CRANFIELD UNIVERSITY

ABDULLAH OMAR ALRABGHI

SIMULATION-BASED OPTIMISATION OF COMPLEX MAINTENANCE SYSTEMS

SCHOOL OF ENGINEERING

PhD Thesis
Academic Year: 2015 - 2016

Supervisor: Prof. Ashutosh Tiwari
Prof. Mark Savill
September 2015

CRANFIELD UNIVERSITY

SCHOOL OF ENGINEERING

PhD Thesis

Academic Year 2015 - 2016

ABDULLAH OMAR ALRABGHI

SIMULATION-BASED OPTIMISATION OF COMPLEX MAINTENANCE SYSTEMS

Supervisor: Prof. Ashutosh Tiwari
Prof. Mark Savill

September 2015

This thesis is submitted in partial fulfilment of the requirements for the degree of PhD

ABSTRACT

There is a potential as well as a growing interest amongst researchers to utilise simulation in optimising maintenance systems. The state of the art in simulation-based optimisation of maintenance was established by systematically classifying the published literature and outlining main trends in modelling and optimising maintenance systems. In general, approaches to optimise maintenance varied significantly in the literature. Overall, these studies highlight the need for a framework that unifies the approach to optimising maintenance systems.

Framework requirements were established through two main sources of published research. Surveys on maintenance simulation optimisation were examined to document comments on the approaches authors follow while optimising maintenance systems. In addition, advanced and future maintenance strategies were documented to ensure it can be accommodated in the proposed framework. The proposed framework was developed using a standard flowchart tool due to its familiarity and ability to depict decision structures clearly. It provides a systematic methodology that details the steps required to connect the simulation model to an optimisation engine. Not only it provides guidance in terms of formulating the optimal problem for the maintenance system at hand but it also provides support and assistance in defining the optimisation scope and investigating applicable maintenance strategies. Additionally, it considers current issues relating to maintenance systems both in research and in practice such as uncertainty, complexity and multi-objective optimisation.

The proposed framework cannot be applied using existing approaches for modelling maintenance. Existing modelling approaches using simulation have a number of limitations: The maintenance system is modelled separately from other inter-related systems such as production and spare parts logistics. In addition, these approaches are used to model one maintenance strategy only. A novel approach for modelling maintenance using Discrete Event Simulation is proposed. The proposed approach enables the modelling of interactions amongst various maintenance strategies and their effects on the assets in non-identical multi-unit systems.

Using the proposed framework and modelling approach, simulation-based optimisation was conducted on an academic case and two industrial cases that are varied in terms of sector, size, number of manufacturing processes and level of maintenance documentation. Following the structured framework enabled discussing and selecting the suitable optimisation scope and applicable maintenance strategies as well as formulating a customised optimal problem for each case. The results of the study suggest that over-looking the optimisation of maintenance strategies may lead to sub-optimal solutions. In addition, this research provides insights for non-conflicting objectives in maintenance systems.

Keywords:

Simulation, optimisation, maintenance, complex systems, manufacturing, industrial case studies.

LIST OF PUBLICATIONS

Peer reviewed journals:

Alrabghi, A. and Tiwari, A. (2016), “A novel framework for simulation-based optimisation of maintenance systems”, *International Journal of Simulation Modelling,* vol. 15, no.1.

Alrabghi, A. and Tiwari, A. (2015), "State of the art in simulation-based optimisation for maintenance systems", *Computers and Industrial Engineering,* vol*.* 82, pp. 167-182.

Alrabghi, A. and Tiwari, A. (2016), “A novel approach for modelling complex maintenance systems using discrete event simulation”, *Reliability Engineering & System Safety.* **(under review)**

Alrabghi, A., Tiwari, A. and Savill, M. (2016), “Simulation based optimisation of maintenance in manufacturing systems: industrial case studies”, Journal of Manufacturing Systems. **(submitted)**

Peer reviewed conferences:

Alrabghi, A., Tiwari, A. and Alabdulkarim A. (2013), “Simulation based optimisation of joint maintenance and inventory for multi-components manufacturing systems”, *2013 Winter Simulation Conference*, 8-11 December 2013, Washington, D.C., USA, pp. 1109-1119.

Alrabghi, A. and Tiwari, A. (2013), "A review of simulation-based optimisation in maintenance operations", *2013 UKSim 15th International Conference on Computer Modelling and Simulation*, 10-12 April 2013, Cambridge, IEEE, pp. 353-358.

ACKNOWLEDGEMENTS

All Praise and thanks to Allah the giver of all knowledge. In His infinite mercy, he has continuously granted me strength and courage.

My profound appreciation to my parents who brought me up and motivated me to acquire knowledge. They taught me that seeking knowledge is a never ending journey. I still recall a line that my father always repeats:

العلمُ يرفعُ بيتاً لا عِمادَ لهُ   والجهلُ يهدمُ بيتَ العزِّ والشَّرفِ

Which translates as: knowledge raises a house that has no pillars, whereas ignorance destroys the house of honour and glory.

I would like to express my deep gratitude to my research supervisors: Professor Ashutosh Tiwari and Professor Mark Savill for their valuable and constructive suggestions during the planning and development of this research work. I would also like to extend my thanks to review panel members for their advice and assistance in keeping my progress on schedule. Special thanks should be given to academic support staff and all colleagues in the Manufacturing Department.

I am particularly grateful for the unlimited support and understanding from my wife and children.

I would also like to acknowledge with much appreciation the crucial role of Cranfield Islamic Society. Their help, cooperation and kindliness in addition to various activities for all family members helped us to adapt to the new environment.

During my stay in Cranfield, I was privileged to make many friends from all over the world. I am thankful for their encouragement and friendly advice.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF NOTATIONS

B	Buffer
i	A single asset in the system where $i = 1 \ldots n$
Labour	Number of maintenance technicians
MA	A single maintenance action resulting from a maintenance strategy
Mc_i	Machine i
MS_i	Maintenance strategy for machine i
n	Total number of assets in the system
$PMfreq_i$	Preventive maintenance frequency for machine i
Q_i	Order quantity for SP_i
s_i	Reorder level for SP_i
SMA	A scheduled maintenance action resulting from a maintenance strategy
SP_i	Spare part for machine i
T	simulation run length

LIST OF ABBREVIATIONS

CBM	Condition Based Maintenance
CDF	Cumulitive Distribution Function
CM	Corrective Maintenance
DES	Discrete Event Simulation
FMEA	Failure Modes and Effects Analysis
GA	Genetic Algorithms
LCC	Life Cycle Costing
MOO	Multi-Objective Optimisation
MTBF	Mean Time Between Failures
NSGA II	Non-dominated Sorting Genetic Algorithms II
OM	Opportunistic Maintenance
PK	zero-to-peak
PM	Preventive Maintenance
PSS	Product-Service System
RCM	Reliability Centred Maintenance
SA	Simulated Annealing
SOO	Single Objective Optimisation
SSP	Solid State Polycondensation
TPM	Total Productive Maintenance
TTF	Time To Failure

1 INTRODUCTION

Maintenance aims to combat the inevitable degradation of assets over their operational lifetime and keep them in a working order. Therefore, maintenance plays an important role in sustaining and improving asset availability, which in turn affects the productivity of the system in interest.

Recently, more attention has been directed towards improving and optimising maintenance in manufacturing systems. Maintenance cost can reach anywhere between 15% and 70% of production costs [1]. Wang [2] observes that there is a large potential for increasing the productivity in current maintenance practices. In some industries, a slight improvement in throughput could result in a significant economic impact [3].

1.1 Maintenance Optimisation

The term optimisation has come to be used to refer to "*the procedure of finding and comparing feasible solutions until no better solution can be found*" [4]. An optimisation problem consists of objectives that are the main performance measures, variables that influence the objectives and constraints which control some aspects of the system in interest [5]. Optimisation algorithms are used to find the optimal solutions by iteratively generating a set of variables and evaluating the problem with the aim of improving the objective function.

Alternatively, optimisation can be used as a synonym for improving certain performance measures of a given system without necessarily formulating an optimisation problem or using optimisation algorithms. For example, simulation runs can be conducted systematically while manually changing values of variables in gradual steps [6; 7].

In this thesis, the term 'optimisation' will be used solely when referring to the former definition. The latter type of optimisation is used only while reporting the state of the art and is referred to as 'manual optimisation'.

1.2 Third Generation of Maintenance Concepts

An optimised maintenance system implies that a number of maintenance decisions such as maintenance strategies and resources are selected to yield the best possible objectives while considering the present constraints in the system. A number of methodologies and concepts are suggested in literature to achieve an optimised maintenance system.

Pintelon and Parodi-Herz [8] trace the development and evolution of maintenance concepts. As illustrated in Figure 1-1, the first generation involved making maintenance decisions when necessary. In general, maintenance systems were simple. As maintenance systems increased in complexity, a second generation of maintenance concepts emerged. Some examples include Life Cycle Costing (LCC), which aims to include both direct and indirect costs when considering maintenance decisions and Total Productive Maintenance (TPM) which is a philosophy that encourages the involvement of all levels of the organisation to develop a program that will enhance the effectiveness of assets.

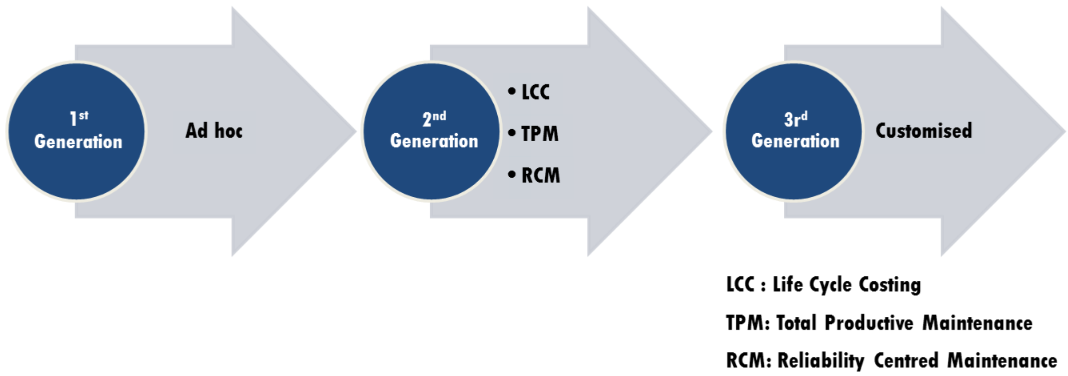


Figure 1-1 Evolution of maintenance concepts. Adapted from [8]

Perhaps one of the most popular maintenance concepts is Reliability Centred Maintenance (RCM). It is a systematic methodology that aims to maximise the equipment reliability. The philosophy behind RCM lies in establishing the following:

- The functions and performance standards of assets in the system
- The types of functional failures

- The causes of failures
- The failure effects
- The failure implications
- Tasks that can be conducted to predict and prevent failure

A vast range of concepts and tools were introduced to complement some of RCM pitfalls and facilitate its use such as delivering a maintenance plan or suggesting more tools for analysing failures.

The availability of a large number of concepts and methodologies contributed to the development of the third generation of maintenance concepts where a systematic approach enables the customisation of available tools to suit both the characteristics of the assets in the system and the business context. An examination of a number of customised concepts [9-12] reveals the following common features:

- The focus is on documenting and synthesising available tools
- A holistic and generic view of maintenance is considered
- As the name implies, the aim is to develop a customised maintenance model for each case

1.3 Complexity in Maintenance Systems

As observed in previous studies [13; 14] , a great deal of research into maintenance optimisation has focused on systems comprising of few units/components or systems with many identical components. Such systems are oversimplified and do not reflect the complexity and interactions in real manufacturing systems.

The complexity of maintenance systems has increased significantly [15; 16]. This is partly due to modern manufacturing systems which involve numerous interactions and dependencies between components. Figure 1-2 outlines the main sources of complexity in maintenance optimisation problems. The inherited uncertainty in the assets behaviour is one of the main contributors to the complexity of the problem. This is further increased by factors such as operating conditions, production schedules, spare parts policies and dependencies between components which affect the degradation pattern or the main performance measures. Increasing the number of assets in the system or the number of applicable maintenance strategies and policies will increase the number of decision variables leading to more complexity in the maintenance problem.

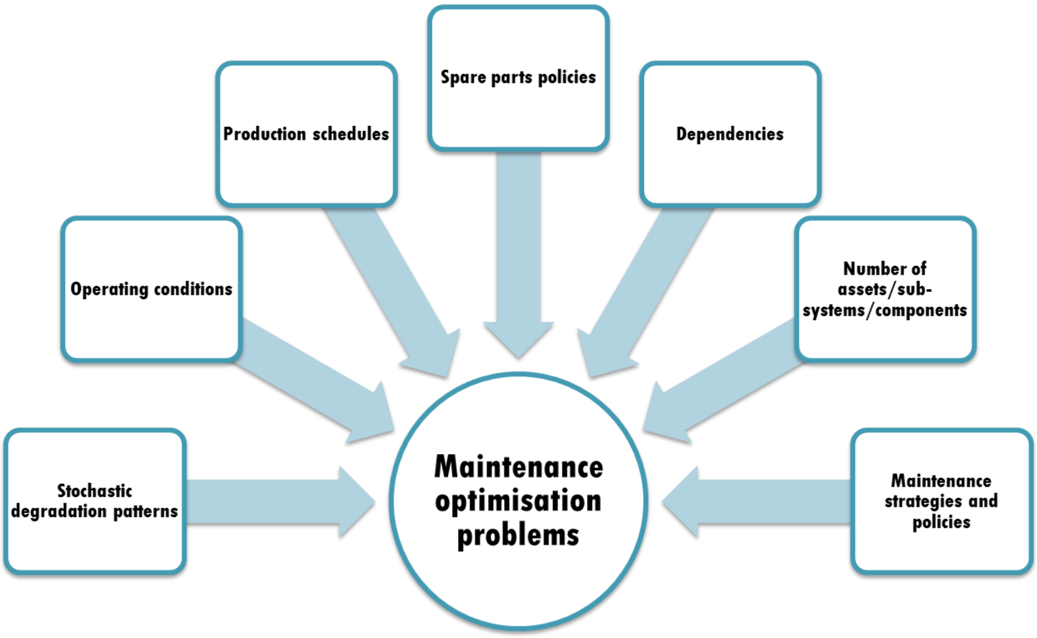


Figure 1-2 Sources of complexity in maintenance optimisation problems

1.4 Simulation-Based Optimisation

It is evident that analytical and mathematical approaches are limited in solving such complex maintenance problems. By developing both analytical and simulation models to solve the same problem, Rezg et al. [17] found that it resulted in a complex analytical model with unrealistic assumptions compared to the simulation model which provided more flexibility and simpler estimations. Several studies have indicated the preference of simulation to optimise maintenance problems over analytical and mathematical approaches [18-21].

Simulation delivers an advantage over analytical approaches because many maintenance policies are not analytically traceable [15]. In addition, it allows experimenting and better understanding of complex systems [22].

Although research on maintenance optimisation was established decades ago [23], the area of simulation-based optimisation in maintenance is now becoming an emerging trend [24; 25]. Simulation has been traditionally used as a tool to understand and experiment with a system. However, connecting the simulation model to an optimisation engine ensures better and faster results. As illustrated in Figure 1-3, simulation based optimisation is an approach whereby an optimisation engine provides the decision variables for the simulation program. The simulation program will run the model and provide the results of the optimisation objective function. This process will continue iteratively between the simulation program and the optimisation engine until it results in a satisfactory solution or a termination due to prescribed conditions [26].

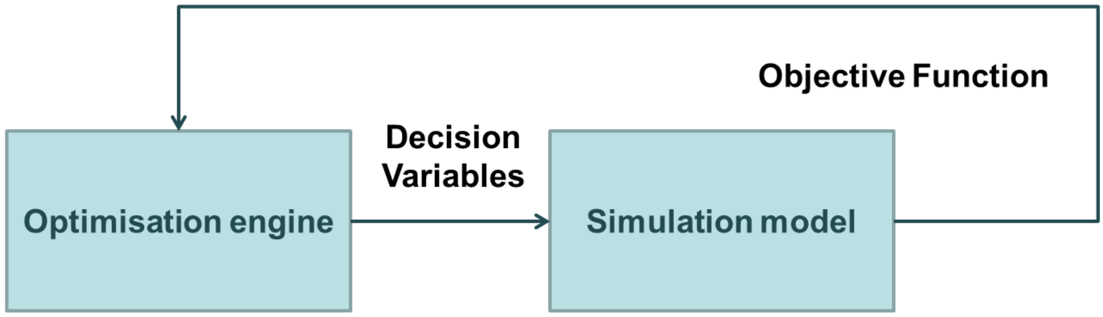


Figure 1-3 Simulation based optimisation approach

1.5 Research Scope

The scope of the current research is illustrated by the shaded boxes in Figure 1-4. Maintenance is studied in the context of production as opposed to maintenance of products or Product-Service Systems (PSS). In PSS, usually the customer pays for benefiting from the use of the asset while the ownership and maintenance responsibilities lies with the manufacturer [27]. In particular, the focus of research is on critical assets in complex maintenance systems in a production environment. The third generation of maintenance concepts is adopted where various tools and methodologies can be used to develop a customised maintenance program.

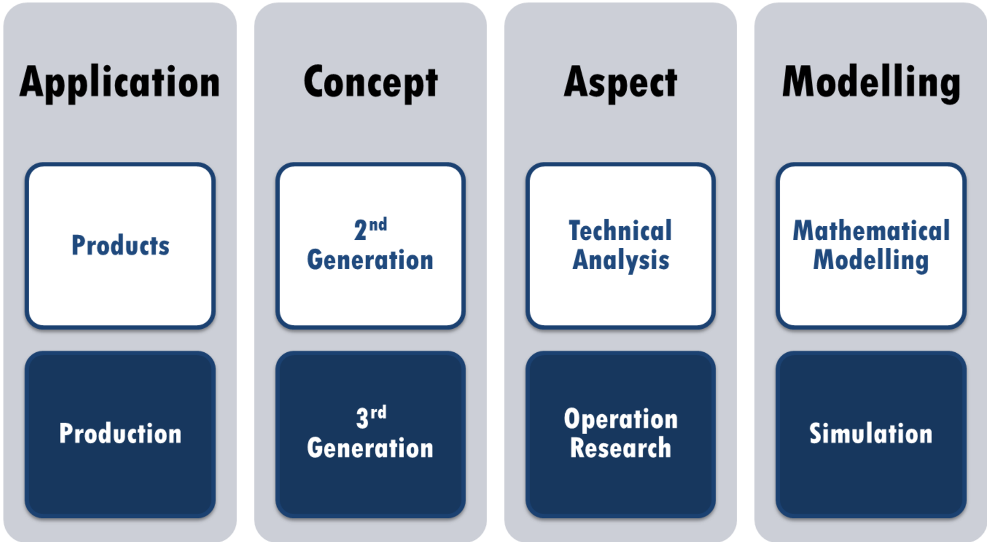


Figure 1-4 Research scope

It is beyond the scope of this study to examine technical analysis such as analysis of failure patterns, dependency between components, physical wear or age-related fatigue characteristics. This research assumes that results of technical analysis are available and can be used as an input to the simulation model. In fact, apart from modelling maintenance on the strategic level, the current study assumes the availability of a valid simulation model for the maintenance system in interest. The focus is on steps that follow technical analysis including problem formulation, optimisation and decision making.

1.6 Thesis Structure

The remaining part of the thesis proceeds as follows: Chapter 2 presents the findings of a systematic review of literature. It begins by detailing the review methodology including the review scope, search keywords and utilised scholarly databases. It then goes on to provide an overview of reviewed papers including application areas and maintenance strategies and policies. Main trends in modelling and optimising maintenance systems are analysed revealing directions for future research.

Analysis of the state of the art in the field resulted in formulating the aim and objectives of this study as outlined in Chapter 3. This is followed by an overview of research methodology used for this study. A separate and detailed methodology section is provided in chapters 2, 4, 5 and 6.

The simulation-based optimisation framework is proposed in the fourth chapter. It first critically examines existing frameworks and then establishes the framework requirements. This is followed by a detailed discussion of different levels and steps of the proposed framework.

In Chapter 5, a novel approach for modelling complex maintenance systems is suggested. The chapter begins by highlighting the need for a novel approach. A generic modelling approach based on Discrete Event Simulation (DES) is developed. In addition, three approaches for common maintenance strategies are provided. The approach is then validated using numerical examples.

The sixth chapter attempts to validate the proposed framework through case studies. A published case study is first presented followed by two industrial case studies. In each case, a description of the manufacturing and maintenance system is provided followed by simulation-based optimisation using the proposed framework.

Chapter 7 provides a discussion of main research findings as well as conclusions. It is composed of five sections: the first section discusses the key findings of the research and considers its implications. The second section outlines the research contributions. The third section identifies the research limitations and explains their potential impact. The fourth section describes directions for future work. Finally, the fifth section concludes this thesis by comparing the objectives with the research achievements.

2 STATE OF THE ART IN SIMULATION-BASED OPTIMISATION OF MAINTENANCE SYSTEMS

2.1 Introduction

A considerable amount of literature has been published on maintenance simulation and optimisation. Dekker [23] provided a comprehensive view and analysis of maintenance optimisation models and applications. It is interesting to note that in his work, simulation has not been mentioned and the emphasis was on mathematical models only. More recently, Sharma et al. [24] observed that there is a potential as well as a growing interest amongst researchers to utilise simulation in optimising maintenance systems. The advancement in technology has enabled researches to use powerful computers and software with decreasing costs. Vasili et al. [28] review highlighted that it is becoming increasingly difficult to rely on static solution techniques to optimise maintenance systems and ignore the dynamic and stochastic nature of current business environments.

Andijani and Duffuaa [29] evaluated simulation studies in maintenance systems in terms of adherence to sound modelling principles such as program verification and validation. Alabdulkarim et al. [30] reviewed the applications of simulation in maintenance systems and categorised it according to the purpose of the study. Their research confirms that research on maintenance simulation is steadily rising. Additionally, they observed that research on the combined use of simulation and optimisation is limited.

Thus, this study provides an exciting opportunity to advance our knowledge on the state of art in the combined use of simulation and optimisation in maintenance systems.

2.2 Review Methodology

This chapter aims to identify and summarise available literature on simulation-based optimisation of maintenance operations. Thus, the scope is focused on research that includes simulating maintenance systems and connecting the simulation model to an optimisation engine.

Research that focus on improving maintainability and reliability at the design stage is disregarded. There have been attempts to simulate maintenance operations through static system models, usually using Monte-Carlo simulation [1; 19]. As time is a significant variable in maintenance operations, only attempts that model it through dynamic system models are within the scope of this research.

A systematic research was conducted by searching for the following keywords in article titles, abstracts and keywords: (maintain* and optim* and simulat*) and (maintenance and optim* and simulat*). Scopus and Web of Science citation databases, two of the largest abstract and citation databases of peer-reviewed literature, were searched to identify the targeted papers. The Scopus search resulted in 15,001 documents in English whereas the Web of Science search resulted in 9,132 documents in English. An overview of the review methodology is shown in the figure below:

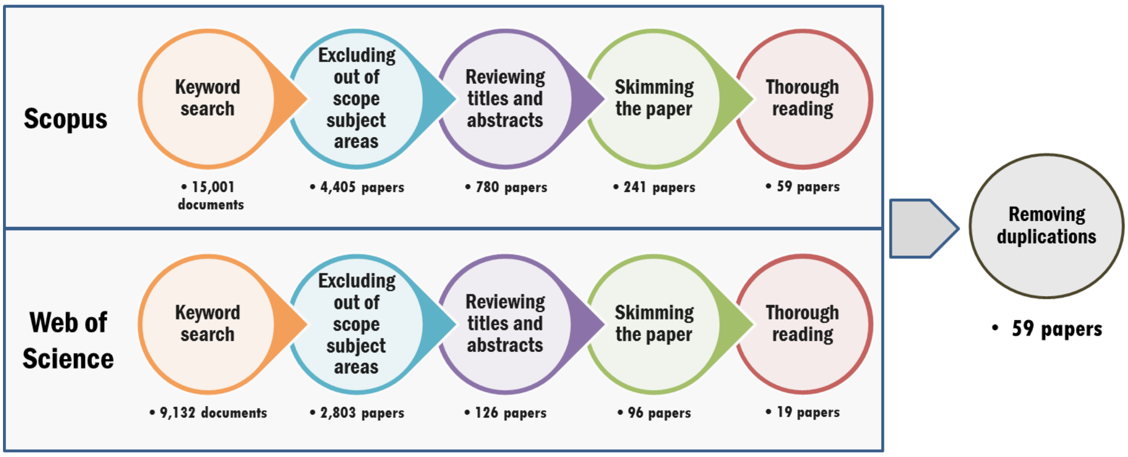


Figure 2-1 Systematic review methodology

The resulting documents were filtered using a systematic methodology as follows:

- Excluding out of scope subject areas such as medicine, social sciences and arts and humanities. The main relevant subject areas are engineering, mathematics, decision sciences and business management.

- Reviewing the titles and abstracts. This includes reading titles and abstracts and excluding papers that do not include simulation optimisation in maintenance.
- Skimming the whole paper to find out the application area as well as optimisation methods and simulation techniques. This was usually obtained by reading the methodology section of the paper.

A further comprehensive reading was conducted through the full documents which yielded 59 articles after removing duplications [3; 6; 7; 14; 17; 18; 21; 31-82]. In order to classify the published literature and outline main trends in modelling and optimising maintenance systems, each paper was analysed to identify relevant features such as application area, maintenance strategies and policies, simulation modelling techniques and software, optimisation methods and software, optimisation objectives and decision variables. A summary version of the analysis for all papers is shown in Appendix A.

2.3 Overview of Reviewed Papers

All the papers were published in the year 2000 or after with the exception of one journal paper published in 1982 [82]. Figure 2-2 shows an increasing trend in publications although it may not be statistically significant. These results match those observed in earlier studies, which found that the use of simulation in maintenance is increasing [24; 25; 30]. The resulting literature comprises of 47 journal articles (80%) and 12 conference papers (20%).

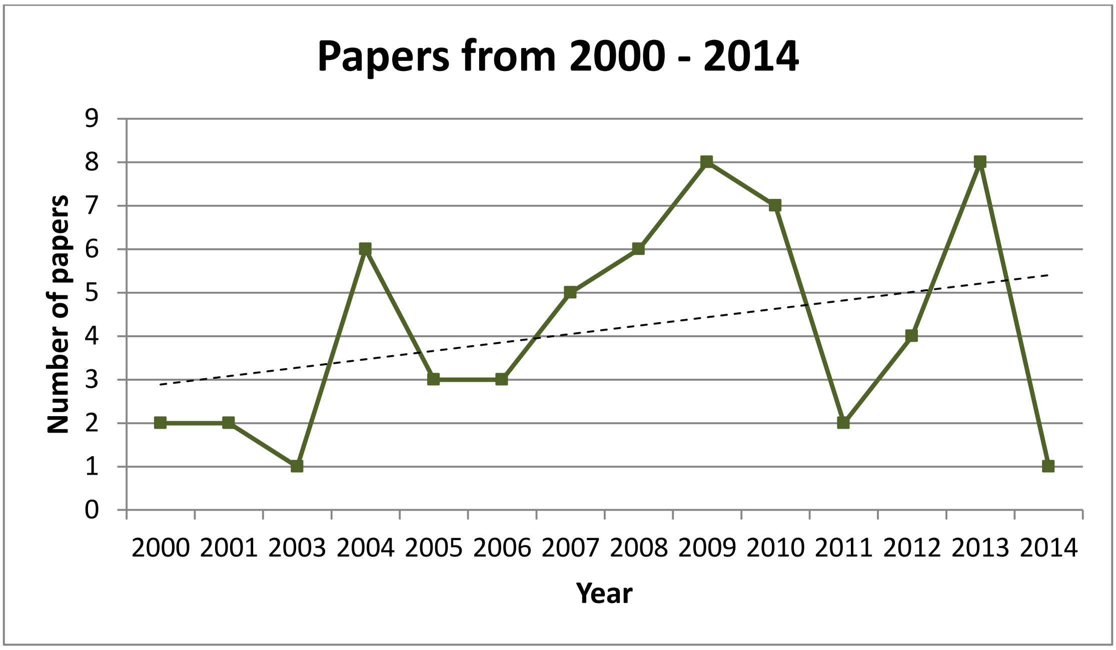


Figure 2-2 Number of publications by year (2000 – 2014) (58 papers)

The United States appears to be leading in this research field followed by France as illustrated in Figure 2-3. They both account for about two-fifths of the literature whereas ten countries account for the second two-fifths.

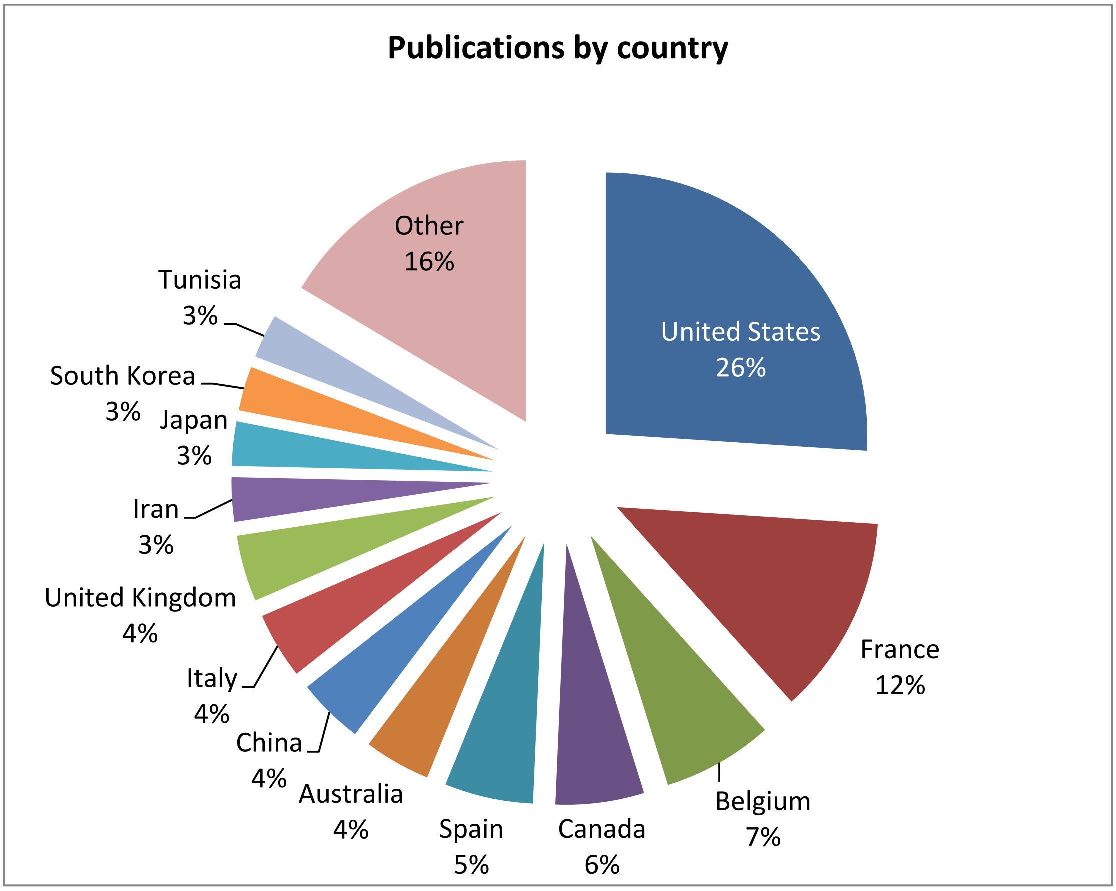


Figure 2-3 Publications by country (59 papers)

The most influential authors are shown in Figure 2-4. Rezg from Lorraine University in France was the most influential author publishing six articles which were cited more than 90 times. Allaoui and Artiba from University Lille Nord de France published only one article which was cited 88 times. It is interesting to note that the top four influential authors work in French research groups. In total, around 150 authors contributed to the field. Around half of them published articles that were cited only 5 times or less.

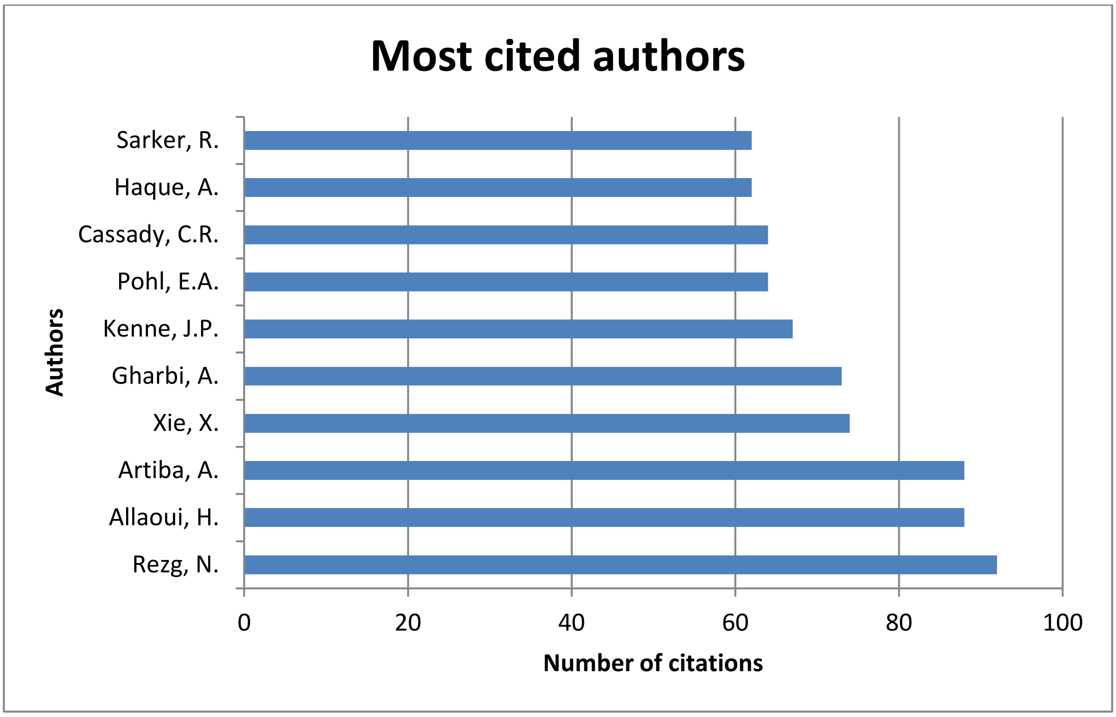


Figure 2-4 Most influential authors

The top publication sources are shown in Figure 2-5. The journal of Computers and Industrial Engineering published more than any other source. This can be explained by the Industrial engineering nature of the problems in the area, especially the area of simulating manufacturing systems and the applications of operation research.

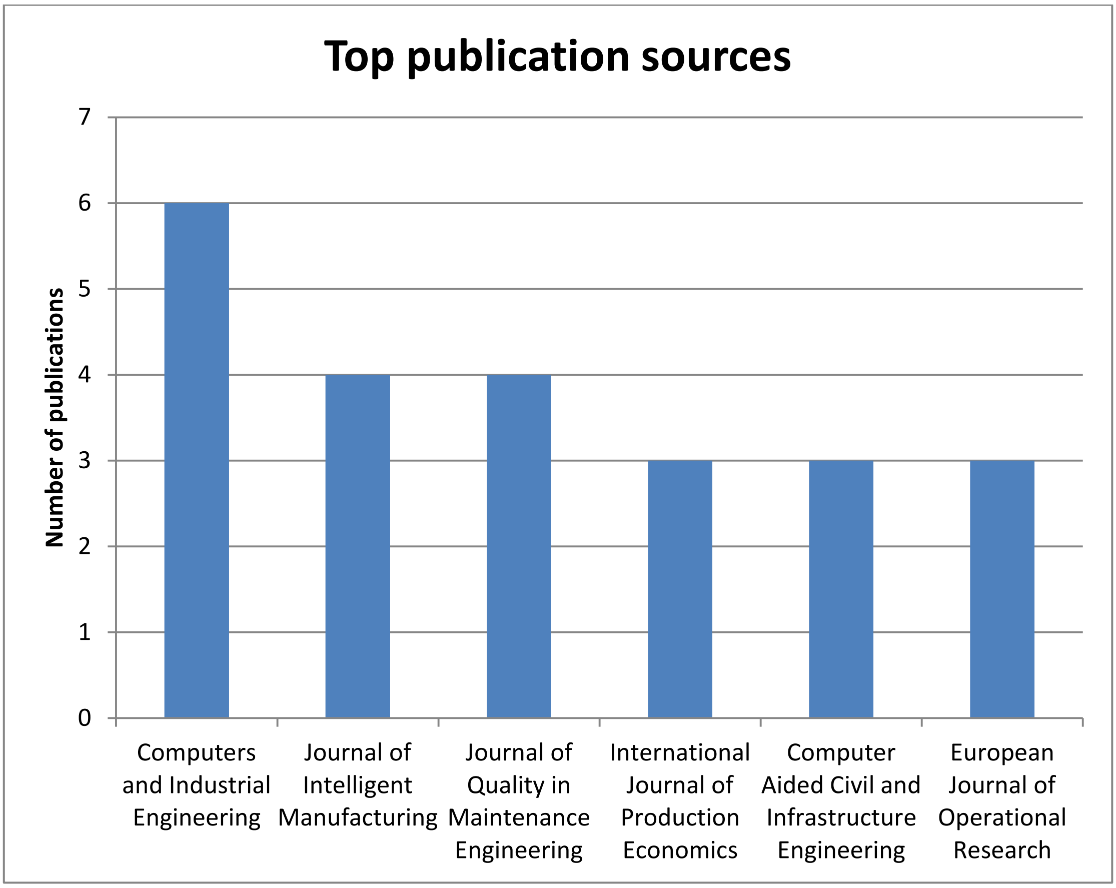


Figure 2-5 Top publication sources

Table 2-1 shows the most eight cited articles. It is interesting to observe that the top five articles are concerned with joint optimisation of maintenance and production or spare parts management.

Table 2-1 Top eight articles based on citations

Publication	Title	Citations
Allaoui and Artiba [21]	Integrating simulation and optimization to schedule a hybrid flow shop with maintenance constraints	88
Sarker and Haque [80]	Optimization of maintenance and spare provisioning policy using simulation	62
Richard Cassady et al. [81]	Combining preventive maintenance and statistical process control: a preliminary investigation	55
Rezg et al. [75]	Joint optimization of preventive maintenance and inventory control in a production line using simulation	47
Gharbi and Kenne [72]	Maintenance scheduling and production control of multiple-machine manufacturing systems	46
Yao et al. [3]	Optimal preventive maintenance scheduling in semiconductor manufacturing	46
Yang et al. [63]	Maintenance scheduling in manufacturing systems based on predicted machine degradation	40
Ng et al. [53]	Optimal long-term infrastructure maintenance planning accounting for traffic dynamics	37

2.3.1 Application Areas

Case studies were conducted in semiconductor manufacturing systems [3; 46; 48], electricity sector [50; 78], automotive industry [61; 65; 66], plastic industry [14], transportation infrastructure [51; 53; 58; 70; 76] and train maintenance facilities [45; 59]. It is however important to note that most researchers tended to use academic case studies. See for example: [6; 17; 21; 52; 54; 57; 60; 80].

While most studies examined maintenance in a production context, few researchers examined maintenance operations for working products such as ships or aircrafts. The low number of published papers on military hardware might be due to the potentially sensitive nature of these systems. Johansson and Jagstam [47] suggested an approach to provide decision support for maintenance planning intended for military equipment while Gupta and Lawsirirat [18] analysed the strategic optimal maintenance actions for a general multi-component system whose health is monitored in real time. Both studies reported the shift towards Product-Service System (PSS) as the main motivation for their research. El Hayek et al. [71] demonstrated the effectiveness of simulation based optimisation for planning maintenance operations for an aircraft gas-turbine. It is observed that there are several differences between maintenance in a production context and maintenance in a PSS context. In the former, issues such as bottlenecks, buffer size and parts waiting in progress have an impact on maintenance planning. In contrast, logistics and transportation are main issues in PSS.

As observed by Goti et al. [14] and Horenbeek et al. [13], little research is directed towards optimising a system composed of several equipment and most of the research has focused on optimising single equipment without considering the production configuration. Indeed, systems comprising of a single machine producing a single product [57] or two exactly identical machines [7; 55] are oversimplified and do not reflect the complexity and interactions in real manufacturing systems.

2.3.2 Maintenance Strategies and Policies

Maintenance strategies can generally be categorised into Corrective Maintenance (CM), Preventive Maintenance (PM) and Condition Based Maintenance (CBM) [23]. As illustrated in Figure 2-6, CM occurs when the asset breaks down resulting in unexpected shutdown and high maintenance cost. PM is scheduled in order to minimise the impact of a sudden breakdown. PM usually consumes fewer resources compared to CM and can be accommodated in the production plans. In fact, PM can be as simple as cleaning filters, lubricating and changing oil preventing a failure of a critical component that is costly and takes time to be delivered. Because the operation schedules and environment change dynamically in the real world, PM can take place without immediate need. To ensure PM occurs only when needed, CBM was introduced. This can be either in the form of regular inspections to evaluate the assets' wear or in the form of sensors streaming data to diagnostic software. Therefore maintenance tasks can be triggered only when the wear reaches a certain level. It is worth mentioning that CBM is sometimes included under the branch of PM [83].

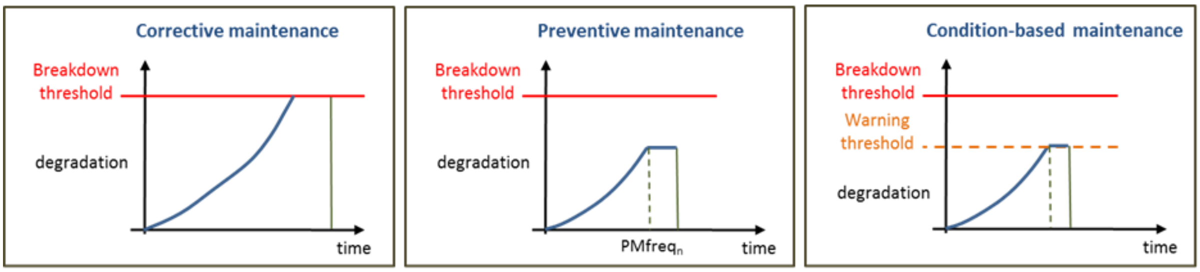


Figure 2-6 Overview of maintenance strategies in the literature

The majority of researchers investigated PM as can be seen from Figure 2-7. This includes policies such as time-based [60; 80] where PM is scheduled every x units of time or age-based [17; 69] where PM is scheduled every x units of operating time. Other variations of preventive maintenance policies include group block replacements for unrepairable systems where a component will be replaced if it fails whereas all other components in the system will be replaced at predetermined intervals and combined block replacements where all components will be replaced at predetermined intervals but if a component fails, it will be replaced as well as all components in operational state [60].

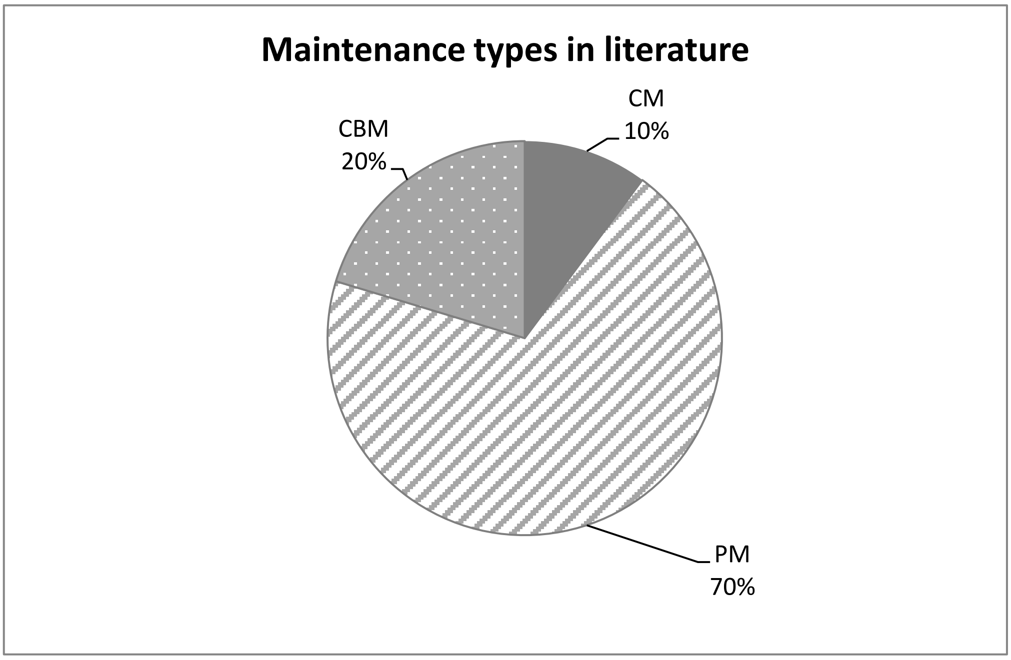


Figure 2-7 Maintenance types in literature

CBM received less attention perhaps because it is relatively new. However, sensors are becoming lower in terms of cost which is encouraging the implementation of Condition Based Maintenance [43]. CBM is becoming increasingly popular especially in PSS or long-term services agreement where sensors are installed on products to monitor its degradation [18]. Periodic inspections are an alternative to sensors but its frequency has to be optimised as it will consume resources and affect performance [78]. Horenbeek and Pintelon [40] investigated prognostic maintenance which is essentially CBM combined with the ability to predict the deterioration of components in the system to see if it is expected to reach the threshold before the next scheduled inspection; If it does then it is replaced immediately. Although the applications of CBM are increasing in the industry [84], it is evident that it is poorly covered in the literature.

Opportunistic maintenance is a policy relevant particularly in situations where down-time is very costly and a shut-down can be exploited to perform other maintenance actions. Murino et al. [55] examined opportunistic maintenance in a continuous production system where stopping one machine could mean bringing the whole production system to a halt. Shenfield et al. [50] examined a fleet of aero-engines where unscheduled maintenance results in cancelled flights and losing customers.

In reviewing the literature, only limited effort was found to be directed towards comparing different maintenance strategies and policies. Xiang et al. [43] and Yang et al. [63] studied a repairable system where preventive maintenance and condition-based maintenance policies were investigated. The focus of Allaoui and Artiba [21] research was on evaluating the effect of various priority rules and heuristics on maintenance scheduling. Horenbeek and Pintelon [40] compared the effect of five different maintenance strategies on one machine, namely CM, block based PM, age based PM, inspection based CBM and CBM with continuous monitoring.

However, on the whole the research is limited in terms of covering main maintenance decisions such as comparing and selecting the optimum maintenance policies in multi-component systems and determining the optimum maintenance resources, in particular, investigating the implications of implementing new CBM strategies in manufacturing systems compared with traditional PM policies. In addition, there is a potential of evaluating heuristics against priority rules set by various optimisation algorithms.

2.4 Simulating and Modelling Maintenance Systems

2.4.1 Modelling Maintenance Systems

It is interesting to observe that the scope of the maintenance models varied significantly in the literature. The main themes are presented in Figure 2-8. For instance, Gupta and Lawsirirat [18] modelled only the asset deterioration, Sarker and Haque [80] added maintenance resources such as spare parts management and Arab et al. [33] added production dynamics such as buffer capacity. The decision of including an element should depend on the level of effect it has on the desired simulation output [85]. Although maintenance resources such as technicians, spare parts and equipment have a direct effect on maintenance cost and scheduling [16; 86; 87], only few researchers incorporated them in the simulation model. In fact, the assumption of readily available maintenance resources is fairly common [17; 21; 33; 38; 60].

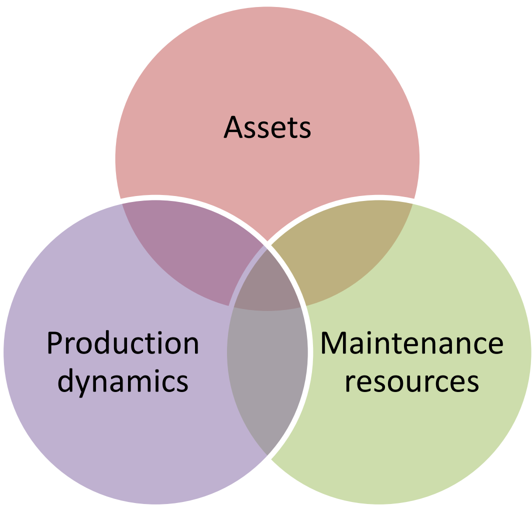


Figure 2-8 Scope of maintenance simulation models in the literature

Three main levels of modelling assets details are observed in the literature. The majority of researchers modelled assets as a whole unit. Therefore, the deterioration, failure and interaction on a subsystem or a component level is not modelled in the simulation. However, some researchers modelled machines as subsystems. Oyarbide-Zubillaga et al. [61] modelled assets as subsystems based on types of maintenance activities such as electric/electronic and hydraulic subsystems. Zhou et al. [42] optimised maintenance for sub-systems connected in series considering the economic dependency, where carrying maintenance tasks in groups has a different cost from carrying it individually. Horenbeek et al. [40] modelled only one subsystem in several machines considering economic, structural and stochastic dependencies. In a more detailed modelling of assets, Roux et al. [60] evaluated three maintenance policies for a system comprising of two independent components. Sarker and Haque [80] optimised maintenance and spare part provisioning policy for 13 identical and independent components.

Gupta and Lawsirirat [18] highlight the fact that meaning of the term ‘component’ differs depending on the context. It is not possible to model a complex system comprising of thousands parts for practical constraints. Therefore it is proposed to consider the components that have significant impact on the asset performance. Tools such as Failure Modes and Effects Analysis (FMEA) that utilise historical maintenance data can be used to identify the most critical components.

Modelling identical units while assuming there are no dependencies between them is one of the assumptions researchers consider to simplify the maintenance system. Other relaxing assumptions include:

- Perfect inspections: inspections reveal instantly the real deterioration state of the asset. See for example: [42; 61]
- Perfect maintenance: maintenance job is done perfectly from the first time and there is no chance of misdiagnosis. It is often referred to as ‘machines are as good as new’ after maintenance actions. See for example: [17; 40; 68]
- Duration of maintenance actions is constant and sometimes it is considered instantaneous. See for example: [40; 60]

- Costs of all maintenance actions are known and constant. Furthermore, cost of CM is always higher than PM cost. See for example: [7; 42; 56; 57]
- Some or all maintenance resources such as spare parts, tools and technicians are always available immediately when needed. See for example [66; 75]
- Failures are detected instantaneously. See for example [17; 34; 75]

Perhaps the most significant aspect is the modelling of machine aging process. Some researchers simplified it by designing only two states for the machine, either working or broken [14]. Additionally, the machine is regarded as good as new after undertaking maintenance tasks. El Hayek et al. [71] considered an improvement factor that incorporates imperfect maintenance. Therefore the machine state after maintenance tasks will not be regarded as good as new, rather it lies somewhere between a broken machine and a new machine depending on the random improvement factor. Furthermore, the duration between preventive maintenance tasks is reduced as the machine ages. To schedule PM, Ramírez-Hernandez et al. [48] modelled a PM window constituting of warning date which is the earliest time a PM can be conducted, due date which is the suggested date for PM and late date which is the latest time to conduct PM.

Accurate modelling of machine degradation process becomes essential for examining CBM where an inspection is conducted periodically to decide which maintenance tasks should be executed [84]. Alternatively, sensors could provide indicators on machines' health such as vibration magnitude and temperature in real time [43]. When indicators' reading exceed a specific threshold, a maintenance task is triggered. Guizzi et al. [54] simulated CBM via Discrete Event Simulation (DES). In their study, the limitation of DES is overcome by triggering special events that increase the machine wear at predetermined intervals.

2.4.2 Simulation Techniques

DES dominates the literature as it was used alone or combined with other modelling techniques by around two thirds of researchers (see Figure 2-9). This should not come as a surprise since it is the most popular technique in modelling manufacturing systems including production planning, maintenance and inventory management [88]. DES is the modelling of a system in which variables' state changes at specific points in time. Thus, the system is modelled by arranging these changes (called events) in a chronological order and the system is updated whenever an event occurs. However, between events, the system remains unchanged and time is advanced to the next scheduled event [89].

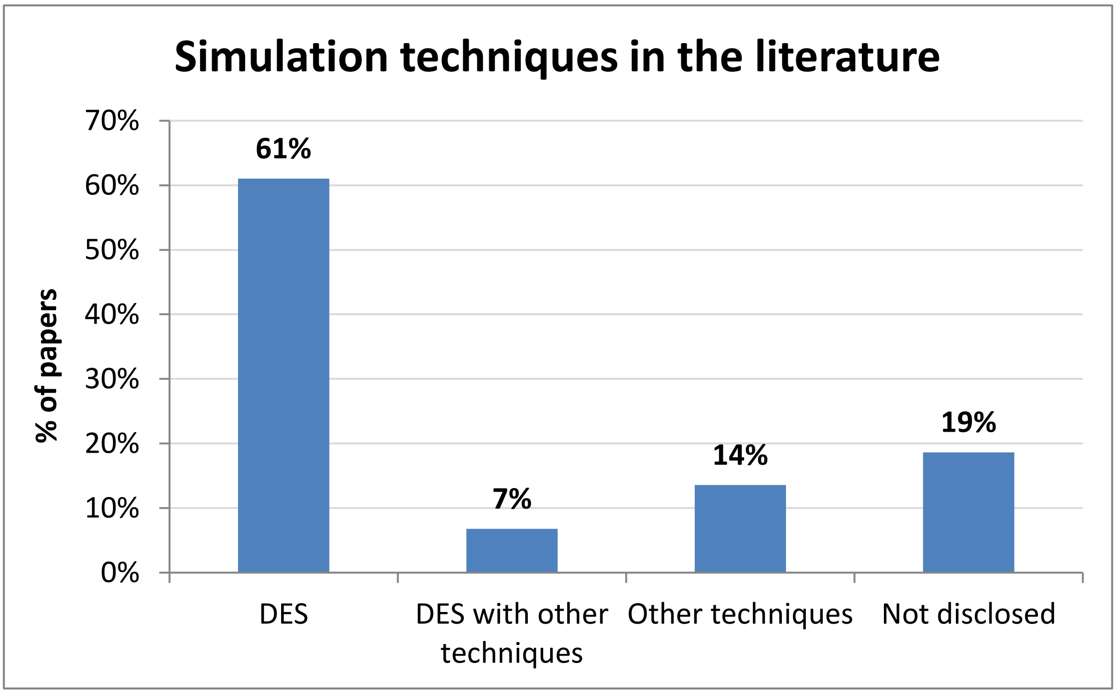


Figure 2-9 Simulation techniques in the literature (59 papers)

Most DES studies utilised process-based specialised simulation software that provide graphical user interface such as Arena [54; 55; 59; 64; 66; 69; 71] which is offered by Rockwell Automation, Promodel [17; 33; 68; 75] which is offered by Promodel Corporation and Witness [36; 61; 65] which is an offering by Lanner Group. Other DES studies utilised general-purpose programs and languages such as C++ [53; 79], Java [52], Matlab [57] and Excel [56]. Specialised simulation software provide several advantages over general-purpose programs such as rapid modelling, animation, automatically collected performance measures and statistical analysis [89].

Some researchers developed a hybrid model combining DES with other modelling techniques to gain further advantages. Xiang et al. [43] and Gharbi and Kenne [72] built a discrete event model to represent the general manufacturing system with the machine degradation process modelled as a continuous element to reflect the fact that machines age as time passes by.

Simulation techniques other than DES were reported in some articles. This includes agent-based simulation [35; 39; 49] and continuous simulation [18; 51].

It is worth mentioning that a considerable number of researchers did not disclose the simulation technique or the software used in the research. This surprisingly includes some recent publications (see for example: [41; 42; 47]). Therefore it might not be possible for an independent researcher to replicate the experiments. In contrast to Andijani and Duffuaa [29] findings, this study confirms that neglecting the simulation technique or language is an issue in literature.

2.5 Optimising Maintenance Systems

2.5.1 Optimisation Methods

The results obtained from the analysis of optimisation methods in the literature are shown in Figure 2-10. Similar to simulation techniques, not all researchers disclosed the optimisation methods they used [3; 42; 48; 80; 82]. Manual optimisation was reported in several articles where simulation runs are conducted systematically while manually changing variable values in gradual steps, see for example: [6; 7; 17; 74]. As can be expected, a serious weakness with this approach is its limitation in terms of exploring the search space and number of variables.

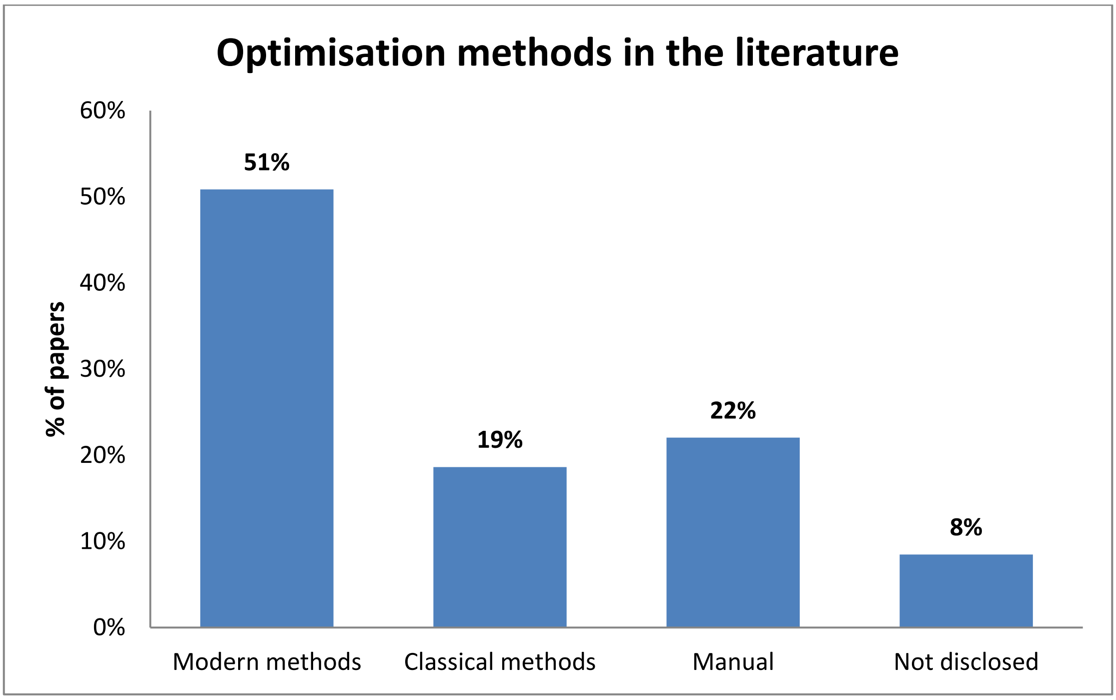


Figure 2-10 Optimisation methods in the literature (59 papers)

Classical optimisation methods [90] that are analytical and utilise differential calculus to find the optimal point such as scatter search [69], Nelder-Mead method [38; 60], cyclic coordinate method [43], the modified powell method [77], Fibonacci algorithms [31] and simple local search [18; 35] were applied to simple manufacturing systems. One criticism of much of the literature on optimising maintenance by classical methods is the lack of analysis of the objective function and the solution space. Therefore, the justification and proper selection of the optimisation method is sometimes absent.

As the complexity of maintenance systems increased [15; 25], modern optimisation methods were utilised as they are more capable of dealing with complex problems [90; 91]. Most of these methods are based on selected behaviours found in nature. It is worth mentioning that these methods are sometimes referred to as non-traditional methods. As shown above in Figure 2-10, modern optimisation methods were utilised in around half of the papers becoming the most reported optimisation approach. The pie chart below shows the breakdown of modern optimisation methods in the literature. It is apparent from this pie chart that only two modern optimisation methods were applied namely Genetic Algorithms (GA) and Simulated Annealing (SA). In fact only few articles reported the use of SA. This reflects an opportunity to research the suitability of other modern optimisation methods to maintenance problems.

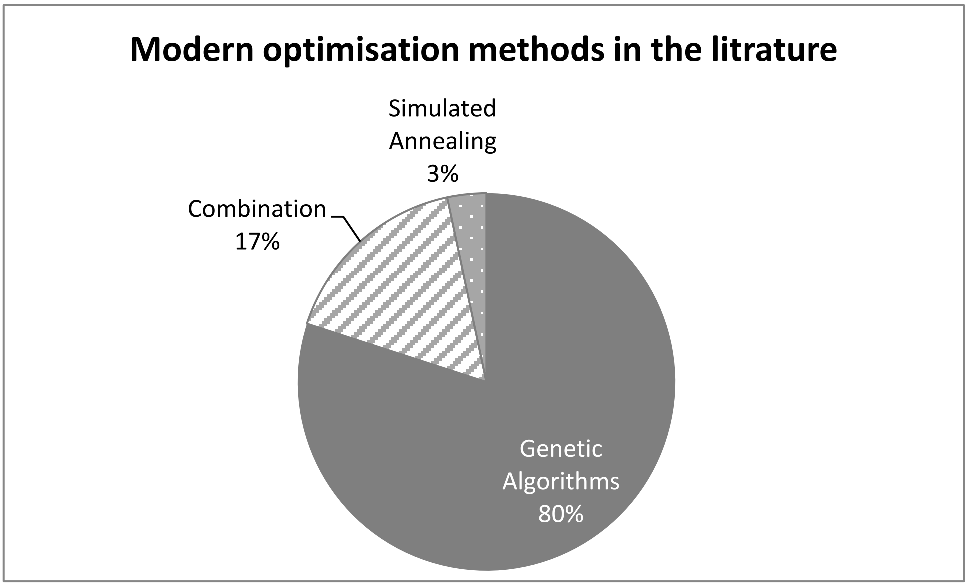


Figure 2-11 Breakdown of modern optimisation methods in the literature (33 papers)

It can be seen that by far the most reported modern optimisation method is GA. It is based on the process of natural selection in biology and it has been applied successfully to a wide variety of practical optimisation problems [90]. In addition, it is well suited for complex simulation based optimisation where there is no prior knowledge of the response surface typology [92; 93].

SA comes from the concept of the annealing process in metallurgy to harden metals. Metals are melted in high temperature at the start and then cooled gradually in a controlled environment to obtain desired attributes. It can be used to solve various types of problems including continuous, discrete and mixed-integer problems [90].

Guuizzi et al. [54] and Murino et al. [55] approach has a significant advantage. In their study they utilised OptQuest, a specialised optimisation tool that allows the utilisation of multiple optimisation algorithms including tabu search, scatter search, integer programming, and neural networks. Ali et al. [64] utilised different optimisation algorithms included in the Intelligent System for Simulation and Optimisation software (ISSOP) such as component wise enumeration, quasi gradient strategy and GA. Yun et al. [41] conducted a two steps optimisation process where both GA and SA are used.

Figure 2-12 shows how optimisation methods were utilised in different maintenance strategies. The use of modern methods and classical methods is comparable in both CBM and PM strategies. However, manual optimisation was used in less than 10% of CBM systems compared to around 20% in PM systems. Optimising CM systems appears to follow a different pattern where modern methods and classical methods were utilised equally.

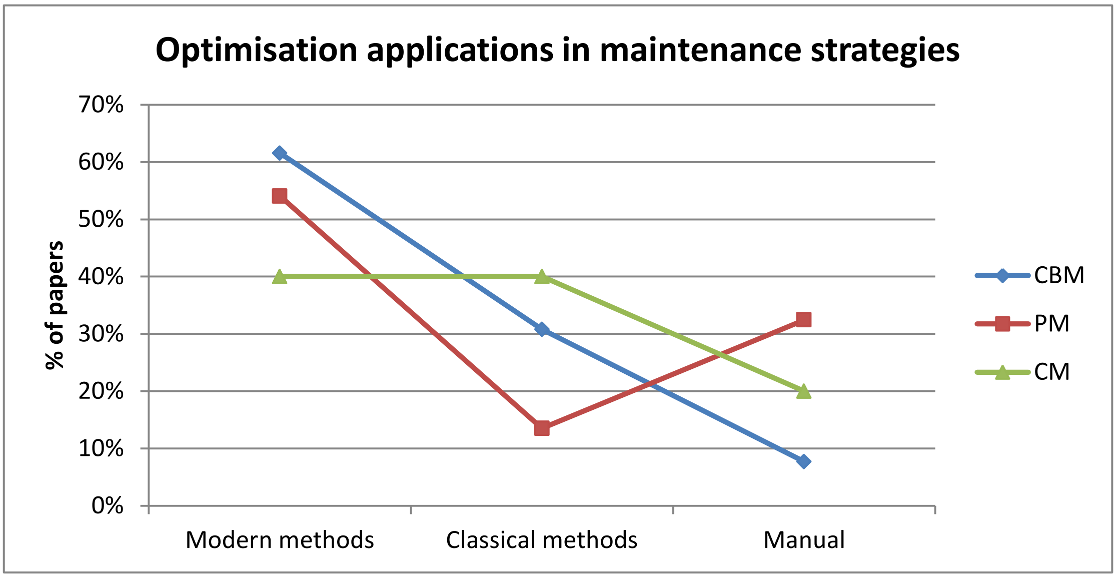


Figure 2-12 Optimisation applications in maintenance strategies

Very limited research was conducted to compare the performance of multiple optimisation algorithms. Dridi et al. [62] compared three different variations of GA: Island Genetic Algorithm (IGA), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Niched Pareto Genetic Algorithm 2 (NPGA-2) on a pipe renewal system. They concluded that the algorithms performance varies based on the size of the pipe network.

2.5.2 Problem Formulation for Optimisation

An optimisation problem can be described by three main elements: design variables, constraints and objective functions. Each will be discussed in details in the following sections.

2.5.2.1 Optimisation objectives

Minimising cost was reported as an objective in more than 70% of the studies (see Figure 2-13). Machines and equipment can be over-maintained which increases preventive maintenance cost or under-maintained, increasing failure rate and its consequences. Usually reactive maintenance is fixed at a higher cost than preventive maintenance and the objective is to minimise the total maintenance cost [18; 43; 60]. Arab et al. [33] correctly argue that maintenance is a part of the manufacturing system and considering maintenance cost alone is not sufficient. To counter that, some researchers developed an objective function that encompasses the total system cost. This might include a penalty for each time unit a machine is unavailable [36; 78], the cost of defective products [61], a penalty for not meeting demand [74; 75] or spare parts management costs [66; 80].

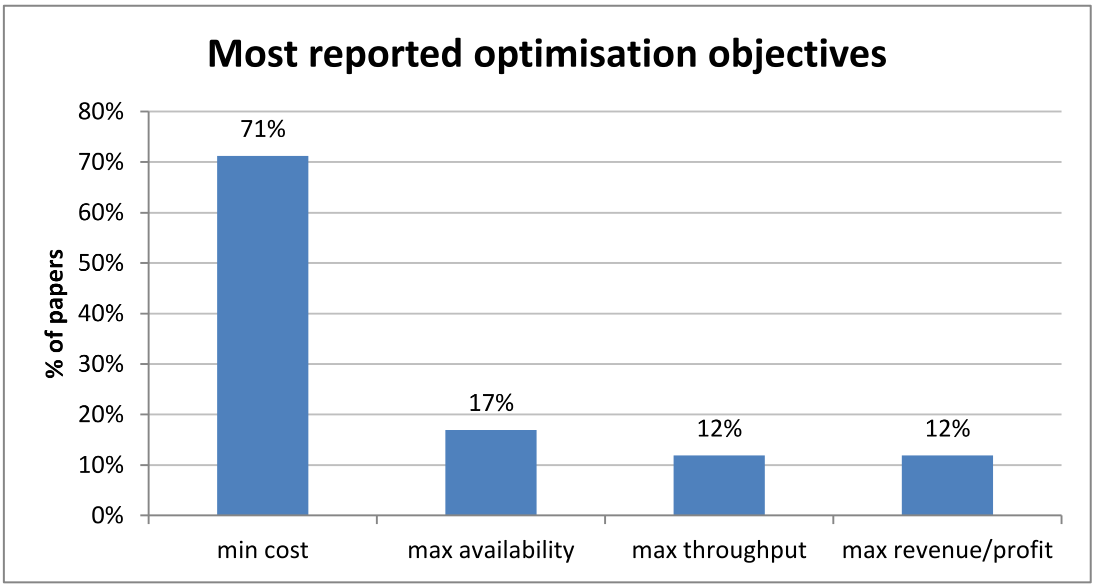


Figure 2-13 Most reported optimisation objectives (59 papers)

Instead of maintenance cost, Roux et al. [38] identified maximising machines availability as the optimisation objective. They argue that it is more appropriate as production costs are much higher than maintenance costs. Such explanation tends to overlook the fact that maintenance costs are significant [3] and can be higher than production costs [1]. Similarly, Boulet et al. [7] maximised availability and maintenance costs were considered manually for each case after the optimisation results.

However, maximum machine availability does not necessarily lead to maximum production throughput in manufacturing settings, which is an optimisation objective in several recent studies [6; 33; 48; 64]. A machine can be available but not in a working state due to many reasons such as shortage of raw material or blockages as a result of bottlenecks. Therefore, it is suggested to consider the manufacturing system as a whole and maximise the production throughput.

In addition to minimising costs, maximising availability and maximising production throughput, other optimisation objectives were identified in the literature. Oyarbide-Zubillaga et al. [61] considered a more holistic approach where the total cost and profit of the system is evaluated. The costs of maintenance tasks as well as defective products contribute to the cost function whereas the profit is calculated by the number of non-defective items produced. The variation in selecting the optimisation objectives might be due to the nature and purpose of the study. For instance, Ramírez-Hernandez and Fernandez [46] formulated the optimisation objective purely on production measures namely to minimise both machine cycle time and work in progress. The purpose of study could have been to support a quality initiative without a particular interest in cutting maintenance resources in the factory. On the contrary, Hani et al. [59] examined a train maintenance facility where the focus was on minimising the parts immobilisation time as well as minimising occupation rates for maintenance workshops. Nevertheless, limited discussion of the optimisation objectives choice was apparent in the literature.

Similar to the situation in many engineering problems [94], maintenance systems might require optimising several objectives simultaneously such as minimising maintenance costs and maximising assets availability. It is observed that researchers used one of the following approaches to solve that:

- Including multiple objectives in one objective function. For example, calculating machine downtime as costs [36; 78] or including a penalty for not meeting demand in the cost function [74; 75]. However, a challenge with this approach is transforming an objective in another objective's unit, for example, estimating how much unavailability of certain equipment would cost or estimating how costly it is to fail to meet the demand. Moreover, these costs are likely to change depending on the market dynamics [40].
- Developing a desirability function where optimisation objectives are assigned weights according to their importance to the decision maker to reach the best compromise [7; 52; 70; 77]. This approach does not require transforming an objective in another objective's unit. Nevertheless, it forces the decision maker to trade-off between objectives by assigning weights and ultimately producing a single result.
- Utilising multi-objective optimisation algorithms that have the ability to solve multiple objectives simultaneously. For instance, Non-dominated Sorting Genetic Algorithm was implemented to minimise costs and maximise profits [14; 61; 65]. It is interesting to note that only a limited number of researchers utilised multi-objective optimisation as shown in Figure 2-14.

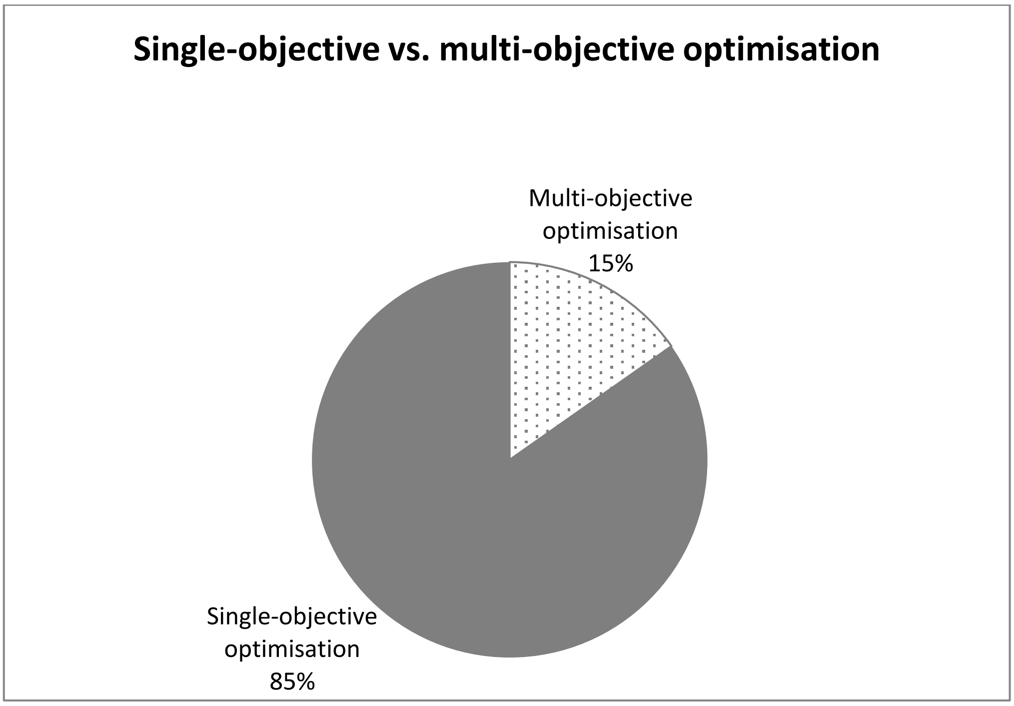


Figure 2-14 Single-objective vs. multi-objective optimisation (59 papers)

2.5.2.2 Decision Variables

Five decision variables were identified as the most reported in the literature as illustrated in Figure 2-15. Determining how frequent should assets be maintained to achieve the best possible solution is a continuing concern within the field. It is the most obvious option in cases where PM is modelled in the system as it can be controlled and its effect on cost and availability is widely accepted.

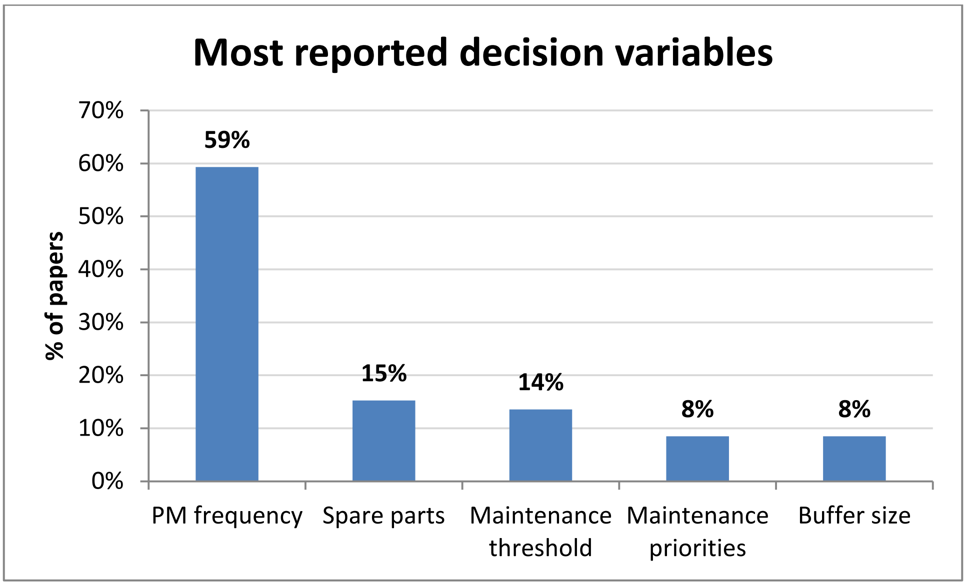


Figure 2-15 Most reported decision variables in the literature (59 papers)

However, when the system in interest incorporates CBM [40; 43; 54] or Opportunistic Maintenance (OM) [42; 50], the obvious decision variable becomes the maintenance threshold that triggers maintenance actions. If information on assets degradation is not streamed by on-line systems, inspections are needed to evaluate the degradation of assets. Inspection intervals were included as a decision variable in some publications [40; 43; 78].

In addition, some researchers optimised maintenance queuing and priority rules for different assets [56; 59]. For example, if more than one machine breaks down or requires preventive maintenance at any given time, which one should be maintained first. It could be that machines in a bottleneck should have a higher priority to enhance the total throughput. It is another significant variable that received little attention. This may be due to the fact that maintenance resources were not considered in the simulation model so resource usage is not a constraint. However, it is evident that assigning different priorities to machines have a direct effect on maintenance performance [6; 46].

Spare parts management is an important component in the maintenance system and has a considerable impact on cost and availability. Several studies showed that optimising maintenance and spare parts policies jointly led to better results compared to optimising them separately [80; 87; 95]. Absence of spare parts when assets are broken extends unavailability. Whereas keeping a large inventory of spare parts results in higher costs.

Several attempts have been made to investigate the effect of production parameters on maintenance systems in manufacturing settings. The work of several authors [6; 17; 96] show that buffer size has an impact on the performance of maintenance operations. The availability of buffer between machines allows maintenance resources to be stretched for a longer time with lesser effect on production rates. Quality initiatives such as lean, six sigma and Just In Time requires the minimisation of Work-In-Progress.

Researchers have not treated maintenance resources in much detail. Only few included maintenance technicians [35; 36; 49; 67] or maintenance equipment [47] as decision variables.

2.5.2.3 Constraints

Constraints are placed on values a decision variable can take [61] or the decision variable value in relation to other variables in the system such as having the maximum stock level of a spare part should be always larger than the reorder point [69]. Alternatively, constraints can be placed at other variables such as the maximum budget that can be spent [53], minimum reliability level [37] or PM window where PM actions have to be taken for each machine [33]. However, it is common to not explicitly define constraints, see for example: [54; 59; 76].

2.6 Overview of Existing Maintenance Optimisation Frameworks

It is interesting to observe that studies in the field do not follow a systematic methodology for optimising maintenance systems. Generic frameworks that guide the optimisation process are well established in the literature. For instance, Deb [91] identified 7 steps that are usually involved in an optimisation formulation process (see Figure 2-16). The first step is to ensure that optimisation is right for the problem in interest, whereas the four subsequent steps are focused on the formulation of the optimisation problem. This is followed by selecting a suitable optimisation algorithm based on the problem's characteristics and obtaining the solution. Likewise, other comparable general models that can be applied to optimise any engineering problem appear in the literature [5].

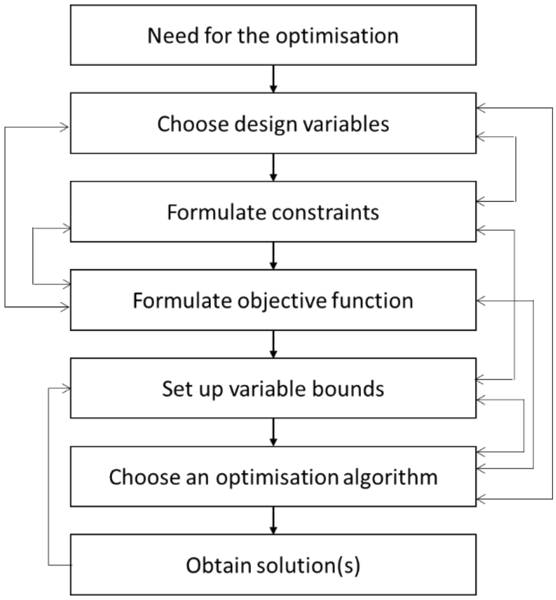


Figure 2-16 Flow chart of a general optimisation process. Source [91]

However, few studies attempted to develop a framework for maintenance optimisation. Chien et al. [97] proposed a customised systematic approach for determining the optimal maintenance policy in automated manufacturing systems. As can be seen in Figure 2-17, the approach utilises simulation, experimental design and regression metamodels. Hence it assumes that it is possible to construct a valid regression model which limits the applicability of the approach in complex problems.

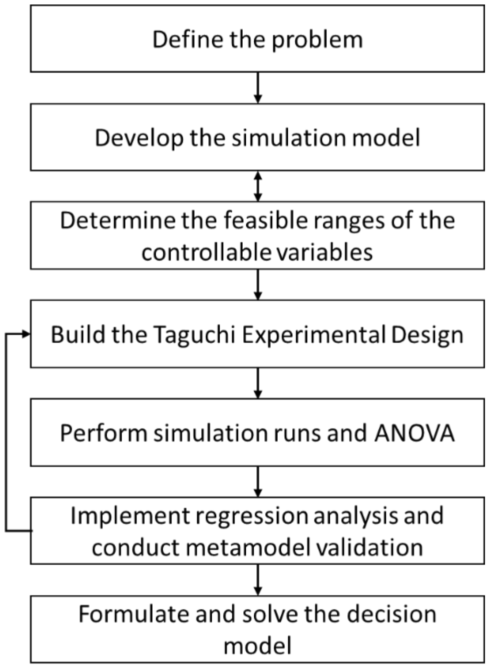


Figure 2-17 Systematic approach for determining the optimal maintenance policy. Source [97]

Riane et al. [98] developed a graphical framework for simulation based maintenance which allows the modelling of a dynamic system and optimises the maintenance policy. As shown in Figure 2-18, the framework begins with the modelling aspect to ensure the behaviour of the system is represented accurately. That is followed by simulating potential maintenance strategies and finally optimisation to obtain the solution. The framework is useful on the high-level. However, it does not provide detailed assistance to the user. For example, how to formulate the maintenance problem, how to decide which maintenance strategies are relevant or which optimisation algorithm is suitable.

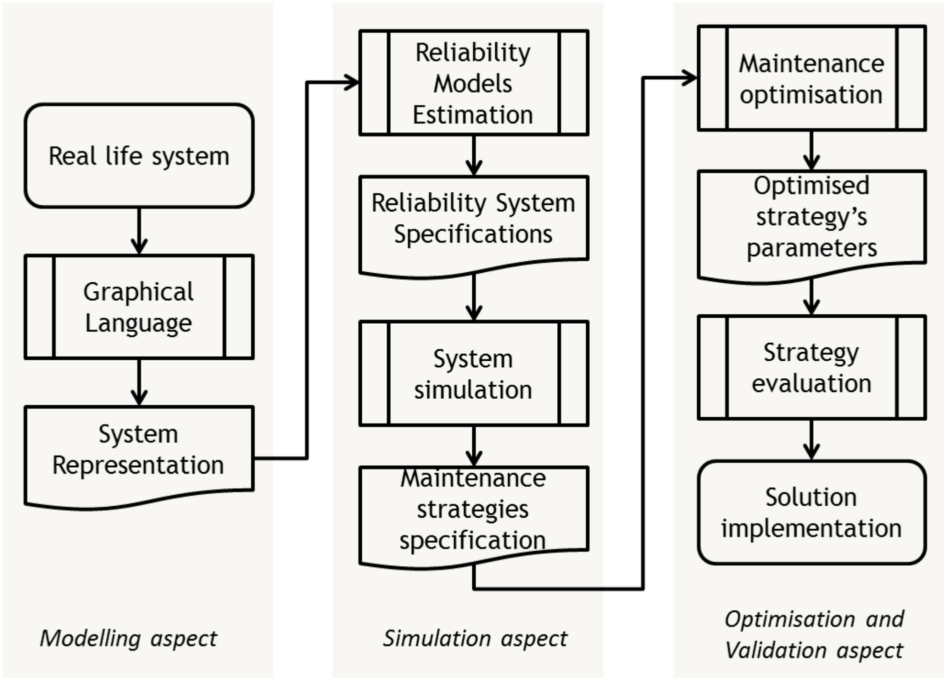


Figure 2-18 Decision making framework for maintenance problems. Adapted from [98]

Horenbeek et al. [11] suggested a generic maintenance optimisation classification framework. It is a result of literature review aimed at collecting factors that have an impact on the optimisation model such as optimisation objectives and parameters. It provides a general overview of all possible maintenance optimisation models making it possible to select the appropriate model based on the user experience. The authors recognised the need for a decision structure that guides both practitioners and academics in implementing the right optimisation models with the available data while considering the specific business context.

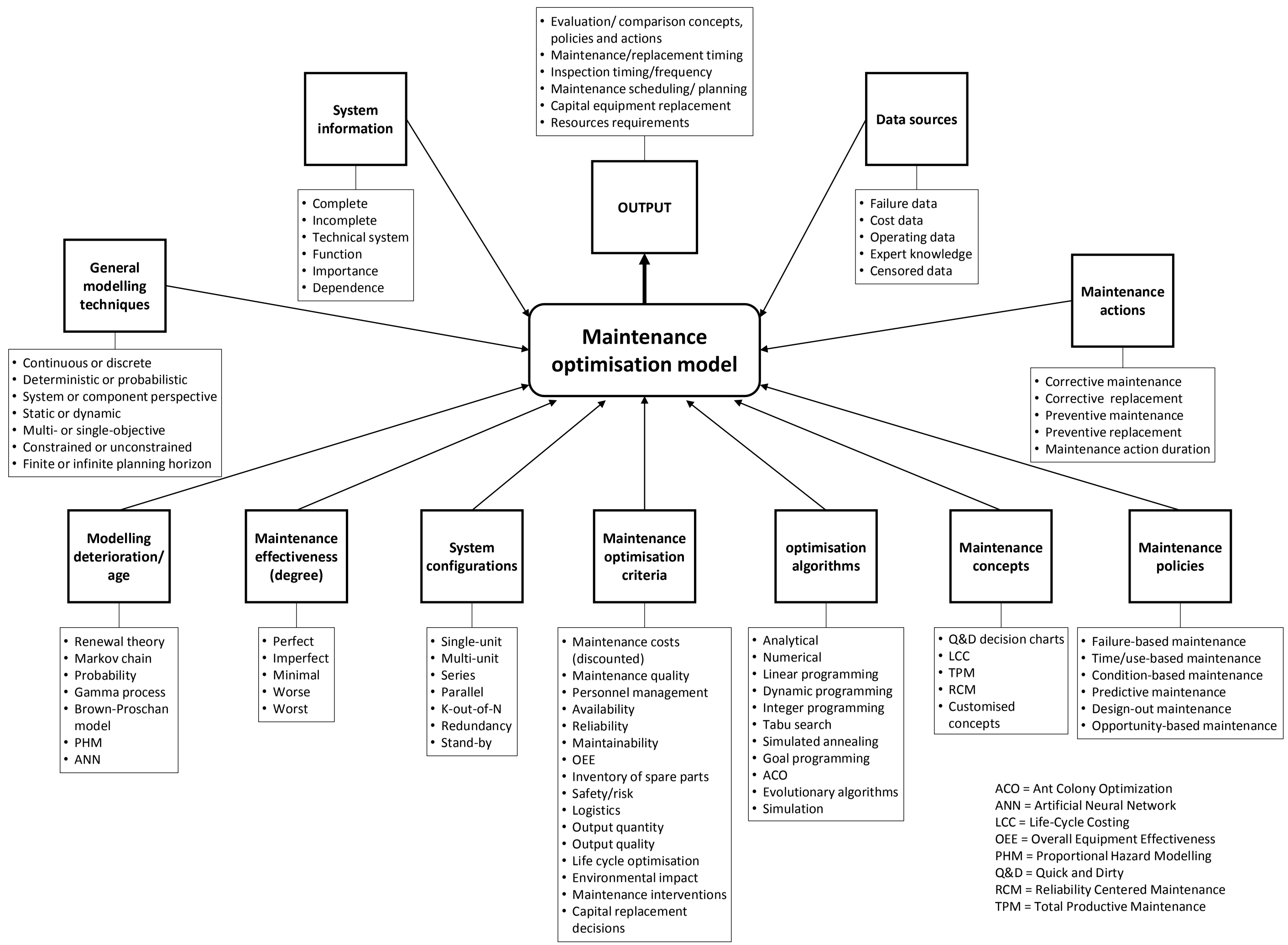


Figure 2-19 Maintenance optimisation classification framework. Source [11]

Overall, present frameworks lack the applicability to complex maintenance systems or do not provide the level of details needed for a typical practitioner or are not designed in a structure that could be followed to make decisions.

2.7 Discussion

Simulation based optimisation has the potential to solve the increasingly complex and dynamic nature of maintenance problems and there is an increasing trend of using simulation to optimise maintenance systems. The current study found that only few real life case studies were published, the academic cases that dominate the literature such as a single machine producing a single product are oversimplified and do not reflect the complexity and interactions in real systems. Moreover, little research is directed towards optimising a system composed of several equipment and most of the research focused on optimising few equipments without considering the operation configuration.

A range of simulation based optimisation applications in maintenance systems across various industries were covered. However, few researchers examined maintenance operations in PSS such as aircraft gas-turbine and military equipment.

Very little was found in the literature on comparing and selecting the optimum maintenance strategy. The majority of researchers investigated variations of PM including time-based PM and age-based PM. However, investigating CBM as a strategy in a production context is poorly covered in the literature.

In general, data availability does not seem to be a challenge for researchers modelling CM and PM systems. Operational data such as cycle times and arrival patterns for raw material can be obtained from field records. Likewise, historical maintenance data such as breakdown patterns and repair times are available. Cost of maintenance actions are usually simplified by using the company's standards or calculating the hour rate based on salary data.

However, obtaining data on the dependency between components appears to be a challenge. For example, estimating the effect of the failure of one component on the degradation of connected components. Gupta and Lawsirirat [18] suggested a dependency factor that is estimated using Failure Mode and Effect Analysis (FMEA), operational data and experts and vendors judgements. In addition, a challenge appears when attempting to model the machine degradation in CBM systems. CBM systems based on visual inspection can be simplified by assuming several fixed states for the asset where the transition from a state to another is based on probabilities obtained from historical records [78]. CBM systems based on on-line sensor data are modelled by fitting the data into a curve and assuming it correctly reflects the change in asset's health over time [40].

Uncertainty is an inherited feature of maintenance systems. Assets' degradation depend on many factors leading to unexpected breakdowns. Human errors during inspection or maintenance can add significantly to this uncertainty. Fitting the data into statistical distributions and then sampling randomly is a common practice used to account for this uncertainty. Special uncertainty parameters that account for human error in visual inspection can be introduced. For example, the longer the crack is on a pipe the more likely that it will be detected correctly [99]. Hennequin et al. [57] integrated fuzzy logic in the simulation to model imperfect maintenance actions according to the different skill levels' of maintenance technicians.

Sensitivity analysis is used to test the robustness of optimisation results in the presence of uncertainty. It helps in evaluating the optimal solution and make the required modifications especially in areas were estimations or simplifications have been made. For example, investigating how variations in assets' threshold levels affect the expected cost of the optimal solution [18]. Because it is difficult to obtain accurate cost data especially for conducting maintenance and inspection activities, it has been subjected to sensitivity analysis in several publications [68; 78; 100; 101]. In addition, sensitivity analysis was used to test the robustness of a suggested model by varying inputs and investigating if the results are in line with the expected outcome [7].

A vast majority of researchers used DES to model maintenance operations. Modelling maintenance resources received little attention and the majority of researchers assumed it was readily available. Modern optimisation methods such as GA and SA were the most reported optimisation methods in literature. Limited research was conducted to compare the performance of multiple optimisation algorithms. One criticism of much of the literature on optimising maintenance using classical methods is the lack of analysis of the objective function and the solution space. Therefore the justification and proper selection of the optimisation method is sometimes absent.

Minimising cost was reported as an optimisation objective in around three quarters of the papers. Moreover, limited discussion of the optimisation objectives choice was apparent in the literature. It is observed that researchers used three approaches to deal with several objectives simultaneously: including multiple objectives in one objective function, developing a desirability function and utilising multi-objective optimisation algorithms. The latter received little attention despite its ability to solve multiple objectives simultaneously and provide the decision maker with flexibility in a dynamic maintenance environment.

Figure 2-21 presents an overview of optimal problem formulation for different types of maintenance optimisation problems. Some decision variables depend on the choice of maintenance strategy while others can be applied to all maintenance systems. In addition, if the problem includes joint optimisation of maintenance and spare parts the inventory policy parameters can be optimised. This could be either the reorder level and maximum stock level or the reorder level and order quantity. If the problem includes joint optimisation of maintenance and production dynamics, buffer size can be considered as a decision variable. Optimisation objectives do not seem to be affected by the type of maintenance system or whether a joint optimisation is present.

<table>
<tr><th rowspan="2"></th><th colspan="4">Maintenance strategy</th><th colspan="3" rowspan="2">General maintenance</th><th colspan="3">Joint optimisation*</th></tr>
<tr><th colspan="2">PM</th><th colspan="2">CBM</th><th colspan="2">Spare parts</th><th>Production</th></tr>
<tr><td rowspan="2">Decision variables</td><td rowspan="2">PM frequency</td><td rowspan="2">maintenance schedule</td><td rowspan="2">inspection frequency</td><td rowspan="2">maintenance threshold</td><td rowspan="2">technicians</td><td rowspan="2">equipment</td><td rowspan="2">maintenance priorities</td><td>reorder level</td><td>reorder level</td><td rowspan="2">buffer size</td></tr>
<tr><td>maximum stock level</td><td>order quantity</td></tr>
<tr><td>Objectives</td><td colspan="10">min cost, max availability, max throughput</td></tr>
</table>

* Joint optimisation refers to the optimisation of maintenance system and spare parts or production

Figure 2-21 Optimal problem formulation for different types of maintenance optimisation problems

Complex maintenance problems often introduce a risk of high computation expenses. Running the simulation repeatedly during optimisation requires a considerable computation time. This can be mitigated by developing a faster meta-model that integrates with the simulation model to speed up the optimisation process [61]. Alternatively, the solution space can be reduced through investigating the effect of parameters on the objective function before engaging the optimisation engine [75; 79], therefore leading to either eliminating some variables or reducing its ranges. High computational facilities and parallel computing can significantly reduce the computation time. Shenfield et al. [50] demonstrated the use of Grid Computing to solve a computationally expensive maintenance problem during which several clusters of computation facilities were utilised. An obvious alternative would be simplifying the problem in hand by reducing the number of variables [68].

The findings outlined in this chapter suggest there are a number of research gaps as follows:

1. Examining maintenance for Product-Service Systems
2. Comparing the performance of optimisation algorithms in maintenance problems
3. Optimising multiple maintenance strategies
4. Optimising complex maintenance systems

5. Optimising maintenance in conjunction with the production system and maintenance resources
6. Utilising multi-objective optimisation
7. Applications on industrial case studies
8. Discussing the optimal problem formulation

The current research aims to address research gaps (3-8) by developing a systematic methodology that provides assistance in formulating the optimisation problem and dealing with issues in complex maintenance problems. In addition, applications on industrial case studies are conducted.

2.8 Summary

Maintenance plays an important role in sustaining and improving assets availability. The aim of this chapter is to report the state of the art in simulation-based optimisation of maintenance operations by systematically classifying published literature, outlining research gaps and guiding future research. Simulation based optimisation has been successfully applied to maintenance operations. Despite the limited research in this developing field, it appears to have a high potential since it allows analysing and optimising complex maintenance systems.

Much of the research in this area is focusing on PM and optimising PM frequency that leads to minimum cost. Discrete event simulation was the most reported technique to model maintenance systems whereas modern optimisation methods such as GA was the most reported optimisation method in the literature.

This study addresses research gaps by developing a framework that guides the experimenting process with different maintenance strategies and policies. Real case studies are conducted on CBM in a production context using multi-objective optimisation.

3 RESEARCH METHODOLOGY

This chapter describes and discusses an overview of methods used in this research. A detailed methodology is provided separately in each chapter of the thesis.

3.1 Research Aim and Objectives

The main aim of this research is to develop a simulation-based optimisation framework for maintenance systems. The research will focus on complex maintenance systems in production facilities.

The research objectives are as follows:

1. Identify current practices, outstanding issues and common limitations related to the field of maintenance simulation and optimisation.
2. Define typical variables, constraints and objectives for maintenance optimisation.
3. Identify the requirements of a simulation-based optimisation framework for maintenance systems.
4. Develop a simulation-based optimisation framework for maintenance systems at operational level.
5. Develop an approach for modelling maintenance strategies and policies in complex systems using Discrete Event Simulation.
6. Validate the proposed framework through industrial case studies.

3.2 Research Design

In general, research design can be categorised into three types: qualitative, quantitative and mixed methods. Qualitative and quantitative approaches reflect extremes in a continuum rather than distinct choices. The formulation of research design for a study is based on the basic philosophical assumptions the researcher holds, the types of research strategies and research methods employed in the research [102].

Research in maintenance optimisation is largely conducted using quantitative approaches. Theoretical models are developed and tested in controlled environments. Naturally, numerical models, statistical analysis and simulation experiments prevail in the field. In addition, the researcher is objective making the analysis and results unaffected by personal beliefs or feelings. The types of data collection strategies are quantitative in nature such as maintenance plans, data sheets of historical records and experimental designs.

Similarly, quantitative approaches seem to be more appropriate for the current research compared to qualitative approaches. Simulation-based optimisation of complex maintenance systems is conducted through collecting numerical data on assets in the system such as MTBF and repair times, fitting collected data into statistical distributions, developing DES models, formulating the optimisation problem and utilising optimisation algorithms to obtain numerical solutions. In addition, the researcher is assumed to be unbiased and has no effect on the study results.

Nonetheless, observations and interviews were conducted while visiting the industry to gain a better understanding of the collected data. Furthermore, developing a simulation-based optimisation framework involves investigating the qualities of existing frameworks. An extensive literature review is required to map current approaches and analyse them. Emerging framework requirements must be taken into account while designing the proposed framework. Therefore, the research includes aspects of qualitative approaches. It can be concluded that the adopted research design is mixed methods.

The research generally applies deductive reasoning where literature is examined with the aim of developing a theory [103]. In this case, a framework is developed based on evaluation of current research in the field of simulation-based optimisation.

3.3 Overview of Research Methodology

Figure 3-1 presents an overview of the methodology followed in this research. Five main stages are outlined. The squares with the white background are research activities in each main stage whereas the parallelograms are the output of the process which represent meeting one of the research objectives. As discussed above, the detailed methodology of each main stage is presented in the relevant chapter.

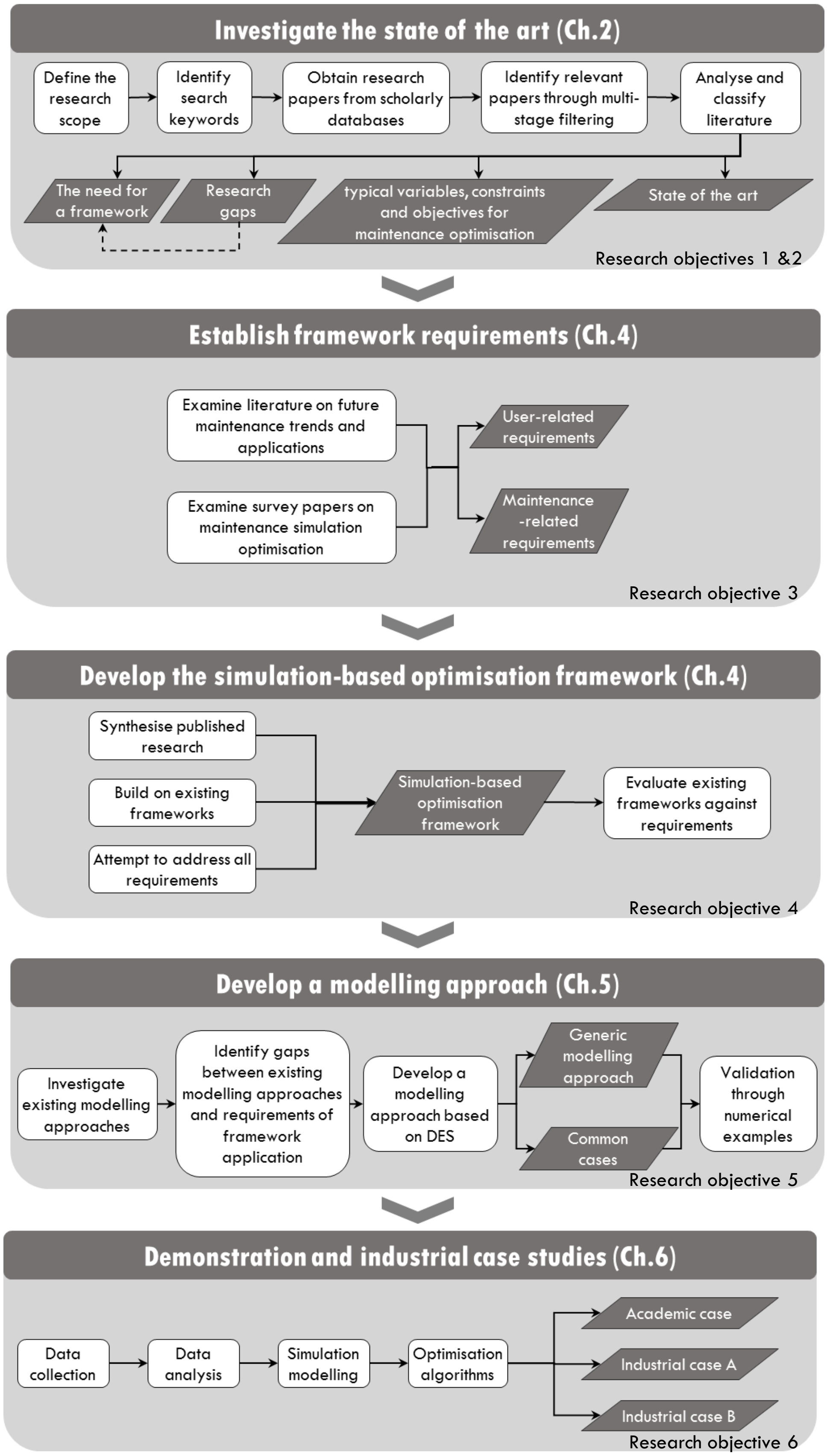


Figure 3-1 Overview of research methodology

3.3.1 Investigating the State of the Art in Simulation-Based Optimisation of Maintenance Systems

For the purpose of understanding and investigating the state of the art in simulation-based optimisation for maintenance systems, a systematic review of literature was conducted. The research scope was clearly defined allowing the formulation of relevant search keywords. Research papers were obtained by running the search queries in two of the largest abstract and citation databases of peer-reviewed literature: Scopus and Web of Science. A multi-stage filtering process resulted in the identification of the target research papers which were analysed producing the following outputs:

1. State of the art in simulation-based optimisation for maintenance systems including current practices, outstanding issues and common limitations.
2. The typical variables, constraints and objectives for maintenance optimisation.
3. Main research gaps.
4. The need for a simulation-based optimisation framework emerging from the research gaps.

A complete review methodology is presented in Section 2.2.

3.3.2 Establishing the Requirements for the Proposed Framework

Prior to developing a proposed framework, requirements were established by examining survey papers on maintenance simulation-based optimisation as well as literature on future maintenance trends and applications.

Survey papers were examined paragraph by paragraph with specific focus on review findings, research gaps and limitations and recommendations for further research. Comments and critiques to the approaches researchers undertake when optimising maintenance systems were documented. Additionally, aspects that need to be considered in future research attempting to optimise maintenance systems were captured.

In parallel, research papers on contemporary maintenance applications and upcoming trends were examined to ensure the framework addresses current and possible future challenges.

Requirements were categorised into user-related requirements and maintenance-related requirements. A detailed methodology is provided in Section 4.2.

3.3.3 Developing the Simulation-Based Optimisation Framework

The simulation-based optimisation framework was developed by synthesising published research in the area, building on existing frameworks and attempting to address all documented requirements.

Framework requirements were studied individually to establish appropriate strategies/tools/techniques that meet each requirement. If applicable, strategies were mapped against the main steps in the framework.

Once strategies for meeting the requirements were established and linked with the framework structure, additional details were included gradually by synthesising published approaches to maintenance optimisation. Therefore, enriching the framework and adding more layers as needed. A novel framework of three levels was developed by attempting to meet all possible framework requirements.

A flow chart approach was adopted to provide a user-friendly decision structure for a typical user. Both the existing frameworks and the proposed framework were evaluated against the requirements. The detailed methodology for developing the framework is described in Section 4.2.

3.3.4 Developing an Approach for Modelling Maintenance Systems

The proposed framework cannot be applied to industrial systems due to the limitations present in existing modelling approaches. The gaps between existing modelling approaches and implementing the framework were identified. Consequently, a novel modelling approach based on DES was developed.

The interactions between maintenance strategies including CM, PM and CBM are modelled by accessing the event queue for assets and altering the timing of the relevant maintenance action.

A generic approach as well as approaches for common cases are provided. In addition, the approach was validated through numerical examples using Witness 14 (Manufacturing Performance Edition). The complete methodology is presented in Section 5.2.

3.3.5 Demonstration and Industrial Case Studies

In order to validate the proposed framework, data was collected from two industrial systems. The main sources of data were manuals and records. This was further clarified by engineers and managers in the industry. Collected data included a list of all equipment in the production line, a detailed record for all maintenance interventions including durations, spare parts involved, cost estimations, maintenance technicians as well as PM plan and execution. Data analysis and distribution fitting were undertaken to provide the required inputs to the simulation model.

Models were developed using Witness, a DES software provided by Lanner. **Witness Optimizer**, a Witness plug-in was used to solve Single Objective Optimisation (SOO). On the other hand, **GAnetXL**, a Genetic Algorithm Optimisation add-in for Microsoft Excel was used to solve Multi-Objective Optimisation (MOO) problems. The framework was validated using a published academic case as well as two industrial case studies. A detailed methodology can be found in Section 6.2.

3.4 Summary

This chapter outlined the research aim and objectives. The research design was discussed and explained. In addition, an overview of the research methodology including main research activities and their link with research objectives was presented. A detailed methodology can be found in each of the remaining thesis chapters.

4 A NOVEL FRAMEWORK FOR SIMULATION-BASED OPTIMISATION OF MAINTENANCE SYSTEMS

4.1 Introduction

In recent years, the maintenance function in manufacturing has been gaining growing interest and significance. Improving maintenance is seen as an investment that will have a positive impact on product quality, asset availability and asset productivity. Simulation based optimisation has a strong potential in supporting maintenance managers to make the right decisions in complex maintenance systems [104].

Surveys such as that conducted by Alrabghi and Tiwari [104] and Horenbeek et al. [11] revealed that the approaches to optimise maintenance varied significantly in the literature. This includes a wide range of optimisation objectives, decision variables and optimisation algorithms. Moreover, very little was found in the literature on comparing and selecting the optimum maintenance strategy. Overall, these studies highlight the need for a framework that unifies the approach to optimising maintenance systems.

The main aim of this research is to develop a simulation-based optimisation framework that supports decision making for maintenance in manufacturing systems. The proposed framework is a systematic approach detailing the steps required to successfully optimise simulated maintenance systems. It can assist in displaying available options for a specific maintenance system as well as guiding both researchers and practitioners to determine which data are required to optimise the maintenance system.

4.2 Research Methodology for Developing the Framework

Figure 4-1 presents the methodology followed in order to develop a framework for simulation-based optimisation of maintenance systems. The existing maintenance optimisation frameworks were investigated previously in Section 2.6 in order to build on its strengths and establish its limitations. As a result, the framework’s structure on high level was developed.

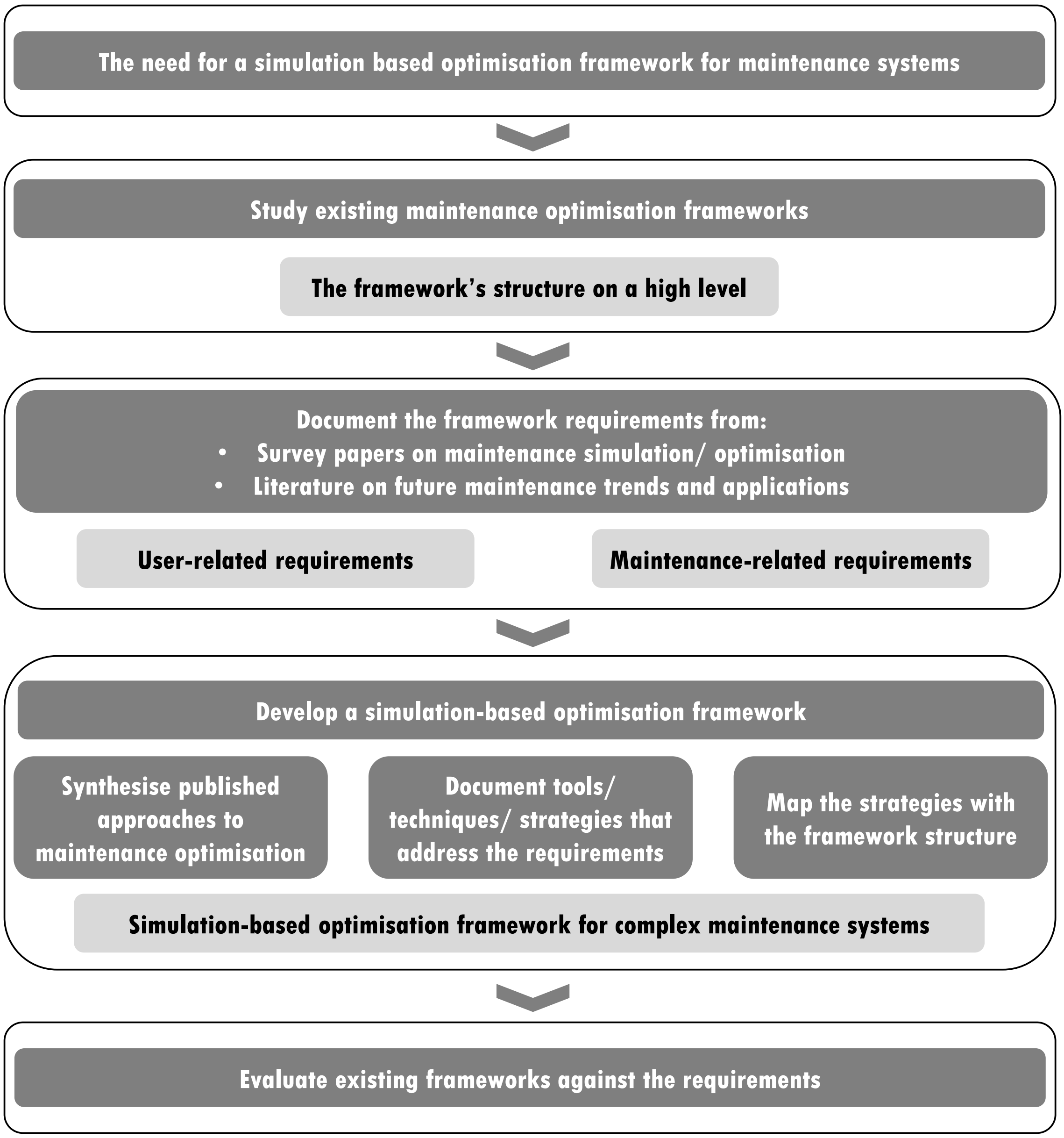


Figure 4-1 Framework development methodology

In order to capture framework requirements, review papers in maintenance optimisation were located. 34 publications were generated by searching in Scopus citation database for 'maintenance', 'optimisation' and 'review' in journal article titles and keywords while excluding papers in life or health sciences. Examining the titles resulted in reducing the number of papers. In order to include papers published in other databases or those that did not use these search terms, citations in the review papers were traced. In total, ten relevant journal articles were incorporated [11; 13; 15; 23-25; 28; 104-106]. Survey papers were examined paragraph by paragraph with specific focus on review findings, research gaps and limitations and recommendations for further research. Comments and critiques to the approaches researchers undertake when optimising maintenance systems were documented. Additionally, aspects that need to be considered in future research attempting to optimise maintenance systems were captured.

In parallel, research papers on contemporary maintenance applications and upcoming trends were examined to ensure the framework addresses current and possible future challenges. The authors searched for the keywords ‘prospective’ or ‘trends’ or ‘future’, all in combination with ‘maintenance’ in the title, abstract or keywords of publications listed in the Scopus database. The search covered journal article titles while limiting the publications date to the last five years and excluding papers in life or health sciences to ensure only timely requirements are captured. To extend the set of relevant publications, reference lists in resulting papers were searched for related papers. In total, ten publications were identified [24; 104; 107-114].

Requirements relating to the simulation and modelling aspects were considered irrelevant as the current research assumes the availability of a valid simulation model of the maintenance system in interest. In addition, only papers related to maintenance in production setting were considered relevant thereby excluding papers considering maintenance in Product-Service Systems such as aviation [115] or power transformers [116].

Framework requirements were categorised into two types: user-related requirements and maintenance-related requirements. The requirements were then studied individually to establish appropriate strategies/tools/techniques that meet each requirement. Relevant strategies were extracted from the extensive literature review conducted in Chapter 2 as well as published sources investigated while documenting the framework requirements. If applicable, strategies were mapped against the main steps in the framework as illustrated in Figure 4-2.

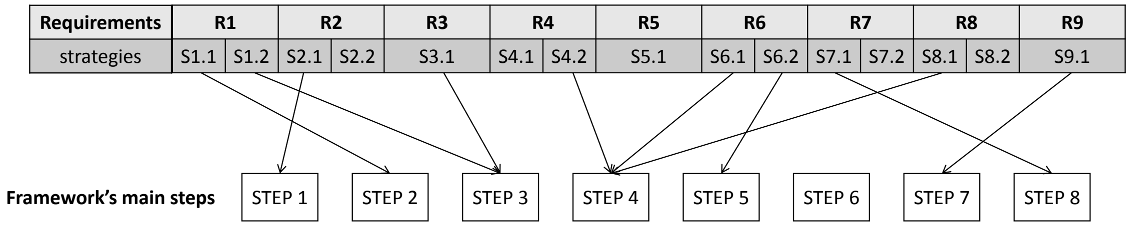


Figure 4-2 Methodology for addressing the requirements (see section 4.3 for list of requirements)

Once strategies for meeting the requirements were established and linked with the framework structure, additional details were included gradually by synthesising published approaches to maintenance optimisation. Therefore, enriching the framework and adding more layers as needed. A novel framework was developed by attempting to meet all possible framework requirements.

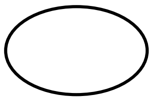
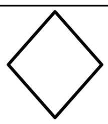
Several tools were considered for the purpose of framework representations. Integrated Definition Methods (IDEFØ) is a function modelling method designed to "*Model the decisions, actions, and activities of an organisation or system*" [117]. It focuses on enhancing the communication between the analyst and the customer during functional analysis by outlining the relationship between different activities. However, it is not intended to be used for describing the sequential steps of a given process.

Decision trees [118] represent all possible outcomes of related decisions in a chronological order. They are used to support decision analysis and decision making in a certain situation by calculating the uncertainty and benefit or loss associated with each decision. Therefore, it is not suitable for the representation of proposed framework since it cannot be used to represent a step-by-step guide.

A flowchart is defined by International Organisation for Standardization (ISO) [119] as "*A control flow diagram in which suitably annotated geometrical figures are used to represent operations, data, or equipment, and arrows are used to indicate the sequential flow from one to another*". Flowcharts display the sequential activities in a given process. If one activity requires additional details, it can be drawn as a sub-process in a hierarchal structure where smaller steps to achieve the main activity can be outlined. In general, it can be expected that most maintenance managers are familiar with flowcharts as it is well-established and used frequently in organisations to describe and document processes.

A standard flowchart tool was used to represent the framework due to its familiarity and ability to depict decision structures clearly. The most frequent used symbols in the framework are shown in Table 4-1. Microsoft Visio 2013 was used to facilitate the development of the framework.

Table 4-1 Standard flowchart symbols. Adapted from [120]

Symbol	Description
	Start/End
	Process
	Pre-defined process
	Decision
	Sequence

Finally, existing frameworks were evaluated to reveal how well they meet the requirements.

4.3 The Framework Requirements

The requirements captured from survey papers in maintenance simulation optimisation as well as papers on future maintenance strategies and applications were grouped into user-related requirements and maintenance-related requirements as follows:

4.3.1 User-related Requirements

Requirement 1: *Assist users with typical uncertainty found in maintenance systems*

A number of authors [23; 100; 104; 106] have reported that the availability of accurate data is a challenge in maintenance optimisation. In practical situations, it is almost always necessary to make assumptions or approximations. The proposed framework therefore has to advise the user on suitable strategies to deal with the typical uncertainty found in maintenance systems.

Requirement 2: *Assist users to adapt maintenance models to their specific business needs*

There is a large volume of published simulation optimisation studies in maintenance. However, the optimal problem formulation varies significantly [23; 104]. The framework has to make an attempt to synthesise the published studies and encompass all possible variations. It can then propose the most suitable parameters for the maintenance problem in hand including the objective functions, decision variables, constraints and optimisation algorithms. This will enable industrial companies to build optimisation models that meet their specific business needs.

Requirement 3: *Enable users to solve multi-objective optimisation*

Traditionally, research in maintenance was investigating SOO problems only. Multi-objective optimisation is an under-explored area in maintenance optimisation [11; 114]. Most engineering problems – including maintenance- require solving multiple objectives simultaneously [94]. The framework needs to allow the decision maker to solve multi-objective problems to provide flexibility in the increasingly dynamic manufacturing environment.

Requirement 4: *Assist users with complex maintenance systems*

Maintenance systems are becoming increasingly complex including thousands of components with various dependencies between them [15]. It may not be possible to optimise all components or assets in the system. Therefore, the user requires assistance in defining the problem scope efficiently. Nevertheless, the optimisation problem may still be complex resulting in high computation expenses. Appropriate strategies will be required to reduce the computation time.

Requirement 5: *An operational decision making tool suitable for maintenance managers and practitioners*

It has been suggested that most published maintenance optimisation models were developed in academia in separation from industry and real practices [11; 24; 106]. This led to many theoretical models that can perhaps be implemented in special cases only. Dekker [23] highlights the difficulty of understanding and interpreting maintenance optimisation models. Technicians, engineers and managers need a user-friendly approach to optimise their maintenance systems. The framework can make use of standardised methodologies that are known to a typical practitioner in the field [106]. In addition, the framework should provide sufficient guidance assuming the practitioner has no or little information on optimisation. This includes a standardised optimisation procedure in addition to instructions on how to correctly interpret the optimisation results. A typical user should be able to use the framework to support operational decision making.

4.3.2 Maintenance-related Requirements

Requirement 6: *Incorporating production dynamics and spare parts management*

A number of studies have examined systems that are inter-related with maintenance such as production dynamics and spare parts [6; 87]. They showed that these systems have a substantial effect on maintenance performance. Furthermore, optimising them jointly with maintenance can yield better results. The framework should consider the environment surrounding the maintenance system and allow the investigation of such important factors.

Requirement 7: *Allow the investigation of several maintenance strategies simultaneously*

There is little work in the literature on optimising several maintenance strategies simultaneously for the same asset [104]. Most researchers assume that a specific maintenance strategy is the optimum. Therefore, the research focus is on optimising the maintenance strategy parameters without investigating alternative strategies [105]. It is possible to have several maintenance strategies applicable for each asset in the system e.g. PM and CBM or perhaps several variations of policies for the same strategy such as time-based PM and age-based PM. The framework should allow the investigation of more than one maintenance strategy yielding the optimum maintenance strategy and policy for each asset in the system.

Requirement 8: *Incorporating possible future maintenance strategies*

Contemporary manufacturing systems are becoming increasingly complex which makes the task of predicting failures and intervening in the right time challenging. CBM aims to monitor the condition of an asset and trigger maintenance actions when deterioration occurs [110]. An advanced alternative strategy is designing self-maintenance machines where assets are able to monitor its health, diagnose faults and maintain its function [107]. It is a methodology that gained popularity recently in the literature. Additionally, it is expected to continue growing both in research and practice. The framework has to consider the possible future applications of CBM and self-maintenance.

Requirement 9: *Integration with e-maintenance*

The framework would have to accommodate the growing interest in the concept of e-maintenance. The ability of gaining remote access to the maintenance information infrastructure through various means, the integration of maintenance with other functions within the organisations, the enhanced collaboration opportunities and the utilisation of real time data to design optimum maintenance strategies are some of the potential benefits of e-maintenance [108]. The framework can extend the use of e-maintenance platforms by advising a systematic and perhaps an automatic procedure to utilise the continuously streaming data and provide decision-making support in real time.

4.4 A Novel Framework for Simulation-Based Optimisation of Maintenance Systems

This simulation based optimisation framework aims to support decision making for maintenance in manufacturing systems at the operational level. By providing a systematic procedure for conducting simulation-based optimisation to improve maintenance systems, it can assist in investigating available options for a specific maintenance system as well as guiding both researchers and practitioners in determining which data are required to implement the research.

4.4.1 First Level of the Framework

The framework on a high level is shown in Figure 4-4. It takes the user through eight main steps that were mainly adapted from generic optimisation frameworks (see for example [91]). However, it is specifically developed for optimising complex maintenance models. Each main step is a sub-process that contains further instructions in a flow chart structure to provide detailed assistance to the user. The framework assumes that there is already a valid simulation model that represents the real maintenance system. The first seven main steps are conducted before engaging the optimisation engine whereas the last main step, namely decision making, is conducted after the optimisation results are obtained. The main contemporary issues in maintenance optimisation that are addressed are shown around the framework.

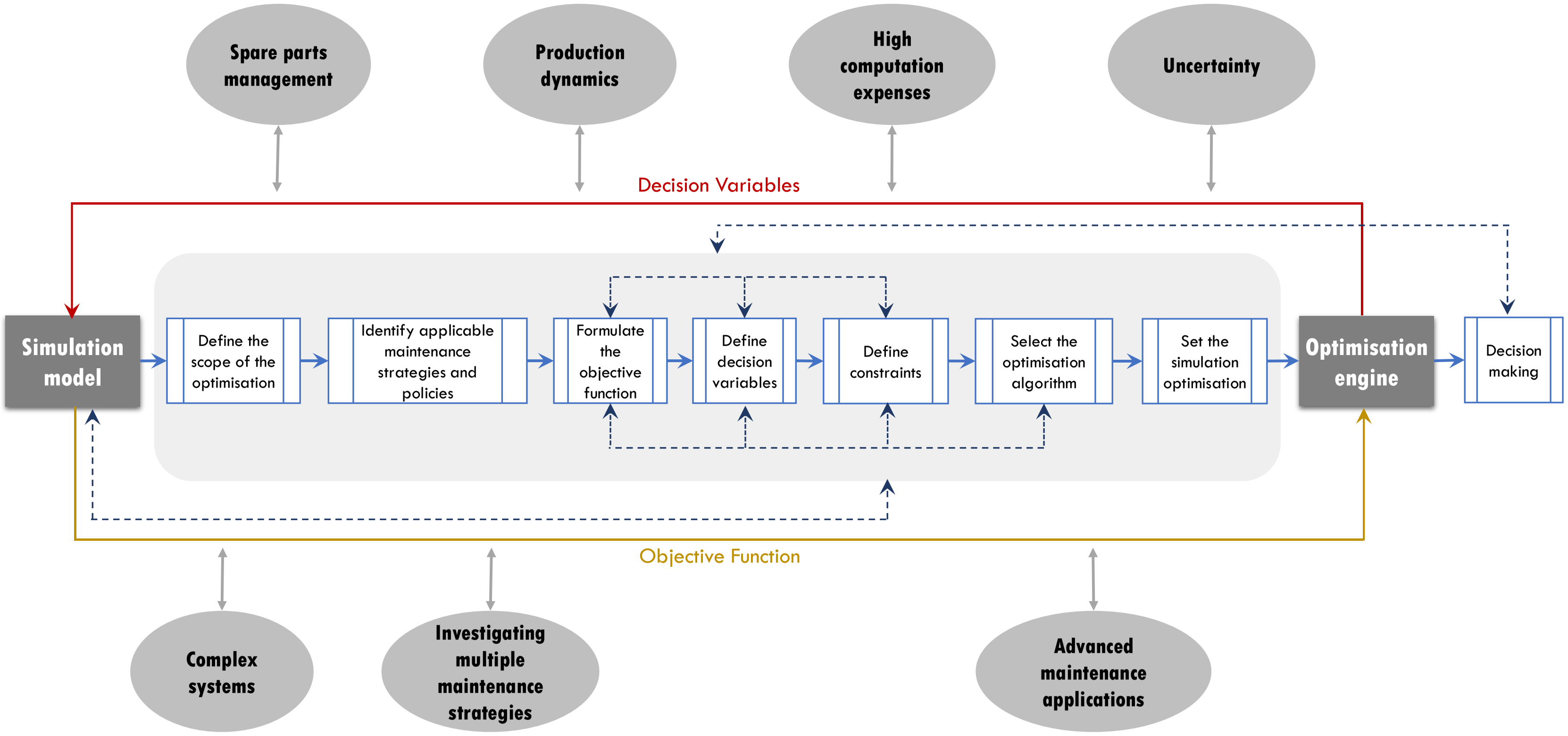


Figure 4-3 Simulation-based optimisation framework for complex maintenance systems on a high level

Specific strategies/tools/techniques are suggested to address each requirement as shown in Table 4-2. These are incorporated in two additional levels of the framework.

Table 4-2 Strategies to meet the framework requirements

	Requirements	Strategies to meet the requirements
1	*Assist users with typical uncertainty found in maintenance systems*	• Stochastic simulation • Specific optimisation algorithms • Sensitivity analysis
2	*Assist users to adapt maintenance models to their specific business needs*	• Identifying suitable optimisation objectives • Identifying suitable decision variables • Identifying suitable constraints
3	*Enable users to solve multi-objective optimisation*	• Formulating multi-objective problems • Utilising suitable multi-objective optimisation algorithms
4	*Assist users with complex maintenance systems*	• Identifying the critical assets in the maintenance system • Utilising measures to reduce computation expenses
5	*An operational decision making tool suitable for maintenance managers and practitioners*	• Representing the framework using a standard flow chart • Developing a comprehensive step-by-step guide
6	*Incorporating production dynamics and spare parts management*	• Defining the optimisation scope
7	*Allow the investigation of several maintenance strategies simultaneously*	• Identifying applicable maintenance strategies • Incorporating the choice of maintenance strategy in the problem formulation
8	*Incorporating possible future maintenance strategies*	• Considering CBM • Considering prognostic technologies • Considering self-maintenance
9	*Integration with e-maintenance*	• Outlining a structure for the online platform

4.4.2 Second Level of the Framework

The second level is shown in Figure 4-5. A description of each main step is as follows:

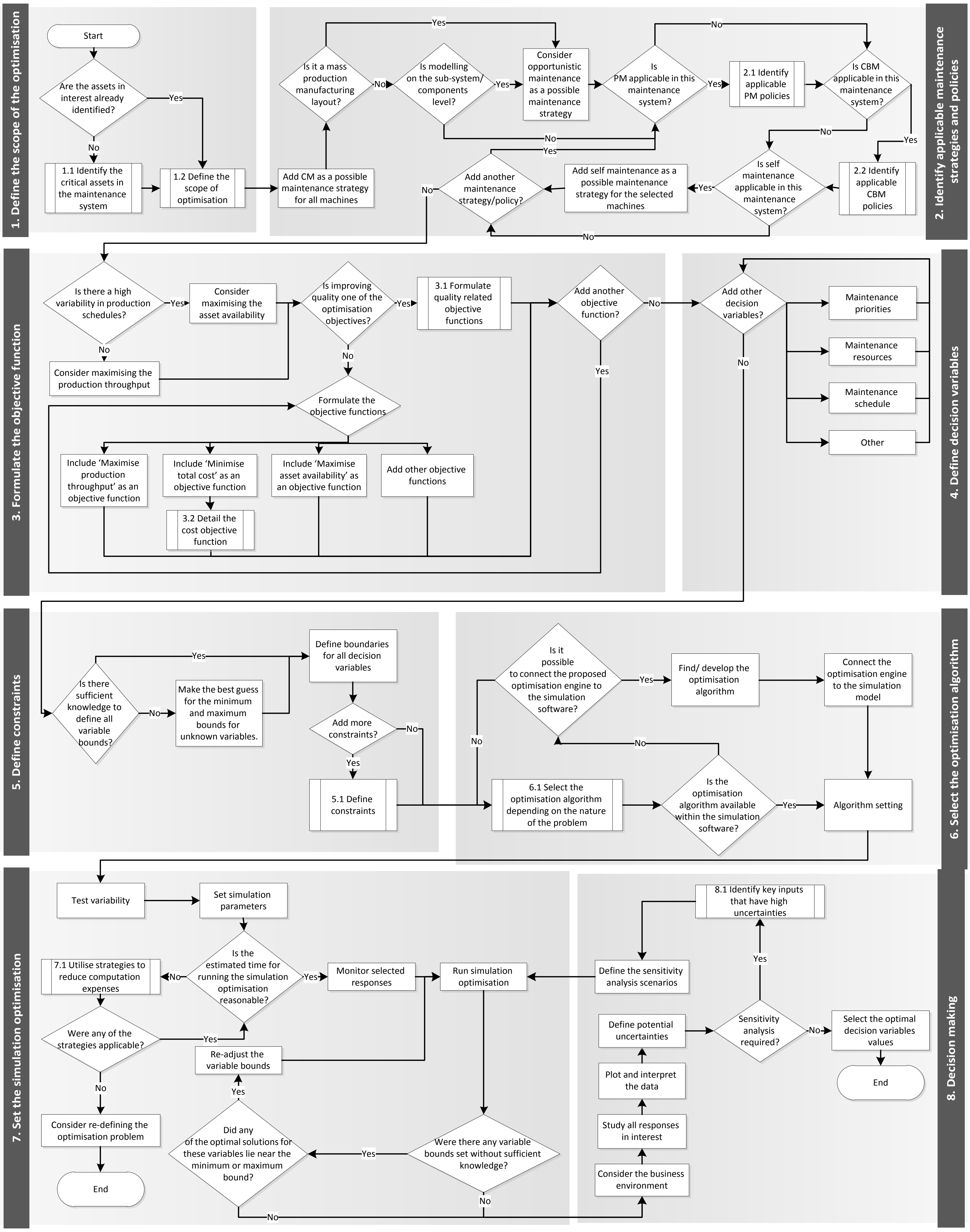


Figure 4-5 The second level of the framework

1) **Define the scope of the optimisation:** As modern manufacturing systems are becoming more complex with many components interacting, it may not be practical to optimise all assets in the manufacturing system. An assessment can be conducted to identify the most critical assets. If the modelling level goes beyond assets to subsystems or components within assets then various tools can be utilised to identify the most critical subsystems/components such as Failure Modes and Effects Analysis (FMEA), operational data and expert and vendors experience. Defining the scope of optimisation also includes the decision of optimising other systems jointly with maintenance such as the production system and/or the spare parts management system. Optimising both systems with maintenance have shown to produce better results [104]. However, including more decision variables will inevitably increase the problem complexity. In addition, the inclusion/exclusion of a system in the optimisation should be affected by the user's ability to alter the decision variables in the real world. In other words, if the maintenance manager was to optimise the maintenance system he/she might not have authority to modify the spare management policies or production parameters. It is worth mentioning that even though some systems might be out of the optimisation scope, it can be still represented in the simulation system.
2) **Identify applicable maintenance strategies and policies:** This step leads the user to investigate what maintenance strategies can be applied in the selected assets. This will depend on the available level of maintenance infrastructure such as skilled technicians and condition monitoring equipment. In addition, the production configuration might affect the range of possible maintenance strategies and policies. For instance, we might want to consider opportunistic PM in continuous production where shutdowns can be exploited [121]. Maintenance strategies are generally categorised into CM, PM or CBM. There are a number of policies within each strategy. For example, CBM can be inspection based or continuous monitoring based. In addition, self-maintenance is included as a strategy to accommodate for possible future applications [107]. In this step, the user can assign several

maintenance strategies/policies for each asset. The framework will then identify the optimum maintenance strategy/policy for each asset.

3) **Formulate the objective functions:** Formulating the objective functions can be affected by production and demand patterns. For example, if there is high uncertainty in demand it might be worth considering maximising asset availability. This will ensure assets are more capable of handling fluctuations in production schedules. However, if uncertainty in production schedules is relatively low it might be worth considering maximising the production throughput. Some optimisation studies are conducted mainly to enhance quality measures. In such cases, objectives such as minimising cycle times and lead times can be included as objective functions. Although minimising cost is an objective in most maintenance optimisation studies [104], detailing the cost function varies widely and depends on several factors such as the defined scope of the optimisation (step 1) as well as the objective function. For example, if spare parts are jointly optimised with maintenance then costs associated with spare part policies need to be detailed. Researchers in maintenance have not treated multi-objective optimisation in much detail despite its significant advantages [11; 104]. This framework allows the user to optimise multiple objectives simultaneously.
4) **Define the decision variables:** Depending on the outcome of preceding steps, controlled variables can be defined. As illustrated in Table 4-3, PM strategies usually involve setting PM frequency as a decision variable whereas CBM usually involves setting inspection frequency and/or maintenance threshold as decision variables. In addition, the scope of the optimisation will have an effect on the choice of decision variables. For instance, if spare parts policies are optimised jointly with maintenance one will be interested in optimising the policy parameters such as maximum and minimum stock levels. Most of the decision variables are defined within previous steps in the framework to avoid adding decision nodes to recall the selected maintenance strategies or optimisation scope. However, some decision variables are not related to outcomes from previous steps such as

number of maintenance technicians, number of inspection equipment or maintenance priorities which can be defined in this step.

Table 4-3 The effect of maintenance strategy choice on the decision variables

Maintenance strategy		Decision variables
PM	time based: periodic	PM frequency
	time based : scheduling	PM time slot
	opportunistic	PM frequency
CBM	online	CBM threshold
	inspections	inspections frequency and CBM threshold
	inspections with prognosis	inspections frequency and CBM threshold
	opportunistic	opportunistic CBM threshold

5) **Define constraints:** Technical knowledge can assist in defining feasible ranges for each variable. If the user is lacking the required knowledge, it may be necessary to make assumptions and redefine the ranges after conducting initial experiments [91]. In addition, the framework enables the user to define a range of constraints related to maintenance resources, maintenance schedule, spare parts, production, costs and other customised constrains.

6) **Select the optimisation algorithm:** This step includes choosing the optimisation algorithm and setting the appropriate algorithm parameters. The sub-process for selecting the optimisation algorithm is adapted from the work of Tiwari et al. [122]. The user is guided through a series of sequential steps to reveal the nature of the optimisation problem at hand. A number of optimisation algorithms or modules that suit each characteristic are suggested. Nine suitable algorithms are suggested for multi-objective optimisation. Likewise, suitable algorithms are proposed for problems that require global search, include handling constraints, require robust search or include handling uncertainty. If the selected optimisation algorithm is not included in the simulation software package then often programming will be required to connect the simulation model to the optimisation algorithm. If that is not possible the framework will ask the user to modify the selected

optimisation algorithm until it becomes applicable in his/her specific situation. If the used optimisation engine provides the required flexibility, optimisation algorithms needs to be set. For example: GA can have different numbers of populations, generations, cross over and mutation parameters. Whereas in SA the parameters are the cooling factor and the initial temperature.

7) **Set the simulation optimisation:** To prepare for the experiments, simulation parameters need to be set [85]. This includes the number of replications since variability and uncertainty are inherited features in maintenance systems. Sufficient warm-up time is required to reach steady-state and mitigate the initialisation bias. Appropriate run length is essential depending on the time frame required. High computational expenses reflected in long estimated runtime is a major issue that might appear at this stage for complex systems. Several strategies for reducing the computation time are suggested such as improving the computation speed using parallel computing, high performance computing or grid computing. Alternatively, special optimisation algorithms can reduce the computation time significantly. In some cases, there will be a need to go back to the previous steps in order to decrease the simulation time by reducing the number of replications or the simulation run-length. Otherwise, the optimisation problem would have to be simplified by minimising the variables' ranges, reducing the number of variables or reducing the number of objective functions if possible. It may be useful to monitor additional parameters that are not defined as objective functions. This is usually defined at this stage in order to have each response recorded with its corresponding solution (the values for the objective functions and the decision variables). At the end of this step the simulation optimisation will be ready to be conducted.
8) **Decision making**: After the optimisation results are produced, they need to be interpreted in light of the current business context. This is particularly important in multi-objective optimisation where one objective might be relatively more important than others depending on business dynamics. Nevertheless, considering the business context is also relevant to single

objective optimisation. There might be multiple combinations of decision variables that result in comparative values for the objective function. Likewise, monitored responses might have an effect on the choice of implemented solution. Therefore, plotting and interpreting data are considered essential. If areas of high uncertainty are identified that are not addressed adequately by stochastic simulation or by special optimisation algorithms then sensitivity analysis is suggested. This can be achieved by investigating which inputs have high uncertainties, followed by defining additional scenarios with the new input values to run the simulation optimisation repeatedly. If no further sensitivity analysis is required, the optimal values can be chosen as the solutions for the problem.

4.4.3 Third Level of the Framework

The third level consists of ten sub-processes that required further details. Sub-processes are numbered sequentially while including the number of the main step first to enable the user to follow it easily. For example, sub-process 1.2 refers to the second sub-process in the first step of the framework.

Sub-process 1.1 is presented in Figure 4-6. As maintenance systems are becoming increasingly complex involving a large number of assets, this sub-process aims to systematically identify the critical assets in the maintenance system to focus the optimisation effort. A number of tools and techniques can be used to assess the criticality of assets. As these tools are well documented, reference is made to some examples such as FMEA and experts opinion. One of the most common methodologies is to establish the types of failures associated with each asset then evaluate its effects and implications. Assets are then categorised according to the level of impact it has. If assets are considered as sub-systems or components in the simulation model, criticality assessment can be conducted to identify the most critical sub-systems or components.

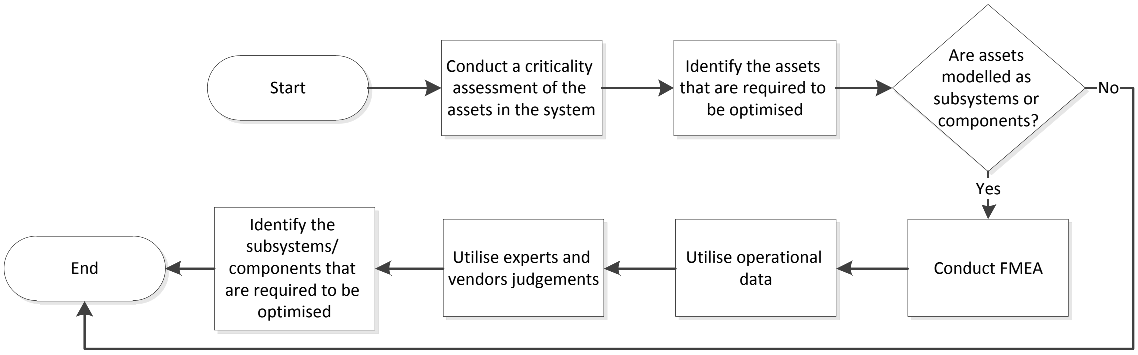


Figure 4-6 Sub-process 1.1: identify the critical assets in the maintenance system

Figure 4-7 shows the second sub-process in the first step of the framework. This sub-process aims to determine whether optimisation will involve other aspects of the manufacturing system in addition to maintenance. In principle, production and spare parts management system should be optimised jointly with maintenance where possible as studies have shown their significant impact on the overall maintenance performance. Spare parts parameters depend on the spare parts management policy. Examples include order quantity and reorder level. Likewise, production parameters vary according to the manufacturing layout. Examples include buffer size and machine cycle times. However, if it is not possible to alter the parameters of production or spare parts management system there will be little use of optimising them if at all.

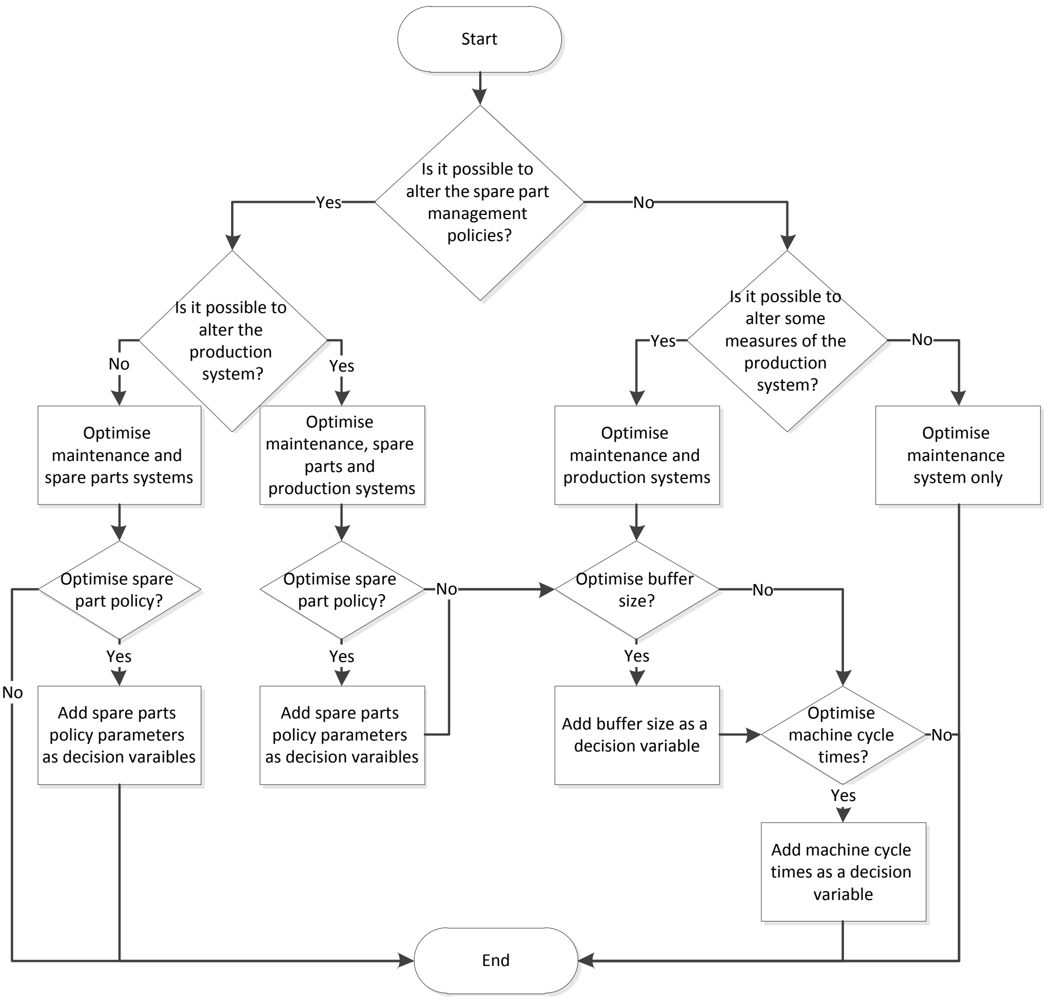


Figure 4-7 Sub-process 1.2: define the scope of optimisation

The second step of the framework, which aims to identify applicable maintenance strategies and policies for each asset, includes two sub-processes. Sub-process 2.1 is devoted to investigating applicable PM policies. As illustrated in Figure 4-8, various PM policies are obtained from literature including time-based PM, age-based PM and opportunistic PM. The selection of PM maintenance policies usually results in defining of one or more related decision variables.

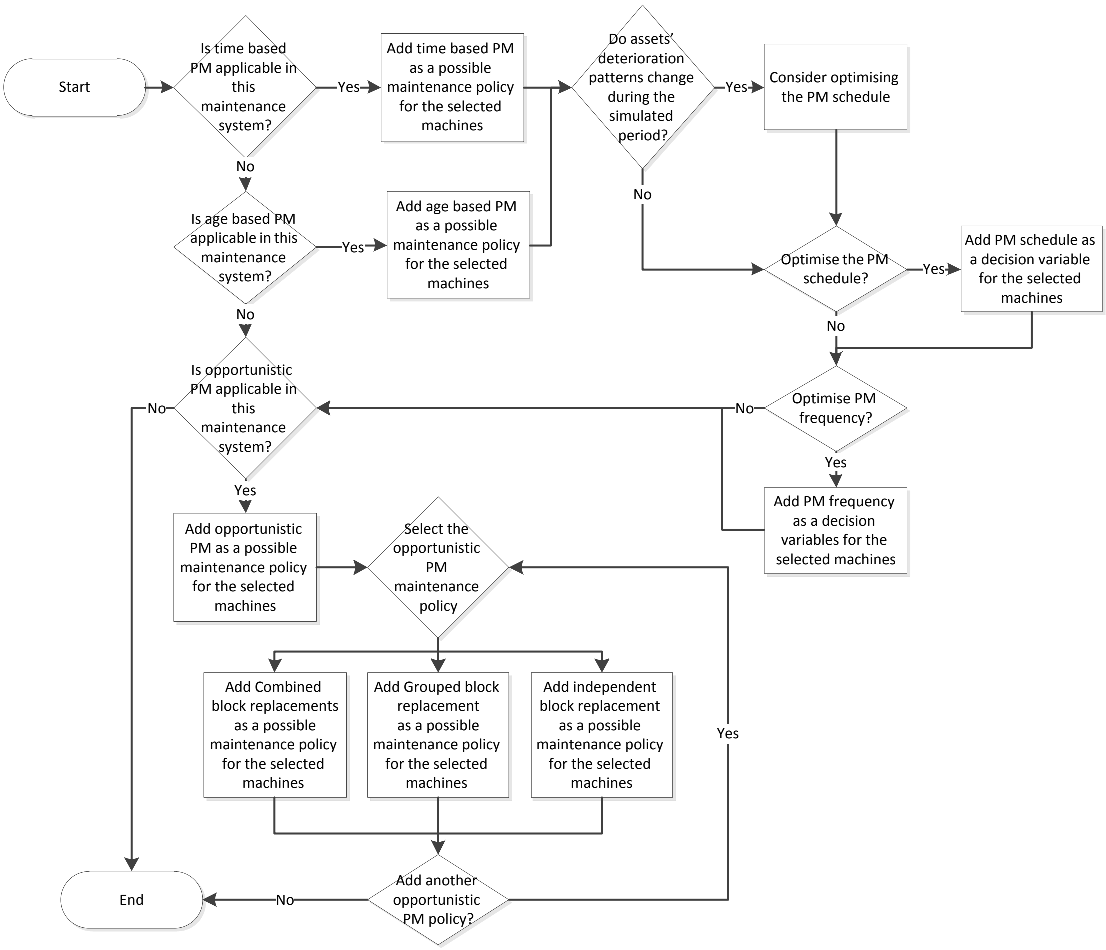


Figure 4-8 Sub-process 2.1: identify applicable PM policies

Likewise, sub-process 2.2 assists in investigating applicable CBM policies for each critical asset in the maintenance system (Figure 4-9). Policies extracted from literature include opportunistic CBM, on-line monitoring CBM and inspection-based CBM. The selection of CBM policies usually results in defining one or more associated decision variables.

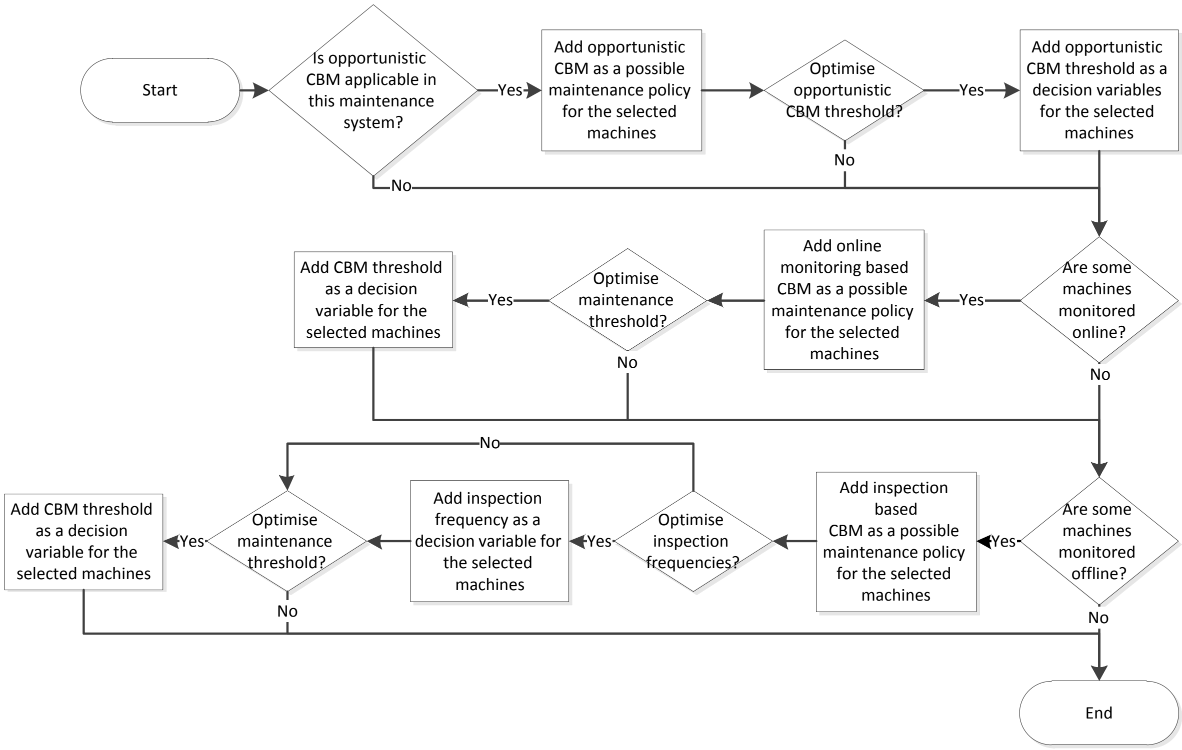


Figure 4-9 Sub-process 2.2: identify applicable CBM policies

If quality improvement is one of the objectives in the current maintenance optimisation, sub-process 3.1 offers a number of quality related objectives to choose from as shown in Figure 4-10. These were extracted from literature. The sub-process also offers flexibility to include objectives out of the provided list.

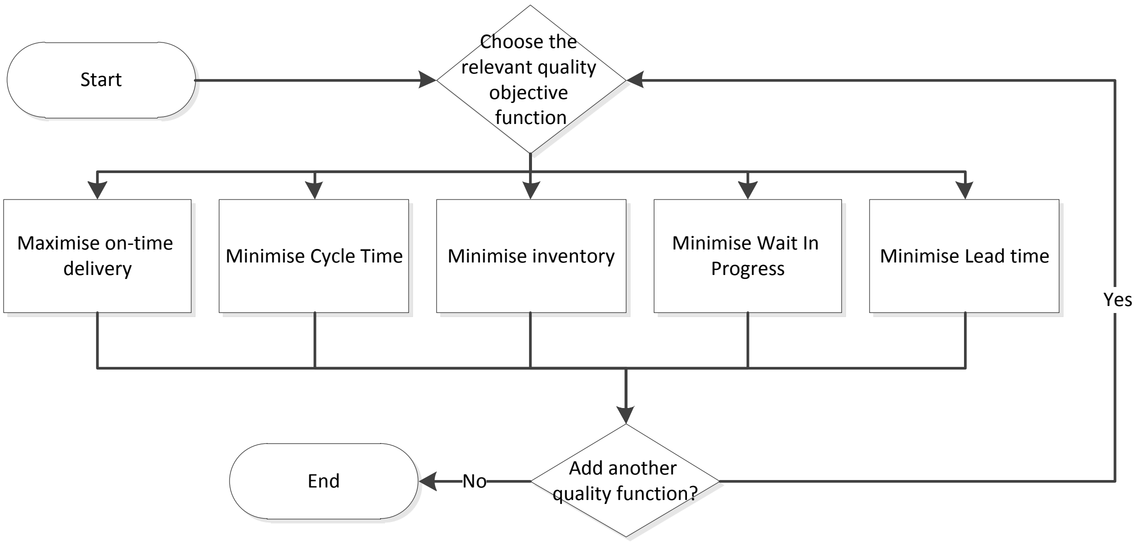


Figure 4-10 Sub-process 3.1: formulate quality related objective functions

Minimising the cost is the most reported optimisation objective in literature. However, the definition of cost varies widely. Figure 4-11 presents sub-process 3.2, which offers guidance on detailing the cost objective function. In addition to costs of maintenance actions, costs of asset unavailability and costs of inability to meet customers demand can be incorporated in the cost objective function. If spare parts management is optimised jointly with maintenance, additional costs can be added such as inventory and order placement costs. The provided cost options were derived from previous studies. Other costs can be added as required.

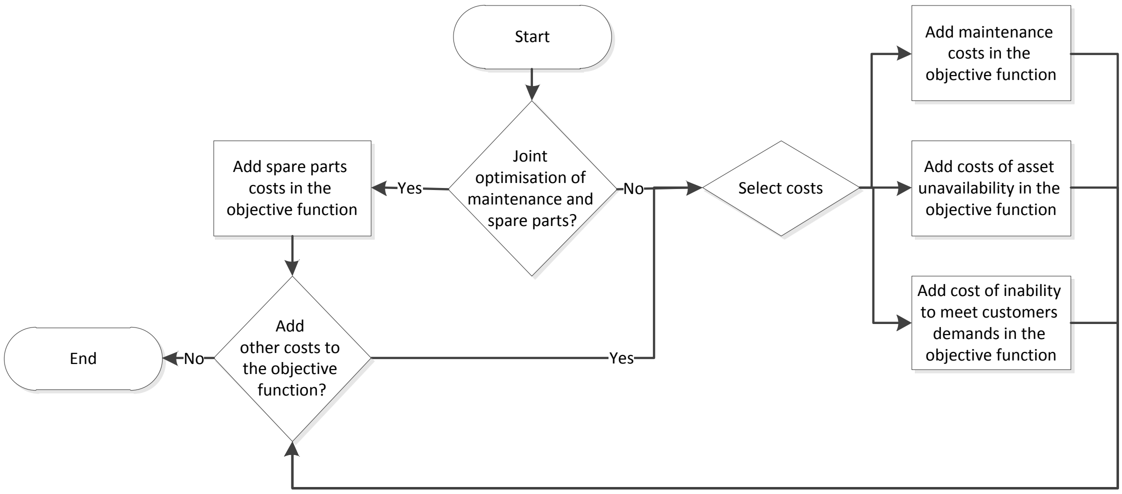


Figure 4-11 Sub-process 3.2: detail the cost objective function

To facilitate defining constraints as a part of formulating the optimisation problem, a number of constraints are obtained from literature and provided in sub-process 5.1 as can be seen in Figure 4-12. Constraints are categorised into constraints on maintenance resources, maintenance schedule, spare parts, production and costs. Similar to the previous elements of the optimisation problem, additional constraints that are not listed in the sub-process can be added as necessary.

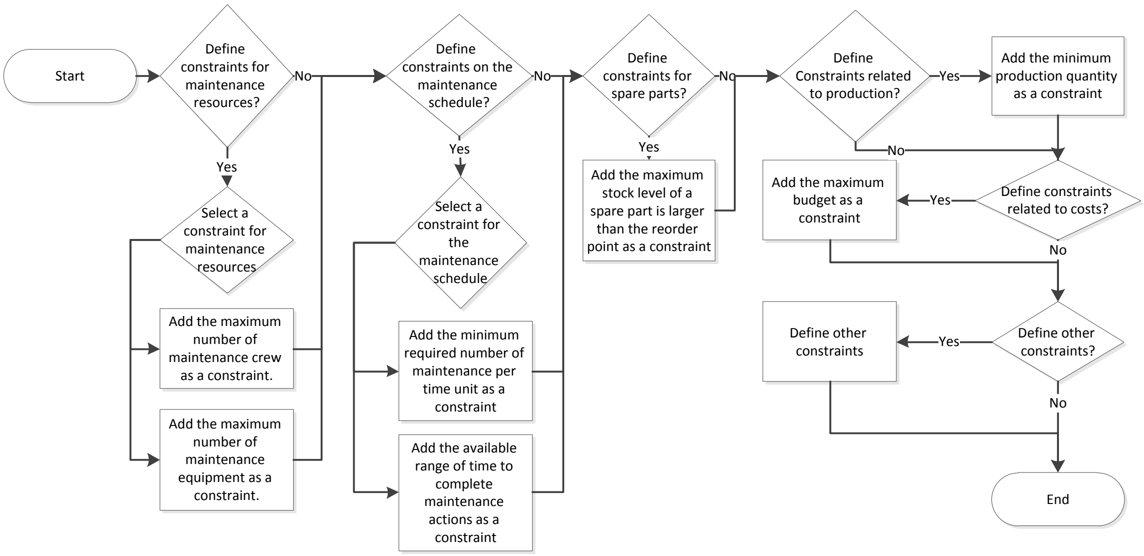


Figure 4-12 Sub-process 5.1: define constraints

Figure 4-13 presents a systematic approach to selecting a suitable optimisation algorithm for the problem in hand (sub-process 6.1). The sub-process is based on a detailed survey on the use of computational optimisation algorithms [122]. Five sequential questions assist in revealing a suitable optimisation algorithm including: Is it a multi-objective problem? Does it require global search? Does it include handling constraints? Does it require robust search and does it require handling uncertainty?

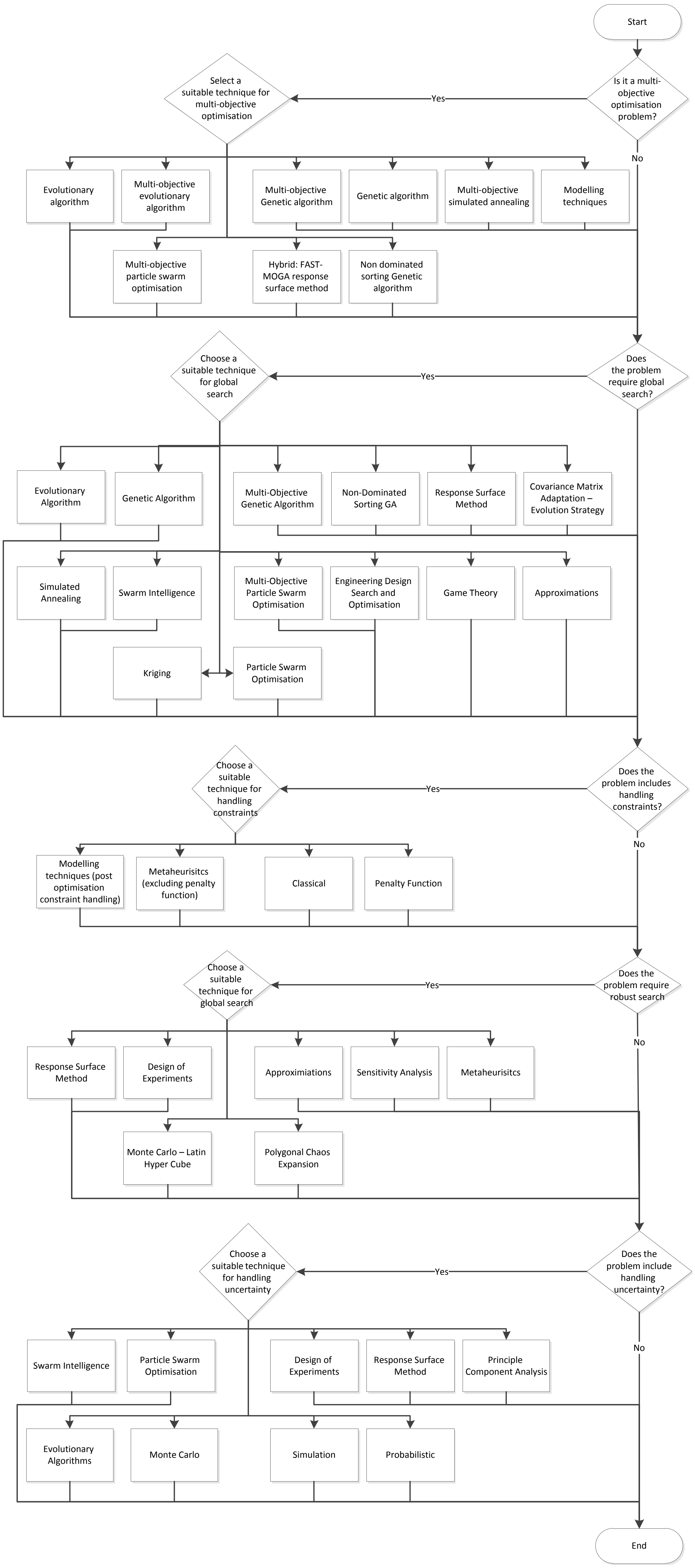


Figure 4-13 Sub-process 6.1: select the optimisation algorithm depending on the nature of the problem

Sub-process 7.1 is designed to provide strategies to minimise the computational expenses and complete the simulation optimisation in the shortest possible time (Figure 4-14). Several strategies are suggested to improve the computation speed including utilising parallel computing, high performance computing and external grid computing. In addition, special techniques that are associated with optimisation algorithms are provided to reduce the computational expenses. As a final resort, the optimisation problem may have to be simplified in order to complete the required simulation optimisation within the available time and cost limits. This includes reducing one or more of the following: number of replications, simulation run-length, variable ranges, number of decision variables and number of objective functions.

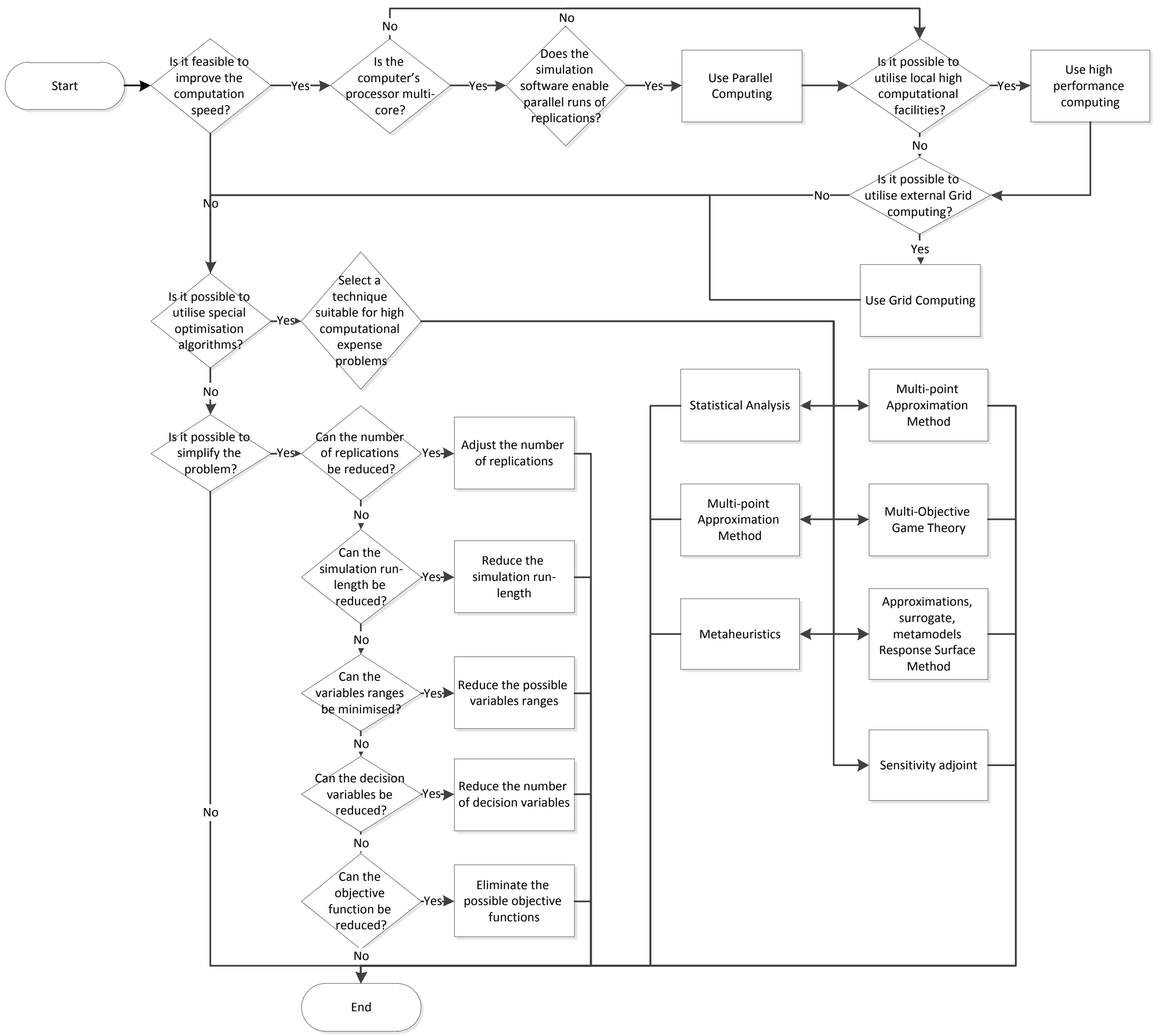


Figure 4-14 Sub-process 7.1: utilise strategies to reduce computation expenses

Common sources of high uncertainty in maintenance are documented from literature and provided in sub-process 8.1 as shown in Figure 4-15. Key inputs to simulation that might have high uncertainty include the effect of human error on repairing and maintaining assets, the effect of human error on inspecting and diagnosing assets, the data obtained from sensors, cost data and estimates and variability in asset degradation profiles. Other sources of uncertainty can be identified in order to conduct the required sensitivity analysis.

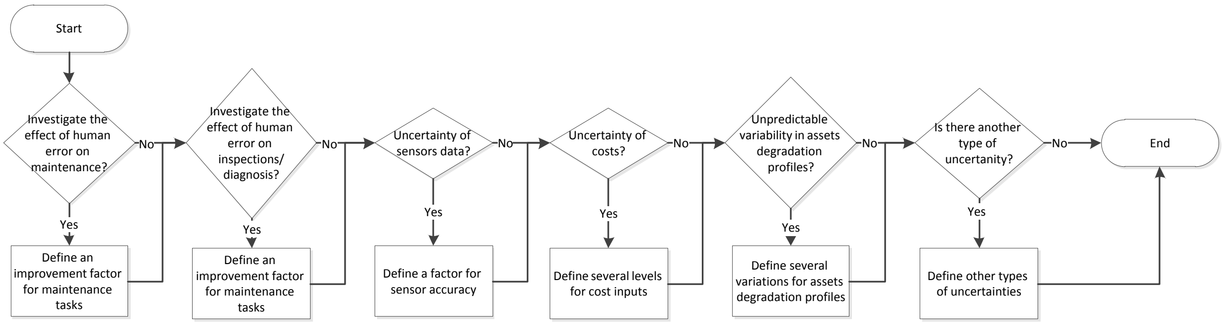


Figure 4-15 Sub-process 8.1: identify key inputs that have high uncertainties

4.5 Discussion

Prior reviews in maintenance optimisation have repeatedly reported the need for a framework that provides adequate level of details to guide both academics and practitioners in optimising complex maintenance systems. This study sets out with the aim of addressing this gap by developing a framework to guide the process of maintenance optimisation through simulation. In contrast to earlier studies, the proposed framework was developed based on an evaluation of existing frameworks in addition to capturing framework requirements. As illustrated in Table 4-4, existing frameworks seem to stand short of meeting most of the requirements.

Table 4-4 Evaluating maintenance optimisation frameworks against the requirements

	Requirements	Chien et al. [97]	Riane et al. [98]	Horenbeek et al. [11]	Proposed framework
1	Assist users with typical uncertainty found in maintenance systems	No	Yes	No	Yes
2	Assist users to adapt maintenance models to their specific business needs	No	No	Yes	Yes
3	Enable users to solve multi-objective optimisation	No	No	No	Yes
4	Assist users with complex maintenance systems	No	No	No	Yes
5	An operational decision making tool suitable for maintenance managers and practitioners	Yes	Yes	No	Yes
6	Incorporating production dynamics and spare parts management	No	No	No	Yes
7	Allow the investigation of several maintenance strategies simultaneously	No	Yes	Yes	Yes
8	Incorporating possible future maintenance strategies	No	No	No	Yes
9	Integration with e-maintenance	No	Yes	No	No

Uncertainty can be addressed partially by defining stochastic inputs in the simulation model. The proposed framework assists users with typical uncertainty by suggesting specific optimisation algorithms **(sub-process 6.1)**. In addition, specific sources of high uncertainties in maintenance systems are identified so the user can decide if any of them are present in the maintenance system **(sub-process 8.1)** and then perform sensitivity analysis. Throughout the framework, the user is advised on the optimisation objectives, decision variables and constraints suitable for the maintenance system in interest. By following the framework steps, the user would have a model that meets his/her specific business needs. If multi-objective optimisation is required, the framework allows the user to formulate the objectives in a systematic way. Furthermore, several multi-objective optimisation algorithms are suggested **(sub-process 6.1)**. It is impractical to optimise numerous components in a complex maintenance system. Therefore, tools and techniques are suggested to select the most critical assets in the maintenance system **(sub-process 1.1)**. Additionally, complex maintenance systems can introduce the risk of high computation expenses. This is dealt with by suggesting various strategies including improving the computation speed, utilising special optimisation algorithms and simplifying the problem **(sub-process 7.1)**. A standard flow chart is utilised to represent the framework since it is familiar to both maintenance managers and academics. The flow chart guides the user starting from defining the scope of the problem to obtaining the solution and interpreting the results in light of the current business environment through a series of steps containing various processes and decision nodes.

The effect of well-documented factors on the maintenance system is considered in the framework. The scope of the optimisation can include production dynamics and spare parts policies based on the user's circumstances **(sub-process 1.2)**. Various maintenance strategies and policies are also put forward for the user **(sub-processes 2.1 & 2.2)**. Multiple strategies and policies can be selected for each asset including advanced maintenance strategies such as CBM and self-maintenance. The optimisation then will yield the optimum strategy along with its parameters for each asset.

However, it is not possible to integrate the proposed framework in its current form with e-maintenance. A software can be developed to suggest inputs as the user progresses from one stage to another. This will make it even easier to apply since only feasible options will displayed. In addition, the data can stream directly from other maintenance data sources such as condition monitoring sensors and maintenance history records to form a comprehensive decision support system.

4.6 Summary

The literature covers a wide range of simulation based optimisation of maintenance systems. This includes a wide range of maintenance strategies and policies, optimisation objectives, decision variables and optimisation algorithms. The purpose of the current study is to develop a simulation based optimisation framework that supports decision making for maintenance in manufacturing systems.

This research identifies nine requirements for the framework. The requirements were established by examining review papers in maintenance optimisation as well as publications in future maintenance applications. Furthermore, existing maintenance optimisation frameworks were examined and evaluated against these requirements.

A novel framework was developed to aid future attempts to optimise complex maintenance systems through simulation. A key strength of the proposed framework is its ability to meet most of the requirements. Current issues addressed by the framework include complexity, uncertainty, high computation expenses and advanced maintenance applications.

5 A NOVEL APPROACH FOR MODELLING COMPLEX MAINTENANCE SYSTEMS USING DISCRETE EVENT SIMULATION

5.1 Introduction

Maintenance aims to retain assets in their operational states. It has emerged as a fundamental success ingredient in the modern industry. Enhancing the performance of maintenance systems through modelling and optimisation has been the focus of a large volume of published studies.

Analytical modelling of maintenance prevailed for a long time. The foundations were laid by researchers such as Barlow and Proschan [123]. This was later developed extensively to include a large number of maintenance optimisation models [23]. In general, most of these models are developed for a specific system comprising of a single unit or several identical components [13]. However, maintenance systems in the industry are becoming much more complex which limits the applicability of analytical modelling techniques [15; 124].

The use of simulation to model maintenance system is on the rise [24]. Simulation enables the modelling of complex behaviour and requires fewer assumptions compared to analytical modelling [104]. Although simulation is well-established in manufacturing in general, it appears to be still developing for maintenance [125].

Few researchers presented conceptual frameworks for modelling maintenance using simulation. Duffuaa et al. [16] developed a generic conceptual model outlining the main elements of a maintenance system. Warrington et al. [126] described an approach for modelling Maintenance Free Operating Periods (MFOP) within DES. Both studies made no attempt to describe approaches to modelling maintenance strategies such as CBM. In addition, validation studies and numerical examples are absent.

Figure 5-1 shows a popular approach used in several DES studies [31; 40; 60]. The maintenance strategy and its parameters are entered manually in the simulation model. The simulation then samples a TTF (Time To Failure). If the scheduled maintenance intervention will occur before the failure, maintenance will be conducted resulting in updating the cost function, scheduling the next maintenance intervention and sampling a new TTF. However, if the breakdown occurred before the maintenance intervention, a CM will be conducted. The process continues running for the simulation run length. One major drawback of this approach is that the maintenance system is modelled separately from other inter-related systems such as production and spare parts logistics. This in turn limits the utilisation of the dynamic feature of DES since interactions between machines and the effect of maintenance on production are not modelled. In addition, this approach is used to model one maintenance strategy only. As a result, the choice of maintenance strategies cannot be optimised using the proposed framework in Chapter 4.

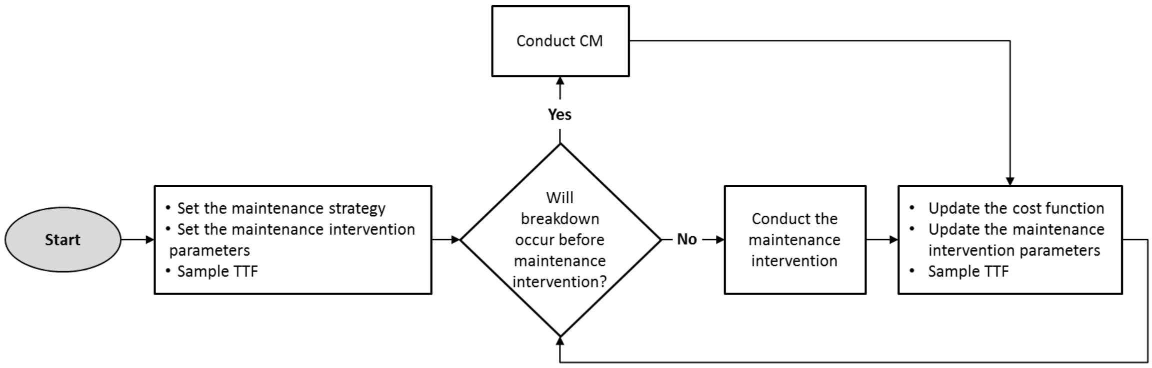


Figure 5-1 An existing modelling approach used in simulation studies. Adapted from [31; 40; 60]

Arab et al. [33] modelled both maintenance and production systems. However, they used manual DES calculations without utilising the strengths of available DES software such as rapid modelling and visual interactive simulation. Oyarbide-Zubillaga et al. [61] used an external tool to model the maintenance system and used that as an input to the DES model.

As stated in Chapter 2, the examination of surveys in the field [104; 106; 124; 127] reveals a number of common research gaps relating to the modelling of maintenance systems:

1- Modelling the maintenance system in isolation of other significant and inter-related systems such as production and spare parts management.
2- Modelling various maintenance strategies and policies simultaneously.
3- Making over-simplifying assumptions resulting in a model that cannot be implemented in real-world systems. Such assumptions include perfect maintenance/ inspections, immediate maintenance actions and a single-unit system.

It appears as if these gaps are a result of the limitations present in the existing modelling approaches. Despite the potential of simulation to model complex maintenance systems, there remains a paucity of studies outlining adequate modelling approaches.

The present study fills a gap in the literature by proposing a modelling approach that can be used to model and optimise maintenance systems in practice. In addition to addressing the above-mentioned limitations, the approach further exploits the advantages of DES such as rapid modelling and visual interactive simulation. As a result, the proposed approach is expected to pave the way for more advanced maintenance applications.

5.2 Methodology

The degradation of operational assets is inevitable. Maintenance actions are designed to improve the condition of assets to keep them in a functional state. Often maintenance strategies can be categorised into CM, PM and CBM. In CM, the asset degrades until it breaks down unexpectedly. PM was introduced to minimise the effect of unscheduled breakdowns by intervening in a planned manner. CBM is an advanced strategy that aims to ensure maintenance intervention is conducted only when needed based on an analysis of the asset’s condition. Predictive maintenance is seen as a part of CBM. The condition of assets is analysed to plan future maintenance actions. OM is closely related to both PM and CBM. Essentially, opportunities such as shutdowns are seized to maintain an asset.

A considerable amount of literature has discussed the details of modelling each maintenance strategy and its implications on assets in the system. This includes the modelling of assets degradation, the degree to which a maintenance action can successfully detect a failure and the degree to which a maintenance action can restore the asset to as good as new [11; 128].

However, in this chapter we are considering a holistic view. As shown in Table 5-1, maintenance strategies affect assets in the system in different ways. The proposed approach enables the modelling of interactions amongst various maintenance strategies and their effects on the assets in the system. Thanks to the flexibility of DES, the proposed approach enables the modelling of various maintenance systems based on models that appear in the literature. Classic examples include perfect/imperfect maintenance, perfect/imperfect inspections, dependencies amongst assets, effect of maintenance on product quality, effect of maintenance on production speed, various approaches to modelling asset degradation and inclusion/ exclusion of maintenance resources such as maintenance equipment, spare parts and technicians.

Table 5-1 Interactions amongst maintenance strategies

	CM	PM	OM	CBM
Might affect other maintenance strategies on the same asset?	No	Yes	No	Yes
Might affect other maintenance strategies on the other assets?	Yes	No	No	No

Witness 14 (Manufacturing Performance Edition) will be used to illustrate the modelling approaches due to its availability within the research group. The same principle can be applied using one of the typical DES softwares.

5.3 A Novel Approach for Modelling Complex Maintenance Systems

Notations:

MA: A single maintenance action resulting from a maintenance strategy.

SMA: A scheduled maintenance action resulting from a maintenance strategy.

n: Total number of assets in the system.

i: A single asset in the system where $i = 1 \ldots n$

T: Simulation run length

A generic approach for modelling maintenance strategies is presented in . The approach assumes the availability of a valid DES model for the manufacturing system in interest. There are no restrictions on the number of assets in the manufacturing system or the number of maintenance strategies defined for each asset. The assets can be either identical or non-identical. Similarly, maintenance strategies can be the same for all machines or each asset can have its unique maintenance strategy.

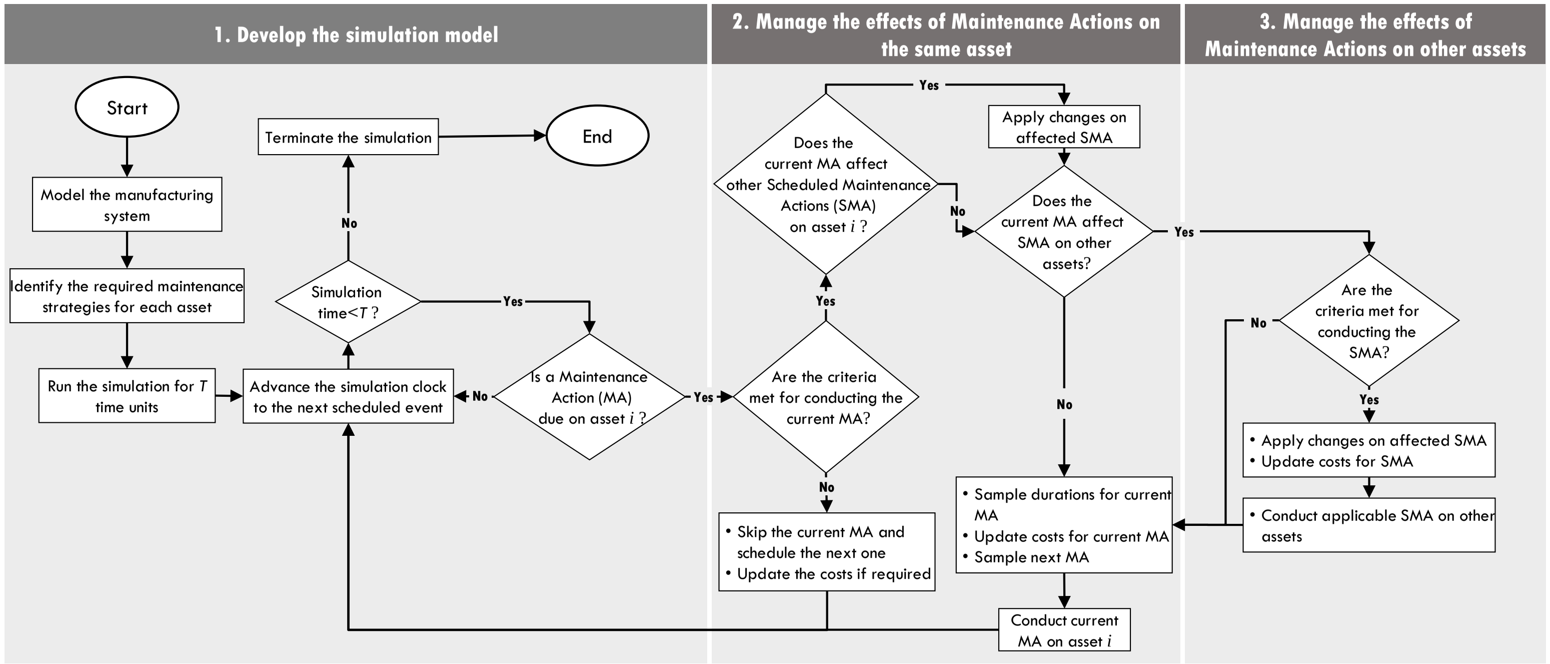


Figure 5-2 A generic approach for modelling maintenance strategies

The approach consists of three steps as follows:

1) Develop the simulation model

The approach begins with modelling the manufacturing system. For example this might include assets, buffers and rules governing machine cycle times and movement of parts within the system.

The required maintenance strategies and policies are then identified for each asset. This includes defining parameters for statistical distributions required by each maintenance strategy to facilitate the modelling of variability in Maintenance Actions (MA) whenever they occur. For example, CM strategy requires the sampling from a statistical distribution to obtain Mean Time Between Failures (MTBF) each time the asset fails. In addition, a sampling from a statistical distribution is required to obtain the repair time. Other variables can be defined if required such as the cost of conducting each *MA*.

When the simulation is run, the simulation clock is advanced to the next scheduled event. If a *MA* is due on one of the assets in the system, the effects on the asset is managed in the next step.

2) Manage the effects of Maintenance Actions on the same asset

Whenever a *MA* is due on asset *i* in the system, a check is conducted to confirm that the criteria is met for the *MA* to be executed. For instance, CBM requires the current relevant condition indicator to exceed a specific threshold in order for the *MA* to be conducted. Likewise, some PM policies will be skipped if the asset was broken down when the *MA* is due. If the criteria is not met, the current *MA* will be skipped, costs will be updated if required and the next *MA* of that maintenance strategy for asset *i* will be scheduled.

However, if the criterion of conducting the *MA* is met, a check will be conducted to determine if the current *MA* was initiated by a maintenance strategy that affects other maintenance actions on the same asset. As illustrated in Table 5-1, maintenance strategies such as PM and CBM affect CM actions. The interactions between maintenance strategies can be implemented by accessing the event queue for asset *i* and altering the timing of the relevant *SMA*. The effects of the current MA on other assets in the system are managed in the next step.

The current *MA* will be conducted on asset *i* after scheduling the next *MA*. Whenever a *MA* is conducted, costs are updated and samples are taken from the relevant distributions to schedule the new timing of an activity or define the repair time for a *MA*.

3) Manage the effects of Maintenance Actions on other assets

The current *MA* might affect *SMA* on other assets in the system. In that case, a check is conducted to confirm the criteria is met for the effects to take place. The event queue for these assets is accessed in order to apply the required changes. Steps 2 and 3 are repeated during the simulation every time a *MA* is due on any asset in the system.

The next section presents detailed approaches for modelling common maintenance strategies namely time-based PM, OM and CBM with periodic inspections. These detailed approaches are special cases from the generic approach described in this section.

5.4 Common Cases

5.4.1 Time-Based Preventive Maintenance

In time-based PM, the asset is maintained periodically to minimise unexpected breakdowns. Figure 5-4 illustrates the approach for modelling a manufacturing system where time-based PM is applied.

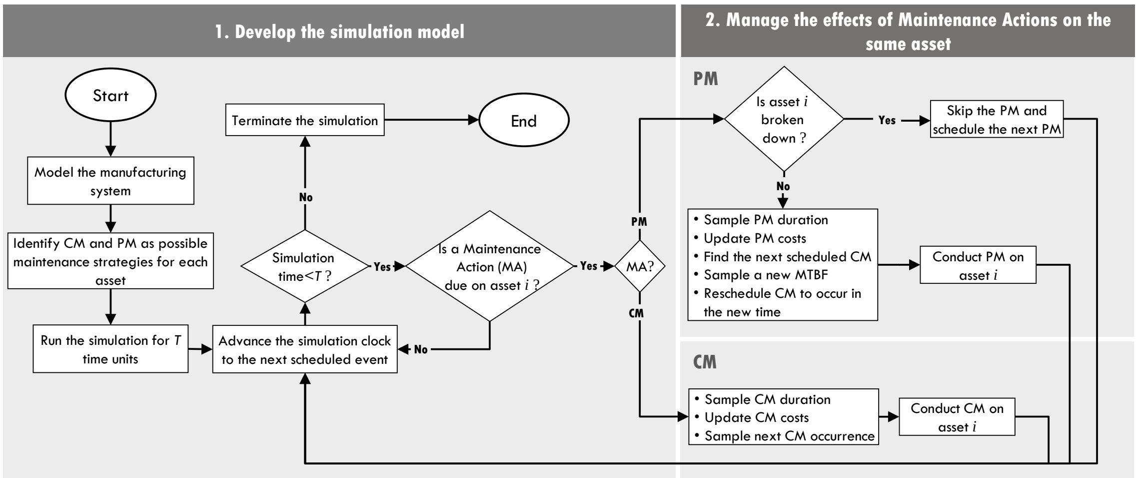


Figure 5-4 An approach for modelling time-based PM

1) Develop the simulation model

As assets can still breakdown unpredictably, both CM and PM are defined as possible maintenance strategies for each asset. Variables related to CM include MTBF, repair times and CM costs whereas variables related to PM include PM frequency, repair times and PM costs. As the simulation clock advances, two maintenance strategies are possible on each asset, either CM or PM.

2) Manage the effects of Maintenance Actions on the same asset

When machines have an unscheduled breakdown, a CM duration is sampled to set the CM repair time, CM cost is added for asset *i*, and MTBF is sampled to schedule the next CM. In addition, CM will be conducted on asset *i* which means it will not be available for production.

However, when PM is due on asset *i*, PM duration is sampled to set the PM repair time and PM cost is added for asset *i*. Additionally, a sample from the MTBF distribution will be drawn and the next CM breakdown will be changed to reflect the fact that PM has occurred. Finally, PM will be conducted on asset *i* making it unavailable for use in the production system. Nonetheless, if the time of PM coincidentally occurred when asset *i* is broken down, the current PM will be skipped and the next PM will run as scheduled.

In this case, the third step of the approach is not required since none of the maintenance strategies considered for asset *i* could affect other assets in the system.

5.4.2 Opportunistic Maintenance

As a strategy, OM utilises the breakdown of an asset to maintain another asset. The approach for modelling OM is illustrated in Figure 5-5.

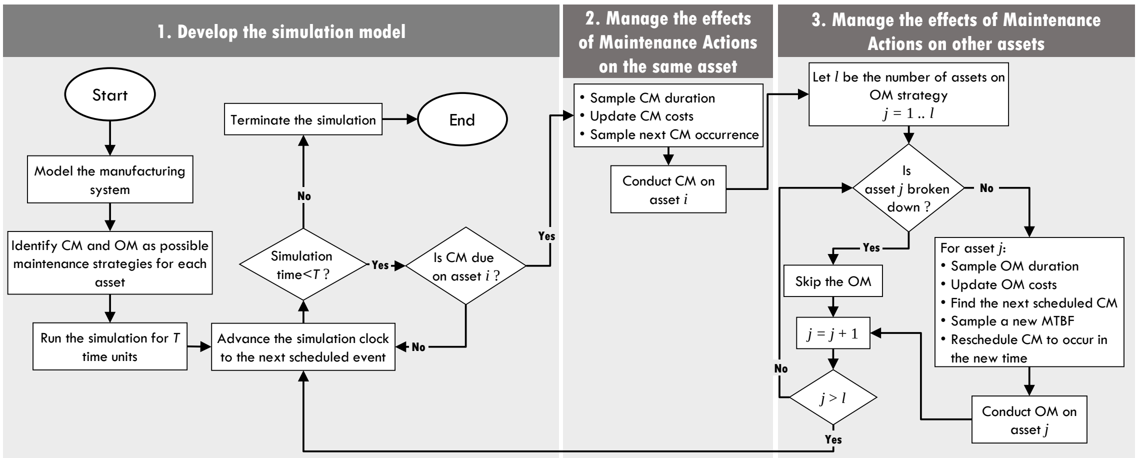


Figure 5-5 An approach for modelling OM

1) Develop the simulation model

CM and OM are identified as maintenance strategies for each asset. Variables related to CM include MTBF, repair times and CM costs whereas variables related to OM include repair times and OM costs. When the simulation starts, the clock will advance running the simulation model until a CM becomes due to an asset in the system. The effects of CM on the same asset are managed in the next step.

2) Manage the effects of Maintenance Actions on the same asset

The asset subjected to CM will be made unavailable to conduct the required maintenance activities. Additionally, CM costs will be incurred and the next breakdown will be scheduled.

3) Manage the effects of Maintenance Actions on other assets

All other machines on OM strategy in the system will be stopped for OM during which an OM cost will be incurred and a sampling for OM duration will take place. In addition, the next breakdown will be rescheduled according to the MTBF sampling. If OM coincidentally occurs while the asset has broken down it will be skipped without incurring any costs.

5.4.3 Condition Based Maintenance with Periodic Inspections

CBM strategy aims to further enhance the overall performance of assets by ensuring maintenance interventions are conducted only when needed. This is achieved by monitoring the condition of the asset and intervening when the condition exceeds a pre-set threshold. Figure 5-6 shows a modelling approach for CBM where the condition of assets is monitored by periodic inspections.

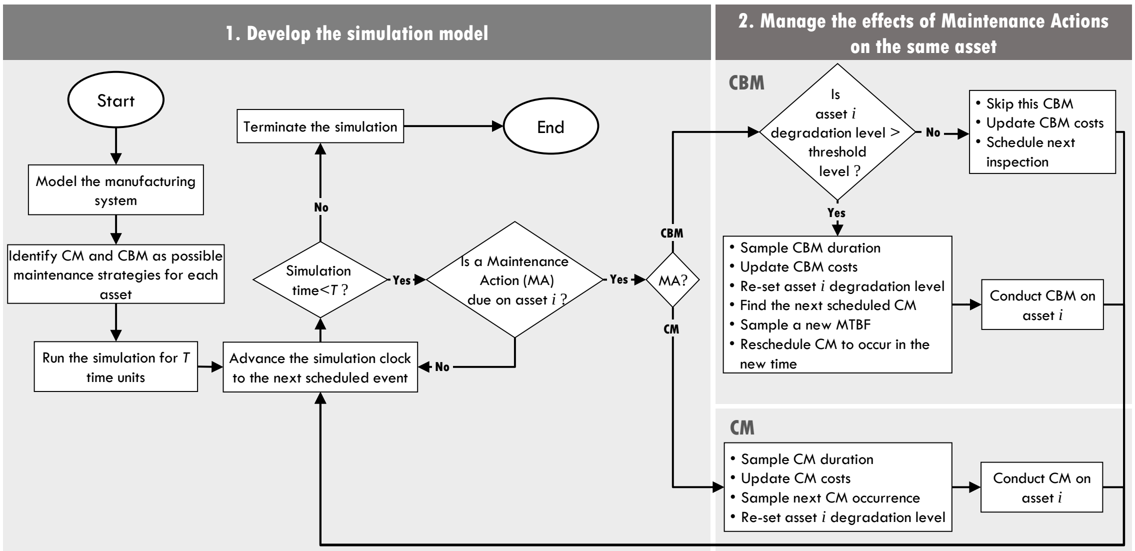


Figure 5-6 An approach for modelling CBM with periodic inspections

1) Develop the simulation model

Both CM and CBM are defined as maintenance strategies for each asset. CM variables include MTBF, repair times and CM costs whereas CBM variables include inspection frequencies, inspection costs, CBM thresholds, CBM repair times and CBM costs. CM and CBM effects are managed in the next step.

2) Manage the effects of Maintenance Actions on the same asset

The path of CM is similar to the one discussed above in time-based PM. However, in this case, the degradation level for asset *i* is set to the normal operation level after each CM.

If the *MA* was periodic inspection as part of the CBM strategy, a check is made to ensure the current wear level of asset *i* exceeds the CBM threshold. A sampling from CBM duration will then take place to conduct CBM on asset *i* in addition to updating CBM costs. The degradation level for asset *i* is set to the normal operation level and the next CM will be rescheduled according to the sampling of MTBF.

If an inspection reveals a value of degradation level less than the CBM threshold then CBM will be skipped and the next inspection will run as scheduled. However, CBM costs will be updated to add the incurred inspection cost.

In this case, the third step is not required as the considered strategies cannot affect other assets.

5.5 Numerical Applications

In this section, we demonstrate the application of the modelling approach through two numerical examples. Output data relating to maintenance strategies are presented for verification purposes.

5.5.1 Description of the Manufacturing System

The modelling approaches are demonstrated on an illustrative manufacturing system. As shown in Figure 5-7, the system includes six machines with buffers between them. Parts are drawn into the system via two parallel lines. The first line consists of machines 1 and 2 whereas the second line consists of machines 3, 4 and 5. Parts from both lines are assembled by machine 6 which then ships the last product out of the system.

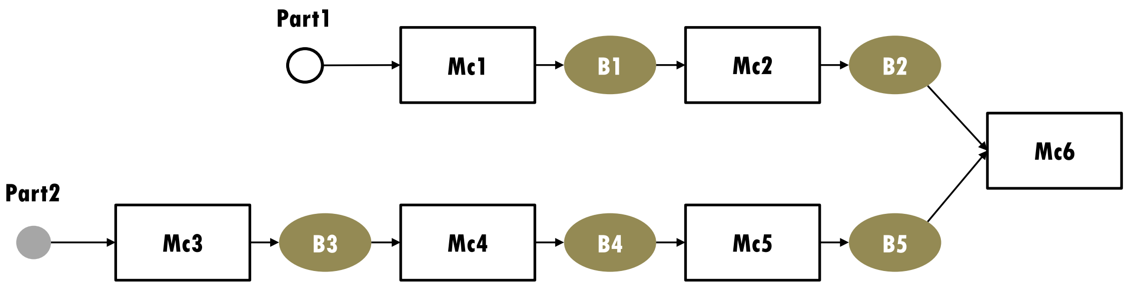


Figure 5-7 Layout of an illustrative manufacturing system

Parts are always available upon demand. Maintenance strategies are only applicable for machines 2, 5 and 6. Cycle times, MTBF data and repair times are represented by statistical distributions and are shown in Table 5-2.

Table 5-2 Cycle times, MTBF data and repair times

Machine	Cycle time	MTBF	Repair time
M1	Uniform (1.2,2.5)	N/A	N/A
M2	Uniform (1.4,1.8)	NegExp (44.2)	Weibull (3,5)
M3	Uniform (1.5,1.75)	N/A	N/A
M4	Uniform (0.8,1.2)	N/A	N/A
M5	Uniform (0.9,1.3)	NegExp (52.6)	Weibull (1.4,3)
M6	Uniform (0.8,1.6)	NegExp (71.8)	Weibull (2,6)

5.5.2 Accessing the Event Queue

Events can be accessed and rescheduled in Witness using four functions as shown in Appendix B. These functions can be used to loop through the scheduled events for a certain asset, identify the affected ones and apply the required changes.

5.5.3 Example 1: Time-Based Preventive Maintenance

In this example, both CM and PM are applicable. Perfect maintenance is assumed meaning a machine becomes as good as new after undergoing either PM or CM.

The approach for modelling time-based PM discussed above will be used here. Both CM and PM variables and matrices are defined as shown in Figure 5-8.

CM
MTBF(i): the mean time between failures for the next CM action on machine *i*
MTBF_Parameters(i): the statistical distribution parameters for mean time between failures.
CM_Duration(i): the total duration for the current CM action for machine *i*.
CM_Duration_parameters (i, p): the statistical distribution parameters for CM repair times.
CM_Cost: a variable to accumulate the CM costs in the system.
No_of_CM: a variable to count the number of CM actions in the system

PM
PMfreq(i): the frequency of conducting PM for machine *i*.
PM_Duration (i): the total duration for the current PM action for machine *i*.
PM_Duration_Parameters (i,p): the statistical distribution parameters for PM repair times.
PM_Cost: a variable to accumulate the PM costs in the system.
No_of_PM: a variable to count the number of PM actions in the system.
Where *i* = 1, 2, 3. *p* = 1, 2.

Figure 5-8 CM and PM variables and matrices

The initialised values for PM matrices are presented in Table 5-3. All other matrices and variables are initialised to zero at the start of the simulation. To illustrate the ability of the approach to model stochastic maintenance operations, PM repair times are sampled from a lognormal distribution using the unique parameters for each machine found in the matrix *PM_Duration_Parameters.*

Table 5-3 Initialised values for PM matrices

Matrix	*PMfreq*	*PM_Duration_Parameters*	
M2 values	50	1	2.2
M5 values	60	2.5	3
M6 values	80	2	3.2

Both CM and PM are defined as breakdown types in machines 2, 5 and 6. As illustrated in Figure 5-9, time between failures is assigned to *MTBF(i)* for CM whereas it is assigned to *PMfreq(i)* for PM. In addition, repair time for CM is assigned to *CM_Duration(i)* whereas in PM it is assigned to *PM_Duration(i)*.

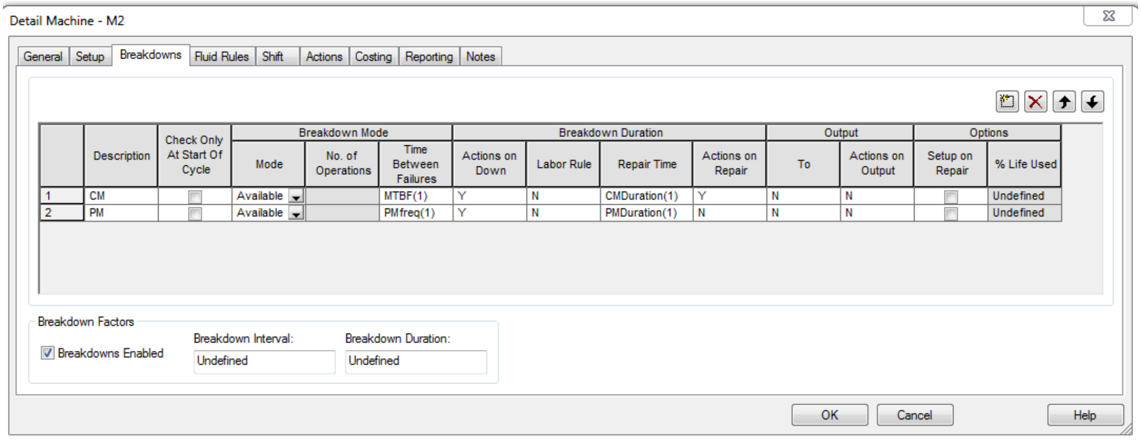


Figure 5-9 Defining CM and PM in the breakdown window for machine 2

If CM is due on one of the assets, CM costs will be incurred, the number of conducted CM will be increased by 1 and both the MTBF and CM repair time will be sampled and updated.

However, if PM is due on one of the machine while it is broken, the PM repair time will be set to zero indicating the skipping of the current PM action. Otherwise, a PM repair time will be sampled. A loop through the scheduled events for that particular machine will then find the next CM action and reschedule it. PM costs as well as the number of PM actions conducted will be updated.

The simulation is run for 500 time units to validate the modelling approach. Table 5-4 presents the results for machine 2. Witness schedules the first breakdown in the simulation by halving its time. Therefore, the first CM occurred at time 22.3 where the MTBF for that instance was 44.6. Similarly, the first PM occurred at time 25 although PMfreq for machine 2 was set to 50 (see Table 5-3).

Table 5-4 Simulation results for verification (M2)

Time	MA	PM			CM
		original CM time	sample MTBF	new CM time	CM duration
22.3	CM				3
25	PM	PM is skipped as machine is under CM			
66.9	CM				3.1
74.6	CM				2.9
75	PM	PM is skipped as machine is under CM			
77.6	CM				5.8
125	PM	153	70.6	195.6	
175	PM	195.6	43.9	218.9	
218.9	CM				2.1
225	PM	255.2	107	329.07	
275	PM	329.07	67.4	342.4	
325	PM	342.4	11.3	336.3	
336.3	CM				4.1
375	PM	388.5	44.5	419.5	
419.5	CM				5.2
425	PM	689.8	53.5	478.5	
475	PM	478.5	18.9	493.9	
493.9	CM				4.7

As expected, CM occurs stochastically throughout the simulation. In addition, if PM is scheduled while the machine is under CM, the PM action will be skipped. Finally, PM actions reschedule the next CM actions by sampling from the relevant distribution. The results are consistent for machines 5 and 6.

5.5.4 Example 2 : Condition Based Maintenance with Periodic Inspections

Relevant maintenance strategies in this example include CM and CBM. CM data and variables are taken from the previous example. CBM variables are defined as shown in Figure 5-10.

Wear (i): wear level for machine *i*

CBM_Threshold(i) : CBM threshold for machine *i*

Inspection _freq (i): the frequency for conducting inspections on machine *i*

CBM_Duration (i): the total duration for the current CBM action for machine *i*

CBM_Duration_Parameters (i,p): the statistical distribution parameters for CBM repair times

Inspection_cost : a variable to accumulate the inspection costs in the system

CBM_Cost: a variable to accumulate the CBM costs in the system

NO_of_CBM: a variable to count the number of CBM actions in the system

Figure 5-10 CBM variables

All CBM variables and matrices are set to zero at the beginning of the simulation except for those shown in Table 5-5. Wear levels are the condition indicators and are assumed to start at the normal operating conditions.

Table 5-5 Initialised values for CBM matrices

Matrix	Inspection _freq	CBM_Duration_Parameters		Wear	CBM_Threshold
M2 values	36	1	2.2	2	9.5
M5 values	72	2.5	3	2.4	10
M6 values	60	2	3.2	2.6	8.75

CM and CBM are defined as breakdown types for machines 2, 5 and 6. *MTBF(i)* is set as the time between failures for CM whereas *Inspection _freq (i)* is set for CBM. *MS* is the function that manages interactions between maintenance actions.

CM will have similar actions to the previous example. However, in this case wear levels will be set to the normal operating conditions following a CM action. In CBM, an inspection will take place to check the condition of the machine. If it does not exceed the CBM threshold, the CBM duration will be set to zero indicating the skipping of the current CBM action. Nonetheless, if the condition exceeds the CBM threshold a CBM action will take place resulting in rescheduling the next CM action.

Table 5-6 shows M6 simulation results for the purpose of validation. As expected, CM timings vary due to the fact that it is being drawn from a statistical distribution. In addition, CBM actions are skipped when the wear level is less than the CBM threshold. However, when the inspection reveals a wear level that exceeds the threshold a CBM action is taken resulting in rescheduling of the next CM action. Likewise, results are consistent for machines 2 and 5.

Table 5-6 Simulation results for verification (M6)

Time	MA	**CBM**				**CM**
		wear level	original CM time	sample MTBF	new CM time	CM duration
29	CM					4
30	CBM	2.6	Wear (6) < CBM_Threshold (6)			
87	CM					1.4
90	CBM	2.6	Wear (6) < CBM_Threshold (6)			
119.4	CM					5
150	CBM	13.4	180.8	28	178	
178	CM					12.7
190.7	CM					6.2
210	CBM	2.6	Wear (6) < CBM_Threshold (6)			
211	CM					1.5
270	CBM	10.7	303.2	38.9	308.9	
308.9	CM					5.4
314.4	CM					3.9
330	CBM	8	Wear (6) < CBM_Threshold (6)			
390	CBM	18.8	410.1	279.4	669.4	
450	CBM	13.4	669.4	91.3	541.3	

5.6 Discussion

This study set out with the aim of developing an approach for modelling complex maintenance systems using DES. A generic approach as well as approaches for common maintenance strategies were presented. Two numerical examples were provided to validate the approach.

The proposed approach enables the modelling of the complexity found in real maintenance systems. In particular, the approach enables the modelling of the following:

- Multi-unit manufacturing systems. Without restrictions on the number of units.
- Non-identical units. Without restrictions placed on the manufacturing or the maintenance characteristics of the units. In other words, each unit in the system can have its own stochastic manufacturing behaviour as well as its own stochastic maintenance behaviour.
- Several maintenance strategies and policies simultaneously. For the purpose of optimisation, each unit can have several applicable maintenance strategies. A variable can dictate the selection of a maintenance strategy. Therefore, the optimisation can result in a different strategy and different parameters for each unit in the system.
- Maintenance integrated with inter-related systems such as production and spare parts management. The proposed approach was designed for easy integration with already developed manufacturing systems. This enables the utilisation of the maturity DES has reached in production and logistics.
- Complex maintenance systems without over-simplified assumptions such as instantaneous repair, perfect maintenance or perfect inspection.

A typical DES software provides additional features that facilitate and speed up the modelling process. For example, machines, labour and breakdown modules are built in most of the DES software packages. In addition, visual animation is displayed which enhances the communication between stakeholders and facilitates the validation process.

Accessing the event queue appeared to be the most suitable approach for the context of this approach. Other approaches were explored during the development of the proposed approach including forced breakdowns and using dummy machines to trigger machine actions. However, the alternative approaches resulted in much more complexity compared to the proposed approach. Using forced breakdown and repair does not seem to be able to handle more than one maintenance strategy for each machine. As a result, the use of additional modules to control maintenance strategies becomes necessary. Similarly, using dummy machines to trigger breakdowns, different maintenance activities and the interactions amongst them result in a simulation that is at least three times as large as the original model. Furthermore, verifying the model becomes difficult.

Nonetheless, relying on accessing of the event queue seems to somewhat limit the generality of the approach to some maintenance strategies. In particular, age-based models cannot be modelled using the proposed approach. This is due to the fact that stochastic breakdowns will be based on the time the asset spends in an operational mode. That will be affected by the stochastic dynamics of both production and maintenance. Therefore, the exact simulation time cannot be known in advance resulting in inability of access to that event.

5.7 Summary

Existing approaches for modelling maintenance rely on oversimplified assumptions which prevent them from reflecting the complexity found in industrial systems. Such assumptions are related to the scope of the simulation model, the number of assets, the manufacturing and maintenance characteristics of assets or the number of applicable maintenance strategies in the model.

Here, we develop a novel approach for modelling complex maintenance systems. The proposed approach enables the modelling of non-identical multi-unit manufacturing systems without restrictions on either maintenance or manufacturing characteristics. The approach can be integrated with DES manufacturing and spare parts models making it possible to build on the success DES achieved in these fields. Numerical examples are provided for the purpose of validation.

This modelling approach will serve as a base for future maintenance optimisation studies. The ability of modelling simultaneous maintenance strategies makes it possible to conduct simulation-based optimisation studies where maintenance strategies are optimised for each asset in the system. In other words, the optimisation engine will explore various maintenance strategies along with its parameters for each asset.

6 FRAMEWORK DEMONSTRATION AND INDUSTRIAL CASE STUDIES

6.1 Introduction

As described in Chapter 2, recent evidence suggests that little research is conducted on the simulation optimisation of industrial case studies. This prospective study was designed to make an important contribution to the field of simulation optimisation by presenting two empirical case studies in addition to an academic case study. Data is collected from a tyre re-treading factory and a petro-chemical plant. In order to demonstrate its applicability to industrial case studies, simulation-based optimisation was conducted using both the proposed framework and modelling approach.

This chapter first outlines the methodology including data collection and analysis, the approach to modelling maintenance systems and optimisation algorithms utilised in the study. This is followed by a demonstration of the framework through an academic case study. Sections 6.4 and 6.5 present the findings of the industrial case studies. Cross case examination and analysis are conducted in section 6.6 and conclusions are presented in section 6.7.

6.2 Methodology

6.2.1 Data Collection

The flowchart in Figure 6-1 illustrates the data collection process followed by the researcher. The aim was to collect maintenance and production data from two manufacturing systems from different sectors. During the initial contact, the discussion was focused on the level of data sharing. The researcher would then proceed to the next level with companies that show interest by organising an explanatory visit. Essential information such as the manufacturing layout and maintenance strategies were captured throughout the visit in an initial assessment form (see Appendix C.1). Based on the aim, two factories were selected. For data confidentiality purposes, these will be labelled as **industrial case A** and **industrial case B**.

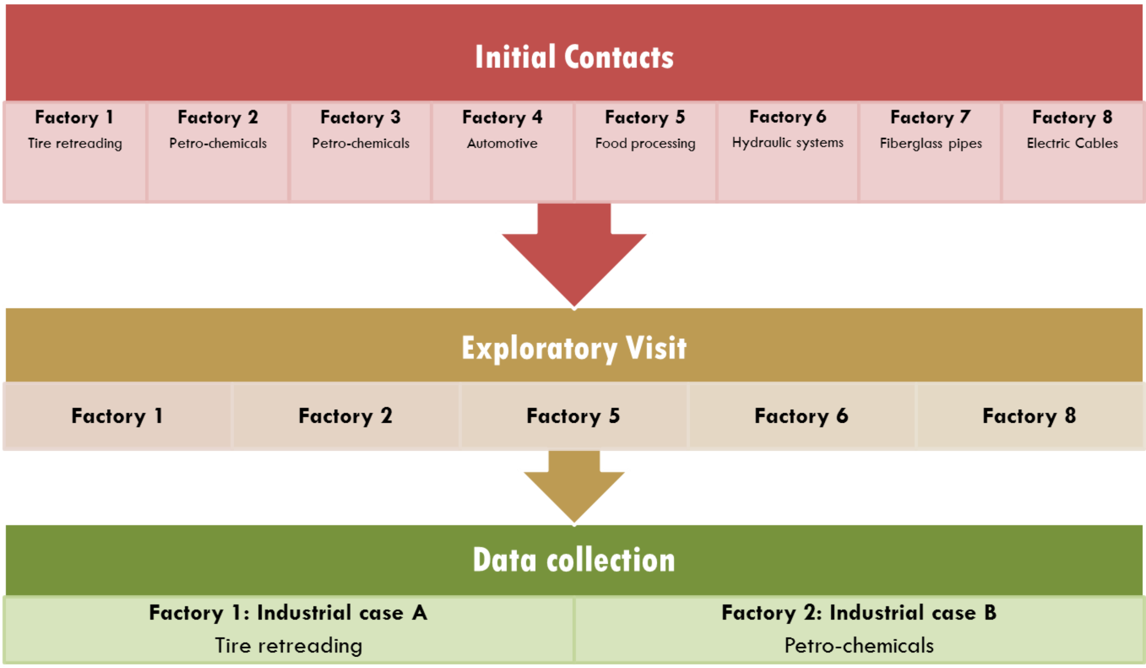


Figure 6-1 Data collection stages

The visit usually started with induction and safety training, followed by a site tour to all the relevant departments and an explanation of the manufacturing processes. A discussion was then conducted to determine which production line will be the focus of the research. That is usually decided based on the most critical assets from the maintenance point of view where maintenance managers are faced with continuous challenges in keeping the equipment available as planned. Interviews and site visits were then scheduled with the relevant production manager to understand the manufacturing process in detail.

The data was collected mainly from manuals and records. This was further clarified by engineers and managers in the industry. However, if the required data was not available due to poor documentation or confidentiality, approximate distributions such as Uniform or Triangular distributions are utilised by collecting available data such as maximum, mode and minimum values [85].

Collected data included a list of all equipment in the production line, the detailed record for all maintenance interventions including durations, spare parts involved, cost estimations, maintenance technicians as well as PM plans and execution. An example of collected data is shown in Appendix C.2.

6.2.2 Data Analysis

Raw data needed to be analysed in order to use it as an input to the simulation optimisation process. For example, raw data included the start and finish date and time of each maintenance intervention for all assets. Therefore, the durations had to be calculated and separated for each asset. In addition, data for different maintenance strategies had to be categorised and analysed independently.

In order to capture the variability in maintenance systems, stochastic data were fitted into statistical distributions [85]. The analysis included plotting the empirical data in a histogram. A statistical software package (Stat-Fit) was used to auto-fit the empirical data into theoretical distributions. At this stage, transforming some of the input data was required in order to obtain a better fit to theoretical distributions. The suggested distribution was further confirmed via goodness of fit tests as well as various graphical approaches such as Probability - Probability Plot and Quantile - Quantile Plot (see Appendix D.1).

Witness does not allow imposing minimum and maximum values on some statistical distributions, which presents a risk of producing infeasible high values in the simulation model [85]. Therefore, times for maintenance actions were restricted to the minimum and maximum values found in the empirical data.

If CBM is investigated in the maintenance system, the degradation process of assets needs to be modelled. Condition of assets is monitored by measuring the vibration levels. The convention used is to measure the vibration signal zero-to-peak (PK) regularly in mm/Sec. A sample of data obtained on condition monitoring is shown in Appendix D.2. It is assumed that only maintenance interventions can enhance the state of assets and that the degradation process is stochastic with independent increments. Therefore, only ascending and stationary trends from the condition monitoring data were analysed. To enable the modelling of degradation increments, the increments are calculated over five day periods. The data points with no increments were considered as ‘no changes in the condition indicator’. Minimum, mode and maximum data points are used as an input to a Triangular distribution that defines the degradation of the asset.

6.2.3 Simulation Modelling

Maintenance strategies were modelled according to the proposed approach described in Chapter 5. Main assumptions include perfect maintenance where assets become as good as new following maintenance interventions and perfect inspections that reveal the real condition of the asset. As shown in Figure 6-2, MTBF is defined as the mean time between the start of any two consecutive failures.

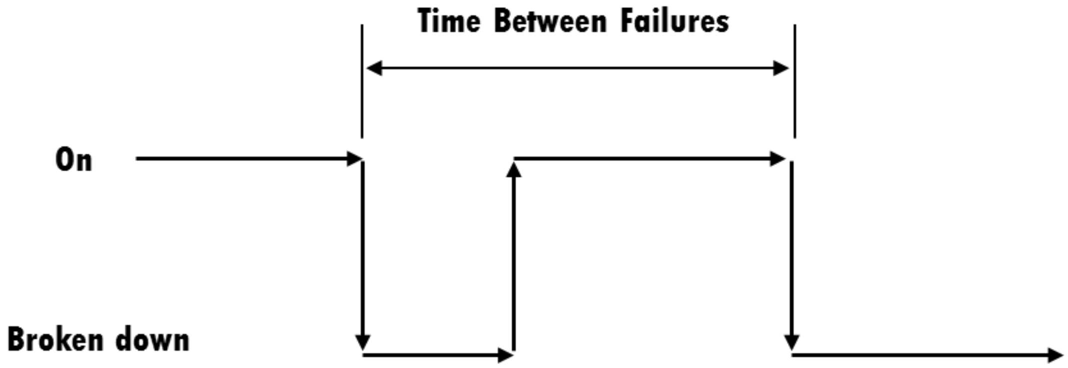


Figure 6-2 MTBF notation

Simulation models were developed by **Witness 14** as it is already available within the research group. Each simulation is run for a number of replications to account for the variability arising from stochastic maintenance and production processes. Replications are conducted by running the same simulation model while changing the streams of random numbers used to sample from statistical distributions. A graphical method [85] is adopted to define a sufficient number of replications. It involves plotting the cumulative mean of the simulation output over a number of replications. The line becomes flat gradually which suggests that sufficient replications have been reached.

As simulation models start with empty conditions (no parts are present in the system), there is a chance of an initialisation bias. Introducing a warm up period enables the model to reach a steady state before beginning the optimisation process. Welch's method [129] cited in [85] is based on calculating the moving average of simulation output using the following formula:

$$\overline{Y}_i(w) = \begin{cases} \dfrac{\sum_{s=-(i-1)}^{i-1} \overline{Y}_{i+s}}{2i-1} & \text{if } i = 1, \dots, w \\ \dfrac{\sum_{s=-w}^{w} \overline{Y}_{i+s}}{2w+1} & \text{if } i = w+1, \dots, m-w \end{cases}$$

Where:
$\overline{Y}_i(w)$ = moving average of window size w
$\overline{Y}_i$ = time-series of output data (mean of the replications)
i = period number
m = number of periods in the simulation run

The moving average $\overline{Y}_i(w)$ is plotted in a line graph. The warm-up period is identified as the point in simulation time where the line becomes flat.

6.2.4 Model Validation

The simulation model was validated considering both white-box and black-box validation approaches [85]. In white-box validation, it is determined whether the internal construct of the model represent the real world with sufficient accuracy. Black-box validation however, aims to determine whether the overall model produce results with sufficient accuracy. The purpose of the simulation model is to represent the production line and its maintenance operations.

White-box validation methods were performed by the researcher and a simulation expert. It included the following:

- Checking the model code: continuously revising the code and checking the data and model logic.
- Visual checks: animating the simulation and monitoring the behaviour of various elements, running the simulation model event by event and comparing the expected behaviour of items against the model.
- Inspecting output reports for individual elements: This includes built-in reports such as asset utilisation, down times, repair times and average time a part spends in the system. In addition, specific output to trace

asset degradation and the effect of maintenance actions were coded to be printed continuously for checks.

Likewise, black-box validation methods were adopted by comparing the simulation results to the current industrial systems. This includes production throughput, asset downtimes and asset availability. Historical data were used for the purpose of comparison. Additionally, knowledgeable experts from the concerned company were engaged to ensure valid representation of the model output.

6.2.5 Single Objective Optimisation

SOO was run using a Witness plug-in, **Witness Optimizer** which provides a number of optimisation algorithms including SA, Hill Climb and Random Solutions. Hill Climb is a local search heuristic algorithm that changes a single element in each iteration depending on the objective function performance. The main advantage of this algorithm is that it uses less memory and it makes rapid progress. However, one of its known limitations is that it performs local rather than global search. This will likely result in local optimum solution while there might be a better global solution as shown in Figure 6-3 [130].

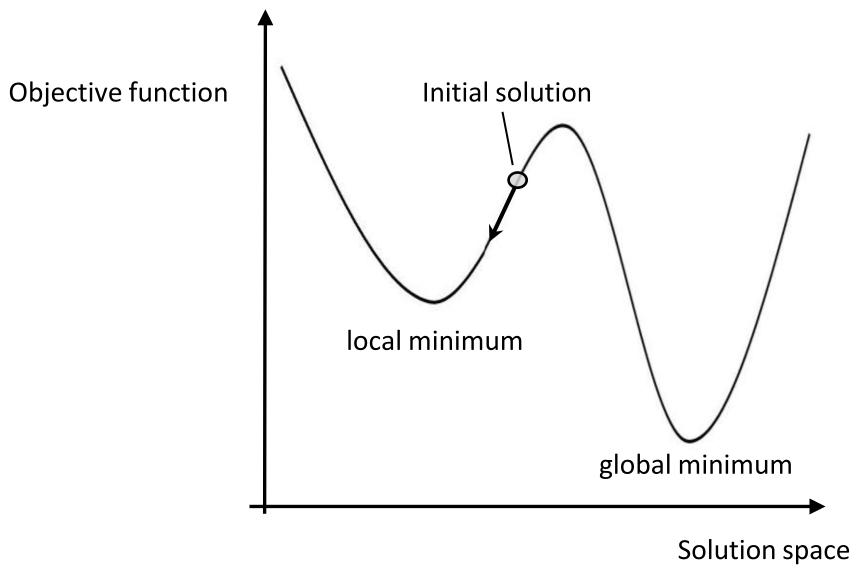


Figure 6-3 Global and local optimum solutions. Adapted from [130]

In contrast, Random Solutions is simply randomising the values of decision variables without a structured algorithm to guide it to better solutions. This method can search globally but without the capability to learn from evaluations. Therefore it is seen as inefficient and unlikely to result in global optimum. It is used to find initial feasible solutions for complex problems [91].

Simulated Annealing (SA) combines the advantages of both Hill Climb and Random Solutions. The concept comes from the annealing process in metallurgy to harden metals. Metals are melted in high temperature at the start and then cooled gradually in a controlled environment to obtain desired attributes. In simulated annealing, the algorithm is controlled by a factor often referred to as the temperature. Similar to the original application, the temperature starts high which allows the algorithm to explore the solution space even if that means accepting worse solutions. However the temperature gradually decreases as the algorithm learns and the focus is switched to finding a local improvement to the best solution so far [130].

Preliminary analysis was conducted by running the optimisation several times while changing the number of evaluation for each algorithm and monitoring the performance. It is observed that all three algorithms struggle to improve the objective function after around 150 evaluations. Therefore the maximum number of evaluations without improvements was set to 200 for all algorithms. Experiments were run using Witness optimizer version 5 which is a product of Lanner Group.

6.2.6 Multi-Objective Optimisation

The simulation model was also linked to an optimisation engine to conduct MOO since this capability is not provided by **Witness Optimizer**. An interface was developed to connect **Witness** to **GAnetXL** [131], a Genetic Algorithm Optimisation add-in for Microsoft Excel. The application is written in C++ to allow interactions with Microsoft Excel.

GAnetXL employs GA which is a population based evolutionary algorithm. The first population which contains the first set of decision variables is created randomly. The decision variables are sent to the simulation model for the purpose of evaluation. In order to produce the second set of solutions, a number of operators are applied including selection, crossover, mutation and elitism operators. The selection operator aims to choose from the old population to fill a mating pool giving more probability to better solutions. Crossover and mutation operators aim to create variations amongst some of the selected solutions in the mating pool to produce a new population. The elitism operator ensures that better solutions are kept from both old and new populations. In the current research, the optimisation process is terminated when it reaches the maximum number of generations [132].

MOO can result in a set of non-dominated solutions. In other words, a set of trade-off solutions where none of them achieve better than the others in all the objectives. **GAnetXL** solves multi-objective optimisation using Non-dominated Sorting GA (NSGA II) where the elitism operator ensures the new populations incorporate the non-dominated solutions [132]. The crossover rate used in this research is 0.8 whereas the mutation rate is 0.05. Similar values for these operators were used in simulation based optimisation of maintenance using GA [40; 47].

The simulation optimisation was run using population size of 50 for 100 generations. The number of generations is increased gradually if the algorithm is showing progress. Similarly, population sizes of 75 and 100 are used. Each combination of population size and generations was run using three different random seeds. Non-dominated solutions from the different random seeds were used to plot the data.

6.3 Academic Case Study

6.3.1 Description of the Manufacturing System

This section demonstrates the framework using a published case study [36]. As illustrated in Figure 6-4, the manufacturing system consists of six non-identical machines. There are buffers after each machine with the exception of machine 6 where processed parts are shipped out of the system. Spare parts provision follows a (s, Q) policy where s is the minimum threshold and Q is the number of units ordered. Only three technicians are available in the maintenance crew.

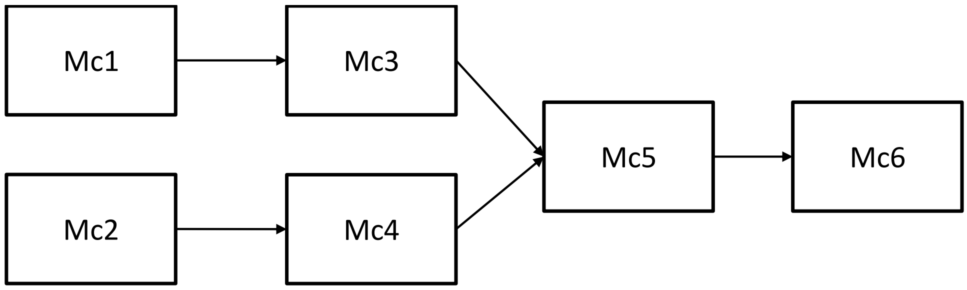


Figure 6-4 The manufacturing system layout. Source [36]

Failure patterns for machines are assumed to follow Weibull and Exponential distributions, two of the most widely used distributions to model lifetime in reliability and maintenance engineering [133]. Cycle times follow Triangular distribution and vary between machines. Repair times for CM and PM tasks follow a Uniform distribution and vary between machines as well. All related distributions along with their parameters are shown in Table 6-1.

Table 6-1 Cycle times, breakdown patterns and repair times for the manufacturing system.

Machine	Cycle time	Breakdown pattern	CM duration	PM duration
Mc_1	Triangle(3, 6, 12)	Weibull(2, 3)	IUniform (1,3)	IUniform (0.2,1)
Mc_2	Triangle(4, 5, 11)	Weibull(4, 2)	IUniform (1.2,3.5)	IUniform (0.8,2.5)
Mc_3	Triangle (3,9,10)	Weibull(2, 2.5)	IUniform (1.7,2.3)	IUniform (1,1.5)
Mc_4	Triangle (5,9,10)	Weibull (3,1)	IUniform (1.5,3)	IUniform (1,1.5)
Mc_5	Triangle (7,9,13)	NegExp (2.5)	IUniform (0.7,2.5)	IUniform (0.5,1.6)
Mc_6	Triangle (5,10,14)	NegExp (3)	IUniform (1,2.2)	IUniform (0.4,1.8)

Spare provision policy is under continuous review and it includes (s, Q) where Q units are ordered each time the stock level reaches s. Lead times are stochastic and follow a uniform(72, 168) distribution.

All machines are subject to CM when their degradation reaches a specific threshold. They are also subject to PM at predetermined intervals ($PMfreq_i$). PM and CM cannot occur at the same time. If a machine is broken down, all PM activities will be postponed until the machine is fixed. If a machine is undergoing preventive maintenance it will not be working and thus its degradation level remains constant. Maintenance resources are centralised. Therefore, in the event of a breakdown or a scheduled maintenance a signal is sent to maintenance technicians. If available, a technician is sent directly to perform the task and will be locked for the duration of the task. Upon the completion of the task, the technician will be sent back to the resources pool. Transportation times from and to the resources pool are neglected. A first-come, first-serve policy is adopted where the priority is given to the first occurring task. Maintenance tasks are assumed to be perfect where the machine becomes as good as new after maintenance actions. In addition, machines are assumed to deteriorate only when in use.

Maintenance cost includes the cost of both preventive and corrective maintenance tasks and is incurred whenever these tasks are executed. The cost of spare parts includes the cost of ordering which is incurred whenever inventory for the spare part of asset i (SP_i) falls below the reorder level s_i and the cost of holding which is incurred for every unit of time a spare part spends in the inventory. Unavailability cost is incurred for every time unit a machine is not available due to maintenance tasks, shortage of spare parts or waiting for labour. The costs are constant during the simulation and are as follows:

- Corrective maintenance = 2000/task
- Preventive maintenance = 750/task
- Holding cost = 2/unit/hour
- Order cost = 100/order
- Unavailability penalty = 300/ unavailable machine hour

Hours were considered to be the time unit for the simulation. The model was run for 10 years = 87600 hours with a warm up period of 1 year = 8760 hours and 3 replications.

6.3.2 Framework Demonstration

The framework is followed step by step as follows:

1. **Define the scope of the optimisation:** Maintenance optimisation is conducted on critical machines only: 1, 4 and 6. In this example, it is

possible to alter the spare management policy. However, it is not possible to alter any production measures. Therefore the optimisation scope will include both maintenance and spare parts policy. Spare parts policy parameters for each machine, namely *s* and *Q* will be considered as decision variables.

2. **Identify applicable maintenance strategies and policies:** CM will be set as a possible maintenance strategy for all three machines. In addition, time-based PM is applicable in all three machines. Therefore, PM frequencies will be considered as decision variables. However, neither CBM nor self-maintenance are applicable to any machine in this manufacturing system.
3. **Formulate the objective function:** Production schedules are mostly stable and this optimisation does not aim to improve quality initiatives. Both minimising the cost and maximising the availability are considered important in this case. Machine unavailability incurs cost and can be incorporated in the cost function. Therefore, minimising the total cost will be the only objective. We consider the optimisation scope when detailing the cost function. As we are optimising maintenance and spare parts jointly, spare parts costs including the order and holding costs will be part of the cost function. In addition, both CM and PM maintenance costs will be detailed and added to the cost function. Hence, the objective function 'Total Cost' can be formulated as follows:

Minimise Total Cost= maintenance cost+ spare parts cost+ unavailability cost

Where,

Maintenance cost = PM cost + CM cost, and,

Spare parts cost= order cost+ holding cost

4. **Define the decision variables:** Nine decision variables have been identified in the previous steps. These are the spare parts policy parameters (*s*, *Q*) as well as the preventive maintenance frequency *PMfreq* for the selected machines (*i*): 1,4 and 6. Three additional decision variables (MS_i) are required to reflect the choice of maintenance strategy, either CM or PM. No more decision variables are required in this problem.
5. **Define constraints:** The maintenance system is well-known and therefore there is sufficient knowledge to define bounds for all decision variables. The

reorder level s_i can range between 0 to 15 while the order quantity Q_i can range between 1 and 15. PM frequency for all machines ($PMfreq_i$) can range between 1 and 3 weeks. *MS* will be either 0 if the selected maintenance strategy is CM or 1 if the selected maintenance strategy is PM. In addition, *MS* will be incorporated in the variable bounds for *PMfreq* to ensure it results in 0 if the selected maintenance strategy is CM [134]. No other constraints are required at this problem. Therefore the problem can be formulated as follows:

$$\text{Minimise Total Cost} = \text{maintenance cost} + \text{spare parts cost} + \text{unavailability cost}$$

$$1\ \text{week} * (MS_i) < PMfreq_i < 3\ \text{weeks} * (MS_i)$$

$$MS_i = 0 \text{ for CM or } 1 \text{ for PM}$$

$$0 < s_i < 15$$

$$1 < Q_i < 15$$

$$\text{Where } i = 1, 4 \text{ and } 6$$

6. **Select the optimisation algorithm:** Following the framework results in the selection of algorithms for SOO. In addition, the current optimisation problem requires a global search. Amongst the available options provided by the framework is Simulated Annealing (SA). It is selected due to its availablility within the simulation software (WITNESS). The results of SA will be compared to two other optimisation algorithms available in WITNESS, namely Hill Climb and Random Solutions. Most of the algorithm settings are left to be set automatically including SA parameters such as splitting large variables, initial parameters, cooling rate and cooling steps. The maximum number of scenarios is set based on the number of possible solutions for the optimisation problem. As illustrated in Table 6-2, the solution space is vast which requires a large number of evaluations. Simplifying the problem may be possible which will be investigated in the next step. The maximum number of evaluations for all algorithms is set to 1,000 whereas up to 200 moves are allowed without improvement.

Table 6-2 Possible solutions for the optimisation

Variables	Ranges		Current possible choices	possible choices after simplification	Remarks
$PMfreq_1$	168	504	336	14	changed from hour to day
$PMfreq_4$	168	504	336	14	changed from hour to day
$PMfreq_6$	168	504	336	14	changed from hour to day
s_1	0	15	16	8	changed from step 1 to step 2
s_4	0	15	16	8	changed from step 1 to step 2
s_6	0	15	16	8	changed from step 1 to step 2
Q_1	1	15	15	8	changed from step 1 to step 2
Q_4	1	15	15	8	changed from step 1 to step 2
Q_6	1	15	15	8	changed from step 1 to step 2
MS_1	0	1	2	2	changed from step 1 to step 2
MS_4	0	1	2	2	no change
MS_6	0	1	2	2	no change
Possible solutions			**4,195,092,529,152,000**	**5,754,585,088**	

7. **Set the simulation optimisation:** Variability analysis is conducted in order to set the required number of replications. As shown in Figure 6-5, the simulation is run repeatedly while the objective function (*Total Cost*) is recorded for each replication. In addition, a moving average is calculated. The moving average line seems to stabilise around the 16th replication and hence the number of replications will be set to 16 to ensure we obtain a better estimate of (*Total Cost*) mean. Warm-up period is set to five days to avoid the initialisation bias since the manufacturing system starts with no parts in machines or buffers. The run length is set to one year to reflect the fact that the maintenance department plans annually for its operations. The cost baseline in the model before optimisation is 1,520,508 cost units.

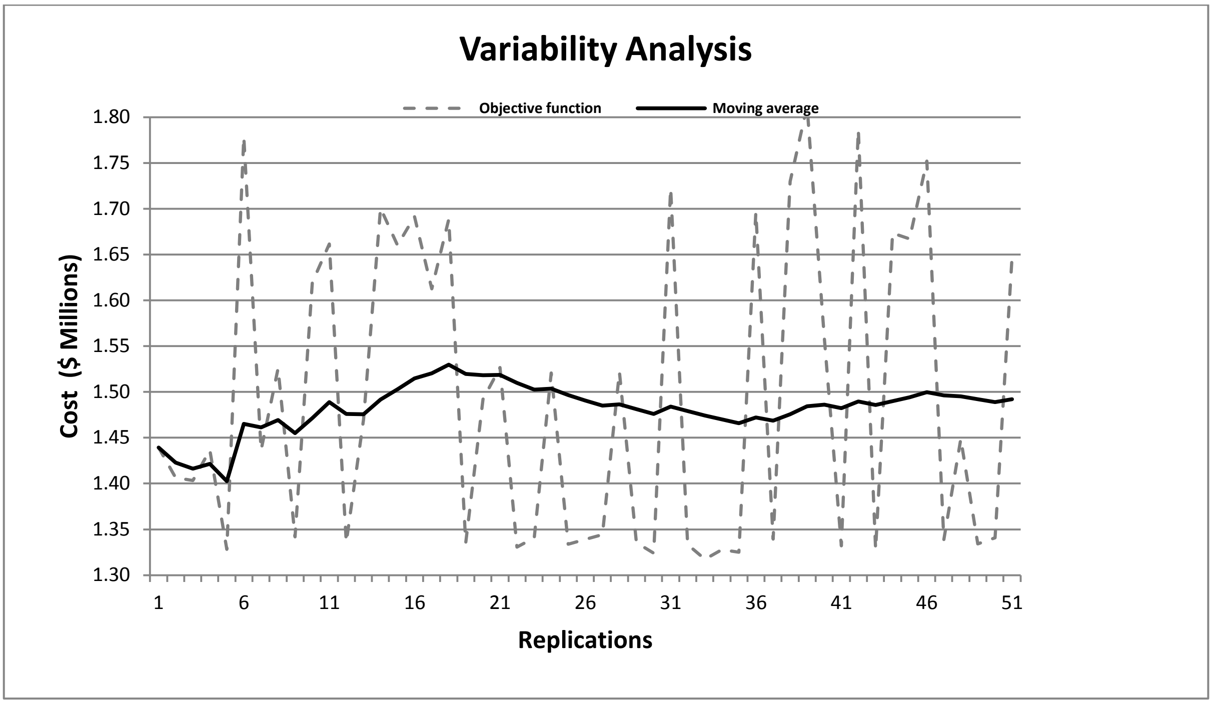


Figure 6-5 Variability analysis for the academic case

One simulation run requires an average of 1 minute and 17 seconds on a PC with Intel Core i7-2600 CPU @ 3.40 GHz. At least several thousand evaluations are required for a problem with similar search space which consumes a long time. A thousand evaluations using SA are run with the current optimal formulation before attempting to simplify the problem. Figure 6-6 shows the objective values (maintenance cost) for each simulation optimisation run. In addition, the best result achieved (minimum maintenance cost) is tracked during the simulation optimisation cycle. The optimisation resulted in cost reduction of 16.6% compared to the base model. The whole simulation optimisation required 18 hours and 45 minutes to run. It is observed that small changes in the variables $PMfreq_i$ have insignificant effect on the total cost. Therefore it seems that simplifying the problem by discretising the decision variables will reduce the solution space with possibly minimal effect on the objective function.

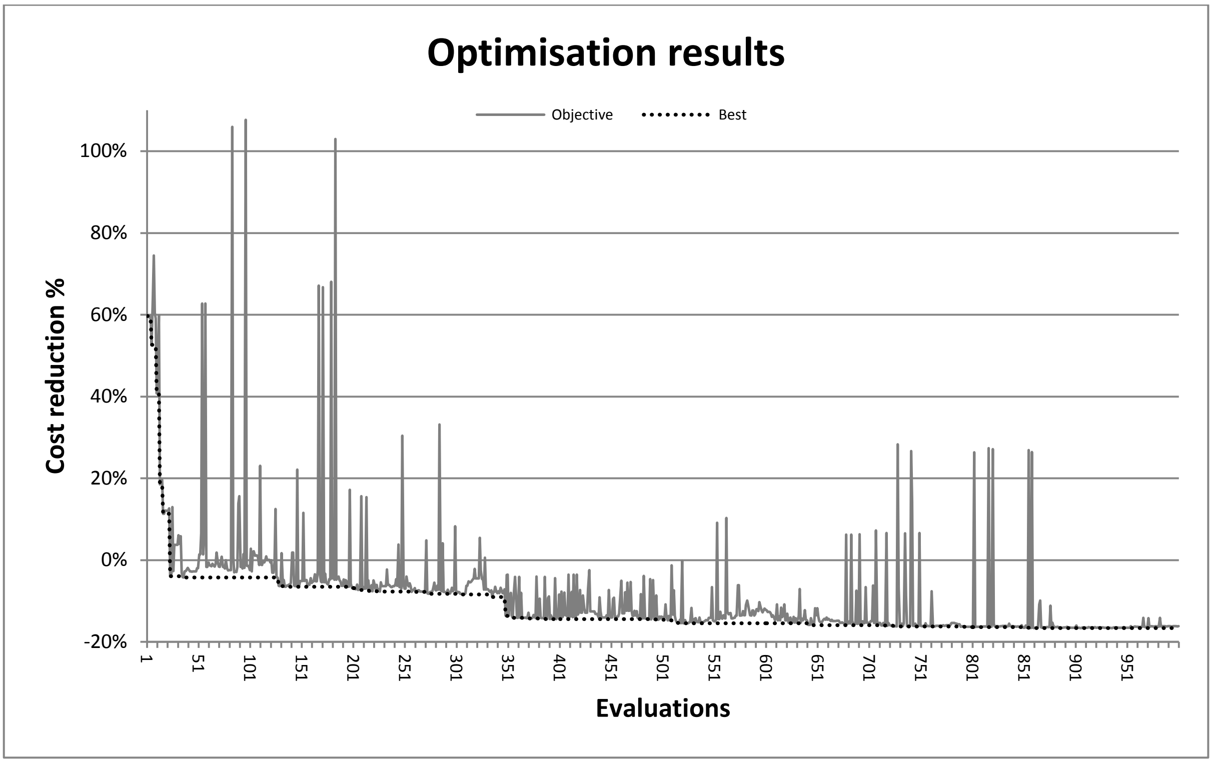


Figure 6-6 Optimisation results before simplifying the problem

The problem can be simplified by planning the PM for each machine by day instead of hour which reduces the possible values for each *PMfreq* from 336 to 14. In addition, both order quantity and order level can change two values at a time halving the number of their possible values. The solution space is reduced drastically as shown in Table 6-2. In addition to cost, the production throughput is considered an important measure to be taken into account when planning maintenance. Therefore, it will be tracked and recorded as a response in all simulation optimisation runs.

Table 6-3 presents a comparison of the best results achieved by each optimisation algorithm for the simplified problem along with computation time and number of evaluations. As described in Section 6.2.4, the maximum number of evaluations without improvements was set to 200 for all algorithms. SA achieved the best result with 16.7% reduction in the total cost compared with the base model. The optimisation was terminated after 684 evaluations because it did not achieve an improvement in the objective function for 200 consecutive evaluations. The total computation time was 15 hours. It is interesting to note that by simplifying the problem, SA achieved a slightly better result consuming much less computation expenses.

Table 6-3 Computation time and best results for different optimisation algorithms

Optimisation algorithm		Number of evaluations	Computation time (hh:mm)	Best result (cost reduction %)
1	Random Solutions	1,000	21:56	-14.5%
2	Hill Climb	459	09:48	-12.9%
3	Simulated Annealing	684	15:00	-16.7%

8. **Decision making:** Figure 6-7 compares the best performance for the three optimisation algorithms. Hill climb converged rapidly but it struggled to achieve significant improvements after the 28th evaluations and it could not achieve any improvement after the 259th evaluation. This result may be explained by the fact that Hill Climb is not capable of conducting global search and therefore is bound to be trapped in a local minimum. This is further supported by the fact that both Random Solutions and SA were able to find better solutions.

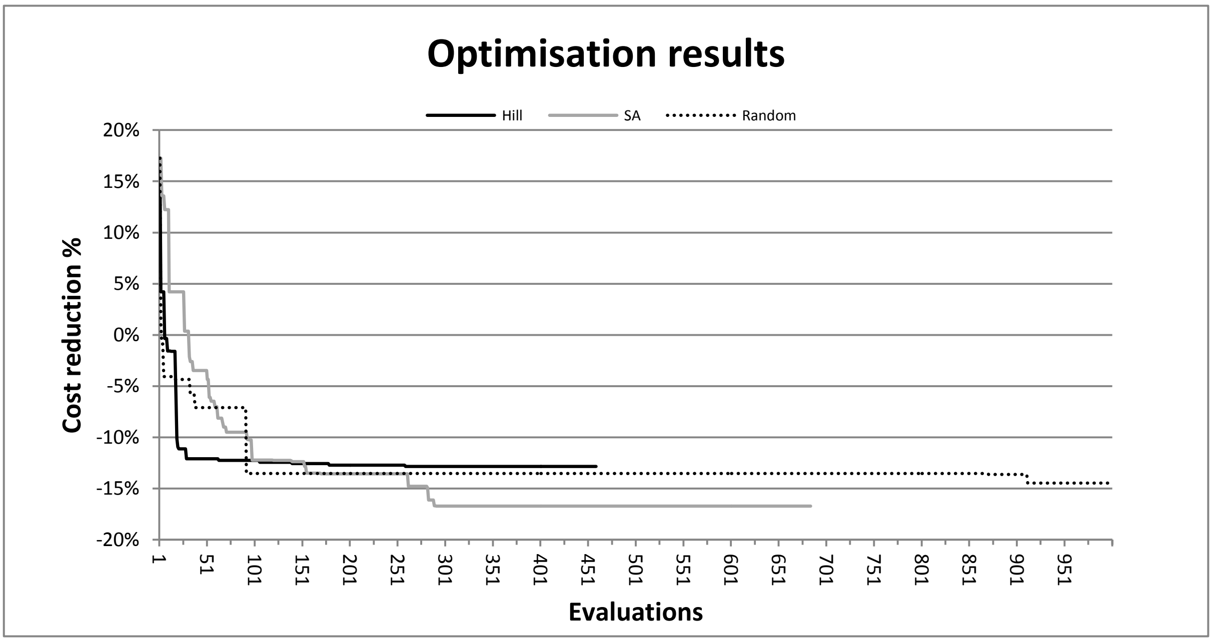


Figure 6-7 Comparison of the algorithms' performance

The firm’s management might consider spending up to 10% more on maintenance if that will result in achieving higher productivity defined by the total throughput of the manufacturing system. Figure 6-8 below provides the outcomes obtained from plotting throughput vs. cost for the best 10% of the SA optimisation results. From the chart, it is apparent that the minimum cost corresponds with the maximum throughput. This could be because the production line has reached its maximum capacity, making additional investments in maintenance infeasible. Therefore the firm's management would not have to attempt to balance throughput and maintenance cost for this problem.

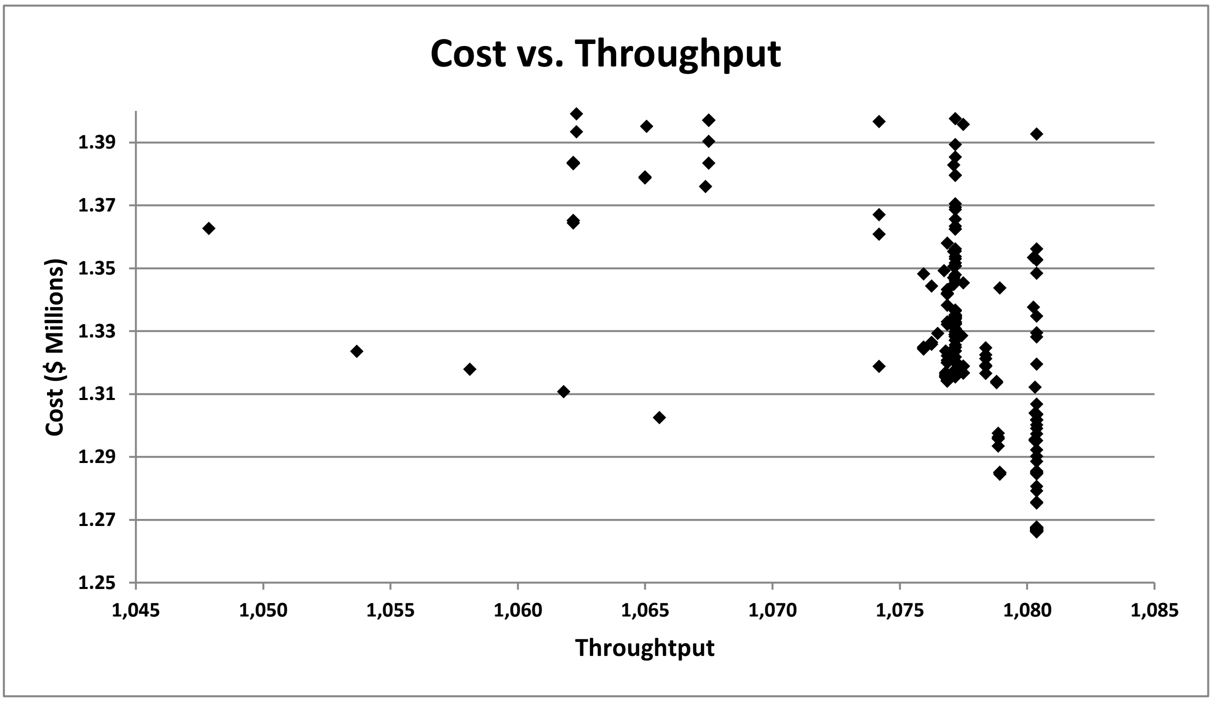


Figure 6-8 Plotting Cost vs. Throughput for the best 10% of the results

Nonetheless, the optimisation resulted in more than 100 solutions where the cost is in the range of 1% more than the minimum cost achieved while the throughput is 1080 which is the maximum value reached. Table 6-4 presents the top ten optimal solutions. From this data, we can see that the optimal maintenance strategy is PM for all machines. In addition, PM frequency does not change for the top ten solutions. Some spare management policy parameters such as Q_4 and Q_5 change resulting in a slight change in the cost function. Other considerations that were not taken into account in this study might affect the choice of the optimal solution such as quantity discounts.

Table 6-4 Top ten optimal solutions

Scenario	A	B	C	D	E	F	G	H	J	I
Cost	1,266,117	1,266,142	1,266,261	1,266,273	1,266,286	1,266,292	1,266,317	1,266,404	1,266,417	1,266,417
$PMFreq_1$	384	384	384	384	384	384	384	384	384	384
$PMFreq_4$	216	216	216	216	216	216	216	216	216	216
$PMFreq_6$	216	216	216	216	216	216	216	216	216	216
MS_1	1	1	1	1	1	1	1	1	1	1
MS_4	1	1	1	1	1	1	1	1	1	1
MS_6	1	1	1	1	1	1	1	1	1	1
Q_1	5	5	5	5	5	5	5	5	5	5
Q_4	5	5	3	5	3	5	3	11	11	11
Q_6	11	7	11	7	7	15	11	5	11	11
s_1	4	4	4	4	4	4	4	4	4	4
s_4	2	2	2	2	2	2	4	2	4	2
s_6	4	4	4	6	4	4	4	4	4	4
Throughput	1080	1080	1080	1080	1080	1080	1080	1080	1080	1080

6.4 Industrial Case A

6.4.1 Description of Factory A

Industrial case A takes place in a tyre re-treading factory comprised of two main production lines:

- Trucks and lorries
- Tractors and heavy equipment

The production line for trucks is considered more critical as it is experiencing greater demand. Therefore it was selected for the case study. As illustrated in Figure 6-9, the production line involves eleven processes as follows:

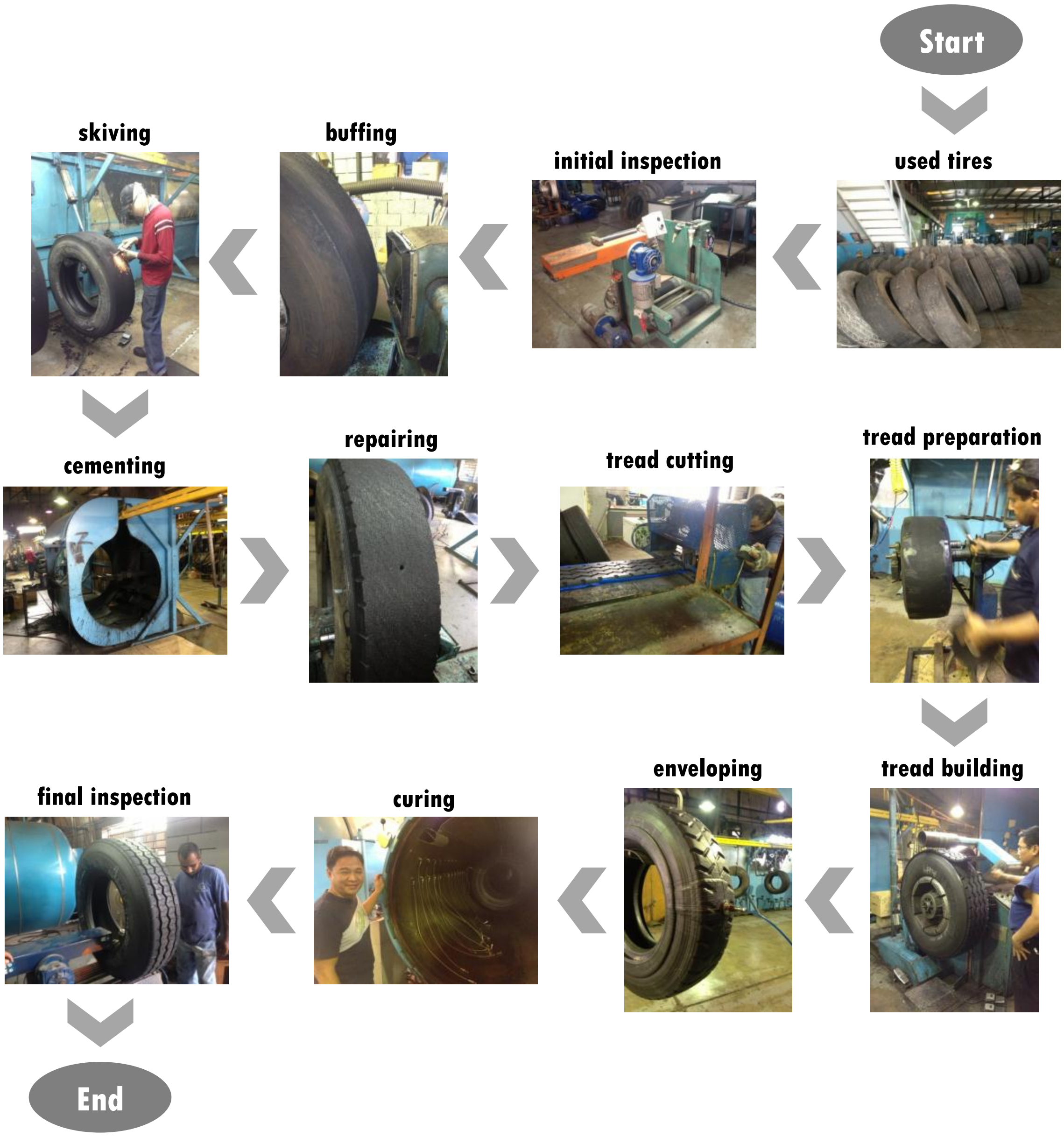


Figure 6-9 Tyre re-treading manufacturing process – trucks production line

1. **Initial inspection**: casing is thoroughly inspected by a technician who determines if it is suitable for re-treading and if so the type of work to be performed on the tyre
2. **Buffing**: the worn tyre tread is entirely removed from the casing. The technician buffs and cuts the tyre to a specific radius and diameter on an expandable station
3. **Skiving**: embedded foreign objects and loss wires are removed to ensure a clean and solid surface

4. **Cementing**: a thin layer of concentrated rubber solution is sprayed on the casing
5. **Repairing**: minor defects such as small punctures and holes are fixed
6. **Tread cutting**: treads are prepared and cut for each tyre according to its size and customer requirements
7. **Tread preparation and building**: a new layer of compact pre-cured tread is built on the tyre casing. A thin layer of special bonding rubber is placed between the pre-cured tread and the casing
8. **Enveloping**: the tyre is bagged in a flexible envelope then vacuumed completely
9. **Curing**: the tyre is positioned in a heated chamber to start the process of vacuumisation under high pressure which results in a homogenous and permanent bonding of the pre-cured tread to the tyre casing
10. **Unloading**: taking the tyres from the chamber and separating it from the envelop
11. **Final inspection**: the re-treaded tyre is inspected thoroughly before shipping to customers

The cycle times for each process are shown in Table 6-5.

Table 6-5 Case A machine cycle times

	Process	Number of workstations	Cycle time (hours)	Setup time (hours)
1	Initial inspection	1	Triangle (0.05,0.08,0.25)	N/A
2	Buffing	1	Triangle (0.08,0.13,0.25)	N/A
3	Skiving	3	Triangle (0.05,0.25,0.5)	N/A
4	Cementing	1	Triangle (0.08,0.1,0.12)	N/A
5	Repair	2	Triangle (0,0.12,0.5)	N/A
6	Tread cutting	1	Triangle (0.07,0.08,0.17)	N/A
7	Tread preparation and building	1	Triangle (0.08,0.17,0.25)	N/A
8	Enveloping	1	Triangle (0.08,0.12,0.20)	N/A
9	Curing	1	Triangle (4,5,6)	0.17
10	Unloading	1	Triangle (0.003,0.03,0.08)	N/A
11	Final inspection	1	Triangle (0.03,0.08,0.12)	N/A

All machines require labour to operate except curing. However, the curing machine needs a labour to set it up which involves loading tyres to the chamber and switching the machine on. Therefore, the curing process can continue to work out of shift hours since it does not need any operators. As shown in Table 6-6, most workers are multi-skilled which enables the production manager to reschedule the workforce regularly to ease bottlenecks.

Table 6-6 Labour skills in case A

	Initial inspection	Buffing	Skiving	Cementing	Repair	Tread cutting	Tread preparation and building	Enveloping	Curing (setup)	Unloading	Final inspection
Labour 1	✓		✓				✓				
Labour 2		✓	✓			✓					
Labour 3			✓	✓							
Labour 4			✓	✓					✓	✓	
Labour 5				✓					✓	✓	
Labour 6			✓	✓	✓						
Labour 7				✓	✓						
Labour 8						✓					
Labour 9		✓					✓				
Labour 10									✓	✓	
Labour 11				✓							✓

There are two possible rejection scenarios for tyres within the production line:

1. 30% are rejected at the initial inspection mainly because they are deemed unsuitable for re-treading
2. 5% are rejected from the skiving area. The operator can see defects in the case now more clearly having the old tread removed. This results in finding some tyres that are not suitable for re-treading

In addition, there is a rework loop:

- 5% of tyres fail the final inspection stage and have to go back to tread preparation and building process and then proceed again as normal

Figure 6-10 shows the simulation layout for Case A.

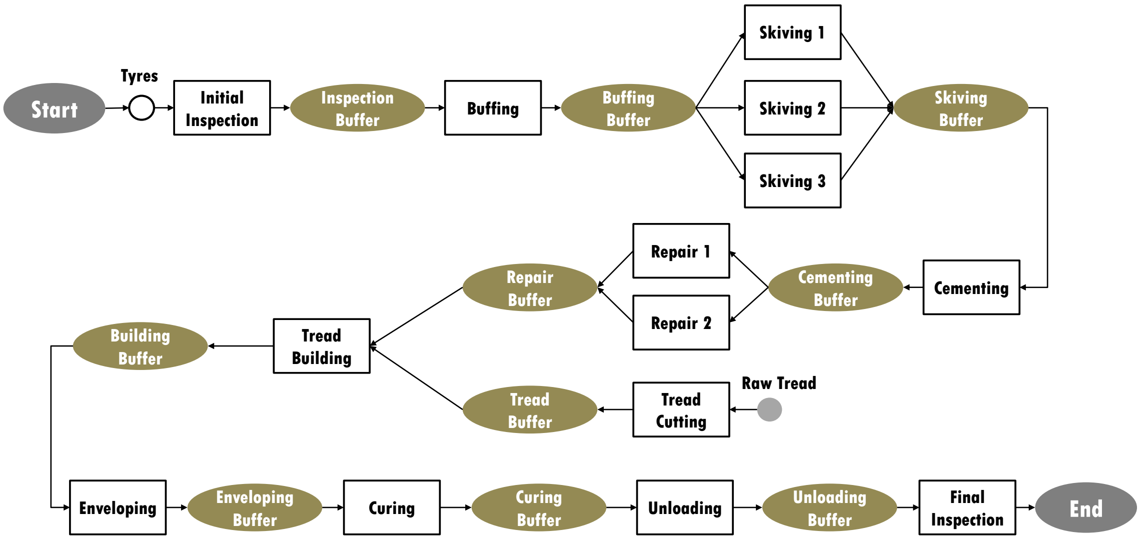


Figure 6-10 Case A simulation layout

6.4.2 Maintenance Operations

Documentation of maintenance interventions is minimal. No records are held for downtimes and reasons of failure. In addition, CM is the only applied maintenance strategy. The explanation given by the factory management was that most breakdowns can be fixed manually by the operator in a relatively short time. However, there are a few incidents where breakdowns resulted in long unavailability but it was not possible to track the details due to poor documentation. Therefore, all maintenance data were captured from the maintenance team. Repair times follow the triangular distribution which uses three parameters: minimum, mode and maximum [85]. MTBF data follow the Uniform distribution which uses minimum and maximum parameters since it was not possible to establish the mode parameters. The most critical processes from maintenance point of view as well as their associated breakdown and repair data are shown in Table 6-7.

Table 6-7 Industrial case A breakdown and repair data

Machine	MTBF (hours)	Repair time (hours)
Buffing	Uniform(160, 192)	Triangle (1, 10,30)
Cementing	Uniform(160, 192)	Triangle (1,1.5,2)
Building machine	Uniform(320, 384)	Triangle (1,4,20)
Enveloping	Uniform(160, 192)	Triangle (1.5,2,2.5)
Curing	Uniform(1920, 2304)	Triangle (24,48,72)

Several assumptions were necessary to model PM. PM repair times are a third of CM repair times. In addition, PM is conducted internally and involves routine maintenance activities such as changing or topping oil, lubricating, cleaning, fixing electric wires …etc. However, CM often involves spare parts and requires professionals from outside the factory. This will be reflected in higher maintenance costs for CM as can be expected. Table 6-8 presents both CM and PM costs in US Dollars ($). CM costs vary depending on the type of failure. For example, the buffing machine frequently breaks down as result of a broken gear which has to be fixed at an external workshop. The enveloping machine breakdown is due to a broken arm and can be fixed internally by replacing the part or using welding.

Table 6-8 CM and PM costs for case A

Machine (Mc_i)	CM costs ($)	PM costs ($)
Buffing (Mc_1)	3,200	300
Cementing (Mc_2)	1,200	200
Building (Mc_3)	450	150
Enveloping (Mc_4)	200	50
Curing (Mc_5)	3,500	400

6.4.3 Simulation Based Optimisation for Case A Maintenance System

The framework is followed step by step as follows:

1. **Define the scope of the optimisation**: The assets in interest are already identified as shown in Table 6-7. Currently, the firm's management is

interested in investigating maintenance strategies only. As the factory is located in an industrial area, spare parts are available locally from several suppliers. Investing in a warehouse for spare parts is not being considered. In addition, the management were not considering investing in creating more buffer spaces for Work In Progress.

2. **Identify applicable maintenance strategies and policies:** In addition to CM, time-based PM is applicable for the critical machines. CBM will require investment and skilled labour which is not a possibility in the current situation.
3. **Formulate the objective function:** The two relevant objectives for this case are maximising the production throughput and minimising the maintenance cost. The maintenance cost function consists of CM and PM costs.
4. **Define the decision variables:** In addition to the maintenance strategy and the PM frequency for each machine, an additional decision variable from the maintenance resources group is considered. Up to two maintenance technicians costing each $24,000 per year can be hired to assist with maintenance actions as opposed to the current situation where operators are conducting the maintenance tasks.
5. **Define constraints:** There is not sufficient knowledge to set the bounds for the PM frequency for each machine. Therefore, an estimate is made based on the minimum and maximum MTBF data. PM frequency bounds will be set to be between half the minimum MTBF and twice the maximum MTBF for each machine. Maintenance strategies (MS_i) can be either 0 or 1 which represents CM and PM respectively. In addition, the variable MS_i will be included in the bounds of $PMfreq_i$ to force it to equal to zero if the chosen maintenance strategy was CM. Maintenance technicians can range between 0 and 2.

The optimisation problem can be formulated as follows:

Minimise: *Maintenance Cost*
Maximise: *Production Throughput*

Subject to:

$$80 * (MS_1) < PMfreq_1 < 288 * (MS_1)$$
$$80 * (MS_2) < PMfreq_2 < 288 * (MS_2)$$

$$160 * (MS_3) < PMfreq_3 < 576 * (MS_3)$$
$$80 * (MS_4) < PMfreq_4 < 288 * (MS_4)$$
$$960 * (MS_5) < PMfreq_5 < 3456 * (MS_5)$$

$$MS_1 = 0 \text{ for CM or } 1 \text{ for PM}$$
$$MS_2 = 0 \text{ for CM or } 1 \text{ for PM}$$
$$MS_3 = 0 \text{ for CM or } 1 \text{ for PM}$$
$$MS_4 = 0 \text{ for CM or } 1 \text{ for PM}$$
$$MS_5 = 0 \text{ for CM or } 1 \text{ for PM}$$

$$0 < \text{Maintenance technician} < 2$$

6. **Select the optimisation algorithm:** The framework suggests suitable optimisation algorithms based on a series of questions. The current optimisation problem is multi-objective. In addition, it requires global search. NSGA II is one of the options provided by the framework for similar problems. As Witness Optimizer does not include the required optimisation algorithm, GANetXL was connected to Witness as described in Section 6.2.
7. **Set the simulation optimisation:** The simulation run-length is set to two years. A variability analysis was conducted to establish the required number of replications. As can be seen from Figure 6-11, throughput begins to stabilise around the 8th replication. However, when considering maintenance cost, the moving average starts to stabilise after the 13th replication. Therefore, the number of replications will be set to 13 for this case.

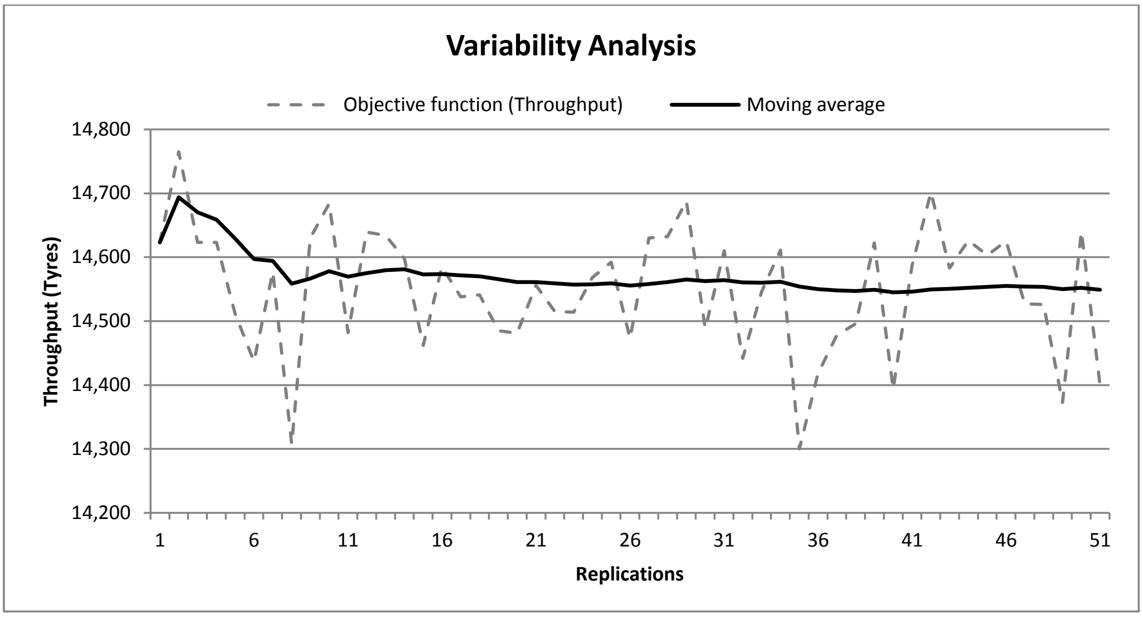


Figure 6-11 Variability analysis for case A simulation model considering throughput as an objective

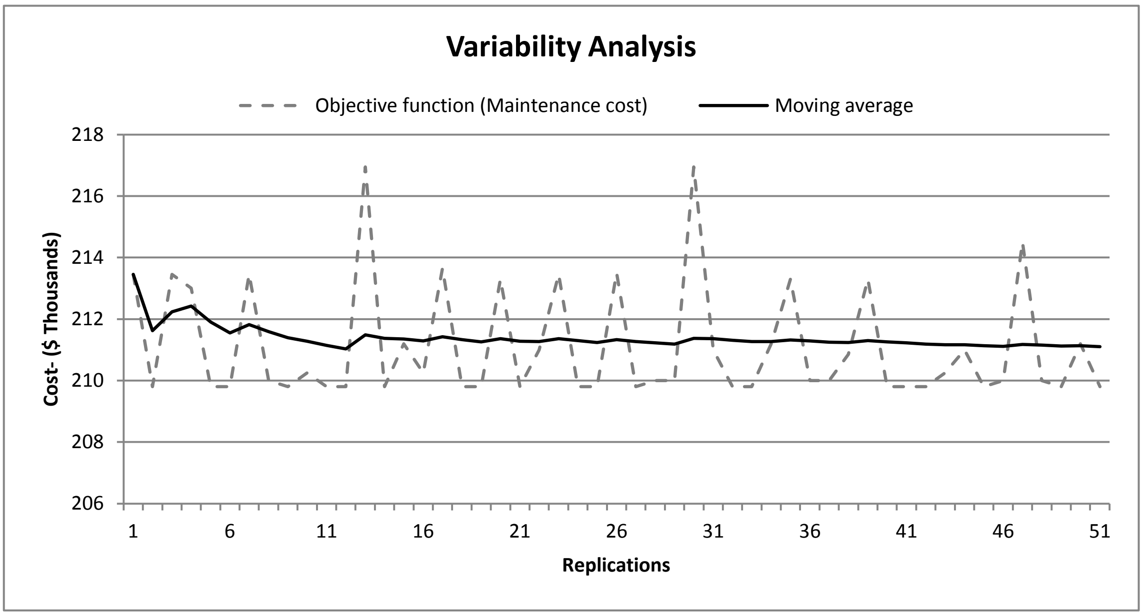


Figure 6-12 Variability analysis for case A simulation model considering maintenance cost as an objective

Similarly, to establish the required warm-up time, an analysis was conducted using Welch's Method. The moving average for production throughput and maintenance cost is plotted in Figure 6-13 and Figure 6-14 respectively. It can be concluded from both figures that 30 days is sufficient for the model to settle into steady state.

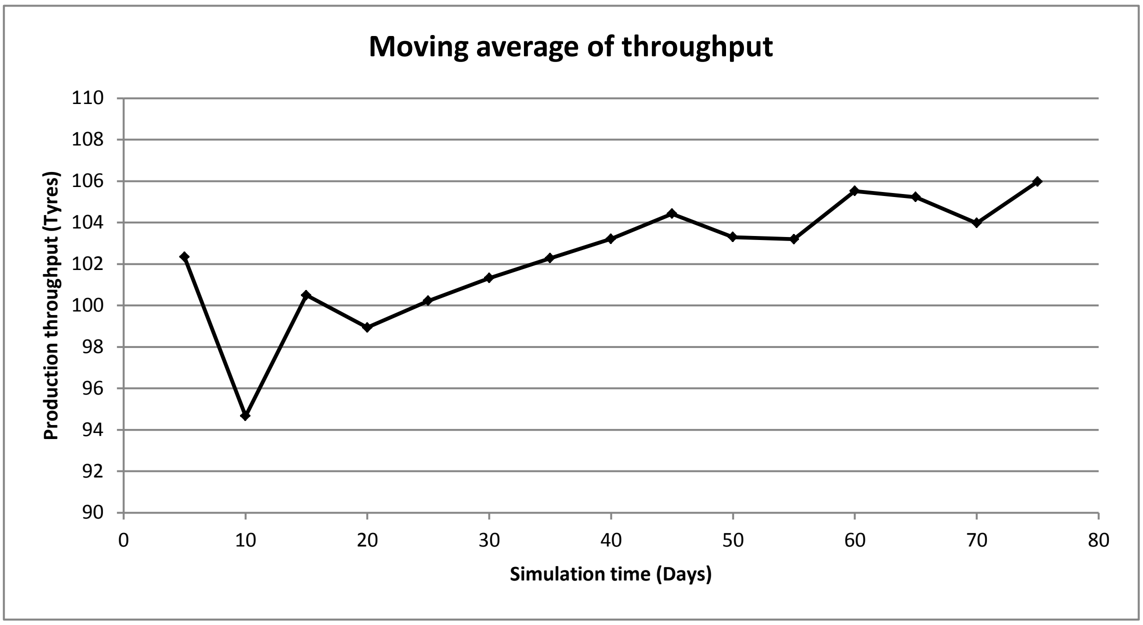


Figure 6-13 Warm-up analysis for case A simulation model considering throughput as an objective

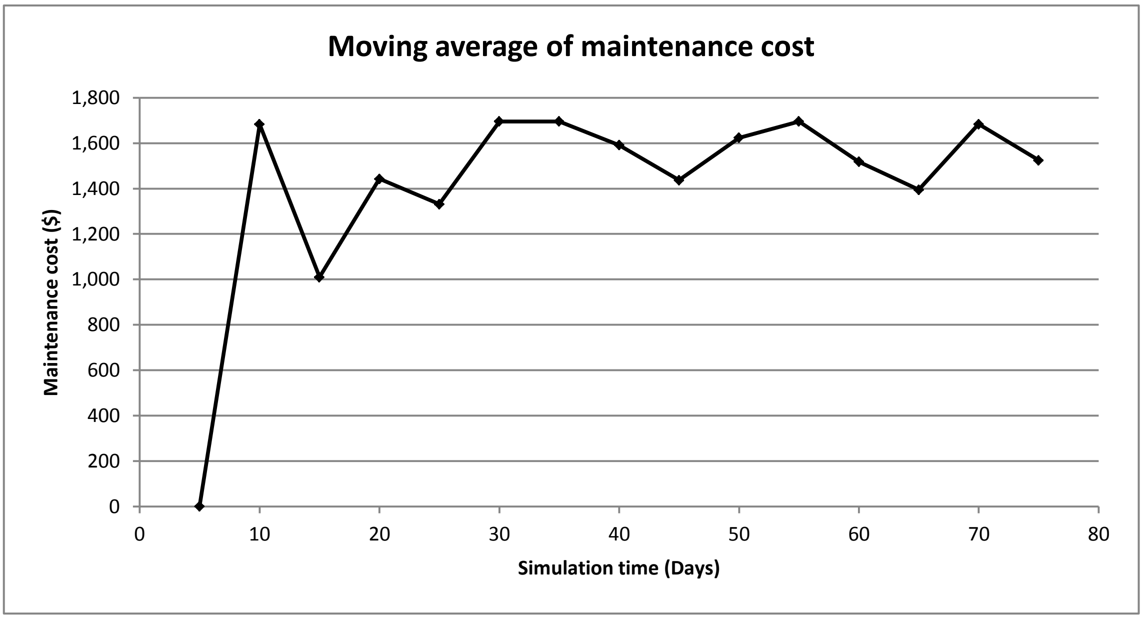


Figure 6-14 Warm-up analysis for case A simulation model considering maintenance cost as an objective

The simulation optimisation was run for a combination of population sizes and number of generations. Each combination was run using three different random seeds. Starting with a population size of 50 and 100 generations, the number of generations is increased gradually as long as GA is making progress. If no significant improvements in the results are apparent, the population size is set to 75 and then 100 and the process is updated. Only non-dominated solutions from the different random seeds were used to plot the data. The full optimisation plan along with computational expenses are shown in Appendix E.1.

The non-dominated optimal solutions for each combination of population size and number of generations are shown in Appendix E.2. It is observed that none of the optimal solutions are close to the boundary set previously for decision variables. Therefore, there is no need to re-set the variables bounds and repeat the experiments.

8. **Decision making:** The current business environment is generally stable. MOO produces a number of non-dominated solutions. This provides flexibility to the decision maker since trade-off analysis can be made as the business environment changes.

   Figure 6-15 presents the results for a population size of 50. The results improved gradually while increasing the number of generations. However, the improvements in 400 generations were limited. It is interesting to observe that higher number of generations produce less spread and fewer solutions. It is possible that the pareto front is narrow. Therefore, as the algorithm converge we get fewer solutions.

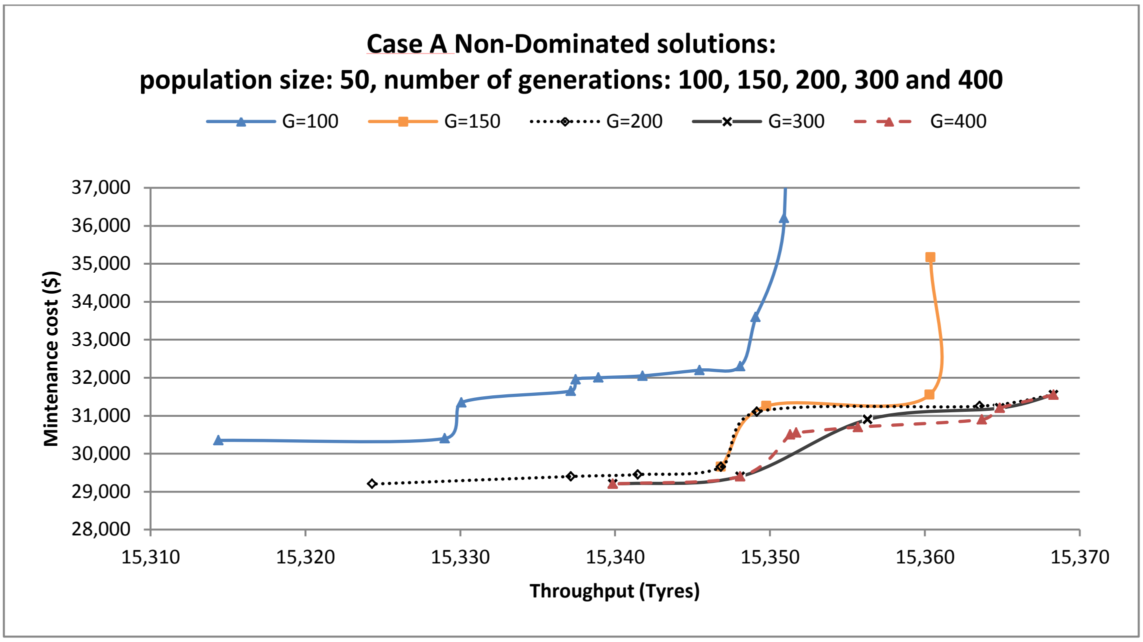


Figure 6-15 Case A Non-Dominated solutions: population size: 50, number of generations: 100, 150, 200, 300 and 400. (Some data points are not shown in the graph)

The algorithm made little progress for different number of generations of population size 75 as shown in Figure 6-16. In addition, changes in the spread or number of solutions are minimal. In general, population size 75 achieved better results compared with population size 50.

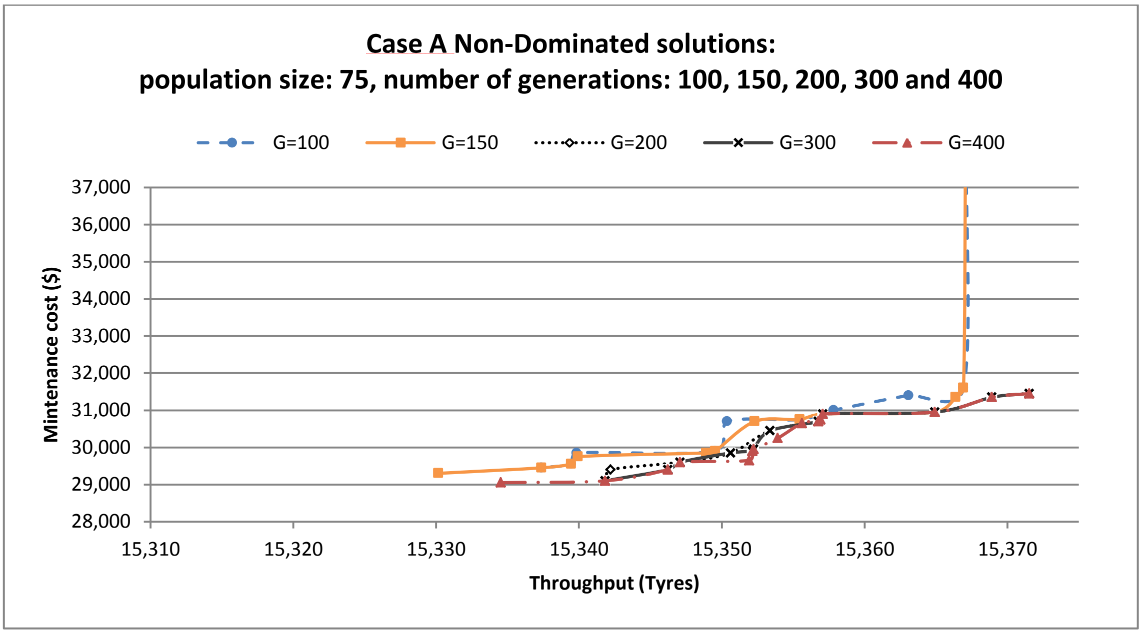


Figure 6-16 Case A Non-Dominated solutions: population size: 75, number of generations: 100, 150, 200, 300 and 400. (Some data points are not shown in the graph)

Population size 100 was run for 100, 150 and 200 generations only due to the limited progress made (see Figure 6-17). The spread was significantly less than that of both population sizes 50 and 75.

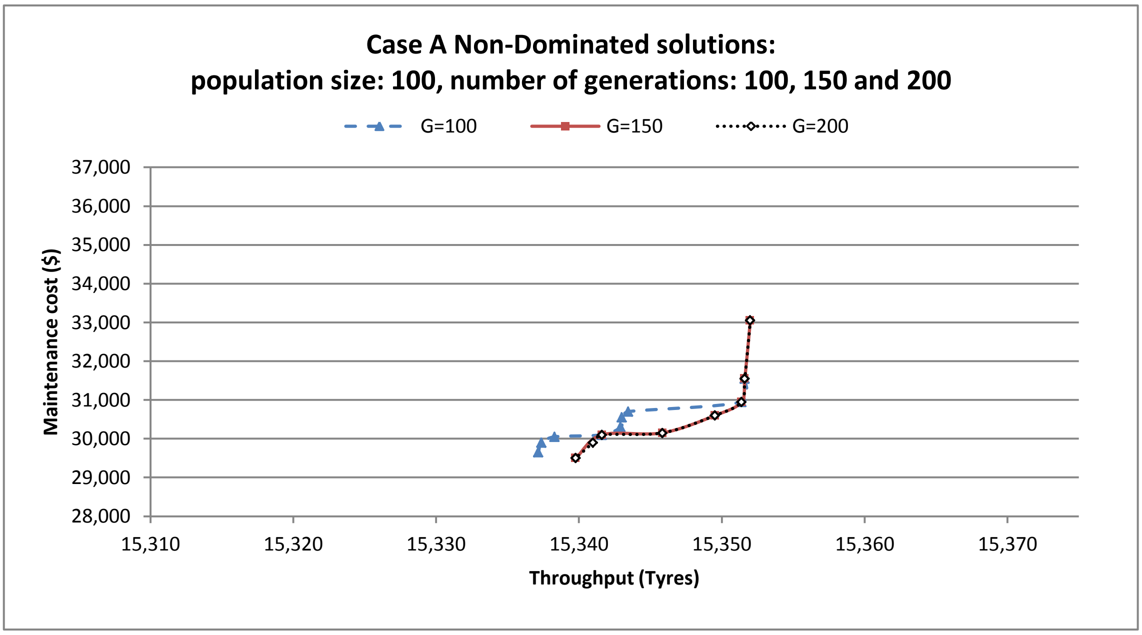


Figure 6-17 Case A Non-Dominated solutions: population size: 100, number of generations: 100, 150, 200

All non-dominated solutions are plotted in Figure 6-18. In addition, the complete solutions including the optimal decision variables for all non-dominated solutions are shown in Appendix E.2. The curve representing population size 75 and 400 generations appears to achieve the best solutions resulting in maximum production throughput and minimum maintenance cost.

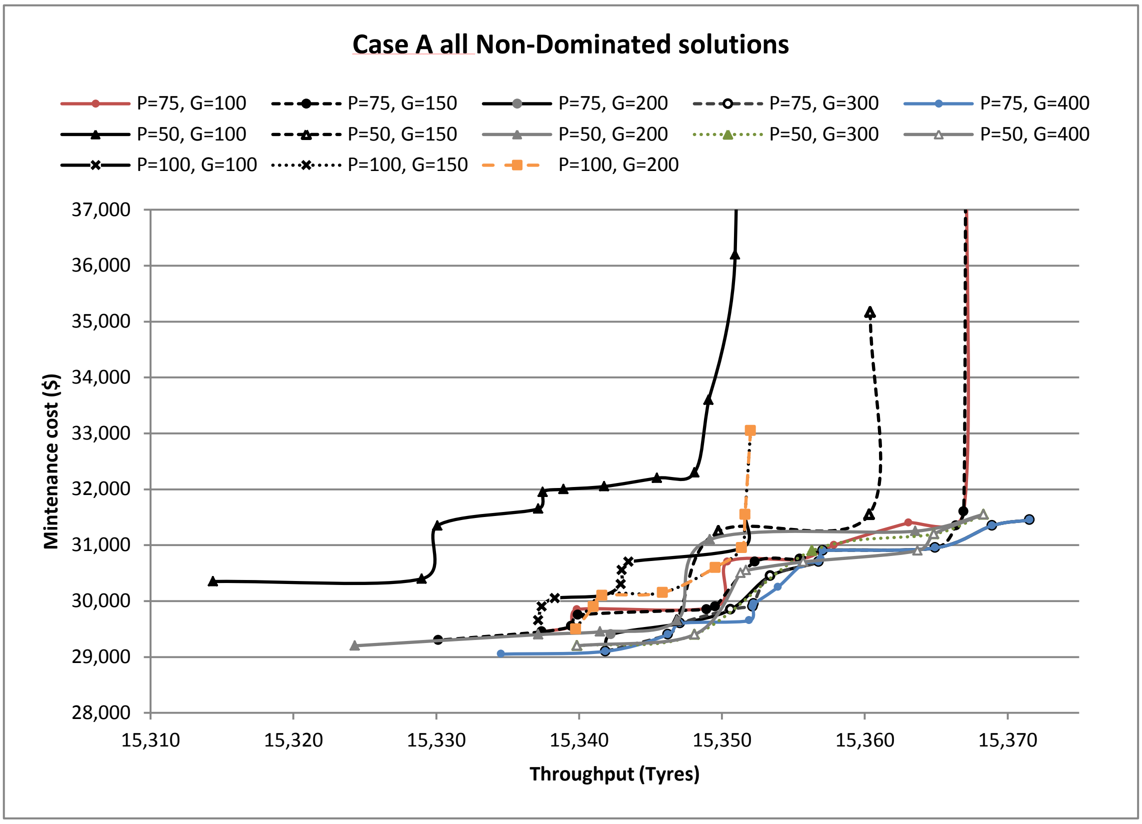


Figure 6-18 Case A all Non-Dominated solutions. (Some data points are not shown in the graph)

The optimal solutions for the population size 75 and 400 generations are shown in Table 6-9. All the optimal solutions consider PM for all machines. In addition, no maintenance technicians are considered. Therefore, it can be concluded that PM is the optimum strategy for all machines and no additional specialised maintenance technicians are required at this stage. Selecting the optimum *PMfreq* from the set of non-dominated solutions depends on the business environment and whether investing more in maintenance can be justified by the increase in the production output.

Table 6-9 Case A non-dominated solutions, population size: 75, number of generations: 400

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput (Tyres)	Cost ($)
158	159	313	158	1,884	1	1	1	1	1	0	15,334.54	29,050.00
158	159	313	156	1,884	1	1	1	1	1	0	15,341.85	29,100.00
160	159	314	135	1,895	1	1	1	1	1	0	15,345.69	29,400.00
160	154	306	145	1,911	1	1	1	1	1	0	15,347.08	29,600.00
160	158	282	147	1,903	1	1	1	1	1	0	15,351.92	29,650.00
160	154	274	145	1,903	1	1	1	1	1	0	15,352.15	29,900.00
160	147	306	147	1,903	1	1	1	1	1	0	15,352.23	29,950.00
160	158	314	159	1,405	1	1	1	1	1	0	15,353.92	30,250.00
160	158	314	159	1,389	1	1	1	1	1	0	15,355.62	30,650.00
159	159	318	154	1,389	1	1	1	1	1	0	15,356.77	30,700.00
160	159	274	157	1,407	1	1	1	1	1	0	15,356.92	30,750.00
160	154	274	159	1,407	1	1	1	1	1	0	15,357.08	30,900.00
159	159	270	152	1,405	1	1	1	1	1	0	15,364.92	30,950.00
160	159	274	143	1,391	1	1	1	1	1	0	15,368.92	31,350.00
160	154	274	147	1,389	1	1	1	1	1	0	15,371.54	31,450.00

6.5 Industrial Case B

6.5.1 Description of Factory B

Industrial case B is held in a large petrochemical company. Its products include: Aromatics, Acetic Acid, Purified Terephthalic Acid (PTA) and Bottle Grade Chips (PET) as illustrated in Figure 6-19.

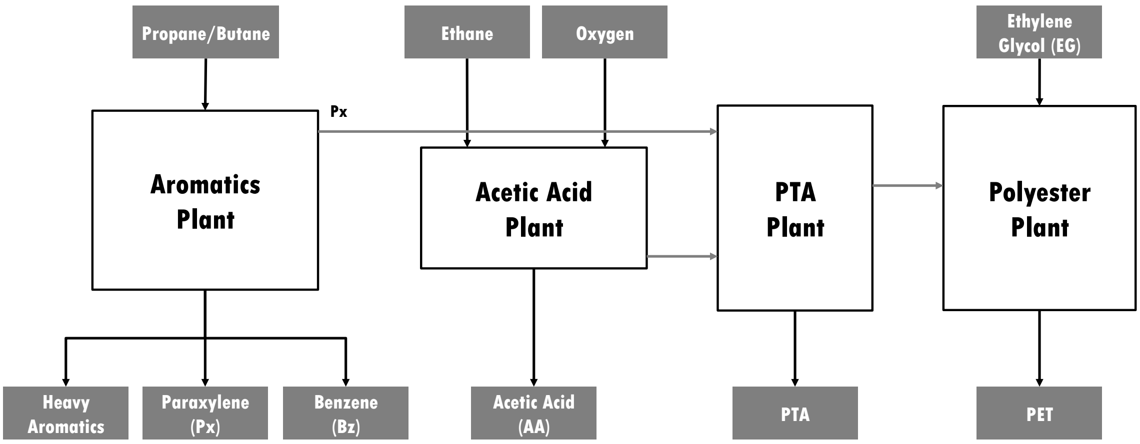


Figure 6-19 Plants in industrial case B

Detailed manufacturing data and accurate maintenance records are continuously updated in the SAP system. However, condition monitoring data are held separately in an asset management software. The focus of the current study is on one production line in the Polyester Plant, namely, Solid State Polycondensation (SSP) line. Polyester is formed by the polycondensation of PTA and Ethylene Glycol (EG) in a continuous manner using specialised catalyst in a series of reactors. The manufacturing process in SSP is illustrated in Figure 6-20.

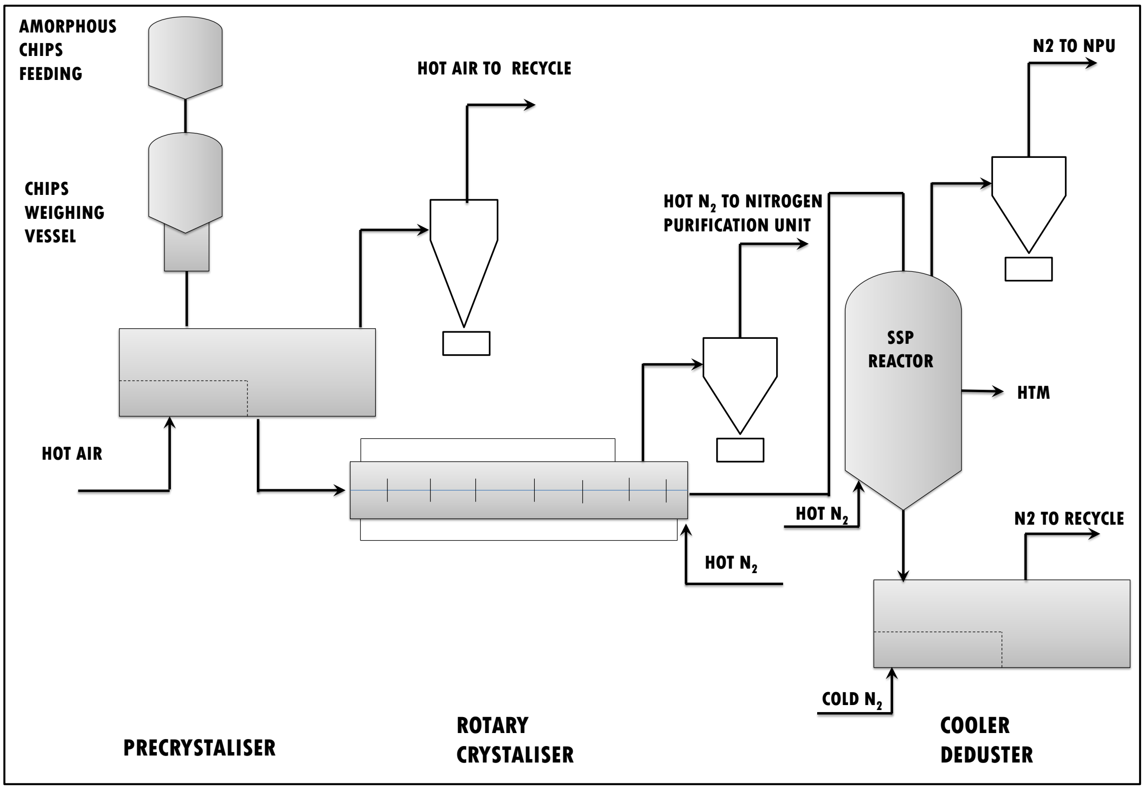


Figure 6-20 SSP flow diagram

Four main processes are involved as follows:

1. Pre Crystallisation:
   - Amorphous chips from the silo are conveyed via pneumatic conveying & rotary feeder into buffer vessels in which throughput of SSP is controlled by loss in weight system
   - Chips are partially crystallised in the fluidised bed with a closed loop hot air system
   - Pre Crystallised chips are fed into purge vessel where air is purged off with hot nitrogen

2. Crystallisation
    - Chips are heated & further crystallised in the Rotary Crystalliser
    - Hot pure Nitrogen from Nitrogen Purification Unit (NPU) is passed through the crystalliser to separate Oligomer, Acetaldehydes & moisture etc.
3. Solid State Polymerisation Reactor
    - Chips from the Crystalliser are fed to SSP reactor via a vertical tube
    - The partially crystallised chips are subjected to high temperature treatment in O_2 and H_2O free environment
    - Removal of volatile impurities (H_2O, EG etc.) is accomplished by diffusion to chips surface and carried out by hot pure nitrogen stream
4. Cooling and de-dusting: The hot chips from reactor are cooled and de-dust for bagging

The residence time for fluids in each stage is shown in Table 6-10.

Table 6-10 Residence time for fluids in each stage

	Stage	Residence time (hours)
1	Pre Crystallisation	Uniform (0.33,0.5)
2	Crystallisation	Uniform (0.5,1.0)
3	Solid State Polymerisation Reactor	Uniform (10,20)
4	Cooling and de-dusting	Uniform (0.67,0.83)

As fluid is continuously moving in the production line, if one machines breaks down, the whole line will be stopped. In addition, if the production line is stopped continuously for two hours or more, it has to be drained. Therefore, all machines will scrap the fluids. The simulation layout is shown in Figure 6-21.

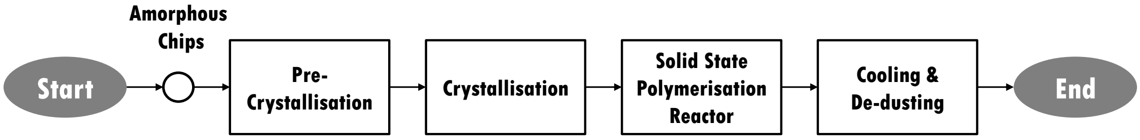


Figure 6-21 Case B simulation layout

6.5.2 Maintenance Operations

A range of maintenance strategies are applied including CM, OM and CBM. Table 6-11 shows CM and OM data. The standard rate for a labour hour is \$144. However, OM costs 66% less since it can occur when the asset has just been maintained. An additional cost of \$5,000 is incurred whenever CM occurs to reflect the fact that unscheduled breakdowns can result in relocation of maintenance and operation resources. CBM requires an investment of \$50,000 per machine to cover the costs of required equipment, software, support and training. Each scheduled inspection costs \$432 which includes taking the measurement and conducting the required analysis.

Table 6-11 CM and OM data for case B

Asset	MTBF	CM Repair time	OM repair time
Pre-Crystalliser	Weibull (0.586, 598)	1/ Gamma (0.564, 0.391)	1/ Beta (0.744, 14.6)
Crystalliser	Gamma (0.61, 3830)	1/ Gamma (0.92, 0.309)	Triangular (1, 12, 180)
Reactor	Weibull (0.676, 969)	1/ Beta (0.507, 1.22)	Triangular (1, 8, 1080)
Cooling	Gamma (0.563, 3350)	1/ Beta (0.529, 1.99)	Triangular (1, 28, 240)

The condition of each machine is modelled according to the data presented in Table 6-12. Inspections are conducted while the production line is operated. Whenever a maintenance action occurs on a machine, the condition is reset to the normal operation level.

Table 6-12 Condition monitoring data for case B

Asset	Probability of no change in the condition indicator	Asset degradation (PK mm/Sec) / 5 days	Normal operation level (PK mm/Sec)
Pre-Crystalliser	63%	Triangular (0.103, 0.207, 0.413)	0.43
Crystalliser	84%	0.1	2.65
Reactor	53%	Triangular (0.105, 0.209, 5.018)	1.85
Cooling	15%	Triangular (0.102, 0.1021, 0.562)	1.85

6.5.3 Simulation Based Optimisation for Case B Maintenance System

The framework is followed step by step as follows:

1. **Define the scope of the optimisation:** Discussions with both production and maintenance teams resulted in the identification of the critical assets as shown in Table 6-10. Spare parts policies are decided centrally for the whole corporation. Therefore, it is not possible to alter spare parts parameters. In addition, it is not possible to invest in extra buffer systems. As a result, the optimisation scope will be limited to the maintenance system only.
2. **Identify applicable maintenance strategies and policies:** In addition to considering CM as a maintenance strategy, OM is considered since the production line is continuous and the opportunity of a breakdown can be seized to conduct maintenance actions. CBM with periodic inspections is applicable and is considered as a possible maintenance strategy. It appears that CBM with periodic inspections is more efficient than time-based PM. This is because in the latter, maintenance is preformed regularly forcing a shutdown without considering the condition of assets. Inspections in CBM are conducted without affecting the operational status of the production line. The production line will be stopped to execute CBM only when it is necessary. Therefore, time-based PM is not considered in this case.

3. **Formulate the objective function:** Maximising production throughput is the main concern for the company. However, this objective has to be achieved at the minimum possible cost. Maintenance costs include the costs of conducting CM, OM and CBM.
4. **Define the decision variables:** The decision variables suggested by the framework are: the maintenance strategy for each machine, the inspection frequency for each machine and the CBM threshold for each machine. No other decision variables are required for this problem.
5. **Define constraints:** OM_i, CM_i and CBM_i are defined as decision variables that represent the selected maintenance strategy for each machine. The value 1 means the maintenance strategy is selected whereas the value 0 means the maintenance strategy is not selected. Since only one maintenance strategy can be selected for each machine at any time, the following constraint needs to be added: $OM_i + CM_i + CBM_i = 1$

   Inspections bounds can be set to take place between 15 and 60 days. CBM threshold values range between the normal operation level and the maximum vibration level. The optimisation problem can be defined as follows:

Minimise: *Maintenance Cost*
Maximise: *Production Throughput*

Subject to:

$$0.43 < CBM\ threshold_1 < 14$$
$$2.65 < CBM\ threshold_2 < 14$$
$$1.85 < CBM\ threshold_3 < 15$$
$$1.85 < CBM\ threshold_4 < 14$$
$$0 < OM_1 < 1$$
$$0 < CM_1 < 1$$
$$0 < CBM_1 < 1$$
$$0 < OM_2 < 1$$
$$0 < CM_2 < 1$$
$$0 < CBM_2 < 1$$
$$0 < OM_3 < 1$$
$$0 < CM_3 < 1$$
$$0 < CBM_3 < 1$$
$$0 < OM_4 < 1$$
$$0 < CM_4 < 1$$
$$0 < CBM_4 < 1$$
$$OM_1 + CM_1 + CBM_1 = 1$$

$$OM_2 + CM_2 + CBM_2 = 1$$
$$OM_3 + CM_3 + CBM_3 = 1$$
$$OM_4 + CM_4 + CBM_4 = 1$$
$$360 < Inspection\ frequency_1 < 1440$$
$$360 < Inspection\ frequency_2 < 1440$$
$$360 < Inspection\ frequency_3 < 1440$$
$$360 < Inspection\ frequency_4 < 1440$$

OM_i, CM_i, CBM_i and $Inspection\ frequency_i$ are integers

6. **Select the optimisation algorithm:** Following the framework flowchart results in selecting multi-objective optimisation as well as a problem that requires global search. As a result, NSGA II is one of the alternative optimisation algorithms that are suitable for this type of problem. It is selected to solve the optimisation problem in hand.
7. **Set the simulation optimisation:** The simulation run-length is 3 years. Figure 6-22 and Figure 6-23 show the variability analysis of the simulation model considering throughput and maintenance cost as the objective respectively. It appears that the objective function stabilise after 11 replications. Therefore, it will be selected as the number of replications for this case.

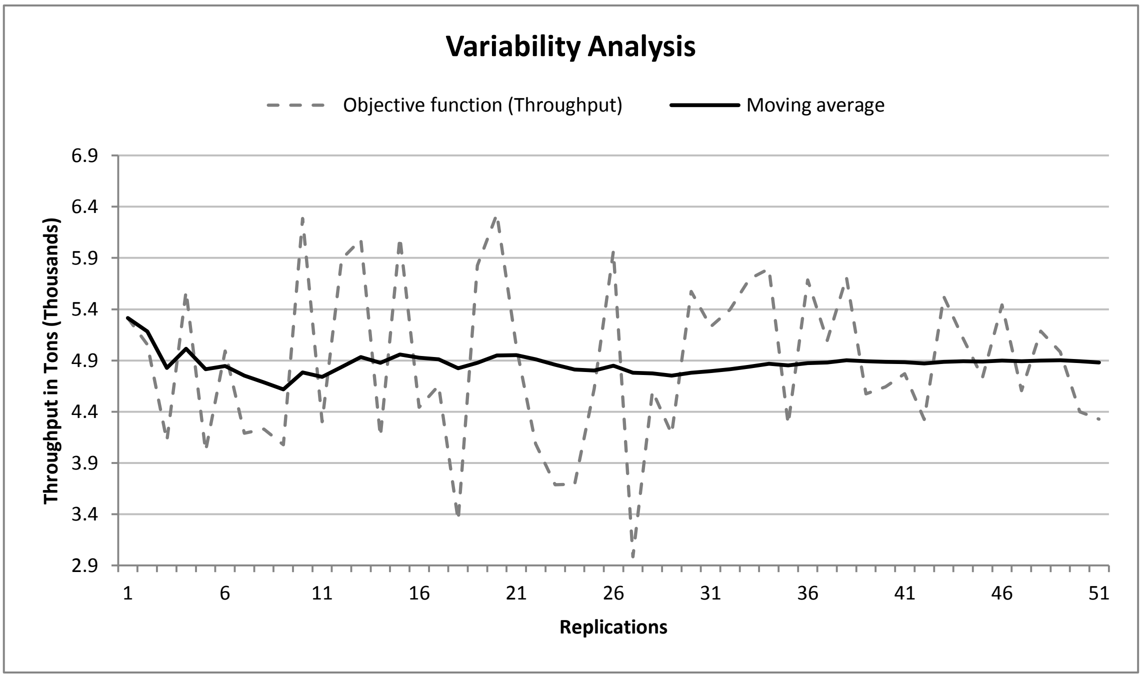


Figure 6-22 Variability analysis for case B simulation model considering throughput as an objective

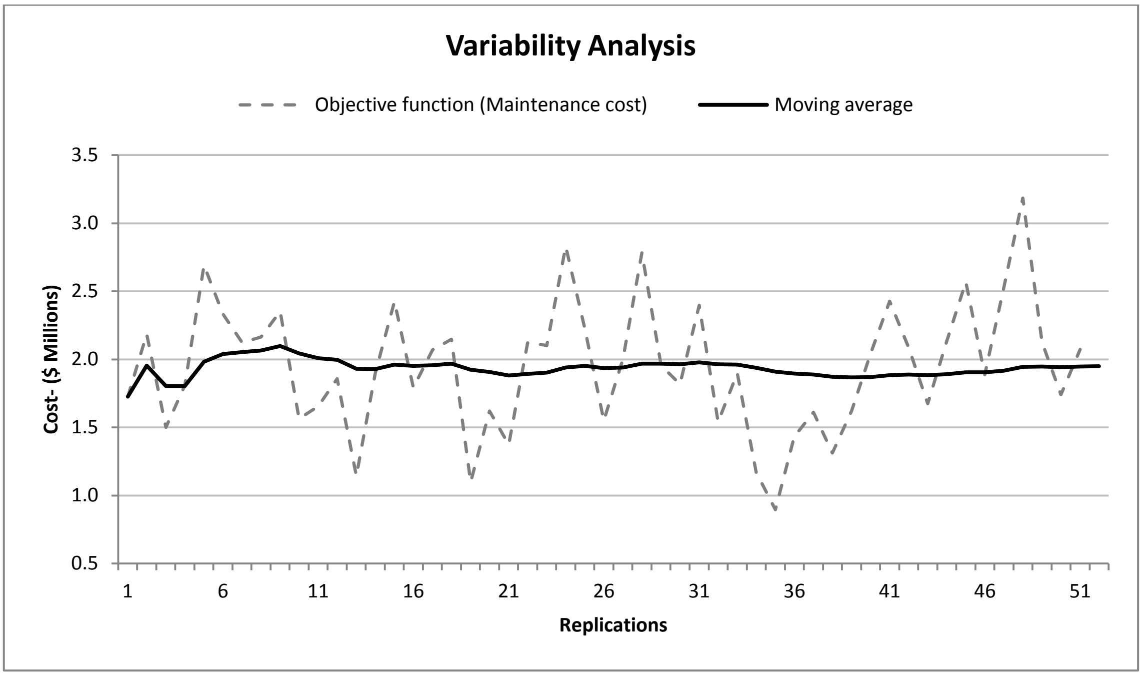


Figure 6-23 Variability analysis for case B simulation model considering maintenance cost as an objective

Figure 6-24 and Figure 6-25 show the analysis conducted on both throughput and maintenance cost respectively to select the required warm-up time. It can be concluded that 25 days are sufficient for the simulation model to reach a steady state since changes in the moving average are minimal after this period.

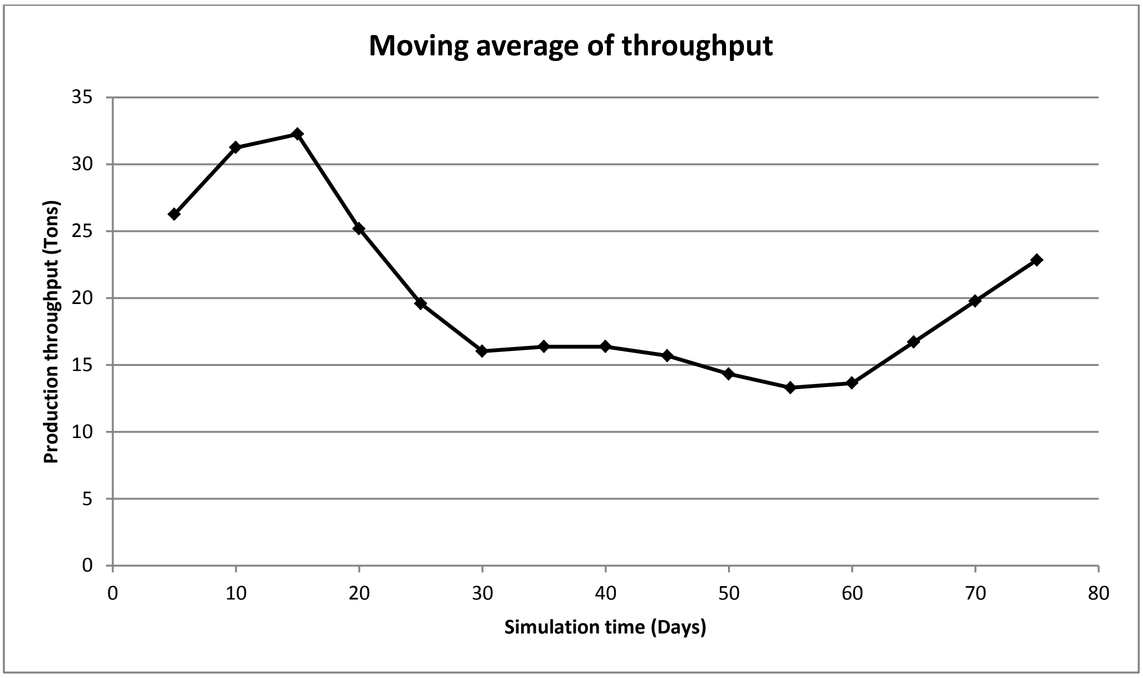


Figure 6-24 Warm-up analysis for case B simulation model considering throughput as an objective

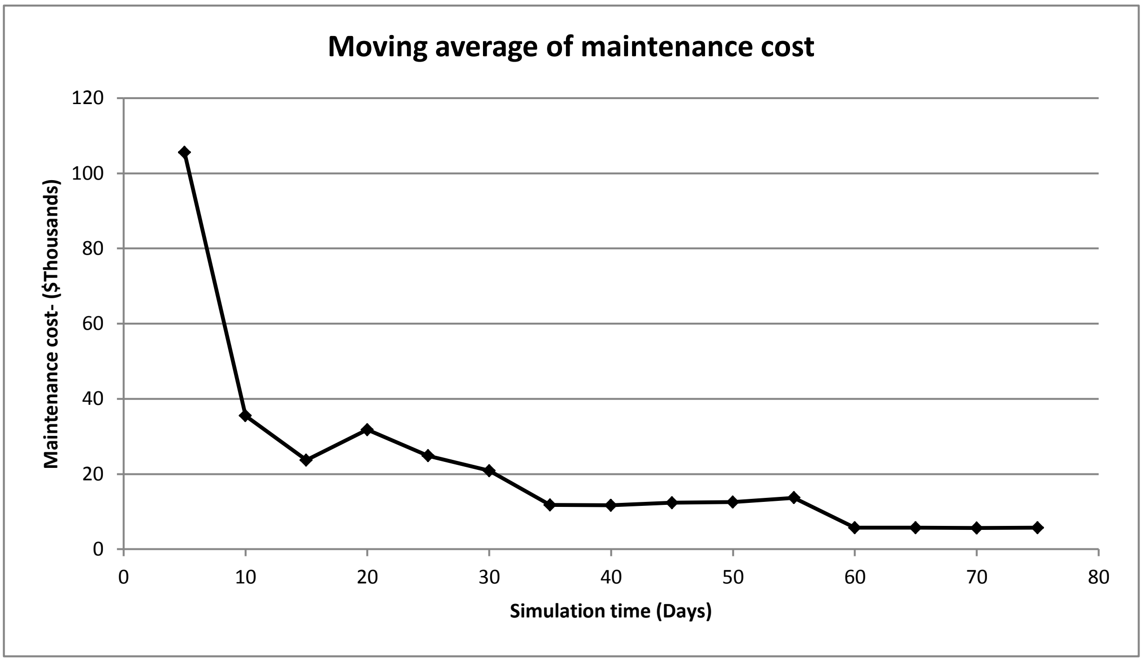


Figure 6-25 Warm-up analysis for case B simulation model considering maintenance cost as an objective

NSGA II was run for a combination of population sizes and generations. The optimisation plan along with the computational expenses are presented in Appendix F.1.

8. **Decision making:** It is interesting to observe that NSGA II produced a limited number of non-dominated solutions as shown in Figure 6-26. In fact, instead of the expected non-dominated front, the optimisation resulted in a single optimal solution. This could be an indication that maintenance cost and throughput are not conflicting objectives in this case. It is also interesting to observe that increasing the number of generations improved the results slightly for population size 50 while it did not improve the results at all for population sizes 75 and 100.

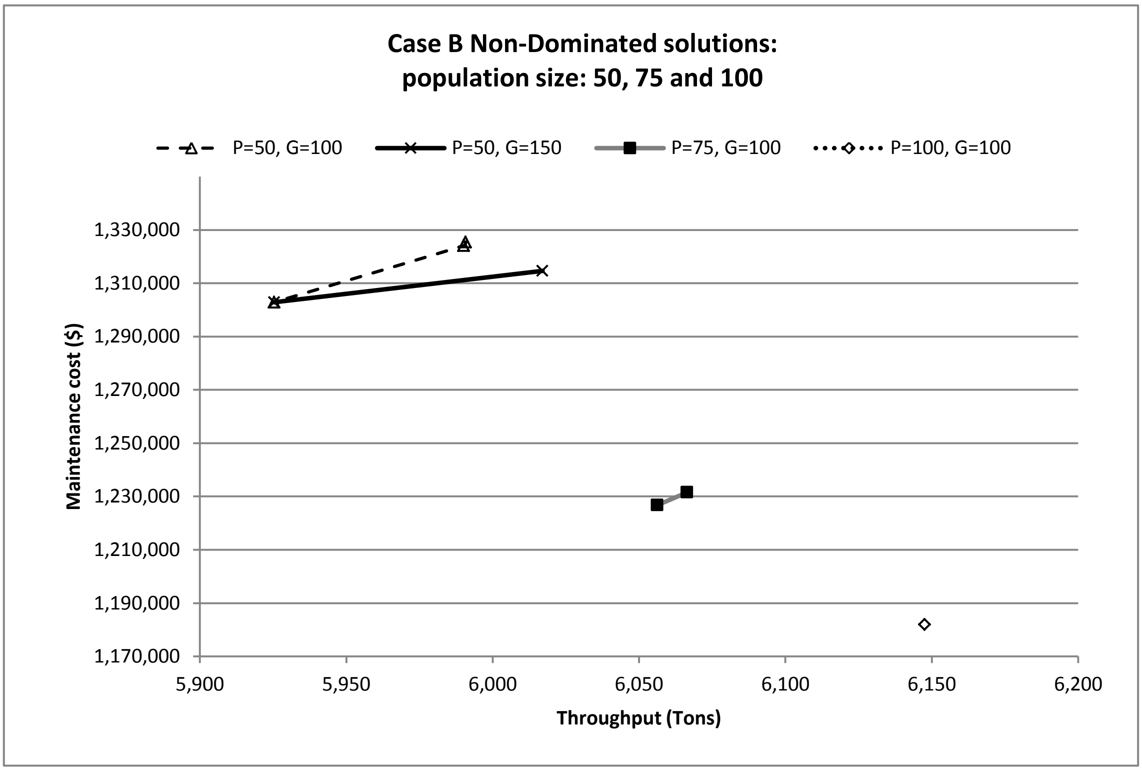


Figure 6-26 Case B all Non-Dominated solutions

The optimal solution is presented in Table 6-13. From this data, we can see that the optimum maintenance strategy is different for each machine. The optimum maintenance strategy for the pre-crystallisation process is CBM. An associated periodic inspection is suggested to be scheduled every 783 hours and CBM to be conducted if the vibration level exceeds 2.41 PK mm/Sec. OM is the optimum maintenance strategy for the crystallisation process. CM is the optimum strategy for both the reactor and the cooling processes.

Table 6-13 Optimal solution for case B

Decision variables	CBM threshold$_1$	2.41
	CBM threshold$_2$	6.11
	CBM threshold$_3$	13.39
	CBM threshold$_4$	6.24
	OM1	0
	CM1	0
	CBM1	1
	OM2	1
	CM2	0
	CBM2	0
	OM3	0
	CM3	1
	CBM3	0
	OM4	0
	CM4	1
	CBM4	0
	Inspection frequency$_1$	783
	Inspection frequency$_2$	1,434
	Inspection frequency$_3$	709
	Inspection frequency$_4$	1,037
Objectives	Cost ($)	1,181,926.31
	Throughput (Tons)	6,147.61

It is surprising to see that CM is the optimum maintenance strategy for two processes while more advanced maintenance strategies are available. This could be attributed to the high expenses associated with the installation of CBM which significantly affects the cost function. As this production line is continuous, OM can result in unnecessary delays for shutdowns. However, it appears that aged-based or time-based PM – implying periodic shutdowns - could prove beneficial for this type of production line.

Although the decision variables CBM threshold and inspection frequency are only significant if the selected maintenance strategy is CBM, it is still considered in the solution string by the optimisation algorithm even if the selected maintenance strategy is CM or OM. The current optimisation engine requires all decision variables to be defined at the same level. It is not possible to include a given decision variable only if another decision variable has certain values. As a result, in some runs, the optimisation algorithm would change the parameters of a maintenance strategy that is not selected resulting in wasting time by conducting meaningless simulation optimisation cycles.

6.6 Discussion

The objective of this chapter is to apply both the proposed simulation-based optimisation framework and the proposed modelling approach to different case studies. As shown in Table 6-14, the examined cases included an academic case and two industrial cases. The applications varied in terms of sector, size, number of manufacturing processes and level of maintenance documentation.

Table 6-14 Main features of cases

	Academic case	**Industrial case A**	**Industrial case B**
Sector	N/A	Tyre retreading	Petro-chemicals
Company size	N/A	Small < 50 employees	Large > 300 employees
Number of manufacturing processes	6	11	4
Maintenance documentation	N/A	Minimal	Updated regularly in SAP
Applicable maintenance strategies	CM and PM	CM and PM	CM, OM and CBM
Optimisation scope	Maintenance and spare parts policies	Maintenance	Maintenance
Optimisation objectives	Min Total costs (maintenance cost + spare parts cost + unavailability cost)	Max throughput Min maintenance cost	Max throughput Min maintenance cost
Decision variables	Maintenance strategy PM frequency Spare parts policy parameters: reorder level and order quantity	Maintenance strategy PM frequency Maintenance technicians	Maintenance strategy CBM inspection frequency CBM threshold

Very little was found in prior studies on discussing the scope of optimisation, investigating applicable maintenance strategies or formulating the optimal problem. However, in the current research, the simulation-based optimisation framework guided the process of connecting the simulation model to the optimisation engine. Application of the framework resulted in different optimisation scope, applicable maintenance strategies and optimal problem formulation for each case.

Observing a typical machine degradation cycle in the simulation models led to the conclusion that production dynamics and labour availability have a significant impact on maintenance performance. A typical machine degradation cycle is shown in Figure 6-27. The machine will degrade as long as it is in use. If there are no parts to be processed due to the breakdown of a preceding machine or due to shortages of raw materials, the machine will become idle and hence its degradation level remains constant. When the degradation level reaches the breakdown threshold the machine will stop working instantly and it will be repaired as soon as there are available spare parts and labour. PM is conducted periodically every *PMfreq*$_i$ unit of time. These results further confirm the risk of ignoring the discussion of involving production dynamics or labour availability in the simulation optimisation [104].

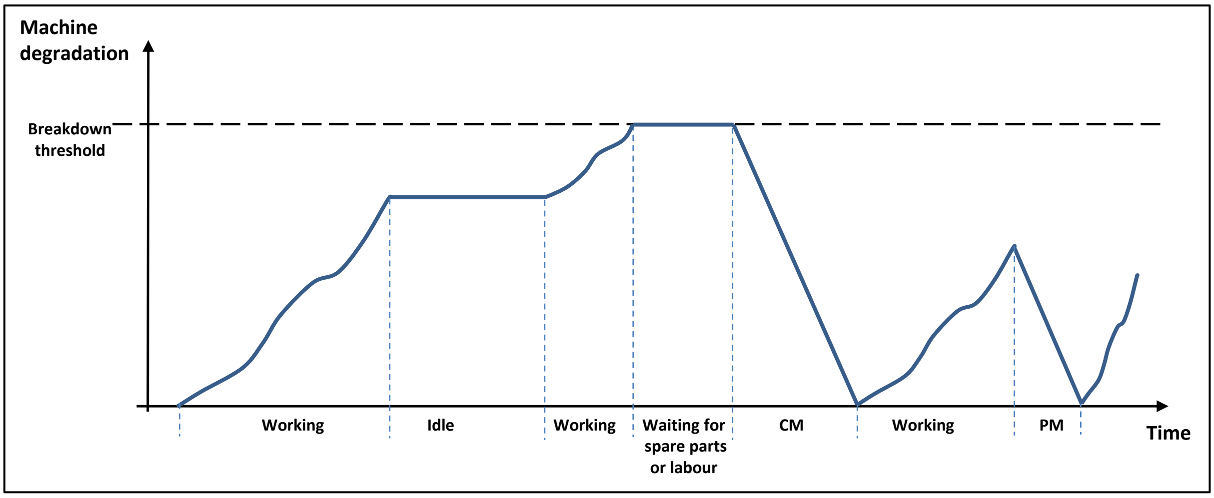


Figure 6-27 A typical machine degradation cycle

While the majority of prior studies focused on optimising the parameters of a given maintenance strategy, the results of industrial case B is one of the first to show the possibility of optimising maintenance strategies resulting in a different maintenance strategy for each asset. Since a change in one element of the simulation model such as buffer capacity or *PMfreq* for any asset in the system might affect the maintenance performance, it is difficult to assume an optimum maintenance strategy for any given asset. Therefore, it is suggested to evaluate all applicable maintenance strategies for critical assets in the system. The modelling of complex industrial systems involving various maintenance strategies was made possible using the proposed modelling approach.

Production throughput and maintenance cost were found to be conflicting objectives in case A. Conducting PM in shorter frequencies seems to increase the maintenance cost and increase the throughput at the same time. Similar trade-off solutions between cost and availability [40; 47], cost and reliability [135] and cost and profit [61] can be found in literature. One unanticipated finding from the academic case was that maintenance cost and production throughput might be non-conflicting in some cases. This could be due to the fact that the production reached its maximum capacity as can be indicated from Figure 6-8. The results of case B might confirm this finding. The two objectives appear to be initially conflicting, but as the solutions converge, only one non-dominated solution emerged indicating that objectives might be in fact non-conflicting [4].

In NSGA II, one may expect better solutions as the population size is increased. However, the results of this study shows that increasing the population size may lead to worse solutions. Population sizes 50 and 75 achieved better solutions in case A compared to population size 100. It is difficult to explain this result, but it might be related to the fact that each optimisation problem requires a certain population size and number of generations to achieve the best balance between diversity and conversion while considering present limitations such as time and computation expenses. In general, it is understood that increasing the population size leads to better diversification in solutions whereas running the algorithm for more generations leads to better conversion to the optimal front [4]. In this case, it is possible that larger population sizes negatively affected the progression of the algorithm towards the pareto front by attempting to achieve better diversity.

It was interesting to find out that none of the factories contacted by the researcher during data collection utilised simulation to optimise their manufacturing systems. This might have somewhat affected the availability of data. In industrial case A, collecting accurate data on manufacturing processes and maintenance operations was seen by the firm's management as a secondary issue. Although maintenance records were available in industrial case B, it required a considerable amount of analysis in order to make it usable for simulation purposes. For example, maintenance orders were created by different SAP users for the same maintenance task. This requires the manual removal of duplicating records in order to obtain accurate repair times.

While investigating multiple maintenance strategies, the optimisation algorithm might search in a useless space because some variables depend on the choice of maintenance strategy. For example, in case B inspection frequency and CBM threshold are relevant only if the selected maintenance strategy is CBM. However, NSGA II would search for inspection frequency and CBM threshold for an asset even if the selected maintenance strategy was CM or OM. This may reduce the algorithm's efficiency and result in running unnecessary simulations.

One of the issues that emerged from these findings is the high computational expenses associated with simulation-based optimisation of complex maintenance systems. Conducting such experiments in timely manner require multiple powerful workstations and inevitably multiple software licenses. This is an important issue for future research.

Notwithstanding these limitations, the current study suggests that the simulation-based optimisation is a promising framework that can be utilised in a wide range of complex industrial systems.

6.7 Summary

In this chapter, the aim was to demonstrate both the simulation-based optimisation framework and the modelling approach using industrial applications. This study has shown that the framework can guide the process of connecting the simulation model to the optimisation engine in case studies that vary in terms of sector, size, number of manufacturing processes and level of maintenance documentation. In addition, the current research is one of the first to optimise various maintenance strategies and its parameters while considering production dynamics and spare parts management. This was possible using the proposed maintenance modelling approach.

The results of this study indicate that optimising the parameters of a given maintenance strategy without optimising the choice of maintenance strategy can lead to sub-optimal solutions. The findings of this research provide insights for non-conflicting objectives in maintenance systems. Minimising maintenance cost might in fact lead to maximum availability or maximum production throughput. This would be a fruitful area for further work.

7 DISCUSSION AND CONCLUSIONS

This study set out with the aim of developing a simulation-based optimisation framework for maintenance systems. This chapter presents a discussion of key research findings and considers its implications. Research contributions are outlined and described. In addition, research limitations are identified and their potential impact is explained. Suggestions for further work and research are put forward. Finally, this thesis is concluded by comparing the objectives with the research achievements.

7.1 Discussion on Key Research Findings

7.1.1 State of the Art in Simulation-Based Optimisation of Maintenance Systems

It is observed that there is a potential as well as a growing interest amongst researchers to utilise simulation in optimising maintenance systems. The state of the art in simulation-based optimisation of maintenance was established by systematically classifying the published literature and outlining main trends in modelling and optimising maintenance systems.

Much of the research assumes PM is the only applicable maintenance strategy. This naturally leads to optimising PM parameters without considering alternative maintenance strategies. CBM received less attention. A possible explanation for this might be that it is less adopted in practice compared to PM. Nonetheless, the investigation of applicable maintenance strategies in the optimised system is rarely discussed.

Most researchers apply their suggested models in academia away from industrial systems. Developing theoretical models and demonstrating their applicability on simple academic case studies seems to have contributed to the gap between academia and practice. By contrast, industrial maintenance systems are becoming notably complex comprising of non-identical multi-assets that have various levels of dependencies amongst them.

In addition, researchers tend to model and optimise maintenance in isolation of other inter-related systems such as production and spare parts management. This can partly explain the fact that minimising maintenance cost and maximising availability are the most reported maintenance objectives whereas maximising throughput received much less attention. In general, only a few attempts are made to discuss the selection of optimisation objectives. Likewise, discussion of the other elements in optimal problem formulation such as decision variables and constraints is minimal.

Single-objective optimisation dominates the literature. The need for solving multi-objective problems is usually dealt with by combining several objectives in one objective. However, such approaches require setting weights that reflect preferences. Multi-objective optimisation can handle several objectives without the need to make compromises between objectives. Once the solutions are obtained, the decision can be made according to the specific environment [4]. Only limited research utilised multi-objective optimisation.

Discrete Event Simulation (DES) was the most reported technique in modelling maintenance systems. This can be seen as an extension to the popularity DES achieved in modelling manufacturing systems in general. Typical DES softwares provide a number of attractive features such as rapid modelling, animation, automatically collected performance measures and statistical analysis.

The use of modern optimisation methods to solve maintenance problems such as GA and SA were the most reported in literature. This may be due to the ability of such optimisation methods to solve the complexity present in maintenance problems. However, limited research was found on comparing the performance of optimisation algorithms.

In general, approaches to optimise maintenance varied significantly in literature. These include a wide range of optimisation objectives, decision variables and optimisation algorithms. Moreover, very little was found in literature on comparing and selecting the optimum maintenance strategy. Overall, these studies highlight the need for a framework that provides a unified approach to optimising maintenance systems. The framework can provide assistance to a user including investigating applicable maintenance strategies, formulating the optimisation problem and dealing with issues in contemporary maintenance systems.

7.1.2 A Framework for Simulation-based Optimisation of Maintenance Systems

Frameworks that guide the optimisation process are well established in literature [5; 91]. These frameworks are generic and can be applied to any optimisation problem. Few frameworks for maintenance optimisation exist. However, they are either inapplicable in complex optimisation problems [97] or do not provide adequate details to an academic/ practitioner in a decision structure [11; 98]. In addition, none of the simulation optimisation studies covered in the review of literature applied one of the existing frameworks or followed a structured approach which further supports the need for a novel framework.

Framework requirements were established through two main sources of published research. Surveys on maintenance simulation optimisation were examined to document comments on the approaches authors follow while optimising maintenance systems. In addition, advanced and future maintenance strategies were documented to ensure they can be accommodated in the proposed framework. Obtained requirements were categorised into two types: user-related requirements and maintenance-related requirements.

Requirements emerged mainly from issues in contemporary maintenance systems as well as gaps in the research. Uncertainty arises from the unpredictable nature of assets in addition to the lack of accurate maintenance data. Conflicting objectives are a feature of most engineering problems including maintenance. Complexity in maintenance systems is increasing as a result of a large number of inter-related components. Research in the field usually attempts to find a solution to a specific maintenance problem which has resulted in a large volume of publications. Consequently, it has become difficult for a user to match a maintenance problem in hand with published maintenance models. In addition, these maintenance models are difficult to understand and interpret. These issues are reformulated and classified as user-related requirements.

Two additional issues were reformulated and classified as maintenance-related requirements. These include: (i) over-looking systems that have a substantial impact on maintenance such as production and spare parts management and (ii) assuming that a given maintenance strategy is the optimum without evidence. Two more requirements were added based on research papers on upcoming trends in maintenance: (i) incorporating new maintenance strategies to ensure the continued applicability of the proposed framework, and (ii) integration with e-maintenance which provides several advantages and is expected to grow in the future.

The proposed framework was developed using a standard flowchart tool due to its familiarity and ability to depict decision structures clearly. It provides a systematic methodology that details the steps required to connect the simulation model to an optimisation engine. Unlike existing frameworks, the proposed framework was developed based on requirements captured from literature. Not only it provides guidance in terms of formulating the optimisation problem for the maintenance system at hand but it also provides support and assistance in defining the optimisation scope and investigating applicable maintenance strategies. Additionally, it considers current issues relating to maintenance systems both in research and in practice such as uncertainty, complexity and multi-objective optimisation. A comparison of both the proposed framework and the existing frameworks against the requirements revealed its ability to address more requirements than any of the existing frameworks.

The proposed framework, while conceptual, would be helpful to guide both researchers and practitioners in attempting to optimise maintenance systems. Moreover, it is possible for a software platform to be deigned based on the framework. This will facilitate its use as well as providing an opportunity for the framework to be integrated with e-maintenance.

7.1.3 A Novel Approach for Modelling Complex Maintenance Systems Using Discrete Event Simulation

The proposed framework outlined in the previous section cannot be applied using existing approaches for modelling maintenance. Analytical models are generally developed for a specific system comprising of a single unit or several identical components which limits their applicability to industrial systems [13]. Other modelling approaches that use simulation [31; 40; 60] have a number of limitations. The maintenance system is modelled separately from other inter-related systems such as production and spare parts logistics. In addition, these approaches are used to model one maintenance strategy only.

A novel approach for modelling maintenance using DES is proposed. The proposed approach enables the modelling of interactions amongst various maintenance strategies and their effects on the assets in a non-identical multi-unit system. The flexibility of DES ensures that a wide range of maintenance models can be simulated including methods for modelling asset degradation, the degree to which a maintenance action can successfully detect a failure and the degree to which a maintenance action can restore the asset to as good as new. The ability of the proposed approach to integrate with manufacturing simulation models without affecting their performance means that it can utilise the success DES achieved in the areas of production and spare parts management. In addition, typical DES softwares provide advantages such as rapid modelling and visual interactive simulation.

The approach is based mainly on the ability to access events queues and alter them in DES. A central function manages the applicable maintenance strategies in the system and the interactions amongst them. In addition to a generic approach, three common cases are provided including Time-Based PM, OM and CBM with periodic inspections. Unlike conceptual frameworks in the literature [16; 126], the proposed approach was demonstrated using two numerical examples.

The proposed approach enables the application of the proposed conceptual framework. Moreover, modelling complex maintenance systems may help to better understand the effect of various maintenance strategies. In addition, it opens the doors to optimising maintenance systems on a strategic level.

7.1.4 Demonstration and Validation

Recent evidence suggests that little research is conducted on the simulation optimisation of industrial case studies [104]. This study was designed to make an important contribution to the field of simulation optimisation by presenting two empirical case studies: a tyre re-treading factory and a petro-chemical plant. In addition, the industrial case studies are used to demonstrate the effectiveness of both the proposed conceptual framework presented in Chapter 4 and the proposed maintenance modelling approach presented in Chapter 5.

Using the proposed framework, simulation-based optimisation was conducted on three cases that vary in terms of industry sector, size, number of manufacturing processes and level of maintenance documentation. Unlike majority of studies in the field, following the structured framework enabled discussing and selecting a suitable optimisation scope and applicable maintenance strategies as well as formulating a customised optimisation problem for each case.

Observing a typical machine degradation cycle in the simulation models led to the conclusion that production dynamics and maintenance resources have a significant impact on maintenance performance which seems to be consistent with findings in earlier studies [16; 33; 86; 87].

In addition, current findings support previous research which highlighted the need for multi-objective optimisation in solving maintenance problems [11; 114]. A set of trade-off solutions were found to be present between production throughput and maintenance cost. Higher maintenance costs lead to higher throughput. These results that highlight conflicting objectives match those observed in earlier studies [40; 47; 61; 135]. However, one interesting finding is that production throughput and maintenance cost may not be conflicting objectives in some cases. Solutions with higher maintenance costs have lower throughput. This result may be explained by the fact that improving maintenance means intervening in the right time to avoid the implications of unexpected breakdowns such as higher costs, longer unavailability and lower throughput. It is possible that at the beginning of the optimisation, the objectives are conflicting while the optimisation algorithms experiment with decision variables and improve the results. However, as the optimal set of variables is reached the objectives are no longer conflicting.

The results of the study suggest that over-looking the optimisation of maintenance strategies may lead to sub-optimal solutions. The complexity of maintenance problems makes it difficult to assume a given maintenance strategy is the optimum for each asset in the system. Modelling multiple maintenance strategies was made possible by the proposed maintenance modelling approach.

The industrial case studies presented suggest that the proposed framework can be utilised in a wide range of complex industrial systems. In addition, it provides support to a user while attempting to optimise maintenance systems through simulation.

7.2 Research Contributions

The main aim of this research is to develop a simulation-based optimisation framework for maintenance systems. The framework development was based on a systematic review of published research. The proposed framework was validated using industrial case studies. What follows is an outline of the main contributions to knowledge achieved from the current research.

Three major contributions emerged from this study:

(i) A simulation based optimisation framework for maintenance systems

(ii) An approach for modelling complex maintenance systems using DES

(iii) Optimising maintenance of industrial systems using both the proposed framework and the modelling approach

7.2.1 State of the Art in Simulation-Based Optimisation of Maintenance Systems

The state of the art in simulation-based optimisation of maintenance was reported by systematically classifying the published literature and outlining main trends in modelling and optimising maintenance systems. With the aim of identifying current practices, outstanding issues and common limitations, analysis was conducted on various aspects including application areas, maintenance strategies and policies, simulation software and modelling techniques, optimisation methods and software, optimisation objectives, decision variables and constraints. In particular, the following research gaps were identified:

1. Optimising multiple maintenance strategies
2. Optimising complex maintenance systems
3. Optimising maintenance in conjunction with the production system and maintenance resources
4. Utilising multi-objective optimisation in maintenance
5. Applications on industrial case studies
6. Discussing the optimisation problem formulation

These research gaps can be addressed by developing a systematic methodology that provides assistance in formulating the optimisation problem and dealing with issues surrounding maintenance problems.

7.2.2 Requirements of the Proposed Framework

This research extends our knowledge by identifying nine requirements for simulation-based optimisation framework for maintenance systems. The requirements were established by examining review papers in maintenance optimisation as well as publications on future maintenance applications. Furthermore, existing maintenance optimisation frameworks were examined and evaluated against these requirements.

7.2.3 Proposed Simulation-Based Optimisation Framework

The conceptual framework is a systematic methodology that provides detailed assistance for optimising maintenance simulation models. A step-by-step flow chart guides a user in defining the optimisation scope, identifying applicable maintenance strategies, formulating the optimisation problem, selecting the optimisation algorithm, setting the simulation parameters and interpreting the results enabling practitioners and researchers to customise the maintenance problem to their specific needs.

Additionally, it considers current issues relating to maintenance systems both in research and in practice such as uncertainty, complexity and multi-objective optimisation. A comparison of the proposed framework and existing frameworks against the requirements revealed its ability to address more requirements than any of the existing frameworks.

7.2.4 Proposed Approach for Modelling Maintenance Strategies and Policies

A novel approach for modelling complex maintenance systems was proposed enabling the modelling of non-identical multi-unit manufacturing systems without restrictions on maintenance or manufacturing characteristics. A generic approach as well as approaches for modelling common maintenance strategies were presented including time-based PM, OM and CBM. The approach can be integrated with DES manufacturing and spare parts models making it possible to build on the success DES achieved in these fields. Additional advantages of using DES include rapid modelling and visual interactive simulation.

The proposed approach enables the modelling of the complexity found in real maintenance systems. In particular, the approach enables the modelling of the following:

- Multi-unit manufacturing systems, without restrictions on the number of units
- Non-identical units, without restrictions placed on the manufacturing or the maintenance characteristics of units
- Several maintenance strategies and policies simultaneously
- Maintenance integrated with inter-related systems such as production and spare parts management
- Complex maintenance systems without over-simplified assumptions such as instantaneous repair, perfect maintenance or perfect inspection

The validation of the proposed approach was achieved through numerical examples.

7.2.5 Demonstration and Industrial Case Studies

Both the conceptual framework and the maintenance modelling approach were validated using three cases that vary in terms of industry sector, size, number of manufacturing processes and level of maintenance documentation. Two of the case studies are from the industry in addition to an academic case study. This is a further contribution since limited empirical case studies can be found in research.

7.3 Research Limitations

7.3.1 Generalisation of Research Findings

The proposed simulation-based optimisation framework was developed for industrial maintenance systems in a production context. It is based on extensive review of literature. In addition, it was validated through an academic case and two industrial systems. In general, it appears that the proposed framework can be applied to maintenance in production systems. However, a note of caution is due here since the generalisation of the framework's applicability cannot be claimed for the whole variety of maintenance systems in industry.

7.3.2 Modelling Age-Based Maintenance Strategies

The proposed modelling approach does not enable the modelling of age-based maintenance strategies. Accessing the events queue in DES is possible for time-based strategies since the exact simulation time of the next stochastic breakdown can be determined. On the contrary, in age-based strategies where breakdowns depend on the time the asset spends in an operational mode, it is more difficult to track the breakdown time. This is partly due to the various variable factors affecting the asset state such as production dynamics and maintenance interventions. Although it may not be possible to track and access the exact breakdown instance in simulation time beforehand, in principle, it is possible to sample from a statistical distribution and reschedule the next breakdown by resetting the available age the asset has before it breaks down.

7.3.3 Validation of Simulation Results

Simulation by definition is an abstract and simplification of a real system. Difficulties of validating simulation models are well documented [85]. A simulation model can be validated partly by comparing its results with the real system. In maintenance systems, simulation models can be validated by comparing production and maintenance results with historical records. In addition, maintenance managers can be engaged in the validation process especially if visual animation is present. However, one of the main advantages of simulation is the ability to experiment with a system without changing any aspect of it in the real world. While it may be possible to validate the as-is model, it is challenging to validate the optimal solution especially when considering new maintenance strategies where no historical records exist.

7.3.4 Computational Expenses in Simulation Optimisation

The ability of simulation to model complex systems comes at the risk of running into high computational expenses. The cost of simulation software and multiple powerful workstations are relatively high. Even then, simulation optimisation will consume a long time as shown in the current research. It may be needed to investigate ways to increase the efficiency of the optimisation algorithms. The search of the optimisation algorithms in useless spaces as found in the current research might lead to loss of efficiency. This is because the choice of some decision variables affect the relevancy of others. Some maintenance strategies require a unique set of parameters such as frequency for PM and various thresholds for CBM. The parameters of CBM are irrelevant if the choice of maintenance strategy is PM. Currently, the optimisation algorithms conduct their search in all parameters for all defined maintenance strategies although only relevant parameters would have an effect on the simulation results. In some instances, the optimisation algorithm would change the parameters of a maintenance strategy that is not selected resulting in wasting time by conducting meaningless simulation optimisation cycles. This can be targeted to increase computational efficiency of simulation optimisation.

7.4 Future Work

7.4.1 A Framework for Maintenance Simulation

Developing a framework for simulating maintenance systems would be a fruitful area for further work. The simulation framework can suggest various modelling approaches based on the current maintenance system characteristics and configuration. It can help in deciding how to model maintenance strategies and what simulation techniques are most appropriate to the system in interest.

7.4.2 Developing a Platform to Enable Integration with E-Maintenance

There is a growing interest in the concept of e-maintenance. The ability to gain remote access to the maintenance information infrastructure through various means, the integration of maintenance with other functions within organisations, the enhanced collaboration opportunities, and the utilisation of real time data to design optimum maintenance strategies are some of the potential benefits of e-maintenance [108]. The proposed simulation-based optimisation framework can be extended further to support integration with e-maintenance. This may enable the utilisation of continuous data streaming to support decision-making in real time.

7.4.3 Reducing Computational Expenses

One of the issues that emerge from these findings is the high computational expenses associated with simulation-based optimisation of complex maintenance systems. Conducting such experiments in timely manner require multiple powerful workstations and inevitably multiple software licenses. A possible area of future research would be to investigate approaches for reducing computational expenses. In addition, the search of the optimisation algorithm in useless space as found in the current research might be reduced to lead to approaches where more efficiency is realised.

7.5 Conclusions

Maintenance plays an important role in sustaining and improving asset availability. This project was undertaken to advance the research and applications of maintenance by developing a simulation-based optimisation framework. In this section, insights from this research are presented followed by a comparison of research findings with the research objectives.

The findings of this research provide the following main insights:

- Nine requirements for the simulation-based optimisation framework of maintenance systems are extracted from review papers in maintenance optimisation as well as publications on future maintenance applications. In addition, existing frameworks do not meet most of these requirements
- This study is one of the first to optimise maintenance strategies simultaneously with their parameters while considering production dynamics and spare parts management. The results of this study suggest that over-looking the optimisation of maintenance strategies may

lead to sub-optimal solutions. The complexity of maintenance problems makes it difficult to assume a given maintenance strategy is the optimum for each asset in the system

- The findings of this research provide insights for non-conflicting objectives in maintenance systems. In some cases, it appears that traditional trade-offs between maintenance cost and asset availability or maintenance cost and production throughput are not present.

The research objectives described earlier are compared with the findings of this study as follows:

1. **Identify current practices, outstanding issues and common limitations related to the field of maintenance simulation and optimisation.**

   The state of the art in simulation-based optimisation of maintenance was reported by systematically classifying the published literature. Articles were analysed based on various aspects including application areas, maintenance strategies and policies, simulation software and modelling techniques, and optimisation methods and software, yielding an outline of research gaps and directions for future research.

2. **Define typical variables, constraints and objectives for maintenance optimisation.**

   The review of the literature revealed a number of typical variables, constraints and objectives for maintenance optimisation. The most reported of these elements were highlighted.

3. **Identify the requirements of a simulation-based optimisation framework for maintenance systems.**

   This research extends the knowledge by identifying nine requirements that are categorised as user-related requirements and maintenance-related requirements. The requirements were established by examining review papers in maintenance optimisation as well as publications on future maintenance applications.

4. **Develop a simulation-based optimisation framework for maintenance systems at operational level.**

   A conceptual framework for optimising maintenance simulation models is proposed. It is a systematic methodology that guides a user in defining the optimisation scope, identifying applicable maintenance strategies, formulating the optimisation problem, selecting the optimisation algorithm, setting the simulation parameters and interpreting the results enabling practitioners and researchers to customise the maintenance problem to their specific needs. Additionally, it considers current issues relating to maintenance systems both in research and in practice such as uncertainty, complexity and multi-objective optimisation.

5. **Develop an approach for modelling maintenance strategies and policies in complex systems using Discrete Event Simulation.**

   A novel approach for modelling complex maintenance systems was proposed enabling the modelling of non-identical multi-unit manufacturing systems without restrictions on either the maintenance or manufacturing characteristics. A generic approach as well as approaches for common maintenance strategies were presented. The approach can be integrated with DES manufacturing and spare parts models making it possible to build on the success DES achieved in these fields. Additional advantages of using DES include rapid modelling and visual interactive simulation. The approach was validated using numerical examples.

6. **Validate the proposed framework through industrial case studies.**

   Two industrial case studies were presented to validate the proposed framework. Following the structured framework on a tyre re-treading factory and a petro-chemical plant enabled selecting the suitable optimisation scope, applicable maintenance strategies and formulating the optimisation problem for each case.

REFERENCES

[1] Wang, L., Chu, J. and Mao, W. (2008), "An optimum condition-based replacement and spare provisioning policy based on Markov chains", *Journal of Quality in Maintenance Engineering,* vol. 14, no. 4, pp. 387-401.

[2] Wang, W. (2008), "Delay time modelling", in Kobbacy, K. and Murthy, D. N. (eds.) *Complex system maintenance handbook,* Springer, London, pp. 345-370.

[3] Yao, X., Fernández-Gaucherand, E., Fu, M. C. and Marcus, S. I. (2004), "Optimal preventive maintenance scheduling in semiconductor manufacturing", *IEEE Transactions on Semiconductor Manufacturing,* vol. 17, no. 3, pp. 345-356.

[4] Deb, K. (2001), *Multi-objective optimization using evolutionary algorithms,* John Wiley & Sons, Chichester, England.

[5] Cavazzuti, M. (2013), *Optimization methods from theory to design scientific and technological aspects in mechanics,* Springer, New York.

[6] Lei, Y., Liu, J., Ni, J. and Lee, J. (2010), "Production line simulation using STPN for maintenance scheduling", *Journal of Intelligent Manufacturing,* vol. 21, no. 2, pp. 213-221.

[7] Boulet, J. F., Gharbi, A. and Kenn, J. P. (2009), "Multiobjective optimization in an unreliable failure-prone manufacturing system", *Journal of Quality in Maintenance Engineering,* vol. 15, no. 4, pp. 397-411.

[8] Pintelon, L. and Parodi-Herz, A. (2008), "Maintenance: An Evolutionary Perspective", in Kobbacy, K. and Murthy, D. N. (eds.) *Complex System Maintenance Handbook,* Springer, London, pp. 21-48.

[9] Rosqvist, T., Laakso, K. and Reunanen, M. (2009), "Value-driven maintenance planning for a production plant", *Reliability Engineering & System Safety,* vol. 94, no. 1, pp. 97-110.

[10] Waeyenbergh, G. and Pintelon, L. (2002), "A framework for maintenance concept development", *International Journal of Production Economics,* vol. 77, no. 3, pp. 299-313.

[11] Van Horenbeek, A., Pintelon, L. and Muchiri, P. (2010), "Maintenance optimization models and criteria", *International Journal of Systems Assurance Engineering and Management,* vol. 1, no. 3, pp. 189-200.

[12] Faccio, M., Persona, A., Sgarbossa, F. and Zanin, G. (2014), "Industrial maintenance policy development: A quantitative framework", *International Journal of Production Economics,* vol. 147, no. Part A, pp. 85-93.

[13] Van Horenbeek, A., Buré, J., Cattrysse, D., Pintelon, L. and Vansteenwegen, P. (2013), "Joint maintenance and inventory optimization systems: a review", *International Journal of Production Economics,* vol. 143, no. 2, pp. 499–508.

[14] Goti, A., Oyarbide-Zubillaga, A. and Sánchez, A. (2007), "Optimizing preventive maintenance by combining discrete event simulation and genetic algorithms", *Hydrocarbon Processing,* vol. 86, no. 10, pp. 115-122.

[15] Nicolai, R. P. and Dekker, R. (2008), "Optimal maintenance of multi-component systems: a review", in Kobbacy, K. and Murthy, D. N. (eds.) *Complex system maintenance handbook,* Springer, London, pp. 263-286.

[16] Duffuaa, S., Ben-Daya, M., Al-Sultan, K. and Andijani, A. (2001), "A generic conceptual simulation model for maintenance systems", *Journal of Quality in Maintenance Engineering,* vol. 7, no. 3, pp. 207-219.

[17] Rezg, N., Chelbi, A. and Xie, X. (2005), "Modeling and optimizing a joint inventory control and preventive maintenance strategy for a randomly failing production unit: analytical and simulation approaches", *International Journal of Computer Integrated Manufacturing,* vol. 18, no. 2-3, pp. 225-235.

[18] Gupta, A. and Lawsirirat, C. (2006), "Strategically optimum maintenance of monitoring-enabled multi-component systems using continuous-time jump deterioration models", *Journal of Quality in Maintenance Engineering,* vol. 12, no. 3, pp. 306-329.

[19] Marseguerra, M., Zio, E. and Podofillini, L. (2002), "Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation", *Reliability Engineering and System Safety,* vol. 77, no. 2, pp. 151-165.

[20] Briš, R. (2008), "Parallel simulation algorithm for maintenance optimization based on directed Acyclic Graph", *Reliability Engineering and System Safety,* vol. 93, no. 6, pp. 874-884.

[21] Allaoui, H. and Artiba, A. (2004), "Integrating simulation and optimization to schedule a hybrid flow shop with maintenance constraints", *Computers and Industrial Engineering,* vol. 47, no. 4, pp. 431-450.

[22] Sebastian, W. (2006), "Simulation of Manufacturing Processes", in Sauer, W. (ed.) *Electronics process technology production modelling, simulation and optimisation,* Springer, London, pp. 119-172.

[23] Dekker, R. (1996), "Applications of maintenance optimization models: a review and analysis", *Reliability Engineering and System Safety,* vol. 52, no. 3, pp. 229-240.

[24] Sharma, A., Yadava, G. and Deshmukh, S. (2011), "A literature review and future perspectives on maintenance optimization", *Journal of Quality in Maintenance Engineering,* vol. 17, no. 1, pp. 5-25.

[25] Garg, A. and Deshmukh, S. (2006), "Maintenance management: literature review and directions", *Journal of Quality in Maintenance Engineering,* vol. 12, no. 3, pp. 205-238.

[26] Amaran, S., Sahinidis, N. V., Sharda, B. and Bury, S. J. (2014), "Simulation optimization: a review of algorithms and applications", *4OR,* vol. 12, no. 4, pp. 301-333.

[27] Baines, T. S., Lightfoot, H. W., Evans, S., Neely, A., Greenough, R., Peppard, J., Roy, R., Shehab, E., Braganza, A., Tiwari, A., Alcock, J. R., Angus, J. P., Bastl, M., Cousens, A., Irving, P., Johnson, M., Kingston, J., Lockett, H., Martinez, V., Michele, P., Tranfield, D., Walton, I. M. and Wilson, H. (2007), "State-of-the-art in product-service systems", *Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture,* vol. 221, no. 10, pp. 1543-1552.

[28] Vasili, M., Hong, T. S., Ismail, N. and Vasili, M. (2011), "Maintenance optimization models: a review and analysis", *Proceedings of the 2011 International Conference on Industrial Engineering and Operations Management,* 22–24 January 2011, Kuala Lumpur, Malaysia, pp. 1131-1138.

[29] Andijani, A. and Duffuaa, S. (2002), "Critical evaluation of simulation studies in maintenance systems.", *Production Planning and Control,* vol. 13, no. 4, pp. 336-341.

[30] Alabdulkarim, A. A., Ball, P. D. and Tiwari, A. (2013), "Applications of Simulation in Maintenance Research", *World Journal of Modelling and Simulation,* vol. 9, no. 1, pp. 14-37.

[31] Asadzadeh, S. M. and Azadeh, A. (2014), "An integrated systemic model for optimization of condition-based maintenance with human error", *Reliability Engineering and System Safety,* vol. 124, pp. 117-131.

[32] Rasmekomen, N. and Parlikad, A. K. (2013), "Maintenance optimization for asset systems with dependent performance degradation", *IEEE Transactions on Reliability,* vol. 62, no. 2, pp. 362-367.

[33] Arab, A., Ismail, N. and Lee, L. S. (2013), "Maintenance scheduling incorporating dynamics of production system and real-time information from

workstations", *Journal of Intelligent Manufacturing,* vol. 24, no. 4, pp. 695-695.

[34] Van Horenbeek, A. and Pintelon, L. (2013), "A dynamic predictive maintenance policy for complex multi-component systems", *Reliability Engineering and System Safety,* vol. 120, pp. 39-50.

[35] Triki, C., Alalawin, A. and Ghiani, G. (2013), "Optimizing the performance of complex maintenance systems", *2013 5th International Conference on Modeling, Simulation and Applied Optimization, ICMSAO 2013,* 28-30 April 2013, Hammamet, Tunisia, IEEE, Piscataway, NJ, pp. 1-6.

[36] Alrabghi, A., Tiwari, A. and Alabdulkarim, A. (2013), "Simulation based optimization of joint maintenance and inventory for multi-components manufacturing systems", *Proceedings of the 2013 Winter Simulation Conference,* 8-12 December 2013, Washington DC, IEEE, Piscataway, NJ, pp. 1109-1119.

[37] Schutz, J. and Rezg, N. (2013), "Maintenance strategy for leased equipment", *Computers and Industrial Engineering,* vol. 66, no. 3, pp. 593-600.

[38] Roux, O., Duvivier, D., Quesnel, G. and Ramat, E. (2013), "Optimization of preventive maintenance through a combined maintenance-production simulation model", *International Journal of Production Economics,* vol. 143, no. 1, pp. 3-12.

[39] Lynch, P., Adendorff, K., Yadavalli, V. S. S. and Adetunji, O. (2013), "Optimal spares and preventive maintenance frequencies for constrained industrial systems", *Computers and Industrial Engineering,* vol. 65, no. 3, pp. 378-387.

[40] Van Horenbeek, A. and Pintelon, L. (2012), "Optimal prognostic maintenance planning for multi-component systems", *European Safety and Reliability Conference: Advances in Safety, Reliability and Risk Management, ESREL 2011,* 18-22 September 2011, Troyes, France, Taylor & Francis Group, London, pp. 910-917.

[41] Yun, W. Y., Han, Y. J. and Park, G. (2012), "Optimal preventive maintenance interval and spare parts number in a rolling stock system", *2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering, ICQR2MSE 2012,* 15-18 June 2012, Chengdu, China, IEEE, Piscataway, NJ, pp. 380-384.

[42] Zhou, Y., Zhang, Z. and Ma, L. (2012), "Maintenance optimisation of a series-parallel system with multi-state components considering economic dependence", *2012 International Conference on Quality, Reliability, Risk,*

Maintenance, and Safety Engineering, ICQR2MSE 2012, 15-18 June 2012, Chengdu, China, IEEE, Piscataway, NJ, pp. 427-431.

[43] Xiang, Y., Cassady, C. R. and Pohl, E. A. (2012), "Optimal maintenance policies for systems subject to a Markovian operating environment", *Computers and Industrial Engineering,* vol. 62, no. 1, pp. 190-197.

[44] Gomez U., E. D., Hennequin, S. and Rezg, N. (2011), "Optimization of a failure - prone manufacturing system with regular preventive maintenance: an IPA approach", *18th IFAC World Congress,* Vol. 18, 28 August-2 September 2011, Milan, Italy, pp. 10422-10427.

[45] Um., I. S., Cheon, H. J. and Lee, H. C. (2011), "A simulation-based optimal design and analysis method for designing a train overhaul maintenance facility", *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit,* vol. 225, no. 5, pp. 523-539.

[46] Ramírez-Hernández, J. A. and Fernandez, E. (2010), "Optimization of preventive maintenance scheduling in semiconductor manufacturing models using a simulation-based approximate dynamic programming approach", *Proceedings of the IEEE Conference on Decision and Control,* 15-17 Dec 2010, Atlanta, GA, USA, pp. 3944-3949.

[47] Johansson, E. C. and Jägstam, M. (2010), "Maintenance planning using simulation-based optimization", *Spring Simulation Multiconference 2010, SpringSim'10,* 11-15 April 2010, Orlando, Society for Computer Simulation International, San Diego, CA, pp. 1-8.

[48] Ramírez-Hernández, J. A., Crabtree, J., Yao, X., Fernandez, E., Fu, M. C., Janakiram, M., Marcus, S. I., O'Connor, M. and Patel, N. (2010), "Optimal preventive maintenance scheduling in semiconductor manufacturing systems: software tool and simulation case studies", *IEEE Transactions on Semiconductor Manufacturing,* vol. 23, no. 3, pp. 477-489.

[49] Tateyama, T., Tateno, T. and Shimizu, K. (2010), "Dynamic work planning by using simulation-based optimization in consideration of workers' skill and training", *Journal of Advanced Mechanical Design, Systems and Manufacturing,* vol. 4, no. 3, pp. 597-604.

[50] Shenfield, A., Fleming, P. J., Kadirkamanathan, V. and Allan, J. (2010), "Optimisation of maintenance scheduling strategies on the grid", *Annals of Operations Research,* vol. 180, no. 1, pp. 213-231.

[51] Fallah-Fini, S., Rahmandad, H., Triantis, K. and de la Garza, J. M. (2010), "Optimizing highway maintenance operations: dynamic considerations", *System Dynamics Review,* vol. 26, no. 3, pp. 216-238.

[52] Boschian, V., Rezg, N. and Chelbi, A. (2009), "Contribution of simulation to the optimization of maintenance strategies for a randomly failing production system", *European Journal of Operational Research,* vol. 197, no. 3, pp. 1142-1149.

[53] Ng, M. W., Lin, D. Y. and Waller, S. T. (2009), "Optimal long-term infrastructure maintenance planning accounting for traffic dynamics", *Computer-Aided Civil and Infrastructure Engineering,* vol. 24, no. 7, pp. 459-469.

[54] Guizzi, G., Gallo, M. and Zoppoli, P. (2009), "Condition based maintenance: Simulation and optimization", *Proceedings of the 8th WSEAS International Conference on System Science and Simulation in Engineering, ICOSSSE '09,* 17-19 Oct 2009, Genova, Italy, pp. 319-325.

[55] Murino, T., Romano, E. and Zoppoli, P. (2009), "Maintenance policies and buffer sizing: an optimization model", *WSEAS Transactions on Business and Economics,* vol. 6, no. 1, pp. 21-30.

[56] Li, L. and Ni, J. (2009), "Short-term decision support system for maintenance task prioritization", *International Journal of Production Economics,* vol. 121, no. 1, pp. 195-202.

[57] Hennequin, S., Arango, G. and Rezg, N. (2009), "Optimization of imperfect maintenance based on fuzzy logic for a single-stage single-product production system", *Journal of Quality in Maintenance Engineering,* vol. 15, no. 4, pp. 412-429.

[58] Wang, S. L., Yang, N. and Schonfeld, P. (2009), "Simulation-based network maintenance planning and scheduling", *Transportation Research Record,* vol. 2100, pp. 94-102.

[59] Hani, Y., Amodeo, L., Yalaoui, F. and Chen, H. (2008), "Simulation based optimization of a train maintenance facility", *Journal of Intelligent Manufacturing,* vol. 19, no. 3, pp. 293-300.

[60] Roux, O., Jamali, M. A., Kadi, D. A. and Châtelet, E. (2008), "Development of simulation and optimization platform to analyse maintenance policies performances for manufacturing systems", *International Journal of Computer Integrated Manufacturing,* vol. 21, no. 4, pp. 407-414.

[61] Oyarbide-Zubillaga, A., Goti, A. and Sanchez, A. (2008), "Preventive maintenance optimisation of multi-equipment manufacturing systems by combining discrete event simulation and multi-objective evolutionary algorithms", *Production Planning and Control,* vol. 19, no. 4, pp. 342-355.

[62] Dridi, L., Parizeau, M., Mailhot, A. and Villeneuve, J. P. (2008), "Using evolutionary optimization techniques for scheduling water pipe renewal considering a short planning horizon", *Computer-Aided Civil and Infrastructure Engineering,* vol. 23, no. 8, pp. 625-635.

[63] Yang, Z., Djurdjanovic, D. and Ni, J. (2008), "Maintenance scheduling in manufacturing systems based on predicted machine degradation", *Journal of Intelligent Manufacturing,* vol. 19, no. 1, pp. 87-98.

[64] Ali, A., Chen, X., Yang, Z., Lee, J. and Jun, N. (2008), "Optimized maintenance design for manufacturing performance improvement using simulation", *Proceedings of the 2008 Winter Simulation Conference,* 7-10 Dec 2008, Miami, USA, IEEE, Piscataway, NJ, pp. 1811-1819.

[65] Oyarbide-Zubillaga, A., Goti, A. and Sánchez, A. (2007), "Determination of the optimal maintenance frequency for a system composed by N-machines by using discrete event simulation and genetic algorithms", *Proceedings of the European Safety and Reliability Conference 2007, ESREL 2007 - Risk, Reliability and Societal Safety,* Vol. 1, 25-27 June 2007, Stavanger, Norway, pp. 297-304.

[66] Ilgin, M. A. and Tunali, S. (2007), "Joint optimization of spare parts inventory and maintenance policies using genetic algorithms", *International Journal of Advanced Manufacturing Technology,* vol. 34, no. 5-6, pp. 594-604.

[67] Vardar, C., Gel, E. S. and Fowler, J. W. (2007), "A framework for evaluating remote diagnostics investment decisions for semiconductor equipment suppliers", *European Journal of Operational Research,* vol. 180, no. 3, pp. 1411-1426.

[68] Zhou, J., Djurdjanovic, D., Ivy, J. and Ni, J. (2007), "Integrated reconfiguration and age-based preventive maintenance decision making", *IIE Transactions,* vol. 39, no. 12, pp. 1085-1102.

[69] Chen, M. C., Hsu, C. M. and Chen, S. W. (2006), "Optimizing joint maintenance and stock provisioning policy for a multi-echelon spare part logistics network", *Journal of the Chinese Institute of Industrial Engineers,* vol. 23, no. 4, pp. 289-302.

[70] Chootinan, P., Chen, A., Horrocks, M. R. and Bolling, D. (2006), "A multi-year pavement maintenance program using a stochastic simulation-based genetic algorithm approach", *Transportation Research Part A: Policy and Practice,* vol. 40, no. 9, pp. 725-743.

[71] El Hayek, M., Van Voorthuysen, E. and Kelly, D. W. (2005), "Optimizing life cycle cost of complex machinery with rotable modules using simulation", *Journal of Quality in Maintenance Engineering,* vol. 11, no. 4, pp. 333-347.

[72] Gharbi, A. and Kenné, J. P. (2005), "Maintenance scheduling and production control of multiple-machine manufacturing systems", *Computers and Industrial Engineering,* vol. 48, no. 4, pp. 693-707.

[73] Shalaby, M. A., Gomaa, A. M. and Mohib, A. M. (2004), "A genetic algorithm for preventive maintenance scheduling in a multi-unit multi-state system", *Journal of Engineering and Applied Science,* vol. 51, no. 4, pp. 795-811.

[74] Kenné, J. P. and Gharbi, A. (2004), "Stochastic optimal production control problem with corrective maintenance", *Computers and Industrial Engineering,* vol. 46, no. 4 special issue, pp. 865-875.

[75] Rezg, N., Xie, X. and Mati, Y. (2004), "Joint optimization of preventive maintenance and inventory control in a production line using simulation", *International Journal of Production Research,* vol. 42, no. 10, pp. 2029-2046.

[76] Cheu, R. L., Wang, Y. and Fwa, T. F. (2004), "Genetic algorithm-simulation methodology for pavement maintenance scheduling", *Computer-Aided Civil and Infrastructure Engineering,* vol. 19, no. 6, pp. 446-455.

[77] Marquez, A. C., Gupta, J. N. D. and Heguedas, A. S. (2003), "Maintenance policies for a production system with constrained production rate and buffer capacity", *International Journal of Production Research,* vol. 41, no. 9, pp. 1909-1926.

[78] Kuntz, P. A., Christie, R. D. and Venkata, S. S. (2001), "A reliability centered optimal visual inspection model for distribution feeders", *IEEE Transactions on Power Delivery,* vol. 16, no. 4, pp. 718-723.

[79] Cavory, G., Dupas, R. and Goncalves, G. (2001), "A genetic approach to the scheduling of preventive maintenance tasks on a single product manufacturing production line", *International Journal of Production Economics,* vol. 74, no. 1-3, pp. 135-146.

[80] Sarker, R. and Haque, A. (2000), "Optimization of maintenance and spare provisioning policy using simulation", *Applied Mathematical Modelling,* vol. 24, no. 10, pp. 751-760.

[81] Richard Cassady, C., Bowden, R. O., Liew, L. and Pohl, E. A. (2000), "Combining preventive maintenance and statistical process control: a preliminary investigation", *IIE Transactions,* vol. 32, no. 6, pp. 471-478.

[82] Petrović, R., Šenborn, A. and Vujošević, M. (1982), "Spares allocation in the presence of uncertainty", *European Journal of Operational Research,* vol. 11, no. 1, pp. 77-81.

[83] Manzini, R., Regattieri, A., Pham, H. and Ferrari, E. (2010), *Maintenance for Industrial Systems,* Springer, London.

[84] Wang, W. (2008), "Condition-based maintenance modelling", in Kobbacy, K. and Murthy, D. N. (eds.) *Complex System Maintenance Handbook,* Springer, London, pp. 111-131.

[85] Robinson, S. (2007), *Simulation : the practice of model development and use,* Wiley, Chichester.

[86] Verma, A., Srividya, A. and Gaonkar, R. (2007), "Maintenance and replacement interval optimization using possibilistic approach", *International Journal of Modelling and Simulation,* vol. 27, no. 2, pp. 193-199.

[87] Bruzzone, A. and Bocca, E. (2012), "Innovative solutions based on simulation combined with optimization techniques for maintenance service management within complex systems", *International Journal of Modeling, Simulation, and Scientific Computing,* vol. 3, no. 2, pp. 1-23.

[88] Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L. K. and Young, T. (2010), "Simulation in manufacturing and business: A review", *European Journal of Operational Research,* vol. 203, no. 1, pp. 1-13.

[89] Banks, J. (2010), *Discrete-event system simulation,* Pearson, Upper Saddle River.

[90] Rao, S. S. (2009), *Engineering optimization theory and practice,* John Wiley & Sons, Hoboken, NJ.

[91] Deb, K. (2005), *Optimization for engineering design: algorithms and examples,* Prentice-Hall, New Delhi.

[92] Biethahn, J. and Nissen, V. (1994), "Combinations of simulation and evolutionary algorithms in management science and economics", *Annals of Operations Research,* vol. 52, no. 4, pp. 181-208.

[93] Bäck, T. and Schwefel, H. (1993), "An overview of evolutionary algorithms for parameter optimization", *Evolutionary computation,* vol. 1, no. 1, pp. 1-23.

[94] Belegundu, A. D. and Chandrupatla, T. R. (2011), *Optimization concepts and applications in engineering,* Cambridge University Press, New York.

[95] Zohrul Kabir, A. and Farrash, S. (1996), "Simulation of an integrated age replacement and spare provisioning policy using SLAM", *Reliability Engineering and System Safety,* vol. 52, no. 2, pp. 129-138.

[96] Azadivar, F. and Shu, J. V. (1998), "Use of simulation in optimization of maintenance policies", *Proceedings of the 1998 Winter Simulation Conference,* Vol. 2, 13-16 December 1998, Washington DC, IEEE, Piscataway, NJ, pp. 1061-1067.

[97] Chien, T. W., Lin, C. and Sphicas, G. (1997), "A systematic approach to determine the optimal maintenance policy for an automated manufacturing system", *Quality and Reliability Engineering International,* vol. 13, no. 4, pp. 225-233.

[98] Riane, F., Roux, O., Basile, O. and Dehombreux, P. (2009), "Simulation based approaches for maintenance strategies optimization", in Ben-Daya, M., Duffuaa, S. O., Raouf, A., et al (eds.) *Handbook of Maintenance Management and Engineering,* Springer, London, pp. 133-153.

[99] Beaurepaire, P., Valdebenito, M. A., Schuëller, G. I. and Jensen, H. A. (2012), "Reliability-based optimization of maintenance scheduling of mechanical components under fatigue", *Computer Methods in Applied Mechanics and Engineering,* vol. 221–222, pp. 24-40.

[100] Gomes, W. J. S., Beck, A. T. and Haukaas, T. (2013), "Optimal inspection planning for onshore pipelines subject to external corrosion", *Reliability Engineering and System Safety,* vol. 118, pp. 18-27.

[101] Valdebenito, M. A. and Schuëller, G. I. (2010), "Design of maintenance schedules for fatigue-prone metallic components using reliability-based optimization", *Computer Methods in Applied Mechanics and Engineering,* vol. 199, no. 33–36, pp. 2305-2318.

[102] Creswell, J. W. (2009), *Research design qualitative, quantitative, and mixed methods approaches,* Sage Publications, Thousand Oaks, California.

[103] DePoy, E. and Gitlin, L. N. (2005), *Introduction to research : understanding and applying multiple strategies,* Mosby, St. Louis, Missouri.

[104] Alrabghi, A. and Tiwari, A. (2015), "State of the art in simulation-based optimisation for maintenance systems", *Computers and Industrial Engineering,* vol. 82, pp. 167-182.

[105] Hong, D. S., Kamaruddin, S. and Azid, I. A. (2012), "Maintenance policy selection: a review towards building proper selection model", *International Journal of Industrial and Systems Engineering,* vol. 10, no. 3, pp. 355-375.

[106] Ding, S. and Kamaruddin, S. (2015), "Maintenance policy optimization: literature review and directions", *The International Journal of Advanced Manufacturing Technology,* vol. 76, no. 5-8, pp. 1263-1283.

[107] Lee, J., Ghaffari, M. and Elmeligy, S. (2011), "Self-maintenance and engineering immune systems: Towards smarter machines and manufacturing systems", *Annual Reviews in Control,* vol. 35, no. 1, pp. 111-122.

[108] Muller, A., Crespo Marquez, A. and Iung, B. (2008), "On the concept of e-maintenance: Review and current research", *Reliability Engineering and System Safety,* vol. 93, no. 8, pp. 1165-1187.

[109] Jantunen, E., Emmanouilidis, C., Arnaiz, A. and Gilabert, E. (2011), "E-Maintenance: Trends, challenges and opportunities for modern industry", *18th IFAC World Congress,* Vol. 18, 28 August-2 September 2011, Milan, Italy, pp. 453-458.

[110] Starr, A., Al-Najjar, B., Holmberg, K., Jantunen, E., Bellew, J. and Albarbar, A. (2010), "Maintenance today and future trends", in Holmberg, K., Adgar, A., Arnaiz, A., et al (eds.) *E-maintenance,* Springer, London, pp. 5-37.

[111] Ojanen, V. (2014), "Maintenance innovations - types, patterns and emerging trends", *2014 IEEE International Conference on Management of Innovation and Technology, ICMIT 2014,* 23 September 2014 through 25 September 2014, Singapore, IEEE, Piscataway, NJ, pp. 321-326.

[112] Campos, J. (2014), "Current and prospective information and communication technologies for the e-maintenance applications", *Journal of Quality in Maintenance Engineering,* vol. 20, no. 3, pp. 233-248.

[113] Liyanage, J. P. (2010), "State of the art and emerging trends in operations and maintenance of offshore oil and gas production facilities: some experiences and observations", *International Journal of Automation and Computing,* vol. 7, no. 2, pp. 137-145.

[114] Ao, Y. (2011), "A review on development and trend of Intelligent Maintenance System", *Advanced Materials Research,* vol. 314-316, pp. 2365-2369.

[115] Marais, K. B. and Robichaud, M. R. (2012), "Analysis of trends in aviation maintenance risk: an empirical approach", *Reliability Engineering and System Safety,* vol. 106, pp. 104-118.

[116] Sharma, B., Arora, A. K. and Kumar, P. (2010), "Modern trends in application, installation, operation and maintenance of large power transformers", *Water and Energy International,* vol. 67, no. 1, pp. 49-58.

[117] Knowledge Based Systems, Inc. (KBSI) (2010), *IDEFØ*, available at: http://www.idef.com/IDEF0.htm (accessed 5 August 2015).

[118] Johnson, E. R. and Tani, S. N. (2013), "Perform Probabilistic Analysis and Identify Insights", in Parnell, G. S., Bresnick, T., Tani, S. N., et al (eds.) *Handbook of Decision Analysis,* John Wiley & Sons, Hoboken N.J., pp. 249-290.

[119] ISO/IEC/IEEE, (2010), *ISO/IEC/ IEEE 24765 Systems and software engineering -- Vocabulary*, ISO/IEC/IEEE, Switzerland.

[120] ISO, (1985), *ISO 5807:1985 Information processing -- Documentation symbols and conventions for data, program and system flowcharts, program network charts and system resources charts*, ISO, Switzerland.

[121] Laggoune, R., Chateauneuf, A. and Aissani, D. (2009), "Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units", *Computers & Chemical Engineering,* vol. 33, no. 9, pp. 1499-1510.

[122] Tiwari, A., Hoyos, P., Hutabarat, W., Turner, C., Ince, N., Gan, X. and Prajapat, N. (2015), "Survey on the use of computational optimisation in UK engineering companies", *CIRP Journal of Manufacturing Science and Technology,* vol. 9, pp. 57-68.

[123] Barlow, R. E. and Proschan, F. (1965), *Mathematical theory of reliability,* Wiley, New York.

[124] Nowakowski, T. and Werbinka, S. (2009), "On problems of multicomponent system maintenance modelling", *International Journal of Automation and Computing,* vol. 6, no. 4, pp. 364-378.

[125] Alabdulkarim, A. A., Ball, P. D. and Tiwari, A. (2014), "Influence of resources on maintenance operations with different asset monitoring levels: A simulation approach", *Business Process Management Journal,* vol. 20, no. 2, pp. 195-212.

[126] Warrington, L., Jones, J. A. and Davis, N. (2002), "Modelling of maintenance, within discrete event simulation", *Annual Reliability and Maintainability Symposium, The International Symposium on Product Quality and Integrity,* 28-31 January 2002, Seattle, WA, IEEE, Piscataway, NJ, pp. 260-265.

[127] Wang, H. (2002), "A survey of maintenance policies of deteriorating systems", *European Journal of Operational Research,* vol. 139, no. 3, pp. 469-489.

[128] Wang, W. (2012), "An overview of the recent advances in delay-time-based maintenance modelling", *Reliability Engineering and System Safety,* vol. 106, pp. 165-178.

[129] Welch, P. D. (1983), "The statistical analysis of simulation results", in Lavenberg, S. (ed.) *Computer Performance Modeling Handbook,* Academic Press, New York, pp. 268-328.

[130] Russell, S. J. and Norvig, P. (2003), *Artificial intelligence: a modern approach,* Prentice Hall/Pearson Education, Upper Saddle River, NJ.

[131] Savic, D. A., Bicik, J. and Morley, M. S. (2011), "A DSS generator for multiobjective optimisation of spreadsheet-based models", *Environmental Modelling and Software,* vol. 26, no. 5, pp. 551-561.

[132] Deb, K. (2011), "Multi-objective Optimisation Using Evolutionary Algorithms: An Introduction", in Wang, L., Ng, A. H. C. and Deb, K. (eds.) *Multi-objective Evolutionary Optimisation for Product Design and Manufacturing,* Springer, London, pp. 3-34.

[133] Ben-Daya, M. (2009), "Failure Statistics", in Ben-Daya, M., Knezevic, J., Raouf, A., et al (eds.) *Handbook of Maintenance Management and Engineering,* Springer, London, pp. 45-73.

[134] Sarker, R. A. and Newton, C. S. (2008), *Optimization modelling : a practical approach,* CRC Press, Boca Raton.

[135] Jamshidi, R. and Esfahani, M. M. S. (2015), "Maintenance policy determination for a complex system consisting of series and cold standby system with multiple levels of maintenance action", *International Journal of Advanced Manufacturing Technology,* vol. 78, no. 5-8, pp. 1337-1346.

APPENDICES

Appendix A : **Analysis of Published Literature on Simulation Based Optimisation in Maintenance**

publication	simulation technique	simulation software	optimisation method	optimisation software	maintenance strategy	real case?	Decision variables									Multi-objective?	opt objective
							PM frequency	inspection frequency	maintenance priorities	spare parts	maintenance technicians	buffer size	maintenance equipment	maintenance threshold	maintenance schedule		
[31]	DES	matlab	Fibonacci algorithm	not disclosed	CBM	no	no	no	no	no	no	no	no	yes	no	no	min cost
[38]	DES	VLE simulator	direct search Nelder-Mead (simplex) method	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	max availability
[33]	DES	Promodel	GA	SimRunner	PM	yes	yes	no	no	no	no	no	no	no	no	no	max total throughout
[39]	agent based	Anylogic	GA	OptQuest	PM	yes	yes	no	no	yes	no	no	no	no	no	no	min cost
[35]	agent based	Java	Approximated Neighbourhood Evaluation (local search)	IBM ILOG CPLEX 12.3	CM	no	no	no	no	yes	yes	no	no	no	no	no	min life cycle maintenance cost
[36]	DES	witness	simulated annealing + random solution + climb hill	witness optimizer	PM	no	yes	no	no	yes	yes	no	no	no	no	no	min total cost
[37]	DES	not disclosed	manual	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost
[34]	DES	not disclosed	Penalty function	not disclosed	CBM	no	Yes	no	no	no	no	no	no	no	yes	no	min cost
[32]	not disclosed	not disclosed	manual	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	max profit
[40]	DES	not disclosed	GA	not disclosed	CBM	yes	yes	yes	no	no	no	no	no	yes	no	yes	cost and availability
[42]	not disclosed	not disclosed	not disclosed	not disclosed	CBM	no	no	no	no	no	no	no	no	yes	no	no	max avg revenue per unit time

[43]	DES for systems states and continuous for machine degradation	not disclosed	direct search cyclic coordinate method	not enough info	CBM	no	yes	yes	no	no	no	no	no	yes	no	no	min cost
[41]	not disclosed	not disclosed	GA + simulated annealing	not disclosed	PM	yes	yes	no	no	yes	no	no	no	no	no	no	min cost
[44]	DES	not disclosed	IPA infinitesimal perturbation analysis	not disclosed	PM	no	yes	no	no	no	no	yes	no	no	no	no	min cost
[48]	DES	PMOST, AutoSche d AP	not disclosed	IBM optimisa tion software library and ILOG CPLEX	PM	yes	yes	no	no	no	no	no	no	no	no	yes	max availability. min PM and inventory costs, max throughput
[50]	DES	MEAROS	GA	not disclosed	PM	no	no	no	no	no	no	no	no	yes	no	no	min cost
[6]	Stochastic Petri-Nets	not disclosed	manually by running simulation scenarios	not disclosed	PM	no	yes	no	yes	no	no	yes	no	no	no	no	min maintenance cost and max through output
[47]	not disclosed	not disclosed	GA NSGA 2	Python	CBM	no	no	no	no	no	no	no	yes	no	no	yes	min shop capacity, min cost and max availability
[45]	DES	automod	evolution strategy	autoStat	CBM	yes	no	no	no	no	no	no	no	no	no	no	max throughput
[46]	approximate dynamic programmin g	automod	markov decision process	automod	PM	no	no	no	yes	no	no	no	no	no	no	no	minimise WIP and CT
[49]	agent based	not disclosed	GA	not disclosed	PM	no	no	no	no	no	yes	no	no	no	no	yes	min working hours and max no of skilled workers
[51]	Continuous	VENSIM	not disclosed	VENSIM	PM	yes	no	no	yes	no	no	no	no	yes	no	no	min distress on roads
[53]	DES : cell transmission model - mesoscopic traffic simulation	C++	GA	C++	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost and travel time for users
[57]	DES	matlab	manual optimisation	matlab	PM	no	yes	no	no	no	no	no	no	no	no	no	max availability or min cost

[54]	DES	Arena	different optimisation algorithms (OptQuest)	OptQuest	CBM	no	no	no	no	no	no	no	no	yes	no	no	min cost
[55]	DES	arena	different optimisation algorithm included in OptQuest	OptQuest	CBM	no	no	no	no	no	no	yes	no	no	no	no	min cost
[7]	DES	visual slam language	manual and anova using multi-criteria decision making	statgraphics	PM	no	yes	no	no	yes	no	no	no	no	no	no	min cost and max availability
[56]	DES	excel	manual optimisation	not disclosed	PM	yes	no	no	yes	no	no	no	no	no	no	no	min maintenance cost
[52]	DES	java language	manually by running simulation scenarios	manually by running simulation scenarios + NEMROD	PM	no	yes	no	no	no	no	no	no	no	no	no	min sys cost or max availability
[58]	DES	not disclosed	GA	not disclosed	PM	yes	yes	no	no	no	no	no	no	no	no	no	max net present worth
[59]	DES	Arena	GA with multi-objective function: pareto (NSGA2) and non-pareto	visual basic	PM	yes	no	no	yes	no	no	no	no	no	no	yes	max production rate- min total immobilization time- min occupation rates
[63]	DES	not disclosed	GA	not disclosed	CBM	no	no	no	no	no	no	no	no	no	yes	no	max profit
[62]	not disclosed	Epanet2.0	GA, NPGA-2, NSGA-II	C++	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost
[60]	DES	resource - action - operation	direct search Nelder-Mead	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost

[64]	DES	Arena	different optimisation algorithm included in ISSOP software such as enumeration, quasi gradient strategy, Monte Carlo strategy and GA	ISSOP (intelligent system for simulation and optimisation)	CM	yes	no	no	no	no	no	no	no	no	no	yes	min costs, max orders and min process time
[61]	DES	witness + Monte Carlo	GA NSGA 2 - multi-objective evolutionary algorithms	matlab	PM	yes	yes	no	no	no	no	no	no	no	no	yes	minimise cost and maximise profit
[65]	DES	Witness	GA NSG2	Matlab	PM	yes	yes	no	no	no	no	no	no	no	no	yes	min cost and max profit
[66]	DES	Arena	GA	not disclosed	PM	yes	yes	no	no	yes	no	no	no	no	no	no	min cost
[68]	DES	Promodel	GA	SimRunner	PM	no	yes	no	no	no	no	no	no	yes	no	no	min cost
[14]	DES	not disclosed	GA multi-objective evolutionary algorithms NSGA-II	not enough info	PM	yes	yes	no	no	no	no	no	no	no	no	yes	min cost and max profit
[67]	not disclosed	C++	GA	C++	CM	no	no	no	no	no	yes	no	no	no	no	no	min cost
[69]	DES	Arena	scatter search	OptQuest	PM	no	no	no	no	yes	no	no	no	no	no	no	max profit
[18]	continuous - Euler scheme	not disclosed	direct search: simple search in the space of decision variables	not disclosed	CBM	no	no	no	no	no	no	no	no	no	no	no	min cost
[70]	Latin hypercube sampling	not disclosed	GA	not disclosed	PM	no	no	no	no	no	no	no	no	no	no	no	min cost or max performance
[71]	DES	ARENA	manual optimisation	not disclosed	PM	yes	yes	no	no	no	no	no	no	no	no	no	max availability
[17]	DES	Promodel	manual and design of experiments	statgraphics	PM	no	yes	no	no	no	no	yes	no	no	no	no	min cost

[72]	DES in general but continuous for machine aging and inventory of products	visual slam language	manual and design of experiments	statgraphics	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost
[3]	mixed-integer programming	IBM EasyModeler	not disclosed	OSL package	PM	yes	yes	no	no	no	no	no	no	no	no	no	max availability. Min inventory, min PM costs, max throughput
[21]	DES	resource - action - operation	simulated annealing	psudo code	CM	no	no	no	no	no	no	no	no	no	no	no	min completion time (of all prescribed jobs) , conformance to promised jobs delivery dates?, min WIP
[73]	not disclosed	MATLAB	GA	not disclosed	PM	yes	yes	no	no	no	no	no	no	no	no	no	min cost
[74]	markov chains	not disclosed	manual and design of experiments	statgraphics	CM	no	no	no	no	no	no	no	no	no	no	no	min cost
[75]	DES	Promodel	GA	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost
[76]	traffic simulator	paramics	GA	not disclosed	PM	no	no	no	no	no	no	no	no	no	yes	no	min total travel time for vehicles
[77]	system dynamics	not disclosed	the modified powell method	direct search	PM	no	yes	no	no	no	no	yes	no	no	no	no	min cost and max availability
[79]	DES	C++ SIM	GA	not disclosed	PM	yes	yes	no	no	no	no	no	no	no	no	no	max throughput
[78]	markov chains	not disclosed	manually by running simulation scenarios	not disclosed	CBM	yes	no	yes	no	no	no	no	no	no	no	no	min cost of inspection, repair and reliability
[81]	DES	not disclosed	EA	not disclosed	PM	no	yes	no	no	no	no	no	no	no	no	no	min cost
[80]	DES	SIMSCRIPT II.5	not disclosed	not disclosed	PM	no	yes	no	no	yes	no	no	no	no	no	no	min cost
[82]	not disclosed	simne	not disclosed	not disclosed	CM	no	no	no	no	yes	no	no	no	no	no	no	not disclosed

Appendix B : Functions used to access the event queue in Witness

Table B-1 A list of functions used in Witness to access the event queue. Source: Witness manual

Function	Definition
GetEventTime (Element Name, Event Index)	returns an integer value that is the number of events that are currently scheduled in the Event Queue for the specified element
GetEventBreakdownNo (Element Name, Event Index)	returns an integer value that identifies the breakdown number of the specified event (according to its order in the machine breakdown window). If the event is not a breakdown event then zero is returned.
GetEventTime (Element Name, Event Index)	returns a real value that is the time that the specified index event is scheduled to occur
SetEventTime(Element Name, Event Index, New Event Time)	sets the scheduled time of the specified event to the new event time

Appendix C : **Data Collection**

C.1 Initial assessment form

PhD research project (*Simulation-Based Optimisation of Maintenance in Manufacturing Systems for Decision Support*)

Cranfield University, UK

Factory: **date:** **city:**

Product types:

Manufacturing layout:

Permission granted to take pictures?

Main contact:

- **Maintenance strategies currently in use (with examples)**
  - Reactive:
  - Preventive
  - Condition based
- **On what basis is maintenance intervention decided?**
  - Manufacturer manuals
  - Experience
  - Analytical methods
  - Other:
- **Data availability:**
  - Data on the following:
    - Total downtime (planned or unplanned) :including waiting time for spare parts and technicians
    - Breakdown time (when did the machine become unavailable?)
    - Repair time
    - Spare parts availability

Availability of historical maintenance records?

C.2 A Sample of Collected Data

Sort field	System Status	Work center	Planner group	Actual work	Reference Date	Counter	Work	PriorityType	Order Type	Plan no.f.op	Normal dur	Actual st	Act. sta	Act.finish d	Actual	Activ	Des	Price	Prior	Priority
1762-A02	CNF ORSP TECO	IU-01	P07	16.000	15/05/2005	00000001	16.0	PB	PM01	1000306754	8.0	14/05/2005	07:30:00	29/05/2005	14:23:24	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	MC-01	P01	7.000	12/06/2005	00000001	8.0	PB	PM01	1000350143	4.0	11/06/2005	00:00:00	13/06/2005	15:00:50	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	9.000	25/07/2005	00000001	10.0	PB	PM01	1000442015	5.0	24/07/2005	00:00:00	24/07/2005	16:00:38	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	4.000	25/07/2005	00000003	4.0	PB	PM01	1000442015	4.0	25/07/2005	08:00:00	25/07/2005	12:00:52	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	8.000	04/08/2005	00000001	8.0	PB	PM01	1000309838	4.0	06/08/2005	08:00:00	06/08/2005	12:28:38	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	2.000	10/08/2005	00000001	3.0	PM	PM01	1000469345	1.5	08/08/2005	10:00:00	10/08/2005	12:00:11	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	EL-01	P01	0.500	16/10/2005	00000001	0.5	PB	PM01	1000600490	0.5	15/10/2005	07:30:00	15/10/2005	13:12:05	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	FA-01	P01	8.000	16/10/2005	00000003	4.0	PB	PM01	1000600490	2.0	15/10/2005	19:07:30	16/10/2005	01:00:41	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	16.000	16/10/2005	00000002	16.0	PB	PM01	1000600490	4.0	16/10/2005	19:30:30	17/10/2005	04:00:37	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	SC-01	P01	8.000	14/11/2005	00000001	8.0	PB	PM01	1000647299	2.0	13/11/2005	00:00:00	13/11/2005	15:01:10	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	IU-01	P01	4.000	14/11/2005	00000002	4.0	PB	PM01	1000647299	2.0	14/11/2005	00:00:00	21/11/2005	14:39:10	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	4.000	28/11/2005	00000001	4.0	PB	PM01	1000649483	2.0	28/11/2005	08:00:00	28/11/2005	10:30:20	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	SC-01	P01	8.000	03/01/2006	00000001	8.0	PB	PM01	1000732508	8.0	01/01/2006	00:00:00	19/01/2006	10:07:09	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	SC-01	P07	4.000	16/02/2007	00000001	4.0	PM	PM01	1001569610	4.0	14/02/2007	00:00:00	19/02/2007	11:50:03	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	05/04/2007	00000003	4.0	PB	PM01	1001687787	2.0	05/04/2007	07:30:00	05/04/2007	23:00:56	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	RG-01	P01	12.000	05/04/2007	00000004	12.0	PB	PM01	1001687787	6.0	07/04/2007	07:30:00	07/04/2007	08:34:29	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	SC-01	P01	4.000	05/04/2007	00000006	4.0	PB	PM01	1001687787	2.0	09/04/2007	00:00:00	09/04/2007	14:16:11	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	8.000	29/06/2007	00000001	8.0	PB	PM01	1001693624	4.0	11/04/2007	12:30:00	11/04/2007	15:45:25	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	4.000	21/04/2007	00000001	4.0	PB	PM01	1001717277	2.0	21/04/2007	10:30:00	21/04/2007	15:00:27	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	MC-01	P01	4.000	29/06/2007	00000004	4.0	PB	PM01	1001693624	2.0	22/04/2007	08:00:00	30/04/2007	12:00:55	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	4.000	27/05/2007	00000001	4.0	PM	PM01	1001794121	2.0	27/05/2007	08:00:00	27/05/2007	12:30:53	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	SC-01	P07	8.000	05/06/2007	00000001	8.0	PM	PM01	1001765498	2.0	05/06/2007	09:00:00	05/06/2007	15:48:05	1PM001	CRYST	0.00	4	4-Low
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	11/06/2007	00000001	4.0	PB	PM01	1001825130	4.0	11/06/2007	08:00:00	11/06/2007	11:00:32	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	EL-01	P01	12.000	17/06/2007	00000001	6.0	PB	PM01	1001838048	6.0	16/06/2007	07:45:00	17/06/2007	14:23:17	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	16.000	29/06/2007	00000002	8.0	PB	PM01	1001693624	4.0	27/06/2007	01:00:00	28/06/2007	02:00:51	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	29/06/2007	00000003	6.0	PB	PM01	1001693624	3.0	28/06/2007	23:00:21	29/06/2007	02:00:22	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	16.000	27/01/2008	00000001	8.0	PB	PM01	1002344552	4.0	27/01/2008	08:10:51	28/01/2008	14:02:05	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	7.000	23/03/2008	00000001	4.0	PB	PM01	1002468866	2.0	23/03/2008	08:00:00	23/03/2008	15:36:58	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	23/03/2008	00000002	6.0	PB	PM01	1002468866	3.0	24/03/2008	10:00:00	24/03/2008	13:45:35	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	32.000	30/03/2008	00000001	16.0	PB	PM01	1002493457	8.0	28/03/2008	12:00:00	31/03/2008	01:19:09	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	12.000	15/04/2008	00000001	8.0	PB	PM01	1002528602	4.0	15/04/2008	08:00:37	15/04/2008	12:30:07	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	1.000	15/06/2008	00000002	4.0	PB	PM01	1002666060	2.0	14/06/2008	00:00:00	14/06/2008	15:19:14	1PM001	CRYST	0.00	4	4-Low
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	15/06/2008	00000003	3.0	PB	PM01	1002666060	1.5	15/06/2008	09:30:01	15/06/2008	12:30:28	1PM001	CRYST	0.00	4	4-Low
1762-A02	CNF ORSP TECO	ME-01	P01	1.000	05/07/2008	00000001	1.0	PB	PM01	1002725104	1.0	05/07/2008	08:00:00	05/07/2008	08:44:05	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	16/09/2008	00000001	6.0	PB	PM01	1002887241	3.0	16/09/2008	07:00:16	16/09/2008	11:00:54	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	6.000	06/10/2008	00000001	4.0	PB	PM01	1002928780	4.0	06/10/2008	00:00:00	06/10/2008	08:18:19	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	8.000	12/10/2008	00000001	8.0	PB	PM01	1002942637	4.0	11/10/2008	07:45:00	12/10/2008	08:19:10	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	4.500	21/03/2009	00000001	3.0	PB	PM01	1003317138	1.5	21/03/2009	00:00:00	21/03/2009	15:25:47	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	RG-01	P01	6.000	15/05/2009	00000002	8.0	PB	PM01	1003450588	4.0	13/05/2009	07:30:00	13/05/2009	15:00:08	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	SC-01	P01	8.000	15/05/2009	00000003	8.0	PB	PM01	1003450588	2.0	16/05/2009	00:00:00	16/05/2009	14:43:42	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	8.000	26/05/2009	00000001	8.0	PB	PM01	1003478316	8.0	26/05/2009	00:00:00	27/05/2009	14:45:01	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	EL-01	P01	2.000	26/08/2009	00000001	2.0	PB	PM01	1003705995	2.0	26/08/2009	00:00:00	26/08/2009	11:26:57	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	2.000	02/02/2010	00000001	2.0	PB	PM01	1004105747	2.0	02/02/2010	11:15:19	02/02/2010	14:15:05	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	4.000	03/04/2010	00000001	4.0	PB	PM01	1004260787	2.0	03/04/2010	08:00:00	03/04/2010	11:59:56	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	SC-01	P01	8.000	09/11/2010	00000002	8.0	PB	PM01	1004890693	2.0	07/11/2010	00:00:00	07/11/2010	15:18:28	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	4.000	09/11/2010	00000001	4.0	PB	PM01	1004890693	2.0	08/11/2010	13:00:00	08/11/2010	15:00:51	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	RG-02	P01	2.000	09/11/2010	00000002	2.0	PB	PM01	1004894992	2.0	09/11/2010	00:00:00	09/11/2010	15:19:04	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	ME-01	P01	4.000	10/11/2010	00000001	4.0	PB	PM01	1004896712	2.0	10/11/2010	08:00:00	10/11/2010	10:00:27	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	ME-01	P01	16.000	01/12/2010	00000001	18.0	PB	PM01	1004951915	18.0	26/11/2010	09:30:00	27/11/2010	08:00:38	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	SC-01	P01	16.000	01/12/2010	00000002	8.0	PB	PM01	1004951915	2.0	27/11/2010	10:00:00	27/11/2010	14:59:46	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	SC-01	P01	16.000	01/12/2010	00000003	8.0	PB	PM01	1004951915	2.0	30/11/2010	10:00:00	30/11/2010	14:58:55	1PM001	CRYST	0.00	1	1-Emergency
1762-A02	CNF ORSP TECO	ME-01	P01	1.000	31/12/2010	00000001	1.0	PB	PM01	1005022513	1.0	20/12/2010	09:43:12	20/12/2010	10:48:55	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF ORSP TECO	ME-01	P01	1.000	04/01/2011	00000001	1.0	PB	PM01	1005069607	1.0	04/01/2011	00:00:00	04/01/2011	08:45:20	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	FA-01	P01	6.000	18/09/2011	00000004	6.0	PB	PM01	1005257588	3.0	25/04/2011	00:00:00	18/09/2011	11:26:54	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	3.000	05/10/2011	00000001	3.0	PB	PM01	1005985582	1.5	02/10/2011	09:00:00	02/10/2011	11:00:00	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	ME-01	P01	1.000	30/10/2011	00000001	1.0	PB	PM01	1006034434	1.0	16/10/2011	03:30:00	16/10/2011	05:00:06	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	32.000	12/11/2011	00000001	24.0	PB	PM01	1006085598	12.0	27/10/2011	07:30:00	01/11/2011	21:46:46	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	2.000	30/11/2011	00000001	2.0	PB	PM01	1006152235	2.0	20/11/2011	08:00:00	20/11/2011	10:00:49	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF ORSP TECO	ME-01	P01	1.000	14/12/2011	00000001	1.0	PB	PM01	1006181354	1.0	30/11/2011	07:30:00	30/11/2011	11:21:06	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	6.000	06/12/2011	00000002	6.0	PB	PM01	1006157095	3.0	01/12/2011	13:00:00	01/12/2011	16:00:25	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	6.000	19/12/2011	00000001	6.0	PB	PM01	1006230499	3.0	15/12/2011	08:30:00	15/12/2011	14:00:27	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	SC-01	P01	24.000	24/12/2011	00000001	8.0	PB	PM01	1006256078	2.0	18/12/2011	07:30:00	28/12/2011	17:23:38		CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	ME-01	P01	8.000	14/03/2012	00000001	8.0	PB	PM01	1006546238	4.0	06/03/2012	08:00:00	07/03/2012	20:00:53	1PM001	CRYST	0.00	3	3-Medium
1762-A02	CNF TECO	ME-01	P01	1.000	16/04/2012	00000001	1.0	PB	PM01	1006601267	1.0	19/03/2012	10:00:00	19/03/2012	11:00:29	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	ME-01	P01	1.000	16/04/2012	00000002	1.0	PB	PM01	1006601267	1.0	27/03/2012	08:01:16	28/03/2012	09:23:10	1PM001	CRYST	0.00	2	2-High (Urg
1762-A02	CNF TECO	SC-01	P01	16.000	16/04/2012	00000003	8.0	PB	PM01	1006601267	2.0	29/03/2012	07:30:00	18/04/2012	16:48:01		CRYST	0.00	2	2-High (Urg

Appendix D : **Data Analysis**

D.1 A Sample of Data Fitting: Pre-Crystallizer CM repair time

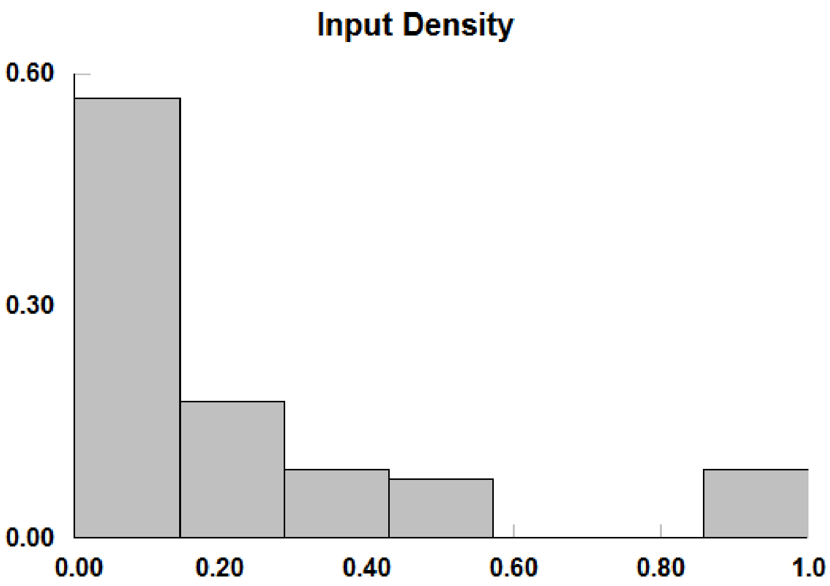


Figure D-1 Histogram of input data

Auto::Fit of Distributions

distribution	rank	acceptance
Gamma(0., 0.564, 0.391)	100	do not reject
Pearson 6(0., 1.29e+005, 0.564, 3.31e+005)	99.4	do not reject
Weibull(0., 0.683, 0.173)	94.	do not reject
Beta(0., 1., 0.592, 3.58)	8.11	do not reject
Lognormal(0., -2.62, 1.87)	6.28	do not reject
Power Function(0., 1., 0.382)	1.07e-003	reject
Chi Squared(0., 0.633)	1.01e-003	reject
Erlang(0., 1., 0.22)	3.94e-004	reject
Exponential(0., 0.22)	3.88e-004	reject
Pearson 5(0., 0.325, 2.92e-003)	0.	reject
Rayleigh(0., 0.253)	0.	reject
Triangular(0., 1.11, 0.)	0.	reject
Uniform(0., 1.)	0.	reject

Figure D-2 Results of Auto-fitting the input data to statistical distributions

goodness of fit

data points	79
estimates	maximum likelihood estimates
accuracy of fit	3.e-004
level of significance	5.e-002

summary

distribution	Kolmogorov Smirnov	Anderson Darling
Beta	0.142	0.537
Chi Squared	0.231	5.7
Erlang	0.194	6.45
Exponential	0.194	6.45
Gamma	6.52e-002	0.486
Lognormal	0.113	1.53
Pearson 5	0.246	6.85
Pearson 6	6.54e-002	0.488
Power Function	0.178	6.44
Rayleigh	0.442	68.3
Triangular	0.346	29.7
Uniform	0.502	70.2
Weibull	6.6e-002	0.523

detail

Beta

minimum	=	0. [fixed]
maximum	=	1.
p	=	0.592222
q	=	3.58459

Kolmogorov-Smirnov

data points	79
ks stat	0.142
alpha	5.e-002
ks stat(79,5.e-002)	0.151
p-value	7.55e-002
result	DO NOT REJECT

Anderson-Darling

data points	72
ad stat	0.537
alpha	5.e-002
ad stat(5.e-002)	2.49
p-value	0.709
result	DO NOT REJECT

Figure D-3 Results of goodness of fit tests

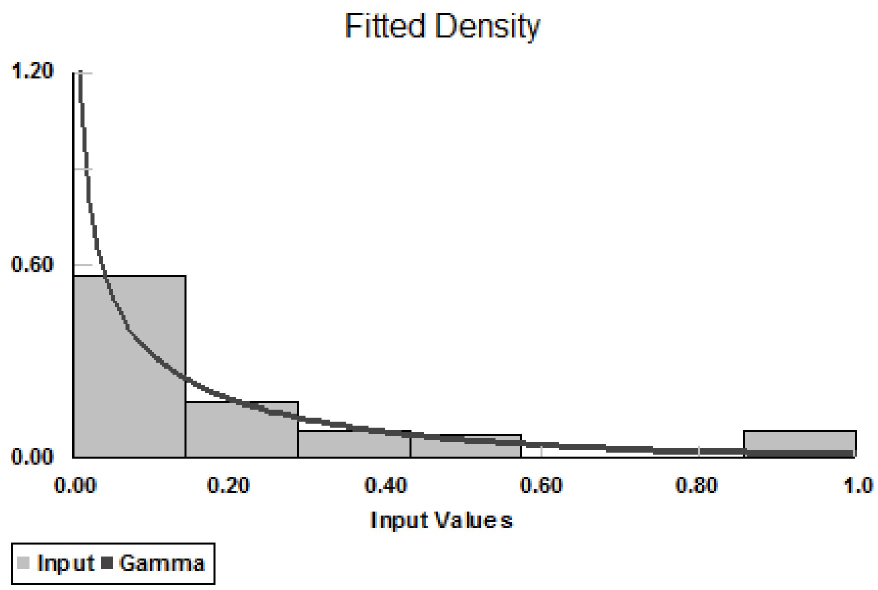


Figure D-4 Histogram comparison of empirical data with Probability Denisty Function of proposed distribution

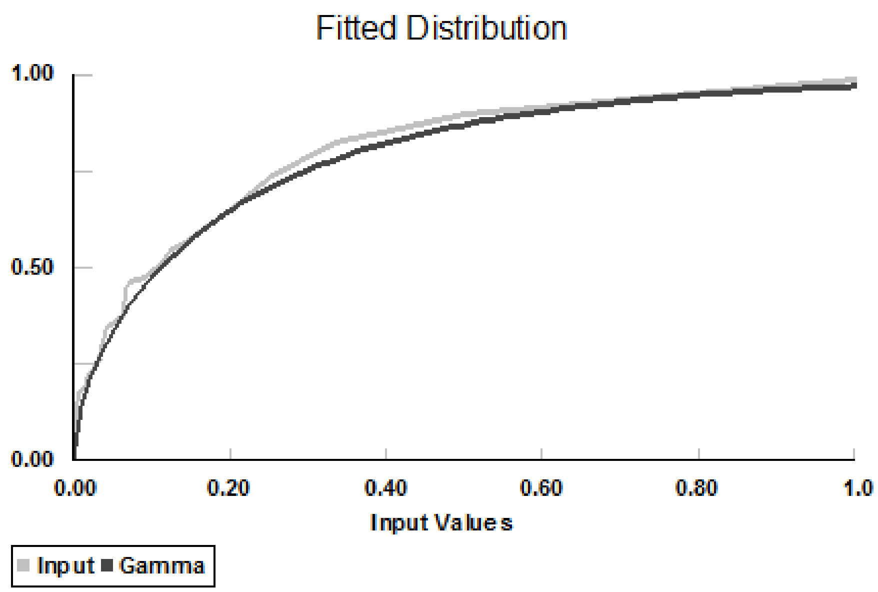


Figure D-5 Cumulitive Distribution Function (CDF) - comparison of proposed distribution with the empirical data

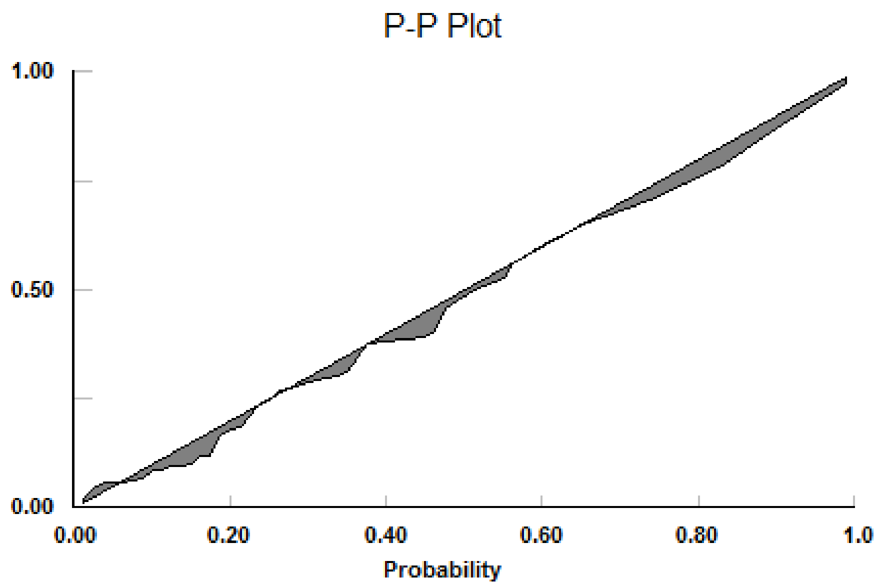


Figure D-6 Probability - Probability Plot of empirical CDF against proposed distribution CDF

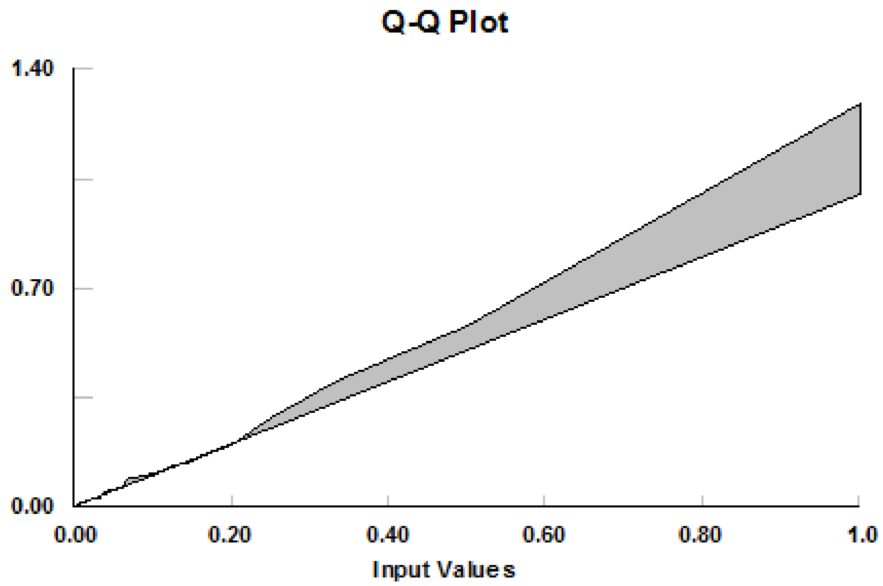


Figure D-7 Quantile - Quantile Plot of empirical inverse CDF against proposed distribution inverse CDF

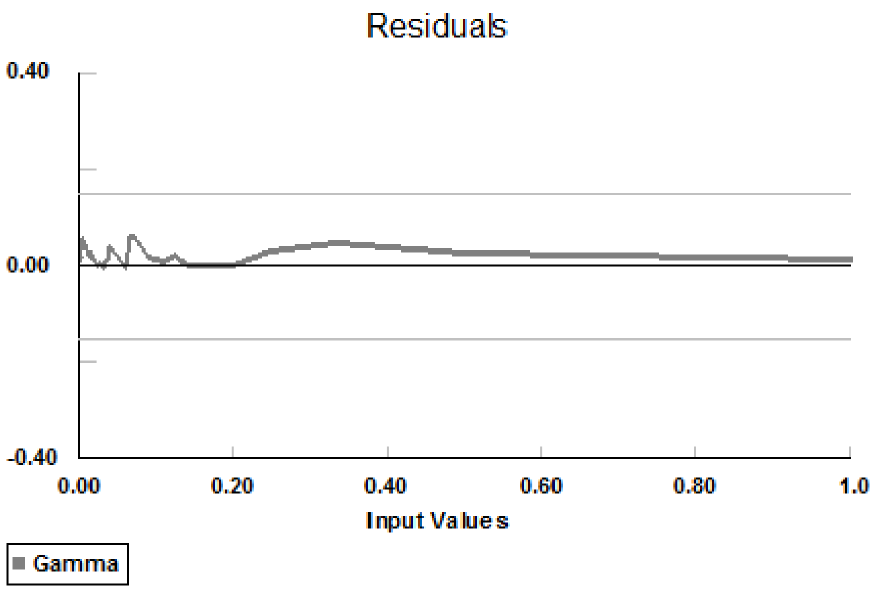


Figure D-8 Probability difference between the empirical CDF and the proposed distribtuion CDF

D.2 A Sample of the Analysis of Asset Conditions: Pre-Crystallizer

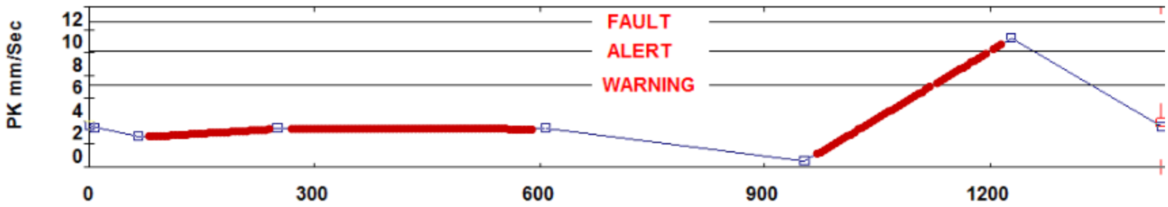


Figure D-9 Capturing data points on ascending and steady lines in the condition graph

Appendix E : Case A Optimisation Results

E.1 Optimisation Plan and Computation Expenses

Experiments were run on PC with Intel Core i7-2600 CPU @ 3.40 GHz

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(50,100)
Estimated time: 36:30 hours</td><td>1427660</td><td>9489665</td><td>600233823</td></tr>
<tr><td>(50,150)
Estimated time: 54:15 hours</td><td rowspan="4">371618932</td><td rowspan="4">9489721</td><td rowspan="4">171113</td></tr>
<tr><td>(50,200)
Estimated time: 17:45 hours</td></tr>
<tr><td>(50,300)
Estimated time: 17:45 hours</td></tr>
<tr><td>(50,400)
Estimated time: 17:45 hours</td></tr>
</table>

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(75,100)
Estimated time: 54:15 hours</td><td rowspan="5">6003759</td><td rowspan="5">333124</td><td rowspan="5">374474</td></tr>
<tr><td>(75,150)
Estimated time: 27:15 hours</td></tr>
<tr><td>(75,200)
Estimated time: 27:15 hours</td></tr>
<tr><td>(75,300)
Estimated time: 54:15 hours</td></tr>
<tr><td>(75,400)
Estimated time: 54:15 hours</td></tr>
</table>

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(100,100)
Estimated time: 74:30 hours</td><td rowspan="3">67442</td><td rowspan="3">2640</td><td rowspan="3">20881</td></tr>
<tr><td>(100,150)
Estimated time: 37:20 hours</td></tr>
<tr><td>(100,200)
Estimated time: 37:20 hours</td></tr>
</table>

E.2 Optimal Solutions

Table E-1 Case A non-dominated solutions, population size: 50, number of generations: 100

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
148	155	307	154	1,906	1	1	1	1	1	0	15,314.38	30,350.00
148	154	306	152	1,906	1	1	1	1	1	0	15,329.00	30,400.00
159	125	318	152	1,869	1	1	1	1	1	0	15,330.08	31,350.00
159	125	286	152	1,869	1	1	1	1	1	0	15,337.15	31,650.00
148	155	307	154	1,392	1	1	1	1	1	0	15,337.46	31,950.00
148	154	306	152	1,392	1	1	1	1	1	0	15,338.92	32,000.00
159	125	286	152	1,805	1	1	1	1	1	0	15,341.77	32,050.00
148	155	306	138	1,394	1	1	1	1	1	0	15,345.46	32,200.00
159	125	316	104	1,869	1	1	1	1	1	0	15,348.08	32,300.00
155	135	274	114	1,392	1	1	1	1	1	0	15,349.08	33,600.00
148	113	242	136	1,394	1	1	1	1	1	0	15,350.92	36,200.00
148	203	306	152	1,394	1	1	1	1	1	0	15,352.85	73,153.85

Table E-2 Case A non-dominated solutions, population size: 50, number of generations: 150

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	155	302	142	1,904	1	1	1	1	1	0	15,346.85	29,650.00
160	155	302	142	1,392	1	1	1	1	1	0	15,349.77	31,250.00
160	155	302	126	1,392	1	1	1	1	1	0	15,360.31	31,550.00
160	153	174	126	1,392	1	1	1	1	1	0	15,360.38	35,165.38

Table E-3 Case A non-dominated solutions, population size: 50, number of generations: 200

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	159	302	158	1,904	1	1	1	1	1	0	15,324.31	29,200.00
160	155	302	158	1,904	1	1	1	1	1	0	15,337.15	29,400.00
160	159	302	142	1,904	1	1	1	1	1	0	15,341.46	29,450.00
160	155	302	142	1,904	1	1	1	1	1	0	15,346.85	29,650.00
160	159	302	140	1,394	1	1	1	1	1	0	15,349.15	31,100.00
160	154	302	142	1,394	1	1	1	1	1	0	15,363.54	31,250.00
160	155	302	126	1,394	1	1	1	1	1	0	15,368.31	31,550.00

Table E-4 Case A non-dominated solutions, population size: 50, number of generations: 300

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	159	302	158	1,848	1	1	1	1	1	0	15,339.85	29,200.00
160	155	302	158	1,848	1	1	1	1	1	0	15,348.08	29,400.00
159	157	315	156	1,382	1	1	1	1	1	0	15,356.31	30,900.00
159	157	314	136	1,390	1	1	1	1	1	0	15,364.85	31,200.00
160	155	302	126	1,394	1	1	1	1	1	0	15,368.31	31,550.00

Table E-5 Case A non-dominated solutions, population size: 50, number of generations: 400

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	159	302	158	1,848	1	1	1	1	1	0	15,339.85	29,200.00
160	155	302	158	1,848	1	1	1	1	1	0	15,348.08	29,400.00
159	159	315	141	1,406	1	1	1	1	1	0	15,351.31	30,500.00
159	159	315	140	1,406	1	1	1	1	1	0	15,351.69	30,550.00
159	159	314	157	1,391	1	1	1	1	1	0	15,355.69	30,700.00
159	157	315	156	1,391	1	1	1	1	1	0	15,363.69	30,900.00
159	157	314	136	1,390	1	1	1	1	1	0	15,364.85	31,200.00
160	155	302	126	1,394	1	1	1	1	1	0	15,368.31	31,550.00

Table E-6 Case A non-dominated solutions, population size: 75, number of generations: 100

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	155	306	155	1,919	1	1	1	1	1	0	15,337.38	29,450.00
160	155	306	147	1,919	1	1	1	1	1	0	15,339.46	29,550.00
160	155	274	147	1,919	1	1	1	1	1	0	15,339.85	29,850.00
160	147	306	151	1,855	1	1	1	1	1	0	15,349.54	29,900.00
160	155	306	151	1,407	1	1	1	1	1	0	15,350.38	30,700.00
160	155	306	147	1,407	1	1	1	1	1	0	15,355.46	30,750.00
160	147	306	159	1,407	1	1	1	1	1	0	15,357.85	31,000.00
160	147	306	159	1,391	1	1	1	1	1	0	15,363.08	31,400.00
160	146	306	159	1,391	1	1	1	1	1	0	15,366.92	31,600.00
158	92	184	148	1,374	1	1	1	1	1	0	15,367.08	38,907.69

Table E-7 Case A non-dominated solutions, population size: 75, number of generations: 150

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
158	156	315	156	1,884	1	1	1	1	1	0	15,330.15	29,300.00
160	155	306	155	1,919	1	1	1	1	1	0	15,337.38	29,450.00
160	155	306	147	1,919	1	1	1	1	1	0	15,339.46	29,550.00
160	154	274	155	1,919	1	1	1	1	1	0	15,339.92	29,750.00
160	154	274	147	1,919	1	1	1	1	1	0	15,348.92	29,850.00
160	147	306	151	1,855	1	1	1	1	1	0	15,349.54	29,900.00
160	159	274	159	1,407	1	1	1	1	1	0	15,352.31	30,700.00
160	155	306	147	1,407	1	1	1	1	1	0	15,355.46	30,750.00
160	154	274	159	1,407	1	1	1	1	1	0	15,357.08	30,900.00
159	159	270	152	1,405	1	1	1	1	1	0	15,364.92	30,950.00
159	159	270	152	1,389	1	1	1	1	1	0	15,366.38	31,350.00
160	146	306	159	1,391	1	1	1	1	1	0	15,366.92	31,600.00
158	92	184	148	1,374	1	1	1	1	1	0	15,367.08	38,907.69

Table E-8 Case A non-dominated solutions, population size: 75, number of generations: 200

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
158	159	313	156	1,884	1	1	1	1	1	0	15,341.85	29,100.00
160	159	306	145	1,903	1	1	1	1	1	0	15,342.23	29,400.00
160	154	306	145	1,911	1	1	1	1	1	0	15,347.08	29,600.00
160	154	274	147	1,911	1	1	1	1	1	0	15,350.62	29,850.00
159	159	318	146	1,405	1	1	1	1	1	0	15,353.38	30,450.00
159	159	318	154	1,389	1	1	1	1	1	0	15,356.77	30,700.00
160	154	274	159	1,407	1	1	1	1	1	0	15,357.08	30,900.00
159	159	270	152	1,405	1	1	1	1	1	0	15,364.92	30,950.00
160	159	274	143	1,391	1	1	1	1	1	0	15,368.92	31,350.00
160	154	274	147	1,389	1	1	1	1	1	0	15,371.54	31,450.00

Table E-9 Case A non-dominated solutions, population size: 75, number of generations: 300

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
158	159	313	156	1,884	1	1	1	1	1	0	15,341.85	29,100.00
159	159	318	136	1,901	1	1	1	1	1	0	15,346.23	29,400.00
160	154	306	145	1,911	1	1	1	1	1	0	15,347.08	29,600.00
160	154	274	147	1,911	1	1	1	1	1	0	15,350.62	29,850.00
160	154	274	145	1,903	1	1	1	1	1	0	15,352.15	29,900.00
160	147	306	147	1,903	1	1	1	1	1	0	15,352.23	29,950.00
159	159	318	146	1,405	1	1	1	1	1	0	15,353.38	30,450.00
159	159	318	154	1,389	1	1	1	1	1	0	15,356.77	30,700.00
160	154	274	159	1,407	1	1	1	1	1	0	15,357.08	30,900.00
159	159	270	152	1,405	1	1	1	1	1	0	15,364.92	30,950.00
160	159	274	143	1,391	1	1	1	1	1	0	15,368.92	31,350.00
160	154	274	147	1,389	1	1	1	1	1	0	15,371.54	31,450.00

Table E-10 Case A non-dominated solutions, population size: 75, number of generations: 400

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
158	159	313	158	1,884	1	1	1	1	1	0	15,334.54	29,050.00
158	159	313	156	1,884	1	1	1	1	1	0	15,341.85	29,100.00
160	159	314	135	1,895	1	1	1	1	1	0	15,345.69	29,400.00
160	154	306	145	1,911	1	1	1	1	1	0	15,347.08	29,600.00
160	158	282	147	1,903	1	1	1	1	1	0	15,351.92	29,650.00
160	154	274	145	1,903	1	1	1	1	1	0	15,352.15	29,900.00
160	147	306	147	1,903	1	1	1	1	1	0	15,352.23	29,950.00
160	158	314	159	1,405	1	1	1	1	1	0	15,353.92	30,250.00
160	158	314	159	1,389	1	1	1	1	1	0	15,355.62	30,650.00
159	159	318	154	1,389	1	1	1	1	1	0	15,356.77	30,700.00
160	159	274	157	1,407	1	1	1	1	1	0	15,356.92	30,750.00
160	154	274	159	1,407	1	1	1	1	1	0	15,357.08	30,900.00
159	159	270	152	1,405	1	1	1	1	1	0	15,364.92	30,950.00
160	159	274	143	1,391	1	1	1	1	1	0	15,368.92	31,350.00
160	154	274	147	1,389	1	1	1	1	1	0	15,371.54	31,450.00

Table E-11 Case A non-dominated solutions, population size: 100, number of generations: 100

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	157	304	142	1,897	1	1	1	1	1	0	15,337.15	29,650.00
160	153	304	140	1,897	1	1	1	1	1	0	15,337.38	29,900.00
160	157	304	142	1,833	1	1	1	1	1	0	15,338.31	30,050.00
160	157	304	140	1,769	1	1	1	1	1	0	15,341.62	30,100.00
160	156	307	152	1,542	1	1	1	1	1	0	15,342.92	30,300.00
160	153	272	142	1,739	1	1	1	1	1	0	15,343.00	30,550.00
160	153	304	140	1,547	1	1	1	1	1	0	15,343.46	30,700.00
160	153	304	126	1,547	1	1	1	1	1	0	15,351.38	30,950.00
158	137	318	138	1,567	1	1	1	1	1	0	15,351.62	31,550.00

Table E-12 Case A non-dominated solutions, population size: 100, number of generations: 150

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	157	312	142	1,897	1	1	1	1	1	0	15,339.77	29,500.00
160	157	304	140	1,769	1	1	1	1	1	0	15,341.62	30,100.00
158	158	314	138	1,567	1	1	1	1	1	0	15,345.85	30,150.00
160	157	312	126	1,547	1	1	1	1	1	0	15,349.54	30,600.00
160	153	304	126	1,547	1	1	1	1	1	0	15,351.38	30,950.00
158	137	318	138	1,567	1	1	1	1	1	0	15,351.62	31,550.00
160	137	282	96	1,547	1	1	1	1	1	0	15,352.00	33,050.00

Table E-13 Case A non-dominated solutions, population size: 100, number of generations: 200

Decision Variables											Objectives	
$PMfreq_1$	$PMfreq_2$	$PMfreq_3$	$PMfreq_4$	$PMfreq_5$	MS_1	MS_2	MS_3	MS_4	MS_5	MT	Throughput	Cost
160	157	312	142	1,897	1	1	1	1	1	0	15,339.77	29,500.00
158	158	314	154	1,567	1	1	1	1	1	0	15,341.00	29,900.00
160	157	304	140	1,769	1	1	1	1	1	0	15,341.62	30,100.00
158	158	314	138	1,567	1	1	1	1	1	0	15,345.85	30,150.00
160	157	312	126	1,547	1	1	1	1	1	0	15,349.54	30,600.00
160	153	304	126	1,547	1	1	1	1	1	0	15,351.38	30,950.00
158	137	318	138	1,567	1	1	1	1	1	0	15,351.62	31,550.00
160	137	282	96	1,547	1	1	1	1	1	0	15,352.00	33,050.00

Appendix F : **Case B Optimisation Results**

F.1 Optimisation Plan and Computation Expenses

Experiments were run on PC with Intel Core i7-2600 CPU @ 3.40 GHz

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(50,100)
Estimated time: 17:36 hours</td><td rowspan="3">2555</td><td rowspan="3">977121</td><td rowspan="3">681</td></tr>
<tr><td>(50,150)
Estimated time: 08:48 hours</td></tr>
<tr><td>(50,200)
Estimated time: 08:48 hours</td></tr>
</table>

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(75,100)
Estimated time: 31:04 hours</td><td rowspan="3">34747</td><td rowspan="3">55999</td><td rowspan="3">18547</td></tr>
<tr><td>(75,150)
Estimated time: 15:32 hours</td></tr>
<tr><td>(75,200)
Estimated time: 15:32 hours</td></tr>
</table>

<table>
<tr><th>(Population, generation)</th><th>Random seed 1</th><th>Random seed 2</th><th>Random seed 3</th></tr>
<tr><td>(100,100)
Estimated time: 38:46 hours</td><td rowspan="3">4667</td><td rowspan="3">955121</td><td rowspan="3">6481</td></tr>
<tr><td>(100,150)
Estimated time: 21:33 hours</td></tr>
<tr><td>(100,200)
Estimated time: 21:33 hours</td></tr>
</table>

F.2 Optimal Solutions

Table F-1 Case B non-dominated solutions, population size: 50, number of generations: 100

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
4.37	4.09	8.92	6.98	0	1	0	1	0	0	0	1	0	0	0	1	1,138	491	943	602	1,302,895.07	5,925.34
8.03	12.61	8.93	6.98	0	0	1	1	0	0	0	1	0	0	0	1	1,114	747	607	602	1,324,137.64	5,990.11
7.76	12.61	8.93	6.98	0	0	1	1	0	0	0	1	0	0	0	1	986	747	1,015	602	1,325,509.58	5,990.80

Table F-2 Case B non-dominated solutions, population size: 50, number of generations: 150

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
4.37	4.09	8.92	6.98	0	1	0	1	0	0	0	1	0	0	0	1	1,138	491	943	602	1,302,895.07	5,925.34
7.76	12.61	8.93	6.98	0	0	1	1	0	0	0	1	0	0	0	1	786	747	607	602	1,314,678.32	6,017.05

Table F-3 Case B non-dominated solutions, population size: 50, number of generations: 200

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
4.37	4.09	8.92	6.98	0	1	0	1	0	0	0	1	0	0	0	1	1,138	491	943	602	1,302,895.07	5,925.34
7.76	12.61	8.93	6.98	0	0	1	1	0	0	0	1	0	0	0	1	786	747	607	602	1,314,678.32	6,017.05

Table F-4 Case B non-dominated solutions, population size: 75, number of generations: 100

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
4.15	13.51	13.23	5.48	0	0	1	1	0	0	0	1	0	0	1	0	639	1,027	391	826	1,226,747.60	6,056.25
5.59	8.36	12.60	4.41	0	0	1	1	0	0	0	1	0	0	1	0	504	1,301	415	1,051	1,231,569.54	6,066.48

Table F-5 Case B non-dominated solutions, population size: 75, number of generations: 150

Decision Variables																				Objectives	
CBM $threshold_1$	CBM $threshold_2$	CBM $threshold_3$	CBM $threshold_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection $frequency_1$	Inspection $frequency_2$	Inspection $frequency_3$	Inspection $frequency_4$	Cost	Throughput
4.15	13.51	13.23	5.48	0	0	1	1	0	0	0	1	0	0	1	0	639	1,027	391	826	1,226,747.60	6,056.25
5.59	8.36	12.60	4.41	0	0	1	1	0	0	0	1	0	0	1	0	504	1,301	415	1,051	1,231,569.54	6,066.48

Table F-6 Case B non-dominated solutions, population size: 75, number of generations: 200

Decision Variables																				Objectives	
CBM $threshold_1$	CBM $threshold_2$	CBM $threshold_3$	CBM $threshold_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection $frequency_1$	Inspection $frequency_2$	Inspection $frequency_3$	Inspection $frequency_4$	Cost	Throughput
4.15	13.51	13.23	5.48	0	0	1	1	0	0	0	1	0	0	1	0	639	1,027	391	826	1,226,747.60	6,056.25
5.59	8.36	12.60	4.41	0	0	1	1	0	0	0	1	0	0	1	0	504	1,301	415	1,051	1,231,569.54	6,066.48

Table F-7 Case B non-dominated solutions, population size: 100, number of generations: 100

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
2.41	6.11	13.39	6.24	0	0	1	1	0	0	0	1	0	0	1	0	783	1,434	709	1,037	1,181,926.31	6,147.61

Table F-8 Case B non-dominated solutions, population size: 100, number of generations: 150

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
2.41	6.11	13.39	6.24	0	0	1	1	0	0	0	1	0	0	1	0	783	1,434	709	1,037	1,181,926.31	6,147.61

Table F-9 Case B non-dominated solutions, population size: 100, number of generations: 200

Decision Variables																				Objectives	
CBM threshold$_1$	CBM threshold$_2$	CBM threshold$_3$	CBM threshold$_4$	OM1	CM1	CBM1	OM2	CM2	CBM2	OM3	CM3	CBM3	OM4	CM4	CBM4	Inspection frequency$_1$	Inspection frequency$_2$	Inspection frequency$_3$	Inspection frequency$_4$	Cost	Throughput
2.41	6.11	13.39	6.24	0	0	1	1	0	0	0	1	0	0	1	0	783	1,434	709	1,037	1,181,926.31	6,147.61