tinit4 - heatLossR3 - dT1 - dT2 - dT3 - dT4			
secondary	oxide	scale=~5...40microm	
reduced	stock	size	4
Tinit5 - heatLossR4 - dT1- dT2 - dT3 - dT4 - dT5			

Table D.4. Work roll thermal design factors functional relationship

Variable	11
HTC	heat transfer coefficient for Roll cooling heat
15...50	kW/m ² K (if HTC considered as one variable to present the f [*]
HTC is depend on the sub groups in the rolling system that have influence the transfer of heat.	
The source of those factors classified in two i.e. The cooling factor and roll stock contac	
The cooling factors	
roll	cooling stand-off distance 10mm
roll	cooling no of nozzles ~ 6
roll	cooling flow rate [l/min] ~ max 40 l/min
roll	cooling pressure ~3.5 bar
same value can be considered for each pass (for multi-pass problems)	
researchers also used the following function to represent HTC for water spray zone	
hws = 2900W ^{0.85} (1 + 0.014Tw), where W is the water flow velocity, in ms ⁻¹ , and TW is the water temperature, in °C	
Roll stock contact factor	
scale size	
contact time	
rolling section type	
material specific heat which can be derived from the relation ($\alpha = K / \rho C$) ; where α = thermal diffusivity	
reduction size k = thermal conductivity	
ρ = density	
C = material specific heat	
Hadly et.a.l devised an empirical equation for HTC cooling; constituting the necessary factors that need to be addressed.	
$H_{cool} = k/c l (pr / \sigma s)^{1/7}$	
$\bar{k} = k_{rk} k_r + k_s$	
The terms $\bar{\sigma s}$ and pr are the mean flow stress and the mean roll pressure, respectively, and $c l$ is a constant, varies respectively depending on the material used, and k_s and k_r are slab work-roll thermal conductivity	

Table D.5. Work roll thermal design factors functional relationship

Variable	12
HTC roll stock contact	(depend on the sub groups in the rolling system that have influence the transfer of heat).
heat-transfer problem in the roll gap as the function of heat-transfer coefficient α and writing the heat-transfer rate or the power of heat transfer.	
$P = \alpha A \Delta T$. Where: $A = w b L$, $L = \sqrt{R t \Delta h}$, $\Delta h = h_o - h_i$ and $\Delta T = T_b - T_r$.	

Appendix - E

Single Pass, Many Objectives Problem Optimisation

Programme Code

The programme code written in R environments written to search, optimal good design solution for work roll system optimisation using thermal analysis and genetic algorithms (GA). The framework is for searching solutions for the multi-objectives single pass optimisation problems with uncertainty presented in Section 6.4, Chapter 6.

Programme code

```
## Single Pass problem:
corus <- function(x)
{
  y <- numeric(2)
  lim <- 1  ## number of samples for estimating then x[1] to x[7]
  (CLT)
  mn <- 0.0  ## mean value for rnorm (do not change!)
  ##std1 <- 0.5  ## individual variances
  ##std2 <- 15.0
  ##std3 <- 1.0
  ##std4 <- 1.7
  ##std5 <- 0.0558
  ##std6 <- 2.0
  ##std7 <- 4.0
  std1 <- 0  ## individual variances
  std2 <- 0
  std3 <- 0
  std4 <- 0
  std5 <- 0
  std6 <- 0
  std7 <- 0
```

```
## Single Pass problem:
corus <- function(x) {
y <- numeric(2)
lim <- 1  ## number of samples for estimating then x[1] to x[7]
(CLT)
mn <- 0.0  ## mean value for rnorm (do not change!)
##std1 <- 0.5  ## individual variances
##std2 <- 15.0
##std3 <- 1.0
##std4 <- 1.7
##std5 <- 0.0558
##std6 <- 2.0
##std7 <- 4.0
std1 <- 0  ## individual variances
std2 <- 0
std3 <- 0
std4 <- 0
std5 <- 0
std6 <- 0
std7 <- 0
storage1 <- seq(1,lim)
storage2 <- seq(1,lim)
storage3 <- seq(1,lim)
storage4 <- seq(1,lim)
storage5 <- seq(1,lim)
storage6 <- seq(1,lim)
storage7 <- seq(1,lim)
cnt <- 1  ## dnc!
while (cnt <= lim){
  st1 <- rnorm(1,mn,std1)+x[1]
  st2 <- rnorm(1,mn,std2)+x[2]
  st3 <- rnorm(1,mn,std3)+x[3]
  st4 <- rnorm(1,mn,std4)+x[4]
  st5 <- rnorm(1,mn,std5)+x[5]
  st6 <- rnorm(1,mn,std6)+x[6]
  st7 <- rnorm(1,mn,std7)+x[7]
```

fitness functions

CH-T_{-surface} <- (-370.8659 + 3.92666667 * x[1] + 0.046222222 * x[1]^2 + 3.02845679 * x[2] - 0.00130938 * x[2]^2 + 0.0000001 * x[3] - 0.0000025 * x[3]^2 - 7.0603175 * x[4] + 0.085079365 * x[4]^2 + 26.9230797 * x[5] + 3.44362939 * x[5]^2 + 3.99055556 * x[6] - 0.04194444 * x[6]^2 - 0.80194444 * x[7] + 0.004701389 * x[7]^2)

SII_{-surface} <- (140.63997 - 10.082111 * x[1] + 0.064200000 * x[1]^2 - 1.2915963 * x[2] + 0.002292222 * x[2]^2 + 0.00144444 * x[3] - 0.000003333 * x[3]^2 + 12.1149569 * x[4] - 0.21604354 * x[4]^2 - 387.34458 * x[5] + 145.751168 * x[5]^2 - 2.6677500 * x[6] + 0.038687500 * x[6]^2 - 1.4585556 * x[7] + 0.011982292 * x[7]^2)

Ch-T_{-9mm} <- (-819.98558 + 9.97380000 * x[1] - 0.31336444 * x[1]^2 + 1.43803309 * x[2] - 0.59030E-3 * x[2]^2 - 0.13506667 * x[3] + 0.095348889 * x[3]^2 - 5.1424209 * x[4] + 0.062201542 * x[4]^2 + 52.8477445 * x[5] - 23.073031 * x[5]^2 + 0.050088889 * x[6] - 0.00849611 * x[6]^2 - 0.22464444 * x[7] + 0.001426597 * x[7]^2)

SII_{-9mm} <- (2913.51841 - 18.435556 * x[1] + 0.508400000 * x[1]^2 - 5.0893000 * x[2] + 0.002138444 * x[2]^2 - 3.9332778 * x[3] - 0.13521667 * x[3]^2 + 14.6337279 * x[4] - 0.18028299 * x[4]^2 - 248.51971 * x[5] + 101.248057 * x[5]^2 + 0.171083333 * x[6] + 0.017137500 * x[6]^2 + 0.108888889 * x[7] - 0.17812E-3 * x[7]^2)

Ch-T_{-15mm} <- (-553.55904 + 10.7411111 * x[1] - 0.35888889 * x[1]^2 + 1.00235802 * x[2] - 4.0321E-3 * x[2]^2 - 0.51055556 * x[3] + 0.094944444 * x[3]^2 - 3.9777324 * x[4] + 0.045913832 * x[4]^2 + 51.7361959 * x[5] - 28.708807 * x[5]^2 - 1.0575000 * x[6] + 0.001652778 * x[6]^2 - 0.29222222 * x[7] + 0.002204861 * x[7]^2)

SII_{-15mm} <- (2316.50677 - 19.781444 * x[1] + 0.553933333 * x[1]^2 - 4.0415037 * x[2] + 0.001683704 * x[2]^2 - 5.6866667 * x[3] - 0.07520000 * x[3]^2 + 11.4528209 * x[4] - 0.13340408 * x[4]^2 - 199.10688 * x[5] + 97.5171611 * x[5]^2 + 0.867388889 * x[6] + 0.009866667 * x[6]^2 + 0.738388889 * x[7] - 0.00434792 * x[7]^2)

```

limf<- 1  ## number of samples for estimating then fit[5] to fit[m]
(CLT)
cnt <- 1  ## dnc!
fstd1 <- 0 ## noise for fitness 1
fstd2 <- 0 ## noise for fitness 2
fstd3 <- 0
fstd4 <- 0
fstd5 <- 0
fstd6 <- 0
storage1f <- seq(1,limf)
storage2f <- seq(1,limf)
storage3f <- seq(1,limf)
storage4f <- seq(1,limf)
storage5f <- seq(1,limf)
storage6f <- seq(1,limf)
while (cnt <= limf){
  r1 <- rnorm(1,mn,fstd1)+fit1
  r2 <- rnorm(1,mn,fstd2)+fit2
  r3 <- rnorm(1,mn,fstd3)+fit3
  r4 <- rnorm(1,mn,fstd4)+fit4
  r5 <- rnorm(1,mn,fstd5)+fit5
  r6 <- rnorm(1,mn,fstd6)+fit6
  storage1f[cnt]<-r1
  storage2f[cnt]<-r2
  storage3f[cnt]<-r3
  storage4f[cnt]<-r4
  storage5f[cnt]<-r5
  storage6f[cnt]<-r6
  cnt <- cnt+1
}
y[1]<-median(storage1f)
y[2]<-median(storage2f)
y[3]<-median(storage3f)
y[4]<-median(storage4f)
y[5]<-median(storage5f)
y[6]<-median(storage6f)
return (y)
}
r1 <- nsga2(corus,7,6,
            generations =500, popsize= 1000,
            cprob=0.7, cdist=20,
            mprob=0.2, mdist=20,
            lower.bounds = c(5, 950, 10, 15, 0.14, 40,
            20),
            upper.bounds = c(15,1250, 30, 50, 1.256,
            80, 100)
            )
plot(r1)

```

Figure E.1. Programme code for single pass problem optimisation

Appendix-F

User Information for Running the Programme

The section gives information guide for running the programme code for the optimisation. The procedures are as follows:

- ✓ Open **RGui** and R console from the drive where R stored or using short cut



icon from the desktop, (double click the icon, to open it)

- ✓ In the RGui tool bar click the **package**, in the dropdown menu appear select **load package**. The selection brings the new box shown on the right in Figure 1.1. The new box contains modules which can be selected depending on job to be executed. In our case MCO, Multi Criterion Optimisation, highlighted in the box is selected. The mco package selected is shown at the end the console. The console also gives useful commands for further demonstration.

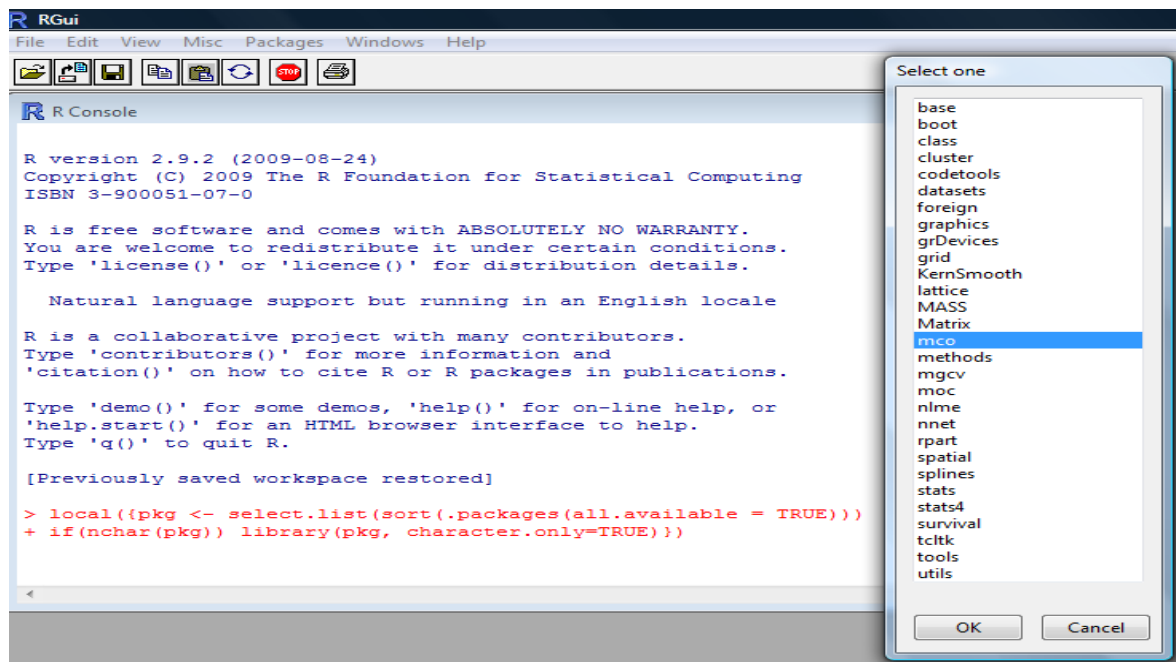


Figure F.1. RGui and R console with available work packages

Calling the Programme Code

The programme code can be called from the folder it has been stored by selecting **file** from the RGui tool bar and choose **open script** from the dropdown menu, then locate

the file and double click to open it. The programme will open in new window. The graph below shows the open programme code file in the console.

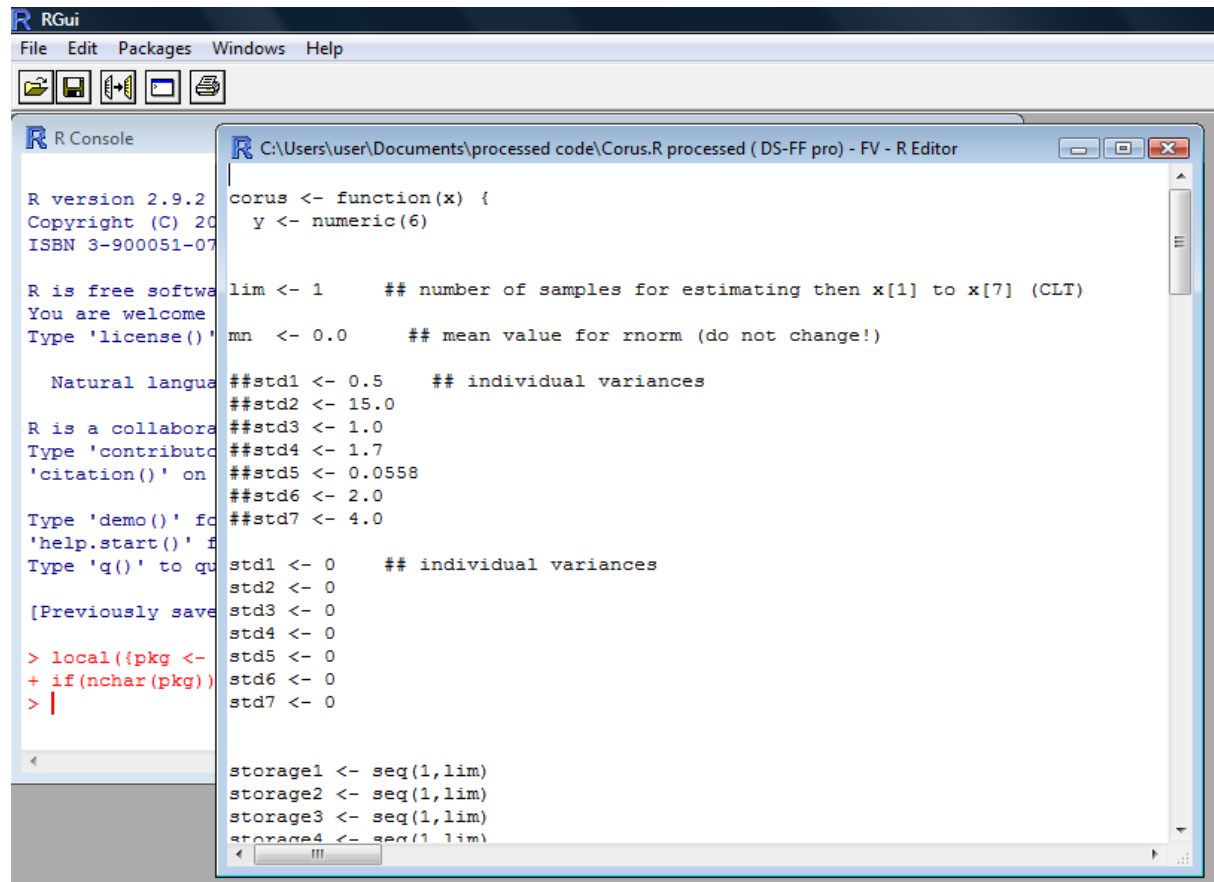


Figure F.2. Example of the program code, ready to run

After setting the required specification, depending on user requirements, such as pop and generation in the generic code shown above, the code can be set for run. To run the programme code locates on **edit** in the RGui tool bar. From the dropdown menu select the **run all** then there you go the programme code begin to run. Graph F.3 below shows completed run from which the results can be saved or displayed. The (r1) in the **plot (r1)** at the end of the run shown in Figure F.4, holds the expected solution from the optimisation. Calling (r1) or may be cut & pest it will display the results. Result from the optimisation consists of the design variable parameters and objectives values of the optimisation problem. It also shows the number of true solutions out of the total population provided at the start of the optimisation run. The graph below shows an example of parameters and values from the optimisation. Figure F.3 and Figure F.4 below show, examples of the run completed programme and solution display after result called, respectively.

The screenshot shows the RGui interface. The R Console window contains the following code:

```

+
+ return (y)
+
+ }
> r1 <- nsga2(corus,7,6,
+             generations =200, popsize= 400,
+
+             cprob=0.7, cdist=20,
+             mprob=0.2, mdist=20,
+
+             lower.bounds = c(5, 950, 10, 15, 0.14, 40, 20),
+             upper.bounds = c(15,1250, 30, 50, 1.256, 80, 100)
+
+             ##mono.con(7,n 14,up=TRUE,lower= -10,upper= 18)
+
+             ##mgcv.control (conv.tol=e-,max.half=0,target.edf=NULL,min.edf=0)
+
+ )
>
> plot(r1)
>
>
>
>
>
>

```

A second window, titled 'C:\Users\user\Docum', shows the following code:

```

corus <- function
y <- numeric(6)

lim <- 1      ## r
mn <- 0.0     ##

##std1 <- 0.5
##std2 <- 15.0
##std3 <- 1.0
##std4 <- 1.7
##std5 <- 0.0558
##std6 <- 2.0
##std7 <- 4.0

std1 <- 0     ## i
std2 <- 0
std3 <- 0
std4 <- 0
std5 <- 0
std6 <- 0
std7 <- 0

```

Figure F.3. Programme code after run completed.

The screenshot shows the RGui interface with the R Console displaying the output of the `nsga2` function. The output is a matrix of optimal solutions.

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]
[1,]	5.000000	950.0000	10.00020	43.33580	0.1400000	79.99955	66.17116
[2,]	5.000043	950.0055	10.00069	41.92137	0.1400009	79.99914	82.70163
[3,]	14.999467	1203.6136	29.99986	15.00012	1.0501501	40.00174	20.00222
[4,]	5.000004	950.0055	10.00003	41.92137	0.1400010	79.99914	79.13044
[5,]	11.637790	1150.5385	29.99984	15.00035	1.2559986	40.07983	60.34309
[6,]	14.989619	1191.2974	29.99900	15.00001	1.2310403	40.00005	20.73206
[7,]	5.169070	954.3995	11.34305	33.87973	0.9782147	43.94977	61.03376
[8,]	6.413825	951.7778	10.12476	17.85622	0.9671649	75.96577	58.36019
[9,]	6.409380	951.7778	10.12476	17.85622	0.6875286	77.83313	55.73474
[10,]	8.170854	952.2229	29.30572	43.61075	0.1676960	79.97945	78.35138
[11,]	5.311465	967.9867	10.17948	26.76620	0.7433496	42.25862	62.60181
[12,]	5.537311	962.4279	19.51584	45.50544	0.9738858	78.87130	73.46213
[13,]	5.000231	952.9078	10.92541	44.21720	0.4253537	79.92301	63.24341
[14,]	5.324416	952.1857	10.01096	41.89275	0.1585579	79.98179	78.54753
[15,]	5.537311	987.0606	20.10951	45.50544	0.6942495	78.87130	73.46213
[16,]	5.311465	967.9867	10.17948	25.69169	0.7688391	42.25862	62.60181
[17,]	5.249846	1000.8871	12.89628	19.36188	0.7373809	76.53157	59.43551
[18,]	5.028749	950.0806	20.78731	31.63113	0.7034902	79.54372	58.08046

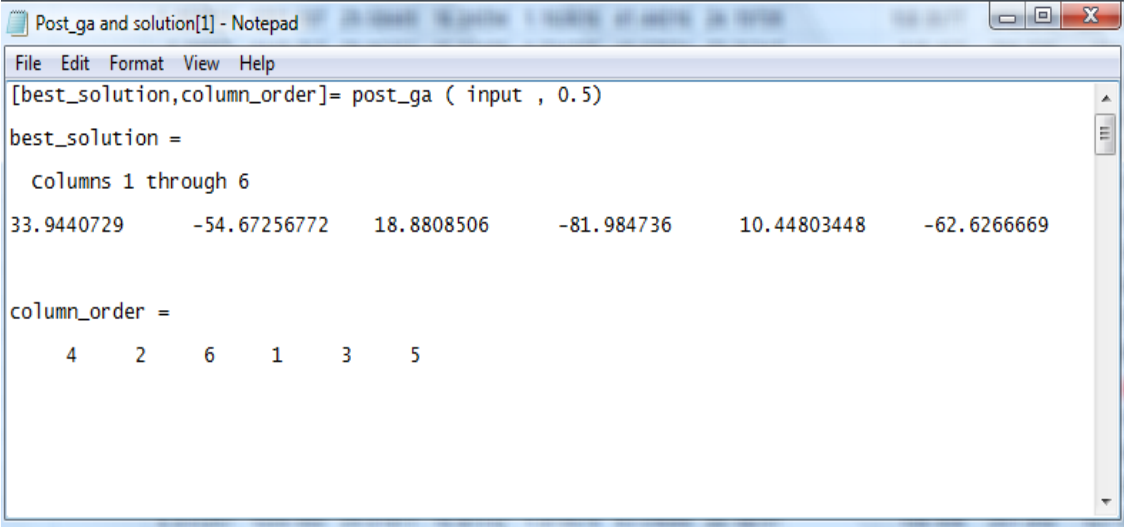
Figure F.4. Population of optimal solutions from the optimisation

Appendix-G

Post GA Result Analysis, for Searching Best Optimal Design Solution/s

Programme Code & Descriptions

Here presented the programme code written in Matlab for analysis result from GA through iterative process of search space reductions to identifies the best optimal design solution,. The post GA result analysis programme code is consists of a processing units. The units are designed to process the input data i.e. the population of solutions found by the algorithm, to reduce the search space and identify the best optimal design solution or two solutions that satisfy the problem objectives. The programme code is generic hence applicable to any dimensional problem. The programme also used in the multi-pass problem solution final best optimal solution search. Description of the programme and its application in the solution search are discussed in Section 6.4-3 and 6.4-4 in Chapter 6. Figure F.1 present example showing the column order and the final best optimal design solution identified by the programme. Figure G.2 presents the programme code.



```
Post_ga and solution[1] - Notepad
File Edit Format View Help
[best_solution,column_order]= post_ga ( input , 0.5)
best_solution =
    columns 1 through 6
    33.9440729    -54.67256772    18.8808506    -81.984736    10.44803448    -62.6266669
column_order =
     4     2     6     1     3     5
```

Figure G.1 Final optimal design solution identified

```
function [solution]=post_ga ( input , percentage)
% Post(GA) optimisation result analysis for indentifying best, optimal
design solution/s (%age reduction)
% /////
% percentage should be in the form like 0.5 ( for 50% )
% solution is a matrix with the solution in output of the GA
% this function should work with any dimension of solution
% example [best_solution,column_order]= post_ga( input , 0.7)
% with "input" as a matrix of value in column order ( es. 400x6)
solution=abs(input);
format longG % I need this to catch the solution value later
[n,m]=size(solution);
somma=zeros(n,1); % somma = sum
% transforming all value in weighted vectors
% solution holds the weighted value of the input data
for i=1:n
    somma(i)=sum(solution(i,:));
    for j=1:m
        solution (i,j)=solution(i,j)/somma(i);
    end
end
% average value of the column
for i=1:m
    mean(i)=(sum(solution(:,i)))/n;
end
% ranking all the column
% The first rows of Ranking Matrix are filled with the number of the
O.F.
% the second rows are the mean values of all the fields in the columns
% and the third rows are filled with number of the column which has
the
% maximum average value sorted in decreasing order
ranking=zeros(3,m);
for i=1:m
    ranking(1,i)=i;
    ranking(2,i)=mean(i);
end
```

```
dummy_var=ranking(2,:);
for i=1:m
    massimo=max(dummy_var);    %Massimo=maximum
                                for j=1:m
                                    if ranking(2,j)==massimo;
                                        ranking(3,j)=i;
                                        dummy_var(j)=0;
                                    end
                                end
end
% making a new matrix with column in the right order
new_order=zeros(n,m);
for i=1:m
    for h=1:m
        if ranking(3,h)==i;
            for j=1:n
                new_order(j,i)=solution(j,h);
            end
        end
    end
end
% at this point you've got a matrix with the column ordered by their
% respective average value now you've got to sort the solution's
% matrix called
% new_order
% percentage reduction
n_rows=percentage*n;
n_rows=round(n_rows);
reduced_matrix=zeros(n,m);
sorted_matrix=new_order;
for i=1:m
    sorted_matrix=sortrows(sorted_matrix,-i);
    for j=(n_rows+1):n
        for h=1:m
            sorted_matrix(j,h)=0;
        end
    end
end
```

```

n_rows=n_rows*percentage;
n_rows=round(n_rows);
if n_rows<1
    n_rows=1;
end
end
reduced_matrix=sorted_matrix;
for i=1:n
    if reduced_matrix(i,m)~= 0;
        con_var=i;
    end
end
recovery = zeros(con_var,m);
for i=1:con_var
    for j=1:m
        recovery(i,j)=reduced_matrix(i,j);
        for h=1:n
            for p=ranking(3,:);          % you have reordered columns
RECALLS
!
                if recovery(i,j)==solution(h,p)
                    recovery(i,j)=input(h,p);
                end
            end
        end
    end
end
column_order=ranking(3,:);
best_solution=recovery;
soluzione=[];
a=[];
for i=1:6
    a=column_order(i);
    soluzione(i)=best_solution(a);      % soluzione = Solution
end
solution= soluzione';
end

```

Figure G.2. The Programme code for searching best optimal design solution search

Appendix-H

Multi-pass Regression Models Factor Value Matrix

The multi-pass models are developed from the FE simulations response data performed using the set-up in Table 5.5, Chapter 5 and the data sampling matrix given in Tables (F1-F.5) below as the input values for generating the regression models. Multi-pass quantitative models of all the responses were generated by fitting the second order model type (main effects, interaction effects and quadratic effects). Existing knowledge was used to define regions of interest, 35 variables were identified and their operating range specified. Table 7.5 shows the factors used in the simulations.

Table H.1. Regression model factor value matrix for Pass-1

Input set	HTC-II	Stock temperature	R/S contact length	HTC-I	Roll speed	Roll temperature	Delay time
1	5	1230	10	15	0.14	40	20
2	10	1230	20	15	0.14	40	20
3	15	1230	30	15	0.14	40	30
4	5	1250	10	32.5	0.2	40	20
5	10	1250	20	32.5	0.2	40	20
6	15	1250	30	32.5	0.2	40	30
7	5	1250	10	50	0.2	40	20
8	10	1250	20	50	0.2	40	20
9	15	1250	30	50	0.2	40	30
10	15	1230	20	50	0.2	60	20
11	5	1230	30	50	0.2	60	20
12	10	1230	10	50	0.2	60	30
13	15	1250	20	15	0.2	60	20
14	5	1250	30	15	0.2	60	20
15	10	1250	10	15	0.2	60	30
16	15	1250	20	32.5	0.14	60	20
17	5	1250	30	32.5	0.14	60	20
18	10	1250	10	32.5	0.14	60	30
19	10	1230	30	32.5	0.2	80	20
20	15	1230	10	32.5	0.2	80	20
21	5	1230	20	32.5	0.2	80	30
22	10	1250	30	50	0.14	80	20
23	15	1250	10	50	0.14	80	20
24	5	1250	20	50	0.14	80	30
25	10	1250	30	15	0.2	80	20
26	15	1250	10	15	0.2	80	20
27	5	1250	20	15	0.2	80	30

Table H.2. Regression model factor value matrix for Pass-2

Input set	HTC-II	Stock temperature	R/S contact length	HTC-I	Roll speed	Roll temperature	Delay time
5	1155	10	15	0.17	40	30	5
10	1155	20	15	0.17	40	40	10
15	1155	30	15	0.17	40	50	15
5	1175	10	32.5	0.23	40	30	5
10	1175	20	32.5	0.23	40	40	10
15	1175	30	32.5	0.23	40	50	15
5	1195	10	50	0.29	40	30	5
10	1195	20	50	0.29	40	40	10
15	1195	30	50	0.29	40	50	15
15	1155	20	50	0.23	60	30	15
5	1155	30	50	0.23	60	40	5
10	1155	10	50	0.23	60	50	10
15	1175	20	15	0.29	60	30	15
5	1175	30	15	0.29	60	40	5
10	1175	10	15	0.29	60	50	10
15	1195	20	32.5	0.23	60	30	15
5	1195	30	32.5	0.23	60	40	5
10	1195	10	32.5	0.23	60	50	10
10	1155	30	32.5	0.29	80	30	10
15	1155	10	32.5	0.29	80	40	15
5	1155	20	32.5	0.29	80	50	5
10	1175	30	50	0.23	80	30	10
15	1175	10	50	0.23	80	40	15
5	1175	20	50	0.23	80	50	5
10	1195	30	15	0.23	80	30	10
15	1195	10	15	0.23	80	40	15
5	1195	20	15	0.23	80	50	5

Table H.3. Regression model factor value matrix for Pass-3

Input set	HTC-II	Stock temperature	R/S contact length	HTC-I	Roll speed	Roll temperature	Delay time
5	1080	10	15	0.32	40	50	5
10	1080	20	15	0.32	40	60	10
15	1080	30	15	0.32	40	70	15
5	1100	10	32.5	0.38	40	50	5
10	1100	20	32.5	0.38	40	60	10
15	1100	30	32.5	0.38	40	70	15
5	1120	10	50	0.44	40	50	5
10	1120	20	50	0.44	40	60	10
15	1120	30	50	0.44	40	70	15
15	1080	20	50	0.38	60	50	15
5	1080	30	50	0.38	60	60	5
10	1080	10	50	0.38	60	70	10
15	1100	20	15	0.44	60	50	15
5	1100	30	15	0.44	60	60	5
10	1100	10	15	0.44	60	70	10
15	1120	20	32.5	0.32	60	50	15
5	1120	30	32.5	0.32	60	60	5
10	1120	10	32.5	0.32	60	70	10
10	1080	30	32.5	0.44	80	50	10
15	1080	10	32.5	0.44	80	60	15
5	1080	20	32.5	0.44	80	70	5
10	1100	30	50	0.32	80	50	10
15	1100	10	50	0.32	80	60	15
5	1100	20	50	0.32	80	70	5
10	1120	30	15	0.38	80	50	10
15	1120	10	15	0.38	80	60	15
5	1120	20	15	0.38	80	70	5

Table H.4. Regression model factor value matrix for Pass-4

Input set	HTC-II	Stock temperature	R/S contact length	HTC-I	Roll speed	Roll temperature	Delay time
5	1005	10	15	0.57	40	70	5
10	1005	20	15	0.57	40	80	10
15	1005	30	15	0.57	40	90	15
5	1025	10	32.5	0.63	40	70	5
10	1025	20	32.5	0.63	40	80	10
15	1025	30	32.5	0.63	40	90	15
5	1045	10	50	0.69	40	70	5
10	1045	20	50	0.69	40	80	10
15	1045	30	50	0.69	40	90	15
15	1005	20	50	0.63	60	70	15
5	1005	30	50	0.63	60	80	5
10	1005	10	50	0.63	60	90	10
15	1025	20	15	0.69	60	70	15
5	1025	30	15	0.69	60	80	5
10	1025	10	15	0.69	60	90	10
15	1045	20	32.5	0.57	60	70	15
5	1045	30	32.5	0.57	60	80	5
10	1045	10	32.5	0.57	60	90	10
10	1005	30	32.5	0.69	80	70	10
15	1005	10	32.5	0.69	80	80	15
5	1005	20	32.5	0.69	80	90	5
10	1025	30	50	0.57	80	70	10
15	1025	10	50	0.57	80	80	15
5	1025	20	50	0.57	80	90	5
10	1045	30	15	0.63	80	70	10
15	1045	10	15	0.63	80	80	15
5	1045	20	15	0.63	80	90	5

Table H.5. Regression model factor value matrix for Pass-5

Input set	HTC-II	Stock temperature	R/S contact length	HTC-I	Roll speed	Roll temperature	Delay time
5	950	10	15	0.98	40	90	5
10	950	20	15	0.98	40	100	10
15	950	30	15	0.98	40	100	15
5	950	10	32.5	1.04	40	90	5
10	950	20	32.5	1.04	40	100	10
15	950	30	32.5	1.04	40	100	15
5	970	10	50	1.1	40	90	5
10	970	20	50	1.1	40	100	10
15	970	30	50	1.1	40	100	15
15	950	20	50	1.04	60	90	15
5	950	30	50	1.04	60	100	5
10	950	10	50	1.04	60	100	10
15	950	20	15	1.1	60	90	15
5	950	30	15	1.1	60	100	5
10	950	10	15	1.1	60	100	10
15	970	20	32.5	0.98	60	90	15
5	970	30	32.5	0.98	60	100	5
10	970	10	32.5	0.98	60	100	10
10	950	30	32.5	1.1	80	90	10
15	950	10	32.5	1.1	80	100	15
5	950	20	32.5	1.1	80	100	5
10	950	30	50	0.98	80	90	10
15	950	10	50	0.98	80	100	15
5	950	20	50	0.98	80	100	5
10	970	30	15	1.04	80	90	10
15	970	10	15	1.04	80	100	15
5	970	20	15	1.04	80	100	5

Appendix - I

Multi-Pass Problem Optimisation Programme Code

The programme code written in R environments written to search, optimal good design solution for work roll system optimisation using thermal analysis and genetic algorithms (GA). The framework is for searching solutions for the many-objectives multi-pass optimisation problems with uncertainty presented in Section 7.2, Chapter 7.

Programme code

```
## corus problem:
corus <- function(x) {
  y <- numeric(2)
  lim <- 1  ## number of samples for estimating then x[1] to
  x[35] (CLT)
  mn <- 0.0  ## mean value for rnorm (d n c!)
  std1 <- 0.5  ## individual variance
  std2 <- 1.0
  std3 <- 1.0
  std4 <- 1.7
  std5 <- 0.003
  std6 <- 2.0
  std7 <- 4.0
  std8 <- 0.5
  std9 <- 2.0
  std10 <- 1.0
  std11 <- 1.7
  std12 <- 0.006
  std13 <- 2.0
  std14 <- 4.0
  std15 <- 0.5
  std16 <- 2.0
  std17 <- 1.0
  std18 <- 1.7
  std19 <- 0.006
  std20 <- 2.0
  std21 <- 4.0
```

```
std22 <- 0.5
std23 <- 2.0
std24 <- 1.0
std25 <- 1.7
std26 <- 0.006
std27 <- 2.0
std28 <- 4.0
std29 <- 0.5
std30 <- 2.0
std31 <- 1.0
std32 <- 1.7
std33 <- 0.006
std34 <- 2.0
std35 <- 4.0
storage1 <- seq(1,lim)
storage2 <- seq(1,lim)
storage3 <- seq(1,lim)
storage4 <- seq(1,lim)
storage5 <- seq(1,lim)
storage6 <- seq(1,lim)
storage7 <- seq(1,lim)
storage8 <- seq(1,lim)
storage9 <- seq(1,lim)
storage10 <- seq(1,lim)
storage11 <- seq(1,lim)
storage12 <- seq(1,lim)
storage13 <- seq(1,lim)
storage14 <- seq(1,lim)
storage15 <- seq(1,lim)
storage16 <- seq(1,lim)
storage17 <- seq(1,lim)
storage18 <- seq(1,lim)
storage19 <- seq(1,lim)
storage20 <- seq(1,lim)
storage21 <- seq(1,lim)
storage22 <- seq(1,lim)
storage23 <- seq(1,lim)
```

```
storage24 <- seq(1,lim)
storage25 <- seq(1,lim)
storage26 <- seq(1,lim)
storage27 <- seq(1,lim)
storage28 <- seq(1,lim)
storage29 <- seq(1,lim)
storage30 <- seq(1,lim)
storage31 <- seq(1,lim)
storage32 <- seq(1,lim)
storage33 <- seq(1,lim)
storage34 <- seq(1,lim)
storage35 <- seq(1,lim)
cnt <- 1    ## d n c!
while (cnt <= lim){
  st1 <- rnorm(1,mn,std1)+x[1]
  st2 <- rnorm(1,mn,std2)+x[2]
  st3 <- rnorm(1,mn,std3)+x[3]
  st4 <- rnorm(1,mn,std4)+x[4]
  st5 <- rnorm(1,mn,std5)+x[5]
  st6 <- rnorm(1,mn,std6)+x[6]
  st7 <- rnorm(1,mn,std7)+x[7]
  st8 <- rnorm(1,mn,std8)+x[8]
  st9 <- rnorm(1,mn,std9)+x[9]
  st10 <- rnorm(1,mn,std10)+x[10]
  st11 <- rnorm(1,mn,std11)+x[11]
  st12 <- rnorm(1,mn,std12)+x[12]
  st13 <- rnorm(1,mn,std13)+x[13]
  st14 <- rnorm(1,mn,std14)+x[14]
  st15 <- rnorm(1,mn,std15)+x[15]
  st16 <- rnorm(1,mn,std16)+x[16]
  st17 <- rnorm(1,mn,std17)+x[17]
  st18 <- rnorm(1,mn,std18)+x[18]
  st19 <- rnorm(1,mn,std19)+x[19]
  st20 <- rnorm(1,mn,std20)+x[20]
  st21 <- rnorm(1,mn,std21)+x[21]
  st22 <- rnorm(1,mn,std22)+x[22]
  st23 <- rnorm(1,mn,std23)+x[23]
```

```

st24 <- rnorm(1,mn,std24)+x[24]
st25 <- rnorm(1,mn,std25)+x[25]
st26 <- rnorm(1,mn,std26)+x[26]
st27 <- rnorm(1,mn,std27)+x[27]
st28 <- rnorm(1,mn,std28)+x[28]
st29 <- rnorm(1,mn,std29)+x[29]
st30 <- rnorm(1,mn,std30)+x[30]
st31 <- rnorm(1,mn,std31)+x[31]
st32 <- rnorm(1,mn,std32)+x[32]
st33 <- rnorm(1,mn,std33)+x[33]
st34 <- rnorm(1,mn,std34)+x[34]
st35 <- rnorm(1,mn,std35)+x[35]
## boundaries
if (st1<5.0) { st1=5.0}
if (st1>15.0) { st1=15.0}
if (st2<1230.0){ st2=1230.0}
if (st2>1250.0){ st2=1250.0}
if (st3<10.0) { st3=10.0}
if (st3>30.0) { st3=30.0}
if (st4<15.0) { st4=15.0}
if (st4>50.0) { st4=50.0}
if (st5<0.14) { st5=0.14}
if (st5>0.2) { st5=0.2}
if (st6<40.0) { st6=40.0}
if (st6>80.0) { st6=80.0}
if (st7<20.0) { st7=20.0}
if (st7>30.0) { st7=30.0}
if (st8<5.0) { st8=5.0}
if (st8>15.0) { st8=15.0}
if (st9<1155.0){ st9=1155.0}
if (st9>1195.0){ st9=1195.0}
if (st10<10.0) { st10=10.0}
if (st10>30.0) { st10=30.0}
if (st11<15.0) { st11=15.0}
if (st11>50.0) { st11=50.0}
if (st12<0.17) { st12=0.17}
if (st12>0.29) { st12=0.29}

```

```
if (st13<40.0) { st13=40.0}
if (st13>80.0) { st13=80.0}
if (st14<30.0) { st14=300.0}
if (st14>50.0) { st14=50.0}
if (st15<5.0) { st15=5.0}
if (st15>15.0) { st15=15.0}
if (st16<1080.0){ st16=1080.0}
if (st16>1120.0){ st16=1120.0}
if (st17<10.0) { st17=10.0}
if (st17>30.0) { st17=30.0}
if (st18<15.0) { st18=15.0}
if (st18>50.0) { st18=50.0}
if (st19<0.32) { st19=0.32}
if (st19>0.44) { st19=0.44}
if (st20<40.0) { st20=40.0}
if (st20>80.0) { st20=80.0}
if (st21<50.0) { st21=50.0}
if (st21>70.0) { st21=70.0}
if (st22<5.0) { st22=5.0}
if (st22>15.0) { st22=15.0}
if (st23<1005.0){ st23=1005.0}
if (st23>1045.0){ st23=1045.0}
if (st24<10.0) { st24=10.0}
if (st24>30.0) { st24=30.0}
if (st25<15.0) { st25=15.0}
if (st25>50.0) { st25=50.0}
if (st26<0.57) { st26=0.57}
if (st26>0.69) { st26=0.69}
if (st27<40.0) { st27=40.0}
if (st27>80.0) { st27=80.0}
if (st28<70.0) { st28=70.0}
if (st28>228.0) { st28=228.0}
if (st29<5.0) { st29=5.0}
if (st29>15.0) { st29=15.0}
if (st30<950.0) { st30=950.0}
if (st30>970.0) { st30=970.0}
if (st31<10.0) { st31=10.0}
```

```
if (st31>30.0) { st31=30.0}
if (st32<15.0) { st32=15.0}
if (st32>50.0) { st32=50.0}
if (st33<0.98) { st33=0.98}
if (st33>1.10) { st33=1.10}
if (st34<40.0) { st34=40.0}
if (st34>80.0) { st34=80.0}
if (st35<90.0) { st35=90.0}
if (st35>100.0) { st35=100.0}
## boundaries
storage1[cnt]<-st1
storage2[cnt]<-st2
storage3[cnt]<-st3
storage4[cnt]<-st4
storage5[cnt]<-st5
storage6[cnt]<-st6
storage7[cnt]<-st7
storage8[cnt]<-st8
storage9[cnt]<-st9
storage10[cnt]<-st10
storage11[cnt]<-st11
storage12[cnt]<-st12
storage13[cnt]<-st13
storage14[cnt]<-st14
storage15[cnt]<-st15
storage16[cnt]<-st16
storage17[cnt]<-st17
storage18[cnt]<-st18
storage19[cnt]<-st19
storage20[cnt]<-st20
storage21[cnt]<-st21
storage22[cnt]<-st22
storage23[cnt]<-st23
storage24[cnt]<-st24
storage25[cnt]<-st25
storage26[cnt]<-st26
storage27[cnt]<-st27
```

```
storage28[cnt]<-st28
storage29[cnt]<-st29
storage30[cnt]<-st30
storage31[cnt]<-st31
storage32[cnt]<-st32
storage33[cnt]<-st33
storage34[cnt]<-st34
storage35[cnt]<-st35
cnt <- cnt+1
}
x[1] <- median(storage1)
x[2] <- median(storage2)
x[3] <- median(storage3)
x[4] <- median(storage4)
x[5] <- median(storage5)
x[6] <- median(storage6)
x[7] <- median(storage7)
x[8] <- median(storage8)
x[9] <- median(storage9)
x[10] <- median(storage10)
x[11] <- median(storage11)
x[12] <- median(storage12)
x[13] <- median(storage13)
x[14] <- median(storage14)
x[15] <- median(storage15)
x[16] <- median(storage16)
x[17] <- median(storage17)
x[18] <- median(storage18)
x[19] <- median(storage19)
x[20] <- median(storage20)
x[21] <- median(storage21)
x[22] <- median(storage22)
x[23] <- median(storage23)
x[24] <- median(storage24)
x[25] <- median(storage25)
x[26] <- median(storage26)
x[27] <- median(storage27)
```

```

x[28] <- median(storage28)
x[29] <- median(storage29)
x[30] <- median(storage30)
x[31] <- median(storage31)
x[32] <- median(storage32)
x[33] <- median(storage33)
x[34] <- median(storage34)
x[35] <- median(storage35)
##### Ch-T = change in temperature and S11 = (Radial stress) in Pass
1,2,3,4 and 5 respectively ##### fitness functions
Ch-T1 <- (-3056.852 + 3.926 * x[1] + 0.046 * x[1]^2 + 2.399 * x[2] +
0.000 * x[2]^2 + 4.900 * x[3] - 0.025 * x[3]^2 - 7.060 * x[4] + 0.085
* x[4]^2 + 433.707 * x[5] + 0.000 * x[5]^2 + 3.990 * x[6] - 0.041 *
x[6]^2 - 1.801 * x[7] + 0.000 * x[7]^2)

S11 <- (5548.314 - 9.771 * x[1] + 0.419 * x[1]^2 - 4.142 * x[2] +
0.000 * x[2]^2 + 1.914 * x[3] - 0.182 * x[3]^2 + 17.218 * x[4] - 0.219
* x[4]^2 - 2961.768 * x[5] + 0.000 * x[5]^2 - 3.334 * x[6] + 0.044 *
x[6]^2 - 1.193 * x[7] + 0.000 * x[7]^2)

Ch-T2 <- (-73899.661 + 3.926 * x[8] + 0.046 * x[8]^2 + 124.916 *
x[9] - 0.052 * x[9]^2 + 4.900 * x[10] - 0.025 * x[10]^2 - 9.300 * x[11]
+ 0.112 * x[11]^2 + 2560.679 * x[12] - 4322.530 * x[12]^2 + 1.079 *
x[13] - 0.021 * x[13]^2 - 6.968 * x[14] + 0.075 * x[14]^2)

S112 <- (-69103.092 - 9.771 * x[8] + 0.419 * x[8]^2 + 120.479 * x[9]
- 0.050 * x[9]^2 + 1.914 * x[10] - 0.182 * x[10]^2 + 37.146 * x[11] -
0.461 * x[11]^2 - 28760.889 * x[12] + 53404.166 * x[12]^2 + 22.565
* x[13] - 0.140 * x[13]^2 - 17.197 * x[14] + 0.213 * x[14]^2)

Ch-T3 <- (-90110.234 + 3.926 * x[15] + 0.046 * x[15]^2 + 163.144 *
x[16] - 0.073 * x[16]^2 + 4.900 * x[17] - 0.025 * x[17]^2 - 7.060 *
x[18] + 0.085 * x[18]^2 + 68.734 * x[19] + 297.839 * x[19]^2 +
3.990 * x[20] - 0.041 * x[20]^2 - 9.977 * x[21] + 0.075 * x[21]^2)

S113 <- (167748.902 - 9.771 * x[15] + 0.419 * x[15]^2 - 297.750 *
x[16] + 0.134 * x[16]^2 + 1.914 * x[17] - 0.182 * x[17]^2 + 17.216 *
x[18] - 0.219 * x[18]^2 - 11074.571 * x[19] + 12297.376 * x[19]^2 -
3.334 * x[20] + 0.044 * x[20]^2 - 25.755 * x[21] + 0.213 * x[21]^2)

```

```

Ch-T4 <- (-78565.251 + 3.926 * x[22] + 0.046 * x[22]^2 + 152.096 *
x[23] - 0.073 * x[23]^2 + 4.900 * x[24] - 0.025 * x[24]^2 - 7.060 *
x[25] + 0.085 * x[25]^2 - 80.185 * x[26] + 297.839 * x[26]^2 + 3.990
* x[27] - 0.041 * x[27]^2 - 0.997 * x[28] + 0.004 * x[28]^2)

SII4 <- (149025.122 - 9.771 * x[22] + 0.419 * x[22]^2 - 277.576 *
x[23] + 0.134 * x[23]^2 + 1.914 * x[24] - 0.182 * x[24]^2 + 17.214 *
x[25] - 0.219 * x[25]^2 - 17223.259 * x[26] + 12297.376 * x[26]^2 -
3.334 * x[27] + 0.044 * x[27]^2 - 2.180 * x[28] + 0.013 * x[28]^2)

Ch-T5 <- (-740.999 + 3.926 * x[29] + 0.046 * x[29]^2 + 0.926 *
x[30] + 0.000 * x[30]^2 + 4.900 * x[31] - 0.025 * x[31]^2 - 7.060 *
x[32] + 0.085 * x[32]^2 - 324.413 * x[33] + 297.839 * x[33]^2 +
3.990 * x[34] - 0.041 * x[34]^2 - 1.802 * x[35] + 0.000 * x[35]^2)

SII5 <- (76406.333 - 9.771 * x[29] + 0.419 * x[29]^2 - 1.453 * x[30]
+ 0.000 * x[30]^2 + 1.914 * x[31] - 0.182 * x[31]^2 + 17.214 * x[32]
- 0.219 * x[32]^2 - 27307.108 * x[33] + 12297.376 * x[33]^2 - 3.334
* x[34] + 0.044 * x[34]^2 - 1.193 * x[35] + 0.000 * x[35]^2)

limf<- 1    ## number of samples for estimating then fit[1] to fit[m]
(CLT)
cnt <- 1    ## d n c!
fstd1 <- 3.0 ## noise for fitness 1
fstd2 <- 3.0 ## noise for fitness 2
fstd3 <- 3.0 ## noise for fitness 3
fstd4 <- 3.0 ## noise for fitness 4
fstd5 <- 3.0 ## noise for fitness 5
fstd6 <- 3.0 ## noise for fitness 6
fstd7 <- 3.0 ## noise for fitness 7
fstd8 <- 3.0 ## noise for fitness 8
fstd9 <- 3.0 ## noise for fitness 9
fstd10 <- 3.0 ## noise for fitness 10
storage1f <- seq(1,limf)
storage2f <- seq(1,limf)
storage3f <- seq(1,limf)
storage4f <- seq(1,limf)
storage5f <- seq(1,limf)
storage6f <- seq(1,limf)

```

```
storage7f <- seq(1,limf)
storage8f <- seq(1,limf)
storage9f <- seq(1,limf)
storage10f <- seq(1,limf)
while (cnt <= limf){
  r1 <- mnorm(1,mn,fstd1)+fit1
  r2 <- mnorm(1,mn,fstd2)+fit2
  r3 <- mnorm(1,mn,fstd3)+fit3
  r4 <- mnorm(1,mn,fstd4)+fit4
  r5 <- mnorm(1,mn,fstd5)+fit5
  r6 <- mnorm(1,mn,fstd6)+fit6
  r7 <- mnorm(1,mn,fstd7)+fit7
  r8 <- mnorm(1,mn,fstd8)+fit8
  r9 <- mnorm(1,mn,fstd9)+fit9
  r10 <- mnorm(1,mn,fstd10)+fit10
  storage1f[cnt]<-r1
  storage2f[cnt]<-r2
  storage3f[cnt]<-r3
  storage4f[cnt]<-r4
  storage5f[cnt]<-r5
  storage6f[cnt]<-r6
  storage7f[cnt]<-r7
  storage8f[cnt]<-r8
  storage9f[cnt]<-r9
  storage10f[cnt]<-r10
  cnt <- cnt+1
}
y[1]<-median(storage1f)
y[2]<-median(storage2f)
y[3]<-median(storage3f)
y[4]<-median(storage4f)
y[5]<-median(storage5f)
y[6]<-median(storage6f)
y[7]<-median(storage7f)
y[8]<-median(storage8f)
y[9]<-median(storage9f)
y[10]<-median(storage10f)
```

```
return (y)
}
r1 <- nsga2(corus,35,10,
            generations=1000, popsize=2000,
            cprob=0.7, cdist=20,
            mprob=0.2, mdist=20,
lower.bounds = c(5, 1230, 10, 15, 0.14, 40, 20, 5, 1155, 10, 15, 0.17,
40, 30, 5, 1080, 10, 15, 0.32, 40, 50, 5, 1005, 10, 15, 0.57, 40, 70, 5,
950, 10, 15, 0.98, 40, 90),
upper.bounds = c(15, 1250, 30, 50, 0.20, 80, 30, 15, 1195, 30, 50,
0.29, 80, 50, 15, 1120, 30, 50, 0.44, 80, 70, 15, 1045, 30, 50, 0.69, 80,
90,15, 970, 30, 50, 1.10, 80, 100)
)
plot(r1)
```

Figure I.1. Programme code for single pass problem optimisation