CRANFIELD UNIVERSITY

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FAULT DIAGNOSTICS FOR ADVANCED CYCLE MARINE GAS TURBINE USING GENETIC ALGORITHMS

School of Engineering

PhD THESIS

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FAULT DIAGNOSTICS FOR ADVANCED CYCLE MARINE GAS TURBINE USING GENETIC ALGORITHM

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ABSTRACT

The major challenges faced by the gas turbine industry, for both the users and the manufacturers, is the reduction in life cycle costs , as well as the safe and efficient running of gas turbines. In view of the above, it would be advantageous to have a diagnostics system capable of reliably detecting component faults (even though limited to gas path components) in a quantitative manner.

This thesis presents the development an integrated fault diagnostics model for identifying shifts in component performance and sensor faults using advanced concepts in genetic algorithm. The diagnostics model operates in three distinct stages. The first stage uses response surfaces for computing objective functions to increase the exploration potential of the search space while easing the computational burden. The second stage uses the heuristics modification of genetics algorithm parameters through a master-slave type configuration. The third stage uses the elitist model concept in genetic algorithm to preserve the accuracy of the solution in the face of randomness.

The above fault diagnostics model has been integrated with a nested neural network to form a hybrid diagnostics model. The nested neural network is employed as a pre-processor or filter to reduce the number of fault classes to be explored by the genetic algorithm based diagnostics model. The hybrid model improves the accuracy, reliability and consistency of the results obtained. In addition significant improvements in the total run time have also been observed. The advanced cycle Intercooled Recuperated WR21 engine has been used as the test engine for implementing the diagnostics model.

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NOTATIONS

Δ	Deviation
Γ	Component flow capacity
σ	Noise standard deviation
ε	Heat exchange effectiveness
η	Component Efficiency
C_D	Nozzle discharge coefficient
f	Fitness
$f(.)$	Function
H	Influence coefficient matrix
J	Objective function
P	Pressure
P_C	Probability of crossover
P_M	Probability of mutation
R	Relative redundancy index
T	Temperature
u	Environment parameter vector with noise
v	Noise vector
w	Environment parameter vector
W_{FE}	Engine fuel flow
x	Performance parameter vector
z	Measurement vector
N_L	LP spool rotational speed
N_H	HP spool rotational speed
F_N	Net thrust
W_A	Engine mass flow
P_0	Ambient pressure
T_0	Ambient temperature

ABBREVIATIONS

AANN	Auto-Associative Neural Networks
AGA	Adaptive Genetic Algorithm
APNN	Adaptive Probabilistic Neural Network
BBN	Bayesian Belief Network
BP	Back Propagation
CBPM	Condition Based Preventive Maintenance
CD	Cumulative Deviation
COEHM	Cognitive Ontogenetic Engine Health Monitoring
COMPASS	Condition Monitoring and Performance Analysis Software System
CR	Confidence Rating
DAM	Delivery Air Manifold
DLE	Dry Low Emissions
DOA	Dedicated Observer Approach
ECM	Engine Condition Monitoring
EGT	Exhaust Gas Temperature
EHM	Engine Health Monitoring
EKF	Extended Kalman Filter
ELM	Engine Life Management
EP	Environment and power setting parameters
FADEC	Full Authority Digital Engine Control
FC	Fault Class
FCM	Fault Coefficient Matrix
FDI	Fault Detection and Isolation
Fin	Fan inner
FL	Fuzzy logic
FOD	Foreign Object Damage
F_{out}	Fan outer
FPT	Free Power Turbine
GA	Genetic Algorithm
GG	Gas Generator
GPA	Gas Path Analysis
GRNN	Generalised Regression Neural Network
GT	Gas Turbine
HDM	Hybrid Diagnostics Model
HE	Heat Exchanger
HOT	Higher Order Terms
HPC	High Pressure Compressor
HPT	High Pressure Turbine
ICL	Intercooler
ICM	Influence Coefficient Matrix
ICR	Inter-Cooled Recuperated
IEKF	Iterated Extended Kalman Filter
IFDM	Integrated Fault Diagnostics Model

IPC	Intermediate pressure compressor
IPT	Intermediate Pressure Turbine
KF	Kalman Filter
LB	Lower Bound
LPC	Low Pressure Compressor
LPT	Low Pressure Turbine
LSHSD	Low Sulphur High Speed Diesel
MISO	Multiple Input Single Output
MLE	Maximum Likelihood Estimation
MOPA	Multiple operating point analysis
NASA	National Aeronautics and Space Administration
NLGPA	Non Linear Gas Path Analysis
NN	Neural Network
NSGA	Non-dominated sorting Genetic Algorithms
O&M	Operation & Maintenance
OEM	Original Equipment Manufacturer
OOP	Object Oriented Programming
PDM	Predictive Maintenance
PHM	Prognostic and health management
PMS	Platform Management System
PPM	Planned Preventive Maintenance
RAM	Return Air Manifold
RBF	Radial Basis Function
RCM	Reliability centred maintenance
RCR	Recuperator
RMS	Root Mean Squared
RR	Rolls Royce
RRAP	Rolls-Royce Aero-engine Performance
SFC	Specific Fuel Consumption
SOAPP	State Of Art Performance Programming
SOPA	Single operating point analysis
SVM	State Variable engine Model
TEMPER	Turbine Engine Module Performance Estimation Routine
TET	Turbine Entry Temperature
UB	Upper Bound
UTC	University Technology Centre
VAN	Variable Area Nozzle
WLS	Weighted Least Squares

GLOSSARY

Activation Function	A function used to transform or squash a neuron's local threshold value to give outputs within defined ranges
Analysis	The process of deducing the performance of the individual components of a gas turbine from gas path measurements.
Bias	Deviation in sensor measurement from its normal value
Bottleneck	The smallest region or layer in an AANN
Condition Monitoring	The gathering of data from a gas turbine in service, in order to understand its condition and optimise its operating costs
Correlation	A measure of the relationship between two parameters, indicating whether changes in one of them are accompanied by changes in other.
Covariance	A statistical measure of how two random variables vary together. The covariance of two random variables a and b is defined as E[(a-a').(b-b')]
Covariance Matrix	A symmetrical matrix showing the covariance of each possible pair of elements in two random vectors.
Crossover	A method of generating a new solution by using parts of earlier solutions
Exponential Smoothing	A commonly used method of smoothing a time series, by adding a weighted value of the current observation to a weighted value of the previous estimate of the true value of the series.
Fitness	A positive value defining the accuracy of solution and it determines the progress of the solution to the next generation
Generation	A cycle of operation which involves selection, crossover and mutation.
Matching	The movement of gas turbine component operating points due to changes in component performance parameters
MOPA	Analysis using two different operating points.
Moving Average	A commonly used method of smoothing a time series, by averaging several points to reduce the effects of random noise in the observations.
Mutation	A method of generating new solutions by making random changes to the existing solutions
Noise	A random measurement error which causes disagreement in repeated measurement.

Normal Distribution	An important probability distribution used widely in the study of variability in measurement, components, etc.
Objective-Function	Summation of the percentages deviation of measurements from their baseline values used for comparing measurements.
Observability	The ability of the instrument to perceive the change in performance.
Outage	Period for which an engine is removed from service
Pareto	A method for choosing a particular string from a group of strings
Population	A group of solutions to the problem
Power Setting Parameter	A gas path measurement that is used to define the power setting of a gas turbine.
Recursive	An algorithm is said to be recursive if the calculations it carries out are dependent on the current input(s) and the results from immediately previous calculations only.
Repeatability	A random component of measurement error caused by numerous small effects which cause disagreements between repeated measurements of the same quantity.
Search Space	A collection of all possible solutions to the problem from which the best solution is chosen.
Selection	A method of separating the good solutions from a pool of solutions
Smearing	Distribution of fault value to other components other than the one under consideration.
String	A potential solution of the GA.
Synaptic weights	Weightings given to connections between neurons.
Handle	A set parameter that is held constant while all the other parameters are measured relative to it.
Deterioration	Reduction in the component's capacity to perform to its design value
Baseline	A quantifiable physical condition of level of performance from which changes are measured.

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CHAPTER-1

INTRODUCTION

1. 1 Gas Turbines for Marine Applications

The 21^{st} century has ushered in a variety of opportunities in terms of global economic investments and thus brought resurgence of interest in marine propulsion. It is a well known fact that the economic power and military might go side by side. this has led to major navies world-wide to update their fleets to give them the crucial *Sea Control* and rewrite their doctrines to the suit the concept of *Blue Water Navy.* In the commercial world the key to success lies in faster and cost effective transportation of passengers and cargo. More stringent emissions regulations and the likely increases in fuel prices have led to industries participating aggressively, in the research and development, in advanced marine propulsion systems and their performance and diagnostics techniques for better exploitation and reduced down times.

The tremendous technological efforts concentrated on and necessary to the growth demanded of the aircraft gas turbine has created inevitable recognition of these highly developed machines for all types of power utilisation. Aero-derivative gas turbines have gained acceptance in the marine propulsion field around the globe and majority are used as main propulsion prime movers for warships. Due to the inherent characteristics indicated below the gas turbines are being used for naval ships and off late in commercial liners.

- High specific power;
- Fast starting and shut down capabilities;
- Rapid acceleration from cold condition to maximum power;
- Good thermal performance;
- Automation, simplicity and reliability;
- Low capital cost and installation man-hours;
- Maintainability and reduction in manning;

With the recognition came the assurance that all aspects of the hostile marine environment and its effects would be given the same thorough study and effective resolution. This study referred as the marinisation of aircraft gas turbines deals with modification of the engine in order to be able to operate and survive in the hostile marine environment.

To fulfil the wide scope of marine propulsion system requirements, few significant areas which need to be addressed as part of marinisation process are -

- Salt atmosphere compatibility ,material and coating development
- Fuels and combustion
- Damage tolerance and shock sustaining capability
- Noise levels
- Reliability
- Maintainability
- Auxiliary system integration
- Operation and optimisation.

Marine gas turbines have been in service for more than two decades and have proved to be reliable and offer significant advantages to the user. Despite well-proven reliable features of these machines, their operation in hostile marine environment has been a cause for concern, both to the manufacturer and the user. The degradation they undergo result in significant performance deterioration and high operating costs. In addition, the last few decades have seen growing economic pressures, which have put tremendous pressure on the industries to cut down on cost to have a competitive edge over their competitors. This has been a major motivation for the application of various traditional and advanced fault analysis techniques for machinery diagnostics.

Marine gas turbines require a different kind of treatment by virtue of their applications and the environment in which they operate, especially engines fitted on combatant vessels. In addition to the above, there are severe constraints on the maintenance of these naval engines due their roles. Unlike the civil freight or passengers cruise liners, where the region of operation, availability of maintenance

facilities and schedules are know before hand, in the case of warships there is a lot of uncertainty involved due the operational commitments, which makes it very difficult to follow a pre-planned maintenance schedule, though efforts are always made to adhere to the planned maintenance activities. Thus, there is a pressing need for an accurate diagnostics model to assess the performance and predict the likelihood of a problem. The research work undertaken specifically addresses the issues of maintainability and reliability of gas turbine engines through advanced fault diagnostics techniques and promotes new opportunities for gas path based diagnostics.

1.2 Engine Condition Monitoring (ECM)

Engine condition monitoring and engine diagnosis have been recognised, for some time, as important assets in making more informed decisions on the usage, maintenance, overhaul or replacement of the engine or one of its components. Deterioration can affect relevant factors such as thrust (or power) and Specific Fuel Consumption (SFC). As a consequence of progressive performance loss, operation of the engine can become cost ineffective or even unsafe. Therefore maintenance techniques must be used to ensure that the gas turbine operated cost effectively and safely. There are several types of maintenance strategies adopted according the individual requirements. Broadly they can be classified into following categories:

1.2.1 Breakdown Maintenance

This sort of maintenance is performed only after the parts have failed or the operational performance limits are not achievable. It suffers from various drawbacks that include compromises on safety, performance and reliability.

1.2.2 Planned Preventive Maintenance (PPM)

This type of maintenance is performed according to a fixed maintenance schedule, which is time or running hours based. It is suitable for safe life designed components and usually involves routine replacement of parts etc. The useful remaining life is based on the fleet statistical usage or manufacturers recommendations and not on an individual engines operational exposure or experience. Its main drawbacks are the replacement of parts that have a significant remaining life or a reduction in operational capability or parts failing before a scheduled maintenance activity.

1.2.3 Condition Based Preventive Maintenance (CBPM)

The technique relies on determination of the condition of the engine for the purposes of overhaul schedule. Also known as Reliability Centred Maintenance (RCM), or Predictive Maintenance (PDM), this technique is now the most popular means of maintenance. Condition based preventive maintenance can sometimes extend parts usage beyond fleet averages based on actual operational usage.

1.2.4 Proactive maintenance

Proactive maintenance is an offshoot of condition based maintenance that emphasizes the routine detection and correction of root cause conditions that lead to performance changes and/or component failure. Conditions are corrected or parts are redesigned based on a root cause failure analysis. Root causes such as vibration and contamination can be monitored automatically, but a deeper study is required for aero thermal problems that require gas path analysis.

1.2.5 Prognostic Maintenance

Like proactive maintenance this is an application of condition based maintenance. The use of prognostics within a health management system is known as prognostic and health management (PHM). The ultimate objective is to integrate the PHM with the logistic system.

Relatively recent advances in computing, data collection and general modelling capability have made it feasible to develop maintenance strategies mainly based on condition monitoring. The greatest effort to develop a comprehensive and cost effective monitoring system has been made for aero engines maintenance. These techniques are being adopted in shore based and marine gas turbines. A key point in any ECM system is the concurrent utilisation of a number of techniques to keep track of various components and subsystem's performance. Some of the common methods employed in ECM are:

- Lubricating oil analysis
- Vibration monitoring
- High pressure turbine exit temperature spread
- Visual inspection / Boroscope inspection
- Transient monitoring
- Life cycle counting
- Exhaust Gas temperature monitoring
- Gas path analysis
- Gas path debris monitoring
- Eddy current checks
- Radiography

Considering the scenario of global civil air transportation market, increasing competition among airlines is pushing towards the application of advanced fault diagnosis techniques to review maintenance philosophies to reduce operating costs (Singh et al, 1999). In this respect, the propulsion system calls for a significant portion of the overall maintenance effort. Figure 1.1 shows that the maintenance cost together with the fuel bill represent 18% of the total costs. Similar is the case with marine and industrial gas turbines. The profit may be seen as large in absolutely term, however, when compared to the revenue and costs, it may be relatively small percentage. Thus, any change in either of the two could have detrimental effect on the total profits.

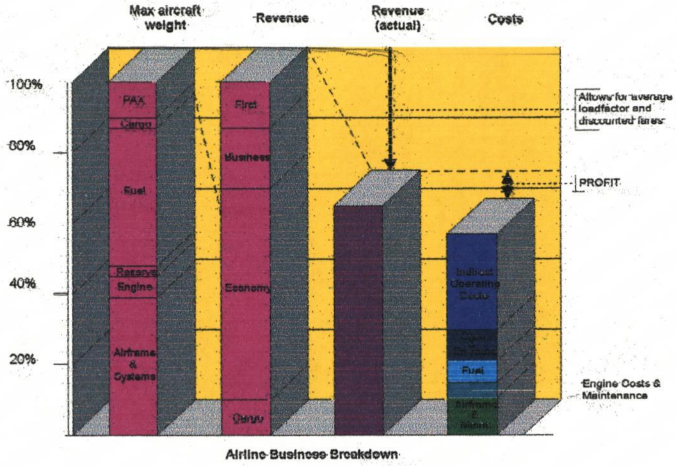


Figure 1.1: Airline Business Breakdown (Singh et al, 1999)

1.3 Reliability of Gas Turbines

To assess the consequence of a certain fault or component deterioration, it is necessary to relate it to availability and reliability issues. As a matter of fact, modern engines have very high level of reliability is broadly accepted. The question that remains is whether the reliability is achieved by using relatively large "safety margins", as these imply additional maintenance, shorter component lives and hence higher costs (Singh, 2003).

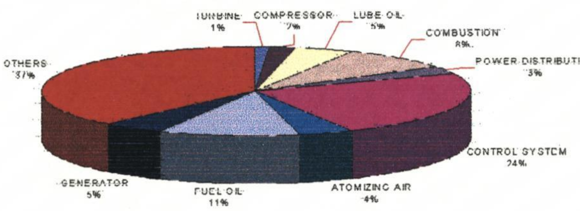


Figure 1.2: Forced Outage Rate (Singh et al, 1999)

When a forced outage occurs, availability is affected depending on the down time required to replace or repair the particular component or system. On one side, engine support system (e.g. control system, fuel system etc..) are statistically responsible for a large number of forced outages. Figure 1.2 shows the forced outage rate of various components and systems. It is clear that the forced outage due to turbines and compressors is only 1% and 2% respectively. Whereas, controls systems account for 24% of the forced outage. However, when the outage is due to a fault in these components (turbines and compressors), the down time required to repair or replace is usually long. Figure 1.3 shows that total downtime associated with the turbines and compressors is 14% and 12% respectively compared to just 6% for the control systems.

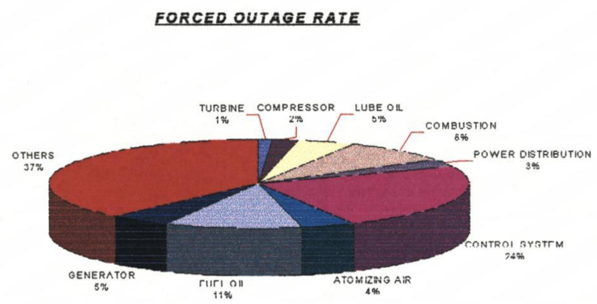


Figure 1.3: Percentage forced outage downtimes for various components (Singh et al, 1999)

The low probability of fault occurrence and the high cost of holding engine component spares entail that they are often not held as spares. However, in certain crucial operations, holding a spare engine also makes economic sense. E.g. if in an oil field, the cost of amount of oil being pumped out is far too much when compared to the cost of an engine such that the downtime would seriously affect the revenue then it would be prudent to keep a spare engine.

1.4 Motivation for the Present Work

The major motivating factors for the taking up this work can be described under the following subjects-

- Techno-Economic issues
- Marine Applications
- Manpower issues

1.4.1 Techno-Economic Issues

The future marine industry will demand ever-increasing power from propulsion engine with the order-winning criteria being 'economy and reliability'. In addition ferocious negotiations by the Original Equipment Manufacturers (OEMs) have intensified the competitive arena with all the participants looking to future business. This competitive environment can only become more intensive as the gas turbine OEMs, such as Rolls-Royce and General Electric , increasingly focus on the servicing of their products in order to secure their economic returns on engine sales and to capture market share. This change in the dynamics of the industry has altered due to the consolidation of overhaul and maintenance services from independent suppliers to the OEMs. Thus the new challenges for the ensuring profitability will be achieved through altering the dynamics of the sector to a service-oriented environment with manufacturers selling not engine products but a blend of engines, maintenance and financing. The concepts like 'Power by the Hour ^{TM}' (trademark held by Rolls-Royce) which are being introduced into the airline industry could very well be a reality for marine propulsions in near future, especially when navies are moving towards lean manning of ships and reduced manpower in ship yards.

1.4.2 Marine Applications

While most of the leading edge fault diagnostics technology have been used for aero-engines, traditionally gas turbine engines on board were maintained according to hard-life concept, whereby components were removed and refurbished after a pre-determined time based on a deterioration rate. Although this did minimise operation disruptions from engine shutdowns, engines were undergoing O&M regardless of actual condition. As new technology was developed and introduced into the market such a high temperature resistant materials and introduction of air-cooled turbine blades, the on board times of the engines increased significantly and the concept of on-condition maintenance were adopted. Thus instead of removing the engine after a fixed time the engine was constantly monitored using instrumentation sets to provide a trigger for maintenance from the engine's performance deterioration and condition.

The relationship between on-board time and maintenance cost must be monitored carefully and analysed, since on board times could be extended too far resulting in unacceptable economic impact. In essence, the solution is to develop knowledge-based tools that will optimise engine life at most operationally cost effective position without any negative impact on reliability .This concept will provide the opportunity to keep the engine on-board as long as possible and to restore its performance at the lowest possible costs during the O&M activities.

1.4.3 Manpower Issues

It is essential that advanced manpower planning be conducted prior to an outage. It should be understood that a wide range of experience, productivity and working conditions exist in shipyards. However, based upon maintenance inspection man-hour assumptions, an average crew composition can we worked out. This planned approach will outline the renewal of parts that may be needed and the projected work scope, showing which tasks can be accomplished in parallel and which tasks must be sequential. Planning techniques can be used to reduce maintenance cost by optimising lifting equipment schedules to be taken up only when ship enters a major refit. Estimates of the outage duration, resource requirements, critical-path scheduling, recommended replacement parts and associated costs can be worked out. In Addition, the development of concepts like Platform Management Systems (PMS) has taken place against a background of diminishing manpower numbers and changing skill levels to match the application of new technologies. These factors have been the principal drivers in the application of increasing level of automation in each new class of vessel. To optimise the manpower levels on future naval platforms and reduce the need for manual logging and analysing will have to be replaced by technology and automation. Traditionally the engine watch keeper during his rounds monitors the impending problems by the senses of sight, touch, hearing and smell and takes action according to his understanding of the problems, the routine manual monitoring of parameters and analyses are tedious perhaps manpower intensive, especially in large ships. Factors like the attentiveness and fatigue levels of the watch keeper need to be considered.

From the above discussion it is evident that the advanced fault diagnostics tools applied to engine health monitoring of machinery have a significant role to play in the future marine propulsion and maintenance management. Such systems may not only help in monitoring the parameters, but also in analysing and simulating scenarios to understand the implications of faults and training personnel.

Within the engine industry itself, the market drivers are 'economy and reliability' namely the demand for power at the lowest possible cost and the highest level of reliability, with determinants like the specific fuel consumption, maintenance and life cycle costs, power to weight ratio, engine noise, Emissions being under customer considerations for their choice of engine. Even with the paradigm shifts in the market place from the selling of a gas turbine engine to actual lifecycle management of the units resulting form the service-oriented 'Power by the Hour' agreement, these drivers still remain. However, their weightings have moved towards greater emphasis on lifecycle service provision. In addition, continued escalation in engine purchase price, costs of spare parts, maintenance operations and soaring fuel costs have made it increasingly desirable for operators to employ engine diagnostics or engine health monitoring which implies the ability to accurately assess the relative health and performance of their engines in a reliable cost effective and technically sound way.

It was recognised that the technology push and market pull creates an opportunity for investigating and developing advanced fault diagnostic techniques which can be used for engine health monitoring and reviewing maintenance strategies. These challenges have necessitated the development of advanced fault diagnostics for marine gas turbines, while keeping in mind that the operational requirements for warships usually outweighs the need for a scheduled maintenance and also the various port may not have adequate refitting facilities. Overall the industry would be benefited by improved safety associated with operating and maintaining gas turbines, reduced overall life cycle costs of engines from installation to retirement, increased up/time availability of all engines within a fleet and providing engineering justification for scheduling maintenance actions with corresponding identifiable economic benefits.

1.5 Objectives & Contributions from the Research Work

The research work is sponsored by Ms Rolls-Royce (Marine & Industrial) and the 'Overseas Research Scheme' award by the Committee of Vice-Chancellors and Principals (United Kingdom). In order to put the objectives of the research work in context, it would be appropriate to briefly describe the background to the present research work:

1.5.1 Background to current research:

- The project based on optimization technique was conceived in 1996, whereby Zedda (1999), funded by Rolls Royce plc, started a PhD to carry out a thorough review of the current technology for performance analysis and diagnosis and then to develop an advanced methodology to carry out such a task. He developed a technique based on the use of Genetic Algorithm (GA) for a well-instrumented engine, the EJ 200, which had an instrumentation suite for a development engine. The technique proved to be a success and was received by the company with enthusiasm.
- Since, the initial tests were with test bed instrumentation sets (which very large compared to the in-service engine), Rolls-Royce decided to investigate this technique for engines with in-service instrumentation. This led to the research work by Gulati (2002) in which he investigated the use of multiple operating point analysis to overcome the lack of information from reduced instrumentation. The engine used for this task was the RB199. This engine was chosen due to the difficulty faced at Rolls Royce in diagnosing faults with this engine. On successful testing with the RB199 engine, the method was suitably modified and tested on a few other engines, like aero Trent 500 and the Industrial RB 211 by Carter (2001).

1.5.2 Choice of GA based diagnostics & Need for Enhancement:

When compared with various other diagnostics technique, the technique based on GA was found to be most suitable of an advanced cycle engine due its inherent capability in preserving the system non –linearity. The technique based on GA had been proved to be robust and had the ability to overcome some of the problems associated with measurement noise and instruments bias. However, a major impediment to its implementation was the long run times of the algorithm. E.g. it would take 36 hours for an engine like the RB211, assuming that a maximum of two components were faulty simultaneously. Such long diagnostics time would not be suitable for any real time application and could lead to non-recoverable damage to the engine if used. Thus the need to enhance the basic model in terms of accuracy and reduced convergence time was felt. Prior to this research work, the technique was tested only on simple cycle engines. Present research deals with the development of a diagnostics model using some advanced concepts in GA and also looks at possibility of integration with other fault diagnostics to form a hybrid model for efficient fault diagnostics. The advanced cycle ICR WR-21 engine model has been used for validating the results.

1.5.3 Research Objective

The objective of the research is to develop a performance assessment and fault diagnostics model for an advanced cycle gas turbine. The salient features of the research work is to-

(a) Identify shift in engine performance and deterioration in component performance.
(b) Identify faulty components with the minimum set of instrumentation suite.
(c) Detect, identify and isolate faulty sensors
(d) Consider the measurement noises and sensor bias while carrying out diagnosis
(e) Investigate the possibility of combining several techniques to develop a hybrid engine fault diagnostics technique with improved accuracy and reduced convergence time.

1.5.4 Contributions from Current Research

It is expected that this PhD will make the following novel contributions:

(a) The use of adaptive GAs and embedded expert system is a new concept in engine fault diagnostics. The use of nested neural network as a pre-processor in a hybrid diagnostics model is also a new concept as until now the fault diagnostics techniques have mostly been used in isolation. This development has created new opportunities in the field of gas path diagnostics with a possibility of finding applications in advanced cycle engines and combined cycle configurations.

(b) A diagnostics model has been developed for the advanced cycle intercooled recuperated WR21 engine with variable area nozzle. The development has led to a substantial reduction in diagnostics time and improvement in diagnostic accuracy. The methodology adopted here brings the diagnostics system closer to application in online fault diagnostics system.

1.5.5 Benefits from Current Research

Most of the sophisticated fault diagnostics techniques have been applied to aero gas turbines. However, these techniques being generic, are eventually finding their way to industrial and marine applications. The availability of such techniques has made industrial and marine users more sensitive to maintenance issues. Even though the present works focuses on aero-thermal performance analysis and fault diagnosis, it would be misleading to assume this technique to be better than the rest. It is pertinent to mention that each the techniques mentioned in section 1.2 have their own importance and contribute to the engine health monitoring. In the current research work, a fault diagnostics system has been developed for the ICR WR21. The technique is generic is nature and can be easily adapted to any engine with minimal modifications to the algorithm. Overall, it is expected that the following benefits will accrue from the development of the diagnostics technique presented in this thesis:

- Improved safety in operating gas turbine engines;
- Reduced overall life cycle cost;
- Optimise maintenance interval and prioritise task to enhance operational availability;
- Engineering justification for scheduling maintenance while identifying corresponding economic benefits;
- Serve as post refit benchmark;
- Training personnel on importance of good maintenance practice (Simulating fault conditions).

1.6 Overview of the Thesis

The followings paragraphs give a brief description of the contents of each chapter which forms part of this thesis:

Chapter-1: Introduction

This chapter provides a broad outline of the gas turbine application in the marine application. It also presents the motivating factors which has led to the research work, and has been discussed under various topics like the techno-economic issues, application in marine field and the impact on manpower. Finally, it discusses the objectives and contributions from the research work and gives an overview of the thesis.

Chapter-2: Engine Fault Diagnostics Techniques- An overview

This chapter gives an overview of the various performance based engine fault techniques available. It also summarises the various engine fault diagnostics techniques available, their advantages and limitations.

Chapter-3: Optimisation Techniques for Engine Fault Diagnosis

This chapter gives an overview of Genetic Algorithms (GA) and their applications to engine fault diagnostics. A discussion on the development diagnostics model for the well instrumented EJ200 and poorly instrumented RB199 is presented.

Chapter-4: Diagnosis of Advance cycle Engine

This chapter presents the concept of marinisation of an aero gas turbine and discusses methods to improve part load efficiency of a marine gas turbine. The chapter also briefly discussed the design of the advanced cycle intercooled recuperated WR21 engine and development of a TURBOMATCH (A Generic engine modelling software) model of WR21.

Chapter-5: Development of Diagnostics for WR21

This chapter describes the development of an engine fault diagnostics tool using GAs for the ICR WR21 engine, its limitations and the need for improvement to the basic form to make it usable for real time applications.

Chapter-6: Advanced Fault Diagnostics model

This chapter describes in detail the new diagnostics model developed using the concept of response surface, elitist model and heuristic manipulation of GA parameters. This chapter also describes a novel way of combining neural network and Genetic Algorithm using the advantages of both the techniques to develop a hybrid technique for improved performance.

Chapter-7: Discussion of results

This chapter presents a discussion on the development of a diagnostics tool for the WR21, the important issues to be addressed and discusses the results from various of test cases. A comparison of the various forms of GA based diagnostics model is also presented.

Chapter-8: Conclusion and Recommendation

This chapter gives the conclusion of the research work carried out. It also gives a summary of the contributions made, limitations of the present research and some recommendations for future developments.

CHAPTER-2

GAS TURBINE ENGINE FAULT DIAGNOSTICS AN OVERVIEW

2.1 Introduction

There are many approaches for gas turbine condition monitoring and fault diagnostics, such as performance analysis, oil analysis, visual inspection, boroscope inspection, X-ray checks, eddy current checks, vibration monitoring, debris monitoring, noise monitoring, turbine exit spread monitoring, etc. Performance analysis based diagnostics is one of the most powerful tools among them, where the analysis of gas turbine gas path parameters provides the information of degradation severity of gas path components. Research in recent years shows that current research efforts on gas turbine diagnostics have been focused on the improvement of reliability, accuracy, computational efficiency, online application and inclusion of more practical considerations such as data pre-processing and validation, measurement noise reduction, multiple component faults, sensor faults, data uncertainty, etc.

In this chapter, technologies relevant to gas turbine performance analysis based diagnostics developed so far and published in the open literature are reviewed, from its beginning of Urban's (Urban, 1967) work until the most recent state-of-the-art technologies. Such technologies include earlier linear and non-linear model-based methods to more advanced artificial intelligence (neural networks, genetic algorithms and expert systems) based methods, and fuzzy logic based approaches, for gas turbine component fault diagnostics on both steady state and transient measurement data. Additionally, data validation and different approaches for filtering noise from the measurements for gas turbine fault diagnostics have also been discussed.

2.2 Engine Performance Analysis

One of the main stimulants to the development of thermodynamic modelling of the gas turbine has been the steady flow nature of the cycle. The steady flow nature of the gas turbine cycle makes it much more amenable to accurate mathematical calculations. The analytical performance model of a gas turbine engine is based on component characteristics and aero-thermo relationships such as the laws of conservation of energy and mass and special conditions such as choked nozzle and bleed. The calculation then proceeds to "match" all the components by satisfying the aero-thermal relationships. Assuming that all component characteristics are accurately defined, the model can provide the engine performance in terms of dependent (measurable) parameters such as pressure, temperature, spool speed etc..

The ease of calculation of the gas turbine cycles has led to the development of many performance modelling tools such as the Rolls Royce's RRAP, Pratt and Whitney's SOAPP and Cranfield's TURBOMATCH systems. If the flow, pressure ratio and efficiency characteristics of the compressor and turbine are known, as well as the pressure loss characteristics of the intake, combustion chamber and exhaust and the temperature rise characteristics of the fuel used, then the performance of the whole engine can calculated.

2.3 Performance Deterioration

In the course of its useful life the gas containment path of any engine is susceptible to encountering a wide variety of physical problems. These include problems such as erosion, corrosion, fouling, built up dirt, foreign object damage, worn seals, excessive tip clearance, burned or warped turbine stator or rotor blades, partially or wholly missing blades, plugged fuel nozzles, rotor disk or blade cracks induced by fatigue or operation outside intended limits, etc. In order to develop an engine deterioration model, the faults have to be classified, quantified and identified (Diakunchak, 1992). Typically, a quantitative representation of physical fault can be described as a change in one or more of the independent parameters which describes individual gas path components performances like the component isentropic efficiency, flow capacity, turbine nozzle guide vane area, exhaust nozzle area etc. It is noteworthy that the independent parameters are determined by the gas turbine's configuration and that they cannot be measured at all.

The following sections describe some of the faults and their effect on the engine performance. The quantification of faults allows simulation of faults in a computer program.

2.3.1 Fouling

Fouling can be defined as the 'degradation of flow capacity and efficiency caused by adherence of particulate contaminants to the gas turbine airfoil and annulus surfaces' (Diakunchak, 1992). Although fouling can occur in both compressor and turbine components, it has been recognized that compressor fouling is one of the most common cause of engine performance deterioration (Aker, 1989). Gas turbines are particularly susceptible to fouling because of the large quantities of air they ingest. The incoming air consists of hard and soft particles. Hard particles such as dust, dirt, sand, rust, ash and carbon particles and soft particles such as oil, unburned hydrocarbons, soot, airborne industrial chemicals, fertilizers, herbicides etc. can provide a source for fouling. In the case of compressor fouling, the change in blade shape causes a reduction in compressor flow capacity and a reduction in compressor isentropic efficiency. The effect of fouling on compressor flow capacity is more significant than the effect on efficiency. Typically, the flow capacity is reduced by 3 -8% and the efficiency by 1% depending on the severity of fouling (Saravanamuttoo, 1985; Diakunchak, 1992). The reduction in mass flow capacity varies with operating speed, ambient temperature and altitudes (Saravanamuttoo, 1985). Furthermore, compressor fouling not only reduces the flow capacity and efficiency, but also reduces the compressor surge margin and this may result in compressor surge (Diakunchak, 1992).

2.3.2 Erosion

Erosion can be defined as 'the abrasive removal of material from the flow path components by hard particles in the air or gas stream' (Diakunchak, 1992). A typical size of the particles is 20μm or more in diameter. The particulates which cause erosion are hard particulates such as dirt, dust, sand, carbon/soot (the carbon particles are produced as a result of inefficient combustion), ash, salt and industrial pollutants. As a result of erosion, the airfoil surface roughness is increased, inlet metal angle is changed (hence airfoil incidence), airfoil profile is changed, airfoil throat opening is changed, blade tip and seal clearances are increased. In some cases the eroded airfoil trailing edge thickness can be beneficial to performance, though it is unacceptable from mechanical integrity considerations (Diakunchak, 1992). The erosion of engine components results in blunting of aerofoil leading edges, thinning of trailing edges and increased surface roughness.

2.3.3 Corrosion

Corrosion can be defined as the loss of material from flow path components caused by the chemical reaction between these components and contaminants that enter the gas turbine with the inlet air, fuel, or injected water/steam. Salts, mineral acids, and reactive gases such as chlorine and sulphur oxides, in combination with water, can cause wet corrosion, especially of the compressor airfoils. Elements like sodium, vanadium and lead in metallic or compound form can also cause high temperature corrosion of the turbine airfoils. Hot end surface oxidation is another form of corrosion (Diakunchak, 1992).

Similar to erosion, corrosion can result in the loss of material and increase in surface roughness. In addition, corrosion results in a loss of performance and service life of the component affected. Typically, compressor corrosion results in a reduction in compressor flow capacity and isentropic efficiency, whilst turbine erosion results in an increase in turbine effective area/flow capacity and a reduction in isentropic efficiency.

2.3.4 Foreign Object Damage (FOD)

Foreign object damage (FOD) can be defined as the cause by which large objects strike the flow path components of the gas turbine engine. These objects enter the engine with the inlet air or are the result of pieces of the engine itself breaking off and being carried downstream. Foreign objects can be things like stones, birds, bolts, tools, etc. Excessive ice formation on the compressor inlet, carbon deposits on fuel nozzles, and engine subcomponents can break loose and result in damage to internal downstream components. Foreign object damage can vary from non-recoverable (with washing) engine performance deterioration to catastrophic engine failure (Diakunchak, 1992).

The effect of FOD on performance degradation varies significantly with the severity of the damage. FOD results in a large reduction of the component isentropic efficiency and in some cases can change the flow capacity of the damaged component. Typically, isentropic efficiency can decrease by 5% (Zhu, 1992). However the value is very much dependent on the severity of the damage. The change in flow capacity depends on the type of FOD damage. In some cases the flow capacity may increase, in other cases it may decrease. An increase of flow capacity can be the result of lost blades. A decrease of flow capacity can be the result of foreign particles blocked in the gas path. A blockage can be caused by desert sand that has been virtually glued to the turbine blades because of the heat.

2.3.5 Thermal Distortion

Thermal distortion is a fault that normally occurs at combustor exit/turbine entry where temperatures are highest. Distortion is caused by problems such as faulty fuel nozzle spray patterns and warped combustor components which cause changes in the radial and circumferential temperature traverse pattern at the combustor exit. This can result in temporary or permanent deformation of downstream components such as cracked, bowed, warped, burned, lost or damaged turbine nozzle guide vanes, area changes, increased leakage, and relative thermal growth between the static and rotating members (English, 1995). High temperature can cause first stage turbine blades to untwist. These blades untwist as a result of creep damage during sustained high temperature operation (Macleod, 1992). Bowed, burned, warped, untwisted or damaged blades can cause a reduction in turbine isentropic efficiency due to increased air leakage and reduced airfoil performance. The damage of the blades can also result in changes to the effective flow area. However, the most significant effect will usually be on turbine isentropic efficiency (MacLeod, 1992).

2.4 Facets of Gas Turbine Fault Diagnosis

The objective of the mathematical modelling process is clear: use component characteristics and thermodynamic relationships to build a mathematical model of a gas turbine from its parts. Analysis, on the other hand can have different objectives depending on what the results will used for. If for instance, the analysis is being done to determine if a gas turbine is acceptable to the customer, then the calculations to determine its acceptability or otherwise will almost certainly be laid down in a contract specification.

Condition monitoring of a gas turbine in service requires an intermediate approach, in which fairly detailed and up-to-date analysis methods need to be agreed between the manufacturer and the end user in order to achieve cost effective maintenance. Using one set of methods to achieve another set of objectives is usually a recipe for confusion and misunderstanding.

It should be noted that the gas turbine performance analyst is rarely asked to explain the absolute levels of overall performance that are calculated. Usually, performance of gas turbines and components is expressed relative to some appropriate datum. For instance, the statement that the specific fuel consumptions the of gas turbine under analysis is 10 gm/KNs is not nearly as useful as the statement that the SFC is 3% worse than expected. A stated compressor efficiency of 89% sounds quite good, until comparison with the results of the rig test shows it to be lower than 2% of the design (Provost, 1994).

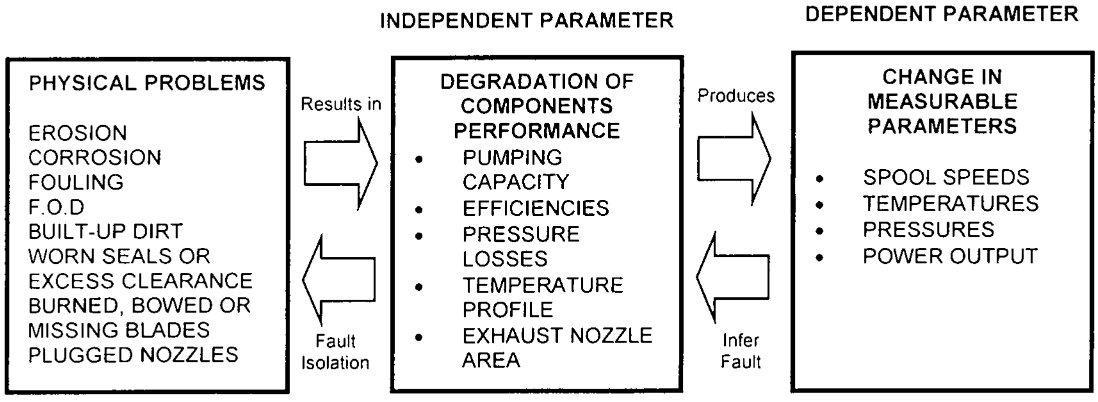


Figure 2.1: Gas Turbine fault diagnosis approach (Urban,1974)

Ultimately, the purpose of gas turbine performance analysis is to identify physical faults by looking for the deviations in measurable parameters like the temperatures, pressures, spool speeds etc. from expectations. Figure 2.1 shows the working relationships in the analytical process (Urban, 1974).

Superficially the analysis process as shown in fig-2.1 looks easy; calculate appropriate component performance parameter deviations from the gas path measurement deviations relative to a datum, then use the results to guide the search for hardware faults. In practice the analysis process is corrupted by errors in the measurements taken to determine how the gas turbine is behaving.

Errors can have serious effects on any analysis, because they result in incorrect component performance calculations which lead to misleading hardware fault diagnosis. As Provost (1994) had rightly said "Every experienced analyst will recall instances of measurement errors discovered when analysing gas turbines on-line that either prevented the test being terminated prematurely (due to incorrect calculation of critical gas-path parameters such as turbine entry temperature) or stopped a potentially worthless or dangerous test from proceeding (fuel leaks in altitude test plants, in which the gas turbines itself is sealed inside a test chamber and not visible by the test crew)" .

Failure to detect measurement errors can have serious financial consequences, as time and effort are spent searching (on the basis of flawed calculations) for non-existent faults in one part of the gas turbine while genuine faults go undetected. Any analyst who ignores the possibility of corruption of his calculations by erroneous measurements is treading on dangerous ground (Provost, 1994). The experienced performance analyst learns to look for characteristic 'signatures' of typical single measurement errors : these are usually recognised by calculation of better than expected performance of one or more components , accompanied by worse than expected performance on other components (so-called 'reciprocal change') . However, when more than one error is present and/or genuine changes in components that make up error 'signatures' have happened , the task of finding errors becomes very much more difficult . It is not unusual for even the most experienced analyst to spend days or weeks trying to produce a credible assessment of overall and component behaviour when multiple errors are present: engineering judgement, trial and error calculations, patience and a certain amount of luck are all required, if any sense is to be made of the results. The need to speed up an inefficient, time consuming and demoralising process is the main motivation behind the research that had been undertaken.

2.5 Performance Analysis Based Diagnostics

In the last three decades, researches have investigated several different techniques for engine fault diagnostics. Performance analysis based technique for engine fault diagnostics has emerged as a powerful tool and tremendous research efforts have been directed towards it. There are several methods investigated and a lot of information is available in the public domain on these and an extensive review of methods that exist today has been provided by Li (2002). The comprehensive review by Li (2002) has been extremely helpful in obtaining a wide range of information and organizing the literature review in this thesis. The contribution of the author is duly acknowledged. The methods available have been broadly classified into three subgroups for ease of presentation. An overview of some of the methods is given in the subsequent sections.

2.5.1 Linear Model-Based Diagnostics Methods

The aero-thermodynamic relationship between gas turbine dependent parameters and independent parameters is complex and highly non linear. Linear diagnostics methods are characterised as such, because they use a linearised representation of engine performance. To simplify the description of such a relationship, a linear approximation at certain operating point (such as maximum power or cruise) was introduced as follow:

$$\bar{z} = H \cdot \bar{x} \tag{2.1}$$

With this assumption, a first Gas Path Analysis (GPA) method was introduced by Urban in 1967(Urban, 1967). Its application to gas turbine condition monitoring and engine fault diagnosis was further described by Urban (Urban 1980 and 1981). A review of Gas Path Analysis was given by Smetana (1975). This GPA method has been widely used in applications, such as those of Passalacque (1974), Staples and Saravanamuttoo (1974), Saravanamuttoo (1974), Danielsson (1977), Lazalier et al. (1978), Grewal (1988), Escher (1995a, 1995b), Nieden and Fiedler (1999) and Simani et al. (2000). In this method, the relationship between various engine measurable parameter deltas and immeasurable component parameter deltas at certain engine operating condition is expressed with a linear Influence Coefficient Matrix(ICM):

$$\Delta\bar{z} = H \cdot \Delta\bar{x} \tag{2.2}$$

The deviation of engine component parameters can be calculated with a Fault Coefficient Matrix(FCM) which is the inverse of the ICM:

$$\Delta\bar{x} = H^{-1} \cdot \Delta\bar{z} \tag{2.3}$$

The generation of the fault coefficients relies on the implantation of known faults in the components. The basic formulation is conceptually simple and provides quick solutions to gas turbine diagnostics and has proven to be successful in many of the commercial fault diagnostics system like TEMPER, COMPASS etc. A detailed description of the method is given in the following section.

2.5.2 Gas Path Analysis (GPA)

The objective of gas path analysis is to determine faults associated with components through the observation of judiciously chosen measurements (dependent parameters). To be implicitly detectable (i.e. implied from their effects on the measurable parameters), the problems or faults must be clearly of a nature and magnitude that will produce an observable change in the measurements. Thus certain problems such as fatigue cracks in rotor disks or blades, or corrosive attacks on the metallurgical structure but not the geometry of turbine blades, are undetectable by analytical technique and must sought by radiography, boroscope or other visual inspection means. A large portion of the potential faults are however amenable to detection by gas path analysis.

Each of the faults whether caused by normal wear, degradation, F.O.D., or abnormal abuse, may be viewed as affecting one or more components in one or more of their basic performance parameters. For example compressor or fan faults will manifest themselves as change in either the air pumping capacity or the adiabatic compression efficiency or both; turbine faults will manifest themselves as changes in either the turbine effective nozzle area size or the adiabatic expansion efficiency or both. These primary independent parameters although fundamental in nature and leading directly to the detection of engine faults are not readily or practically measurable. The parameters which can be measured are typically the various temperatures, pressures, fuel flow and rotor speeds throughout the engine. These parameters are dependent variables whose absolute values depend on the absolute levels of all primary independent variables. Therefore, since changes in these dependent variables are brought about by changes in the primary independent variables, differences in these parameters from their baseline expected values can be used to implicitly determine which elements of the gas path have undergone distress or departed from their initial or expected condition. It should be stressed that any parameter in itself is not necessarily indicative of fault in any particular element. For example, at any given rotor speed, a change in compressor discharge pressure does not mean there is a compressor fault. The change may also be due to a change in compressor or turbine fault.

At any given operating condition, two bits of information is available, what the engine manufacturer or user experience says the nominal measured parameter value should be, and what the observed value actually is. The observed values should be used for purposes of analysis. The data must first be corrected for factors such as installation losses associated with test cells, instrumentation calibration errors, effects of bleed and effects of Reynold's number. Once corrected, a gross delta value for each parameter is obtained as shown in figure 2.2.

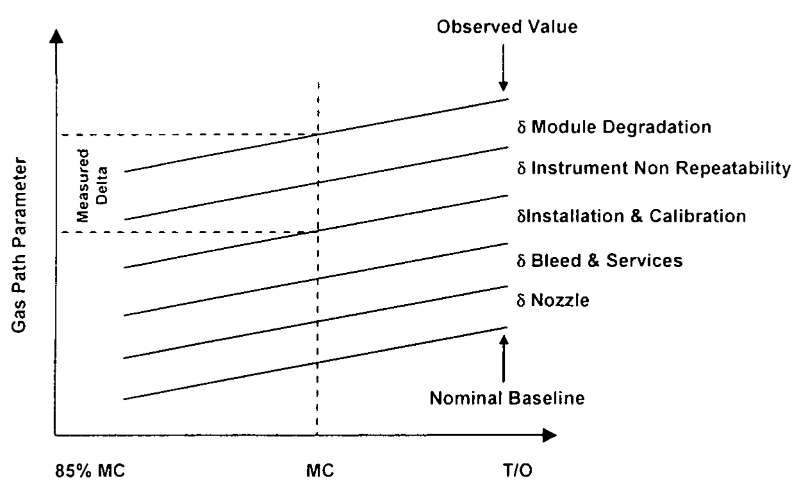


Figure 2.2: Calculation of measurement of deltas

This is composed of two factors, the net delta due to deviant module, which is the portion of the diagnostic interest, and the portion due to instrumentation non-repeatability and possibly the presence of other unsought problems such as model errors, baseline errors etc. GPA could be linear or non-linear and both these methods are described in the succeeding sections.

2.5.2.1 Mathematics of GPA

Theoretically there exists a relationship between the measured parameters and the independent parameter. Let us consider an arbitrary condition where z is dependent on 2 independent variable x & y. If the baseline value of z_0 is known for a given values of $x = x_0$ and $y = y_0$, then the function z can be expanded using Taylor series

$$z = z_0 + \frac{\delta z}{\delta x} \Big|_{x=x_0} \times (x - x_0) + \frac{\delta z}{\delta y} \Big|_{y=y_0} \times (y - y_0) + \ldots\ldots\text{(HOT)} \qquad (2.3)$$

as magnitude of changes in independent parameters are likely to be small, Higher Order Terms(HOT) can be neglected and equation (2.3) can be rewritten as

$$\frac{z - z_0}{z_0} = \frac{x_0}{z_0} \times \frac{\delta z}{\delta x} \Big|_{x=x_0} \times \frac{(x - x_0)}{x_0} + \frac{y_0}{z_0} \times \frac{\delta z}{\delta y} \Big|_{y=y_0} \times \frac{y - y_0}{y_0} \qquad (2.4)$$

It is customary to define performance shifts in terms of percentage deviation from baseline therefore defining

$$\Delta z = \frac{z - z_0}{z_0} \times 100 \qquad (2.5)$$

Substituting equation (2.5) in equation (2.4) we get

$$\Delta z = \left\{ \frac{x_0}{z_0} \times \frac{\delta z}{\delta x} \Big|_{x=x_0} \right\} \times \Delta x + \left\{ \frac{y_0}{z_0} \times \frac{\delta z}{\delta y} \Big|_{y=y_0} \right\} \times \Delta y \qquad (2.6)$$

all terms inside curly brackets are constants, in mathematical terms called coefficients and equation (2.6) can be written as:

$$\Delta z = C_1 \times \Delta x + C_2 \times \Delta y \tag{2.7}$$

The above equation defines a relationship between change in dependent parameter z to change in independent parameter x & y. However in reality we are likely to measure a set of dependent parameters to detect a set obtain the independent parameters, the general form of the equation can be written as:

$$Z_e = H_e \times X_e \tag{2.8}$$

Z_e : Set of engine parameter measurements

X_e : Set of engine module deviations

H_e : Set of influence coefficients determining relationship between dependent and independent parameters.

Where, H_e is called the Influence Coefficient Matrix (ICM). In our study we would be interested in obtaining X_e, therefore, mathematically-

$$X_e = H_e^{-1} \times Z_e \tag{2.9}$$

The matrix H^{1} which is inverse of the ICM is the Fault Coefficient Matrix(FCM). Thus knowing the dependent parameters, calculating the ICM and hence the FCM, it is possible to estimate magnitude, nature and location of the degradation. A schematic diagram of GPA is given in Fig-2.3.

Where:

- $\Delta\bar{z}$ is measurement deviation vector

$$\Delta\bar{z} = \bar{z} - \bar{z}_0 = \begin{bmatrix} \Delta z_1 \\ \Delta z_2 \\ \cdots \\ \Delta z_M \end{bmatrix} \tag{2.10}$$

- $\Delta\bar{x}$ is component parameter deviation vector

$$\Delta\bar{x} = \bar{x} - \bar{x}_0 = \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \cdots \\ \Delta x_3 \end{bmatrix} \qquad (2.11)$$

- H is the "Influence Coefficient Matrix" (ICM)

$$H = \left.\frac{\partial \bar{z}}{\partial \bar{x}}\right|_0 = \begin{bmatrix} \frac{\partial h_1(\bar{x})}{\partial x_1} & \frac{\partial h_1(\bar{x})}{\partial x_2} & \cdots & \frac{\partial h_1(\bar{x})}{\partial x_N} \\ \frac{\partial h_2(\bar{x})}{\partial x_1} & \frac{\partial h_2(\bar{x})}{\partial x_2} & \cdots & \frac{\partial h_2(\bar{x})}{\partial x_N} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial h_M(\bar{x})}{\partial x_1} & \frac{\partial h_M(\bar{x})}{\partial x_2} & \cdots & \frac{\partial h_M(\bar{x})}{\partial x_N} \end{bmatrix}_0 \qquad (2.12)$$

By inverting the ICM we have made several assumptions regarding the relationship between the dependent and independent parameters which carry with them certain constraints. The following are assumed-

- A set of accurate measurement deltas are available , i.e. there exists a method to faithfully reduce raw observed engine data to a measurement delta level;
- The faults coefficients are an accurate engine model descriptor; the faults occurring in the engine are among those being sought;
- The fault coefficients are invertible (i.e. the changes in the unknown are adequately manifested in the observations);
- The measurements are repeatable and free of noise;

The assumption that the relationship between the independent and the dependent parameters is linear becomes a serious limitation when the degraded point shifts further away from the original operating point (where the matrix was created). It was found that when the deviation increases beyond 1% the linear GPA becomes unreliable (Gulati, 2002c). This led to the development of Non-Linear GPA. The solution to this problem is to run the linear GPA iteratively by creating new ICMs and FCMs with the degradation values obtained in the previous step, until the algorithm converges to a pre-defined error bound.

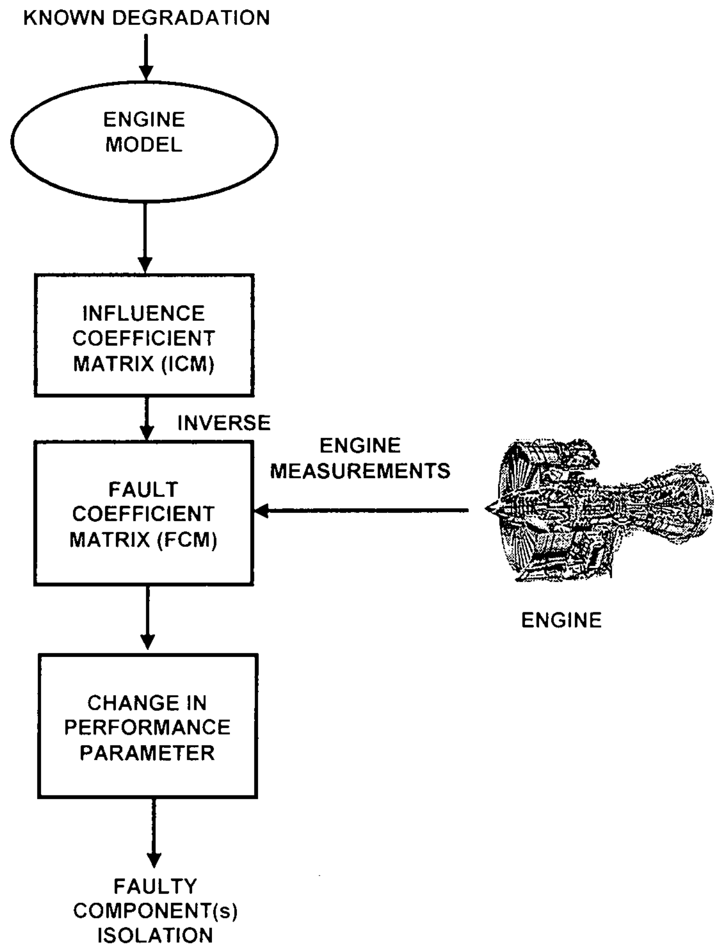


Figure 2.3: Schematic diagram of GPA

2.5.2.2 Advantages and Limitations of GPA

GPA shows powerful diagnostics potential due to the following capabilities:

- Modular Approach: the technique isolates faults at component level by identifying the variation in the corresponding performance parameters of the component;
- Multiple faults capability: the technique is able to allow for detection of faults in more than one component;

- Fault Quantification: The technique is able to express the fault severity in terms of percentage deviation from respective baseline values;
- Identification and use of appropriate measurement selections that are sensitive to the desired faults;
- Selection of independent variables that represent the fault with least RMS;

Despite great deal of research on this subject, there exist certain fundamental limitations to this method

- Non-Linearity: The generation of fault matrix linearises the relation between the state variables or the independent variable with the dependent leading to inaccuracies for large magnitudes of faults.
- The requirement of a large instrumentation suite for effective diagnosis is a major hindrance in its application in real life situations. Additional sensors lead to increased cost. Fewer sensor leads to the phenomenon of "smearing".
- The scheme does not cater for sensor bias, which is a phenomenon not so uncommon in practical application.
- Measurement noise: The diagnostic scheme does not have provision for taking into account measurement noise. Gas turbines usually operate in harsh environments leading to measurement non-repeatability, which in some cases could be as large as the measurement deviation being sought.

To overcome the limitations of GPA, estimation techniques like Weighted Least Square(WLS) analysis , Kalman Filters(KF) and its variants have been used. The technique based on KF and WLS, which have been reported to be the predominant technique adopted by major OEMs (Doel, 1994; Stamatis et al, 1992). With these techniques remaining as the core of the diagnostics model, additional algorithms have been incorporated for improved diagnostics capability. E.g Rolls Royce uses the "Concentrator" method and GE uses the "Fault Logic".

2.5.3 Kalman Filter for Gas Turbine diagnostics

The Kalman Filter (KF) is an optimal observer in a linear system having white uncorrelated measurement/process noise. The filter has been formulated for both continuous and discrete time systems. For simplicity only the discrete time formulation is considered. Since any practical application of Kalman filtering techniques will be implemented on a digital computer, the discrete time formulation is particularly well suited. A Kalman filter typically incorporates discrete – time measurement samples and finds application as shown in figure 2.4

The main assumptions for a KF application, which are also applicable for gas turbine diagnostics are:

(a) These are normally applied as linear models. Though there are means of extending the linear concept to some non-linear applications.

(b) Noise is independent from one sampling time to the next.

(c) Noise is assumed to be Gaussian in terms of amplitude and it is assumed that at any given point of time, the probability density of Gaussian noise amplitude takes on the shape of a normal bell-shaped curve.

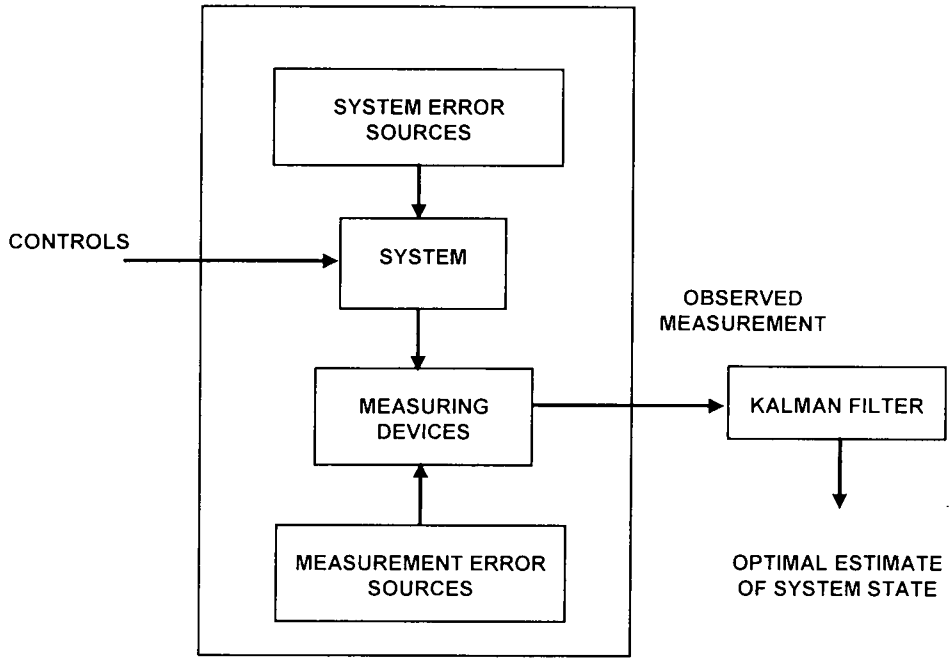


Figure 2.4: A typical Kalman Filter Application (Gulati, 2002c)

The estimation technique described here is applied to a discrete process defined by the following sets of equations :

$$z_k = H_k x_k + v_k \qquad \text{Measurement equation} \qquad (2.13)$$

$$x_k = \Phi_{k-1} + w_{k-1} \quad k = 1,2 \quad \text{System equation} \qquad (2.14)$$

Where,

- $z_k \in R^M$: Measurement vector
- $x_k \in R^N$: State Vector
- $H_k \in R^{MxN}$ x : Model Matrix
- $v_k \in R^M$:Measurement noise, assumed to be Gaussian, white (i.e. uncorrelated), zero mean with covariance matrix R_k

- $\Phi_k \in R^{NxN}$: Transition matrix
- $w_k \in R^N$:Process noise, assumed to be Gaussian, white, zero mean, with covariance matrix Q_k

Matrices H_k and Φ_k, measurement and process noise statistics are assumed to be known. The following initial conditions are assumed-

$$E[x(0)] = \hat{x}_0 \qquad (2.15)$$

$$E[(x(0) - \hat{x}_0) \cdot (x(0) - \hat{x}_0)^T] = P_0 \qquad (2.16)$$

Where the operator E[.] is the mean value.

Another assumption is that process and measurement noises are uncorrelated

$$E[w_i \cdot v_j] = 0 \text{ for all } i \text{ and } j. \qquad (2.17)$$

the Kalman filter produces a recursive estimation x of the state vector at time k based on the current measurement vector z and the previous state vector estimation x_{k-i} .This feature can be exploited for real time application provided the above hypothesis are all correct, the Kalman filter provides the minimum variance, unbiased and consistent estimate of the state vector, given a set of measurement vectors.

The estimate is minimum variance as it minimizes the following quantity:

$$J_k = E[\tilde{x}_k^T(+) \cdot \tilde{x}_k(+)] \tag{2.18}$$

Where,

- $\tilde{x}_k$ is the estimation error : $\tilde{x}_k = \hat{x}_k - x_k$.
- (+) means that the quantity has been updated with the measurement vector z_k .
- (-) means that the quantity has been evaluated just before the measurement.

An unbiased estimation is one whose expected value is the same as the quantity to be evaluated

$$E[\hat{x}_k] = x_k \tag{2.19}$$

A consistent estimate is one which converges to the true value of x as the number of the measurement increases.

The following equations make up the Kalman filter (Gelb,1974):

$\hat{x}_k(-) = \Phi_{k-1} \cdot \hat{x}_{k-1}(+)$	: State estimate extrapolation	(2.20)
$P_k(-) = \Phi_{k-1} P_{k-1}(+) \Phi_{k-1}^T + Q_{k-1}$	: Error covariance extrapolation	(2.21)
$\hat{x}_k(+) = \hat{x}_k(-) + K_k(z_k - H_k \cdot \hat{x}_k(-))$	: State estimate update	(2.22)
$P_k(+) = (I - K_k H_k) P_k(-)$	: Error covariance update	(2.23)
$K_k = P_k(-) H_k^T (H_k P_k(-) H_k^T + R_k)^{-1}$	: Kalman gain matrix	(2.24)

As shown by equation (2.18) the KF minimizes a quadratic cost function step by step i.e. after each measurement. It can be shown that if the system is linear as given by equations (2.13) and (2.14), then minimization over the time steps is the same as the minimization of the complete cost function evaluated over the whole set of measurements.

It can be shown (Bryson and Ho,1975) that for a linear system describe by equations (2.13) & (2.14) and subject to the above assumptions the solution provided by the

Kalman filter is optimal with respect to every common criterion(minimum variance, maximum likelihood , minimum error). Moreover the technique is recursive.

Though when used with linear GPA, Kalman filters improve the diagnostics accuracy, but the issues of non-linearity has still not been addressed. Drawbacks in the application of KF techniques to the linear GPA are (Zedda, 1999c):

(a) **Prior knowledge tuning:** the choice of the process noise covariance matrix is often arbitrary. There usually exists no statistically significant population of faulty engines to base the performance parameter's standard deviations assigned on it. Sensitivity studies can be helpful but the deviations of the state vector elements may be strong.

(b) **Smearing effect:** often only a limited number of components and sensor are fault affected, while the KF tends to smear the faults over a large number of engine's components and sensors.

(c) **System model and divergence:** the Kalman filter produces an optimal solution provided the hypotheses about the system are correct. In the case of gas turbine diagnostics, even though we might assume equation (2.13) to be sufficiently precise, almost nothing is known about equation (2.14), which describes the temporal evolution of the fault. As the method should be able to detect deterioration due to various kinds of fault, both slowly varying (erosion, corrosion, fouling) and abruptly varying (FOD), equation (2.14) is not available. Therefore, it should be somehow estimated and this can impair the final diagnostics accuracy. In fact the use of technique to completely estimate equation (2.14) introduce errors and as measurements are collected and used by the algorithm the system learns the wrong state too well. The consequence is divergence, i.e. the estimated solution becomes and more distant from the actual solution.

(d) **Non linearity and optimality:** the errors due to approximations of non linear systems with a linear one may not be negligible even if no estimation technique is employed (Escher,1995a; Singh and Escher,1995b). Therefore a non linear estimation technique seems more suitable. The application of a non-linear version of Kalman filter though is no easy task. Many problems are associated with the use of the common

Extended Kalman Filter(EKF) and Iterated Extended Kalman Filter(IEKF), as pointed out by Jazwinski(1970) and Haupt et al (1995). The main drawbacks are that the estimates are often biased and suboptimal (i.e. the cost function is not minimised).

2.5.4 Weighted Least Squares(WLS) Method

A GPA solution from WLS perspective is obtained from a linear function of the differences between the measurements and their predicted values. The gain matrix used in computing the solution may be obtained from the ICM and assumed variance from state variables and measurement errors. Urban (1980) and Volponi (1982) showed that WLS techniques could be used to reduce the sensitivity to measurement error. Following their lead, modern test cell and on-wing gas path programs use the WLS or closely related algorithm. Based on the principle of WLS, General Electric uses a program called TEMPER, a gas path analysis tool for commercial turbine engine module performance estimation. An assessment of the technique is provided by Doel (1994a, 1994b).To evaluate engine component performance correctly, sensor error must be considered in the analysis. WLS facilitates the determination of engine state in the presence of sensor error. WLS is based on a model of the measurement process given by-

$$z = h(x) + \gamma \tag{2.25}$$

where:

z is the measurement vector such as spool speed, pressures and temperatures etc.

x is the state vector of performance parameters such as component efficiencies and capacities etc.

$h(x)$ is a $p \times n$ matrix representing the non-linear effects of sate variable upon measurements.

γ is a vector of the noise and bias in measurements.

For the WLS analysis to succeed, it must be possible to determine the state vector x, from the available measurements. This require the dimension of the measurement vector to be equal or exceed that of the state vector. Further, it must be possible to choose a subset of z that yields a unique solution for x, i.e. the engine must be observable from the available measurements. To avoid difficulties associated with nonlinear optimization, the non-linear model, $h(x)$, is replaced by a linear approximation, Hx. The resulting approximation to equation 2.25 is-

$$z = H(x) + \gamma \tag{2.26}$$

the probability density function for the likelihood of z being obtained from an initial state vector x, whose designation would be $p(x/z)$ where $p(x/z)$ is a decreasing monotonic function of the quadratic form J, where:

$$J = 1/2\left\{x^T M^{-1} x + (z - Hx)^T R^{-1} (z - Hx)\right\} \tag{2.27}$$

Solving by minimizing J with respect to x will give the state vector estimate with the highest conditional probability. The optimal solution x_o is:

$$x_o = \left(M^{-1} H^T R^{-1} H\right)^{-1} H^T R^{-1} z \tag{2.28}$$

The true measurements z_0 for the engine state x_o is:

$$z_o = H.x_o \tag{2.29}$$

Using these true values the estimated measurement error can also be computed as follows:

$$v_o = \left[I - H\left(M^{-1} + H^T R^{-1} H\right)^{-1} H^T R^{-1}\right] z \tag{2.30}$$

And the corresponding solution residual, J_o is obtained by using x_o in equation 2.27.

The algorithm is linear in z and therefore the solution error is proportional to the measurement deviation. In case the turbine efficiency is doubled, the solution error would also be doubled, as the percent error remains fixed. Hence, the weighted least-squares algorithm provides best results when measurement deviations are small. In order to cater to this limitation of the WLS algorithm, GE has included something-called fault logic in their program TEMPER. The fault-logic is used to search for large deviations in component performance, or for large measurement errors, when the solution residual is large. The solution residual J_o provides the mechanism for recognizing that a specific case is far from nominal conditions. TEMPER assumes that J_o follows the Chi-squared distribution and the fault logic in invoked whenever the residual exceeds the 95 percent limit.

Thus the salient features of the GE approach according to Doel (1994a & 1994b) can be summarized as follows-

- The technique is based on the weighted least squares algorithm for gas path analysis as described earlier on in this section.
- Weighted least square algorithm provide better result for small deviations, and in order to address this problem a feature called "fault logic" is incorporated to determine large deviations.
- The technique cannot solve the problem of smearing which is common to conventional GPA methods. Smearing is basically underestimation of the actual fault and attribution of the remainder fault to other engine components and to measurement error.
- The algorithm is linear for the measurement vector, whereas the gas turbine performance is highly non-linear.
- The approach is able to reduce problems associated with measurement noise but does not address problems such as measurement bias. It is felt at GE that there are no algorithmic ways to eliminate problem of measurement bias and this problem can only be solved by introducing more sensors, which has its own penalties. The other option is to improve sensor performance.
- A problem is the input requirements for the algorithm. Comprehensive data analysis and careful judgment is required for the statistical and baseline inputs as accurate baselines are critical for augmentation strategies for implementation of the fault logic.
- There are a number of potential problems such as combustor performance, HP turbine performance, turbine cooling etc. not observable by the technique.

- TEMPER does not provide any aid in interpreting the results and there have been a number of cases where it has identified the same component repeatedly even though it has been overhauled.

The reason why KF and WLS based estimation technique have been applied to linear GPA is that they seem to show the following advantages (Zedda, 1999c):

(a) Optimality- in both the techniques, a cost function is minimized;

(b) Recursivity: memory and computing requirements are limited;

(c) Prior knowledge – knowledge about the statistics of engine component deterioration can be introduced through the initial values of the state vector and its covariance matrix;

(d) Measurement noise- the actual measurement noise can be assumed to be white and Gaussian, as the Kalman filters require;

(e) Sensor errors: they can be estimated through augmentation of the state vector to include the unknown sensor biases.

2.5.5 Non-Linear Model-Based Diagnostics Methods

This type of diagnostic methods is based on accurate modelling of non-linear steady state gas turbine performance. Gas turbine modelling techniques have been reviewed by many researchers, such as Bird and Shwartz (1994) and Sanghi et al. (2000). At steady state conditions, the dependent and independent parameters of gas turbines can be expressed with a non-linear relationship-

$$\bar{z} = F(\bar{x}) + \bar{v} \tag{2.31}$$

The idea of the non-linear model-based methods is shown in Figure 2.4. The real engine component parameter vector $\bar{x}$ determines engine performance represented by the measurement vector $\bar{z}$ With an initial guessed parameter vector $\hat{\bar{x}}$, the engine model provides a predicted performance measurement vector $\hat{\bar{z}}$. An optimization approach is applied to minimize an objective function as follows (Li, 2002):

$$\text{Objective Function} = \sum \phi(\left\|\bar{z}_i - \hat{\bar{z}}_i\right\|) \tag{2.32}$$

Which is function of the difference $\bar{e}$ between the real measurement vector $\bar{z}$ and the predicted measurement vector $\hat{\bar{z}}$. A minimisation of the objective function is carried out iteratively until the best predicted engine component parameter vector $\hat{\bar{x}}$ for real $\bar{x}$ is obtained.

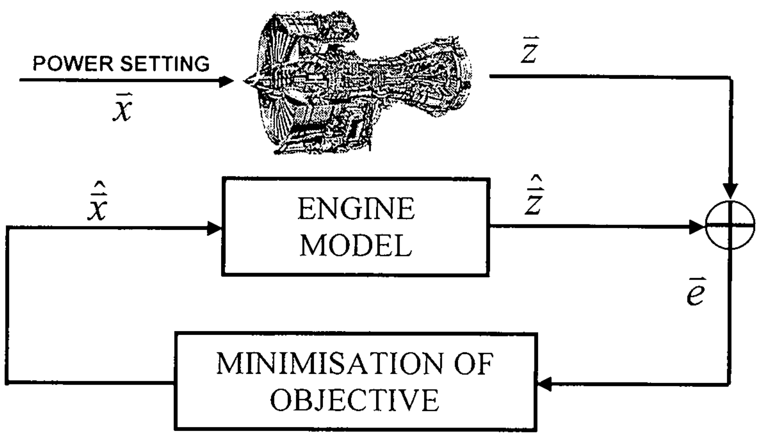


Figure 2.5: Non-Linear Engine Fault Diagnostic Model (Li, 2002)

An iterative non-linear GPA approach based on Urban's method (Urban, 1967, 1972, 1974) for non-linear fault diagnostics was explored by House (1992) for a single shaft gas turbine for helicopters, further development of the non-linear method was done by Escher (1995a, 1995b) with a Newton-Raphson technique and a computer code, PYTHIA, was developed. The Non Linear GPA is described in the following section:

2.5.6 Non-Linear Gas Path Analysis (NLGPA)

Linear GPA models that are available have severe limitations and it has therefore been recognized that there is a powerful case for improving the accuracy of the GPA systems and hence the requirement of Non-linear GPA. The theoretical relationship between M independent parameters $\bar{x}$ and N dependent parameters y can be expressed in mathematical terms as follows:

$$Y = F(x) \tag{2.33}$$

Where vector x contains elements x_i ($i = 1,...,M$), vector **y** contains elements y_j ($j = 1,..N$), and vector function F contains element functions F_i ($x_1,...,x_M$). In the neighbourhood of **x**, each of the functions F_l can be expanded in a Taylor series. The linear equations can be obtained by neglecting the 2nd and Higher Order Terms(HOT). This linear GPA is then used successively and an exact solution is obtained by the Newton-Raphson technique. A schematic diagram of the non linear GPA process is shown in figure 2.6.

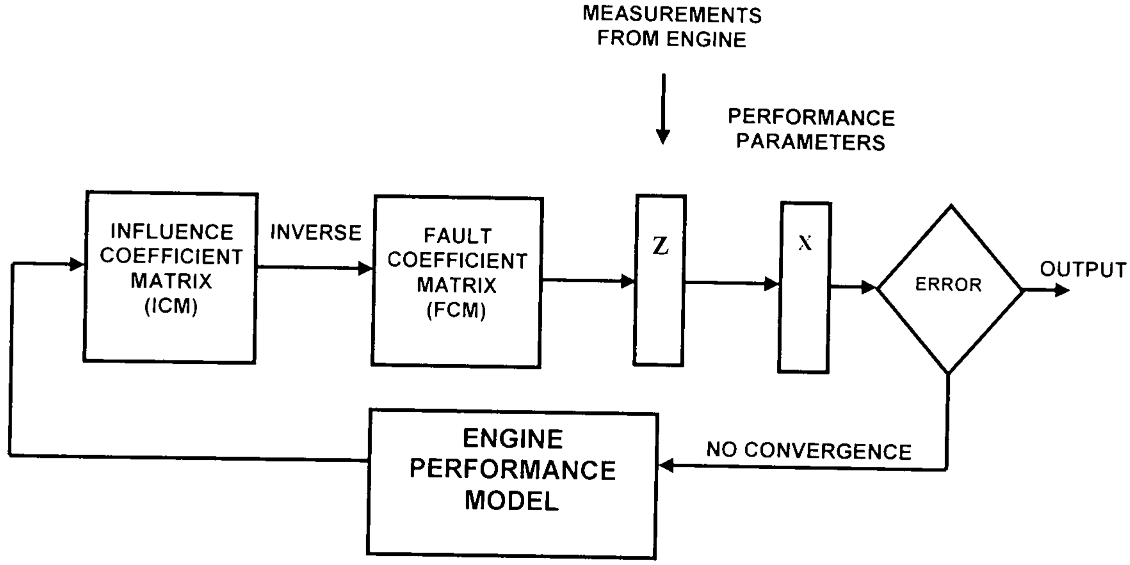


Figure 2.6: A schematic diagram of non-linear GPA

Essentially, in this technique an ICM is generated taking into account a small deterioration in the engine component performance. The ICM is then inverted to get the FCM. The FCM is then multiplied with the vector of engine measurements (obtained from a deteriorated engine). This gives a vector of change in engine component performance parameters. From the results obtained, a new ICM is generated and this process is continued till the solution converges to a predefined limit. Figure 2.7 clearly shows the advantage of using Non-linear GPA over linear, where one finds that the exact solution is much higher than the solution obtained by Linear GPA.

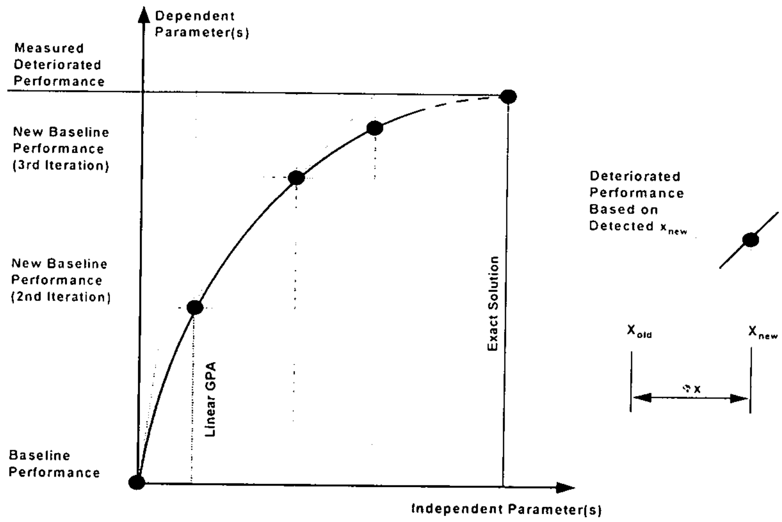


Figure 2.7: Comparison of Linear vs. Non Linear GPA (Escher, 1995)

2.5.7 Non Linear Kalman Filters

Some of the drawbacks of Kalman filters have been already discussed earlier in the chapter. The issue of non linearity will have to be further analyzed. It is worth pointing out that when the system is characterized by non-linearity, the performance of the possible estimation techniques should be tested through simulation, as non linear estimators behaviour is somewhat unpredictable and the same applies to linear estimators used for non-linear systems. Nonetheless, some hints about the estimation of performance can be extracted by the classic filtering theory. An analysis of this kind is attempted here. For the moment complete knowledge of the fault dynamics, even in terms of process noise is assumed The various possible situations are considered in the following paragraphs (Zedda, 1999c):

(a) If an actually linear system has to be processed, then the most sensible choice is a common Kalman filter, as it is optimal with respect to any reasonable minimization criterion (especially minimum variance and maximum likelihood). Moreover, the solution is achieved through recursive technique, which can be very useful due to the limited computing power required.

(b) If the system is actually non-linear, a linearization can be done and the common linear KF can be applied in a straightforward way, in this case, though the difference between the actual and the simulated behaviour of the system may be large and may lead to divergence, i.e. ever increasing distance between the state and the estimate. In practices, the onset of divergence manifests itself by inconsistency of the residuals with their predicted statistics. Residuals become biased and larger as more measurements are collected and processed. A similar behaviour of the estimator is observed when a measurement becomes biased (Kerr et al, 1992). If divergence effects are added to the "smearing" effect, typical of KF, the estimation accuracy may become unacceptable. As far as gas turbine diagnostics is concerned, the linearization of a process characterised by such large non-linearity as a gas turbine engine is probably responsible for inaccuracies of the estimation, especially when time varying multiple faults are present. In some instances, divergence does occur (Urban and Volponi, 1992).

(c) If the effect of the non linearity of the system of the estimation accuracy is ascertained, a non linear version of the KF can be used to try to approximate the engine behaviour better. The most commonly used filtering techniques are the Extended Kalman Filter (EKF) and the Iterated Extended Kalman Filter (IEKF). A brief comparison between the linear and non-linear versions of the KF is given below. It can be shown (Bryson and Ho, 1975) that the KF minimizes the cost function given by

$$J=\frac{1}{2}(x(0)-\hat{x}_0)^T\cdot P_0^{-1}\cdot(x(0)-x_0)+\frac{1}{2}\sum_{i=1}^{k-1}w_i^T Q_i w_i+\frac{1}{2}\sum_{i=1}^{k-1}(z_i-H_i x_i)^T\cdot R_i^{-1}\cdot(z_i-H_i x_i) \tag{2.34}$$

Moreover, minimization is achieved in a recursive fashion. For linear problem, the minimum variance and the maximum variance and the maximum likelihood coincide and therefore the KF can be considered as the best choice, provided the modelling of the process is sufficiently accurate. If the process is non-linear then the cost function to be minimized is:

$$J = \frac{1}{2}(x(0)-\hat{x}_0)^T \cdot P_0^{-1} \cdot (x(0)-x_0) + \frac{1}{2}\sum_{i=1}^{k-1} w_i^T Q_i w_i + \frac{1}{2}\sum_{i=1}^{k-1}(z_i - h_i(x_i))^T \cdot R_i^{-1} \cdot (z_i - h_i(x_i)) \tag{2.35}$$

A solution minimising the cost function (2.35) ensures maximum likelihood and approaches minimum variance asymptotically as the number of measurements increases. Therefore, the aim of a non linear filter would be minimize a cost function, possibly in a recursive way. It can be shown that the EKF and IEKF produce biased and sub optimal estimates due to linearization of the cost functions. From a practical point of view, this means low accuracy in the estimation of the engine's health.

As a matter of fact, the most non-linear squares estimation algorithms require a choice between an optimal solution and a recursive formulation. If recursitvity is a paramount requirement, then optimality is compromised. As third possible solution has actually been suggested by Haupt et al (1995), the proposed estimation technique splits the problem of cost function minimization into a linear first step and non linear second step by defining new first step states that are non linear combinations of the unknown states.

2.6 Artificial Intelligence Techniques for Diagnostics

Artificial Intelligence (AI) currently encompasses a huge variety of subfields, from general-purpose areas such as perception and logical reasoning, to specific tasks such as playing chess, proving mathematical theorems, writing poetry, and diagnosing diseases. Often, scientists in other fields move gradually into artificial intelligence, where they find the tools and vocabulary to systematize and automate the intellectual tasks on which they have been working all their lives. Similarly, workers in AI can choose to apply their methods to any area of human intellectual endeavour. In this sense, it is truly a universal field. One of the applications of AI in recent times has been its application to engine and sensor fault diagnostics. There are several techniques which have been investigated and a brief review of the some of the techniques is presented in the following sections.

2.6.1 Artificial Neural Network Applied to Engine Fault Diagnosis

Artificial Neural Networks (ANN) can be defined as parallel distributed processors able to store knowledge as experience and make it available for use. It has found some favour with few researchers and has been extensively investigated for use in fault diagnosis.

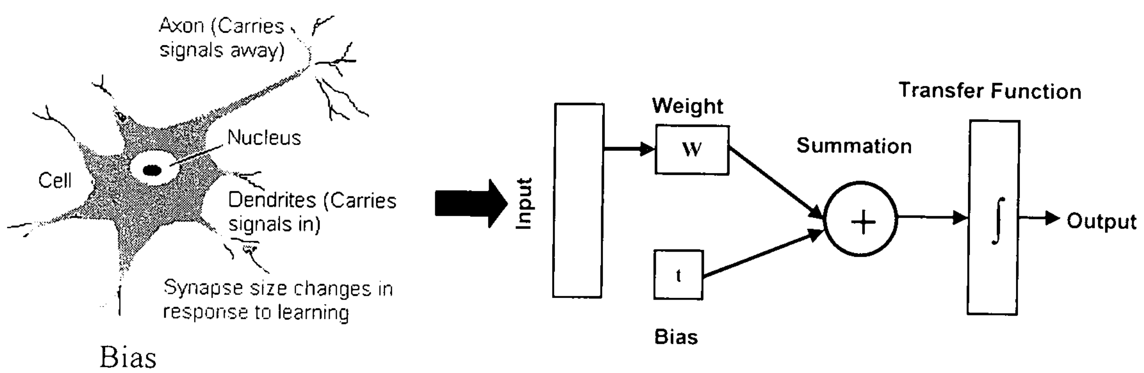


Figure 2.8: Biological Neuron vs. Mathematical Neuron

ANN is a non-linear estimator, which can be trained to map inputs to outputs in a framework that loosely mimics the learning process performed by the brain. Figure 2.8 shows a comparison between a biological neuron and mathematical neuron. The mathematical network that we are interested in has the following features:

- The network is made up of units called neurons, each performing a weighted sum of its own inputs. The sum is then passed through a function to the output.
- The knowledge is stored in inter neuron connections called weights. This knowledge for the weights is acquired through training (also called learning). The purpose of the learning phase is to determine the NN parameters, which will enable the network to function properly in operating phase. The NN can be classified according to the kind of training. If the training algorithm uses different input and output patterns the learning is called *supervised*, if the training algorithm has to extract information just from the input patterns the

learning is named *unsupervised*. If input and output patterns are the same, the training is *self supervised* and the net performs auto association.

The most popularly used artificial neural network in gas turbine diagnostics is the Multi-Layer Perceptron (MLP) with back propagation training. It is also called the Feed-Forward Back-Propagation Neural Network (FFBPNN).The configuration of a typical MLP is shown in Figure 2.9. FFBPNN is a supervised network, where sensed information is propagated forward from input to output layers while calculated error are propagated backward and used to adjust synaptic weights of neurons for better performance. Typically, such a network is made of an input layer where input values are received through input neurons, one or more hidden layers where functional relationship are expressed with a set of weights connecting succeeding neurons, and an output layer where output neurons receive output values. Training of the net is through a learning algorithm named back-propagation where the weights are modified based on the input-output patterns. As per the neural network developed by Pong-Jeu Lu et al (2000) in training the back-propagation network, the synaptic weights are corrected using the following algorithm,

$$\Delta w_{ij}(n) = \eta\left(-\frac{\partial E(n)}{\partial w_{ij}}\right) + \alpha \Delta w_{ij}(n-1) \qquad (2.38)$$

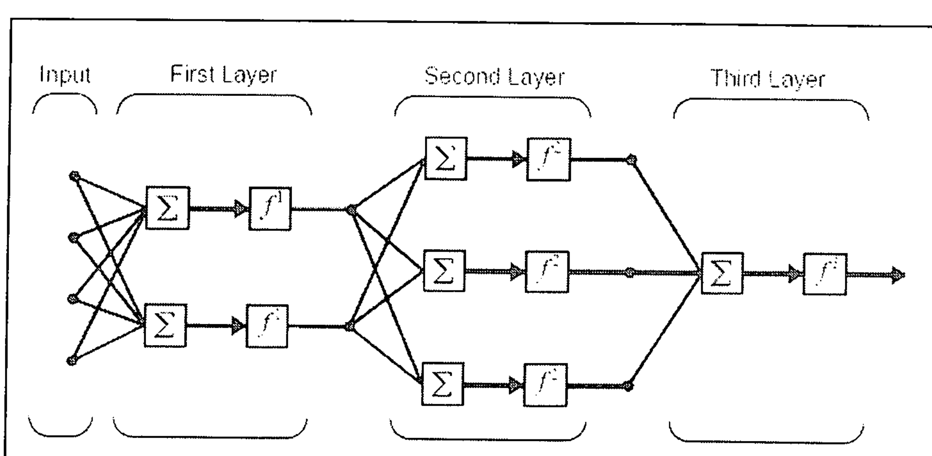


Figure 2.9: A typical Multilayer Perceptron

Where, E is the targeted error, η and α are the learning rate and momentum constant respectively and both these are kept within [0,1] and the appropriated values are determined by a trial and error method. Once trained the NN operates in the second phase i.e. the operating phase.

The main features of the neural networks are as follows:

- They make use of information provided from data used for training the network. This makes them particularly suited for finding solutions to problems for which there are no exact algorithmic solution, but only a large number of examples. In general ANN have been shown to significantly improve symptom interpretation in mathematically difficult to describe systems and process (Barschdorff, 1991);
- Solutions can be provided for cases, which have never been encountered before. i.e. they generalize from examples;
- They are inherently non-linear;
- They are best suited for data fusion. Different kinds of data (vibration, thermodynamic, electrostatic data for a gas turbine) could be used altogether to produce an answer, even though no such comprehensive theoretical model exists;

Most of the features outlined above make neural networks very suitable to deal with a number of diagnostic tasks and their application to gas turbine monitoring is on the rise. In addition to those outlined above the following make these specifically amenable to gas turbine diagnostics:

(a) The large level of noise affecting measurements in gas turbines could be coped with by ANN;

(b) Even though some parameters have to be chosen at design phase and at the beginning of training, there is no such critical parameter as the one required in KF based techniques to set the standard deviation of the performance parameters;

(c) ANN could be trained on-line to monitor the engine health in real time;

(d) ANN is capable of dealing with the large non-linearity characterizing the relation between measurements and performance parameters of engine;

(e) ANN could be used to perform data fusion for gas turbine diagnostics: vibrations, Aero-thermodynamic, gas path debris data represent a comprehensive input to a ANN based system;

The advantages which the ANN provide led to different neural networks being used in gas turbine engine fault detection, diagnosis and accommodation. Early applications of ANN to aircraft engine diagnostics were carried out by Denny (1965) and Dietz et al. (1989), and to the Space Main Engine by Whitehead et al. (1990a, 1990b). The application of Feed-Forward Back-Propagation neural networks to gas turbine diagnosis has been by far the most popular type of ANN. The application of ANN along with linear GPA have been studied by Torella and Lombardo (1995) and specific component analysis such as fuel system fault detection have been studied by Illi et al (1994). Torella and Lombardo (1996) also described the computation of a Learning Rate Factor(LRF) for improving the learning rate FFBPNN .

Zedda and Singh (1998) introduced a modular neural network system (Figure-2.10) to tackle large-scale diagnostic problem and applied it to Garrett TFE 1042 engine. The module classifies the input measurement vectors according to the fault category (A or B). This kind of classification overcomes the problem of low diagnostics accuracy usually obtained when the two categories are mixed. Moreover, since the characteristics of the fault categories are different, separate diagnostics can be developed. Such a system has the unfortunate drawback of a large number of nets and long training time.

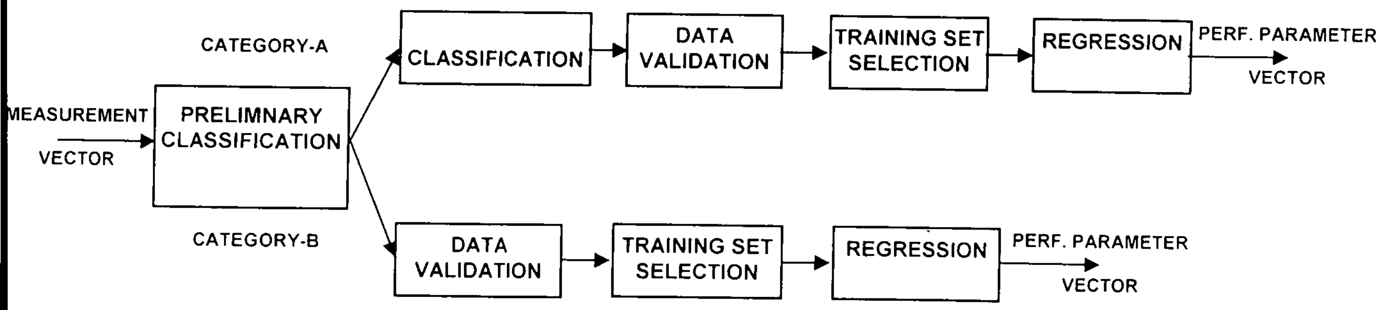


Figure 2.10: Modular ANN system for fault diagnostics (Zedda & Singh, 1998)

Kanelopoulos et al. (1997) presented a network architecture to perform sensor and component fault diagnosis step by step using multiple neural networks. The authors suggested the use of different networks to isolate the sensor faults and component faults as this would provide a better result than using a single network for the combined task. This has been further extended by Ogaji (2003) to generate a cascaded network to isolate component and sensor faults.

Napolitano et al (1996) compared the approaches of ANN and KF for Sensor Fault Diagnostics, Isolation and Accommodation (SFDIA). The authors applied ANNs in the form of decentralised networks to perform SFDIA. The application of multiple nets makes it possible to infer if the errors are to be minimised for this and others complex applications, then more than one net need to employed with each, applied to a specific problem.

Eustace and Merrigton (1995) applied Probabilistic Neural Network(PNN) to diagnose faults in any engine within a fleet of 130 GE low bypass F404 military engine. The authors used a statistical correlation technique to select five out of eight available engine monitoring parameters as input to the network. The approach is interesting considering the fact that even for healthy engine the parameters vary from engine to engine. Results from the network show an accuracy of 87.6% which is acceptable considering the variability in the baseline.

An Adaptive Probabilistic Neural Network (APNN) was presented by Sun et al. (2000) where the Maximum Likelihood Estimation Method was used to obtain the optimal Bayesian estimation and was more adaptive and fit better to quantitative diagnosis for multiple faults.

Cifaldi and Chokani (1998) discussed the use of ANN with the FFBPNN delta learning rule in predicting the performance of six components (diffuser, compressor, burner. turbine, nozzle and shaft) of a turbojet engine while simultaneously giving an overview of its possible application to vibration related faults. The authors reported that the burner, compressor and turbine efficiency trends were well predicted while the efficiency trends of diffuser and nozzle were poorly predicted which has been attributed to the choice of instrumentation.

Volponi et al. (2000) introduced a hybrid neural network where part of the network model was replaced by influence coefficients and reported that the accuracy of such a network was favourable compared to back-propagation net and Kalman Filter approach (results for the same is presented later). Sun et al. (2000) employed a hybrid training rule to improve its convergence. Lu et al. (2000) compared two feed-forward back-propagation neural networks with a similar configuration, one with four inputs and another with eight inputs, and found that both achieved high success rates. Kobayashi and Simon (2001) applied a feed forward network in their hybrid diagnostic technique, where the neural networks were used to estimate engine health parameters, and a Genetic Algorithm was used for sensor bias detection and estimation. Green and Allen (1997) discussed the need to incorporated ANN with other AI techniques to obtain a Cognitive Ontogenetic Engine Health Monitoring (COEHM) system with estimation of lifing, diagnostics and prognostics capabilities.

Applications of ANN for nuclear power plant diagnostics have been investigated by Guo and Uhrig (1992), Parlos et al (1994) and Tsai and Chou (1996). It has also been used for plant state identification by Barlett and Uhrig (1992) and Tsoukalas (1994) and for optimisation by Fakuzaki et (1992). Its application to plant parameters prediction has been given by Sofa et al (1990). ANNs have also been used for detection of mechanical damage like gearbox and bearing house faults by Paya et al (1997), propulsion system rotor unbalance by Huang et al, 2001) and GT blade fault diagnosis by Angelakis et al (2001).

2.6.1.1 Advantages and Disadvantages of Neural Networks

ANNs are being looked at by various researchers an effective paradigm for engine fault diagnostics. The advantages they offer are in terms of being able to deal with the non-linear nature of gas turbine performance, the ability of the network to learn with time, and their advantages in terms of being very good data fusion techniques are seen as the one being for the future. But there are certain drawbacks that make their utility limited for gas turbine diagnostics. These are:

A study carried out by Pong-Jeu Lu et al (2000) indicates the difficulty ANNs have when diagnosing faults with noisy data. They developed a back propagation neural network based diagnostic system and trained it using data supplied by Pratt &Whitney for the PW 4000 engine. The results were very encouraging for noise free data where the success rate was 100%, which is expected, but when noise was included in the data the technique failed.

Another major drawback of neural networks as reported by Zedda & Singh (1999) is the requirement of large amount of training data and the long time required to train the networks. Trained networks with frozen network weights would require retraining the networks if and engine undergoes overhaul.

As the number of operating points increases, the diagnostics error is bound to increase except an alternative means of data correction to standard day condition is devised (Ogaji, 2003).

2.6.1.2 Comparison of Neural Networks and Kalman Filter

A comparison carried out by Volponi et al. (2000) indicates that neural networks do not perform as well as the KF based technique. The comparison was carried out using simulated data for single component faults for a two-spool engine having two sets of instrumentation suites. In one case 4 measurements and the other one 8 measurements are considered. The results for the first choice are presented in table 2.1:

	8 Measurements	4 Measurements
Kalman Filter	96.9%	91.1%
Neural Network	90.7%	93.5%
Hybrid	97.8%	91.1%

Table 2.1: Comparison of results from ANN and KF

The results indicate the following:

- Kalman filters perform better as the number of measurement increase;
- The reduction in accuracy for neural networks is surprising and cannot be explained;

- Hybrid techniques are the best amongst the three;
- These results are for single component faults and there will definitely be a reduction in accuracy in the case of multiple component faults;
- A maximum of 93.5% accuracy for the neural network for single component faults is not acceptable;

2.6.2 Genetic Algorithm Applied to Engine Fault Diagnosis

Genetic Algorithm (GA) based diagnostics is a model based approach, which is theoretically similar to those of non-linear model-based methods described in the previous section. In other words, GA are applied as an effective optimization tool to obtain a set of engine component parameter that produce a set of predicted engine dependent component parameters through a non-linear gas turbine model that best matches the measurement. The solution is obtained when an objective function (or cost function), which is a measure of difference between predicted and measured engine dependent parameters, achieves its minimum value. Compared with typical calculus-based optimization methods, GA has several distinctive features (Zedda and Singh, 1999)

- The diagnostic method using GA does not require calculation of complex functions or complex derivatives and therefore any non-smooth function can be optimized;
- They use probabilistic rules rather than deterministic rule to create strings for the subsequent generations. This makes it possible for the algorithm to proceed in different paths every time it runs;
- constraints can be dealt with in a very different way, such as by means of penalty functions or design of specific operations;
- the method uses a global search and therefore avoid getting stuck in local minimum;

Three operations are typically used in Genetic Algorithm; they are selection operation which chooses the strings for the next generation according to a "survival of the fittest" criteria. crossover operation which allows information exchange between strings in the form of swapping of parts of the parameter vector in an attempt to get fitter strings, and mutation operation which introduces new or prematurely lost information in the form of random changes applied to randomly chosen vector components.

A gas turbine engine and sensor fault diagnostic system in the presence of measurement noise and biases was presented by Zedda and Singh (1999a, 1999b). Estimation is performed through optimization of an objective function by means of a real coded Genetic Algorithm (GA) required by the technique concerns the measurement noise and the maximum allowed number of faulty sensors and engine components. The method is suitable for development engines where a relatively large number of measurements are available. It was applied to a three spool military turbofan engine RB199 (Zedda and Singh, 1999a) and two spool low bypass military turbofan engine EJ200 (Zedda and Singh, 1999b) and showed high level of accuracy.

Gulati et al (2000, 2001) combined a multiple point diagnostic approach (Stamatis et al., 1991) and Genetic Algorithm approach (Zedda and Singh, 1999a, 1999b) and produced a GA based Multiple Operating Point Analysis (MOPA) method for gas turbine fault diagnostics. This approach is suitable for diagnostic problems where limited instrumentation is available. It was applied to RB199 engine and showed good results. Similar method was also applied to a PW100 engine by Gronstedt (2001), where a gradient method was implemented to refine the estimate. The subject of application of Genetic Algorithm to engine fault diagnosis is dealt in much greater detail in chapter-3. The application of evolution strategy also has been investigated by Sampath & Singh (2003) and Sampath et al (2003).

2.6.3 Expert Systems for Engine Fault Diagnosis

An Expert System (ES) is a computer program that represents and reasons with knowledge of some specialist subject with a view to solving problems or giving advice. Incidentally, one of the first ES to be developed, called MYCIN was used for diagnosing disease in human beings. It is usually built by assembling a knowledge base which is then interpreted by an inference engine. The core of the expert system is called the shell and embeds the knowledge base within it. The end user of the application interacts with the shell via the inference engine, which uses the knowledge available in the knowledge base to answer questions, solve problems, or offer advice, Jackson (1999). The configuration of a typical expert system is shown in Figure 2.12.

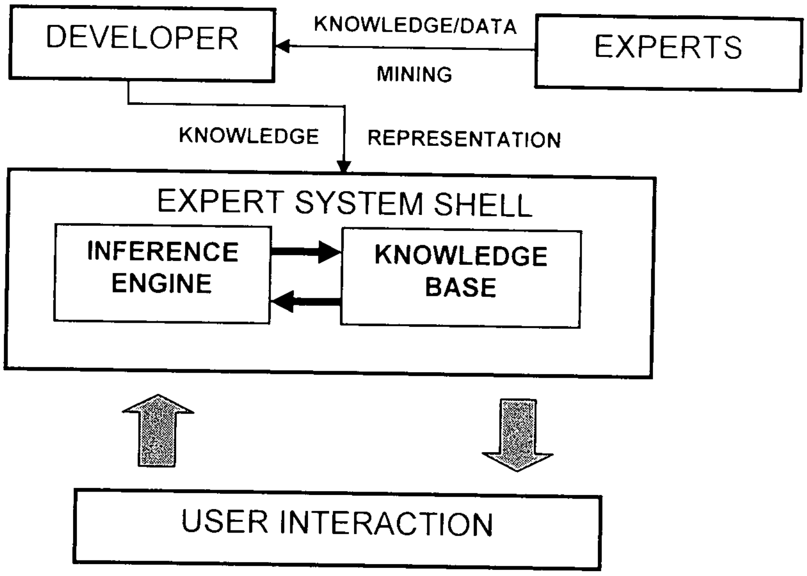


Figure 2.11: Configuration of an Expert System

Different ES have been developed so far, such as rule-based, model-based and case-based systems. Initial attempts to integrate ES with GPA failed mainly due to insufficient instrumentation set to permit meaningful modular diagnosis and also from insufficient computing capability (Doel and LaPierre, 1989; Doel ,1990). Doel (1990) concluded that the expert systems technologies were not going to make jet engine diagnostic and maintenance procedures "smart" but they could add a lot of new capability that will make them more effective and more convenient. Earlier gas turbine fault diagnostics were carried out by gas turbine users by comparing the measurement parameter deviation patterns with fault signatures supplied by manufacturers. Most ES are developed on shells which could be generic such as CLIPS (written in C language and a open source software), PROLOG, LISP etc. or could be designed to meet specific objectives like the GE's GEN-X (GENeric eXpert system). Further development of ES and application of pattern recognition/matching methods were presented by Winston et al. (1991), Dundas et al. (1992) and more recently by Lee and Singh (1996). The most popular type of expert systems used in gas turbine fault diagnostics is knowledge and rule based expert systems. Typical examples of such type of expert systems are ENGDOC (Gibbs, 1984), TEXMAS (Collinge, 1988) for the Lycoming T53 engine, HELIX (Simmon et al.,1987; Hamilton, 1988) for a twin-engine gas turbine helicopter engines, XMAN (Jellison et al., 1987) for TF-34 engine, IFDIS for the TF30 engine (Frith, 1989; Forsyth and Larkin, 1989), SHERLOCK for helicopter engines (Winston et al., 1991), etc. More recently, it has been shown that these methods can be applied to gas turbine EHM by Vivian and Singh (1995), Charchalis and Korczewski (1997), DePold and Gass (1998), Diao and Passino (2000), Forsyth and Delaney (2000) and Pettigrew (2001). Meher-Homji et al. (1993) described a hybrid expert system where both expert systems and algorithm approaches were utilized for gas turbine condition monitoring and diagnostics. The declaration of a fault by the inference engine is normally done by comparing engine component deviations with predefined datum values. The application of ES to EHM can be summarized with the following points:

- Understanding the problem domain i.e. types of faults sought;
- Expectation from the system i.e. qualitative or quantitative analysis;
- Building a knowledge base or data mining. i.e. engine simulation data or field data.
- Methodology for representing the acquired knowledge- Building RULES
- Interaction with the shell through the inference engine

2.6.4 Bayesian Belief Networks(BBN) for Fault Diagnostics

A belief network is a graphical representation of a probability distribution that represents the cause and effect relationship among predisposing factors, faults and symptoms. It is a form of graph, consisting of nodes representing variables and arcs representing the probabilistic dependencies between these variables. Each node contains a conditional probability distribution that describes the relationship between the node and the parents of that node. In fact, the nodes can represent anything, an observation, a fault or some intermediate value. The list of possible states for each node must be mutually exclusive and collectively exhaustive.

Most recent work on the BBN for engine fault diagnostics has been done by Kadamb (2003) in which the independent parameters are designated as the parent node and dependent parameter as child node. The relationship between the parent node and child node has been defined through the links and each link has a probability associated with it. The links between parent node and child node are established only if that particular child node (measurement) is affected by the fault. A typical layout of BBN is shown in figure 2.10.

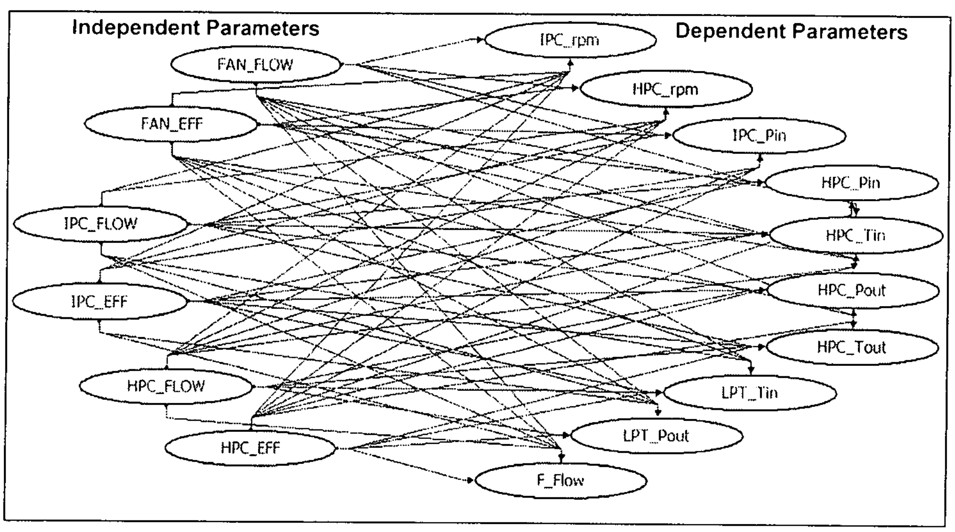


Figure 2.12: Typical BBN layout (Kadamb, 2003)

A detailed analysis of Bayesian Belief Network (BBN) for turbofan engine diagnostics was given by Romessis et al. (2001). A static pattern analysis approach was proposed by Patel et al. (1996) and Arkov et al. (1997), where the observation of gas turbine status was expressed by a probability density or histogram approach and any deviation of the engine from its normal condition can be indicated by a low likelihood of the observation.

The qualities of a Bayesian belief network that make it work well with a problem for diagnostic are given below:

- Allow the introduction of many types of data. The data can be qualitative, continuous numbers or discrete numbers.
- Support multiple simultaneous faults.
- Can find specific hardware faults.
- Engine model hardware changes can be easily entered into the network. For techniques such as neural nets it takes a long time to retrain the system.
- Generic faults can be included in the system to catch problems areas not covered by any of the more specific faults whilst, systems such as neural nets would need enough information and test cases for training.

But for the problem of gas turbine fault diagnosis, these suffer from various drawbacks, which are:

- It requires a substantial time and effort to gather information for building a knowledge base.
- Belief network maintenance requires someone familiar with it to be able to change it in a timely manner.

Use of such a technique can address the issue of an integrated diagnostic problem, but the problem of solving the GPA still remains. The use of a system that integrates test measurements and gas path analysis program results with information regarding operational history, build-up work scope, and direct physical observation in a Bayesian belief network can help in a cost effective diagnosis using value of information calculations (Palmer, 1998). In this case the Bayesian belief network is combined with the results of gas path analysis; hence some of the drawbacks of GPA would be inherently present in such a system.

2.6.5 Fuzzy Logic for Engine Fault Diagnosis

A Fuzzy Logic (FL) system is a non-linear mapping of an input feature vector into a scalar output (Kosko, 1997; Ganguli, 2001) or in other words it is a method to formalize the human capability of imprecise reasoning. The flexibility of the fuzzy logic systems in handling uncertainties has played a key role in their wide usage for various engineering applications. Such reasoning represents the human ability to reason approximately and judge under uncertainty, Ross (1995). As per Ganguli (2001) a typical Multi-Input Single-Output (MISO) fuzzy logic system performs a mapping from $V \in R^m$ to $W \in R$ using four basic components: rules, fuzzifier, inference engine and defuzzifier.

$$f : V \in R^m \rightarrow W \in R \tag{2.39}$$

where:

- $V = V_1 \times V_2 \times .... \times V_n \in R^m$ is the input space and $W \in R$ is the output space.

A typical fuzzy logic system is shown in figure- 2.13. A fuzzifier maps crisp input numbers into fuzzy sets characterized by linguistic variables and membership functions. An inference engine maps fuzzy sets to fuzzy sets and determine the way in which the fuzzy sets are combined. A de-fuzzifier is sometimes used when crisp numbers are needed as an output of the fuzzy logic system. Combined with expert systems, neural networks, genetic algorithm or other techniques, fuzzy logic can be used for gas turbine diagnostics.

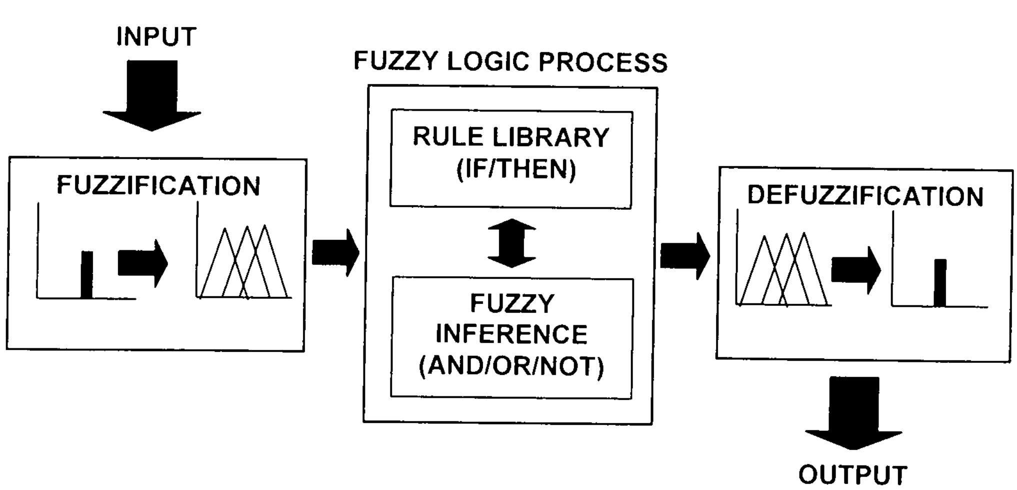


Figure 2.13: Configuration of a Rule Based Fuzzy Logic System (Marinai, 2003)

A fuzzy logic based expert system for gas turbine engine fault isolation was developed Ganguli (2001a and 2001b).The results showed FL to have good success rates except for the IPC and HPC where fault isolation accuracies were given as 97% and 94% respectively . Ganguli (2001a) had mentioned that fuzzy detector based on noisy data gives several false alarms. Similar approach was used to automate the reasoning process of an experienced power plant engineer (Ganguli, 2001c). Tests with simulated data show that prediction accuracy can reach over 90% with only four cockpit measurements. If additional pressure and temperature probes are considered, the fault isolation accuracy rises to as high as 98%. Tang et al. (1999) presented a fuzzy logic reasoning together with a neural network for a jet Engine condition Monitoring and fault Diagnosis (EMD) system that classifies all possible faults into three categories: gas path components, instrument sensors, and rotor or oil subsystem. Three operations (AND, OR and NOT) were used in its inference engine. A rule based fuzzy expert system RSLExpert for gas turbine fault classification was provided by Applebaum (2001), where the fuzzy filter was used for residual evaluation to transform the quantitative knowledge of the residual vector of measurement deltas into the qualitative knowledge of faulty characteristics and faults.

Recently, Marinai et al (2003) have discussed a way of implementing a FL system to isolate and quantify the performance parameter changes due to components' degradation taking into account the measurements noise through a non-linear approach. Results from test carried out on the IPC showed good fault identification. Ogaji et al (2003) carried out a comparison of the ANN based method and FL based method and reported similar accuracy from both the systems. They also concluded the accuracy of the FL can be improved with more rules.

Fuster et al. (1997) introduced a gas turbine diagnostics model where the uncertainty of component parameters was expressed by fuzzy logic likelihood value and the fault symptoms were described by *True* or *False*. An adaptive model for accurate simulation of gas turbine performance with the possibility of adapting to engine particularities was developed and described for the first time by Stamatis et al. (1990a). In this method, modification factors (MF) which are the ratio of parameter values of reference performance maps and the values of the actual maps were introduced. The modification factors for every component was obtained through a Non-linear Generalized Minimum Residual method (Stamatis et al., 1990a). Observation of the changes of modification factors between nominal and deteriorated engine can lead to detection of the location and the kind of fault of the engine, Stamatis et al. (1990b). Proper selection of modification factors with optimization can also be used for fault detection of gas turbine components and sensors.

From the above discussions it can been seen that FL offers solutions to problems where concepts are subjective, quantities are known only imprecisely and system model are descriptive rather that analytical (Isik, 1991).

2.6.6 Other Model based methods for Engine Fault Diagnostics

In the fundamental sense, performance monitoring and diagnosing faults involves processing of engine measurements. In all cases, a comparison of some parameter values of an engine under examination to the corresponding values of an engine which is considered "healthy" is performed in order to derive the relevant conclusions. The parameters used and the way of deriving them characterizes each different diagnostic method. Most of the methods described above rely on generation of residuals, which are the difference between the real measurements and the estimates (measurements) generated using a performance model of the engine. There are various methods developed by various researchers in order to generate the residuals. These have not been applied successfully and are:

- Chow et al (1984) have proposed a method that checks the parity of the mathematical equations of the system by using the actual measurements and once the predefined error bounds are exceeded then a fault is declared.
- Brown et al (1997) have proposed a technique that reconstructs the output of the system from the measurements with use of observers or Kalman Filters using the estimation error as a residual for detection and isolation of the faults. This is called the Dedicated Observer Approach (DAO).
- The principle component analysis that, has been proposed by Dunia et al (1998) tries to capture measurement correlation by searching for linear relationships between measurements. This method has been applied for isolation of process faults.

- Basseville (1998) and Gomez et al (1999) have proposed a parametric statistical approach. In this method changes in the mean value of a residual are monitored.

The techniques using GPA require a performance model of the engine. The accuracy of the performance model is paramount for accurate diagnostics. A good match between actual and engine performance model can give accurate diagnostic results. In addition to the techniques presented till now that rely on GPA there are a number of methods proposed by a few researchers at the University of German Armed Forces that are model based monitoring and diagnostic systems. These are now discussed in brief.

A model based technique proposed by Lunderstaedt et al (1988) makes use of linear GPA where the characteristic maps are assumed to be known only at the fault free condition. Lunderstaedt et al (1988) proposed to start of by re-writing the basic GPA vector as:

$$x = f(z) \qquad (2.40)$$

where: x is the performance parameter vector and z the measurement vector and f is the inverse of the vector H from equation--.

Expanding equation 2.40 in Taylor's series around an operating point x_o and evaluated in fault free condition x_{ff} and a faulty one x respectively:

$$x_{ff} \cong x_o + \left.\frac{\partial f}{\partial z}\right|_{o\_char} \left(z_{ff} - z_o\right) \qquad (2.41)$$

$$x \cong x_o + \left.\frac{\partial f}{\partial z}\right|_{o\_meas} \left(z - z_o\right) \qquad (2.42)$$

When the Taylor's expansion is evaluated in the fault free case the derivatives are calculated as gradients of the characteristics, whereas in the faulty case they are determined directly by the performance parameters definitions. Subtracting eq 2.42 from eq 2.41 and then normalizing it we get the following:

$$\Delta x = Q.\Delta z \qquad (2.43)$$

In order to take into account the sensor errors and measurement noise the equation is modified as under:

$$\Delta x = Q.(\Delta z - \delta\Delta z - \gamma) \tag{2.44}$$

where $\delta\Delta z$ is the sensor error vector and γ is the measurement noise vector. Estimation is then carried out.

A number of other model based diagnostic techniques have been proposed by other researchers, quite notable among them people from the same university and the one developed by Roesnick (1986) that showed some promise is discussed below:

According to Roesnick (1986) the first step is to define a model that allows the failure diagnostic of the components of the gas turbine and for the model development there is a requirement for thermodynamic cyclic analysis. The cyclic process analysis uses three parameter groups. The first including flow parameters like pressures, temperatures and mass flows at the individual stations of the engine. The second consisting of module efficiencies and pressure ratios are called the module parameters and the third parameter group are the environment parameters like ambient conditions and power setting parameters. Roesnick (1986) goes on to say that all these parameters are dependent on the engine power balance and module characteristics and therefore are not directly applicable for engine diagnosis. He defines a new parameter group that characterizes the place and size of module deterioration. This is independent of the total engine state and is required to define the failure diagnosis model. There is a requirement to have some sort of module information such as compressor maps for the compressor. In case of a module failure the difference between the maps and for nominal and failed case would present the module change. The module change leads to an operating point change, as a result of which the changes in parameters of the map do not lead to correct diagnosis. Module changes are obtained by using information of the nominal map and the change in parameter.

According to Da-Guang Chen et al (2001) a Model Identification-Based approach applied to engine fault analysis can take into account non-linearity of engine performance model and incorporates engine balance technique into the iteration process. Their technique is similar to the ones proposed by researchers at Germany and the conclusions that can be drawn from their work are:

- The Model Identification-Based diagnostic method can be used to detect and isolate gas turbine engine single and multiple faults quantitatively.

- This method takes the non-linearity of the model into account, therefore it is expected that this method will be effective to highly non-linear system.
- The "engine balance technique" incorporated into the iteration process inherently acts like a filter to noise, therefore, this method has certain ability to depress the interference of noise.

2.6.7 Drawbacks of Model Based Methods

Though the proposed methods were shown to be more accurate than conventional GPA based methods, the work done on model based systems indicates some major drawbacks that make their implementation unlikely:

- Some of the results presented by Da-Guang Chen et al (2001) indicate that though the problem of non-linearity has been addressed but smearing still takes place
- It has not been possible to deal with measurement bias in any of the work done so far.
- Though the technique proposed by Da-Guang Chen at al (2001) is capable of dealing with a certain amount of noise, but the other methods are not able to do so.
- Another important issue is the requirement of an accurate thermodynamic model of the engine. This is not available and what is normally available is an average engine model with the actual engine being anywhere between the maximum to minimum engine. Since the actual engine differs from an average engine or the thermodynamic model of the engine and there are no methods incorporated in the developed methods to take this into account, the technique would fail in cases of actual engine data.

2.7 Fault Diagnosis with Transient Data

Traditionally engine fault diagnosis has been performed at steady state conditions. There are several problems which can only be detected by transient data analysis. E.g bearing fault, some control problems etc. In addition, gas turbine performance deviation due to component faults is likely to be magnified during transients compared with the same parameter deviations at steady states.

For example, some combat aircraft can operate for up to 70% of the total mission time with their engines in non-steady-state conditions, Merrington (1989). Therefore, gas turbine fault diagnostics may be achieved using transient measurement data. A parameter estimator using a matrix method (Merrington, 1988) and a Least Square Estimate (LSE) (Merrington, 1989) were described to simulate a gas turbine engine transient process from consistent non-linear idle/max or max/idle transient data and were used as an estimator for fault diagnosis, where two fault cases were discussed: one was a biased exhaust gas temperature sensor error and the other was a changed final nozzle schedule. An overview of transient diagnostics for gas turbine engines was given by Meher-Homji and Bhargava (1992). A survey of the methods and applications of gas turbine steady and transient state modeling for fault diagnosis was provided by Bird and Schwartz (1994).A piece-wise linear State Variable engine Model (SVM) for the simulation of engine performance in real-time and a Kalman filter algorithm was used to estimate both the cause and level of off-nominal engine performance was presented by Luppold et al. (1989). The method was suitable for diagnosing engine faults caused by hardware failure, FOD, battle damage, etc. Further development of this method resulted in the second generation of Kalman Filter algorithm (an Observer Model) for the real time operation of detection and estimation of gas turbine damages caused by normal wear, mechanical failures, and ingestion of foreign objects, Kerr et al. (1992). Lunderstaedt and Junk (1997) diagnosed engine high pressure turbine fault with non-stationary measurement of RB199 engine by applying linear GPA to discrete points on a non-stationary process for non-linear parameter estimation and neural networks for the calculation of the non-stationary reference base lines. Henry (1988) analyzed the transient performance shift of F404 engine due to different reasons, such as throttle overshoot, effect of inlet screen, inlet temperature change and compressor damage. Fault signatures observed from the transient measurements, which were different from one to another due to different faults, were used to detect engine faults. Recently, the development of a diagnostics model based on genetic algorithm using transient data of a turbofan engine was shown my Sampath et al (2003). Figure 2.14 shows a comparison of acceleration of HP spool (N_H) of a clean engine and a faulty engine.

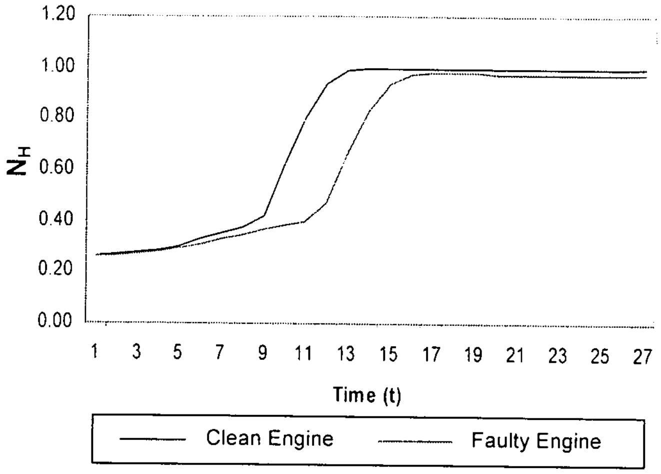


Figure 2.14: Typical measurement deviation during transients

The specific approach used in this method is to compare model-based information with measured data obtained from the engine during slam acceleration. The measured transient data is compared with a set of simulated data from the engine transient model, under similar operating conditions and known faults, through a Cumulative Deviation (CD). The CD is the deviation between the parameters obtained from the transients of clean engine (Baseline) and the engine with a fault and is the difference between the areas subtended by the curves in figure 2.14. The CDs obtained from the comparisons are minimized for the best match using Genetic Algorithm (GA). A diagnostics model based on ANN has been investigated by Ogaji et al (2003).

2.8 Instrumentation & Data Validation

In the preceding sections, a comprehensive study of the various fault diagnostics system has been presented. Perhaps, one aspect which is common to all the methods is the requirement of reliable instrumentation and validation of data before it can be used with the diagnostics model. Data uncertainty, the measurement noise causing data scattering around their true values are source of inaccurate fault diagnosis. Data averaging and filtering using different technologies are effective ways of reducing the impact of measurement noise and improving diagnostic accuracy.

Both these requirements are discussed separately in the following sections-

2.8.1 Instrumentation

It has been discussed earlier that number of sensors, type of sensors and position of the sensors have a profound influence on the diagnostics. Also, the importance of instrument accuracy needs no emphasis: A faulty instrument could lead to the diagnosis of non existent fault or genuine faults to go undetected. The measurement uncertainty issues have been tackled in following three ways:

- improvement in sensor design;
- use of more comprehensive instrumentation sets;
- the development of a statistical model to take into account measurement errors;

Theoretically, Improvements in engine diagnostics can be achieved simply by adding more and more reliable instrumentation to monitor the engine's health. However, the instrumentation itself has its own mean-time to failure. Additionally, inappropriate or badly maintained instrumentation can lead to the detection of spurious faults, leading to unnecessary expensive maintenance actions. The instrumentation has substantial costs associated with its installation and use, which rise as the amount of instrumentation included is increased. However, cost savings are limited by the capability of the technique employed, the design and the maturity of the engine in use, the fuel utilised, the operating environment and the operating profile. Figure 2.15 illustrates how an excessive use of instrumentation results in a loss rather than a gain in terms of Return On Investment (ROI). However, when cost of monitoring is juxtaposed with cost of failure, Myrick (1982), Simmons and Lifson (1985) agree that total plant losses associated with equipment failure far outweighs the cost of an extensive multi-parameter monitoring system.

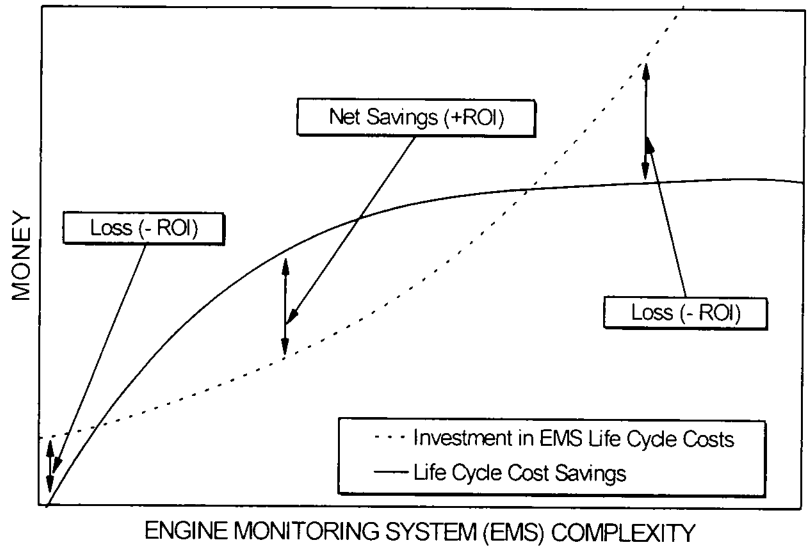


Figure-2.15: Return on Investment (ROI) of Engine Monitoring System(EMS).

Foremost for any set of chosen instrumentation are accuracy and repeatability. It is very important that the specifications for performance are established beforehand and in case the GPA based ECM system shares sensors with the engine control system, the specifications must be compatible. Items, which should be included in the specifications of an instrument, are as follows (Gulati, 2002c):

- Operating temperature range
- Operating pressure range
- Acoustic environment
- Vibration Levels
- Accuracy
- Lifetime (false alarms)
- Response rates
- Volume
- Weight
- Electrical interface

- Electromagnetic interference
- Calibration requirements
- Maintenance requirements
- Repeatability

While defining the specifications it is important to consider the operating environment. The most important point to consider while developing a diagnostic system for GPA is the issue of observability, i.e. the capability to identify faults with a set of measurements. This would define the minimum number of instruments and the measurements that are absolutely necessary.

2.8.2 Data Validation for fault Identification

The biggest problem in dealing with the data obtained form the engine is the presence of noise in the measurement. It is an unavoidable phenomenon and has to be dealt separately in order to be able to obtain meaningful diagnosis from the engine data.

Fundamentally, gas turbine diagnostics is the based on the analysis of deviations of component parameters from their baseline conditions. The accuracy of all diagnostic systems is partially determined by the quality of the measurement. Unfortunately, measured data are usually contaminated by sensor noise, disturbances, instrument degradation and human errors. In order to improve the reliability of diagnostic results, it is very important to clean or correct the measured data before they are fed into any diagnostic systems. Usually, a measured parameter changes around its actual value and may be expressed statistically with a probability density function. The true value of a parameter can be approximated by its averaged measurement which is normally obtained with rolling average method, where an average value is obtained with numerical average of certain preceding points. The disadvantage of rolling average is that it wastes the initial data points and is slow in responding to trend changes, DePold and Gass (1998). An exponential average equivalent of a ten point rolling average was introduced by DePold and Guass (1998) to reduce the measurement noise, where with each new data point 15% of the remembered average is replaced by new data. The exponential equivalent of 10 point moving average is:

$$EXP\_Average(t)_{10} = Exp\_Average(t-1)_{10} * 0.85 + New\_Data * 0.15 \quad (2.46)$$

The advantage of this method is that since only the last average is retained, these can respond instantaneously to step changes in trend. The exponential averaging method allows statistical bands to be carried with little overhead. Unlike a moving average an exponential average can be changed at the moment of the trend change detection, so the statistical bands also show the discontinuity.

More recently, different data filtering methods were explored by Ganguli (2001b) for removing noise from data while preserving sharp edges that may indicate a trend shift in gas turbine measurements. Compared with linear filtering, a non-linear filter, FIR median hybrid filter, was found to be far more superior in accurately reproducing the root signal from noisy data. A health residual, a scalar norm of the gas path measurement deltas, was used to partition the faulty engine from the health engine.

2.8.2.1 Neural Networks for Noise

Auto-Associative Neural Network (AANN) can also be used to filter measurement noise to improve input data quality and was introduced by Roemer(1998) and Mattern et al. (1997,1998). Neural networks for trend change detection and classification to diagnose performance changes also have been studied. The instantaneous average value and the standard deviation of each critical parameter is input to the AANN and the network is then used to eliminate bad data much the same as analysts would with the rules of thumb.

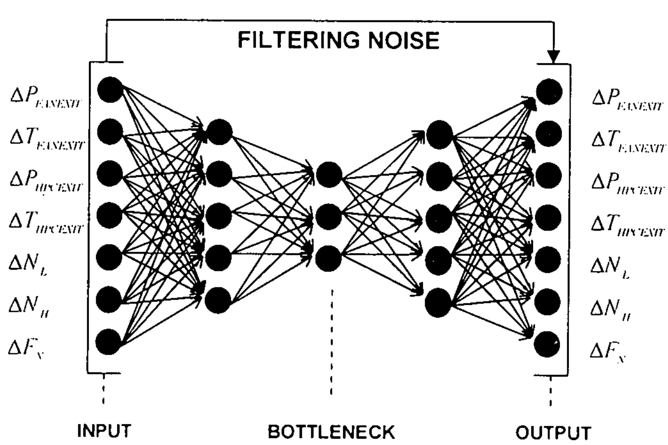


Figure 2.16: Typical AANN for filtering noise

In addition to the use of neural networks for removal of noise, there are numerous other conventional methods that are discussed in the following section.

2.8.2.2 Linear filters

These have been used widely in the industry, and they take a weighted sum of a number of previous measurements and are represented as:

$$x_l = \sum_{i=0}^{l-1} b_i x_{l-1} \tag{2.47}$$

Where i is the filter length and b_l is he sequence of weighting coefficients which define the characteristics of the filter. The weighting coefficients have to satisfy the following condition:

$$\sum_i b_i = 1 \tag{2.48}$$

Though easy to implement and computationally efficient, linear filters have a number of disadvantages that make its use very limited. The main drawbacks are:

- These are single scale in nature, therefore there is a trade-off between accurate representation of temporarily localized changes and efficient removal of noise.
- Linear filters have limited use for gas turbine applications, as these require removal of local trend shifts from globally noisy data.
- These represent the measurements with basic functions with a broader temporal localization and narrower frequency localization.

2.8.2.3 Non-Linear Filters

These are multi scale and have been developed to overcome the inability of the linear filters. Ganguli (2001b) has used a FIR Median Hybrid filter (FMH), which is a non-linear filter together with fuzzy logic to filter out noise. His results indicate that non-linear FMH filter can accurately reproduce the root signal from noisy data, though the disadvantage is that these are batch filters and therefore suffer from a time lag. This shortcoming can be removed by faster sampling of the measurements.

A FMH is a median filter that uses pre-processed inputs from *m* linear finite impulse response (FIR) filters (Heinonen & Neuvo, 1987) and the filter output is the median of the *m* values which in turn are outputs of *m* FIR filters. According to Ganguli (2001b) the FMH filter have the following features:

- FMH filtering is batch filtering and is most effective in capturing sharp changes in piece wise constant signals.
- These tend to return some noise, but repeated application of the FH filter can remove noise much better.
- The final signal is a root signal that will not change with further filtering.
- These are superior to linear filters because of the ability to preserve linearized features while eliminating errors.
- There is a price for the better quality of output data and this is in terms of a time delay, which can be overcome by faster sampling.

All the current day techniques whether conventional or intelligent system based methods, in the real sense, do not really have the ability to deal with bad quality data. This has been presented by various researchers and has also been observed in this chapter.

2.9 Summary & Conclusion

In this chapter a wide range of advanced diagnostics techniques have been reviewed and their suitability for engine fault diagnostics has been examined. No doubt, a lot of effort has gone in area of engine fault diagnostics. However, most of the investigations carried out have been to provide a qualitative assessment of the problem though the quantitative aspects were considered by only a few researchers. From the discussions it has also emerged that measurement noise hinders accurate diagnostics and various methods have evolved for validating data. It can be concluded that each of the technique discussed has its own advantages and limitations. There is no single technique which can address all the issues concerning fault diagnostics. At this point, it can be said that, a prudent way would be to try and incorporate the strengths of one technique to offset the shortcomings of the other. This clearly calls for the development of a technique which is robust and can effectively deal with noise and sensor bias. The next chapter presents the development of a diagnostics model using genetic algorithm which attempts to deal with some of the problems discussed.

CHAPTER 3

OPTIMISATION TECNIQUE FOR ENGINE FAULT DIAGNOSTICS

3.1 Introduction

In chapter-2, a comprehensive review of various engine fault diagnostics techniques available in the public domain has been carried out and the relative merits and demerits have been evaluated with respect to the problem in hand. It was also concluded that among the various fault diagnostics technique available, no single technique stands out as superior to others. Each technique has its own advantages and limitations and the techniques complimentary to each other. One of the subjects which attracted the author's attention was the application of Genetic Algorithms (GAs) for engine fault diagnostics. GAs have applicability in a wide range of fields and have given a new direction to research in the field of engine diagnostics. It has been reported that the initial results obtained using GAs were very promising (Zedda, 1999c).

This chapter presents an overview of the background to the development of engine fault diagnostic based on GA optimisation. An analysis of the technique developed for the EJ200 using test bed instrumentation and its application to the RB199 (using in-service instruments) along with the enhancement made to the technique using multiple operating points analysis is presented.

3.2 An Overview of Genetic Algorithm

Genetic algorithms are a part of evolutionary computing, which is a rapidly growing area of Artificial Intelligence (AI). Genetic algorithms are inspired by Darwin's theory on evolution. The metaphor underlying the genetic algorithm is that of natural evolution. In evolution the problem each species faces is the one of searching for beneficial adaptations to a complicated and changing environment. The GAs follow step by step the procedure followed by the natures principle of survival of the fittest. The algorithm is started with a set of randomly chosen population. Solutions from one population are taken and used to form a new population. This is motivated by a hope, that the new population will be better than the old one. Solutions which are selected to form new solutions (offspring) are selected according to their fitness, the more suitable they are, the more chances they have to reproduce. This is repeated until some termination criterion (i.e. maximum number of generations, maximum fitness etc.) is satisfied.

3.2.1 Basics of Genetic Algorithm

The concept of GA can be explained with the help of a simple example. Let us consider there exists a function $y = f(x)$, where y is continuous between the interval [a, b]. If we need to find out the maximum value of the function, one way is to find all the values between a and b and then find the maximum value, but the number of possible values is infinite and therefore at this juncture we need to apply some optimization technique which would do this for us. Instead, what we can do is to generate a finite number of random solutions between a and b and apply GA to optimize the result.

These new search algorithms have achieved increased popularity as the researchers have recognised the shortcomings of the calculus based and enumerative schemes. The GAs are different from traditional optimisation method in the following way (Goldberg, 1989)-

(a) GAs work with a coding of the parameter set, not the parameters themselves.

(b) GAs search from a population of points and not a single point

(c) GAs use payoff (objective function) information, not derivatives or other auxiliary knowledge.

(d) GAs use probabilistic transition rules, not deterministic rules

In the context of this technique, a *string* refers to a possible solution and a collection of possible solutions or *strings* is called *population*. The *fitness* of the *string* is a function of an objective function and is inversely proportional to it. The best *string* would therefore have the highest *fitness* which means that the value of objective function would be minimum.

3.2.2 Terminology used in Genetic Algorithm

The nomenclature essential with GAs is also borrowed from the vocabulary of natural genetics (Goldberg, 1989).

- Allele: An allele is the value of the gene. It is in the form of 0 and 1 for a binary representation and between 0 and 9 for real coded GA's.
- Chromosome: a chromosome is a data structure that holds a string of task parameters, or genes. The string may be stored as a binary bit string or as floating point (real coded representation).
- Fitness: The fitness of an individual gives an idea of how well it performs the given task. The given task may be minimizing a certain objective function, in which case a high level of fitness for an individual indicates that it has a low objective function value. The higher the fitness value more will be the chances of this individual surviving to the next generation.
- Gene: A gene is a subsection of a chromosome that usually encodes the value of a single parameter.
- Genotype: This represents a potential solution to a problem.
- Genetic drift: This is the name given to changes in gene/allele frequencies in a population over many generations, resulting from chance rather than from selection. It normally occurs in small populations and can lead to some alleles becoming extinct, thus reducing the genetic viability in the population.
- Niche: A niche is a group of individuals that have similar fitness. Normally in multimodal or multi-objective optimization, a technique called sharing is used to reduce the fitness of those individuals that are in the same niche. This prevents the population from converging to a single solution, so that stable sub-populations can be formed, each one corresponding to a different objective or peak.
- Phenotype: This is a particular chromosome defined externally by the user.

- Schemata: is a similarity template describing a subset of strings with similarities at certain positions.

3.2.3 Genetic Algorithm Operators

Genetic algorithms work from a randomly generated population and the transition rules in GAs are stochastic. In the basic form of GA optimisation, the population is subjected to three operations, namely, Selection, Crossover and Mutation. The three operators are described in the following sections-

3.2.3.1 Selection

Selection is the process where the individual strings go into the next generation based on their fitness values. The fitness is calculated based on the objective function value and is generally its inverse unless mapped differently. The higher the fitness the greater is the probability of the individual being selected to the next generation.

There are various means of implementing the selection operator in an algorithmic form. Perhaps the easiest is to create a weighted roulette wheel, where each current string in a population has a roulette wheel slot sized in proportion to its fitness (Golberg, 1989). This is not in use because of many of its disadvantages and the most commonly used ones are:

- **Proportionate reproduction** A simple measure of the probability of survival can be given by the following formula:

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{3.1}$$

Where,

- P_i is the probability of the i^{th} string to be replicated
- f_i is the fitness value of the i^{th} string
- N is the number of strings

There are several other methods for sampling this probability distribution, namely: Monte Carlo or roulette wheel selection (Baker, 1987; Goldberg, 1989), stochastic remainder selection (Baker, 1987; Goldberg, 1989), and stochastic universal selection (Baker, 1987; Goldberg, 1989).

- **Ranking Selection**: the population is first sorted from the best to the worst and then each individual is copied as many times as it can, according to a non-increasing assignment function, and then proportionate selection is performed according to assignment (Baker, 1987; Goldberg, 1989)
- **Tournament Selection:** in this method of selection, the population is first shuffled and then it is divided into a fixed number of elements say '*k*'. The best individual according to the fitness is then chosen for survival. This process is then repeated *k* times.

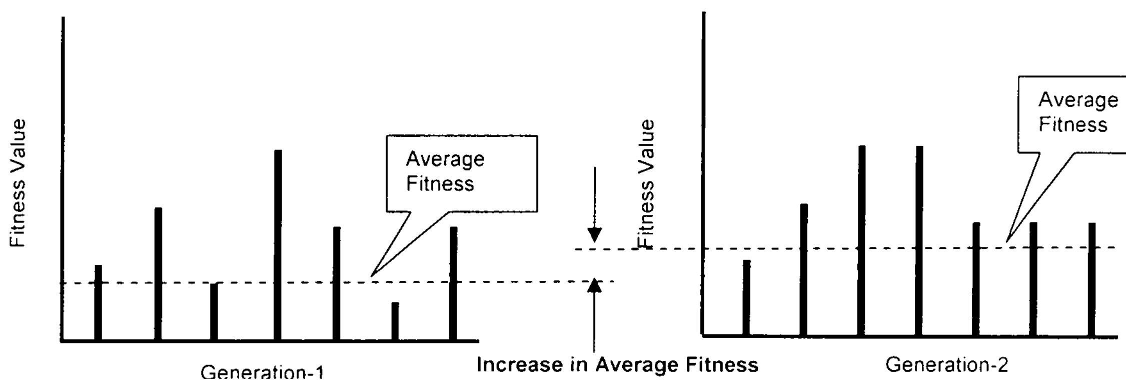


Figure 3.1: Selection Process

The process of selection is shown in figure 3.1. It can be seen that the average fitness has improved in the subsequent generation due to multiple copies of stronger strings and removal of weak strings.

3.2.3.2 Crossover

After selection, the newly formed individuals enter a mating pool for further genetic operations. One such operation is the crossover, where each pair of individuals represented by strings undergo crossover. The parents contribute some portions to form off-springs. If the length of the string is '*k*' then a random number between *1- (k-1)* is chosen. If this number is called *'cut'*, then the parents swap the characters between 1 to *'cut'* and therefore the offspring has information from both its parents.

y_1= 1001 | 0111 = 151

y_2= 1100 | 1101 = 205

after crossing over

y'_1= 1100 0111 = 199

y'_2= 1001 1101 = 157

New Fitness value for Crossover

Figure 3.2: A Schematic of Simple Crossover

3.2.3.3 Mutation

The mutation operator plays a secondary role in the simple GA. It works by randomly changing the value of a string position and is needed because, even though the reproduction and crossover effectively search and recombine extant notions, occasionally they might be overzealous and lose some potentially useful genetic material.

Fitness value before Mutation

y_2= 1 0 0 1 1 1 0 1 = 157

y'_2= 1 0 1 1 1 0 1 1 = 187

New Fitness value after Mutation

(Randomly flipping the digits at positions 3,6 and 7)

Figure 3.3: A Schematic of Simple Mutation

3.2.4 Coding Method in Genetic Algorithm

There are mainly two types of coding being used in genetic algorithm. They are-

a) Binary Coded GAs.

b) Real (Floating point) coded GAs.

3.2.4.1 Binary Coded GA

The binary coded GA is a system where the optimisation parameter (objective function) is represented in a binary form e.g. 187 will be coded as 1 0 1 1 1 0 1 1 . Binary coded GAs have been used traditionally and are quite popular. Some of the advantages and limitations of binary coded GA are -

Advantages of binary coded GA:

- Since the optimization parameter is represented in bit form, analysis of binary vectors is rather simple.
- Genetic operations like crossover and mutation on binary strings are simple.
- A binary alphabet enables maximization of the number of schemata available for genetic processing.

Limitations of binary coded GA:

- **Premature Convergence:** This phenomenon occurs when early in the run, some super individuals acquire more representatives because of their high fitness with respect to the rest of the population. Early convergence to these strings can happen if they relate to a local minimum, which may be far away from the global minimum. Early loss of diversity in the population can be prevented by attenuating the competition among strings through a number of techniques. Dynamic mapping of objective function is one way to do it.
- **Poor local tuning:** An outstanding advantage of GAs as opposed to typical calculus method based hill climbing techniques is the global search they can perform. However, a predictable pitfall is the inability to refine the solution once the area of the global minimum has been reached. A straight forward approach

would be to use the GA as a pre-processor to perform the initial search, before turning the search process over to a system that can employ domain knowledge and guide the local search. This is due to two main factors-

- In GAs a sort of hill climbing is realized through combination of selection and mutation. When compared with techniques which are specifically designed for hill climbing. Local search actually requires utilization of higher order and longer defining lengths than those suggested by fundamental theorem.
- Local tuning is also made difficult by the intrinsic resolution capability of mapping of the real parameters onto binary strings. This problem is particularly serious when the parameter domains are large, many parameters have to be handled and high precision is required. In this case the length of the binary solution vector is quite significant. For such problems, the performance of generic algorithms is quite poor.

As per Janikow and Michalewicz (1991) these limitations come to light when using the binary GA for multidimensional, high precision numerical problems as this results in large search spaces and then the performance of the GA becomes poor.

3.2.4.2 Real Coded GA

In order to solve the problems associated with binary coded GAs, real coded GAs needed to be developed by using special genetic operators. Experiments conducted by Janikow and Michalewicz (1991) and Michalewicz (1996) clearly show that the drawbacks of binary coding can not only be overcome by using real coded GAs but also the latter are "faster, more consistent from run to run, and provide a higher precision (especially with large domains where binary coding would require prohibitively long representation). At the same time their performance is enhanced by special operators to achieve high (even higher than binary representation) accuracy". In addition the floating-point representation is easier to design for solving specific problems. Some salient features of Real Coded GA

- **Representation**: each string consists of a real (floating point) vector. The precision of such representation is dependent on the machine. The real coding can represent a much wider domain when compared with its binary counter part.
- **Selection** – is performed in the similar way to the binary coded GA where a fitness function is calculated for each string and the fitter individuals move on to the next generation.
- **Crossover**: vectors are paired off and a random crossover point is chosen in accordance with the given probability of crossover (P_C).
- **Mutation** on the basis of a given probability of Mutation (P_M), vector elements are randomly varied within predefined limits.

The algorithm is analogous to its binary counter part in implementation where an initial population is generated randomly and all strings are assigned their fitness value calculated from an objective function. The genetic operation is carried out using the three fundamental operators namely, Selection, Crossover & Mutation.

It is worth noting, that for the same value of the probability of mutation (P_M), the simple random mutation described above is somewhat more random than the mutation used for binary strings, where changing a random bit does not imply producing a totally random value from the domain. Therefore, a new operator has been introduced, which performs dynamic mutation.

If $x(t)$ is vector with n elements. Then

$$x(t)=\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \\ \vdots \\ x_n \end{bmatrix} \qquad (3.2)$$

is the parameter vector at generation t and its k^{th} element is selected randomly for mutation, after that the vector will be:

$$x(t) = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x'_k \\ \vdots \\ x_n \end{bmatrix} \tag{3.3}$$

Where,

$$x'_k = \begin{cases} x_k + \Delta(t, UB - x_k) & \text{if a random digit is 0} \\ x_k - \Delta(t, x_k - LB) & \text{if a random digit is 1} \end{cases}$$

and

- UB is the upper bound of the range allowed for the considered vector element
- LB is the lower bound
- $\Delta(t,y)$ being close to 0 and increases as t increases. The following function can be used:

$$\Delta(t,y) = y \cdot (1 - r\left(1 - \frac{t}{T}\right)^b) \tag{3.4}$$

where,

- r is a uniform distribution random number in the range [0,1]
- T is the maximum number of generations
- b is a constant determining the degree of dependency on the iteration number (e.g. b=5).

The function $\Delta(t,y)$ is shown in figure 3.4 for two values of t, while in beginning large mutation changes are likely to happen, in the second part of the run the large changes are unlikely. The dynamic mutation operator warrants much better convergence and enables overcoming of the blocking problem. Figure 3.4(a) show the mutation in the beginning of the process and figure 3.4(b) shows towards the end of the process.

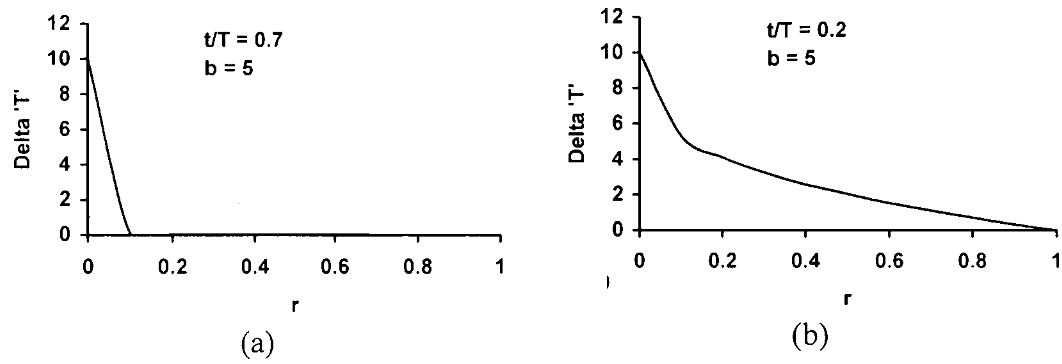


Figure 3.4: Dynamic Mutation

A comparison with a binary coded GA (Janikow and Michalewicz, 1991) can be summarized in the following advantages:

The main advantages of real coded GA's are as follows:

- The use of real coded GA is simpler to implement.
- Real Coded GAs are more suited for hill-climbing problems that are difficult. This is mainly due to the way mutation is carried out. Mutation for real coded GAs perturbs the current solution a little by adding or subtracting a delta value, whereas for binary representation there is usually a bitwise complement operator for mutation.
- Accuracy is higher for real GAs as the probability of deception is reduced due to dimensional reduction.
- Convergence times for real GAs have been shown to be lower than binary GAs.

3.2.5 Mapping objective functions to fitness form

Fitness is the key to the selection procedure and is the most important part of the GA. The GA tries to optimize the objective function by maximizing the fitness and the objective function is dealt with indirectly through the fitness value. In many problems, the objective is more naturally stated as the minimization of some cost function *g(x)*. Even if the problem is stated as in a maximisaion form, it does not guaranteed that the utility function will be a non negative for all x as we require in fitness function. As the result it is often necessary to map the underlying natural objective function to a fitness function form through one or more mappings. One simple way to map the fitness is simply multiply the cost function by minus one. However, this still does not guarantee a non negative fitness value. The most commonly used cost to fitness transformation is (Goldberg, 1989)-

$$f(x) = C_{max} - g(x) \quad when\ g(x) < C_{max} \qquad (3.5)$$

$$= 0 \text{ otherwise}$$

There are a variety of ways to choose the coefficient C_{max}. It may be taken as an input coefficient, as the largest $g(x)$ value observed thus far, the largest value of the current population etc..

When the natural objective function formulation is profit function then maximized profit leads to the desired performance, but still does not guarantee a non negative fitness function. In that case the following transformation can be applied

$$f(x) = u(x) + C_{min} \quad when\ u(x) + C_{min} > 0 \qquad (3.6)$$

$$= 0 \quad \text{otherwise}$$

Thus, mapping of the fitness has to be done carefully, as it can eventually lead to better convergence of the GA. Mapping can either be linear or non-linear.

3.2.6 Fitness Scaling

When the population is chosen randomly and GA process starts, it is common to have a few extraordinary individuals in a population of mediocre colleagues. If left to the normal selection rule ($pselect_i = f_i / \sum f$), they would take over a significant proportion of the total population and this situation is undesirable and is a leading cause for premature convergence. In the later generations, there might still be significant diversity in the population. However, the average fitness may be close to the population best fitness. If this situation is left alone then average members and best members get the same number of copies into the next generation and the survival of the fittest becomes a random walk among the mediocre. In view these conditions, a fitness scaling procedure has been adopted. A linear mapping mechanism developed by Goldberg (1989) is:

$$f' = a.f + b \qquad (3.7)$$

where f' is the fitness, f the objective function and a, b are constants.

The values of a and b are important and these have to be chosen carefully as these could prevent or cause premature convergence depending on how they are used. The main aim is to have less competition in the beginning so that diversity is maintained and increase competition towards the later stages for convergence to a correct solution.

Linear mapping can still cause premature convergence and a lot depends on the two constant values of a and b. Research by Chen et al (1994) has shown (for a minimization case) that non linear mapping in the form of equation 3.8 gives better results.

$$f' = \frac{1}{f} \tag{3.8}$$

The fitness versus objective function relationship now becomes a hyperbolic one and a high objective function leads to a lower value of fitness and vice versa.

3.2.7 Selection of population size

The population size is an important parameter to be decided in using GA for optimisation. Low population could cause premature convergence, inability to deal with noise, deception and multimodal problems. Using a population that is very large also has its own problems, which are the requirement of more computational resource and long run times, which may not justify the small gains achieved in accuracy. For a GA to do well there has to be sufficient population diversity to cover a wider search space and to create selective pressure for only the best to get selected. Under these conditions the average fitness of the population always goes up with generations. Several researchers have investigated ways to determine the best population size for a problem using genetic algorithms. Grefenstette (1984) applied a GA to control the population size of the main GA, and Goldberg (1989) has provided a theoretical analysis of optimal population sizes. Michalewicz (1996) has presented a method of GA with a varying population size. While carrying out testing of the GA for gas turbine diagnostics a number of population sizes were considered to arrive at an optimal one and these will be presented in the later stages of the thesis when the results are presented.

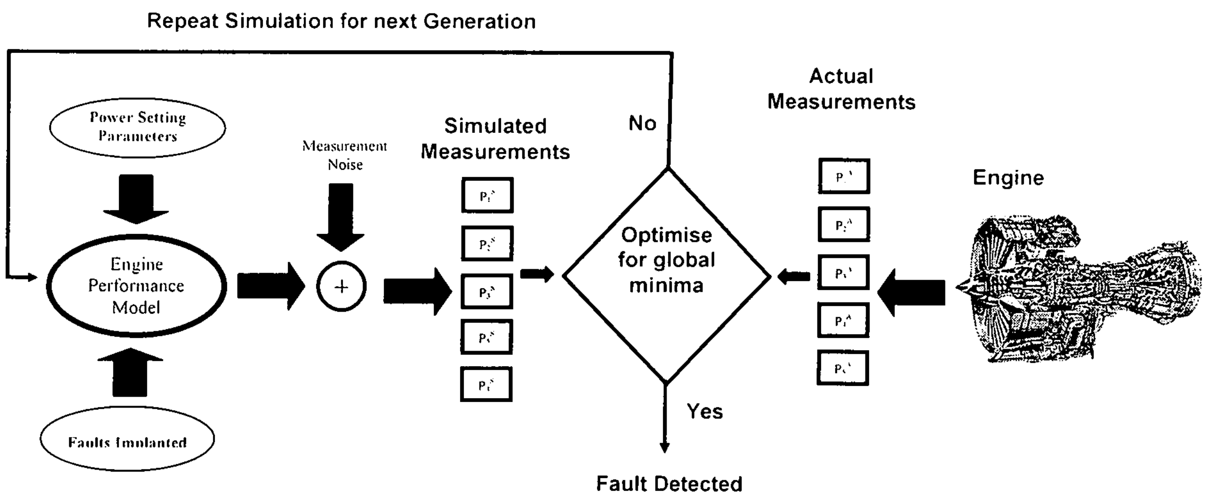
3.2.8 Start and stop criteria for GA:

One of the important criteria for running a GA is to decide on the starting and stopping criteria. The starting will be usually linked with the population size i.e. once the predefined number of random individuals have been generated, the algorithm can apply the operators on them. In addition, the probability of crossover (P_C), probability of mutation (P_M) are required as inputs for starting a GA. However, the stopping criteria is dependent on the application of the problem and would normally to -

- Stop after a fixed number of generations.
- Stop once the population has stabilized i.e. the individuals have a similar fitness level and further improvement is not significant.
- Stop once the objective function value has reached a certain predefined level.

3.3 Strategy for Engine Fault Diagnostic

Investigation of newer techniques with ability to take into account the measurement noise and possible sensor bias while preserving the non-linearity of the system led to the development of engine diagnostics based on optimization techniques.



P^S : Simulated parameter (measurement)
P^A : Actual parameter (measurement) from engine

Figure 3.5: Schematic Diagram of Diagnostic Strategy

Broadly, the strategy adopted here is to obtain a set of measurements from an engine performance model by planting known sets of faults and comparing it with the measurements from an actual engine. The simulated measurement set closest to the actual measurement set is indicative of the faults. A schematic diagram of the strategy is shown in figure 3.5.

The method appears to be simple and straight forward until we consider the number of possible solutions from which the algorithm needs to select the best solution. Several thousand combinations of faults could be generated depending on a number of factors such as number of engine components, number of performance parameters associated with each component, size of steps chosen between lower and upper limits of deterioration, level of accuracy of instruments selected etc.. Simulated measurements can be obtained by simulating the engine performance model at each of the above fault conditions while considering measurement noise. A search space developed by varying the deterioration in mass flow from –3.5% to +3.5% and deterioration in efficiency from 0 to 3.5% for HPC of a two spool engine (test model) and comparing it with data generated by introducing 2.75% efficiency deterioration in HPC is shown in figure 3.6. Each point on the surface plot is a potential solution and the best solution is the point having the lowest objective function. Figure 3.7 shows the search space obtained by just varying the fuel flow and ambient pressure for the EJ200. It shows the complexity involved in the optimisation process.

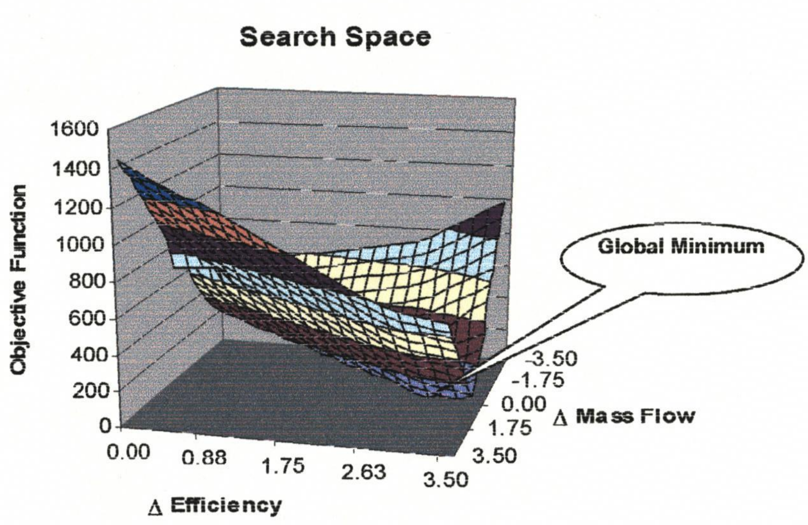


Figure 3.6: Search space for a HPC deterioration by 2.75% (Sampath et al, 2002b)

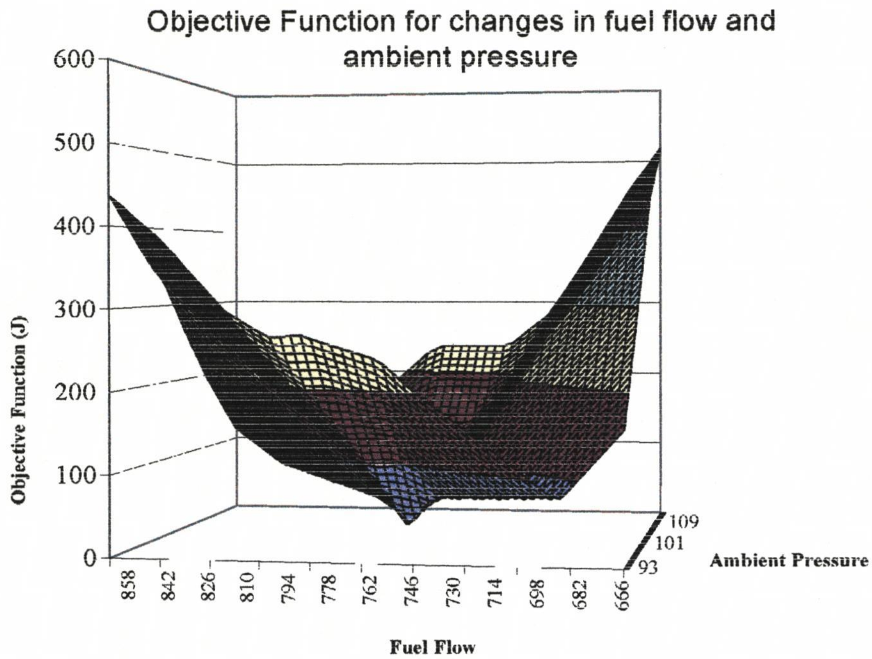


Figure 3.7 : Search space obtained by varying fuel flow and ambient pressure (Zedda, 1999c)

An important point to be noted here is that, the measurements which are obtained from the engine are of different types i.e. temperatures, pressures, spool speeds etc.. each of them come from different types of sensors which have different magnitudes and different measuring principles. It is indeed a challenging task to try and match them. Figure 3.8 shows a set of measurement obtained from by implanting known faults into the engine performance model. One set of measurement is obtained from an engine under investigation. The measurements will be matched and the best match will indicate the fault in the engine and by working backwards the faulty components can be identified.

It would be practically impossible to compare each parameter from the actual engine with its counter part from the simulated data as it would make the optimisation a very complicated process. A better way to compare the actual and simulated parameter would be to combine all these values into a single objective function.

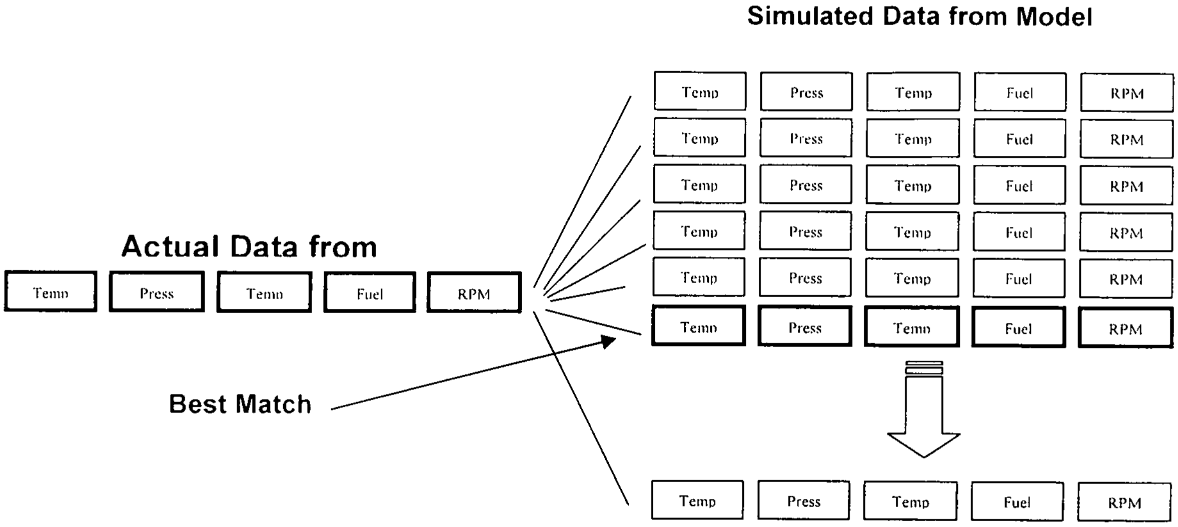


Figure 3.8: Matching measurements to identify faulty components

3.3.1 Implementing the Diagnostic Strategy

Having broadly established the diagnostic strategy, the next step is to address specific issues involved in the implementation of the strategy. As described earlier, the process would involve comparing a set of measurement from the actual engine with that of the measurements from the performance model with implanted faults.

3.3.1.1 Objective function for GA Diagnostics

Since the GAs work with objective functions and also due to the nature of the input data (measurements), there is a need for a system to compare the measurements. Figure 3.9 shows the general layout of the objective function which will be required. P denotes a parameter (which could be temperature, pressure etc.). The superscript 'A' & 'S' means the measurement is from an actual engine and from engine simulation model respectively. The vector consisting of the measurement deviations is to be converted into an objective function. In general the required objective function should have the following characteristics:

- Represent the problem adequately - The objective function developed must be such that a comparison of the measurements vectors could be made while considering system noise.
- Computationally not expensive: Since GA is an optimisation process which starts with a set of randomly chosen solutions (strings) and converges to a solution over a number of generations, it is a time consuming process. Each string is obtained by running the engine performance model twice and therefore the calculation of the objective function should be simple and should not involve computationally expensive functions or derivatives.

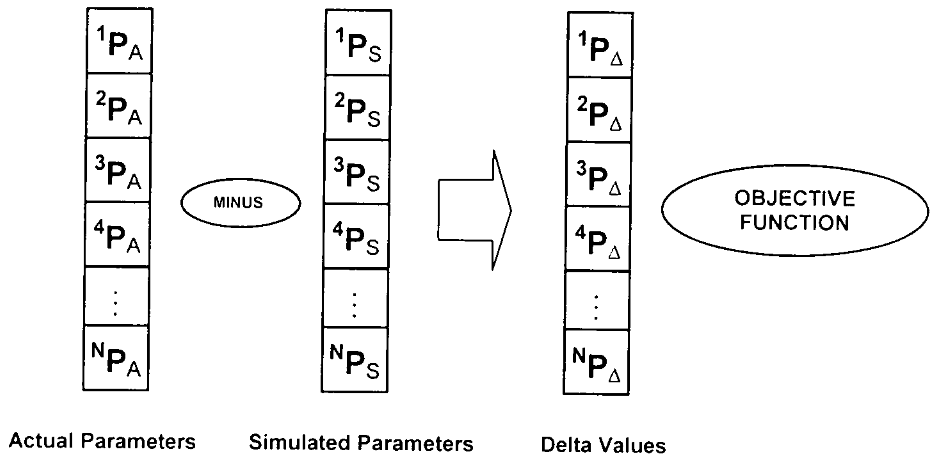


Figure 3.9: Layout for objective function

3.3.1.2 Search Techniques for GA Diagnostics

The next step is to use a suitable search technique to identify the best solution from a population of potential solutions. This can be accomplished in three ways:

- **Sequential search technique**: Perhaps, the most obvious method of finding the solution is to run the engine model with all possible combination of component faults and compare this with the actual engine data to get the closest match. This idea sounds quite logical till we consider the number of permutations possible (Sampath & Singh, 2002a). E.g. If an example of WR21 engine is considered, which has 2 compressors, 3 turbines, combustor, intercooler and recuperator, which is a total of 8 components (C=8). If each component has 2 performance parameters (P=2). If the performance is assumed to be linear $y=mx+c$ there are 2 operations on the performance O=2. If we estimate a changes to be +/- 5% from the base line, at an accuracy of +/- 0.1% then this would give 100 different options then E=100. If there are 2 instruments with each component and at the entrance and exit of the gas turbine then I=14. If we keep the instrumentation error to +/- 2% and with an accuracy of +/- 0.1 % then A=40. Assuming that each model takes 1 second to run then total time taken

=C*P*O*E*I*A*(1/3600)

=8*2*2*100*14*40*(1/3600)

=569 Hrs or appx 23 days.

Though it can be argued that an increase in the processing power of the processor can reduce the time required but the example considered is very simple. In reality we would want to examine the data from a more complicated instrumentation set or possibly transient data.

Having seen the complications involved and the kind of time frame required for solving such a problem, it would be prudent to investigate some techniques which would simplify the problem and perform an effective search within the vast search space.

- **Random search technique**

Another method of looking at the problem is to carry out a random search in the search space of possible solutions. After an open ended number of guesses the best solution is selected, but the reliability of such system would be doubtful.

- **Random search technique by directing the search to a solution**

Optimisation technique based on Genetic Algorithm (GA) can be used for this kind of problem. GA has shown tremendous potential as optimisation techniques and could be effectively employed for such problem. Instead of generating all the faults and comparing it with the actual data we generate at few solutions at random to form the population of the first generation. By using the principle of genetic algorithm we move to the next generation. New strings are produced by selection, crossover and mutation and the same are checked for suitability. In this way new solutions can be obtained till a point is reached where there is no further significant improvement in fitness or a predefined number of generations have been completed.

3.3.2 Working of GA Diagnostics model

Typically the diagnostics algorithm based on GA starts off with a *population* that is created at random and the objective function value for each of these *strings* from the population is calculated. The objective function to be minimised is mapped onto a fitness function. The larger the *fitness,* the higher the probability of *survival.* The mapping of the objective value onto the fitness function could be linear or non-linear. The aim of the algorithm is to reach the global minimum by successfully overcoming the local minima. The GA then works over a number of iterations or *generations* during which the population is subjected to selection, crossover and mutation. Figure 3.10 shows schematic diagram of a typical generation.

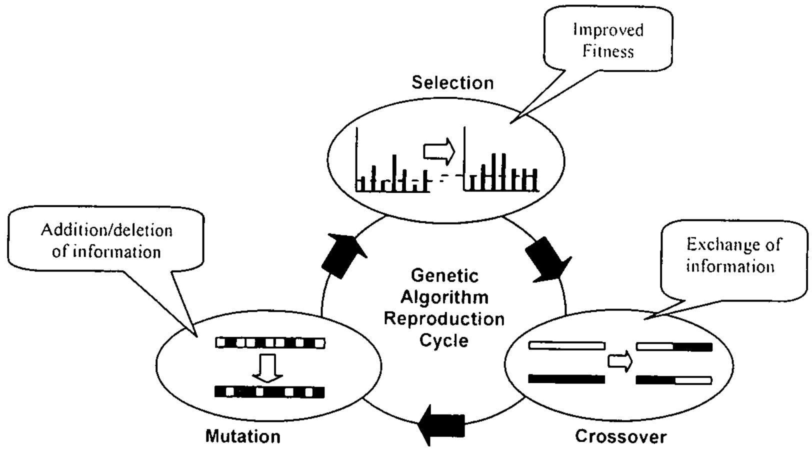


Figure 3.10: One generation in GA diagnostic model (Sampath & Singh, 2002a)

Figure 3.11 shows the value of objective function plotted for a give population. It shows the difficulty involved in carrying out a search in the presence of several local minima. Conventional calculus based technique have the disadvantage of getting trapped in local minima. The blue lines represent the randomly chosen population in the beginning of the search process. The green lines represent the population after *N* generations. It can be observed that the later generations have strings which are close to the solution or it consists of fitter individuals. The red line represents the solution or the best string in the population. It may not necessarily the best solution possible, but could be the best or close to the correct value.

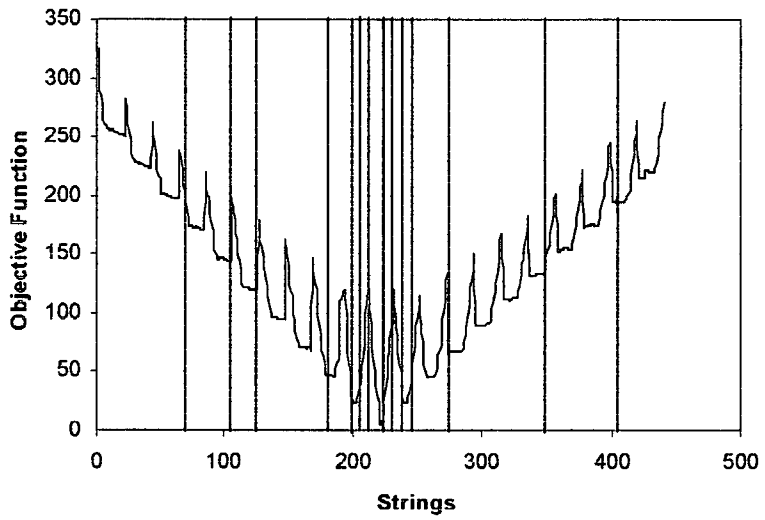


Figure 3.11: GA Diagnostics Working Principle

3.3.3 Mathematical form of the Diagnostic Strategy

The mathematics of GA diagnostics has been formulated by Zedda (1999c). A function which defines a relationship between the dependent and independent parameters without measurement noise or sensor bias is given as-

$$z - h(x) \tag{3.9}$$

where,

- $z \in R^M$ is the measurement vector and M is the number of measurements
- $x \in R^N$ is the performance parameter vector and N is the number of parameters
- $h(.)$ is the vector valued function.

$h(.)$ is provided by the simulation program and is non linear. If we consider the noise to be present then the model has to appropriately modified as follows

$$z = h(x)+v \tag{3.10}$$

where, v is the measurement noise vector.

In the presence of sensor biases, the equation (3.10) is further modified to

$$z = h(x)+b+v \tag{3.11}$$

where b is the measurement bias vector,

equation(3.11) defines the relationship for a certain operating point. If dependence on the operating point is written explicitly:

$$z = h(x,w)+b+v \tag{3.12}$$

where $w \in R^P$ is the vector of the environment and power setting parameters(e.g. inlet conditions and fuel flow) and P is the number of parameters. Usually v is assumed to have Gaussian Probability Density Function (PDF) and moreover to have independent components. Therefore, the joint PDF is the product of independent PDFs.

$$p(v) = \frac{1}{\left(\sqrt{2\pi}\right)^M} \prod_{j=1}^{M} \left(\frac{1}{\sigma_j}\right) e^{-\frac{1}{2}\sum_{j=1}^{M}\left(\frac{v_j}{\sigma_j}\right)^2} \tag{3.13}$$

where σ_j is the standard deviation of the j^{th} measurement. It should also be noted that w is affected by noise as well as biases like the other measurements

$$u = w + b_w + v_w \tag{3.14}$$

where:

- u is the vector of measured values
- w is the vector of actual values
- b_w is the vector of biases
- v_w is the vector of noise

Having defined the problem in equations (3.12) & (3.14), we need to find a solution to it. The aim would be generate a certain number of random solutions and compare it with the actual solution obtained. An objective function is to be decided which is a measure of the consistency between the actual the predicted measurements. Various factors concerning measurement noise and biases should be accounted for and the objective function should not be computationally intensive.

A classic choice for the objective function at a given operating point would be-

$$J(x)=\sum_{j=1}^{M}\frac{\left[z_j-h_j(x)\right]^2}{\left(z_{odj}\sigma_j\right)^2} \tag{3.15}$$

z_{odj} is the value of the j^{th} measurement in the off-design un-deteriorated condition. The minimization of the above objective function provides the maximum likelihood solution for the non-linear problem at hand. Another suitable function is the absolute deviation.

$$J(x)=\sum_{j=1}^{M}\frac{\left|z_j-h_j(x)\right|}{z_{odj}\sigma_j} \tag{3.16}$$

Measurement noise is accounted for using the standard deviation σ_j

The uncertainty affecting the environment and power setting parameter can be considered by modifying the objective function to-

$$J(x)=\sum_{j=1}^{M}\frac{\left[z_j-h_j(x,w)\right]^2}{\left(z_{odj}(w).\sigma_j\right)^2} \tag{3.17}$$

and equation (3.16) becomes

$$J(x)=\sum_{j=1}^{M}\frac{\left|z_j-h_j(x,w)\right|}{z_{odj}(w).\sigma_j} \tag{3.18}$$

The technique has the following advantages:

(a) Inherently robust to measurement bias;

(b) Relies fully on non-linear models;

(c) Relatively unaffected by "smearing" whereas other methods like KF and WLS based approaches are affected;

(d) It is much easier to account for noise and bias in the measurements;

3.3.4 Optimisation through Fault Classes

It order to reduce the "smearing" effect, which is so common to most of the conventional methods, a constrained optimisation is carried out (Zedda, 1999c). It is assumed that not more that two components (four performance parameters) are simultaneously faulty. The engine components (whose faults are sought) are distributed into fault classes and the algorithm searches for one fault class at any time. If there are N components then the total number of fault classes is given by $N + {}^{N}C_2$. Essentially the algorithm looks for single component faults and then dual components faults by pairing different components. More than two component faults also can be investigated but it will increase the number of fault classes and hence will be computationally expensive. This method was validated on the EJ200 and the RB199 and a brief description of its implementation on these engines is presented in the following sections:

3.4 GA Based Diagnostic System For The EJ 200

A diagnostics system based using test bed instrumentation was developed by Zedda (1999c) for the EJ200. The EJ200 (fig 3.12) engine is low-bypass ratio, mixed flow reheated two-spool military turbofan used on the European Fighter Aircraft (EFA) or "Euro-Fighter".

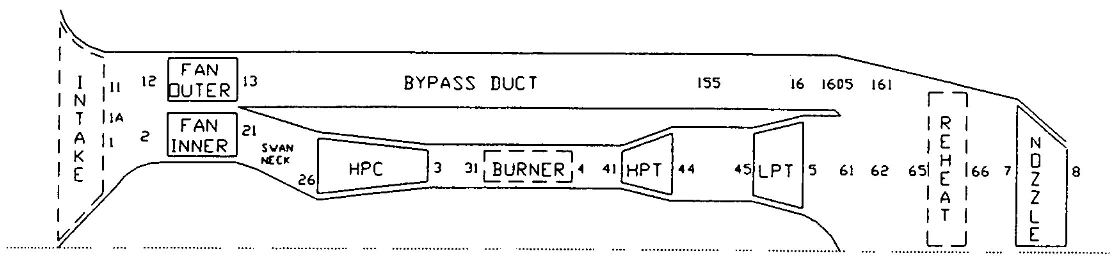


Figure 3.12: Schematic diagram of EJ200 engine

The engine has the following characteristics:

Bypass Ratio	0.4:1
Pressure Ratio	25:1
Compressor Stages	3 LP, 5 HP
Combustion System	Annular Vaporizing
Turbine Stages	1 HP, 1 LP
Power Range	20,000 lbf (90kN)- with reheat 13,500 lbf (60kN) without reheat

Table 3.1: EJ200 Engine Data

The diagnostic parameters that correspond to the EJ200, shown in a schematic form in figure 3.12 and that interrelate through their aero-thermodynamic relationships as shown previously in figure 2.1 are:

1. **10 Independent Parameters (Performance Parameters)**:
   - Fan overall flow function (Γ_{FAN});
   - Fan outer efficiency (η_{FANOUT});
   - Fan inner efficiency (η_{FANIN});
   - HP compressor flow function and efficiency (Γ_{HPC},η_{HPC});
   - HP turbine flow function and efficiency (Γ_{HPT},η_{HPT});
   - LP turbine flow function and efficiency (Γ_{LPT},η_{LPT}); and,
   - Nozzle discharge coefficient (C_D);
2. **13 Dependant Parameters (Measurements)**:
   - Engine inlet airflow (W_{1A});
   - Fan outer exit total pressure and temperature (P_{13},T_{13});
   - Fan inner exit total pressure and temperature (P_{12},T_{12});
   - Core inlet airflow (W_{12});

- HP compressor exit total pressure and temperature (P_3,T_3);
- LP turbine exit total pressure and temperature (P_5,T_5);
- Net thrust (F_N);
- HP spool rotational speed (N_H); and,
- LP spool rotational speed (N_L);

3. **3 Parameters are used to set the Operating Point**:

- Fuel flow (W_{FE}); and,
- Ambient total pressure and temperature (P_0,T_0).

3.4.1 Performance Simulation model for the EJ200

The model used in Zedda's (1999c) work was provided by Rolls-Royce. It is a non linear steady state performance simulation program called RRAP. Full thermodynamic calculations using enthalpy and entropy, are performed. In general gas properties are averaged one dimensional values at any cross section of the gas path. Some two dimensional values for pressure and/or temperature distortion through the compression process are used. Combustion and expansion are strictly one dimensional. Each rotating component is represented by a performance characteristics consisting of tabulation of non-dimensional groups for flow, work, rotational speed and isentropic efficiency. The air system is represented by series of bleeds removed from the gas stream between compressors and inter-stage. Bleed flows are usually assumed to be fixed percentage of a main gas stream flow. Internal calculations are performed in double precision.

3.4.2 Diagnostic Model Coding

The codes developed for the project have been written in standard FORTRAN 77 according to the sponsor's requirement. Minimum use of built in functions have been used. A large number of numerical subroutines have been obtained from Press et al (1992). All codes developed for diagnostics are double precision and the numerical subroutines from Press et al (1992) have been suitably modified accordingly. All programs have been compiled with digital Visual FORTRAN 5.0.

3.4.3 EJ200 Fault Classes

For the purpose of engine diagnostics of the twin spool engine the following six components are considered: (a) Fan Outer (b) Fan Inner (c) HPC (d) HPT (e) LPT (f) Nozzle.

The total number of fault classes depend on the number of components. For the EJ 200, which has 6 components, in the case of single component fault there will be 6 fault classes. In the case of two faulty components the number of fault classes will be the fault classes comprising of single component faults plus combinations of two each from the various components (table 3.2). Thus, there will be $6+{}^6C_2=21$ fault classes. Similarly for three faulty components the number of fault classes will be $6+{}^6C_2+{}^6C_3=41$.

Fault class	Component	Fault Class	Component
1	Fan (O)	12	Fan(I) + HPC
2	Fan (I)	13	Fan(I) + HPT
3	HPC	14	Fan(I) + LPT
4	HPT	15	Fan(I) + Nozzle
5	LPT	16	HPC + HPT
6	Nozzle	17	HPC + LPT
7	Fan(O) + Fan (I)	18	HPC + Nozzle
8	Fan(O) + HPC	19	HPT + LPT
9	Fan(O) + HPT	20	HPT + Nozzle
10	Fan(O) + LPT	21	LPT + Nozzle
11	Fan(O) + Nozzle		

Table 3.2: Fault Classes for the EJ 200

3.4.4 Salient features of EJ200 Diagnostic System:

The structure of the diagnostic system is shown in figure 3.13. Simulated or measured data together with the operating point and the environment and power setting parameters are input to the GA optimiser. The model uses measurements from a single operating point and the simulated measurements are obtained using the same operating condition. It is therefore called the Single Operating Point Analysis (SOPA) model. This optimiser then interacts with the Non-linear performance simulation code of the particular engine during each generation of the algorithm. The results are then obtained after a fixed number of generations. Salient features of the diagnostics system by Zedda (1999c) is as follows:

- The objective function, which depends on the performance parameter vector (efficiencies and flow capacities) and the environment and power setting parameter vector (e.g. inlet pressure and temperature and fuel flow) has been defined in equation 3.18.
- The population is initialised randomly within constraints for the efficiencies, flow capacities and environment and power setting parameters. The constraints can be varied by the user depending on the requirement.
- Fault identification is done by dividing the engine into fault classes where each fault class represents a particular fault (single or two components). Each fault class refers to one possible outcome in terms of faulty components. Fault classes are created in order to constrain the GA based optimization approach to prevent "smearing".
- Fault classes are processed by the three principle operators in genetic algorithms, i.e. the selection, crossover and mutation. As the GA progresses in each generation, the population in the fault class that has the strings with higher fitness values increase at the expense of low fitness strings in other fault classes.
- Selection is based on fitness value, i.e. those strings that have a high fitness will get selected for the next generation and others will die out. The selection is extended to the entire population. As generations progress the strings from one fault class produce more offsprings depending on the fitness. Concentration on one or two engine components is then achieved.
- The crossover operator is applied to strings which are members of the same fault class depending on the probabillity of crossover (PC). Crossmating between different fault classes is not allowed and is between pairs of strings.

- Mutation is applied to each string by adding or substracting a random value from it while satisfying the constraints. In simple terms, selection extended to the whole population forces concentration on the faulty engine components, while crossover and mutation help selection to refine the solution.
- Real coded GA is used for representing the strings.
- Real noise levels were superimposed to the clean measuements provided be the simulation code.

In order to show the working of the technique, a comparison between typical results provided by the diagnostics system and a straigtforward maximum likelihood-based optmisation with allowance for noise and bias without constraints on the number of fault affected parameters is presented in table 3.3.

Parameters	Actual(%)	Predicted(%)	Maximum Liklihood
$\Delta\Gamma FAN_{OUT}$	**-3.00**	**-2.99**	**-2.90**
$\Delta\Gamma FAN$	0.00	0.00	-0.27
$\Delta\eta FAN_{IN}$	0.00	0.00	-0.33
$\Delta\Gamma HPC$	**3.00**	**2.99**	**2.91**
$\Delta\eta HPC$	**-1.00**	**-1.03**	**-0.41**
$\Delta\Gamma HPT$	0.00	0.00	-0.56
$\Delta\eta HPT$	0.00	0.00	-0.11
$\Delta\Gamma LPT$	0.00	0.00	-0.72
$\Delta\eta LPT$	0.00	0.00	-0.2
ΔC_D	0.00	0.00	-0.27
Power Setting Parameters			
Wf	811.728	811.603	811.231
P1	83.688	83.773	83.574
T1	312.020	312.094	311.890

Table 3.3: Comparison of GA Diagnostic model with Maximum likihood method (Zedda, 1999c)

The first column lists the faults implanted. The second column displays the predicted values by the GA based diagnostics system and the third column consists of the results from the maximum likelihood based method. The GA based method has successfully identified the faulty components. "Smearing" is considerably reduced and concentration achieved. Several such fault conditions were examined and it was found that the capability of GA based diagnostic model to identify the fault in the presence measurement noise and sensor bias was very encouraging.

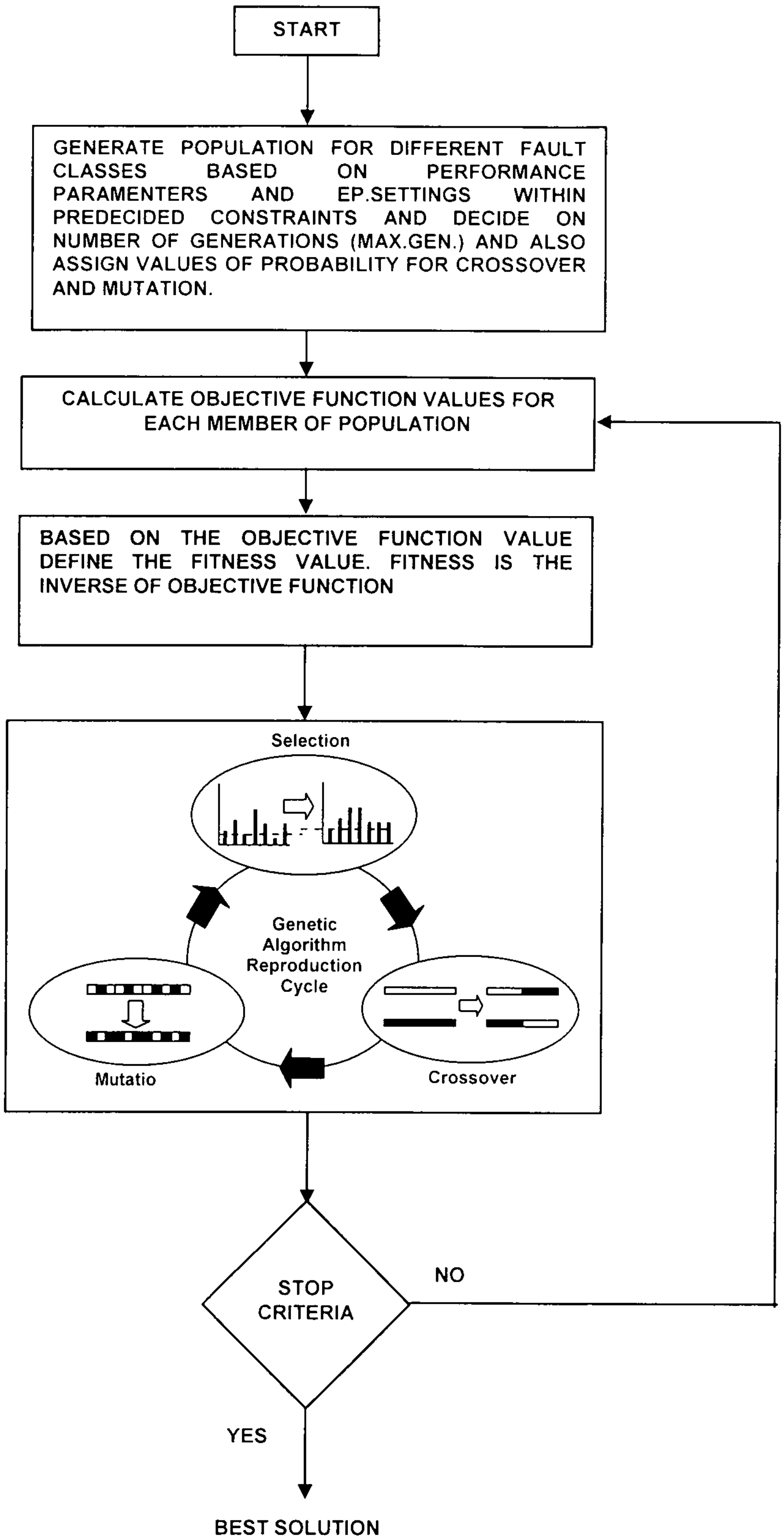


Figure 3.13: Flow chart of the diagnostics principle

3.5 GA Based Diagnostic System for the RB199

After the successful application of gas for engine fault diagnostics by Zedda (1999c) using test bed instrumentation set, Gulati (2002) undertook the task of investigating a diagnostics system for the RB199 using the in-service instrumentation. The level of instrumentation is much lower than the EJ 200 for which the technique was initially developed. in addition to the lower level of instrumentation, the RB199 has an additional spool (2 more components). The aim was to modify the software suitably for the RB199 and conduct tests to establish the suitability of the technique for poorly instrumented engine.

3.5.1 Description of the RB 199 Engine

The RB199 engine is a low-bypass, mixed flow, reheated three-spool military turbofan engine used on the "Panavia" Tornado.

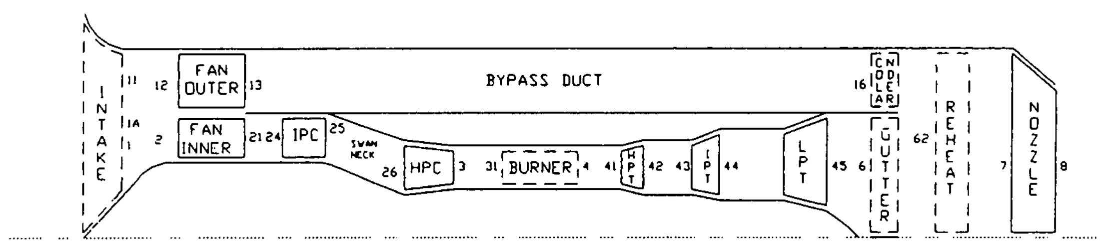


Figure 3.14: Schematic of the RB199 Engine

The engine characteristics are as follows-

Bypass Ratio	1.02:1
Pressure Ratio	23:1
Compressor Stages	3 LP, 3 IP, 6 HP
Combustion System	Annular Vaporizing
Turbine Stages	2 LP, 1 IP, 1 HP
Power Range	16,700 lbf (74.1 kN) with reheat 9,550 lbf (42.5) without reheat

Table 3.4: Engine data of the RB199 Engine

The diagnostic parameters that correspond to the RB199, shown in schematic form in figure 3.14 and that interrelate through their aero-thermodynamic relationships as shown previously in figure 2.1 are:

14 Independent Parameters (Performance Parameters):

- Fan overall flow function (Γ_{FAN});
- an outer efficiency (η_{FANOUT});
- Fan inner efficiency (η_{FANIN});
- IP compressor flow function and efficiency (Γ_{IPC},η_{IPC});
- HP compressor flow function and efficiency (Γ_{HPC},η_{HPC});
- HP turbine flow function and efficiency (Γ_{HPT},η_{HPT});
- IP turbine flow function and efficiency (Γ_{IPT},η_{IPT});
- LP turbine flow function and efficiency (Γ_{LPT},η_{LPT}); and,
- Nozzle discharge coefficient (C_D);

9 Dependant Parameters (Measurements):

- Engine inlet airflow (W_{1A});
- Fan outer exit total pressure and temperature (P_{13},T_{13});
- IP compressor exit total pressure (P_{25});
- HP compressor exit total pressure and temperature (P_3,T_3);
- Net thrust (F_N);
- HP spool rotational speed (N_H); and,
- LP spool rotational speed (N_L);

3 Parameters are used to set the Operating Point:

- Fuel flow (W_{FE}); and,
- Ambient total pressure and temperature (P_0,T_0).

3.5.2 Performance Simulation model for RB199

The model used for Gulati's (2002) work was provided by Rolls-Royce. It is a non linear steady state performance simulation program named RRAP with similar features like the EJ200 described earlier.

3.5.3 Diagnostic Model Coding

Similar to Zedda's (1999c) work the codes developed for the project have been written in standard FORTRAN 77 according to the sponsor's requirement. Minimum use of built in functions have been used . a large number of numerical subroutines have been obtained from Press et al (1992). All codes developed for diagnostics are double precision and the numerical subroutines from Press et al have been suitably modified accordingly. All programs have been compiled with digital Visual FORTRAN 6.0.

3.5.4 RB199 Fault Classes

For diagnostics purpose of the twin spool engine the following six components are considered: (a) Fan Outer (b) Fan Inner (c) IPC (d) HPC (e) HPT (f) IPT (g) LPT (h)Nozzle.

The RB199 has 8 components compared to 6 for the EJ 200. Division of these components into fault classes for diagnostics as defined in section 3.4.3 would result in 36 fault classes (table 3.5) compared to the 21 for EJ 200.

Fault class	Component	Fault class	Component	Fault class	Component
1	F_{out}	13	F_{out}, IPT	25	IPC, LPT
2	F_{in}	14	F_{out}, LPT	26	IPC, Nozzle
3	IPC	15	F_{out}, Nozzle	27	HPC, HPT
4	HPC	16	F_{in}, IPC	28	HPC, IPT
5	HPT	17	F_{in}, HPC	29	HPC, LPT
6	IPT	18	F_{in}, HPT	30	HPC, Nozzle
7	LPT	19	F_{in}, IPT	31	HPT, IPT
8	Nozzle	20	F_{in}, LPT	32	HPT, LPT
9	F_{out}, F_{in}	21	F_{in}, Nozzle	33	HPT, Nozzle
10	F_{out}, IPC	22	IPC, HPC	34	IPT, LPT
11	F_{out}, HPC	23	IPC, HPT	35	IPT, Nozzle
12	F_{out}, HPT	24	IPC, IPT	36	LPT, Nozzle

Table 3.5: Fault classes for the RB199 Engine

Consequent to the increased number of fault classes, ideally the RB 199 engine should have more measurements. However, the engine has only 9 instruments available for diagnostics and 14 performance parameters to be estimated.

3.5.5 Salient Features of RB199 Diagnostic System :

The structure of the diagnostic system is similar to EJ200 as shown in figure 3.13. The only difference being the number of instrumentations used for diagnostics.

Salient features of diagnostics system for RB199 by Gulati is as follows:

- The objective function, which depends on the performance parameter vector (efficiencies and flow capacities) and the environment and power setting parameter vector (e.g. inlet pressure and temperature and fuel flow) has been defined in equation 3.18.
- The population is initialised randomly within constraints for the efficiencies, capacities and environment and power setting parameters. the constraints can be varied by the user depending on the requirement.
- The technique aims to identify a maximum of two simultaneously faulty components.
- Three operators; selection, crossover and mutaion are used.
- Selection is based on fitness value, i.e. those strings that have a high fitness will get selected for the next generation and others will die out. The selection is extended to the entire population. As generations progress the strings from one fault class will form more offsprings depending on the fitness. Concentration on one or two engine components is then achieved.
- The crossover operator is applied to strings which are members of the same fault class depending on the probability of crossover (P_C). Crossmating between different fault classes is not allowed and is between pairs of strings.
- Mutation is applied to each string by adding or substracting a certain value from it and at the same time satisfying the constraints.
- Real coded GA is used for representing the strings.

- Real noise levels were superimposed to the clean measuements provided be the simulation code.
- Single operating point analysis is used.

Parameters	Actual(%)	Predicted(%)
$\Delta\eta_{FANOUT}$	0	0
$\Delta\Gamma_{FAN}$	0	0
$\Delta\eta_{FANIN}$	0	0
$\Delta\Gamma_{IPC}$	0	0
$\Delta\eta_{IPC}$	0	0
$\Delta\Gamma_{HPC}$	**-2.0**	**-1.0**
$\Delta\eta_{HPC}$	**-2.0**	**-2.6**
$\Delta\Gamma_{HPT}$	**-2.0**	**-2.0**
$\Delta\eta_{HPT}$	**-2.0**	**-2.2**
$\Delta\Gamma_{IPT}$	0	0
$\Delta\eta_{IPT}$	0	0
$\Delta\Gamma_{LPT}$	0	0
$\Delta\eta_{LPT}$	0	0
C_D		

(a)

Parameters	Actual(%)	Predicted(%)
$\Delta\eta_{FANOUT}$	0	0
$\Delta\Gamma_{FAN}$	0	0
$\Delta\eta_{FANIN}$	0	0
$\Delta\Gamma_{IPC}$	0	0
$\Delta\eta_{IPC}$	0	0
$\Delta\Gamma_{HPC}$	**-2.0**	**0**
$\Delta\eta_{HPC}$	**-1.0**	**0**
$\Delta\Gamma_{HPT}$	**-2.0**	**-1.5**
$\Delta\eta_{HPT}$	**-1.0**	**-1.7**
$\Delta\Gamma_{IPT}$	0	0
$\Delta\eta_{IPT}$	0	0
$\Delta\Gamma_{LPT}$	0	0
$\Delta\eta_{LPT}$	0	0
C_D	0	**-0.4**

(b)

Table 3.6: Results from the RB199 engine diagnostics (Gulati, 2002c)

The system has been extensively tested with various types of imlplanted faults. For the purpose of testing, both real as well as simulated data were used. Fault was implanted in the HPC and the HPT. Randomly generated noise within $\pm 3\sigma$ level was added and one instrument was biased. Results for this are presented in table 3.4. The results for the case where the level of deterioration is high (table 3.4(a)) are just about acceptable and the technique is capable of identifying the faulty components but accuracy in terms of quantification is not high. The same components were then tested by implanting a slightly lower fault level as shown in table 3.4(b) and it can be observed that even the components are not correctly identified. It can be concluded that for lower levels of faults the accuracy of diagnosed fault by technique based on SOPA is poor.

3.5.6 Analysis of the Diagnostics Systems developed using SOPA

In the preceding sections the developments of diagnostics system for two engines have been discussed. The diagnostics model for EJ200 used the test bed instrumentation and that of the RB199 engine used in-service instrumentation. It has been brought out that though the methodology was same, the diagnostics capability was different in each case. Conclusion can be drawn from this that the fault prediction of diagnostics model based on SOPA is suitable for engines with test bed instrumentation or engines where a large number of measurements are available. It was reported by Gulati (2002) that study with increased measurements for the RB199 clearly showed an increase in accuracy for diagnosis and brought it in line with that experienced for the EJ 200. Since, it would not be possible to increase the number of instruments for an in-service engine, a technique based on measurements from multiple operating points was investigated by Gulati (2002c).

3.6 Multiple Operating Point Analysis (MOPA)

If the number of measurements is more than the number of performance parameters and power setting parameters to be determined, the technique based on GPA or GA optimisation using single operating point would result in high degree of accuracy. However, if the number of measurements is far less than the number of performance parameters a more judicious choice of algorithm would be needed. One technique to overcome this problem is to use information available from different operating points and is known as Multiple Operating Point Analysis (MOPA), as shown by Stamatis and Papailiou (1988). In MOPA, the choice and number of operating points is critical to diagnostic accuracy. It has been claimed by Stamatis and Papailiou (1988) that better accuracy is obtainable when operating conditions are far from each other. When deteriorated engine performance is simulated, as no exact information about the actual map's modification is usually available, the fault's effect is obtained by a simple shift of the map itself. If this simplification is accepted, utilisation of operating points located far from one another on the map should enable maximum exploitation of the model's non-linearity. On the other hand Doel (1993) noted that a different working point means different aerodynamic conditions and in this sense efficiencies and flow capacities can significantly change with the operating condition. In order to address the issue of number of operating points, the concept of relative redundancy was introduced by Zedda & Singh (1999a) which is described in the following section.

3.6.1 Relative redundancy

The accuracy of MOPA would to a great deal depend on the augmented matrix $k\,X\,m$ (k is the number of operating points and m being the measurement vector)being greater than the number of performance parameters 'n'. In order to understand this, the concept of relative redundancy index 'R' is introduced. In the single operating point analysis, for the diagnostic technique to work satisfactorily, the measurements not affected by bias should be more than unknowns (Zedda, 1999c) i.e. the performance parameters being determined and the environment and power setting parameters, and this can be represented as under:

$$M - M_{bias} > N_{perf} + EP \qquad (3.19)$$

where

M is the number of measurements

M_{bias} is the number of biased measurements and

N_{perf} is the number of fault affected performance parameters

In case of use of multiple operating point analysis (MOPA), this would become:

$$L \cdot (M - M_{bias}) > N_{perf} + L \cdot EP \qquad (3.20)$$

where L is the number of operating points and EP the parameters used to define the operating point of the engine (i.e. $EP = 3$; inlet pressure and temperature and fuel flow (W_f)).

Thus MOPA should make the analysis of poorly instrumented engines possible due to more extensive analytical redundancy. The relative redundancy index introduced by Zedda (1999c) is-

$$R = \frac{L \cdot (M - M_{bias})}{N_{perf} + L \cdot EP} \tag{3.21}$$

The accuracy of the diagnostic technique should increase with increased relative redundancy. Use of more operating points allows to increase the relative redundancy and therefore should lead to better accuracy as shown in figure 3.15.

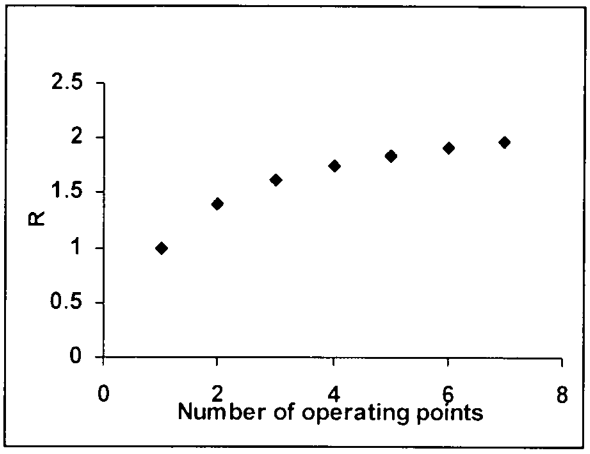


Figure 3.15: Relative redundancy index versus no. of operating for EJ200 (Zedda, 1999c)

3.6.2 Analysis of Relative Redundancy Index

Analysis of the results plotted in figures 3.15 indicates that two operating points would suffice for the cases (for 0 and 1 or at most 2 measurements being baised), though three should do the job perfectly with a good amount of margin (Gulati, 2002). But due to the approximate nature of 'R', due to noise and non-linearity, the graph (figure 3.15) obtained by plotting 'R' with respect to the number of operating points needs to be viewed in a statistical sense. A large increase in the number of operating points would lead to:

- Reduction in the rate of increase of the relative redundancy index with increasing number of operating points, which is akin to the law of diminishing returns.

- Very high computational resources necessary to evaluate the objective function with increase in the number of operating points. When $L = 5$ an evaluation may require a time of at least 5 times longer than with a single operating point.
- A very large number of operating points is likely to cover a rather wide area in the component maps. Therefore, the assumption of constant performance parameter variations is less acceptable
- The objective function becomes harder to optimize as the number of operating points increases.

MOPA makes the analysis of poorly instrumented engines possible due to more analytical redundancy. However, figure-3.15 shows that the gains achievable up to three operating points are significant and then the relative advantage in terms of accuracy and computational effort are lost.

3.6.3 Multi-Objective Optimisation

Multi objective optimization requires an approach, which is different from the single objective optimization. It is clear that if there are two objectives to be optimized, it might be possible to find a solution which is best with respect to the first objective, and another solution, which is best with respect to second objective. As the number of operating points increases beyond one, the objective function could be obtained by simply adding up single objective cases. This would then be as follows-

$$J_{KL}(\mathbf{x},\mathbf{w}) = \sum_{m=1}^{OP} \sum_{\substack{j=1 \\ j \neq K,L}}^{NM} \frac{\left| z_{jm} - h_{jm}(\mathbf{x},\mathbf{w}_m) \right|}{z_{odjm}(\mathbf{w}_m) \cdot \sigma_j} \tag{3.22}$$

where: OP is the number of operating points

The aggregate approach to obtain a single objective function from two or more objective function as shown in Eq-3.22 is the simplest form of multi-objective optimisation. There are several other classical methods of addressing the multiple objective issue like the min-max formulation, method of distance functions etc.. However, these classical approaches result in a compromise solution and if some objective functions are noisy or have discontinuous variable spaces, these methods may not work (Gulati, 2000c).

The technique used in this work is based on the Non dominated Sorting Genetic Algorithm (NSGA) proposed by Srinivas and Deb (1994) based on several layers of classifications of individuals. In order to proceed with this technique it would be convenient to classify potential solutions into *dominated* and *non-dominated.* As solution x is *dominated,* if there exists a feasible solution y not worse than x on all coordinates (for minimization problems), i.e.

$$f_i(x) \leq f_i(y) \quad \text{for all} \quad 1 \leq i \leq k \tag{3.23}$$

If the solution is not dominated by any other feasible solution, it is called the *non-dominated* or *pareto-optimal* solution. In this technique the *population* is ranked on the basis of non-domination. All *non-dominated strings* are classified into one category or *front* and accorded a large dummy fitness value proportional to the *population* size. The same fitness value is assigned to give an equal reproductive potential to all these *non-dominated* individuals. In order to maintain diversity in the *population*, these classified individuals are then shared with their dummy fitness values. Sharing is achieved by performing selection operation using degraded fitness values, which are obtained by dividing the original fitness value of an individual by a quantity proportional to the number of individuals around it. This causes multiple optimal points to coexist in the *population.* After sharing, this *front* of *non-dominated* individuals is ignored temporarily to process the rest of *population* in the same way to identify individuals for the second *non-dominated front.* These new set of points are then assigned a new dummy fitness value which is kept smaller than the minimum shared dummy fitness of the previous *front.* This process is continued until the entire population is classified into several *fronts.* Since, individuals in the first *front* have the maximum fitness value, they always get more copies than the rest of population. This concept of *pareto optimality* is used to estimate the *fitness* values of the *population* for *selection* in genetic algorithm.

A schematic diagram of the technique is shown in figure 3.16. It can observed that the objective functions for strings from different operating points are calculated independently. The objective functions are compared for pareto-optimality and then ranked. After the ranking and fitness assignment, the strings from different operating points proceed separately for further genetic operation.

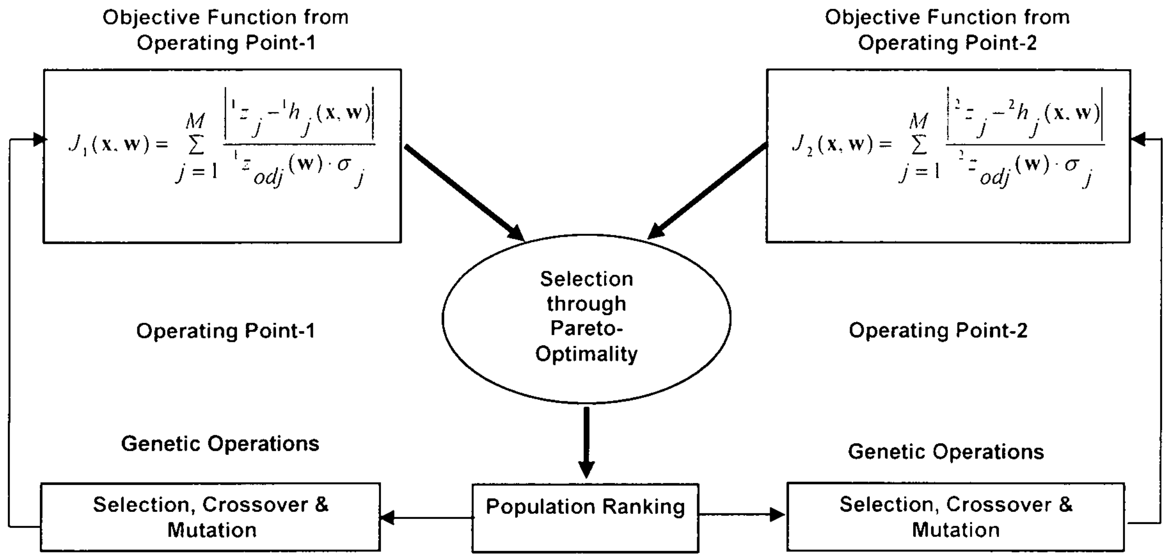


Figure 3.16: Schematic diagram of MOPA

3.6.4 A Diagnostic System for RB199 Engine using MOPA

An engine diagnostics technique based on GA optimisation has been developed for the Rolls-Royce RB199 engine, but it can be applied to any engine with a similar instrumentation set. Validation of the technique has been carried out with simulated and real data.However, most of the testing was done on simulated data and only four engines with actual test data were used due to the limited availability of such data.

Initially the simple aggregate of objective function was considered but the diagnostic accuracy was poor. Table 3.7 shows the difference in diagnostic accuracy between three schemes and shows that the *pareto-optimal* method for selection gave the best results.

PARAMETER	ACTUAL (%)	PREDICTED (%)		
		SOPA	MOPA	MOPA
$\Delta\Gamma_{FAN}$	-3.0	-2.92	-3.0	-3.0
$\Delta\eta_{FAN\ IN}$	0.0	0.0	0.0	0.0
$\Delta\eta_{FANOUT}$	0.0	-2.61	-1.77	0.0
$\Delta\Gamma_{IPC}$	0.0	0.0	0.0	0.0
$\Delta\eta_{IPC}$	0.0	0.0	0.0	0.0
$\Delta\Gamma_{HPC}$	-3.0	0.0	-1.31	-2.98
$\Delta\eta_{HPC}$	-1.0	0.0	-0.09	-1.18
$\Delta\Gamma_{HPT}$	0.0	0.0	0.0	0.0
$\Delta\eta_{HPT}$	0.0	0.0	0.0	0.0
$\Delta\Gamma_{IPT}$	0.0	0.0	0.0	0.0
$\Delta\eta_{IPT}$	0.0	0.0	0.0	0.0
$\Delta\Gamma_{LPT}$	0.0	0.0	0.0	0.0
$\Delta\eta_{LPT}$	0.0	0.0	0.0	0.0
C_D	0.0	0.0	0.0	0.0
Environment and Power seting paremeters				
Operating point 1				
Wf (g/s)		**630.00**	**660.00**	**660.00**
P ambient (KN/m^2)		101.32	101.32	101.32
T ambient (K)		288.15	288.15	288.15
Operating point 2				
Wf (g/s)		-	**620.00**	**620.00**
P ambient (KN/m^2)		-	101.32	101.32
T ambient (K)		-	288.15	288.15
RMS error -		1.10	0.70	0.05

Table 3.7 : A comparison of different schemes (Sampath et al, 2002b)

3.7 Summary

In this chapter, a diagnostics model based on GAs was presented. The initial implementation of the model on the well instrumented EJ200 was encouraging and the same was modified and applied to a relatively poorly instrumented engine, the RB199. Analysis of the diagnostics technique developed for the engines indicate that the technique was capable of dealing with only a few component faults and gave better results for high levels of deteriorations. This problem has been effectively dealt with by the MOPA. The results obtained from MOPA were more accurate and consistent.

The technique developed offers much promise in diagnosing faults in gas turbine engines. Keeping in mind the objective of developing an engine fault diagnosis for the advanced cycle marine gas turbine, it was felt that the fault diagnosis technique based on GA optimisation would be most appropriate considering the simplicity in implementation and robustness of the technique in the face of measurement noise and sensor bias.

The development of a diagnostics model for the advanced cycle ICR WR21 has been presented in chapter-5. However, a description of the engine is provided in chapter-4.

CHAPTER-4

ADVANCED CYCLE GAS TURBINE FOR MARINE APPLICATION

4.1 Introduction

In order to achieve the ultimate objective of developing an accurate and reliable diagnostic model for the advanced cycle marine gas turbine, it is very important to understand the engine design and its performance characteristics. This chapter looks at the basics of marinisation of an aero gas turbine, typical operating profile of marine engine and the change in design required for effective increase in part load efficiency. For the purpose of diagnostics, an engine performance model of the ICR-WR21, which is thermodynamically similar, has been developed using the in-house engine performance modelling software called TURBOMATCH. The various modifications carried out to make the TURBOMATCH engine model compatible with the diagnostics model have also been presented.

4.2 Gas Turbines for Marine Propulsion

While gas turbines are used both for merchant and Naval applications, their primary application has been in the navies of the world. Both aero-derivatives and industrial gas turbine have been used for marine applications. Marine propulsion systems requirements differ significantly from the land based units. Owing to large vessel inertia, engine acceleration time is generally not critical. The marine environment certainly presents a more severe operating environment than the industrial type of environment.

The most prudent way to develop a marine gas turbine is to derive the experience gained from the development and operation of a proven aero gas turbine and incorporate necessary changes to the aero gas turbine for marine application. This policy is widely accepted and implemented by major marine gas turbine manufacturers. Some of the salient features of the marinisation process is as follows-

- **Change of Fuel:** For the marine gas turbines, liquid fuels are most likely to be considered and diesel is a natural choice due to safety consideration. Therefore all problems associated with combustion of this fuel must be considered. Marine gas turbines use Low Sulphur High Speed Diesel (LSHSD) or other heavy fuels in commercial vessels. One of the primary requirements in marinisation process is the modification of the combustors to sustain combustion with the new fuel for a given operating envelope.

- **Energy Balance**: when a modification to an existing aero-engine is carried out, certain components will have to be modified or completely removed to suit the new role. E.g. conversion of a turbo fan engine would necessitate the replacement of the fan with a LPC. Such modifications will require recalculation of the work and energy requirements. It may need changes in turbine design or change in engine mass flow.

- **Need for Power Turbine:** A marine engine used for propulsion would invariably need a power turbine for transmitting the power to the ship's propeller through the reduction gear box. The power turbine design will need to take into account the propeller design and match the speed for efficient utilisation of power. The power requirement for a ship's propeller follows a classical cubic law as shown in figure 4.1.

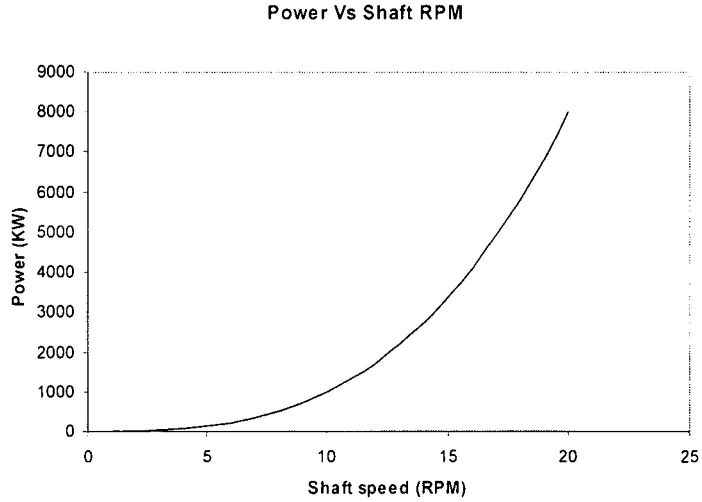


Figure 4.1: Cubic law for power turbine

- **Shock & Vibration:** Gas turbines used on board naval ships have a mandatory requirement to qualify shock and vibration tests as prescribed under MIL standards. To qualify such tests, the bearing of the gas turbine need to be strengthened and the overall weight needs to be increased by using a base frame and enclosure to enable the engine to withstand underwater shocks.

- **Sound Attenuation and IR Suppression:** Provision for attenuation of structure borne noise and air borne noise has to be made for marine application. The use of "DRES-BALL" device or water injection for reducing the temperature of exhaust is to be made.

- **Material Selection & Protective Coating:** in general the internal effects of operating in the marine environment are:
  (a) Corrosion of compressor section parts resulting from the ingestion and deposition of salts;
  (b) Corrosion of turbine section from highly corrosive molten salt;
  (c) Sulphidation of turbine section from burning sulphur bearing salts;

Sulphidation is a serious problem and requires a thorough understanding of the mechanism of attack. The marinisation process necessitates the choice of appropriate materials for the engine components and coatings to prevent degradation to exposed parts.

4.3 Operating Profile of Marine Gas Turbine

A major disadvantage of the gas turbine in the naval use is its poor specific fuel consumption at part load. If we consider a Naval vessel having a maximum speed of 36 knots, and a cruise speed of 18 knots with the power required proportional to the cube of the speed, the cruise power will be only one eighth of the maximum power, indeed much time will be spent at speeds less than 18 knots. To overcome this problem, combined power plant containing gas turbines with conventional steam turbines or Diesel have been used which are popularly called as-

(a) COSAG- Combined Steam and Gas Turbine

(b) CODAG- Combined Diesel and Gas Turbine

(c) COGOG- Combined Gas or Gas

(d) COGAG- Combined Gas and Gas

(e) CODLAG- Combined Diesel, Electric and Gas Turbine

Most of these combinations were basic simple cycle gas turbines and the configuration made the propulsion system quite complicated in terms of engine exploitation and amount of space occupied (especially in the case of COSAG). A gas turbine used for propulsion in a naval ship would typically operate at part load conditions most of the time as shown in figure 4.2.The matter of efficient exploitation of the equipment has also been a matter of dispute between the maintainer and the user.

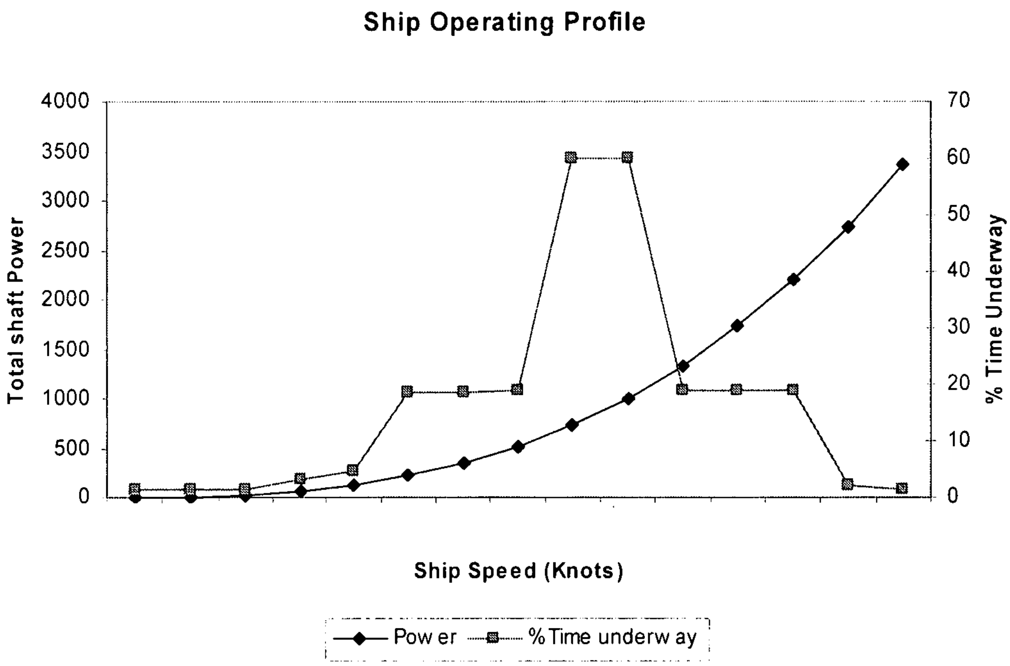


Figure 4.2: Typical operating profile of a naval gas turbine (Dupuey, 1982)

4.4 The Intercooled & Recuperated Gas Turbines

The nature of operation of a marine gas turbine dictates the need for a gas turbine which is fuel efficient at lower powers. In the following sections, various methods that can be used for improving the cycle efficiency are presented in the following sections:

4.4.1 Heat Exchange Cycle

The basic principle of a heat exchange cycle is to recover the heat from the exhaust gas. This in turn reduces the heat input in the combustor, leading to reduced fuel supply to the combustor.(Figure 4.3)

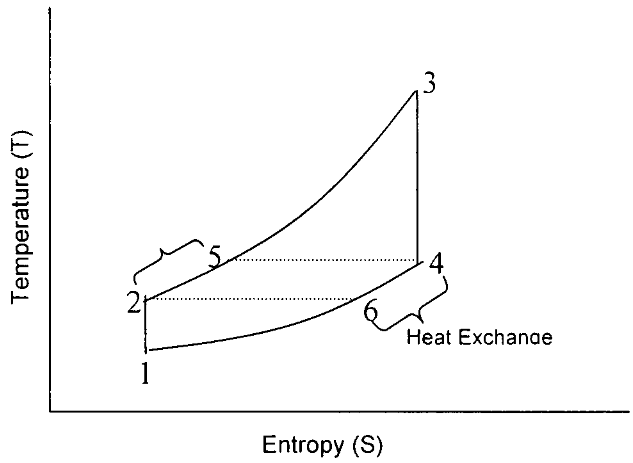


Figure 4.3: Heat Exchange Cycle

The cycle efficiency is given by-

$$\eta = \frac{c_p(T_3 - T_4) - c_p(T_2 - T_1)}{c_p(T_3 - T_5)} \tag{4.1}$$

With ideal heat exchange, $T_5=T_4$, and substituting the isentropic *p-T* relations the expression reduces to-

$$\eta = 1 - \frac{r^{(\gamma-1)/\gamma}}{t} \tag{4.2}$$

Thus the efficiency of the heat-exchange cycle is not independent of the maximum cycle temperature and it clearly increases with increase in *t*, the efficiency increases with decrease in pressure ratio unlike the simple cycle whose efficiency increases with the increase in pressure ratio(Figure 4.4). The curves fall with increasing pressure ratio until a value corresponding to $r^{(\gamma-1)/\gamma} = \sqrt{t}$ is reached and at this stage the equation (4.2) reduces to

$$\eta = 1 - \left(\frac{1}{r}\right)^{(\gamma-1)/\gamma} \tag{4.3}$$

This is the pressure ratio for which the specific work output reaches a maximum and for which $t_4 = t_2$. For higher values of r the heat exchanger would cool the air leaving the compressor and reduce the efficiency. The specific work output is unchanged by the addition of a heat-exchanger

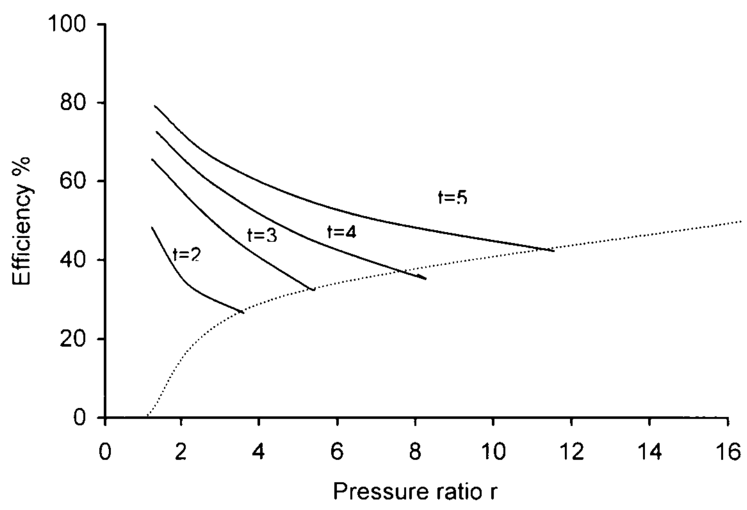


Figure 4.4: Efficiency-Simple cycle with heat exchanger

4.4.2 Inter-cooled Cycle

An improvement in the specific work can be obtained by splitting the compressor and inter-cooling the gas between the LP and HP compressor. Assuming that the air is cooled to T_1 it can be shown that the specific output is maximum when the pressure ratio of the LP and HP are equal (Figure-4.5).

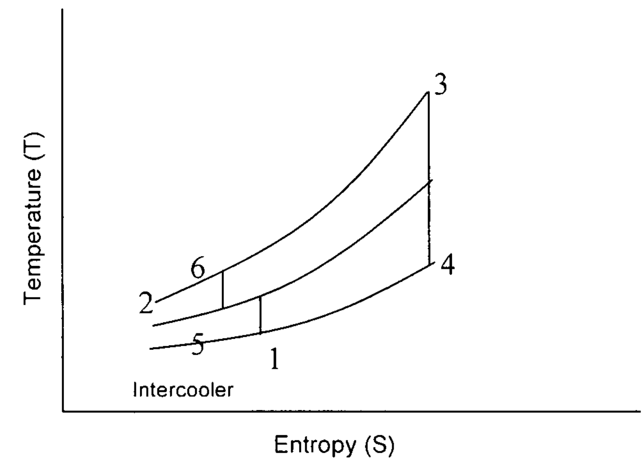


Figure-4.5 : Inter-cooled Cycle

The reduction in efficiency due to inter-cooling can be overcome by adding a heat exchanger. The higher exhaust gas temperature can be utilised in the heat exchanger. Figure 4.6 shows the improvement in Specific Fuel Consumption (SFC) for a complex cycle engine.

4.5 Methods of Improving Part Load Performance

Earlier in the chapter, it was pointed out the part load performance of gas turbine intended for naval use is of great importance, as considerable portion of the running time is spent at low power. Early studies of these applications resulted in the consideration of complex arrangement incorporating inter-cooling, reheat, heat-exchanger. The sole justification for the marked increase was great improvement in part-load specific fuel consumption.

Initially such complex arrangements did not prove to be very successful despite their undoubted thermodynamic merit, the main reason being their mechanical complexity. Detailed off-design performance calculations of gas turbines with heat exchangers would have to account for heat-exchanger effectiveness with engine operating conditions. Heat-exchanger effectiveness depends on fixed parameters of heat transfer area and configuration of the HE(e.g. cross flow, counter flow etc..).

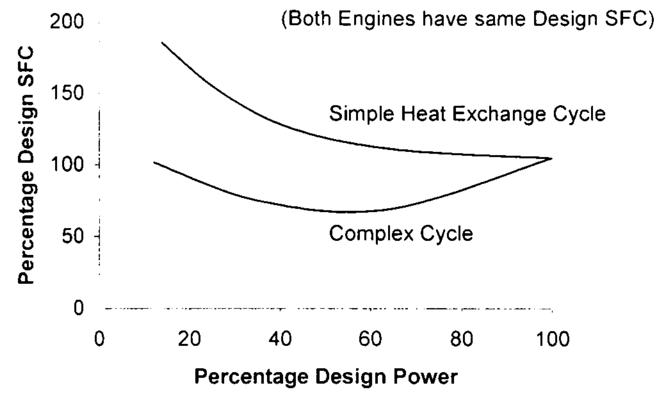


Figure-4.6: Intercooled Cycle

The inclusion of HE will cause an increase in pressure loss between compressor delivery and turbine inlet and also an increase in turbine outlet pressure, although the additional pressure loss will result in reduction in power, they will have little effect on the equilibrium running line and part load behaviour of engines with and without heat exchanger will be similar. Fundamentally, the gas turbine thermal efficiency is dependent on turbine inlet temperature and the rapid drop in T_{03} with decreasing power is the basic cause for poor part load performance of the gas turbine. The variation for a hypothetical engine with HE is shown in figure-4.7.

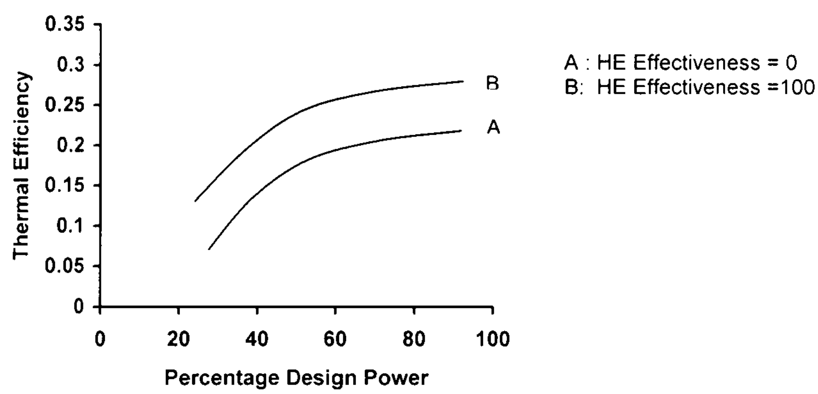


Figure-4.7: Comparison of thermal efficiency with HE

The shape of the curve remains virtually unchanged. This is fundamentally due to the fact that in each case there is a similar drop in TET as power is reduced. In the light of the above, variable area power turbine stators are used for better part load performance.

4.5.1 Variable Area Nozzles (VAN)

The concept of using moving blades or geometry to alter the characteristics of turbo machinery has been in existence for many years. One of the earliest devices mentioned in the literature consisted of a movable wall in a rectangular nozzle passage of a steam turbine (Rahnke, 1969). It varies the area to optimise the nozzle expansion ratio. Today variable stator vane in the high pressure ratio, axial -flow compressor is a well known example of variable geometry to optimise engine performance.

The variable area power turbine nozzle gives the following advantages.

- An increase in engine braking
- Improvement in part load fuel efficiency
- Improvement in engine starting characteristics
- Improvement in engine acceleration characteristics
- Over speed protection for Power turbine
- Reduction in engine creep torque

In addition to the various advantages, it also has a few disadvantages like complicating the engine and fuel control system, added manufacturing cost and introduction of leakage introduced into the flow path.

To explain this concept, let us take the example of a turbojet as the turbojet and free power turbine engine are thermodynamically same and they impose the same operating restrictions on the gas generators, thus the variable power turbine stators will have the same effect on the gas generators as the variable nozzle. Increasing the area of variable nozzle in a turbojet moves the running line away from the surge line, while decreasing the area moves the running line towards the surge line, the latter shows an increase in turbine inlet temperature at low powers, it is also likely that the compressor efficiency will be improved as the surge line is approached. Both these effects will improve the part load SFC.

Ideally, the area of the variation of the power turbine stators can be controlled so that the turbine inlet temperature is maintained at its maximum value as power is reduced. Operation at constant gas generator turbine inlet temperature will cause an increase in temperature at the entry to the power turbine, because of the reduced compressor power and the temperature of the gas entering the heat exchanger will be high.

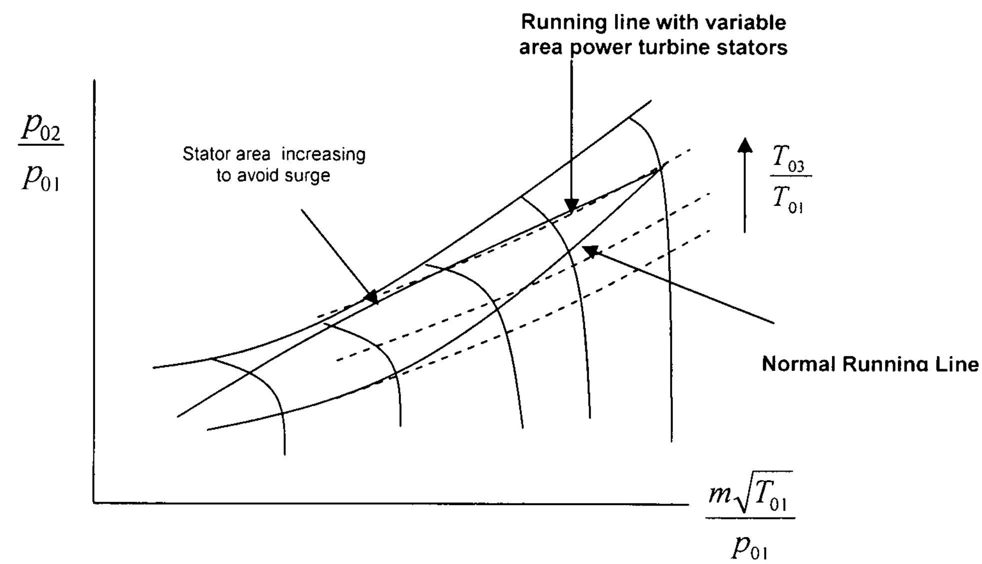


Figure-4.8: Effect of VAN on engine steady state running line

It should be noted that the operation at constant gas-generator turbine inlet temperature with reducing power will cause an increase in temperature at entry to the power turbine, because the reduced compressor power, the temperature of the hot gases entering the heat exchangers will also be raised. Temperature limitations in either of these components may restrict operation in this mode. The use of a variable geometry power turbine is particularly advantageous when combined with heat exchanger, because the increased turbine outlet temperature is utilised. The efficiency of the power turbine will obviously be effected by the position of variable stators, but with careful design the drop in turbine efficiency can be made more than offset by maintaining a higher temperature at part load. Area variations of +/- 20 percent can be obtained with acceptable losses in the turbine. A facility for increasing the stator area is also advantageous with respect to starting and accelerating the gas generator. If stators are rotated still further, the gas generator flow can be directed against the rotation so the flow impinges on the back of the power turbine blade. This can result in a substantial degree of engine braking which is extremely important in vehicular application and more so in marine application in delicate manoeuvres as the ships do not have brakes.

4.6 ICR- WR21 Marine Gas Turbine

Since the introduction of gas turbines for main propulsion of US navy warships in the DD963 Spruance class destroyers in the early 1970s, the navy has investigated methods of improving fuel efficiency, reliability and maintainability to reduce operating costs, increase availability and improve the capability of US surface combatants. These efforts beginning with modifications to existing engine led to a series of studies in 1980's to investigate advanced cycle engines. The US Navy laid down certain stringent technical specifications and placed a challenge to the industries to develop an engine fulfilling the requirements. The development team included Westinghouse, Roll-Royce, Allied Signal Aerospace systems and equipment and CAE. A sectional view of the ICR WR21 engine is shown in figure 4.9.

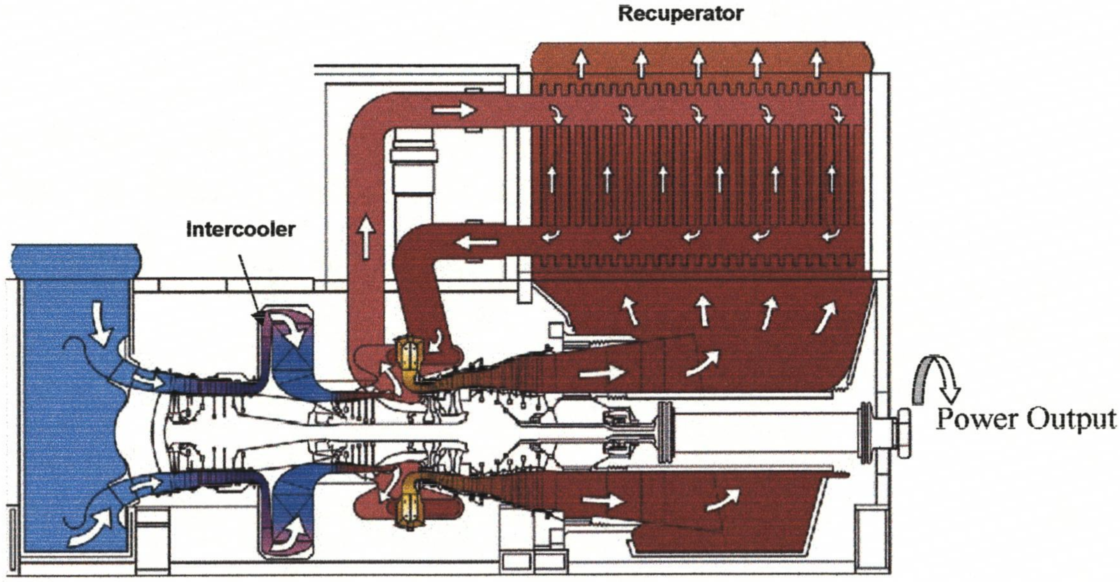


Figure 4.9: Cross-section view of the WR-21 engine
(Courtesy Rolls Royce Marine)

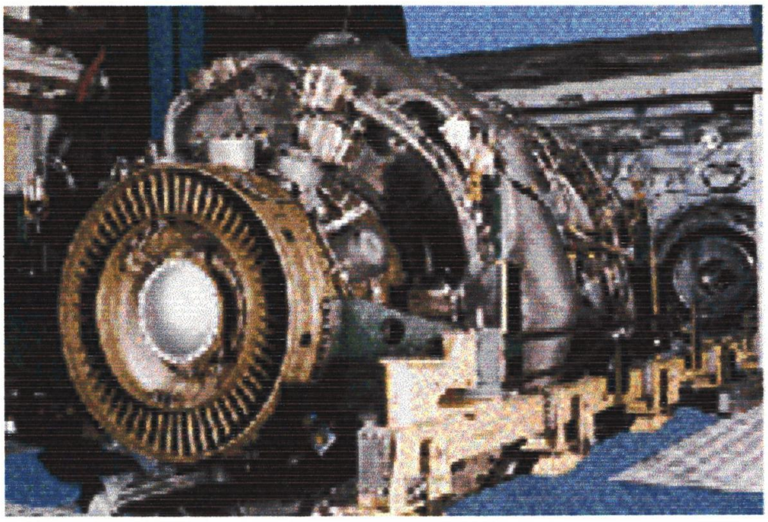


Figure 4.10: WR-21 engine on test bed
(Courtesy Rolls Royce Marine)

The ICR WR-21 engine system (figure 4.10) is an advanced cycle gas turbine engine utilising an intercooler and recuperator resulting in 30% reduction in annual propulsion fuel consumption for a typical surface combatant . The WR21 has an almost flat s.f.c curve from 100%- 30% power as shown in figure 4.11. The low SFC is intended to translate into extended combatant operating range for a given fuel capacity, more un-refuelled time on station for a given time and fuel capacity. The new engine also offers significant performance flexibility by enabling conventional diesel cruise/gas turbine sprint machinery to be replaced by a single a WR21. This leads to major space savings and stronger hull structures resulting from fewer deck penetrations.

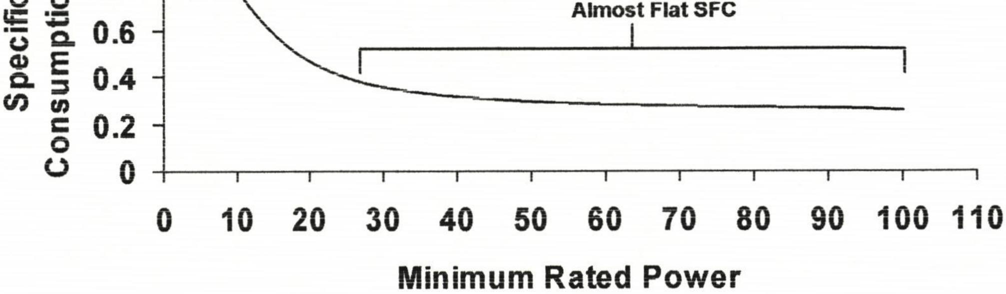


Figure 4.11: ICR WR21 Specific Fuel Consumption Profile

The design consists of a two spool gas generator with an intercooler between the two compressor and a recuperator between the HP compressor and combustor which preheats the compressed air by recovering the heat from the exhaust gas. The basic description of the WR21 follows:

4.6.1 ICR WR21 Design Overview:

The following paragraphs give a brief overview of the engine design

- **Gas Generator :** The core of the WR21 gas generator is derived from the Rolls-Royce RB211 aero-engine family. The IPC and HPC are derived from the RB211-535. The IPC is a compact 6 stage fixed geometry, axial flow compressor with a compression ratio of 3.49. The first stage of the IPC has been modified relative to the aero-engine to increase the flow capacity by 4%. The HPC is a compact 6 stage fixed geometry axial flow compressor with a pressure ratio of 4.9. All stages are common to the aero-engine. Between the IPC and HPC is an intermediate case which supports the on engine intercooler system, houses the internal gearbox and provides the air flow path from the IPC intercooler heat exchangers and back into the HPC. The combustor section of the WR21 consists of 9 radial can-annular combustors, the Delivery Air Manifold(DAM) is required to deliver the air from the HPC to the recuperator inlet and Return Air Manifold (RAM) to distribute the air returning from the recuperator to the 9 combustor cans. The radial configuration has kept the spacing for the HPT bearing and the Intermediate Pressure Turbine (IPT) bearings the same as on that of the aero engine and is compatible with Dry low emissions program to allow easy retrofit of DLE combustors. The HPT is a single stage axial flow turbine based on the aero RB211- 524. The blades and vanes are film coated and have been modified to decrease the turbine capacity. The IPT is based on the RB211-535 and is also a single stage turbine. The blade profile have been modified to increase the flow capacity. The vanes are un-cooled single crystal alloys.

- **Free Power Turbine:** The power turbine is a new design , 5 stage power turbine based on Rolls Royce Trent 700-800 designs. The FPT is designed for 3600 rpm at 100% power. A single stage Variable Area Nozzle(VAN) is used to maintain the engine temperature at part power to maximise the effectiveness of the recuperator. The VAN is actuated by hydraulic actuators and single geared ring. The VAN is fully closed at 40% power and fully open at 100% power.

- **Intercooler:** The intercooler consists of two systems, the on-engine system and the off-engine fresh water/sea water heat exchanger module. The on-engine system consists of five CuNi plate-fin, counter flow heat exchangers. The compressor air is cooled with 50-50 freshwater/glycol coolant flow of 900gpm. The off-engine cooler module consists of the plate-frame heat exchanger, a 40 hp coolant pump/motor, de-aerator, reservoir tank and associated valves and the heat exchanger is supplied with 1400 gpm sea water flow by the ship sea water system

- **Recuperator:** The recuperator system consists of heat exchanger cores made up of four core sections each, two sets of inlet and outlet ducting including bypass and isolation valve and pneumatic valve actuator. The recuperator heat exchanger cores are fin-plated and counter flow exchangers made of 14-4 CrMo stainless steel. The recuperator can be operated in normal operating mode as well as bypass mode in which the compressor air is directed from the inlet duct to the outlet duct without entering the recuperator and returned directly to the combustor. In this mode the engine is capable of achieving full power level, however with increased fuel consumption. The bypass mode is also used during start-up and for short term cleaning of recuperator.

4.6.2 Statistics of WR21 Performance

Typical engine performance data for WR21 is as follows

	100 % POWER	30% POWER
Output Power	33,800 Bhp	12,500 Bhp
SFC	0.329 lb/hp-h	0.336 lb/hp-h
PT inlet temp	852 °C	852 °C
Exhaust Temp	355 °C	272 °C
Pressure Ratio	16.2	8.1
Air Mass Flow	161 lb/sec	86 lb/sec

Table 4.1: WR21 Engine Performance Data

4.6.3 Modelling ICR WR21 with 'TURBOMATCH'

The performance model of the engine is an important component of the gas path analysis and is in fact the backbone of the any gas path analysis based diagnostics model. The accuracy and consistency of the performance code has a profound effect on the final outcome of the diagnosis model and therefore requires serious consideration right from the beginning of the development of a diagnostics model.

A reliable engine performance code requires an accurate thermodynamic model of the engine. The accuracy of the model will be greatly influenced by the accuracy of the individual component maps, method of calculations, tolerances and precision considered etc.. Rolls-Royce uses the non-linear engine performance code called the RRAP for their engine development programmes. Using RRAP would have been an ideal choice for the work, however after consulting the sponsors it was decided that the in-house engine model would be used for development of the diagnostic code.

The aforesaid model has been developed using the TURBOMATCH program (Palmer, 1967) which has been developed at Cranfield University. This is a modular program which allows the calculation of the performance of any open cycle gas turbine engine under steady state conditions. The program consists of various pre-programmed routines called BRICKs, which simulate the performance of different components/modules in a gas turbine engine. An engine model is created by assembling the appropriate component BRICKS such as compressors, turbines, combustors etc. Each BRICK requires inlet data and the component characteristics to generate outlet data for the component being modelled. Inlet and outlet data are termed as "station vector" data since they correspond to corrected total pressure, total temperature air mass flow and fuel flow at the engine stations. Compressor and turbine components have user defined or built-in component characteristics in order to calculate the engine performance. Based on the aero-thermo relationships, the program will provide gas temperatures and pressure to various stations of the engine individual component performance and the overall engine performance. The program enables to simulate variable or fixed geometry for compressors and/or turbines.

The following factors influenced the decision to use TURBOMATCH model for diagnostics purpose-

- The software is generic in nature and can be adapted easily to design any engine.
- A diagnostics model for a advanced cycle engine was being investigated for the first time and would require modifications to the performance code to deal with the diagnostics problem. Using TURBOMATCH would give the flexibility to modify the engine at anytime.
- Sufficient expertise exists within the department to make the necessary modifications and debug the performance code.

The engine has been assembled by individual component blocks arranged in a series and linked thermodynamically. Each component block or a BRICK is defined by its own component characteristics map. Figure 4.2 shows the model developed for WR21.

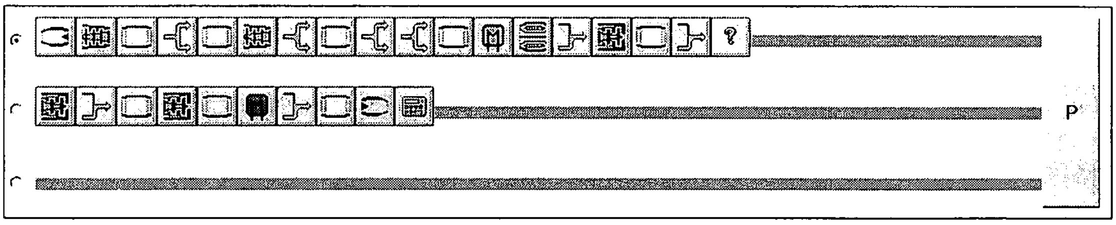


Figure 4.12: Turbomatch model of WR21

The front end (graphical form) of the model has been shown using software called PYTHIA (Escher, 1995a). A Schematic diagram of the assembled BRICKS is shown in Appendix-A. The TURBOMATCH input file for WR21 is placed at Appendix-B. Design point engine performance is shown in Appendix- C.

4.6.4 Modifications to TM-ICR WR21 Performance Model

The TURBOMATCH model of the WR21 engine had to be modified to make it compatible with the diagnostics model. The following modifications were carried out-

4.6.4.1 Tolerance adjustments

One of the problems encountered while using TM model of the WR-21 was the coarse level of accuracy of the program. In the performance model, the error tolerance was set to 0.001 and the maximum number of iterations was limited to 20. This proved inadequate, especially in the simulation of fault conditions in intercooler and recuperator. Additionally, it was observed that, for consecutive runs of the performance model under similar operating conditions, the measurements obtained were not the same. This necessitated the reduction of convergence criteria (error tolerance) to 0.00001 and an increase in the number of iterations to 70.

4.6.4.2 Modification to Power Law Index

The WR21 engine has been developed primarily for marine application and would therefore be coupled to a propeller through a reduction gear. In marine applications, the power turbine rotational speed and power output follow the classic cubic law. These modifications have been incorporated in the program code.

4.6.4.3 Development of Intercooler BRICK

One of the main features of the test engine (WR21), is the inclusion of intercooler, recuperator and theVAN. The original TURBOMATCH code did not cater for an intercooler explicitly and the DUCTER brick was being used as an intercooler. An exclusive intercooler brick (INTCLR) was developed, which could be used in the performance model like any other component.

4.6.4.4 Fault Condition Simulation for Intercooler & Recuperator

The fault conditions for intercooler have been included in the form of leakage factor and fouling factor on a scale of 1-10 (which means percentage change). However, the model is not stable for leakage factors above 4% for intercooler. In reality the intercooler is quite robust and leakages are extremely rare and therefore faults have been simulated for values less than 4%. Though the recuperator BRICK already existed, but the faults could not be simulated. Modifications have made to the program code to take into account fault conditions.

4.6.4.5 Turbomatch as Subroutine

During the process of diagnostics, the performance model is required to be called several times to evaluate the objective functions of the strings. This necessitates the performance model to be called as a subroutine interactively with new sets of fault condition. The way Turbomatch existed, it could be only run independently as a standalone program and off-design conditions could be simulated through a script file manually. Modifications have been carried out to make the program as a subroutine in diagnostics model.

4.6.4.6 Error Trapping

Since the diagnostics is dependent on the output of the performance code, any premature termination of the performance code will either lead to erroneous results or an early termination of the host program and therefore there is a need for it to exit gracefully in case of non-convergence or indicate to the main program of any errors. Several modifications have been made to the performance code to meet these criteria.

4.6.5 Deterioration Simulation

Deteriorated components can be simulated by modifying the appropriate component may characteristics. Since the maps, stored in TURBOMATCH, relate to a particular size of a component, they need to be scaled for the clean and for the deteriorated performance. In the clean condition or performance simulation a chosen design point establishes the scaling factors for maps. These factors are stored in TURBOMATCH and they are applied to all subsequent off-design point calculations. However, in a deteriorated performance simulation the stored scaling factors are adjusted by the appropriate change of the independent parameters. Examples of fouled compressor map and eroded turbine map are shown in Appendix-D.

4.6.6 Engine Performance Model Validation

The engine performance model developed using TURBOMATCH was tested under various conditions to establish its correctness. At the request of the sponsor, explicit comparison data has been omitted from this thesis, however all that needs to be said is that the model is broadly in agreement with the performance test data of the actual engine. It is pertinent to mention at this point that for diagnostics purposes relative changes in performance parameters are more important than absolute values of performance parameters, and so from that point of view, the current work using TURBOMATCH meets its project objective. A comparison of the engine under two modes: VAN enabled and VAN disabled, is shown in Appendix-E. The results show the effect of VAN on engine parameters and the conformity of the developed model to thermodynamic principles.

4.7 Summary

This chapter discussed the salient features of the marinisation of an aero gas turbine and the methods to improve part load efficiency of an engine. The development of an engine performance model involved extensive modifications to the existing TURBOMATCH code and addition of new BRICKS to suit the diagnostics requirement. The engine (TURBOMATCH model) simulation showed that performance of the developed model is reasonably close to the performance of the actual engine.

As shown earlier in chapter 3, the engine performance model is a key component of the diagnostics model and its consistency and robustness is important for accurate fault diagnostics. Having, developed and evaluated the performance of the advanced cycle WR21 engine, the next step is to develop an appropriate diagnostics model. The next chapter discusses the development of a diagnostics model for the WR21 engine and the advantages and limitations of the diagnostics model.

CHAPTER-5

DIAGNOSTICS MODEL FOR AN ADVANCED CYCLE ENGINE

5.1 Introduction

The GA based diagnostics method discussed in chapter-3 shows several advantages, but has limitations when the number of measurements is small. These limitations could be attributed to the poor observability i.e. the inability of the given instrumentation to perceive the changes in the engine performance and identify the faulty component. This is particularly true for lower fault levels, faults in components that have a number of minima and for cases where a high amount of noise and model inaccuracy exists. The limitations due to fewer instruments have been overcome by using MOPA.

Having studied the fault diagnostics method based on GAs and the relative advantages it provides, it was decided to develop a diagnostics method for the WR21 based on the same principle. The objective is to, based on the contributions of predecessors, develop a diagnostics model which should be:

- Able to diagnose fault in an advanced cycle engine;
- Reliable with high success rate;
- Modular and easy to adapt to any other engine;
- Applicable to multiple sensor and multiple component faults;
- Able to identify an optimum instrumentation set for the engine (from diagnostics point) to be fitted on an in-service engine.

The technique for the WR21 is based on MOPA and uses the concept of pareto-optimality. This chapter presents an overview of the development of a diagnostics model and discusses some keys issues involved in the development process and finally discusses the results obtained from diagnostic model.

5.2 Engine Fault Diagnostics Model for ICR WR-21

The WR21 engine is a two spool intercooled and recuperated advanced cycle engine with variable area nozzle in front of the FPT. A detailed description of the engine has been given in chapter-4. A schematic diagram of the engine is shown in figure 5.1.

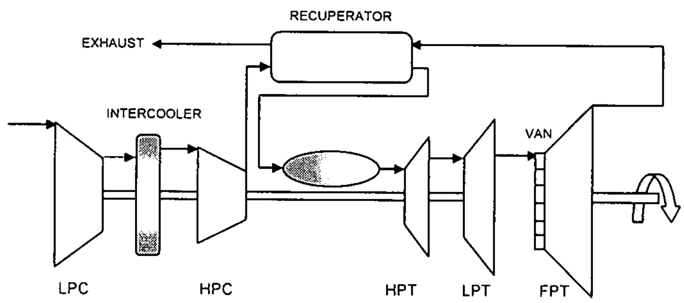


Figure 5.1: Schematic Diagram ICR WR21

A description of the development of a Multiple Operating Point Analysis (MOPA) based diagnostics framework for the ICR WR21 engine and other aspects involved with the setting up of the diagnostics procedure is presented in the following sections:

5.2.1 Performance Simulation model for WR-21

The performance model used for the diagnostic model has been developed using an in-house engine performance simulation code called TURBOMATCH. The design, development and enhancements made to the engine model have been presented in detail in chapter-4.

5.2.2 Diagnostic Model Coding

The codes developed for the project have been written in standard FORTRAN 90/95 according to the sponsor's requirement. The program is highly modular and heavily uses 'structures' is FORTRAN to emulate the benefits of an Object Oriented Programming (OOP) approach. The intention was to make it user friendly and generic in nature to adapt it to any engine in future with minimal modifications to the existing code. Minimum use of built-in functions have been made. All the modules of the program have been compiled with Digital Visual FORTRAN (DVF) Version 6.0.

5.2.3 WR21 Fault Classes and Performance Parameters

For the purpose of engine diagnostics of the twin spool engine the following seven components are considered:

- LPC
- HPC
- INTERCOOLER
- HPT
- LPT
- FPT
- RECUPERATOR

It is noteworthy that although a change in combustor outlet temperature profile is usually caused by a fault in the combustor, the combustor deterioration is not considered to directly affect the engine performance (Escher, 1995a). Combustion efficiency normally remains constant with time (Diakunchak, 1992). Therefore the combustor faults have not been considered in the diagnostic model.

The diagnostic framework for the WR-21, which has 7 components, in the case of single component fault will have 7 fault classes. In case dual component faults are considered, the total number of fault classes will comprise of fault classes with single components and fault classes with combinations of any two components. Thus, there will be $7{+}^{7}C_{2} = 28$ fault classes. In order to reduce the "smearing" effect, a constrained optimisation is used .It is assumed that not more that two components (four performance parameters) are simultaneously faulty. The distribution of the fault classes is shown in table 5.1. Two performance parameters are associated with each component i.e. the efficiency and flow capacity. In the case of intercooler and recuperator the performance parameter monitored are fouling factor and leakage factor.

Fault Class	Components in Fault Class		Performance Parameters(PP) of Components			
	Component-1	Component-2	PP_{Comp-1}	PP_{Comp-1}	PP_{Comp-2}	PP_{Comp-2}
FC-1	LPC	-	EF	FC	-	-
FC-2	HPC	-	EF	FC	-	-
FC-3	ICL	-	EF	FC	-	-
FC-4	HPT	-	EF	FC	-	-
FC-5	LPT	-	EF	FC	-	-
FC-6	FPT	-	EF	FC	-	-
FC-7	RCR	-	FF	LF	-	-
FC-8	LPC	HPC	EF	FC	EF	FC
FC-9	LPC	ICL	EF	FC	FF	LF
FC-10	LPC	HPT	EF	FC	EF	FC
FC-11	LPC	LPT	EF	FC	EF	FC
FC-12	LPC	FPT	EF	FC	EF	FC
FC-13	LPC	RCR	EF	FC	FF	LF
FC-14	HPC	ICL	EF	FC	FF	LF
FC-15	HPC	HPT	EF	FC	EF	FC
FC-16	HPC	LPT	EF	FC	EF	FC
FC-17	HPC	FPT	EF	FC	EF	FC
FC-18	HPC	RCR	EF	FC	FF	LF
FC-19	ICL	HPT	FF	LF	EF	FC
FC-20	ICL	LPT	FF	LF	EF	FC
FC-21	ICL	FPT	FF	LF	EF	FC
FC-22	ICL	RCR	FF	LF	FF	LF
FC-23	HPT	LPT	EF	FC	EF	FC
FC-24	HPT	FPT	EF	FC	EF	FC
FC-25	HPT	RCR	EF	FC	FF	LF
FC-26	LPT	FPT	EF	FC	EF	FC
FC-27	LPT	RCR	EF	FC	FF	LF
FC-28	FPT	RCR	EF	FC	FF	LF

EF : Efficiency FF: Fouling Factor LF : Leakage factor FC: Flow Capacity

Table 5.1: ICR WR21 Fault Class Distribution

5.2.4 Environment & Power Setting Parameters

The WR21 diagnostics model operates on the principle of multiple operating point analysis and therefore two operating points were considered for diagnostics. The choice of operating point is an important aspect of the diagnostics model. Operating points which are very close may not provide any additional information while operating points far away from each other means different aerodynamic conditions which means that the change in efficiencies and flow capacities with change in operating condition is significant. A detailed analysis on the choice of operating points is presented in chapter-7. The operation of performance model has been considered in two modes. (a) MODE-1: TET as handle (b)MODE-2 : Power as handle. The operating points used in diagnostics are shown in table 5.2.

MODE-1 (TET AS HANDLE)					
	Fuel Flow (W_{FE}) lb/s	Ambient Temp (T_0) deg K	Ambient Press (P_0) Atms	Humidity (%)	VAN Angle degrees
OP-1	2.20	308.15	1.0	N.A	5
OP-2	2.00	308.15	1.0	N.A	4
MODE-2 (Power as Handle)					
	Power (HP)	Ambient Temp (T_0) deg K	Ambient Press (P_0) Atms	Humidity (%)	VAN Angle degrees
OP-1	26,400	308.15	1.0	N.A	5
OP-2	24,000	308.15	1.0	N.A	4

Table 5.2: Environment and Power Setting Parameter for WR21 Diagnostics

5.2.5 Selection of Instruments

The WR-21 engine will be primarily used for marine propulsion directly or as a source of power in an all-electric ship configuration. Due to the nature of its application (where there are no space or weight constraints like in aircraft engines) it was easier to choose the instruments. The WR-21 is still undergoing trials and therefore uses the test bed instrumentation and the number of instruments to be used on the production engine when fitted on board a ship has not been finalized.

The choice of sensors play an important role in the final outcome of the diagnostics process as the only information available from any engine is the sensed parameters. One of the aims of this work was to establish an optimum instrumentation set which could be fitted on the engines used on–board ships and which could cater to the diagnostics requirements adequately.

One approach to obtaining an appropriate sensor set is by deliberately implanting faults in the GT components and observing simultaneous effects on the measurement performance parameter and hence seeking the optimal combination of dependent variables that can describe such faults. This combination will facilitate the choice of types and locations of the sensors required for the diagnosis of the faults also the gas path.

Ogaji and Singh (2002) and Ogaji et al (2002) have undertaken a study on the optimisation of measurement sets for gas path fault diagnostics in GTs. The studies involved the use of non-linear GPA techniques to obtain various measurements combinations that demonstrated high degree of observability for the fault combinations implanted on a thermodynamic engine model.

Experiments were conducted with various sets of instruments and the following instrument suite has been chosen due to the following reasons:

(a) The chosen instrument is representative of the engine in the diagnostics sense. As discussed earlier the observability of the chosen instrument is an important parameter for selection.

(b) Consultations with the sponsor brought out the possibility of using these instruments for collection of data from engines when fitted on-board ships.

SL. NO	DESCRIPTION	NOMENCLATURE	TYPE OF SENSOR
1	HP Compressor (Inlet)	P_2	Pressure
2	HP Compressor (Exit)	P_3	Pressure
3	Intercooler Differential	P_{ICD}	Pressure
4	HP Compressor (Inlet)	T_2	Temperature
5	HP Compressor (Outlet)	T_3	Temperature
6	Combustor (Inlet)	T_{31}	Temperature
7	Power Turbine (inlet)	T_{43}	Temperature
8	Power Turbine (Exit)	T_5	Temperature
9	HP Shaft Speed	N_H	Tachometer
10	LP Shaft Speed	N_L	Tachometer
11	VAN Angle	A_{VAN}	Position Sensor

Table 5.3: ICR WR21 Instrumentation Set

It can be seen that the first measurement towards the hot end is the FPT inlet temperature. The VAN position is an important parameter as the control system will try to change the value of VAN angle in order to maintain a constant power turbine inlet temperature. However, the sensor measuring VAN angle is not used by the diagnostics model.

5.2.6 Performance Parameters Monitored

The WR-21 engine's health is modelled using seven components and for the purpose of diagnostics, two performance parameters for each component are monitored. In all 14 independent parameters are monitored by 10 sensors. It may not be adequate for a traditional GPA diagnosis. However, from the point of GA based diagnosis using MOPA, it seems to be a comfortable situation. Among the performance parameters monitored are the Leakage Factor (LF) and Fouling Factor(FF) for the intercooler and recuperator. The fouling factor reduces the heat exchange efficiency of the intercooler/recuperator and therefore affects the engine performance. Table 5.4 shows the various performance parameters monitored for the WR-21 engine.

SL NO	COMPONENT	PERFORMANCE PARAMETER MONITORED	
1	LPC	Efficiency Change ($\Delta\eta$)	Flow Capacity Change ($\Delta\Gamma$)
2	HPC	Efficiency Change ($\Delta\eta$)	Flow Capacity Change ($\Delta\Gamma$)
3	ICL	Fouling Factor (ΔFF)	Leakage Factor (ΔLF)
4	HPT	Efficiency Change ($\Delta\eta$)	Flow Capacity Change ($\Delta\Gamma$)
5	LPT	Efficiency Change ($\Delta\eta$)	Flow Capacity Change ($\Delta\Gamma$)
6	FPT	Efficiency Change ($\Delta\eta$)	Flow Capacity Change ($\Delta\Gamma$)
7	RCR	Fouling Factor (ΔFF)	Leakage Factor (ΔLF)

Table 5.4: ICR WR21 Engine Performance Parameters

5.3 WR 21 GA Diagnostics Model

The structure of the diagnostic system for WR-21 engine is shown in figure 5.2. The diagnostics model receives the engine measurements from two different operating points (steady state) and the two power setting parameters as input. Different faults are implanted into the performance model and measurements for the corresponding fault conditions at different operating point are obtained. The measurements are optimized using MOPA similar to the method discussed for the RB199 in chapter-3.

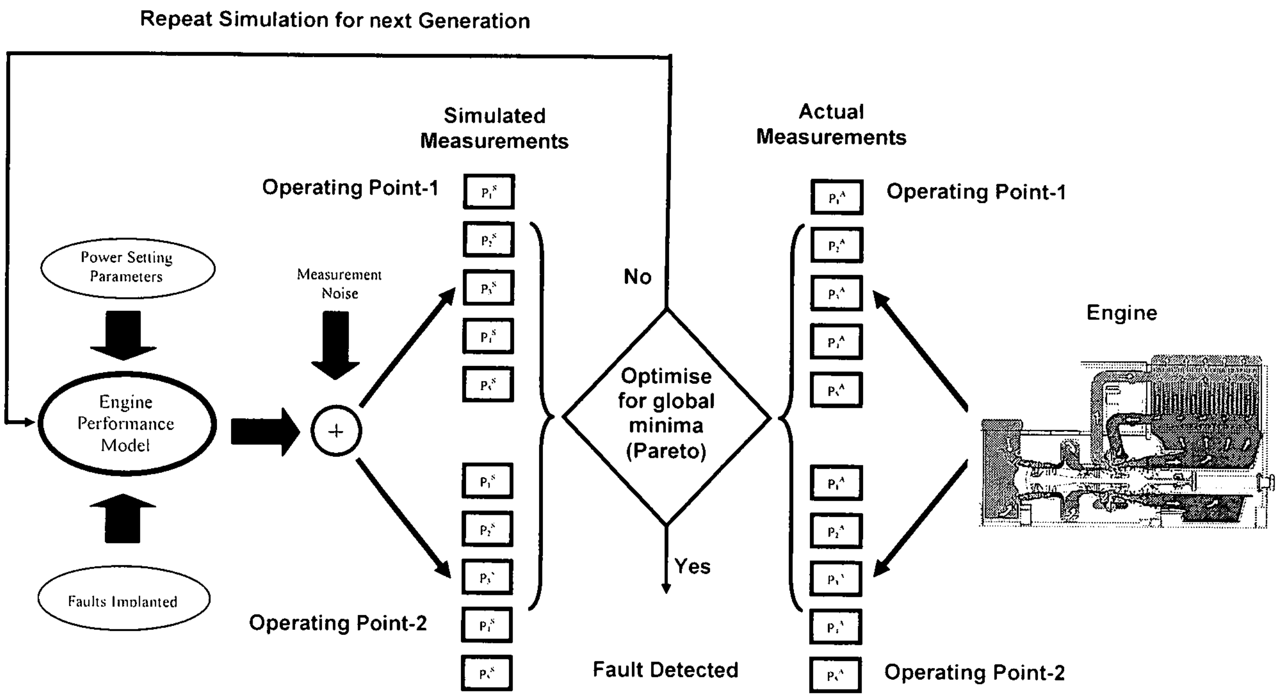


Figure 5.2: Schematic Diagram WR21 Diagnostics Strategy

5.3.1 Objective Function for optimisation

The objective function to be optimised is a function of the performance parameter vector (efficiencies and flow capacities) and the environment and power setting parameter vector (e.g. ambient pressure and temperature and fuel flow). There are two expressions which can used for optimisation as given by Zedda (1999)-

$$J(x)=\sum_{j=1}^{M}\frac{\left[z_j-h_j(x,w)\right]^2}{\left(z_{odj}(w).\sigma_j\right)^2} \tag{5.1}$$

If the noise values considered are pure gaussian, then equation 5.1 can be used otherwise the eqution 5.2 is more robust for optimisation.

$$J(x)=\sum_{j=1}^{M}\frac{\left|z_j-h_j(x,w)\right|}{z_{odj}(w).\sigma_j} \tag{5.2}$$

5.3.2 Constraints on Performance Parameter

The diagnosis process is carried out by the optimization of a given function. The GA optimization process starts with a set of randomly chosen population (collection of strings). These strings are obtained by implanting faults (deviations in performance parameters) into the performance model and getting a set of measurements in return. The measurements are then compared with the actual measurements obtained from an engine. However, a constraint is placed on the range, within which the algorithm will generate the strings. The following constraints have been placed

- Efficiency Change ($\Delta\eta$) : 0 to -3.5 %
- Flow Capacity Change ($\Delta\Gamma$) : -5.0 % to +5.0 %
- Leakage Factor (ΔFF) : 0-10%
- Fouling Factor(ΔFF) : 0-10%

Leakage Factors and Fouling factors are applicable to the intercooler and recuperator. The fouling factor basically changes the heat exchange effectiveness (ε) of the heat exchangers and the leakage factor causes the working fluid to escape to the atmosphere. During the process of genetic operation, particularly mutation, care is taken that the value of deviation is maintained within the predefined bounds.

5.3.3 Constraint on number of faulty components

While sensible assumptions can be made regarding the range of variation of the performance parameters 'x', it is important to place constraint on the number of components faulty simultaneously. The need for such a constraint arises due to "smearing" effect. It is assumed that not more than two components are simultaneously faulty in the WR-21 diagnostics model.

5.3.4 Measurement Noise

The presence of noise in a real life situation cannot be ruled out. Whenever Gaussian Probability Distribution Functions (PDF) can be considered a reasonable model of the noise, the equation (5.1) can be used. However, in reality the measurement noise PDF may not be perfectly Gaussian, for a number of reasons:

- In practice the occurrence of readings outside of the Gaussian Model's three standard deviation range is common (Zedda, 1999).
- Modelling errors are inevitably present in the simulation models of gas turbine performance.

In view of the above, the objective function using the absolute values (equation 5.2) and not the squares of the values is more suitable for the given problem. Table 5.5 shows the standard deviation values for senor non-repeatability as provided by the sponsor.

SL NO	DESCRIPTION	STANDARD DEVIATION	TYPE OF SENSOR
1	HP Compressor (Inlet)	0.25/3	Pressure
2	HP compressor (Exit)	0.25/3	Pressure
3	Intercooler Differential	0.25/3	Pressure
4	HP Compressor (Inlet)	200.0/(3*measured value)	Temperature
5	HP Compressor (Outlet)	200.0/(3*measured value)	Temperature
6	Combustor (Inlet)	200.0/(3*measured value)	Temperature
7	Power Turbine (inlet)	200.0/(3*measured value)	Temperature
8	Power Turbine (Exit)	200.0/(3*measured value)	Temperature
9	HP Shaft Speed	0.1/3	Tachometer
10	LP Shaft Speed	0.1/3	Tachometer
11	PT Shaft Speed	0.1/3	Tachometer
12	VAN Position	-	Position Sensor

Table 5.5: Instrument Noise Standard Deviation

Standard deviation (σ) values for environment and power setting parameters are:

- σ_{T_0} = (250/(3.0*measured value)) (Ambient temperature)
- σ_{P_0} = 0.1/3. (Ambient pressure)
- σ_{WFE} = 0.5/3. (Fuel flow)

5.3.5 Test Data Generation

As described earlier the WR-21 is a development engine and no statistics of its performance in actual ship board applications is available yet. The process of engine fault diagnostics requires that the measurements be collected from a degraded engine and compared with parameters obtained from an engine model. However, it was not possible to get data from actual operational engine and therefore simulated measurements have been used for fault diagnostics. The module GENERATE (Part of the diagnostics program and is explained in chapter-6) has been specifically developed to generate test data. The test data generation needs the following inputs from the user-

- Mode of Operation (MODE1/MODE2)
- Environment and Power setting parameters (two different operating point)
- Fault condition (deviations in performance parameters)
- Number of sensors biased
- Levels of sensor bias

The test data generator module in turn feeds the above data into the engine performance code and gets a set of measurements which can be used as input to the optimisation module. A sample of a generated test data is shown in Appendix-F.

5.3.6 Sensor Fault Detection

Zedda (1999c) had developed a method for the identification of biased sensors. The method explained here was developed for the EJ200 and subsequently used for the RB199 by Gulati (2002c). The same method has been adapted for the WR-21 engine diagnostics model.

Zedda (1999c) showed equation (5.2) can be modified to deal with measurement bias as the presence of a bias will introduce inconsistency between the actual and predicted measurements. The way the optimisation-based diagnostics handles the measurement biases relies on the concept of the relative redundancy. If no bias affected the measurement then the minimisation of the objective function (equation 5.2) would estimate $(\boldsymbol{x},\boldsymbol{w})$ so that the equations used in the terms of the summation would be mutually consistent. The inconsistency due to biased measurement would manifest itself with larger values of objective function, since no $(\boldsymbol{x},\boldsymbol{w})$ can be found to correspond to predicted measurements fitting sufficiently well the real one. The problem can be overcome by elimination in the summation of function (5.2) the M_{bias} terms corresponding to the biased measurements. Then the remaining terms are mutually consistent and the optimised function will reach a low value . For the technique to work it is necessary that

$$M - M_{bias} > N_{Perf} + P \tag{5.3}$$

This redundancy relative to the number of fault affected performance parameters is required because if $M - M_{bias} = N_{perf} + P$ then any choice as to the identity of the biased measurements would produce a consistent solution.

In the case considered the relative redundancy is guaranteed by the assumption about the maximum number of faulty engine components, which is acceptable for fault diagnosis. In this respect it is worth noting that the sensor validation task can be feasible even if the number of measurements is smaller that the number of performance parameters (M<N), provided the inequality (5.3) still holds. Due to the large level of measurement noise, the larger the LHS with respect to the RHS the better it is, as the redundancy is larger.

Typical SFDIA techniques proceed in three sequential steps: whenever a fault is the instrumentation set is detected the faulty sensor is isolated then the measurement is possibly accommodated. The approach described here is different and made of two steps. M_{bias} is chosen at the onset of the analysis so that an M_{bias} number of measurements are not used in the objective function. The first step is the optimisation that produces an estimation of the performance parameters $\boldsymbol{x}$ and the environment and power setting parameter $\boldsymbol{w}$. As knowledge of possible measurement biases can be useful for the future analysis, the second step consists of running the simulation code in the synthesis mode to calculate, given the estimated (x,w), the values of the M_{bias} measurements not used in the optimisation. If the difference between the actual and predicted measurements is larger than a threshold based on the noise standard deviations, then SFDIA is effected, otherwise the outcome of the analysis is that no bias is present and estimation (x,w) has been done by using the subset of measurement providing the best consistency.

Since the identity of the faulty sensors is unknown, a combinatorial search has to be done for every $(\boldsymbol{x},\boldsymbol{w})$ to find the selection providing the lowest value. If for example, 4 biases are assumed to be present, every time the objective function *J(x,w)* has to be evaluated during the optimisation procedure, the following set of functions are calculated be sequential elimination of 4 measurements;

$$J_{klmn}(x,w) = \sum_{\substack{j=1 \\ j\neq k,l,m,n}}^{M} \frac{\left|z_j - h_j(x,w)\right|}{z_{odj}(w)\cdot\sigma_j} \tag{5.4}$$

the value assigned to the objective function will be :

$$J(x,w) = \min_{k,l,m,n} J_{klmn}(x,w) \tag{5.5}$$

in general, the number Q of evaluations of *J(x,w)* to choose from is equal to the number of possible combinations (Zedda, 1999).

$$Q = \begin{pmatrix} M \\ M_{bias} \end{pmatrix} = \frac{M!}{M_{bias}!(M - M_{bias})!} \tag{5.6}$$

When dealing with engines, the following points will have to me made-

(a) Noise is taken into account by weighting the terms to be added in the objective function. The minimum value will not be zero but the minimisation is finished, a simple check on the magnitude of the objective function can suggest if there is anything wrong with the analysis.

(b) A large redundancy is usually available as the number of fault affected is assumed to be significantly smaller than the number of sensors.

Environment and power setting parameters biases are dealt with in a different way, as they basically affect most of the terms in the summation. A bias in any of these parameters is likely to increase the value of most terms and therefore of the overall sum. Whereas, a two step SFDIA is carried out for biased measurements, SFDIA is automatically performed for the environment and power setting parameters, as they have to be guessed by the optimiser.

5.3.7 Setting GA Parameters

In order to get the GA diagnosis process started, an initial population of strings (potential solution) needs to be generated. This is a supervised generation as all the strings generated are within the constraints. The following GA parameters are to be set initially for the process to progress:

(a) Population Size: The importance of the population has been discussed earlier in chapter-3. In case of a very low population there are problems of premature convergence, inability to deal with noise, deception and multimodal problems. Using a population that is very large also has its own problems, like the requirement of more computational resource that may not justify the small gains achieved in accuracy. There is no fixed rule about the size of the population and it is a matter of experience. An initial population of 80-100 strings per fault class has been used in this work. The aim is that the initial population reasonably covers the entire range of possible faults i.e. there is sufficient diversity in the population.

(b) Probability of Crossover (P_C): there is no strict rule to set this parameter and is again a matter of experience. Various values between 0.1 to 1.0 were investigated and the P_C for the WR21 Diagnostics have been set to 0.6.

(c) Probability of Mutation (P_M): Mutation causes small changes in the performance parameters at random. Mutation is an important parameter in the diagnostics as it produces new strings and therefore increases the diversity. It is usually kept at 0.05 to 0.1 in the case of binary coded GAs. However, engine diagnostics being a special case, the probability of mutation (P_M) case, after experimenting with various value it has been set at 0.4.

5.4 Operation of GA Diagnostics Model

The process of GA diagnostics starts with the generation of specified number of strings (initial population) randomly within the specified range. The objective function for each string is calculated and mapped against as fitness value such that a high fitness indicates a low value of objective function which in turn means a close match of actual and simulated parameters. After the evaluation of fitness, the strings undergo three basic genetic operations: selection, crossover and mutation.

- **Selection/Reproduction:** Selection is the procedure where the individual strings go into the next generation based on their fitness values. The higher the fitness the greater is the probability of the individual being selected for the next generation. The algorithm used for selection procedure is SUS – Stochastic Universal Sampling algorithm (Baker, 1987).
  - SUS: this algorithm has been developed by Baker (1987). According to Baker, on a standard spinning wheel there is a single pointer that indicates the winner. The Stochastic universal sampling algorithm is analogous to a wheel with 'N' equally spaced pointers, a result of which is that a single spin results in 'N' winners. This algorithm has a zero bias, which means that the absolute difference between an individual's actual sampling probability and its expected value is zero. In terms of efficiency of computational time, this algorithm requires the minimum resources to get a zero bias when compared to other techniques available for such purposes.
  - Pareto-Optimal Optimisation: in the case of MOPA, two sets of population from different operating points are generated. Fitness values are assigned to strings using the concept of pareto-optimality. The technique has been explained in section 3.6.3.
- **Crossover**: the operation produces a new offspring which constitutes parts from parents. The change in composition of the performance parameter vector would produce a new string.
- **Mutation:** mutation is an important process as it produces entirely different strings by making small changes to a randomly chosen element of a performance parameter vector.

When a set of population has been subjected to the three operations mentioned above, it is said to have completed one generation. The string with the highest fitness value in a generation is taken to be the closest match between the actual and simulated measurements. The process records the value of the lowest objective function, the values of performance parameter deviation(s) and environment and power setting parameters producing the lowest objective function. The same procedure is repeated again and the string with highest fitness value is identified. If the fitness of the current string is higher than the string from the previous generation, the current string is assumed to be the solution else the string from the previous generation remains to be the solution. This process is repeated till a predefined number of generations are completed. On completion of one fault class, the same search process is repeated with the next fault class for same number of generations. On completion of the search process with all the fault classes, the fault class having the lowest objective function is indicative of the faulty component(s). The performance parameters producing the lowest objective function are indicative of the magnitude of the faults.

5.4.1 Population Compensation

One of the difficulties in running the GA diagnostics is the problem of performance model convergence. It is possible that the engine performance model may not converge for certain values or may reach the maximum iterations limit. In such cases the objective function will not be calculated and hence a string will be lost. If repetition of such condition is allowed then the population size will decrease. In order to compensate for the lost string, the diagnostics systems regularly monitors the population size and generates new strings to compensate for the lost ones.

5.4.2 Results from Engine Fault Diagnosis

Some of the results obtained from the engine diagnostics model are presented in this section:

(A) FAULT CASE-1 :

COMPONENTS		COMPONENT-1		COMPONENT-2		FAULTY SENSORS	
Comp-1	Comp-2	$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$	Sen-1	Sen-2
LPT	-	-2%	+3%	-	-	-	-

Table 5.6: Fault case -1 (Single component fault)

Fault case-1 is a simple case with a single component fault and no measurement noise & sensor bias. Figure 5.3 shows the search space for LPT. Every point on the surface plot is a potential solution but the best solution is the string having the lowest objective function. It is evident from the figure that the search space is fairly smooth and global minimum is clearly defined. Intuitively, one could say that the optimisation process would be fairly simple and the algorithm would converge in a reasonably short time with minimum resources.

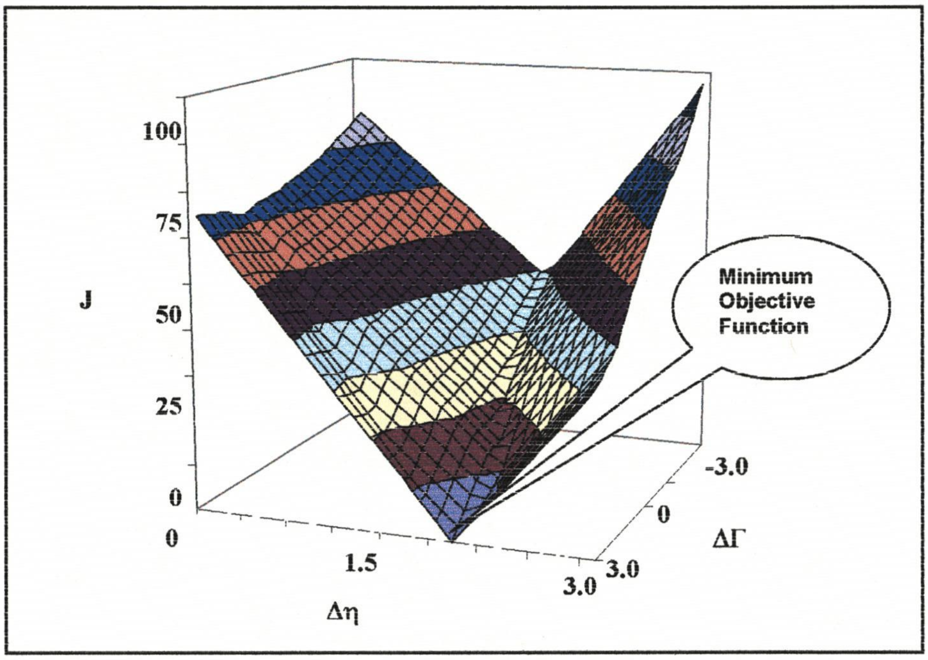


Figure 5.3: Search Space for LPT Fault

The result from fault diagnostics is shown in table 5.7. The result shows the input measurements which are simulated for a given fault condition. From the table it can be observed that the diagnostic model has not only identified the component correctly but has also quantified the fault correctly. The diagnostics process starts with the assumption that environment and power setting parameters are biased. These parameters are also subjected to the GA optimisation process and algorithm identifies the correct values.

```
Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/97                              TIME/DATE: 13:14:29 [13-Jan-02]

      ENGINE MEASUREMENTS (Operating Point: 1)
      ---------------------------------------
       1  HP Compressor(In)              2.510387659072876  (Pressure    )
       2  HP Compressor(Exit            11.438918113708496  (Pressure    )
       3  IC Differential                0.051232337951660  (Pressure    )
       4  HP Compressor(In)            312.959960937500000  (Temperature)
       5  HP Compressor(Exit)          513.784912109375000  (Temperature)
       6  Combustor Entry              794.278564453125000  (Temperature)
       7  Power Turbine(In)           1119.839599609375000  (Temperature)
       8  Power Turbine(Exit)          852.171020507812500  (Temperature)
       9  HP Shaft Speed(RPM)         8249.178710937500000  (Tachometer )
      10  LP Shaft Speed(RPM)         6271.975585937500000  (Tachometer )

      ENGINE MEASUREMENTS (Operating Point: 2)
      ---------------------------------------
       1  HP Compressor(In)              2.449075222015381  (Pressure    )
       2  HP Compressor(Exit            10.841490745544434  (Pressure    )
       3  IC Differential                0.049981117248535  (Pressure    )
       4  HP Compressor(In)            311.830383300781250  (Temperature)
       5  HP Compressor(Exit)          505.241882324218750  (Temperature)
       6  Combustor Entry              774.855468750000000  (Temperature)
       7  Power Turbine(In)           1082.610351562500000  (Temperature)
       8  Power Turbine(Exit)          828.068298339843750  (Temperature)
       9  HP Shaft Speed(RPM)         8149.934570312500000  (Tachometer )
      10  LP Shaft Speed(RPM)         6111.773437500000000  (Tachometer )

         Fault Detected (Change in Component Performance Parameters in %age)
     ---------------------------------------------------------------------------
                  Component -1              |              Component-2          |
     ---------------------------------------------------------------------------
          Efficiency       |      Mass Flow     |    Efficiency      |    Mass Flow     |
     ---------------------------------------------------------------------------
         -1.9903 (LPT)        2.9653 (LPT)         0.0000 (   )        0.0000 (   )

                  Estimated Environment & Power Setting Parameters
     ---------------------------------------------------------------------------
                  Operating Point-1          |            Operating Point-2         |
     ---------------------------------------------------------------------------
     Power/Fuel    | Temperature  | Pressure    | Power/Fuel  | Temperature | Pressure|
     ---------------------------------------------------------------------------
    26412.1406       308.1270       1.0002     24023.8535      308.0819        0.9999
     ---------------------------------------------------------------------------

                                 Faulty Sensors
     ---------------------------------------------------------------------------
                  Sensor-1                   |                  Sensor-2            |
     ---------------------------------------------------------------------------
       Sensor-1  Position |          Type        | Sensor-2  Position  |      Type       |
     ---------------------------------------------------------------------------
                 -        |           -          |          -          |        -        |
     ---------------------------------------------------------------------------

     ***************************************************************************
```

Table 5.7: Diagnostics for single Component fault

INTERCOOLED RECUPERATED-WR21 FAULT CLASS ANALYSIS

FC	Min.Obj. Function	Best String	Efficiency Comp1	Efficiency Comp2	Flow Capacity Comp1	Flow Capacity Comp2
1	4.3721	2	-1.4653 (LPC)	0.0000 ( )	0.1192 (LPC)	0.0000 ( )
2	3.8228	1	-2.7862 (HPC)	0.0000 ( )	-0.6649 (HPC)	0.0000 ( )
3	4.7777	1	-1.9497 (I/C)	0.0000 ( )	1.0606 (I/C)	0.0000 ( )
4	3.9468	1	-2.3099 (HPT)	0.0000 ( )	1.9929 (HPT)	0.0000 ( )
5	**0.8446**	**2**	**-1.9903 (LPT)**	**0.0000 ( )**	**2.9653 (LPT)**	**0.0000 ( )**
6	4.0959	1	-1.7613 (FPT)	0.0000 ( )	-0.0706 (FPT)	0.0000 ( )
7	5.8946	1	-1.0233 (R/C)	0.0000 ( )	1.1761 (R/C)	0.0000 ( )
8	4.5922	1	-0.7779 (LPC)	-0.4860 (HPC)	0.3764 (LPC)	1.1549 (HPC)
9	4.6442	2	-0.8943 (LPC)	-0.7429 (I/C)	1.9884 (LPC)	0.6526 (I/C)
10	5.8592	1	-1.2734 (LPC)	-1.9227 (HPT)	0.1726 (LPC)	0.4154 (HPT)
11	3.8422	2	-1.6287 (LPC)	-1.4903 (LPT)	-0.6245 (LPC)	1.7209 (LPT)
12	7.2369	1	-1.9262 (LPC)	-2.0881 (FPT)	2.7205 (LPC)	-0.5665 (FPT)
13	4.8389	2	-0.7345 (LPC)	-1.7153 (R/C)	1.6054 (LPC)	1.3655 (R/C)
14	1.9531	1	-1.5377 (HPC)	-1.3527 (I/C)	-1.2024 (HPC)	0.1471 (I/C)
15	5.9061	2	-0.3005 (HPC)	-2.6482 (HPT)	-0.3999 (HPC)	0.0483 (HPT)
16	4.4693	1	-0.2230 (HPC)	-0.5101 (LPT)	-2.1568 (HPC)	0.6686 (LPT)
17	6.7506	1	-2.5231 (HPC)	-0.3809 (FPT)	-2.3552 (HPC)	0.9873 (FPT)
18	4.4511	1	-1.2569 (HPC)	-1.1942 (R/C)	-1.0561 (HPC)	1.2824 (R/C)
19	6.1135	1	-0.7783 (I/C)	-0.6650 (HPT)	0.4866 (I/C)	-2.2518 (HPT)
20	7.8588	2	-1.0646 (I/C)	-2.9048 (LPT)	1.3889 (I/C)	0.8632 (LPT)
21	7.1733	2	-0.0459 (I/C)	-0.3922 (FPT)	1.3387 (I/C)	-1.1106 (FPT)
22	5.0425	2	-1.9787 (I/C)	-0.8087 (R/C)	0.6842 (I/C)	1.1191 (R/C)
23	8.5266	2	-0.3454 (HPT)	-0.0740 (LPT)	-0.1058 (HPT)	-2.5466 (LPT)
24	3.6035	2	-0.9043 (HPT)	-0.4419 (FPT)	-0.4328 (HPT)	-0.0177 (FPT)
25	4.3155	1	-2.4158 (HPT)	-1.0690 (R/C)	1.4940 (HPT)	0.3890 (R/C)
26	4.9665	2	-0.1771 (LPT)	-0.0777 (FPT)	1.0823 (LPT)	1.5914 (FPT)
27	5.5562	1	-2.8358 (LPT)	-1.9183 (R/C)	1.5937 (LPT)	1.5894 (R/C)
28	4.8543	2	-2.4600 (FPT)	-1.0191 (R/C)	-0.3962 (FPT)	0.0987 (R/C)

Table 5.8: Minimum objective functions for a single Component fault

The diagnostics model, at the end of its search of one fault class, retains the string producing the minimum objective function. This procedure continues till all the fault classes are searched. Then the minimum objective functions of all the fault classes are compared and the fault class with the lowest objective function is indicative of the faulty component(s). In this case, it is fault class-5. The minimum objective functions of each class along with the strings producing it have been shown in table-5.8. A comparison of the minimum objective functions is shown in figure 5.4. It is evident that the objective function associated with fault class-5 is distinctly the lowest (or the global minimum) and the second lowest objective function is significantly large when compared with it. This gives more confidence in the result obtained.

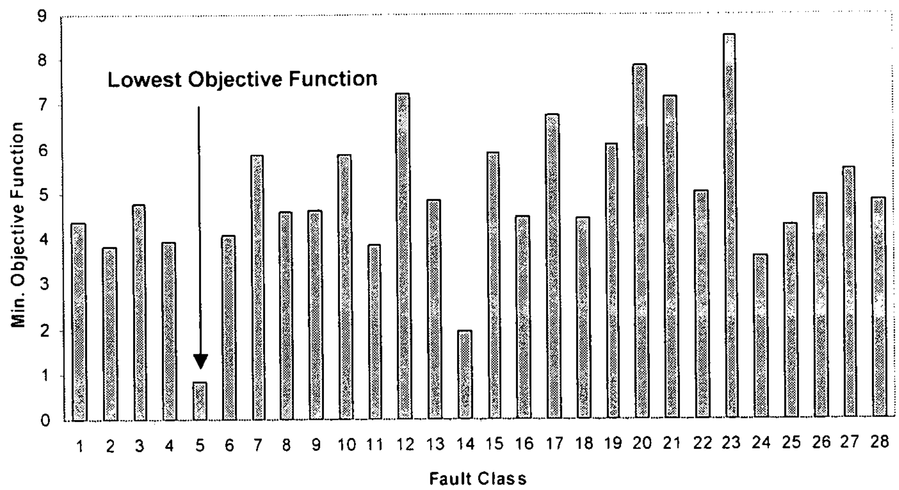


Figure 5.4: A Comparison of minimum objective functions (Fault case-1)

FAULT CASE-2

COMPONENTS		COMPONENT-1		COMPONENT-2		FAULTY SENSORS	
Comp-1	Comp-2	$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$	Sen-1	Sen-2
LPC	HPT	-1%	-3%	-2%	3%	HPC(in) (Temp)	

Table-5.9: Fault Case-2 (Multiple component fault)

The second fault case considers a more complicated case. Two components are simultaneously faulty and one sensor is biased. The diagnostics result for the given fault condition is presented in table 5.10. The faulty components have been identified correctly and the component performance deviations have been quantified reasonably close to the implanted values. Table -5.11 shows the minimum objective functions of all fault classes along with the strings associated with them. In the case of multiple component faults, it is not possible to plot a search space for a preliminary assessment of the diagnostics as there are four variables and therefore some kind an intelligent inference will have to be made from the search spaces of single components. The diagnostics module has identified the faulty sensor also accurately.

```
Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 164                          TIME/DATE: 11:26:02 [26-Mar-02]

ENGINE MEASUREMENTS (Operating Point :1)
---------------------------------------
 1  HP Compressor(In)              2.483951568603516  (Pressure    )
 2  HP Compressor(Exit            11.707879066467285  (Pressure    )
 3  IC Differential                0.050692796707153  (Pressure    )
 4  HP Compressor(In)            313.246948242187500  (Temperature)
 5  HP Compressor(Exit)          519.848999023437500  (Temperature)
 6  Combustor Entry              799.344726562500000  (Temperature)
 7  Power Turbine(In)           1125.060424804687500  (Temperature)
 8  Power Turbine(Exit)          856.787475585937500  (Temperature)
 9  HP Shaft Speed(RPM)         8139.945800781250000  (Tachometer )
10  LP Shaft Speed(RPM)         6389.403320312500000  (Tachometer )

ENGINE MEASUREMENTS (Operating Point :2)
---------------------------------------
 1  HP Compressor(In)              2.424779653549194  (Pressure    )
 2  HP Compressor(Exit            11.112280845642090  (Pressure    )
 3  IC Differential                0.049485206604004  (Pressure    )
 4  HP Compressor(In)            312.088745117187500  (Temperature)
 5  HP Compressor(Exit)          510.319183349609375  (Temperature)
 6  Combustor Entry              775.481994628906250  (Temperature)
 7  Power Turbine(In)           1082.279663085937500  (Temperature)
 8  Power Turbine(Exit)          827.828247070312500  (Temperature)
 9  HP Shaft Speed(RPM)         8059.117675781250000  (Tachometer )
10  LP Shaft Speed(RPM)         6238.931640625000000  (Tachometer )
```

Fault Detected (Change in Component Performance Parameters in %age)

Component -1		Component-2	
Efficiency	**Mass Flow**	**Efficiency**	**Mass Flow**
-1.1100 (LPC)	**-2.9231 (LPC)**	**-2.1469 (HPT)**	**2.8522 (HPT)**

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26399.7930	308.1270	1.0002	24006.4980	308.1879	1.0001

Faulty Sensors

Sensor-1		Sensor-2	
Sensor-1 Position	Type	Sensor-2 Position	Type
HPC (IN)	**Temperature**		

```
*****************************************************************************
```

Table 5.10: Diagnostics Results for Fault case -2

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

FC	Min.Obj. Function	Best String	Efficiency Comp1		Efficiency Comp2		Flow Capacity Comp1		Flow Capacity Comp2	
1	6.7505	1	-1.2016	(LPC)	0.0000	( )	-2.3396	(LPC)	0.0000	( )
2	9.0606	2	-2.7494	(HPC)	0.0000	( )	-1.0003	(HPC)	0.0000	( )
3	5.9135	2	-1.6652	(I/C)	0.0000	( )	1.9898	(I/C)	0.0000	( )
4	6.7319	2	-1.7452	(HPT)	0.0000	( )	2.9760	(HPT)	0.0000	( )
5	7.3923	1	-2.9343	(LPT)	0.0000	( )	0.4016	(LPT)	0.0000	( )
6	5.5666	2	-2.6675	(FPT)	0.0000	( )	-0.3746	(FPT)	0.0000	( )
7	6.7886	1	-0.4854	(R/C)	0.0000	( )	1.9903	(R/C)	0.0000	( )
8	5.8615	1	-1.7671	(LPC)	0.2904	(HPC)	-2.8467	(LPC)	-0.4542	(HPC)
9	5.8142	1	-1.5328	(LPC)	-1.6411	(I/C)	-2.3188	(LPC)	0.0686	(I/C)
10	**2.3451**	**1**	**-1.1100**	**(LPC)**	**-2.8522**	**(HPT)**	**-2.9231**	**(LPC)**	**2.8522**	**(HPT)**
11	7.2606	2	-1.4000	(LPC)	-1.2723	(LPT)	-1.8538	(LPC)	1.2552	(LPT)
12	4.2362	2	-0.3372	(LPC)	-1.3253	(FPT)	-2.0860	(LPC)	-0.0651	(FPT)
13	6.5680	1	-1.9860	(LPC)	-0.6222	(R/C)	-2.7450	(LPC)	0.4100	(R/C)
14	5.3516	1	-0.5432	(HPC)	-1.5986	(I/C)	0.8651	(HPC)	1.3629	(I/C)
15	5.8133	1	-0.9397	(HPC)	-2.7255	(HPT)	-1.5678	(HPC)	2.8094	(HPT)
16	6.6194	1	-0.5964	(HPC)	-2.5524	(LPT)	-0.2493	(HPC)	-0.1929	(LPT)
17	6.6270	2	-0.3266	(HPC)	-2.6149	(FPT)	-1.0158	(HPC)	-0.7725	(FPT)
18	6.2473	2	-1.4848	(HPC)	-1.6298	(R/C)	0.6226	(HPC)	1.8201	(R/C)
19	4.4438	2	-1.2100	(I/C)	-1.4469	(HPT)	1.5231	(I/C)	2.8522	(HPT)
20	6.1016	1	-0.5086	(I/C)	-1.7781	(LPT)	1.5722	(I/C)	1.1325	(LPT)
21	4.4159	1	-0.1685	(I/C)	-2.1258	(FPT)	1.8673	(I/C)	-0.9842	(FPT)
22	6.4770	2	-1.9322	(I/C)	-1.3166	(R/C)	1.2007	(I/C)	1.9777	(R/C)
23	5.7875	1	-2.7214	(HPT)	-1.4607	(LPT)	2.8805	(HPT)	-0.3911	(LPT)
24	4.6026	2	-0.9806	(HPT)	-0.5152	(FPT)	2.7922	(HPT)	1.5112	(FPT)
25	2.3878	1	-2.1301	(HPT)	-1.4615	(R/C)	2.9062	(HPT)	1.9774	(R/C)
26	3.8488	2	-2.9521	(LPT)	-2.7340	(FPT)	-1.5314	(LPT)	-2.5981	(FPT)
27	5.8154	1	-1.6447	(LPT)	-1.6304	(R/C)	0.6370	(LPT)	1.6370	(R/C)
28	4.1963	2	-1.3633	(FPT)	-1.0570	(R/C)	-0.8979	(FPT)	1.7962	(R/C)

Table 5.11: Diagnostics Results for Fault case -2

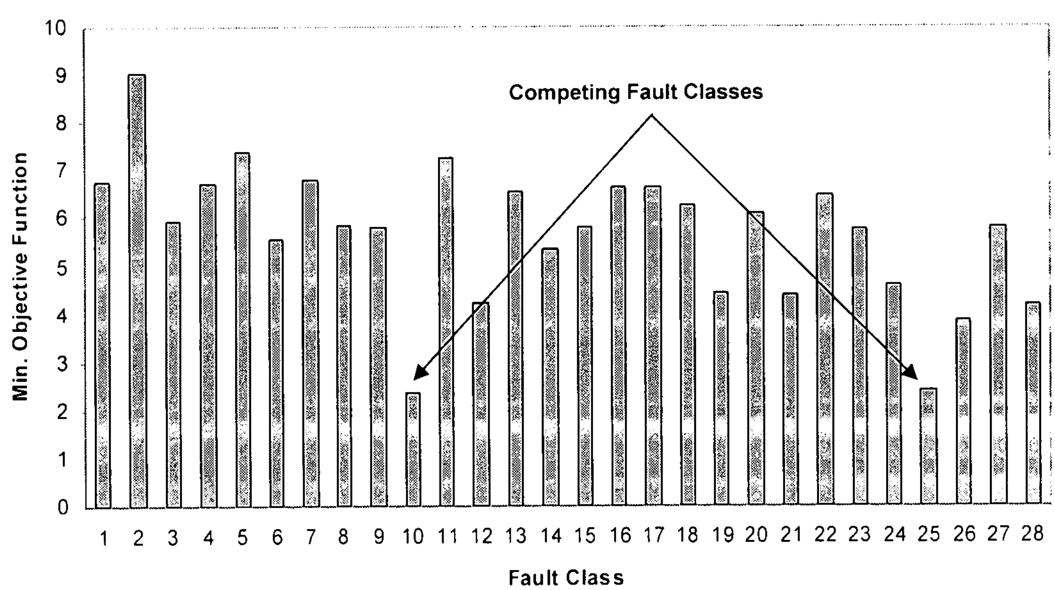


Figure-5.5: Comparison on Min. Objective Functions for Fault Case-2

A comparison of minimum objective funtions of various fault classes is shown in figure 5.5. It can be seen that there are two fault classes with very close values of objective funtions. (FC-10 & FC-25). This is an important observation from the diagnostics point of view. Such fault classes are called competing fault classes. Since the whole process of GA diagnostics is based on random application of the genetic operators, it is possible that the string producing the best objective function crosses-over with another stirng to produce an offspring which may not produce the minimum objective fucntion. Such a situation can arise through mutation of the best string also. Another, important observation from the above results is that the competing fault classes have one component common among themselves i.e. HPT. It can be inferred that that the common component is defintely faulty and other component has to be ascertained.

FAULT CASE-3

COMPONENTS		COMPONENT-1		COMPONENT-2		SENSORS	
Comp-1	Comp-2	$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$	Sen-1	Sen-2
HPC	LPT	-2%	-4%	-1%	3%	HPC(in) (Temp)	HPC (Exit) (Press.)

Table 5.12: Fault case - 3 (Multiple component fault)

The third fault case considers two simultaneously faulty components and two biased sensors. The diagnostics result for the given fault condition is presented in table 5.13. It can be seen that the components have not been identified correctly, while the faulty sensors have been identified correctly Table 5.14 shows the minimum objective functions for all fault classes and a comparison of the minimum objective functions is shown in figure 5.7. This is a special case and has been shown to explain the difficulty in identifying a faulty component in the face of competing fault classes. The result shows that there are six competing fault classes. A close look at the fault classes shows that FC- 16 produced the second lowest objective function. The faults quantified are also very close to the implanted fault. It shows that, had there been better local tuning in FC-16, the objective function could have been further reduced and the faulty components could have been identified correctly.

Performance Engineering Group,Cranfield University
Test Case:WR21/DIAG/ 172 **TIME/DATE: 22:05:43 [03-Jul-02]**

ENGINE MEASUREMENTS (Operating Point :1)

1	HP Commpressor(In)	2.576585054397583	(Pressure)
2	HP Compressor(Exit	11.489476203918457	(Pressure)
3	IC Differential	0.052583456039429	(Pressure)
4	HP Compressor(In)	313.356994628906250	(Temperature)
5	HP Compressor(Exit)	509.261535644531250	(Temperature)
6	Combustor Entry	793.626953125000000	(Temperature)
7	Power Turbine(In)	1119.988159179687500	(Temperature)
8	Power Turbine(Exit)	852.309631347656250	(Temperature)
9	HP Shaft Speed(RPM)	8165.344726562500000	(Tachometer)
10	LP Shaft Speed(RPM)	6275.961914062500000	(Tachometer)

ENGINE MEASUREMENTS (Operating Point :2)

1	HP Commpressor(In)	2.511474370956421	(Pressure)
2	HP Compressor(Exit	10.889840126037598	(Pressure)
3	IC Differential	0.051254510879517	(Pressure)
4	HP Compressor(In)	312.222808837890625	(Temperature)
5	HP Compressor(Exit)	500.878997802734375	(Temperature)
6	Combustor Entry	774.106750488281250	(Temperature)
7	Power Turbine(In)	1082.562255859375000	(Temperature)
8	Power Turbine(Exit)	828.033264160156250	(Temperature)
9	HP Shaft Speed(RPM)	8072.222656250000000	(Tachometer)
10	LP Shaft Speed(RPM)	6118.035644531250000	(Tachometer)

Fault Detected (Change in Component Performance Parameters)

Component -1		Component-2	
Efficiency	Mass Flow	Efficiency	Mass Flow
-0.2814 (LPT)	2.9899 (LPT)	-1.6860 (FPT)	1.2107 (FPT)

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26405.5234	308.2270	1.0002	24007.5352	308.2270	1.0002

Faulty Sensors

Sensor-1		Sensor-2	
Sensor-1 Position	Type	Sensor-2 Position	Type
HPC(IN)	Temperature	HPC(EXIT)	Pressure

****

Table 5.13: Results for fault case-3

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

FC	Min.Obj. Function	Best String	Efficiency Comp1		Efficiency Comp2		Flow Capacity Comp1		Flow Capacity Comp2	
1	9.8775	2	-2.0383	(LPC)	0.0000	( )	0.2947	(LPC)	0.0000	( )
2	7.2645	1	-1.8139	(HPC)	0.0000	( )	-0.8644	(HPC)	0.0000	( )
3	10.5931	1	-1.8660	(I/C)	0.0000	( )	0.8317	(I/C)	0.0000	( )
4	7.0777	1	-1.8858	(HPT)	0.0000	( )	0.3651	(HPT)	0.0000	( )
5	5.0514	2	-3.0000	(LPT)	0.0000	( )	2.9997	(LPT)	0.0000	( )
6	8.5998	1	-0.7960	(FPT)	0.0000	( )	0.5784	(FPT)	0.0000	( )
7	10.9678	1	-0.1873	(R/C)	0.0000	( )	0.1175	(R/C)	0.0000	( )
8	8.4048	1	-0.4963	(LPC)	-1.6096	(HPC)	1.4937	(LPC)	-1.0300	(HPC)
9	9.6694	2	-0.8576	(LPC)	-0.1765	(I/C)	0.5438	(LPC)	0.4735	(I/C)
10	8.5873	2	-0.7409	(LPC)	-1.4221	(HPT)	1.2420	(LPC)	0.3291	(HPT)
11	6.2847	2	-0.6468	(LPC)	-1.7247	(LPT)	2.9799	(LPC)	2.9983	(LPT)
12	9.0015	1	-1.1645	(LPC)	-1.1408	(FPT)	1.7067	(LPC)	-0.7798	(FPT)
13	10.0626	2	-1.5904	(LPC)	-0.9274	(R/C)	0.5414	(LPC)	0.4481	(R/C)
14	7.6765	1	-1.9424	(HPC)	-0.2566	(I/C)	-1.1710	(HPC)	0.2608	(I/C)
15	8.2776	1	-0.2502	(HPC)	-2.2059	(HPT)	-2.6534	(HPC)	1.3449	(HPT)
16	**4.6654**	**2**	**-1.7866**	**(HPC)**	**-1.1377**	**(LPT)**	**-3.6910**	**(HPC)**	**2.8591**	**(LPT)**
17	6.7519	1	-2.9300	(HPC)	-0.1963	(FPT)	-0.4566	(HPC)	-1.3994	(FPT)
18	7.3848	1	-2.2935	(HPC)	-0.2896	(R/C)	-1.3420	(HPC)	0.0503	(R/C)
19	8.3517	1	-0.4850	(I/C)	-0.8773	(HPT)	0.4440	(I/C)	-0.8781	(HPT)
20	4.9364	2	-1.0037	(I/C)	-2.6140	(LPT)	0.8465	(I/C)	2.8918	(LPT)
21	9.7193	2	-1.0138	(I/C)	-0.6894	(FPT)	0.4183	(I/C)	-0.1765	(FPT)
22	10.7311	2	-1.0533	(I/C)	-0.2838	(R/C)	1.4782	(I/C)	0.2433	(R/C)
23	4.8573	1	-1.2213	(HPT)	-2.3589	(LPT)	1.2028	(HPT)	2.9911	(LPT)
24	4.7452	1	-2.4464	(HPT)	-2.0171	(FPT)	-2.0260	(HPT)	-2.3086	(FPT)
25	7.6808	2	-1.4978	(HPT)	-0.6545	(R/C)	-0.1761	(HPT)	0.2778	(R/C)
26	**4.6130**	**1**	**-0.2814**	**(LPT)**	**-1.6860**	**(FPT)**	**2.9899**	**(LPT)**	**1.2107**	**(FPT)**
27	5.9594	1	-2.9240	(LPT)	-0.8492	(R/C)	2.4560	(LPT)	0.7313	(R/C)
28	9.4390	2	-1.9518	(FPT)	-1.7690	(R/C)	-0.3404	(FPT)	0.0303	(R/C)

Table 5.14 : Minimum objective function for fault classes (Fault case-3)

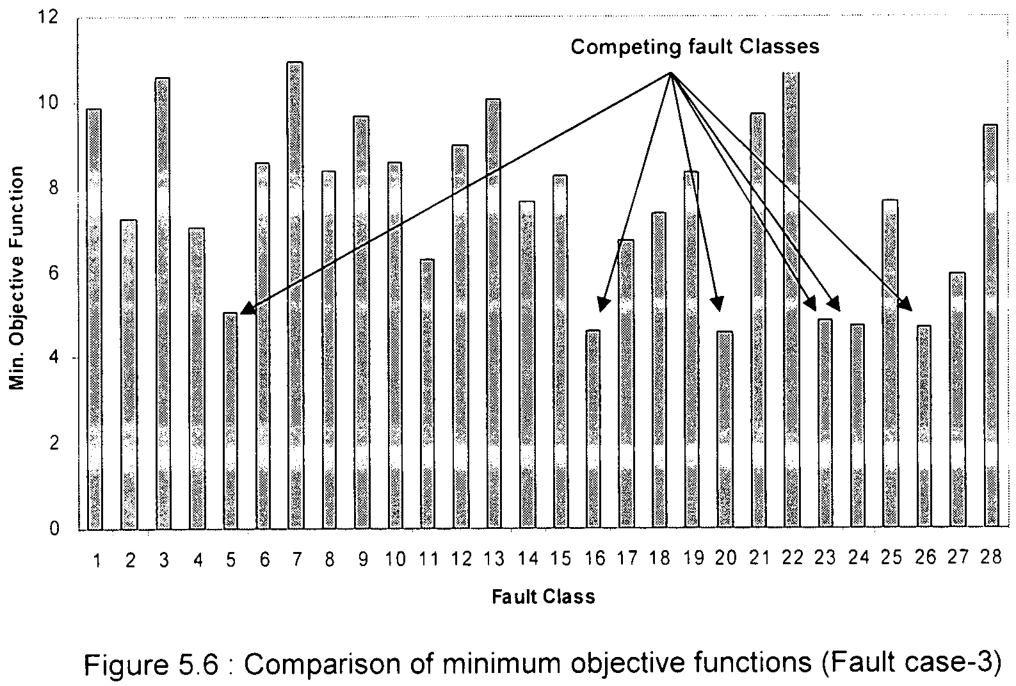


Figure 5.6 : Comparison of minimum objective functions (Fault case-3)

The occurrence of competing fault classes is not uncommon in this type of optimisation, especially for multiple component faults. As mentioned earlier, due to the random nature of GA optimisation it is possible that the good solutions are lost in the earlier generations. It is a matter of chance that which fault class produces the minimum objective function among the competing fault class to be declared as the fault. It can also be seen that out of the six competing fault classes, five fault classes contain LPT as the common component and the input test data has LPT as one of the faulty components.

5.5 Limitations and need for Enhancement

The above-mentioned process has several advantages it has several limitations due to its dependence on the engine performance model which is the slowest process in the chain of events. Some of limitations are summarised below-

5.5.1 Long convergence time

A major limitation of the diagnostics system is its long convergence times. It has been seen that, for an engine like the WR21 which has 28 fault classes for dual components fault, the algorithm takes approximately 19-22 hours to converge. In the case of 3 components fault it would take much longer. The fitness evaluation needs objective function, which in turn needs the engine performance model to be run twice i.e. once at clean off-design condition and once using the implanted fault. The engine performance model is an iterative process and takes long time to converge when compared with the other process within the diagnostics framework.

5.5.2 Competing Fault Classes

On many occasions, multiple component faults often lead to competing fault classes, which need further analysis for a definite solution. The model will choose the fault class with the lowest objective function while another objective function which is close in magnitude could be indicative of the fault and has not been able to reach a much lower value due to improper local tuning.

5.5.3 Retention of good solutions

It is possible that a good solution was generated in an earlier generation and was lost due to crossover or mutation. In the present form, the diagnostics model lacks a mechanism to retain the good solutions produced in the earlier generations.

5.6 Summary

This chapter presented the development of a diagnostics model based on GA optimisation technique for the ICR WR21 The method is simple to implement and is robust in the face of measurement noise and sensor bias. From the above discussions it is also evident that despite its accuracy and robustness the technique has certain limitations and needs further enhancement. The choice of instruments is clearly an important issue and needs careful consideration. There is also a need for better tuning of the GA operators (the probability of cross over & mutation, etc.) to converge to the correct values. Another major issue which needs attention is a method to reduce the total run time. The total runtime could be reduced if the number of calls to performance model is reduced.

The next chapter discusses the various enhancements made to the basic technique to improve its performance and overcome some of the problems associated with the basic technique and also explores new opportunities to build a more robust diagnostic model.

CHAPTER-6

ADVANCED FAULT DIAGNOSTICS MODEL

6.1 Introduction

Improvements in the field of advanced numerical methods for scientific computation, artificial intelligence, mathematical tool (Software) etc. have had tremendous impact on applied science such as engine performance and fault diagnostics. Despite great deal of research in the field of advanced diagnostics involving various techniques, no single 'magic formula' has emerged which can effectively address all aspects of engine fault diagnostics. While some techniques are good at classifying the faults, others are good at quantifying the faults. A prudent approach would be to utilise the strong points of each technique to offset the limitations of the other.

This chapter presents the development of an advanced diagnostics model by modifying the basic GA based technique while addressing some of the issues concerning accuracy and convergence speed by using knowledge augmented operators. The estimation architecture also combines ANN and GAs for engine fault diagnostics at steady state conditions. The hybrid approach takes advantage of the ability of the ANN to classify, while the quantification of faults is done by the GA optimiser.

6.2 Strategy for Advanced Fault Diagnostics Model

The diagnostics system developed for the advanced cycle ICR WR21 was able to detect the component faults and instrumentation faults to reasonable accuracy. However, the model has its own limitations, particularly the long run times and therefore has necessitated further enhancement. It has been clearly brought out that the centre of gravity of the algorithm lies in the calculation of the objective function, which in turn is mapped to the fitness function. The fitness function is the parameter which dominates the search process.

The calculation of the objective function (equation 5.2) requires the performance model to be run twice (clean condition and faulty condition). Therefore, any reduction in the number of calls to the performance model can significantly reduce the overall run time of the algorithm.

After carrying out a detailed study of the problem, several techniques have been worked out to overcome the limitations, while enhancing the accuracy, consistency and reliability of the diagnostics system. The new approach has been taken up under three categories: (a) Search Accuracy (b) Convergence Speed (c) Hybrid model.

6.2.1 Search Accuracy

One of the limitations in the basic GA based diagnostics model is the lack of a mechanism to retain good solutions in the earlier generations. A genetic algorithm is a random process and it is possible that good solutions or probably the best solution is generated in an earlier generation. Since the genetic operators, particularly crossover and mutation, are applied randomly, it is possible that a string with high fitness value gets mutated to form a weak string. Such conditions are possible in the earlier generations, when the magnitude of changes (mutations) is large. The mutation value diminishes during the later generations and therefore the danger of a string changing completely is reduced. The accuracy of the system could be enhanced by using the concept of elitist model in GAs. The process preserves the good solution from the earlier generations and keeps historical evidence to ensure that the best solution is never lost.

Another limitation with the basic diagnostics model is that the GA parameters (population size, PC, PM, No. of generations) are introduced at the beginning and remain constant throughout the process. These parameters, when varied appropriately, can influence the accuracy and the progress of the optimisation process. The accuracy and reliability of the search process can be enhanced by the use of an embedded expert system (Inference Engine) which can assess the process continuously through a reasoning logic and direct the search process accordingly. A termination condition can be enforced depending on the progress of the search process.

6.2.2 Convergence Speed

The speed of convergence of the performance model is beyond the control of a diagnostics engineer, but one way to overcome this problem is to make fewer calls to the performance code. Perhaps, the use of a function or a response surface which is a suitable representation of engine performance model for the initial generations to eliminate the weaker individual can reduce the total run time.

It is believed that the processing power of the computer will continue to increase and therefore it is not likely to be a limitation. However, in order to get quick results with the possibility of online fault diagnostics in the future, the concept of parallel computing could be implemented, where the analysis of fault classes can be off-loaded to different processors.

6.2.3 Hybrid Model

The diagnosis of multiple component faults lead to a large number of fault classes to be explored, which in turn leads to large run times. The number of fault classes that need to be searched could be further reduced by developing a hybrid system in which a pre-processor algorithm can be used to classify the fault classes into appropriate groups and suggest a single/group of fault classes to be explored by the GA optimiser.

6.3 Implementing the Strategy

Using the above-mentioned points as broad guidelines, a diagnostics model with advanced capability and reduced convergence time has been developed The various techniques used in the model are described in detail in the following sections-

6.3.1 Adaptive Genetic Algorithm

Adaptive Genetic Algorithm (AGA) is a new concept in engine fault diagnostics. The engine performance model is an iterative process and could converge in 2 iterations or in 20 iterations and in certain cases it may not converge even after the maximum number of iterations. As described earlier, the problem of long run-time for the fault diagnostics model is due to the large number of times the engine performance model is run. This in turn, is directly dependent on GA parameters like the number of strings, the number generations and the number of fault classes to be searched. A reduction in the number of any of these parameters can have a significant impact on the total run-time of the algorithm. However, it must be ensured that the reduction in run-time does not comprise the accuracy of the result.

The AGA is a process where the GA parameters are dynamically varied depending on the progress of the search. The process starts in a similar way to the basic GA diagnostics model, but after a few generations, based of certain statistical parameters, the GA parameters are controlled. The Adaptive GA has been implemented using the following steps:

6.3.1.1 Master- Slave Configuration

This method consists of a master GA controller which monitors the functioning of a slave GA model, which is same as the basic diagnostic model. The master evaluates the performance of the slave GA after every generation. It obtains various statistical parameters to assess the population as described in figure 6.1.

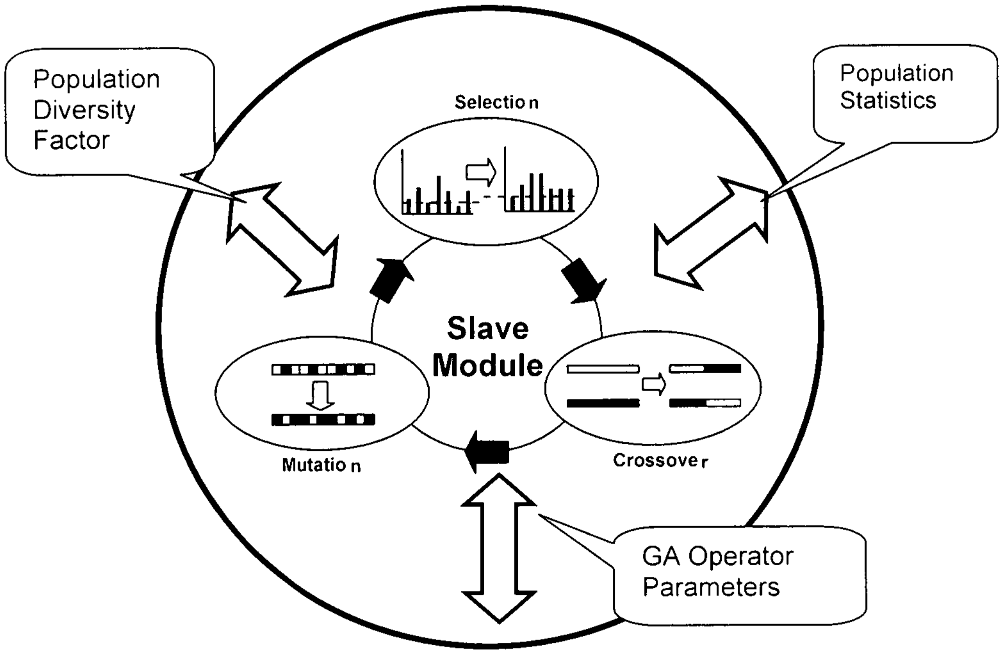


Figure 6.1: Adaptive GA model Organisation

6.3.1.2 Population Diversity Factor

The population diversity factor (σ_{DF}) is a measure of diversity in the population within the search space. A large diversity factor indicates the possibility of the search algorithm covering a wider search area and a higher probability of reaching the global minimum. It is desired that the diversity factor be high during the initial generations to eliminate the possibility of local minima. However, in the later generations a lower diversity factor is desired for better local tuning. The diversity factor is given by:

$$\sigma_{DF} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(J_i - \bar{J})^2} \qquad (6.1)$$

where,

N is the population size

J is the objective function

6.3.1.3 Population Size

The population size is a critical parameter in the GA process. A low population level implies problems of poor convergence, deception, multimodality etc. A large population requires large computational resources, which will eventually translate into long run times, sometimes without any relative gain. The fitness functions are calculated by obtaining parameters from a fully converged performance model. It is also possible that for certain conditions the performance model may not converge and an objective function obtained from such measurement will not indicate the true fitness of the string. The algorithm has a built-in mechanism to withdraw such strings from the population. Such condition will lead to gradual reduction in the population size. In the case of the Master-Slave configuration the "Population Compensation" feature described in section 5.4.1 is disabled. Therefore, the population size is under the control of the Master algorithm.

In the case of certain fault classes involving the intercooler and the recuperator, the rate of convergence of the engine performance model is poor, and therefore the strings are withdrawn at regular intervals, causing a reduction in the population, thereby limiting the search space. It is also possible that the embedded expert system (part of AGA discussed later in the chapter) directs an increase in the population size under certain circumstances and if this situation is not controlled, it can lead to an increase in the population size. Such increased population will lead to further increase in convergence time. The master monitors the slave for a drop or rise in the population and takes appropriate actions.

6.3.1.4 Population Mean Fitness

Population fitness is obtained by summing the individual fitness of the strings and dividing by the total population size and is expressed as:

$$\overline{F} = \frac{\sum_{i=1}^{N} F_i}{N} \tag{6.2}$$

where,

F is the fitness of a given string

In the beginning of the search process the population fitness is expected to be low due to the high diversity in the population. Eventually after a few generations, the population fitness increases indicating convergence of algorithm.

6.3.1.5 Fitness Improvement

The population fitness improvement is a measure of the performance of the GA and indicates convergence of search process. The master monitors the fitness at the end of each generation and compares with the previous generation. The fitness improvement from k^{th} to $(k+1)^{th}$ generation is given as-

$$\Delta F(\%) = \frac{\overline{F}_{k+1} - \overline{F}_k}{\overline{F}_k} \times 100 \tag{6.3}$$

In general, the average fitness of the population is expected to increase as the generations progress as the population will consists of more fitter individuals. However, the magnitude of fitness improvement starts to diminish. Figure 6.2 shows the fitness improvement plotted against the number of generations for an optimisation process for fifty generations. It can be observed that the fitness improvement is large in the initial generations and diminishes towards later generations, indicating that the model is reaching convergence.

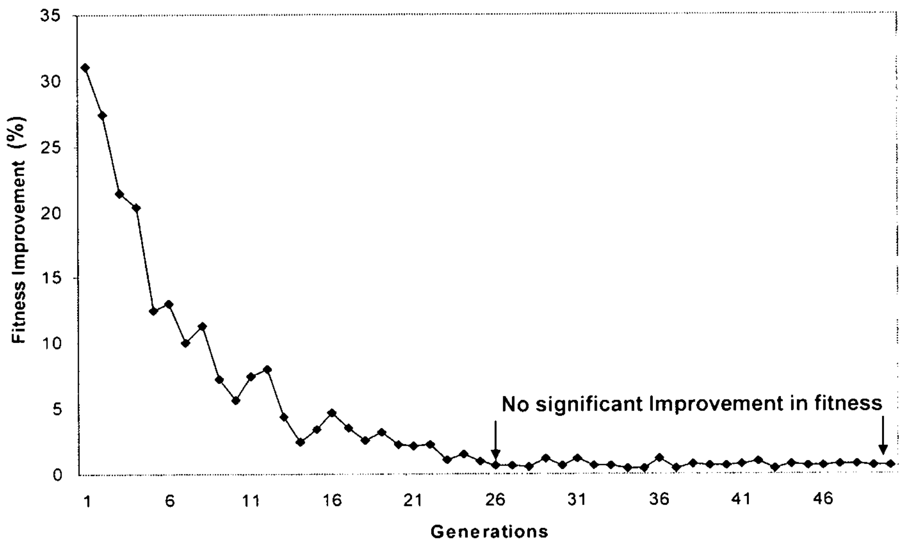


Figure 6.2: Fitness improvement over generations

6.3.2 Embedded Expert System (Inference Engine)

One way to speed up the algorithm is to use non-payoff information to guide genetic operators more directly towards better strings. In a sense, we can augment the random choice in operators like mutation and crossover by using knowledge specific to a particular problem. The earliest work in this area was performed using knowledge-augmented mutation operators. Bosworth et al (1972) encoded multidimensional parameter optimisation problems using real operators. They used crossover and developed several mutation operators incorporating non-payoff information. They used Fletcher-Reeves (a conjugate gradient method) and golden search together as a mutation operator. However, the use of knowledge augmented need not be restricted to mutation and can be extended to other GA parameters like the crossover, the population size, the number of generations etc.

Essentially, there are two primary factors in genetic search: population diversity and selective pressure. Many other methods/parameters used to 'tune' the genetic search are really indirect means of affecting selective pressure and population diversity. Increasing the selective pressure focuses on the top individuals in the population but the 'exploitation' of genetic diversity is lost. Reducing the selective pressure increases 'exploration' because more genotypes and thus more schemata are involved in the search. The diagnostic accuracy is improved due to the ability of a GA-based technique to retain full non-linearity and deal with measurement noise. Although genetic algorithms are randomised in a certain way, they efficiently exploit historical information to obtain new search points with expected improved performance.

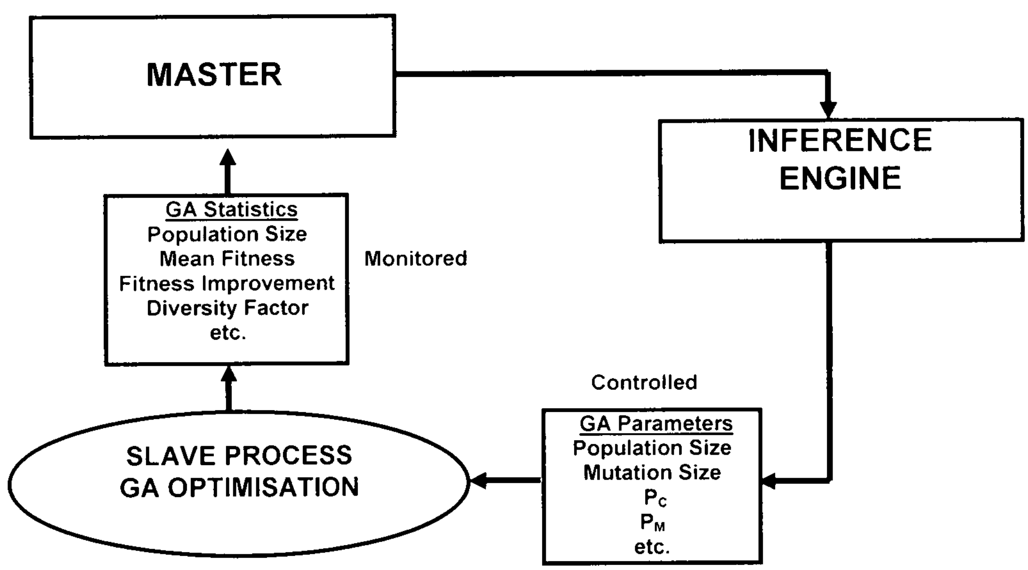


Figure 6.3: Schematic diagram of an embedded expert system

The basic function of the inference engine is to accumulate evidence for/against the value of a particular GA parameter and primarily use a backward chain reasoning process to reach conclusions. Input data from a pre-processing algorithm (described later) and a knowledge database are used by the inference engine to deduce facts or conclusions. When conclusions matching a specified pattern are made, a special set of high priority goals can be activated, thereby enabling the inference engine's forward chaining reasoning capability. E.g when the master feels that the diversity factor is low it will direct the population manager (program module) to increase the population by a predefined percentage.

The master algorithm could also vary the GA parameters like the probability of crossover and mutation in order to increase the exploration potential of the population. In cases where the population fitness does not show significant improvement, the master will be directed to selectively withdraw under performing individuals and monitor the fitness for further generations. If even after that this, the fitness does not improve, the master will assume that the algorithm has converged to a solution and stop the search for that fault class and move on to the next fault class.

A schematic diagram of the system is shown in figure 6.3. The master monitors certain parameters like the population size (N), diversity factor, mean fitness etc. and forwards it to the expert system. A rule-based system (IF-THEN) has been built into the model, which assess the situation and directs the alteration of the GA parameters like the population size, P_C, P_M etc.A simple example of the working of the system is shown in figure 6.4, where the population size is controlled by the master. One of the monitored parameters (fitness improvement), is shown to be influencing the population size.

The population starts with 100 strings. The master controls the population size based on the fitness improvement. When there is no further fitness improvement on only small improvement, the master directs an increase in population to increase the diversity factor. There is only a slight improvement in the fitness and therefore the master withdraws the strings selectively to reduce the population size and finally terminates the search process. This technique is an important development in reducing the total run time of the algorithm.

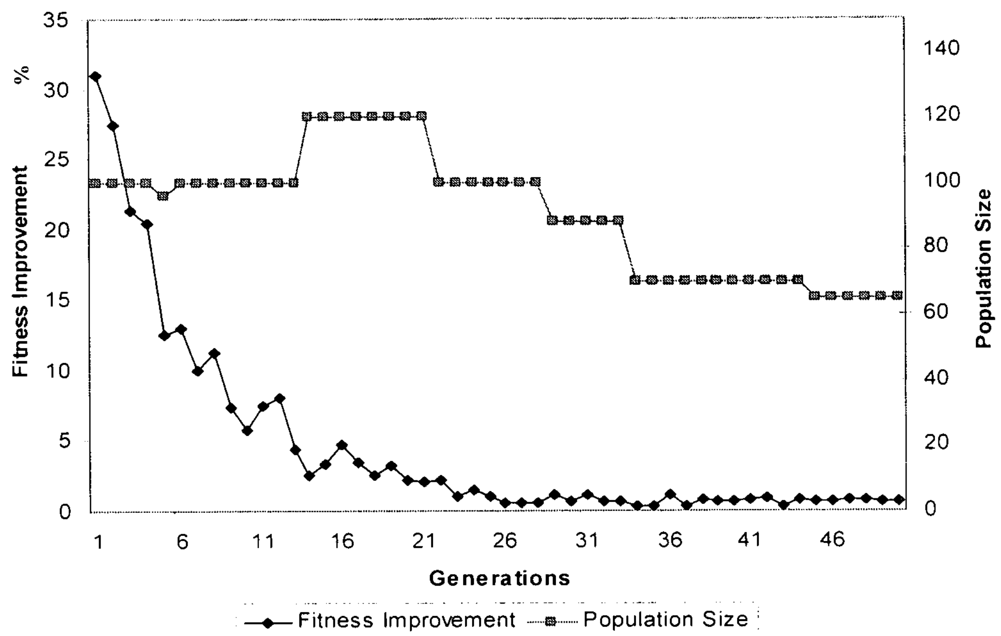


Figure 6.4: Variation in population size with fitness improvement

6.3.3 Elitist Model Concept

While the master-slave concept and the embedded expert system concepts have the advantage of reducing the total run time, but it is possible that the accuracy has been compromised during the process of manipulating the population. In order to prevent this, the elitist model concept is implemented as shown in figure 6.5. Since the process of population generation is a random process and the GA operators are applied to randomly chosen strings or pairs of strings, it is possible that some of the strings produced in the earlier generations are close to the global minimum (therefore indicative of the fault). However, such strings could be lost during subsequent generations due to crossover or mutation. In the elitist process, a certain percentage of promising individuals are placed in an elite pool on completion of a generation. During the subsequent generations, the good individuals from that generations are compared with the strings in the elite pool and swapped with comparatively weak ones. In this manner the best individuals are preserved over many generations and introduced in the main population towards the later generation for effective local search.

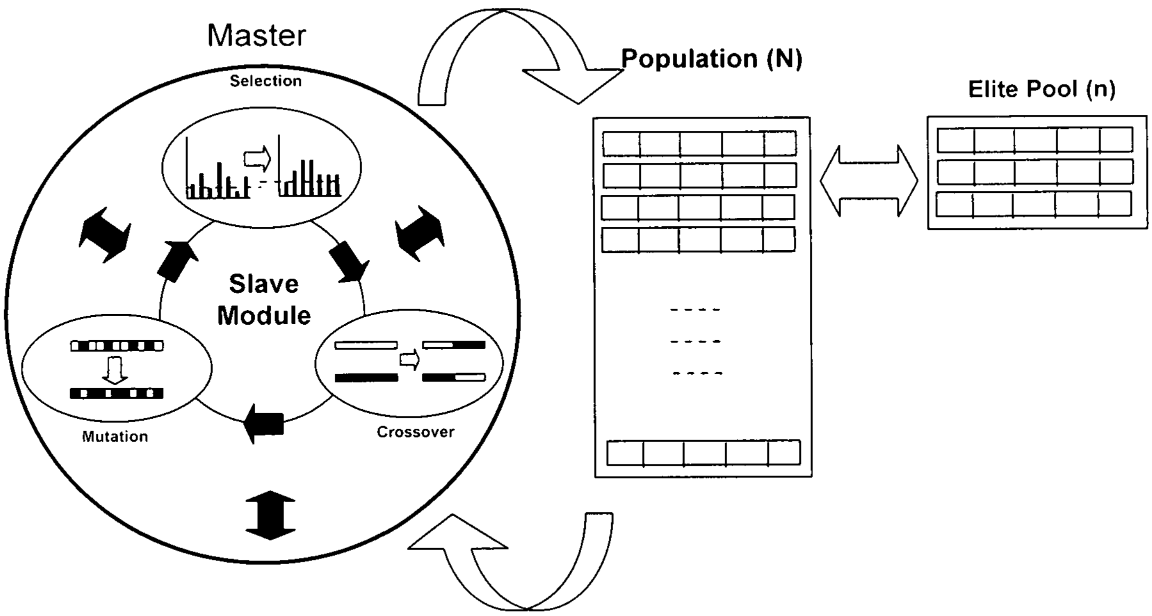


Figure 6.5: Elitist Model Strategy

6.3.4 Response Surface Method

In many problems we have specific knowledge that allows us to construct approximate models of our problem. In turn, modelling capability allows us to create more or less accurate approximations to our objective function. With genetic algorithms, this knowledge can be put to good use by reducing the number of full-cost functions evaluations. In many optimisation and search problems, a single function evaluation is fairly costly process, involving many layers of subroutines, numerical or symbolic computation, iterations and various coding and decoding functions. As a result, if savings in computation time are possible through approximate, perhaps rough estimation, of the objective function , they are worth pursuing so that more evaluations can be performed in the same time. This observation is particularly relevant to genetic algorithms, as we expect GAs to behave robustly under error and noise because of their population -sampling approach.

As described earlier, the engine performance model forms the heart of the diagnostics model and is also responsible for the slow performance of the GA diagnostics model. The engine performance model is an iterative process and the relations between various parameters are highly non-linear. One way to improve the speed is to use a response surface to approximate the objective functions instead of using the performance model.

A response surface is a complex non-linear function representing the engine performance model. The aim of the response surface method is to obtain an objective function of a given string without having to run the performance code. This method, which completely avoids the performance model, is very useful in the earlier generations of the GA diagnostics model. A suitable representation of the performance code is essential in order to implement this technique, which can be beneficial in speeding up the overall process. The rationale behind this concept is to avoid spending time on evaluating strings which are to be anyway discarded in the initial generations.

Data for response surface is generated using the engine performance model. It is very similar to generating the search space by varying the engine performance parameters (component flow capacities and efficiencies) in small steps from its baseline values and implanting it into the engine performance model. A set of measurements are obtained for these conditions and compared with corresponding engine baseline parameters. The sum of the deviations is the objective function. This data is used to generate a response surface. The various methods to generate response surface will be discussed later in this chapter

In order to implement the response surface method, the traditional objective function needs to be modified by splitting it into two objective functions. Since the response surface is created by implanting faults and comparing it with baseline values, the objective function obtained from the response surface will be with respect to the baseline and needs to be compared with the objective function obtained from the actual data and baseline. The modified objective function is given by :

$$\Delta J = \left| \sum_{j=1}^{NM} \frac{\left| z_j^b - h_j(x, w) \right|}{z_{odj}(w).\sigma_j} - \sum_{i=1}^{NM} \frac{\left| z_i^b - z_i^s \right|}{z_{odj}(w).\sigma_i} \right| \qquad (6.4)$$

The parameters are the same except for the superscripts *'b'* and *'s'*, which mean baseline and simulated respectively. A schematic diagram of the modified objective function is shown in figure 6.6. A set of measurements is obtained from the engine and is compared with the corresponding baseline (clean parameters) measurements. An objective function is calculated which is designated as J_1. This is required to be calculated only once. The other objective function, J_2 is directly obtained from the response surface. The optimisation of ΔJ (difference between J_1 & J_2) tends to achieve the best solution or more appropriately, eliminates the bad solutions.

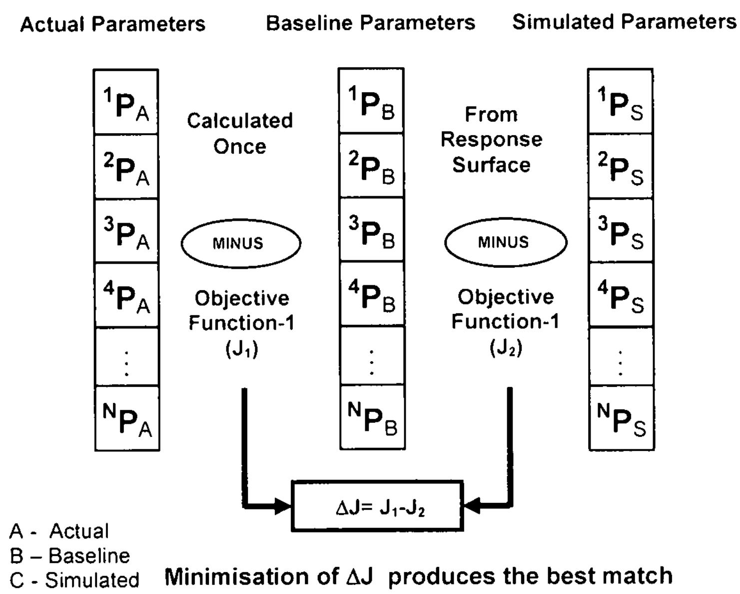


Figure 6.6: Modified objective function

At this point it is pertinent to mention that the optimisation of ΔJ shown in equation (6.4) may not produce the exact match for the reason that faults with different signatures could also have similar values of objective function. The fault signatures producing J_1 and J_2 could be different and it is not same as calculating J between the faulty data and the simulated parameter using the equation (5.2). However, what is important at this stage is to identify the strong individuals and create a condition for the weak individuals to be eliminated early in the search process. The calculation of J_1 gives the sum of deviations from the baseline. This value indicates that, deviations producing J_2, which are close to J_1 in magnitude are likely candidates for further examination. At this point, the signs of deviations are not considered as they will be eliminated when objective function is calculated with measurements obtained from performance model using equation (6.1). Some of the ways to develop a response surface which have been investigated are enumerated below-

6.3.4.1 Surface Fit -General Regression (Gaussian Functions)

This method involves the development of a general regression function using Gaussian functions as shown in equation 6.5 to represent a complex function like the search space. The aim is to evolve an equation which can readily return an objective function when given a set of deviation is engine performance parameter. Once the regression coefficients have been obtained, the reanalysis and sensitivity analysis represented by equations 6.5 & 6.6 require trivial computational effort. The constants and coefficients have been obtained using the MATLAB statistical toolbox.

$$f(x,y) = Ae^{(-b_1x-b_2y)} + Be^{(-b_3x-b_4y)} + \dots\dots\dots\dots \tag{6.5}$$

in the case of engine fault analysis the equation can be re-written as-

$$J_{RS} = Ae^{(-b_1\Delta\eta-b_2\Delta\Gamma)} + Be^{(-b_3\Delta\eta-b_4\Delta\Gamma)} + \dots\dots \tag{6.6}$$

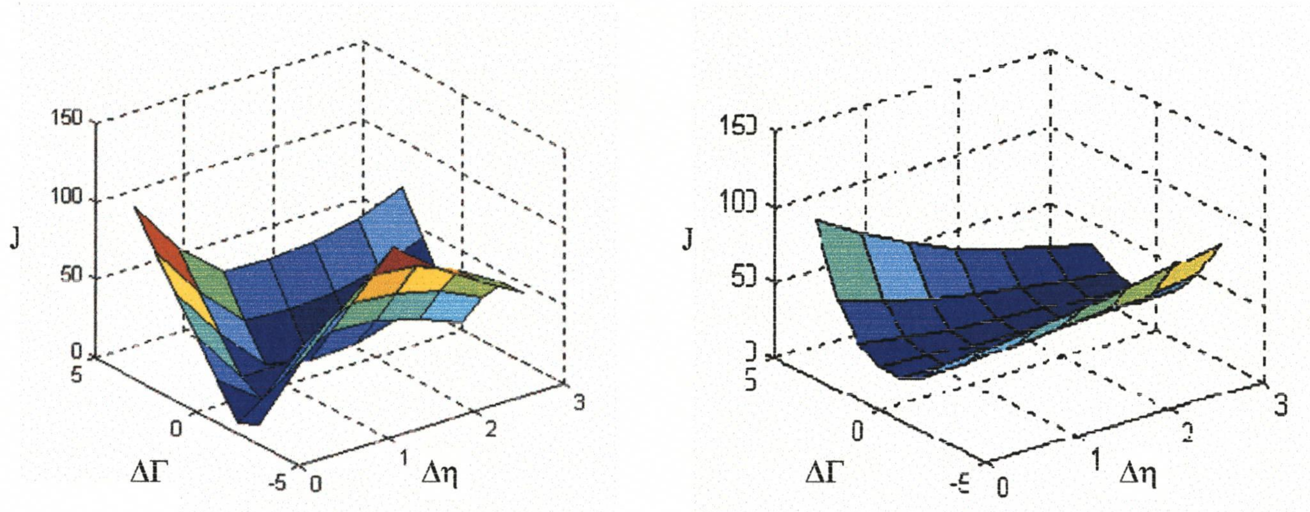


Figure 6.7: Function Approximation using Gaussian Function

A comparison of the search space obtained from the above equation with the actual search space is shown in figure 6.7. It is evident that the surface obtained from this technique is very general and smoothed out concealing the surface details. Such techniques are fast and easy to compute but the results are suitable for smooth functions and not for highly non linear engine performance model.

6.3.4.2 Radial Basis Functions (RBF)

RBFs have attracted a great deal of interest due to their rapid training, generality and simplicity. They have been widely used for Generalized Regression Neural Networks (GRNN). They are several orders of magnitude faster in training when compared to the standard back propagation but have a major disadvantage: after training, they are generally slower to use, requiring more computation to perform a classification or function approximation. It can approximate any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Furthermore, it is consistent, that is, as the training set size becomes large, the estimation error approaches zero.

GRNN is, in essence a method for estimating *f(x,y)*, given only a training set and is based on the following formula from statistics

$$E[y \mid x] = \frac{\int_{-\infty}^{\infty} y f(x,y)\,dy}{\int_{-\infty}^{\infty} f(x,y)\,dy} \tag{6.7}$$

where

y = output of the estimator

x =the estimator input vector

$E(y|x)$ = the expected value of out , given the input vector x

$F(x,y)$ = the joint probability density function (pdf) of x,y

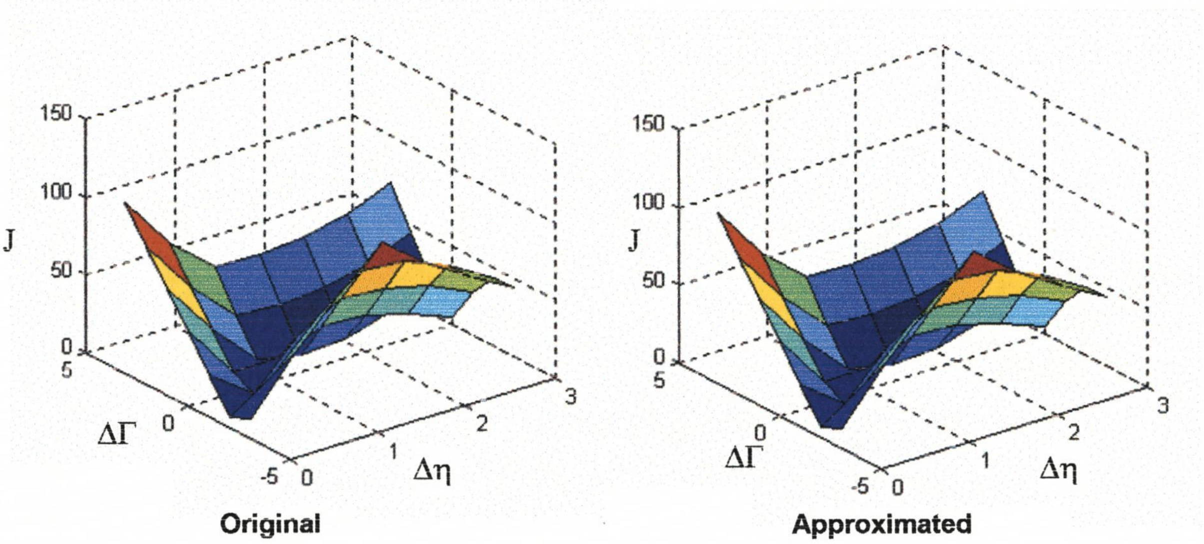


Figure 6.8: Function Approximation using Radial Basis Function

The accuracy of the estimated function is very high (as shown in figure 6.8), as long as the input vector is close to the training vector. The RBFs are highly localized and therefore need large amounts of training data. The large amount of training data creates a large number of nodes. Though the training is very quick, the function approximation is a computationally intensive process.

6.3.4.3 Feed Forward Back Propagation Network (FFBPN)

Having investigated the possibility of representing the search space in the form of a response surface using the first two options and carefully considering the advantages and disadvantages of the process, it was decided to investigate the possibility of using a FFBPN for the generation of a response surface. The FFBPN is a standard neural network widely used for classification.

The FFBPN are known to represent complex functions very accurately when trained with appropriate and adequate samples. A typical training data is shown in table 6.1. Fault class-2 has been trained using a network (8-20-20-1 structure). Training data was generated by implanting faults in the engine performance model and the objective function calculated with measurements obtained.

Network Input Data
(Engine Performance Parameters)

FAULT CLASS: 2

Sl.	Flow-Cap	Effy	J	Sim-J
1,	-3.0000,	-0.0000,	2.0427,	0.0000
2,	-3.0000,	-0.5000,	3.1228,	0.0000
3,	-3.0000,	-1.0000,	4.2269,	0.0000
4,	-3.0000,	-1.5000,	5.3498,	0.0000
5,	-3.0000,	-2.0000,	6.4931,	0.0000
6,	-3.0000,	-2.5000,	7.6618,	0.0000
7,	-3.0000,	-3.0000,	8.8373,	0.0000
8,	-2.0000,	-0.0000,	1.8688,	0.0000
9,	-2.0000,	-0.5000,	2.0942,	0.0000
10,	-2.0000,	-1.0000,	3.2336,	0.0000
11,	-2.0000,	-1.5000,	4.3933,	0.0000
12,	-2.0000,	-2.0000,	5.5735,	0.0000
13,	-2.0000,	-2.5000,	6.7781,	0.0000
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33,	1.0000,	-2.0000,	7.8833,	0.0000
34,	1.0000,	-2.5000,	9.5933,	0.0000
35,	1.0000,	-3.0000,	11.3116,	0.0000
36,	2.0000,	-0.0000,	2.0767,	0.0000
37,	2.0000,	-0.5000,	3.7091,	0.0000
38,	2.0000,	-1.0000,	5.3507,	0.0000
39,	2.0000,	-1.5000,	7.0042,	0.0000
40,	2.0000,	-2.0000,	8.6793,	0.0000
41,	2.0000,	-2.5000,	10.3509,	0.0000
42,	2.0000,	-3.0000,	12.0971,	0.0000
43,	3.0000,	-0.0000,	2.8526,	0.0000
44,	3.0000,	-0.5000,	4.4494,	0.0000
45,	3.0000,	-1.0000,	6.0568,	0.0000
46,	3.0000,	-1.5000,	7.6868,	0.0000
47,	3.0000,	-2.0000,	9.4801,	0.0000
48,	3.0000,	-2.5000,	11.3060,	0.0000
49,	3.0000,	-3.0000,	13.1517,	0.0000
END				

Network Target Data
(Objective Function)

Table 6.1: A typical training data (for fault class-2)

The faults implanted and corresponding objective function form the network input data. Training data is generated separately for each fault class and the network is trained to return an objective function for a particular fault class only.

A comparison of the estimation is shown in figure 6.9. The approximation is quite accurate for the same set of data points. This method is a good compromise between speed and accuracy when compared with the other methods described earlier. The networks are trained for specific fault classes for specific operating points.

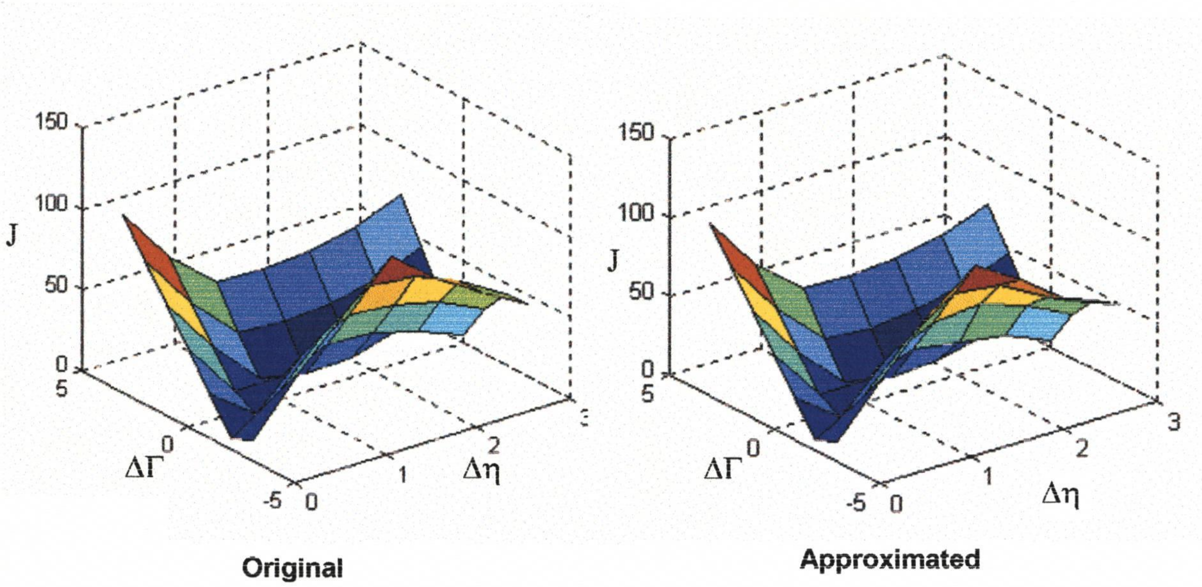


Figure 6.9: Function Approximation using FFBPN

The response of the network to randomly generated test data is shown in table 6.2. The variation in performance parameters for a single component fault is shown is shown column 2 and 3 (flow capacity & efficiency respectively). These variations are generated randomly and the objective function (with respect to baseline) obtained using an engine performance model is shown in column 4. The objective functions obtained from response surface is shown in column 5 and it can be observed that the output of the network is close to the objective functions in column 4. For the purpose of eliminating weaker strings in the initial generation, this accuracy is deemed reasonable. The attractiveness of the response surface approach is that the accuracy of the final results almost exclusively depends on the accuracy of the response surfaces' data and on the amount of data points available. MATLAB was used for training the networks and the trained network was imported into the diagnostics model.

Simulated fault condition (Performance parameters)

Objective Function from Response Surface

Sl	Flow-Cap	Effy	J	sim-J
1,	1.5244,	-2.7578,	10.8772,	10.9003
2,	-1.9718,	-0.1636,	1.3295,	1.4410
3,	-2.6872,	-0.9055,	3.6872,	3.6416
4,	1.2230,	-2.8468,	10.9594,	10.9698
5,	2.4871,	-2.0263,	9.0940,	9.1126
6,	1.7920,	-1.4337,	6.6255,	6.6211
7,	-1.3897,	-2.2181,	6.0237,	6.0104
8,	1.4740,	-1.7439,	7.4185,	7.4095
9,	-2.6970,	-2.2039,	6.6744,	6.7042
10,	2.6517,	-2.6591,	11.5232,	11.5002
11,	1.1389,	-0.3446,	2.4197,	2.4402
12,	-1.9380,	-2.2502,	6.1236,	6.0697
13,	-1.6667,	-2.1481,	5.6646,	5.6580
14,	-1.0761,	-0.3544,	1.0565,	1.0953
15,	0.1008,	-0.9225,	3.2802,	3.2713
16,	0.8164,	-0.9779,	4.2298,	4.1933
17,	-2.6019,	-2.7594,	7.9088,	7.9234
18,	0.3322,	-1.9357,	7.0318,	6.9924
19,	1.5718,	-0.3822,	2.9536,	2.9857
20,	-0.3134,	-2.5194,	8.4010,	8.4027

Objective Function from Performance Model

Table 6.2: Response to a random input for single component fault

6.4 Development of a 3-Stage GA Diagnostics Model

Various techniques to improve the performance of the diagnostics model in terms of accuracy and speed of convergence have been examined individually and their merits discussed. A 3-stage Integrated Fault Diagnostic Model (IFDM), as shown in figure 6.10, has been developed which incorporates the different methods discussed. The objective of the 3-stage model is to extract the benefit of each technique at appropriate stages of the diagnostics process. The IFDM model is described as follows:

Stage-1: The process starts with random generation of the population similar to the basic GA-based model. The difference here is the use of a response surface to obtain the objective functions instead of using the performance model (to calculate). The optimisation progresses one fault class at a time. The response surfaces for all the fault classes are developed by training the Feed forward back propagation networks. Once trained, the network weights are frozen so that the network can be re-generated during the diagnostics process. The objective function obtained from the response surface is used to calculate the fitness of the strings in the initial stages of the diagnostics process. The diversity factor will be high in the beginning and there may be many strings which are weak and need to be eliminated. The response surface approach helps in eliminating the weak individuals without having to run the performance model. The use of the response surface increases the exploration potential of the search space as more strings can be generated at the start of the diagnostics process .This technique increases the speed during the initial phase to a magnitude of several order quicker than the conventional search.

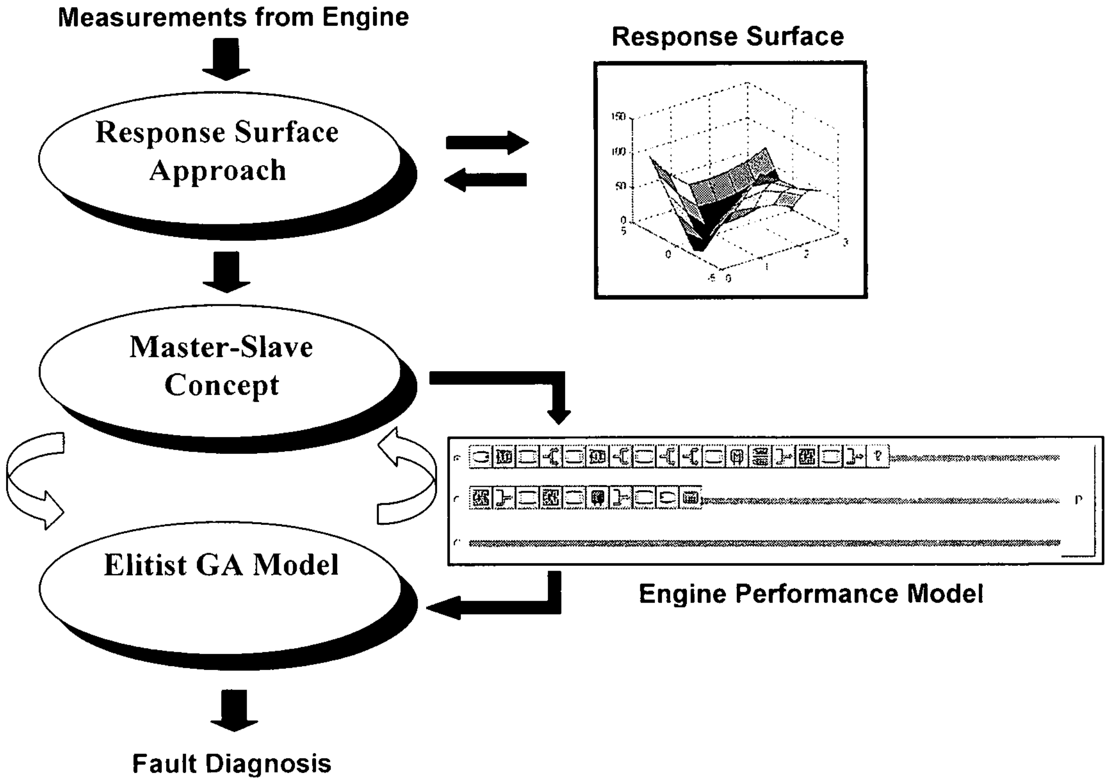


Figure 6.10: Schematic diagram of 3 stage diagnostic model

Stage-2: By the time the process reaches stage-2, most of the weak individuals are eliminated from the population over a number of generations. The concept of adaptive GA is applied in stage-2 to improve the quality of the population. This process is carried out with the master-slave configuration which monitors the slave module based on certain predefined parameters. The master interrogates an embedded expert system (consisting of IF-THEN rules) and seeks direction. All the fitness calculations during stage-2 use parameters from the engine performance model. The master also monitors the fitness improvement history to establish a termination condition. Early termination of the search process for fault classes not likely to give a solution can reduce the overall run time of the diagnostics process.

Stage-3: in reality, this works in close coordination with stage –2. In stage-3, certain percentage of the good strings are identified and preserved in an elite pool which is not subjected to the genetic operations. This ensures that the potential solutions are preserved over generations. On completion of a generation, the best strings are compared with the elite pool and the better strings from the main population are swapped with the weaker individuals from the elite pool. In this way the elite pool always contains the best solution from all the generations at any given time. Towards the later generations, on instructions from the master GA, the individuals from the elite pool are introduced into the main pool and more individuals are created in the vicinity of the individual from the elite pool. This concept ensures more localized search towards the end.

6.5 Hybrid Model- Combining GA and ANN

When problem specific knowledge exists, it may be advantageous to consider a GA hybrid. Genetic algorithms can be crossed with various problem specific search techniques to form a hybrid that exploits the global perspective of the GA and the convergence of the problem specific technique. A number of authors have suggested such hybridization (Bethke, 1981; Bosworth et al, 1972; Goldberg, 1983). However, there is not much published work describing the results of GA-hybrid studies. Nonetheless, the idea is simple, has merit and may be used to improve ultimate genetic search performance.

There are several fault diagnostics techniques and optimization techniques which can be combined with GAs to form a hybrid system for efficient fault diagnostics. Researchers like Gulati (2002) have suggested the use of GA for a broader search and the use of calculus-based methods for local search. The approach adopted here is to identify a method which could be used to reduce the number of fault classes so that the GA module can be used to search the fault classes for faulty components and quantify the fault. The rationale behind this is to avoid searching fault classes which are not likely to have faulty components.

For the problem in hand, an analogy can be drawn with the diagnostic engineers of yesteryears, when modern-day engine fault diagnosis techniques were in their infancy and when an analyst would make an intelligent assessment based on certain thumb rules. The method used was similar to the fault tree method in which the branches of the fault tree are traversed by eliminating certain criteria to arrive at the fault. The fault tree technique has the limitation that only single component faults can be identified. However, in the case of the proposed hybrid system, a Fault Class Classifier (FCC) is expected to identify the likely fault class(es) and the GA optimizer could subsequently explore the fault classes and quantify the faults associated with the components.

Extensive literature study showed that feed forward back propagation network remains an effective paradigm and is by far the most commonly applied neural network for classification problems. Ogaji and Singh (2002) have used the concept of cascaded neural networks for component and sensor fault identification. An informal count indicates that more than 85% of published applications have used FFBPN. In difficult applications where the input/output relationships are nonlinear and/or involve high order correlations among the input variables, back propagation has produced accurate results. The disadvantage of its slow training is partially offset by its rapid computation in the forward direction.

It was felt that the ability of the ANN to classify the given data with a relatively small network can be used to act as a preprocessor for the GA diagnostics. Even if the neural network is able to classify the given data as single or multiple component fault the search time is reduced to 25% of the original time in the case of single component faults (the GA module has to search only first 7 fault classes) or to 75% of the original time in case of multiple components fault (the GA module has to search 21 fault classes). A schematic diagram of the concept of the hybrid model is shown in fig-6.11. The hybrid model consists of a Nested Neural Network (NNN) in which each network has a limited task of classifying the data into subgroups. One way to classify is to train a network for all possible combinations of faults. But the training set required to fully represent all possible combinations of health parameters and sensor biases will be prohibitively large. It would take excessive time to train such a neural network and their performance might not reach satisfactory levels. In the light of the above, the problem domain has been partitioned into smaller and specific tasks. A node in the NNN is trained to classify the given input into any one of the subcategories, usually two or more subcategories or BRANCH nodes (described later) .

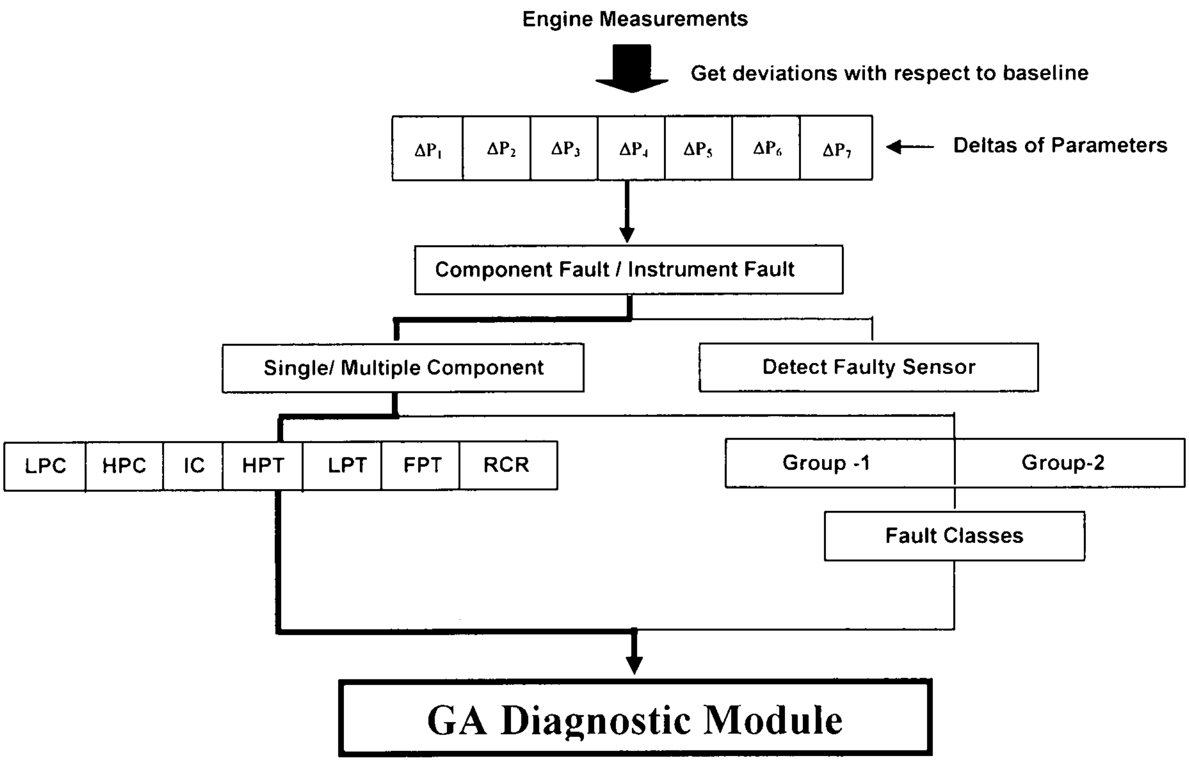


Figure 6.11: Concept of Hybrid model

This approach has been found to be more accurate when compared to training a single large network to identify the faulty components. The dark line shows the flow of the algorithm to arrive at the final stage, for an arbitrary set of measurements. The nodes are classified into 'BRANCH' nodes and 'TERMINAL' nodes. The bottom most level of each branch/path consists of terminal nodes. The 'TERMINAL' nodes have an important task of extracting and submitting the fault class(es) for optimisation by GA Module.

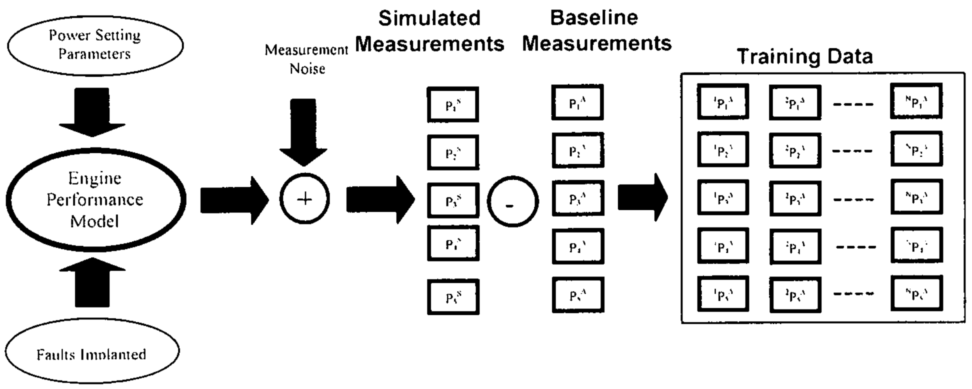
Input data from an engine is fed into the NNN pre-processor. The first step is to identify whether the input data was generated due to a faulty component or a faulty sensor. Once the classification has been made, the data is forwarded to the next level. If the input data is associated with a component fault, then it is forwarded to a node classifying the input data into Single or Multiple component faults. In the same way, the input data traverses through the BRANCH nodes and arrives at the TERMINAL node. A terminal node will classify the input data to a single fault class or a group of fault classes to be explored by the GA optimizer.

6.5.1 Type of Training and Network Size

Whether in classification or regression , it is necessary to employ appropriate training algorithms. For feed forward back propagation network, various training algorithms such as resilient backpropagation, delta-bar-delta, conjugate gradient algorithms. Levenberg Marquardt, Bayesian regularisation etc. are available. The choice of algorithm is usually a trade-off between many factors such as minimum RMS error obtainable, length of training time or speed of convergence, memory requirements, nature of the problem. The choice of algorithm is left to the user and the type of problem being solved.

In the present work, several algorithms were tested and the conjugate gradient method was found to be most suitable from the point of speed of convergence and memory requirement. The algorithm gave good results by improving the generalisation especially with respect to classification, which is the main requirement in the model. The radial basis functions were also experimented but they need a large amount of nodes and the gives particularly good result if the input data is close to the training data.

The number of layers and number of processing elements per layer are important decisions to be made during the design of an ANN. The number of processing elements in the input and output layers are fixed by the number of input measurements and required output vectors respectively and therefore only the number of hidden layers and number of processing elements in the hidden layers are to be determined. There are no best solutions to this problem and is again dependent of the nature of the problem being addressed. In general, as the complexity in the relationship between the input data and the desired output increases, then the number of processing elements in the hidden layer should also increase. The number of processing element may also depend on the amount and the quality of training data. In is noteworthy that less number of processing elements would mean there are insufficient network parameters (weights and biases) to undertake the required tasks which leads to under learning of the problem domain while more that necessary processing elements in the hidden layers would lead to poor generalisation as the features of the training patterns are memorised making the network less capable to apply knowledge learned to patterns that were not included in the training process though within the problem domain in other words the network becomes useless on new data sets.



P^S : Simulated parameter (measurement)
P^B : Actual parameter (measurement) from engine
P^Δ : Measurement Deviation

Figure 6.12: Schematic Diagram of Data Generation

6.5.2 Data Generation for Training

A non-linear thermodynamic model of the behavior of the engine was used to generate data for training the neural networks (A detailed description of the engine model has been given in chapter-4). A schematic diagram of the data generation process is shown in figure 6.12. Patterns of measurement deltas for training are generated using a computer simulation code. A series of know faults are implanted into the engine model and corresponding sets of measurements are obtained from the engine model. The measurement deviations from their corresponding baseline values are presented to the network for training.

Some of the salient features of the data generation process is:

- A marine gas turbine operates at sea level and therefore it is assumed that it operates in a constant pressure environment.
- Ambient temperature may vary depending on the place but the data has been generated for a deviation of 20 deg from ISA SLS condition.
- The operation of the gas turbine is dependent on the specific mission profile of the ship and, in general, it implies operating most of the time at part load condition. However, for the purpose of training the networks, the data has been generated for the same operating point for which GA based diagnostics is to be carried out (as shown in Table 5.2).
- Training data is generated separately for different operating points.
- Training data is generated separately for different nodes (network).
- Training patterns are generated in two groups

    (i) Faults with no noise or bias
    (ii) Faults with noise and no bias
    (iii) Measurements with noise and bias (for sensor fault detection)

The process of test data generation has been accomplished using a program developed in MATLAB ver 6.0 which can directly interact with the performance code to obtain the required measurement set.

6.5.1.1 Addition of noise to Data generated

In order make the simulated data resemble real data, noise is added to the measurement set. White noise with zero mean and having a Gaussian distribution is added to the measurements generated. The standard deviations for individual sensor has been given in chapter-5(as provided by the sponsor). The sigma values basically indicate the spread of the individuals in a given population set. E.g the 1σ given value given indicates that 68% (34% on either side of mean) of population fall within the range between the population mean and sigma value. 2σ indicates that 95% population falls between mean and 2σ. And a value of 3σ indicates 99.7% of population between the range mean and 3σ.

Given the value of sigma, random noise with zero mean can be generated. Figure shows the noise levels generated with σ=0.25.

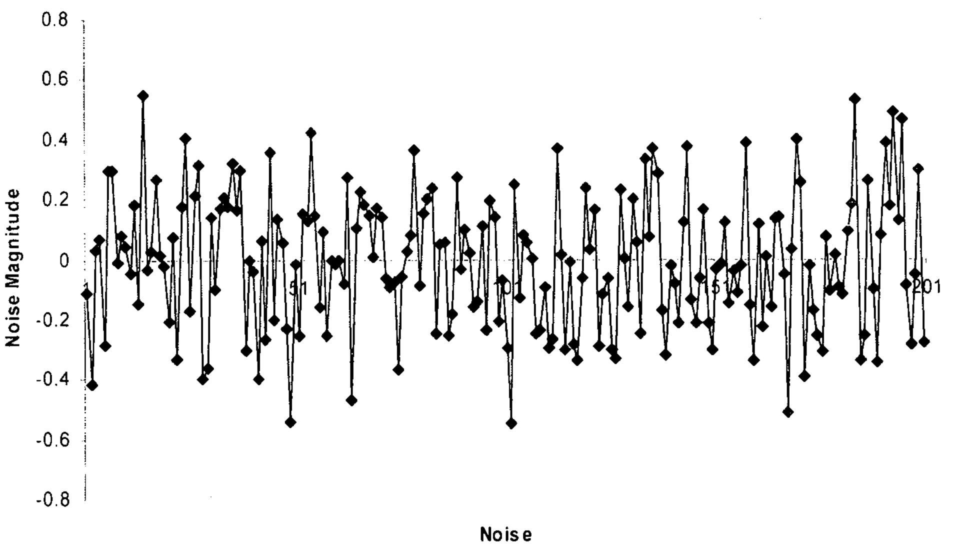


Figure 6.13: Sample of noise used in training data

As discussed earlier, the magnitude of 68% of the noise values generated, will be between -0.25 and 0.25 as the mean in this case is taken as zero. Figure 6.14 shows the distribution for 100000 samples of noise generated. It can be observed that the data has a mean of zero and has a perfect bell shape. The noise values are generated depending on the σ of that particular sensor and added to the measurements.

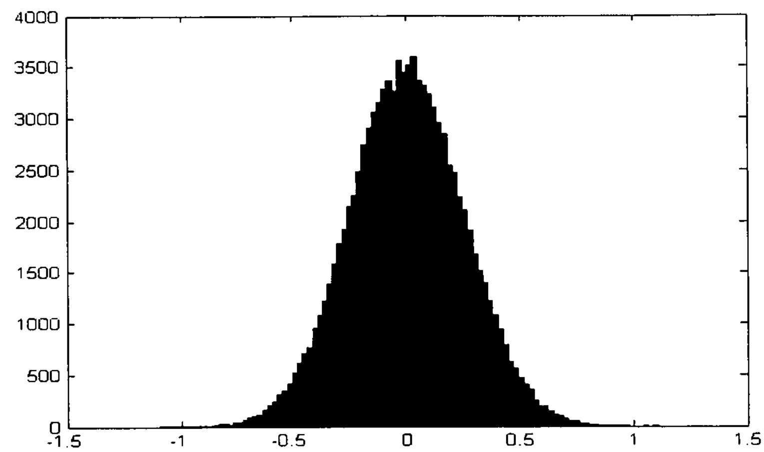


Figure 6.14: Distribution of Noise generated

6.5.2 Training the Networks

As mentioned earlier, the networks are classified as 'TERMINAL' and 'BRANCH' networks. The BRANCH networks classify the input data into subgroups and forward it to the appropriate network for further classification. The TERMINAL networks are expected to identify the fault class(es) to be optimized. The TERMINAL networks form the last layer of the NNN. Table 6.3 shows a typical instruction set for generating training data for a TERMINAL network.

NEURAL NETWORK TRAINING INSTRUCTION SET

NODE :11 Note:- Enter '00' for Auto-Associate Network
Network Type : FFBP
Network Status : TERM
Network Input : Measurements
Network Configuration :[8][20][3] Note:- Mirrored For AAN
Input Vector Size :10
Fault Classes Involved : 7
Target Vector Size : 3
Target Category : 7
No of Training Sets :2500
Target Set :-

Target Vector

Category	ID	Target			Component
Fault Class-1	1	0	0	1	LPC
Fault Class-2	2	0	1	0	HPC
Fault Class-3	3	0	1	1	ICL
Fault Class-4	4	1	0	0	HPT
Fault Class-5	5	1	0	1	LPT
Fault Class-6	6	1	1	0	FPT
Fault Class-7	7	1	1	1	RCR

Target Vectors represent faulty components

Table 6.3: A typical instruction set for training

The instruction set gives the type of network and the configuration of the network. It also gives the composition and size of the target set. It can be observed that this particular network is trained to identify the fault class suspected of having a single component fault.

Measurements deviations from Base line (Un-deteriorated Condition)

Sl.	Sensor-1	Sensor-2	Sensor-3	Sensor-4	Sensor-5	Sensor-6	Sensor-7	Sensor-8	Sensor-9	Sensor-10
1,	0.557820.	0.073299,	0.557562,	-0.060568,	-0.307398,	-0.461859,	-0.396502,	-0.457145,	-0.234463,	-1.945982,
2,	0.738743,	0.140595.	0.738419,	-0.072176,	-0.381592,	-0.720013,	-0.628681,	-0.724288,	-0.252132,	-1.814817,
3,	0.920470.	0.208183,	0.920212,	-0.083863,	-0.456441,	-0.980420,	-0.862765,	-0.993653,	-0.269940,	-1.683033.
4,	1.102894,	0.275936,	1.102943,	-0.095647,	-0.532016,	-1.243101,	-1.098828,	-1.265379,	-0.287909,	-1.550729,
5,	1.288273,	0.344671,	1.288016,	-0.107324,	-0.608926,	-1.511606,	-1.339865,	-1.543019,	-0.306177,	-1.416666,
6,	1.472218,	0.413755,	1.472152,	-0.119196,	-0.685477,	-1.780002,	-1.580847,	-1.820392,	-0.323643,	-1.282518,
7,	1.656239,	0.482764,	1.656289,	-0.131253,	-0.762649,	-2.049671,	-1.822864,	-2.099097,	-0.341499,	-1.148331.
8,	0.332061,	0.034031,	0.331726,	-0.037916,	-0.188307,	-0.253411,	-0.215246.	-0.248529,	-0.151812,	-1.305576,
9,	0.515527.	0.102416,	0.515394,	-0.049066.	-0.262310.	-0.512070,	-0.448151,	-0.516287.	-0.169607.	-1.174868.
10,	0.696221.	0.169405.	0.696250.	-0.060538.	-0.336099,	-0.769565.	-0.679693.	-0.782728,	-0.187427.	-1.045531.
-	---------	---------	---------	---------	---------	--------	---------	--------	--------	--------
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Number of training Patterns

Table 6.4: ANN input data for training

TRAINING DATA FOR NODE: 1

Node-ID : 11
Network : FFBPN
Node Type : TERM
Target Size : 3
Target Categories : 7

Target vector

Performance Parameters causing the fault

Component ID

	Target vector				Performance Parameters causing the fault				Component ID
1	0	0	1	(LPC)	-3.00	0.00	0.00	0.00	1
2	0	0	1	(LPC)	-3.00	0.50	0.00	0.00	1
3	0	0	1	(LPC)	-3.00	1.00	0.00	0.00	1
4	0	0	1	(LPC)	-3.00	1.50	0.00	0.00	1
5	0	0	1	(LPC)	-3.00	2.00	0.00	0.00	1
--	-	-	-	- - - -	- - -	- - -	- - -	- - -	-
61	0	1	0	(HPC)	-2.00	2.50	0.00	0.00	2
62	0	1	0	(HPC)	-2.00	3.00	0.00	0.00	2
63	0	1	0	(HPC)	-1.00	0.00	0.00	0.00	2
64	0	1	0	(HPC)	-1.00	0.50	0.00	0.00	2
65	0	1	0	(HPC)	-1.00	1.00	0.00	0.00	2
66	0	1	0	(HPC)	-1.00	1.50	0.00	0.00	2
67	0	1	0	(HPC)	-1.00	2.00	0.00	0.00	2
---	-	-	-	- - - -	- - -	- - -	- - -	- - -	--
333	1	1	1	(RCR)	2.00	1.00	0.00	0.00	7
334	1	1	1	(RCR)	2.00	1.33	0.00	0.00	7
335	1	1	1	(RCR)	2.00	1.67	0.00	0.00	7
336	1	1	1	(RCR)	2.00	2.00	0.00	0.00	7
----	---	---		----	----	----	----	-----	----
END									

Table 6.5: Typical network target data

The training data consists of the deltas in measurements as input to the network and component identity (in binary form) as the target vector. The network is trained to classify the data into fault classes.

A typical input data for the network is given in table 6.4 and target data is given in table 6.5. The network tries to match each input data with the corresponding target data by adjusting the weights.

Node Type : L3N1
Node Status: BRAN
Node-ID : 31
Inputs Size : 10
No. of Layers: 3
Layer 1 : 8 TF : tansig
Layer 2 : 12 TF : logsig
Layer 3 : 3 TF : purelin

Input Min-Max :

-3.2778	-3.0949	-3.2779	-0.7465	-1.4483	-4.4087	-3.9388	-4.7260	-2.0384	-2.3543
3.8384	2.6102	3.8383	0.2831	2.0300	2.1170	2.2263	2.2027	3.5640	2.7342

Input Weight Matrix:

0.1412	0.6962	0.5095	-0.2806	-0.2422	0.5848	0.2301	0.3493	0.3822	0.9508
1.7858	0.8852	0.7414	0.0555	0.4123	2.3768	-1.1516	-0.7987	0.0663	0.4631
-1.0118	0.6764	-0.6226	-2.4641	0.0826	0.6083	0.6673	0.1028	-0.1180	-2.4802
0.9728	-3.0819	0.1064	1.3611	1.5367	0.9719	0.2018	-0.3257	-0.1454	-0.4820
-1.1038	-0.6555	-0.2613	0.0676	-1.4358	0.9396	-0.7740	0.3161	0.2187	1.6512
-1.9571	-0.4661	-1.3288	2.2057	-0.1407	-0.8392	0.6645	0.2438	-0.1621	0.4566
0.6462	-0.6982	-0.2416	0.2801	0.9775	0.8792	-1.2021	-1.1465	0.2210	-2.0256
-1.5284	-0.1597	-0.4188	0.2824	2.8078	0.2972	0.1402	0.2535	0.2920	1.2121

Layer Weights:1-2

1.6097	2.3945	0.0926	0.0426	0.5989	-1.8735	1.6019	-0.8334
0.3491	1.8403	1.3604	-1.5790	1.3631	2.8392	2.0031	-2.3911
2.2486	1.0589	-0.3199	0.3020	-1.9945	2.0349	-0.2212	-0.0336
1.6791	-0.8257	2.2021	0.7613	-2.5772	0.6792	2.3032	-0.2815
-2.0890	0.1597	-1.9705	-1.2230	-0.7445	-1.5200	-1.4687	-1.2276
-0.9172	2.9922	-0.8665	2.5043	-0.4696	1.7466	3.0047	0.3634
0.3343	-2.1800	-1.0700	1.6237	-0.0111	1.0031	1.3211	-2.0506
-0.8394	2.7201	1.9904	0.5734	1.6904	0.5993	-0.3475	-0.5135
0.5674	1.7146	-0.6695	2.3599	0.9328	-2.5902	0.5953	1.2340
-1.7165	0.2774	2.7412	0.9654	-0.5913	-0.8501	2.5726	-0.7844
0.3785	-1.2760	-2.7412	-2.0399	-0.2691	-0.8809	1.1386	1.0870
1.3647	2.3661	-0.7781	-2.0468	0.4919	-2.0952	-1.3352	-0.9779

Layer Weights:2-3

0.7296	0.4011	-0.1444	-1.6255	-0.1908	2.6894	-0.6491	-0.6074	0.7493	0.6367	-0.7079	-0.1676
0.0200	2.4656	-0.3603	-1.9109	0.0206	0.2327	-0.0723	1.1458	-1.5766	1.0717	-0.5187	1.0787
0.1092	-1.7166	-0.2513	-0.4887	-1.7669	-1.1712	0.7584	0.1741	1.8094	1.0257	1.0840	0.8719

Bias Vector- 1

-1.8030	-0.7222	0.4460	-0.2565	0.3664	-0.9374	0.6636	-0.6435

Bias Vector- 2

-3.7340	-2.3694	-2.4319	-1.5779	1.3981	0.6242	0.1805	-1.2716	1.8610	-2.8418	3.1633	3.5725

Bias Vector- 3

-0.2177	-1.2517	-0.3464

Table 6.6: Representation of a Trained Neural Network

Since the input data is generated by implanting know faults into the engine performance model, working backwards we can know the fault. However, at this stage we are only interested in classifying, and not quantifying, the fault.

The Neural-Network Toolbox in MATLAB has been used for training all the networks. The weights obtained as the result of training the network are frozen and used in the diagnostics model to regenerate the same networks. A typical set of frozen network weights for a trained network (8-12-3 structure) is shown in table 6.6.

6.5.3 Confidence Rating of Networks

Once the individual networks have been trained to classify data into specific subgroups, they can be integrated to form a nested neural network for different levels of classification. Before entrusting the networks with the classification job, a Confidence Factor (CF) of each network has to be established to have confidence in the final output from the NNN. The CF of each network is obtained by simulating the network output with a large amount of randomly generated data set for that particular node. This is an important aspect of the HDM as the GA module depends on the classification ability of NNN. As it was described earlier that the nodes, particularly the TERMINAL nodes, are not constrained to give one fault class, but can suggest a set of fault classes to the GA module. This facility has been provided to reduce the probability of a wrong fault class being given to the GA module. While classifying the fault classes the CF of that nodes plays an important role in the number of fault classes being suggested. The higher the CF the lesser will be the number of fault classes suggested and also more confidence in the fault classes suggested. An explanation for this method has been provided in chapter-7 when the results are discussed.

High CF is particularly necessary in the BRANCH nodes as the decision made at the branch level is crucial for the progress of the solution in the correct direction. It is also possible that under some extreme conditions the network makes a wrong classification in the beginning, which can lead to input data being passed through the incorrect branches. To avoid such situation, different networks topologies can be used for classification. Different topologies would mean longer training time. However, once the networks are trained for a particular operating point, the classification is instantaneous. Examples of two topologies are shown in figure 7.23 & 7.24 to illustrate this principle. The difference in the configuration is the arrangement of nodes. The first two levels are common in the example shown, though need not necessarily be same. In the first scheme, node-1 classifies the data into component fault or sensor fault.

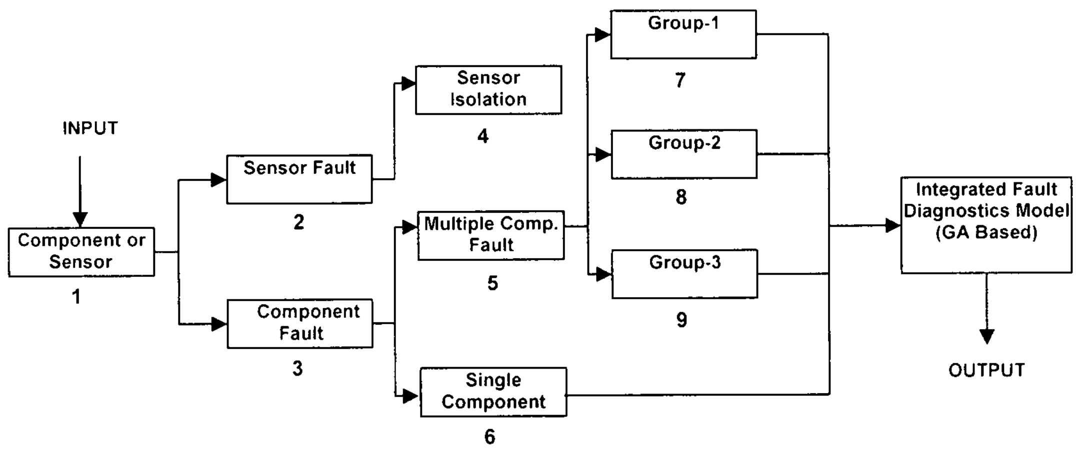

Figure 6.15: Nested Neural Network (Type-A)

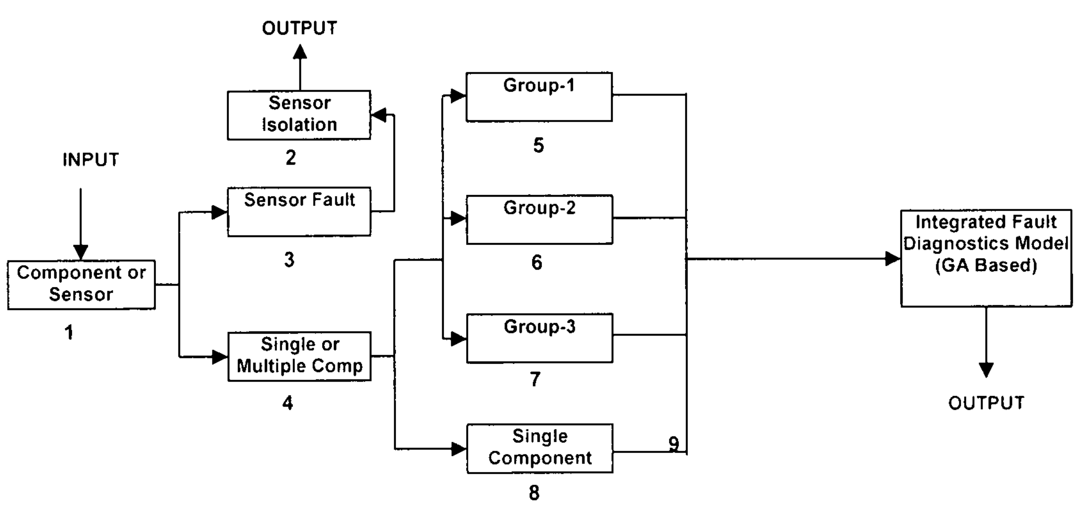

Figure 6.16: Nested Neural Network (Type-B)

If it is a component fault then it passes the data to node-2 which classifies between single or multiple component faults. If identified as multiple component faults, the data is passed to the next network where it is further classified into group-1, group-2 or group-3 and subsequently into fault classes to be optimized.

The second network starts in a similar way like the first one and is identical up to the second level. Node-4 then classifies the data into one of the four subgroups; group-1, group-2,group-3 or group components fault classes with single components.

The input test pattern introduced to the networks is same. If the same fault classes are identified by both the networks, one could have more confidence in the fault classes identified. If the configuration suggests different fault classes then all the all the faults classes identified by the NNNs could be investigated or only the commons fault classes could be used. This is entirely dependent of the accuracy of the networks. The choice of training algorithm, the amount of data and the quality of data used for training play an important role in the final accuracy of the NNNs. The two networks described above only suggests that such a methodology can be adopted if required. Additionally, the same network configuration can be trained for two different operating points. However, in the present work only one type of network has been investigated. The classification accuracy was found to be adequate for the problem in hand.

6.5.4 Working of the Hybrid Model

The NNN preprocessor in the HDM comprises of fifteen nodes, each with different function to perform. The nomenclature adopted here is: L- Level and N- Node. Therefore, L1N1 means a node-1 in level -1. The functions of individual nodes are shown in Table 6.7. The networks represented by the nodes are Multi Layer Perceptrons (MLP) except L2N2 which is an Auto-Associative Neural Network, used specifically for sensor fault detection. The configurations of the networks and the fault classes used to train them are shown in table 6.8.

NODE	DESIG	FUNCTION
LIN1	SFCF	Classifies Sensor fault and Component Fault
L2N1	CMPF	Classifies between Single or Multiple Component Faults
L2N2	SFD	Identifies Sensor Fault
L3N1	SCMPF	Identifies fault classes in case of single component fault
L3N2	MCMF	Classifies multiple fault component faults into subgroups
L4N1	GROUP-1	Classifies the faults with compressors into LP and HP groups
L4N2	GROUP-2	Classifies the faults with turbines into subgroups
L4N3	GROUP-3	Classifies the faults with ICL and RCR into subgroups
L5N1	LPC-GP	Identifies fault classes with LPC as a common component
L5N2	HPC-GP	Identifies fault classes with HPC as a common component
L5N3	HPT-GP	Identifies fault classes with HPT as a common component
L5N4	LPT-GP	Identifies fault classes with LPT as a common component
L5N5	FPT-GP	Identifies fault classes with FPT as a common component
L5N6	ICL-GP	Identifies fault classes with ICL as a common component
L5N7	RCR-GP	Identifies fault classes with RCR as a common component

Table 6.7: NNN nodes and their functions

NETWORK	TYPE	CONFIGURATION	FCS-INVOLVED IN TRAINING
LIN1	MLP	10-30-30-2	FC-1 : FC-28
L2N1	MLP	10-30-30-2	FC-1 : FC-28
L2N2	AANN	10-30-4-30-10	MEASUREMENTS
L3N1	MLP	10-25-25-3	FC-1: FC-7
L3N2	MLP	10-30-30-2	FC-8: FC-28
L4N1	MLP	10-25-25-2	FC-8:FC-18
L4N2	MLP	10-25-25-2	FC-23:FC28
L4N3	MLP	10-25-25-2	FC-19:FC22
L5N1	MLP	10-25-25-3	FC-8:FC-13
L5N2	MLP	10-25-25-3	FC-14:FC-18,FC-8
L5N3	MLP	10-25-25-3	FC-23:FC-25,FC-19,FC-15,FC-10
L5N4	MLP	10-25-25-3	FC-26,FC-27,FC-23,FC-20,FC-16,FC-11
L5N5	MLP	10-25-25-3	FC-28,FC-26,FC-24,FC-21,FC-17,FC-12
L5N6	MLP	10-25-25-3	FC-19,FC-20,FC-21,FC-22,FC-14,FC-9
LFN7	MLP	10-25-25-3	FC-28,FC-27,FC-25,FC-22,FC-18,FC-13

Table 6.8: NNN nodes configuration and fault classes used for training

A schematic diagram of the network developed has been shown in figure-6.13. The input data, which is in the form of a measurement deviation is introduced to the node at the top level (L1N1). This node determines if the faulty pattern is due to sensor bias or component fault. If the fault identified is a sensor bias, then an AANN is called to

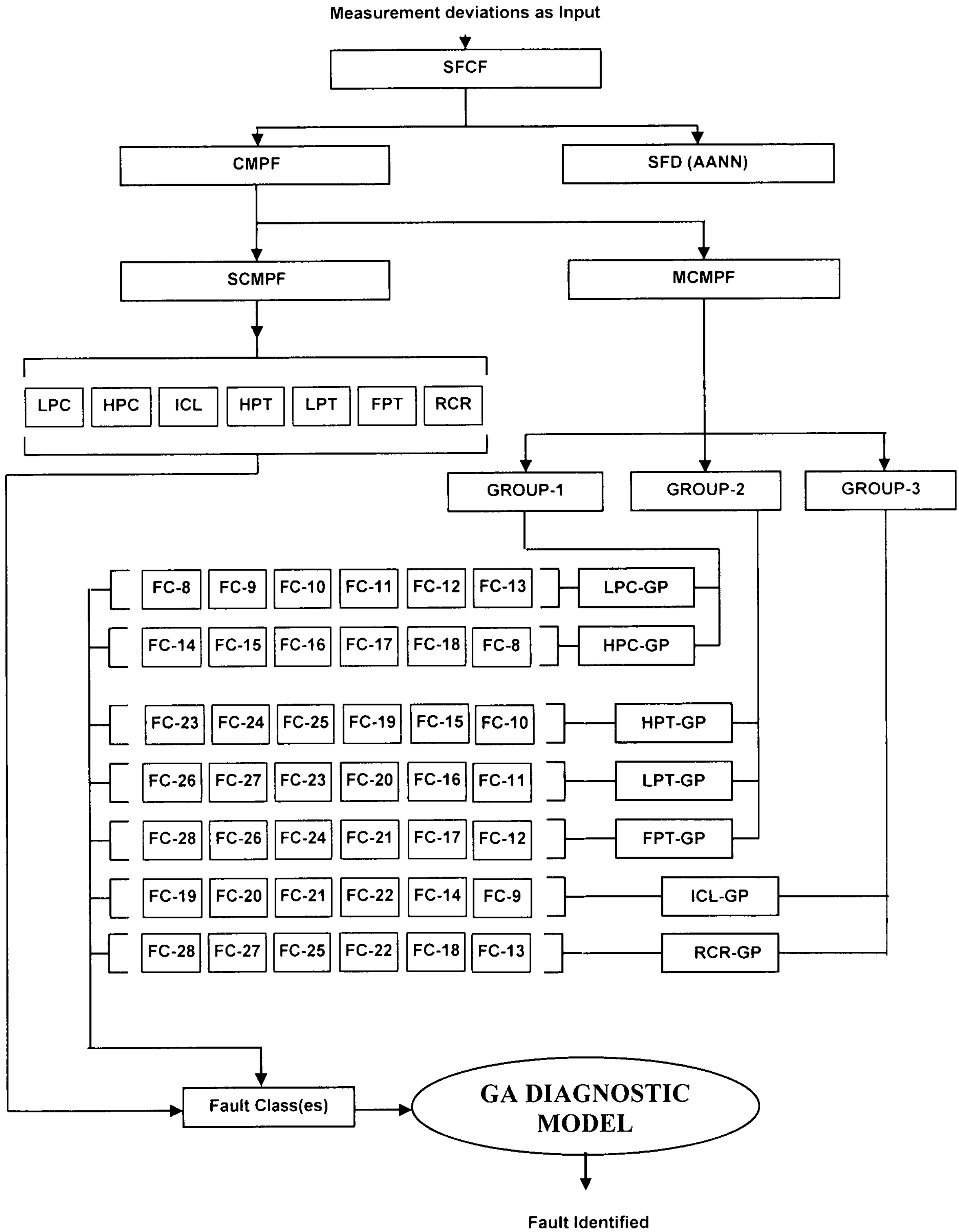

Figure 6.17: Schematic Diagram of Network Classification

determine the magnitude of fault. If the fault is classified as a component fault, it is passed on to the next node to classify it into a single component or multiple component faults. If the input pattern is associated with the single component fault, the network will try to identify fault class containing the faulty component. At this point it is pertinent to mention that the node can identify more than one fault class.

If the input pattern is identified to have multiple component faults, then it is further subdivided into 3 groups as shown in the figure-6.13. Each node further classifies the input data and forwards it to the node at the next level. Similar to the single component faults the last level of nodes can suggest a single fault class or a set of fault classes.

6.6 Fault Diagnostics Tool for ICR WR21 Engine

An engine fault diagnostics model for the ICR WR21 engine has been developed incorporating IFDM with the NNN to form a hybrid diagnostics model. The program is highly modular and user friendly and can be adapted to any other engine with minimum modifications. A schematic diagram of the diagnostics tool has been shown in figure 6.16.

The program essentially comprises of a GA diagnostics model and the NNN classifier. A set of measurement is given as input to the program. The signal processing block filters the noise from the measurement and passes it on to the fault class analyser. The fault class analyzer analyses the fault classes by generating objective functions for each fault class by incrementing the performance deviations in predefined steps within the constraints. The minimum objective function of each fault class is compared and a set of fault classes most likely to contain the faulty components are forwarded to the summation block. The NNN receives a set of measurement and classifies it into a small group of fault classes to be optimized. The fault classes obtained from the FCA and NNN are compared in the summation block and an AND operation is carried out to include all the fault classes. The FCA also passes information of the fault class to the inference engine which updates its database and has a prior knowledge of the problem. The GA optimizer is the 3-stage integrated fault diagnostics model and optimizes the fault classes provided by the previous stage.

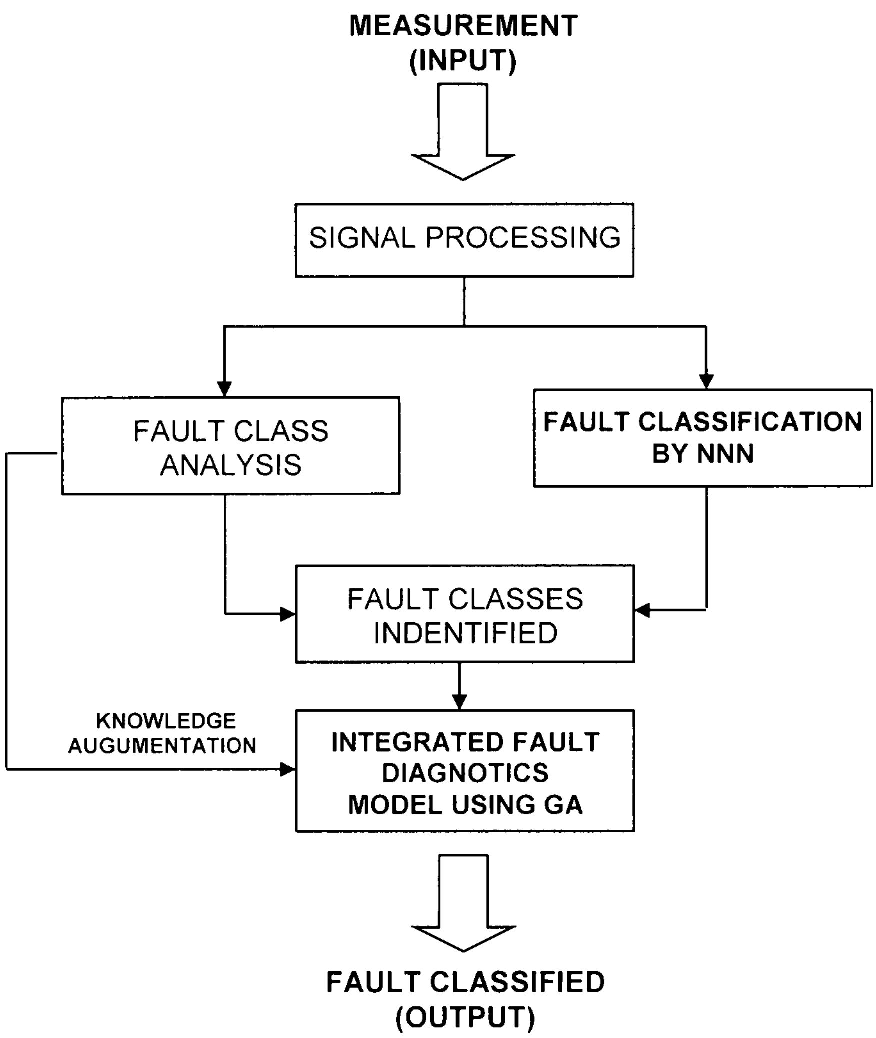

Figure 6.18: Schematic diagram of the diagnostics tools for the ICR WR21

6.6.1 ICR WR21 Diagnostics Program Structure

The program has been developed in FORTRAN 90/95 and compiled using Digital Visual Fortran Ver 6.0. It uses the Neural Network tool box of the MATLAB 6.0 for training the neural network. The structure of the program is shown in figure- 6.17.

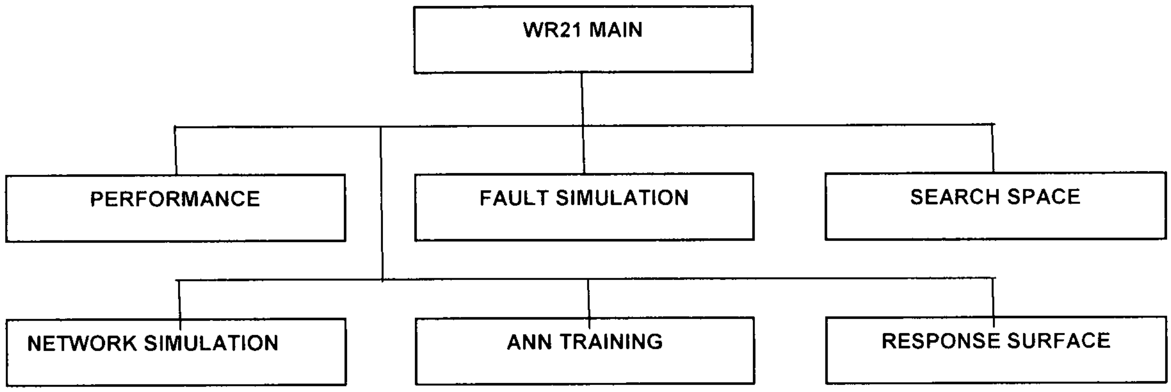

Figure 6.19: Schematic diagram ICR WR21 diagnostics program

The WR21 MAIN module is the central module which controls the other model. The PERFORMANCE module is associated with the performance analysis of the engine and contains the engine performance code. The FAULT SIMULATION module is used to generate faulty simulated data for diagnostics. This module has the options for adding sensor noise and sensor bias to the measurement data. The SEARCH SPACE module generates the search space for the required components. It also has a subroutine to perform the fault class analysis. The ANN TRAINING module is used for generation of data for the NNN and stores the trained network. The NETWORK SIMULATION generates data for simulating the neural network and obtains the confidence rating for individual networks. The RESPONSE SURFACE module is associated with the generation of data for development of response surface for each fault class. A Graphical User Interface (GUI) has also been developed for easy handling of the diagnostics model and has been shown in Appendix- G.

6.7 Summary

In this chapter a description of an integrated diagnostics system based on GA optimisation combined with ANN to form a hybrid diagnostics system has been presented. The IFDM uses a knowledge augmented optimisation to direct the progress of the GA search. The IFDM also speeds up the algorithm by the use of a response surface for each fault class. Additionally, the method also uses the elitist concept to preserve the accuracy. The combination of IFDM with ANN makes the overall fault diagnostics more efficient, quicker and reliable. With the development of these techniques, it is envisaged that there will a significant impact on the engine fault diagnostics. The integrated system will help in reducing the total run time and therefore could be run several times so that the final result can be viewed in a statistical sense. This could eventually also lead to the possibility of GA based fault diagnostics system to be employed for online engine fault monitoring. A discussion of results based on the fault diagnostics using the above method is presented in the next chapter.

CHAPTER-7

DISCUSSION OF RESULTS

7.1 Introduction

The development of a diagnostics model based on MOPA for the ICR WR21 engine has been presented in chapter-5 and some results discussed. The limitation of the technique led to the development of the advanced diagnostic method which encompasses the IFDM and the HDM and has been described in chapter-6. This chapter will discuss the results obtained from the tests carried out with the diagnostics framework developed.

The discussion of results has been organised in four parts the first part presents an analysis of the MOPA based diagnostics model for the WR21. Issues like, the choice of operating point. the number of operating points etc. are discussed. The second part discusses the results obtained from the MOPA based diagnostics and its limitations. The third part discusses the NNN classification features and its usefulness. The fourth part discusses the results from HDM and finally a summary of the chapter is provided.

7.2 Discussion on the Objective Function

The development of an objective function is fundamentally derived from the principles of GPA, where a set of measurement is obtained from the engine model by implanting know faults. The highlight of the objective function is, the preservation of non-linearity of the engine model. The other advantage of the objective function is the ability to deal with sensor noise and bias of instruments fitted on the engine as well as the instruments used to measure the environment and power setting parameters. The objective function developed by Zedda (1999c) which has been used in this research work is-

$$J(\mathbf{x},\mathbf{w}) = \sum_{j=1}^{M} \frac{\left|z_j - h_j(\mathbf{x},\mathbf{w})\right|}{z_{odj}(\mathbf{w}) \cdot \sigma_j} \qquad (7.1)$$

This objective function has been found to be most appropriate for work. A detailed derivation of the objective function has been provided in the chapter-3. The objective function would be minimized when the numerator is least. Such condition would occur when the correct value of the performance parameters (x) and the environment and power setting parameter (w) is reached. The value of the function will not be zero in such case but will consist of a term that is a function of the measurement noise, model inaccuracy and measurement bias. Since the standard deviations of all the sensors (measurements) are known and noise is assumed to be Gaussian, it would be easy to detect measurement bias, as these would fall way outside the 3σ limit. Even if noise is not Gaussian the chosen objective function would be most suitable as explained in chapter 3.

7.3 Analysis of WR-21 Diagnostics Model Based on MOPA

The development of a MOPA based diagnostics model for the WR-21 required certain critical issues to be addressed. These issues are applicable in general to all engines. Some results from the initial investigations with the diagnostics model for the RB199 has also been shown to support the case.

7.3.1 Complexity in optimisation

The aim of the optimization technique is to be able to achieve a particular goal by minimizing an objective function. In the case of gas turbine diagnostics, we have to be able to reach the global minimum for cases that have all the possible difficulties such as: multimodality, deception, isolated optimum and collateral noise that make optimization difficult. The use of classical techniques for multi-objective optimization such as summation of the different objective functions could not give accurate results, as each of the objective function could give an optimal solution that is a local minimum and the optimized result for the sum would also tend to be in one of the local minimums. The optimization technique chosen in this case relies on the use of the concept of pareto-optimality. The concept of pareto-optimality has been used after specifically tailoring it for the purpose of gas turbine diagnostics. The method has been described in chapter-3.

Tests were conducted using three different schemes for the WR-21 and the results are shown in table 7.1. It is evident from the results shown, that the accuracy shown by the MOPA using pareto-optimality is superior to the MOPA by sum method.

ACTUAL FAULT (%)		PREDICTED FAULT(%)		
		SOPA	**MOPA** (Sum)	**MOPA** (Pareto)
$\Delta\eta_{LPC}$	**-0.5**	**-0.82**	**-0.42**	**-0.49**
$\Delta\Gamma_{LPC}$	**-2.0**	**-1.26**	**-1.75**	**-1.98**
$\Delta\eta_{HPC}$	0	0	0	0
$\Delta\Gamma_{HPC}$	0	0	0	0
$\Delta\eta_{ICL}$	0	0	0	0
$\Delta\Gamma_{ICL}$	0	0	0	0
$\Delta\eta_{HPT}$	**-0.8**	**- 0.92**	**-0.72**	**-0.81**
$\Delta\Gamma_{HPT}$	**1.5**	**2.13**	**1.39**	**1.52**
$\Delta\eta_{LPT}$	0	0	0	0
$\Delta\Gamma_{LPT}$	0	0	0	0
$\Delta\eta_{FPT}$	0	0	0	0
$\Delta\Gamma_{FPT}$	0	0	0	0
$\Delta\eta_{RCR}$	0	0	0	0
$\Delta\eta_{RCR}$	0	0	0	0
Environment and Power seting paremeters				
Operating point 1				
Power (hp)		26400.00	26400.00	26400.00
P ambient (Atms)		1.00	1.00	1.00
T ambient (K)		308.15	308.15	308.15
Operating point 2				
Power (hp)		-	24000.00	24000.00
P ambient (KN/m^2)		-	1.00	1.00
T ambient (K)		-	308.15	308.15
RMS error -		0.28	0.07	0.008

Table 7.1: Comparison of different diagnostic schemes

Even though the multiple operating point analysis technique based on summation gave better results than single operating point analysis, the accuracy is not very high. One of the reasons for this can be explained by analyzing the search space. The chances of the various objectives functions of a string having the lowest sum and getting stuck in local minima is always present. This would lead to higher fitness and hence higher chance of survival for this string. At the same time some other string having one of the objectives in a local minima and the other(s) in a position from where they can find the global minima, but having a higher sum would get lower fitness and hence less chance of survival into the next generation. From the above results it can be concluded that the MOPA based on pareto-optimality is a better option for fault prediction and therefore used for the WR-21 diagnostics model.

7.3.2 Number of operating points

The choice of the number of operating points is very important, as the objective function becomes more complex with an increase in the number of operating points. The factors making it more complex are, the increased number of environment and power setting parameters, which are all assumed to be affected by noise and bias. It has been brought out earlier in chapter-3 that the gains achievable up to three operating points are significant, beyond which the relative advantage in terms of accuracy is not worth the computational effort.

The choice should therefore be such that the approximate nature of Relative Redundancy Factor (R) is taken into account by aiming for a value that is around 1.5, which gives a margin of error of 50%. This should be done keeping in mind that, as the number of operating points increases the requirement of computational resources also increases proportionately.

PARAMETER	ACTUAL (%)	PREDICTED (%)		
		1-OP	2-OPs	3-OPs
$\Delta\eta_{LPC}$	0	0	0	0
$\Delta\Gamma_{LPC}$	0	0	0	0
$\Delta\eta_{HPC}$	-1.0	-0.826	-1.102	-1.068
$\Delta\Gamma_{HPC}$	-3.0	-2.439	-2.983	-3.011
$\Delta\eta_{ICL}$	0	0	0	0
$\Delta\Gamma_{ICL}$	0	0	0	0
$\Delta\eta_{HPT}$	0	0	0	0
$\Delta\Gamma_{HPT}$	0	0	0	0
$\Delta\eta_{LPT}$	-2.0	-1.462	-1.874	-1.918
$\Delta\Gamma_{LPT}$	4.0	2.893	3.928	4.103
$\Delta\eta_{FPT}$	0	0	0	0
$\Delta\Gamma_{FPT}$	0	0	0	0
$\Delta\eta_{RCR}$	0	0	0	0
$\Delta\eta_{RCR}$	0	0	0	0
Environment and Power seting paremeters				
Operating point 1				
Power (hp)		26400.00	26400.00	26400.00
P ambient (Atms)		1.00	1.00	1.00
T ambient (K)		308.15	308.15	308.15
Operating point 2				
Power (hp)		-	24000.00	24000.00
P ambient (Atms)		-	1.00	1.00
T ambient (K)		-	308.15	308.15
Operating point 3				
		-	-	22000.00
		-	-	101.32
		-	-	308.15
RMS error -		0.37	0.04	0.039
RUN TIMES (Hours)		12	21	29

Table 7.2: Fault predictions with different operating points

Testing for the WR-21 model was carried out using one, two and three operating points. A comparison of the fault prediction using different numbers of operating points is shown in table 7.2. It can be observed that the accuracy of fault prediction achieved using three operating points is marginally higher than the fault predictions using 2 operating points. However, the time taken was 8 hours more than that taken by 2 operating points. Therefore there is no relative advantage in using more operating points. The diagnostics model for the WR21 uses two operating point for MOPA.

7.3.3 Choice of operating points

Another important issue while dealing with MOPA is the choice of operating points, i.e. how far apart should the operating points be and at what power range the observability for fault detection is good. If the operating points are far apart, then there is the possibility of the performance parameters (like efficiencies of components) changing due to the changed power setting. For a very low difference, there is the risk of interdependency. It was observed that, for lower power settings the observability was poor. Additionally, for very high power levels there were a number of cases where the mutation operator caused the strings to exceed some of the key control parameters such as TET etc. It has been found that for all engines, there is certain range of power settings for which the observability of the faults is very good (Gulati, 2002c). This varies from engine to engine and needs to be identified prior to the diagnosis. This range also limits the maximum number of operating points that can be used, the other limit being the computational resources needed for more operating points. The tests were conducted in three bands in terms of distance between operating points (changing power while keeping the other environment parameters constant). Case-1 : 1-5 %, Case-2: 6-10% and Case-3: 16-20%. Table 7.3 shows the best results obtained in each band . It can be observed that case-2 gave the best results. In case-1 the operating points are so close that the algorithm was unable to obtain much information from 2 points and in the case-3 the points are far and the aerodynamic conditions are different, which means that the efficiencies and mass flows are different and therefore it gave results with poor accuracy. After a thorough investigation it was concluded that the optimum choice of operating points would be to choose 2 points within the band shown by case-2. i.e. a difference of 6-10 % in power setting.

ACTUAL FAULT (%)		PREDICTED FAULT (%)		
		Case 1	Case 2	Case 3
$\Delta\eta_{LPC}$	0	0	0	0
$\Delta\Gamma_{LPC}$	0	0	0	0
$\Delta\eta_{HPC}$	**-1.0**	**- 0.26**	**-0.92**	**-0.89**
$\Delta\Gamma_{HPC}$	**-3.0**	**-1.76**	**-3.16**	**-2.65**
$\Delta\eta_{ICL}$	0	0	0	0
$\Delta\Gamma_{ICL}$	0	0	0	0
$\Delta\eta_{HPT}$	0	0	0	0
$\Delta\Gamma_{HPT}$	0	0	0	0
$\Delta\eta_{LPT}$	0	**-0.13**	0	0
$\Delta\Gamma_{LPT}$	0	**1.24**	0	0
$\Delta\eta_{FPT}$	**-0.5**	0	**-0.46**	**-0.42**
$\Delta\Gamma_{FPT}$	**2.0**	0	**1.98**	**1.88**
$\Delta\eta_{RCR}$	0	0	0	0
$\Delta\eta_{RCR}$	0	0	0	0
Environment and Power seting paremeters				
Operating point 1				
Power (hp)		20500	22000	24000
P ambient (KN/m^2)		1.00	1.00	1.00
T ambient (K)		308.15	308.15	308.15
Operating point 2				
Power (hp)		20000	20000	20000
P ambient (KN/m^2)		1.00	1.00	1.00
T ambient (K)		308.15	308.15	308.15
RMS error -		0.75	0.06	0.11

Table 7.3: Comparison of results for different numbers of operating points

7.3.4 Instrumentation

The choice and number of instruments available greatly influence the direction in which diagnostics proceeds. A large number of instruments makes the search space easier to traverse and diagnostics based on single objective optimisation could be performed. A reduced number of sensors make the search space more complicated and require more computational resource to be utilized. A search space is the objective functions plotted against the changes in flow capacity and efficiency. Essentially every point on the search space is a potential solution and it decides the quality of the population for the GA search. Figure 7.1 shows the search space plot for the LP compressor of WR21 with 9 sensors fitted on the engine, if we observe the bottom portion of the plot, it appears that there are many minimum points close to each other that the GA may not notice a significant fitness improvement over many generations and be content with any close value. This however does not mean that the engine is insensitive to variation in engine performance parameter.

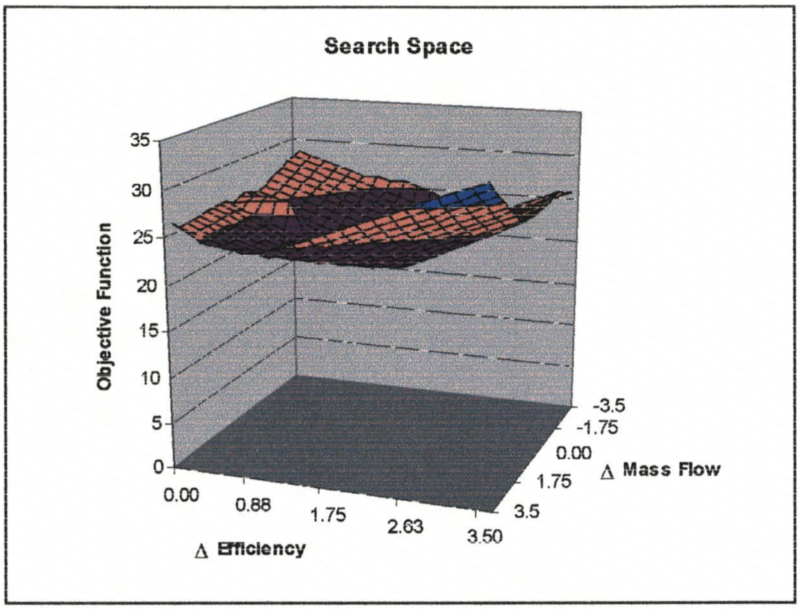

Figure-7.1: Search Space for LPC with 9 Instruments

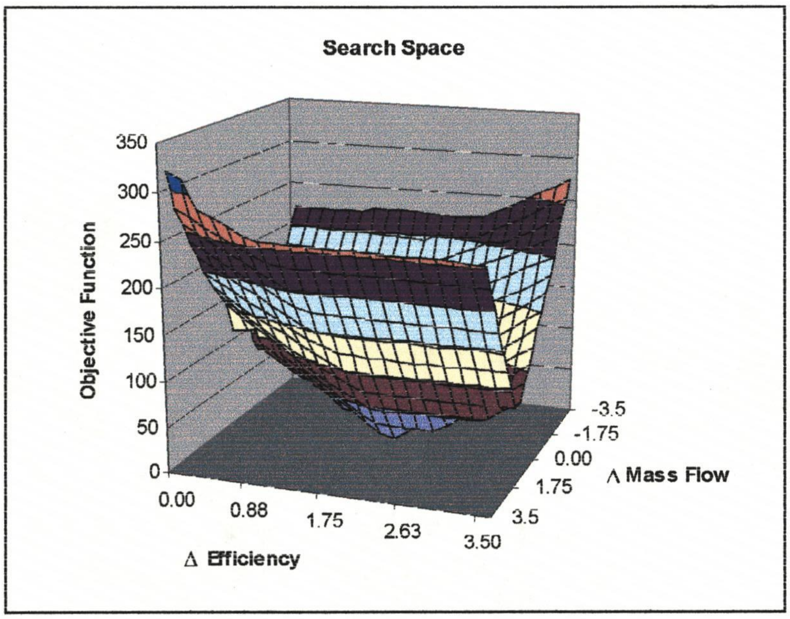

Figure-7.2: Search Space with 16 Instruments

For the same engine, under similar conditions a search space generated with 16 instruments, shown in figure 7.2, is completely different. Here the search space shows a distinct convergence to a minimum value of objective function. Another important observation which was made during the analysis is that the search spaces for the compressors are more complex than turbines. Which means that the faults associated with compressors are more difficult to identify. A discussion on this with suitable figures is presented below-

7.3.5 Analysis of Compressor Search Spaces

Experiments were conducted to study the behaviour of search spaces of various engine components. It was found that the search space for a compressor is more complex despite the fact that most of the measurements are towards the compressor side. In order to explain the behaviour, few results from the initial study of the RB199 engine have also been included. The search space for HPC of WR21 is shown in figure 7.3.

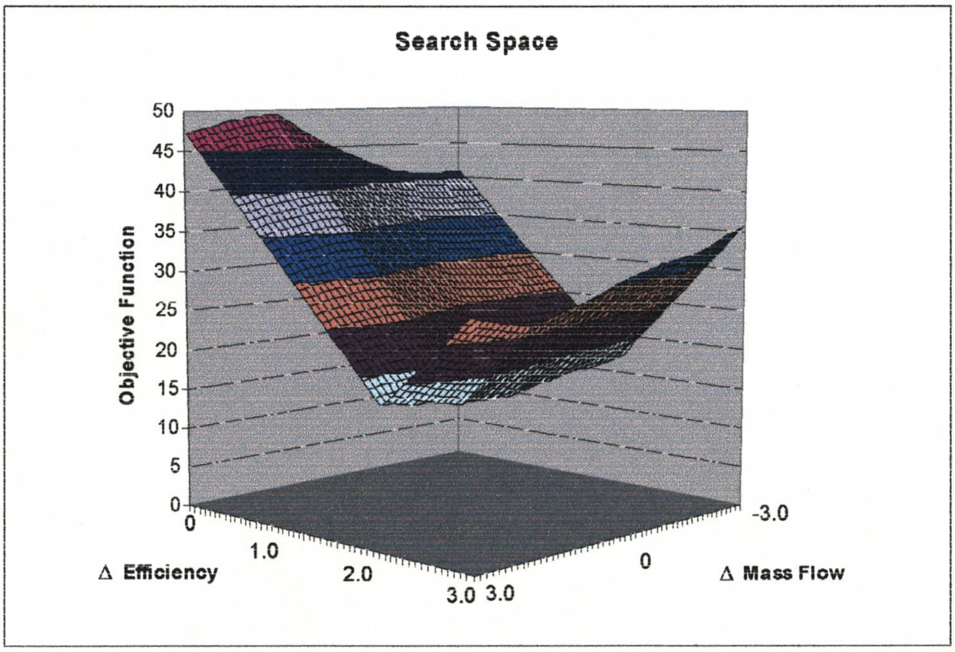

Figure 7.3: Search space for HPC of ICR WR21

The bottom of the search space appears flat and seems to indicate that for a given value of efficiency change (or very close values) there are many values of flow capacity deviations which could give close values of objective function. This condition poses great difficulty for the optimizer to select the best individual from a population of strings producing similar values of objective function, while the performance parameters producing them are very different. Despite the fact that the WR-21 has two sensors each (one temperature and one pressure) on the inlet and exit of the HP compressor, the fault identification in the HPC appears difficult.

Similar search space analysis was for conducted for the RB199 engine prior to the WR21 and the results were identical. The search space for IPC of the RB 199 engine is shown is figure 7.4. It can be seen that it has a flat bottom similar to the WR21 HPC which makes it difficult for the optimizer to detect the actual fault.

It has been observed that during the search process the problems are mainly encountered at the bottom of the search space, particularly for compressor, which is nearly flat with a global minimum value being not very different from many other local minima present. Under these circumstances it would not be possible to reach the absolute global minimum by using hill climbing techniques or other conventional techniques such as the calculus based methods.

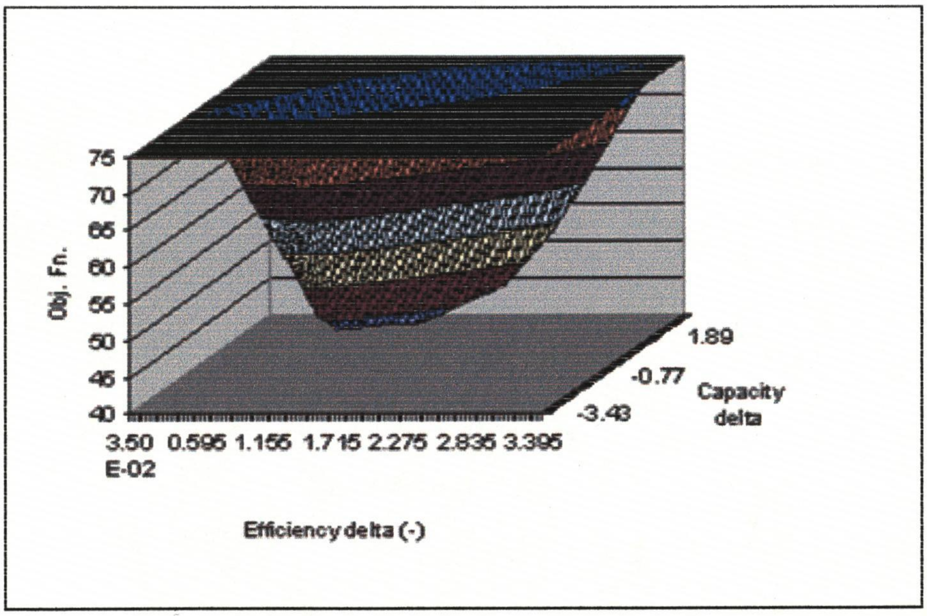

Figure 7.4: Search Space for a IPC of RB199 (Sampath et al, 2002b)

The use of a GA based technique even with local tuning methods such as evolutionary technique was not able to increase the accuracy for most cases. This is because once trapped in a local minimum, the string will keep getting a higher level of fitness and hence more chances of its survival. Tuning with the help of varying the rate of mutation helped to some degree, but then with a high probability of mutation, consistency reduced and therefore probability of mutation was kept at 0.4.

7.3.6 Analysis of Turbine Search Spaces

Search space analysis of turbine show that they are relatively smoother and have distinctly defined global minimum when compared with compressor search spaces. A search space for the HPT of WR21 is shown in figure 7.5. The search space of HPT of WR21, indicates that there is probably one value of deviation in component efficiency (or very close) and one value of the deviation in flow capacity which will produce the minimum objective function and the performance parameter producing it will be indicative of the component fault.

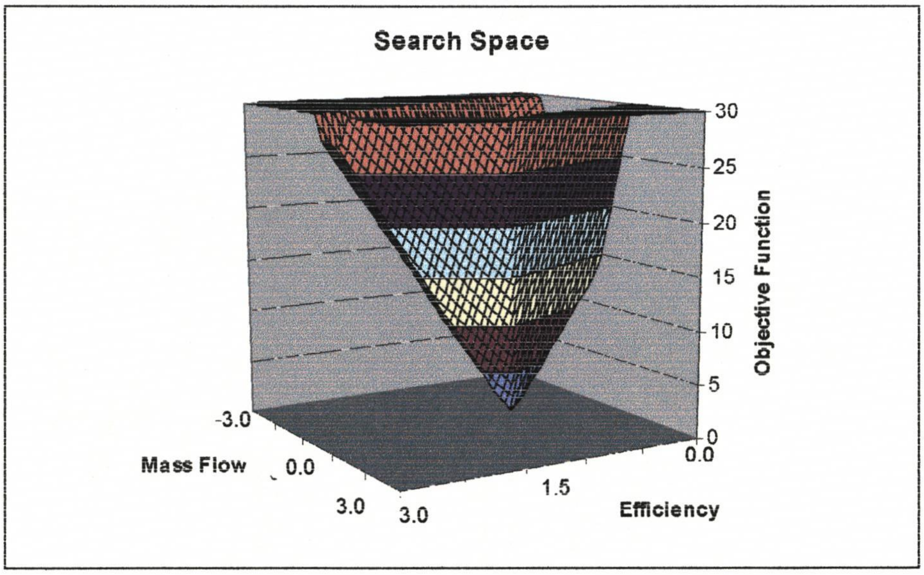

Figure 7.5: Search Space for a HPT of WR21

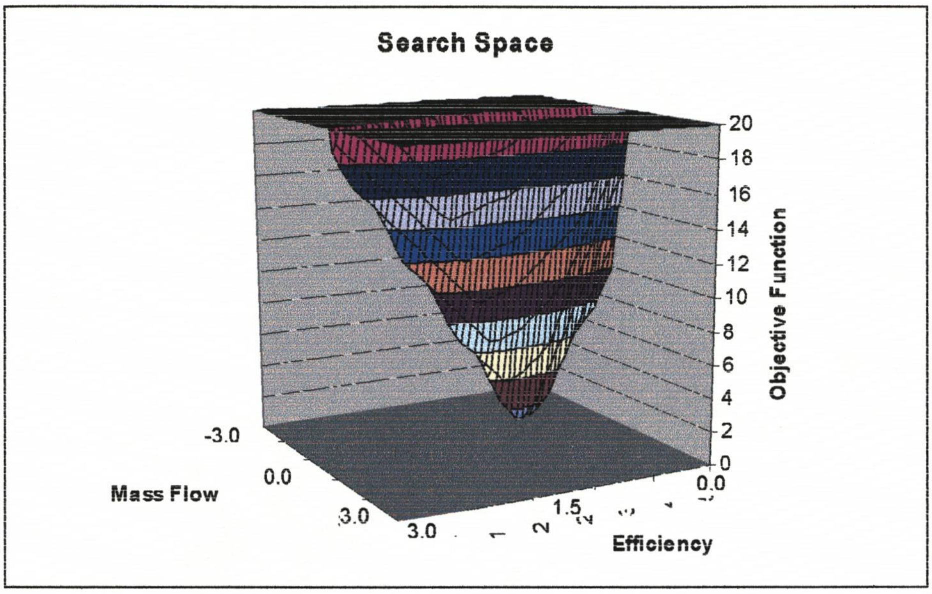

Figure 7.6: Search Space for a FPT of WR21

A search space for the FPT of WR21 shown in figure 7.6 which also has a distinct global minimum. Investigation with search space for the RB199 engine also gave similar results. A search space for the LPT of RB199 is shown in figure 7.7.

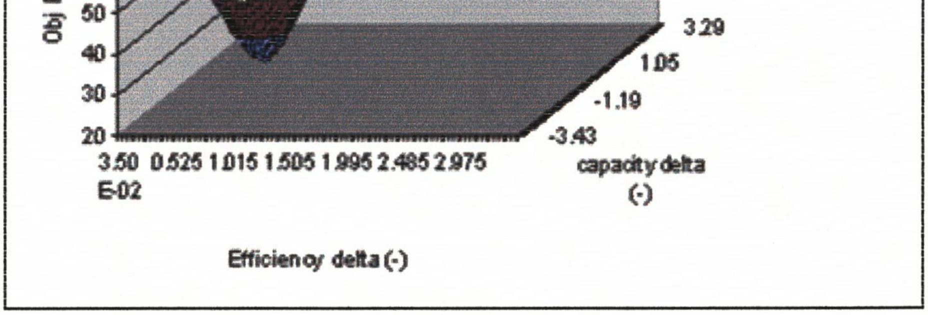

Figure 7.7: Search Space for a Turbine (Sampath et al, 2002b)

The following broad conclusions can be drawn from the search space analysis of the turbines are:

- The search space is relatively smooth when considered as a function of the performance parameter only.
- The chances of reaching a global minimum quickly and accurately are high.
- From the GA optimisation point of view, a small population going through less number of generations (when compared to compressors) will be able to detect the fault reasonably accurately.

7.3.7 Engine Performance Model:

Some of the problems experienced during the diagnostics process could also be attributed to the thermodynamic model used (convergence criteria, tolerances, types of variables that are used). The variables could be single precision instead of double precision which could also cause numerical errors. Mostly, the models are precompiled, the accuracy and speed depends on the kind of compilation that has been used: fully optimized or partly optimized.

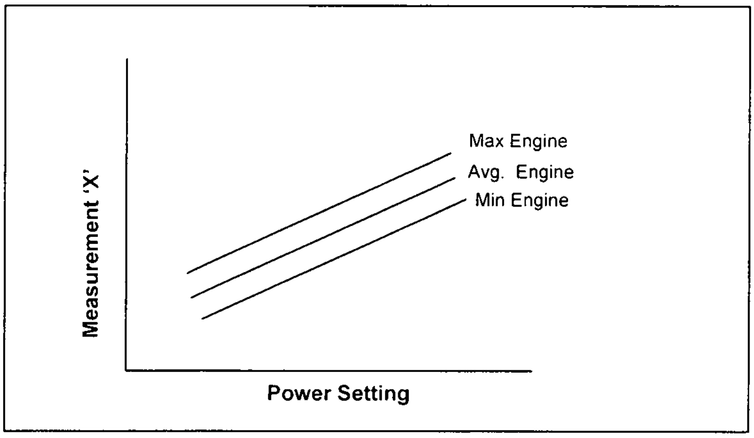

Figure 7.8: Representation maximum, average & minimum engine (Gulati, 2002c)

Model accuracy assumes great importance for techniques using the engine model to generate data and identify faults. A typical performance model represents an average engine while in reality the engine being diagnosed could be between a maximum engine and a minimum engine. This concept is illustrated in figure 7.8.

The figure shows a typical variation of a measurement with respect to the change in power level. If the actual engine was minimum engine then the model based on average engine would identify a non existent fault. One to way to overcome this is to generate data by uniformly deteriorating all the components or few components by a small value in addition to the faults implanted as suggested by Gulati (2002c).

7.3.8 Quality of Information (Observability)

While the number of the sensors used is important, it is also important to see that how well these sensors can observe the changes taking place to the engine due to a fault. A small instrumentation set which can perceive the changes effectively is more desirable than a large number of instrumentation set with repeating parameters or low observability. The importance of search space analysis has been shown earlier. Search spaces for variation in performances parameters of two components and environment and power setting parameters cannot be plotted at the same time. However search spaces plotted for single component faults are sufficient to give an idea of the model and suitability of the instruments from the observability point of view. Different combinations of instruments were investigated for the WR-21 and also discussed with the sponsor about the possibility of placing these sensors before settling for the present set of instruments.

7.3.9 GA Parameters

In addition to the various issues associated with instrument selection the optimization of GA parameters (no. of strings, no. of generations, probability of cross over, type of cross over, mutation rate etc..) are critical to the success of this technique. The results shown earlier were obtained using 100 strings per fault class and running these for 100 generations. The rationale behind choosing these values is explained below:

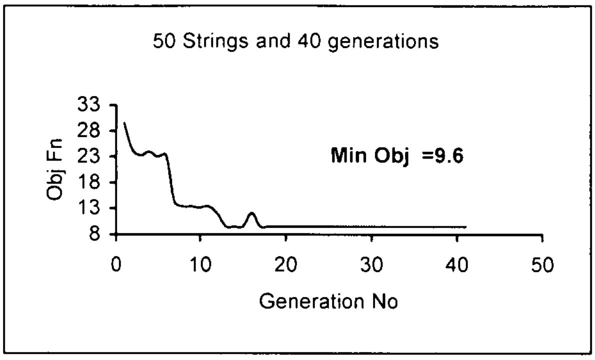

Figure 7.9: Convergence of Objective function (Case-1)
(Sampath et al, 2002c)

Ideally, the GA parameters critical to the progress of the search process should be optimized. This necessitates another optimizer and would make the process more complicated by introducing a number of unknowns in the system. Perhaps, an easy way to go about it, is to use the trial and error method to identify an appropriate numbers of strings and generations for the optimisation. Figure-7.9 shows the results of optimisation using 50 strings and 40 generations. When compared with a case with 100 strings as shown on figure 7.10, the case involving 50 strings stabilizes much earlier than the one having 100 strings. The minimum objective function achieved in case-1 is 9.6 and there is no improvement in objective function after 20 generations. This is because the not much information is available within the population and possibly the algorithm has been trapped in a local minimum.

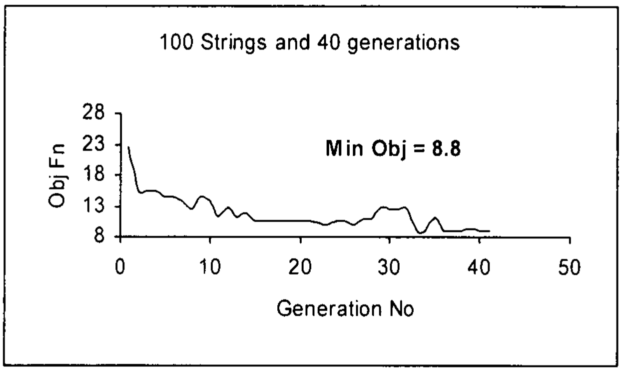

Figure 7.10: Convergence of Objective function (Case-2)
(Sampath et al, 2002c)

In case-2, the minimum objective function achieved after 40 generations is 8.8 and it can be seen that the model has not settled at any particular value of the objective function and could probably settle to a value if allowed to go through few more number of generations. The population has sufficient diversity and the chance of extracting the correct string from the population is much higher.

Analysis of the 2 cases reveals that the use of fewer strings will lead to an inaccurate result in terms of either the wrong component being identified or the predicted result being very different from the actual in terms of deviation efficiency, capacity and power setting parameters.

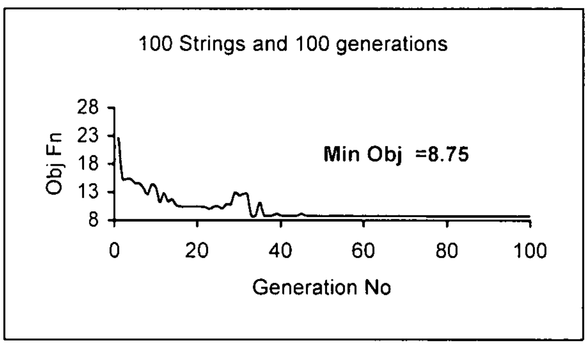

Figure 7.11: Convergence of Objective function (Case-3)
(Sampath et al, 2002c)

An experiment with a third case consisting of 100 strings going through 100 generations was conducted. Figure-7.11 shows results obtained with 100 strings and 100 generations. The lowest value of objective function obtained was 8.75 which is marginally better than case-2. It can be observed that the optimization has settled down to a steady value of the objective function at around the 50th generation and thereafter there is no significant improvement in the value of the objective function. From the above study, it is evident that the initial population should have sufficient number of strings and have a high diversity factor such that the whole search space is covered. In order to achieve the required consistency in terms of accuracy, the use of 100 strings and 100 generations was found to give acceptable results for different types of faults and the same has been used in the diagnostics model for the WR21.

The other parameters which are of importance in a GA based engine diagnostic model are the probabilities of crossover (P_C) and mutation (P_M). The values of which were also arrived at after extensive testing. These are 0.6 for crossover and 0.4 for mutation. The P_C is kept constant for all generations. The level of mutation (i.e. the magnitude by which a parameter is altered) is held constant up to 70% of generations after which it is non-uniform and reduces as generations progress.

7.4 Results from Initial Diagnostics Model For WR-21

The development of a diagnostics model based on the concept of MOPA has been discussed and the various important aspects of the diagnostics model have been presented. Several test cases were run to validate the diagnostic model and a few are presented in this chapter. The fault data for input to the diagnostics model has been generated using the same performance model, which is used by the diagnostics model. The simulated faulty data is generated by implanting known set of faults into the performance code and a set of measurements is obtained. Simulated faulty data for case-1 is shown in table 7.5. The diagnostics process is started by setting GA parameters like the population size, number of generations, probabilities of crossover (P_C) and probability of mutation (P_M).etc..

As discussed earlier, the process of engine diagnostics involves a constrained optimisation in which the upper and lower limits of potential faults are predefined. This has been implemented to avoid the search for faults which are in zones , that could lead to catastrophic faults. The objective of the diagnostics model is to be able to predict faults before they occur. A summary of various constraints on the performance parameters is shown in table 7.4. The values shown are percentage deviations of performance parameter from their baseline value.

Fault	Component-1 PP Limits				Component-2 PP Limits			
Class	Efficiency(%)		Flow Capacity(%)		Efficiency(%)		Flow Capacity(%)	
	Min	Max	Min	Max	Min	Max	Min	Max
FC-1	0.00	-3.50	-5.00	5.00	-	-	-	-
FC-2	0.00	-3.50	-5.00	5.00	-	-	-	-
FC-3	0.00	-10.00	0.00	10.00	-	-	-	-
FC-4	0.00	-3.50	-5.00	5.00	-	-	-	-
FC-5	0.00	-3.50	-5.00	5.00	-	-	-	-
FC-6	0.00	-3.50	-5.00	5.00	-	-	-	-
FC-7	0.00	-10.00	0.00	10.00	-	-	-	-
FC-8	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-9	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00
FC-10	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-11	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-12	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-13	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00
FC-14	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00
FC-15	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-16	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-17	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-18	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-19	0.00	-10.00	0.00	10.00	0.00	-3.50	-5.00	5.00
FC-20	0.00	-10.00	0.00	10.00	0.00	-3.50	-5.00	5.00
FC-21	0.00	-10.00	0.00	10.00	0.00	-3.50	-5.00	5.00
FC-22	0.00	-10.00	0.00	10.00	0.00	-10.00	0.00	10.00
FC-23	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-24	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-25	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00
FC-26	0.00	-3.50	-5.00	5.00	0.00	-3.50	-5.00	5.00
FC-27	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00
FC-28	0.00	-3.50	-5.00	5.00	0.00	-10.00	0.00	10.00

Table 7.4: Constraints on performance parameters

The population is produced with the 0-3.5% variation in efficiency (reduction from its base line value) for all components (except ICL & RCR). The deviation in flow capacity for a component is varied between -5% to +5% from its baseline value. For the ICL & RCR, leakage factor and fouling factor are varied on a scale from 1 to 10. In the practical sense, fouling factor indicates some percentage reduction in the heat effectiveness (ε) of the heat exchangers and leakage factor indicates the loss of working fluid to atmosphere. The aim is to define a quantity that can be used to generate a fault condition and which can be identified by the diagnostic model.

7.4.1 Fault Case-1 : Single Component Fault with 1 sensor biased

FAULT CASE-1 : Fault Implanted : HPC - ($\Delta\eta$: -3.00 % $\Delta\Gamma$: -4.00%) , HPC Exit (Temp) sensor faulty

Sl No	Station	Operating Point-1	Operating Point-2	Sensor Type	Units
1	HP Compressor(In)	2.4686	2.4076	Pressure	Atmosphere
2	HP Compressor(Exit	11.7087	11.1117	Pressure	Atmosphere
3	IC Differential	0.0504	0.0491	Pressure	Atmosphere
4	HP Compressor(In)	313.2969	312.1558	Temperature	Degree Kelvin
5*	HP Compressor(Exit)	521.5140	512.0514	Temperature	Degree Kelvin
6	Combustor Entry	792.6706	769.6127	Temperature	Degree Kelvin
7	Power Turbine(In)	1115.9117	1074.2185	Temperature	Degree Kelvin
8	Power Turbine(Exit)	848.8079	820.7999	Temperature	Degree Kelvin
9	HP Shaft Speed(RPM)	8208.4912	8129.8457	Tachometer	RPM
10	LP Shaft Speed(RPM)	6280.5479	6132.2026	Tachometer	RPM

* Indicates biased Instrument

Table 7.5: Simulated measurements with fault implanted (Fault Case-1)

Fault case-1 considers a single component fault. The efficiency and flow capacity of HPC has reduced by 3% and 4% respectively. Noise values are added to the measurements obtained from the performance model. Depending on the sensor chosen to be biased, a value of approximately 10-12σ is added to that particular measurement to simulate a sensor fault condition. Sensor faults are added only to sensors 1 to 8, as the tachometers are generally very accurate and consistent in measuring the rotational speeds of the shafts.

The diagnostics process has been described earlier, the objective functions are calculated and the lowest objective function for each class is retained. Once all the fault classes have been searched, the minimum objective functions from all the fault classes are compared and the fault class associated with the lowest objective function is indicative of the faulty component(s). Result from the diagnostics model for fault case - 1 is shown in table 7.6. The GA optimisation started with 100 strings and went through 100 generation to arrive at the solution. The diagnostics process took 19 hrs and 44 mins to converge.

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 217 TIME/DATE: 19:32:23 [15-Feb-03]
Fault Class Analysis

FC	MOF	Time	Efficiency Change (Δη) - Percentage				Flow Capacity (ΔΓ)- Percentage			
			Component-1		Component-2		Component-1		Component-2	
			Δη	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID	ΔΓ	Comp-ID
FC-1	66.985	41	-2.9936	LPC	-	-	0.3106	LPC	-	-
FC-2	6.535	44	-2.9977	HPC	-	-	-4.1201	HPC	-	-
FC-3	88.609	44	-1.9450	ICL	-	-	1.9726	ICL	-	-
FC-4	16.439	42	-2.8840	HPT	-	-	0.0569	HPT	-	-
FC-5	44.159	43	-2.9883	LPT	-	-	1.4837	LPT	-	-
FC-6	55.543	43	-1.4346	FPT	-	-	0.8447	FPT	-	-
FC-7	92.864	43	-0.0826	RCP	-	-	1.9635	RCP	-	-
FC-8	41.664	43	-1.6500	LPC	-1.5961	ICL	2.0236	LPC	1.5245	HPC
FC-9	68.476	41	-2.5038	LPC	-0.2788	HPC	0.2253	LPC	0.1135	ICL
FC-10	34.239	43	-0.2152	LPC	-2.7097	HPT	-1.8751	LPC	-0.3236	HPT
FC-11	28.611	43	-2.4577	LPC	-2.8652	LPT	-0.4357	LPC	2.2961	LPT
FC-12	55.043	44	-1.2233	LPC	-1.5429	FPT	1.1373	LPC	0.0701	FPT
FC-13	71.217	45	-2.5607	LPC	-1.1172	RCP	0.4058	LPC	0.4099	RCP
FC-14	19.765	41	-2.1282	ICL	-0.7708	HPC	1.2203	HPC	0.3053	HPC
FC-15	15.409	43	-1.4288	ICL	-1.4506	HPT	0.4339	HPC	0.4445	HPT
FC-16	11.903	42	-2.7331	ICL	-0.9499	LPT	-0.3368	HPC	0.4918	LPT
FC-17	30.878	41	-1.9966	ICL	-0.0262	FPT	1.3467	HPC	0.7564	FPT
FC-18	10.309	42	-2.8562	ICL	-1.5714	RCP	0.3263	HPC	0.1307	RCP
FC-19	25.444	44	-1.3465	HPC	-2.4667	HPT	0.1676	ICL	-0.7332	HPT
FC-20	28.582	40	-0.6280	HPC	-2.8753	LPT	1.5576	ICL	2.2542	LPT
FC-21	73.985	44	-0.9473	HPC	-2.1197	FPT	0.5447	ICL	-0.1576	FPT
FC-22	89.592	40	-1.9875	HPC	-0.1152	RCP	1.9896	ICL	1.9858	RCP
FC-23	23.033	42	-2.5228	HPT	-0.6410	LPT	0.6047	HPT	0.3293	LPT
FC-24	34.347	42	-2.0559	HPT	-0.1751	FPT	0.9242	HPT	0.6380	FPT
FC-25	37.199	43	-2.5076	HPT	-0.1318	RCP	-1.6660	HPT	0.3243	RCP
FC-26	30.895	40	-1.1297	LPT	-1.0873	FPT	2.4597	LPT	1.9218	FPT
FC-27	38.738	45	-2.9025	LPT	-0.4206	RCP	2.2393	LPT	1.9979	RCP
FC-28	62.933	41	-1.5273	FPT	-0.4543	RCP	0.5137	FPT	0.0061	RCP
		1184								

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26404.5488	308.1469	1.0002	24014.0488	308.2270	1.0002

Fault Detected (Change in Component Performance Parameters

Component-1				Component-2			
Δη	Comp-ID	ΔΓ	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID
-2.9977	HPC	-4.1201	HPC	-	-	-	-

Sensor fault Detection

Faulty Sensor -1		Faulty Sensor-2	
Sensor ID	Sensor Type	Sensor ID	Sensor Type
HPC (Exit)	Temperature	-	-

Table 7.6: Results of a single component fault

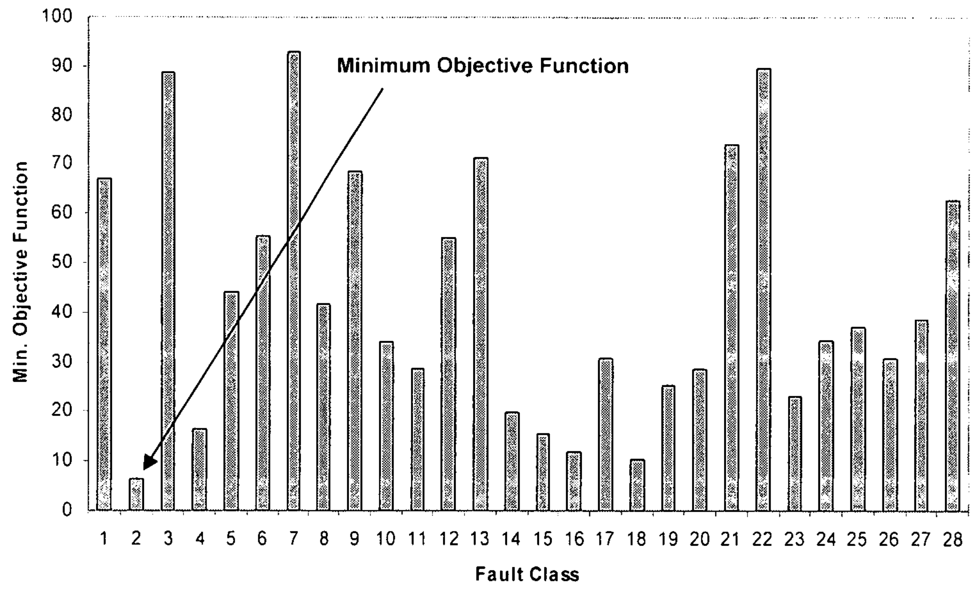

Figure 7.12: Minimum objective functions for fault case-1

The fault considered in case-1 is a very simple case of single component fault and one faulty instrument. The diagnostic method has been able to detect the faulty component and quantify the fault accurately. It has also been able to identify the faulty sensor correctly. The minimum objective function from each fault class is plotted in figure 7.12. It can be seen that the minimum objective function for fault class-2 is clearly the lowest when compared with the others and therefore the component associated with the fault has been detected as the faulty component. After conducting several tests with different components and analyzing the results, it can be said that single components faults are relatively easier to detect. The results from the diagnostics model for varying magnitudes of efficiency and flow capacity for HPT is shown in figure 7.13 and figure 7.14 respectively. The RMS error between the implanted fault and predicted fault is shown is figure 7.15. It can be observed that the RMS error for fault with large magnitude is less, which means that large faults are easily detected by the fault diagnostics model. This is because, signatures created by large faults are more distinguishable when compared with signatures from small fault levels, particularly when the noise levels are high. On few occasions the presence of measurement noise can give an impression of a fault.

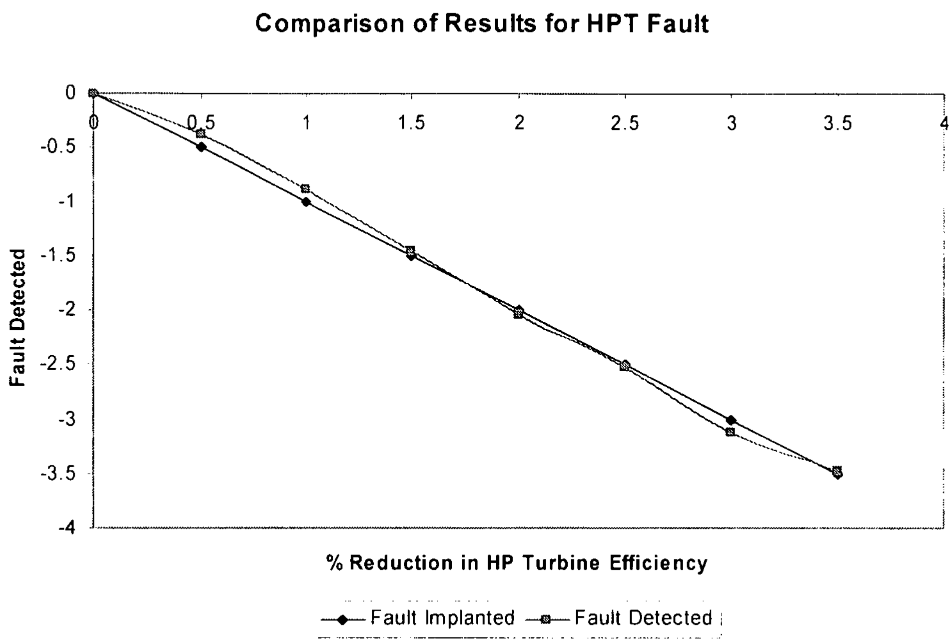

Figure 7.13: Fault predicted for different level of deviation in efficiency

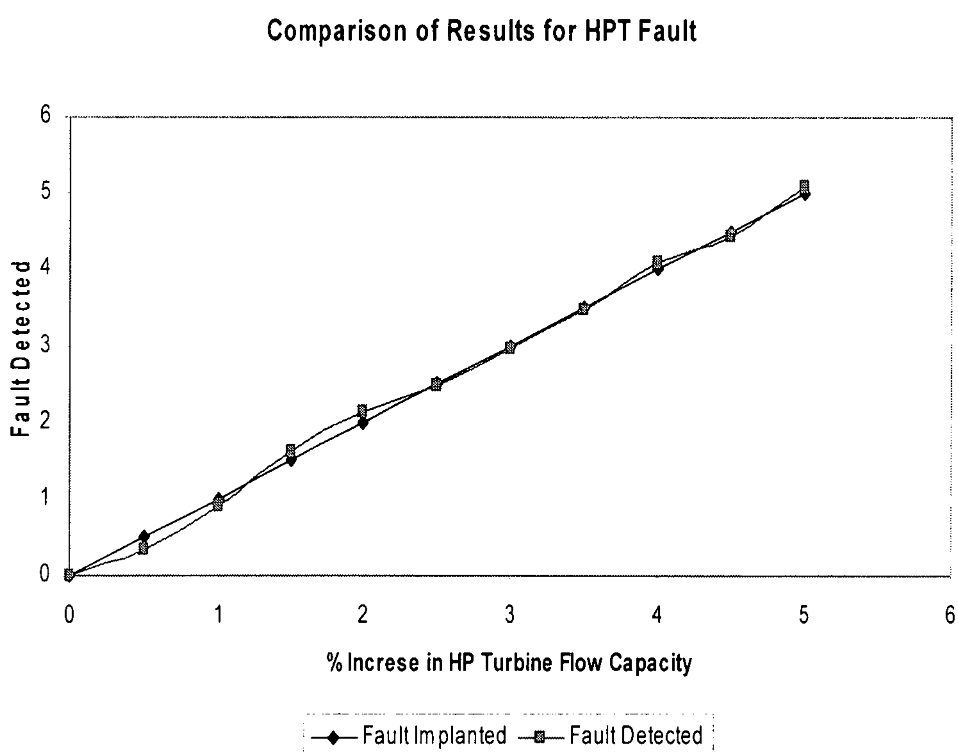

Figure 7.14: Fault predicted for different level of deviation in flow capacity

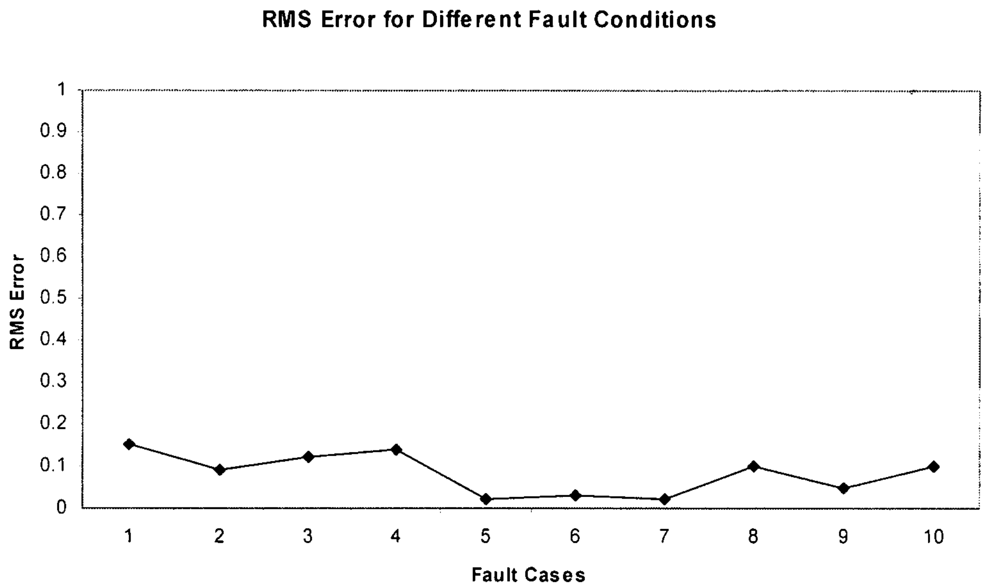

Figure 7.15: RMS error in predicted fault

7.4.2 Fault Case-2: Multiple Component Faults with 2 sensors Biased

FAULT CASE-2 : Fault Implanted : LPC – ($\Delta\eta$: -1.00 % $\Delta\Gamma$: -3.00%) , HPT- ($\Delta\eta$: -2.00 % $\Delta\Gamma$: 4.00%)

Sl No	Station	Operating Point-1	Operating Point-2	Sensor Type	Units
1*	HP Compressor(In)	2.5200	2.4570	Pressure	Atmosphere
2	HP Compressor(Exit	11.4203	10.8221	Pressure	Atmosphere
3	IC Differential	0.0514	0.0501	Pressure	Atmosphere
4	HP Compressor(In)	312.8828	311.7689	Temperature	Degree Kelvin
5	HP Compressor(Exit)	514.5628	506.0643	Temperature	Degree Kelvin
6	Combustor Entry	799.2399	779.9763	Temperature	Degree Kelvin
7	Power Turbine(In)	1126.1593	1089.1025	Temperature	Degree Kelvin
8*	Power Turbine(Exit)	857.7009	833.7476	Temperature	Degree Kelvin
9	HP Shaft Speed(RPM)	8258.4756	8160.9365	Tachometer	RPM
10	LP Shaft Speed(RPM)	6254.1577	6093.7715	Tachometer	RPM

* Indicates biased Instrument

Table 7.7: Simulated measurements with fault implanted (Fault Case-2)

Fault case-2 considers two faulty components and two faulty sensors. The diagnostics started with 100 strings and went through 100 generations similar to case-1. The algorithm took 22 hrs 19 minutes to converge. The results obtained from the diagnostics model is shown in table-7.8

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 227 TIME/DATE: 15:57:50 [11-Mar-03]

Fault Class Analysis

FC	MOF	Time	Efficiency Change (Δη) - Percentage				Flow Capacity (ΔΓ)- Percentage			
			Component-1		Component-2		Component-1		Component-2	
			Δη	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID	ΔΓ	Comp-ID
FC-1	56.162	48	-1.5835	LPC	0.0000	-	-0.6190	LPC	0.0000	-
FC-2	71.221	51	-1.3223	ICL	0.0000	-	-1.7490	ICL	0.0000	-
FC-3	59.756	55	-0.0238	HPC	0.0000	-	1.1043	HPC	0.0000	-
FC-4	50.642	50	-1.9347	HPT	0.0000	-	2.7854	HPT	0.0000	-
FC-5	51.640	54	-0.6681	LPT	0.0000	-	-1.2274	LPT	0.0000	-
FC-6	67.371	45	-1.1462	FPT	0.0000	-	0.0836	FPT	0.0000	-
FC-7	59.766	54	-0.3779	RCP	0.0000	-	1.5128	RCP	0.0000	-
FC-8	53.516	43	-1.4478	LPC	0.0949	ICL	-0.3594	LPC	-0.4055	ICL
FC-9	57.943	52	-0.6344	LPC	0.2002	HPC	1.1108	LPC	1.3959	HPC
FC-10	17.991	54	-0.9267	LPC	-2.1364	HPT	-3.2561	LPC	3.8972	HPT
FC-11	58.215	52	-1.0233	LPC	-0.6898	LPT	-0.8533	LPC	-0.3488	LPT
FC-12	58.559	49	-1.6576	LPC	-0.6859	FPT	0.3125	LPC	-0.8368	FPT
FC-13	56.094	53	-1.6242	LPC	-1.3621	RCP	0.5493	LPC	0.9185	RCP
FC-14	59.769	48	-0.1651	ICL	-0.1150	HPC	-0.7267	ICL	0.9320	HPC
FC-15	41.596	47	-1.0118	ICL	-0.9209	HPT	-1.2461	ICL	2.6492	HPT
FC-16	55.767	53	-0.1164	ICL	-0.8855	LPT	-1.6915	ICL	-0.5838	LPT
FC-17	71.052	52	-0.0151	ICL	-0.9369	FPT	-1.6136	ICL	0.0706	FPT
FC-18	65.024	54	-0.0367	ICL	-1.2796	RCP	0.1925	ICL	1.5979	RCP
FC-19	24.680	47	-0.5828	HPC	-0.0066	HPT	1.2301	HPC	2.4198	HPT
FC-20	44.266	48	-0.2204	HPC	-0.3722	LPT	0.2142	HPC	-0.8493	LPT
FC-21	62.337	51	-0.7979	HPC	-0.1020	FPT	1.2713	HPC	-0.3686	FPT
FC-22	60.749	46	-0.3737	HPC	-0.2710	RCP	1.8550	HPC	1.3030	RCP
FC-23	33.136	52	-0.7309	HPT	-0.3307	LPT	2.3726	HPT	-1.0441	LPT
FC-24	45.188	42	-1.1254	HPT	-0.1769	FPT	2.3160	HPT	0.2388	FPT
FC-25	25.736	48	-0.0511	HPT	-0.2323	RCP	2.5878	HPT	1.5541	RCP
FC-26	42.603	49	-0.4698	LPT	-0.7449	FPT	-0.9764	LPT	-0.3886	FPT
FC-27	47.964	50	-0.2409	LPT	-0.4529	RCP	-0.6033	LPT	0.4725	RCP
FC-28	69.976	46	-1.3979	FPT	-1.5013	RCP	-0.8216	FPT	1.5710	RCP
		1399								

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26426.3906	308.2079	1.0003	23992.2910	308.2154	1.0012

Fault Detected (Change in Component Performance Parameters)

Component-1				Component-2			
Δη	Comp-ID	ΔΓ	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID
-0.9267	LPC	-3.2561	LPC	-2.1364	HPT	3.8972	HPT

Sensor fault Detection

Faulty Sensor -1		Faulty Sensor-2	
Sensor ID	Sensor Type	Sensor ID	Sensor Type
HPC (In)	Pressure	FPT(Exit)	Temperature

Table 7.8: Results for Fault Case-2

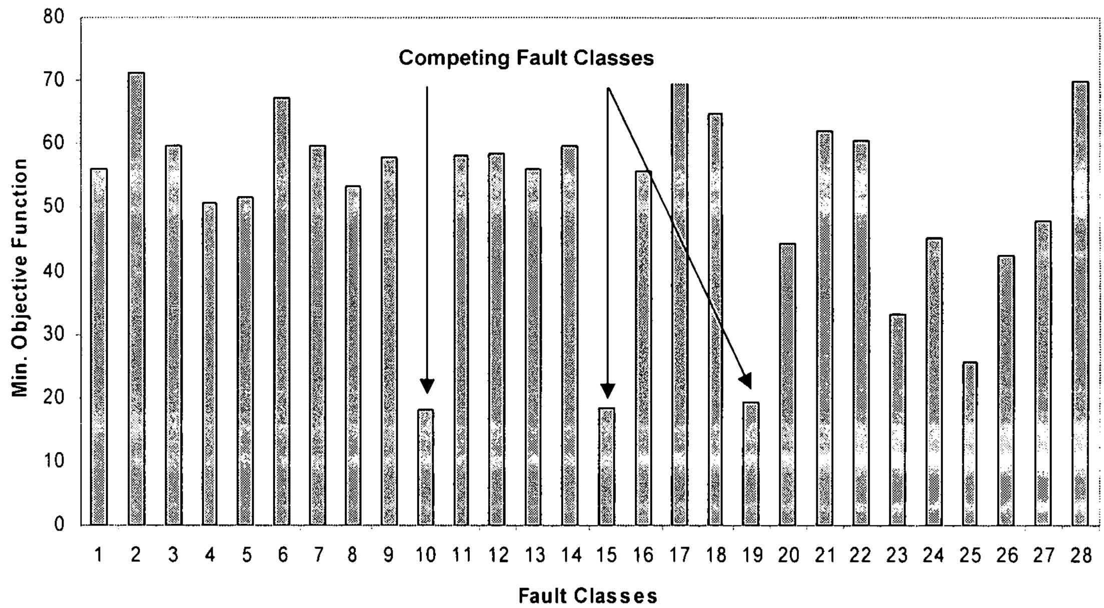

Figure 7.16: Minimum objective functions for Case-2

The accuracy of fault prediction and sensor fault detection has been high. A comparison of minimum objective function from each fault class has been shown in figure 7.16. It can be observed that fault classes 10, 15 and 19 have very close values of objective function. These are termed as competing fault classes. During the search process, the probability that any one of the fault classes could be declared faulty is always high. Since the genetic operators are random in nature it is possible that the string producing the best objective function could be randomly modified by the crossover or mutation operators. This is one of the limitations of this method. It can be observed that, among the competing fault classes, there is one component which is common to all the FCs i.e. HPT.

It noteworthy that the same fault class with similar magnitudes of deviation was considered in chaper-5 and the competing fault classes in that case were different. The algorithm identified fault classes 10 and 25 as competing fault classes. This proves that the genetic algorithms follow stochastic transition rules. This characteristics of the GAs makes it possible to obtain a global minimum even the face of randomness , noise and model inaccuracies. This ability is the basic strength of GA.

7.5 Advantages and Limitations Of MOPA

The use of a GA based optimization technique for engine fault diagnostics (using MOPA) has been examined for the RB199 engine by Gulati (2002c) and for the ICR WR21 engine in the present work. The method has been shown to be accurate even in the presence of a large amount of noise, sensor bias and model inaccuracies. The advantages from the diagnostics model are as follows:

- The lack of information from fewer number of measurements for poorly instrumented engines can be overcome by the use of the technique based on multiple operating point analysis and the concept of pareto-optimality. Multiple operating points provide high relative redundancy for accurate component and sensor fault diagnosis.

- The problem of "smearing" experienced with many other methods has been effectively dealt by dividing the engine into a number of fault classes. Each fault class is examined separately and the minimum objective function from that fault class is retained. All the fault classes are searched sequentially and the fault class having the lowest value of objective function is assumed to be containing the faulty component(s). In this method, only components of the fault class with minimum objective function are identified as having deviations in efficiency and flow capacity whereas the others are designated a value of zero.

- The issue concerning non-linearity of the gas turbine operation has been addressed by the development of an objective function which can also deal with measurement noise and sensor bias adequately.

Though the results obtained from GA based diagnostics technique have been very encouraging but there are still a number of drawbacks with this method that need to be addressed before it can truly become a widely accepted technique. The main drawbacks are as follows:

- A major limitation of the based optimization technique is the long run times involved in detecting a fault. A GA requires an initial population and the members of this population produce offspring and as generations progress these members get better and fitter. The larger the number of generations the better for convergence. Even under best circumstances the GA based optimizer requires a minimum of 100 strings per fault class which then have to go through 100 generations. For an engine of the type of WR21 which has 28 fault classes (for a maximum of 2 components being faulty), this would require the performance model to be run at least $28 \times 100 \times 100 \times 2 = 560000$ times. This requires at least 22 hours for convergence. In case the performance model is slower than this, then the time increases. This is especially true for the Trent 500, for which there are 45 fault classes and the model runs for 900000 times (Sampath et al, 2002c) , but the model being slower, it takes at least 36 hours for convergence, which can be reduced significantly if the model is speeded up.

- Dividing the engine into a number of fault classes and then trying to identify one of these as faulty solves the problem of "smearing". However, this has an effect on the maximum number of components that can be identified. For the purpose of this research it has been assumed that a maximum of two components are faulty. It is possible to look at more components, but this would lead to more fault classes and hence more time for convergence.

- As discussed earlier, during the search process it is also possible that the algorithm identifies more than one fault class i.e. the competing fault classes. While it can be said with some amount of confidence that the common component in the competing fault classes could be faulty, but to ascertain the magnitude of fault is a difficult task. Such situations need a careful assessment of the final results. Under such circumstances, a prior knowledge of the system would be highly beneficial.

7.6 Steps Towards Effective GA Diagnostics

The importance of search space analysis has been discussed earlier in the chapter. It would be beneficial to develop the search spaces for the particular engine using the available measurements. An initial assessment of the problem could aid in the decision to choose SOPA or MOPA for diagnostics. Though the search spaces can be plotted for only for one component at a time (with some variations in the power setting parameters), this is still reasonable enough to take a decision. The search spaces are likely to become less complex as the number of measurements increases, though the observability is an important issue for consideration.

In cases where the search space is very complicated, as in the case of RB 211 (industrial) (Carter, 2001), which has only three measurements, the use of three operating points could be considered. Anything beyond three operating points is likely to introduce complications as shown by Zedda (1999c). Fault diagnostics for engines with poor instrumentation suite should aim at identifying the faulty components correctly rather than look for very high degree of accuracy in quantifying the faults. In practical applications, small difference in the quantification of fault identified would not necessitate any change in the type of remedial action taken, however, it is important to identify the correct component(s).

The next step is to be able to identify the range of power setting points that are likely to give accurate results. This could be defined as observability with respect to the power setting. Very low power setting is not suitable due to the observability issue whereas high power is not suitable due to the fact that mutation can sometimes lead to points that fall outside the operational envelope, as a result of which the performance model may not converge. Having decided on the technique to be employed and the range of operating points to be used, the algorithm can be tailored for a particular engine.

7.7 Results from Advanced Diagnostics Model

The advantages and limitations of the diagnostic model based on MOPA have been presented in the previous section. In order to overcome some of the limitations like the long run times and competing fault class, an advanced diagnostics model has been developed. The advanced model is further categorized into two parts: The 3-stage Integrated Fault Diagnostics Model (IFDM) and a Hybrid Diagnostics Model (HDM). The developments of the models have been discussed in detail in chapter-6. An analysis of the method supported by results is presented in the following sections.

7.7.1 3- Stage Integrated Fault Diagnostics Model (IFDM)

The three stage Integrated Fault Diagnostics Model consists of 3 constituent models: Adaptive GA model, Response surface model and elitist model. The adaptive GA works in a Master-slave configuration which is closely linked to an embedded expert system. The master monitors the slave process for critical parameters. The master interrogates the expert system which has a built-in logic in the form of rules (IF-THEN). The various GA parameters like population size, no of generations, PC, PM etc.. are varied appropriately to arrive at a solution.

The method using response surface during the earlier generations to obtain an objective function can reduce the total run time significantly. The aim is to reduce the computational effort and time spent on evaluating strings which are to be anyway discarded during the selection process. Evaluating 100 strings involves 200 calls to the performance code and going through 100 generations would require 20000 calls to the engine performance model for one fault class. The algorithm takes approximately 35-40 minutes to search one fault class and needs to search 28 fault classes to identify a multiple component fault. Figure 7.17 shows the results from an IFDM with only the response surface model enabled. The figure shows the time taken for each generation for fault class-4.

During the first 25 generations, the objective functions are calculated using the response surface. Engine performance model is used to calculate the objective functions from the 26^{th} generations onwards. It can been seen that the time taken for 100 strings in the initial generations is less than a second, whereas, the same number of strings processed with the performance code, the time taken on an average is about 26 seconds per generation. Using this method, the total time for one fault class has been reduced by approximately 10 minutes and for 28 fault classes, the time saved is approximately 5 hours. The overall gain in speed is significant. As mentioned earlier in chapter-6, the response surface helps in eliminating weaker individuals in the beginning of the search process. Its use should be restricted only to the initial generations.

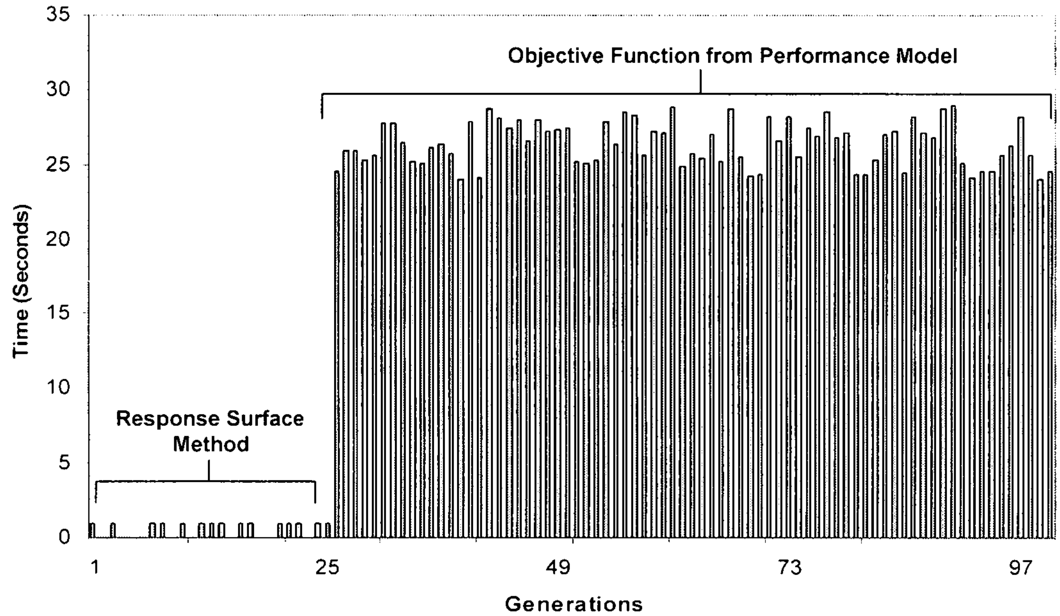

Figure 7.17: Summary of time taken for fault classes in IFDM

The choice of the number of generations for which the response surface method should be used is up to the user and depends on the accuracy of the response surfaces generated. Response surfaces with high accuracies can be used for larger number of generations. Response surfaces are trained using ANN and therefore require large amount of training data. However, the advantage is that they can be trained independently and the trained network can be used for diagnostics at a later stage. The main disadvantage is that, with change in power setting the networks have to be retrained. After several trials, it has been established that, its application should normally be restricted to about 25% of the total number of generations to get the benefits.

7.7.1.1 Fault Class Analysis (FCA)

Fault class analysis is an important preliminary assessment technique, to take certain informed decisions on the setting up of the diagnostics process. A discussion on the search space analysis has been presented earlier in this chapter. It was also brought out through the search space analysis, that the faults associated with compressors are more difficult to detect when compared with turbine faults. A limitation of the search space analysis technique is, that it can be plotted only for single component faults. However, the search space for single component faults can provide a reasonably good idea of the observability of the sensors used.

The fault class analysis method is similar to the search space analysis method, in which objective functions are obtained by varying the efficiency and flow capacity of a component in small steps of desired size. The objective functions are obtained for all the fault classes sequentially and the fault class producing the lowest objective function is considered to be indicative of the fault. The approach is very similar to the actual GA diagnostics model but here the aim is to generate strings which cover the entire range of the performance parameter deviations defined for the diagnostics. The number of strings generated is up to the user. A large population will give an effective coverage of the whole range but will take more time. The aim of such an exercise is to identify the fault class(s) which are likely to give a solution to the diagnostics problem. The fault class analysis approach is restricted only to giving prior information to the IFDM and not to influence or bias the search process by the diagnostic model. The IFDM retains the information as part of its internal logic and may use it to allocate resources appropriately during the search process.

The results from fault class analysis are shown in table- 7.9. It can be seen that the FCA has detected FC-10 to be faulty. However, it has also recommended that fault classes 4, 15, 19 & 23 should also be investigated as the minimum objective functions from these fault classes are also comparable. From the case studies taken up earlier, it can be seen the fault classes identified are again competing classes. This information is useful to the IFDM.

INTERCOOLED RECUPERATED WR21- FAULT CLASS ANALYSIS

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ FC/144 TIME/DATE: 12:10:21 [11-Aug-02]

Fault Class Analysis

FC	FC Components		Deviation in Performance Parameter				Objective Function Calculated			
	Comp-1	Comp-2	Component-1		Component-2		OBJ-1	OBJ-2	OBJ-SUM	Fault
			$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$				
FC-1	LPC	-	-0.00	2.20			56.0105	53.9703	109.9808	-
FC-2	HPC	-	-1.00	0.20			46.4889	46.7114	93.2003	-
FC-3	I/C	-	-2.00	0.00			52.2449	48.5493	100.7943	-
FC-4	HPT	-	-1.80	3.00			17.1808	16.3264	33.5072	✓
FC-5	LPT	-	-1.40	0.60			49.7431	48.4312	98.1742	
FC-6	FPT	-	-2.00	-0.20			37.3416	38.8100	76.1516	-
FC-7	R/C	-	-0.00	0.00			58.5995	54.6535	113.253	-
FC-8	LPC	HPC	-0.00	-1.00	-1.00	1.00	49.0687	46.2879	95.3566	-
FC-9	LPC	I/C	-0.00	1.00	-2.00	0.00	50.9416	48.2140	99.1556	-
FC-10	LPC	HPT	-0.00	-1.00	-2.00	3.00	14.7833	13.1088	27.8920	✓
FC-11	LPC	LPT	-2.00	1.00	-0.00	1.00	49.0768	49.4699	98.5467	-
FC-12	LPC	FPT	-3.00	-3.00	-2.00	-3.00	29.3808	23.1000	52.4808	-
FC-13	LPC	R/C	-0.00	3.00	-0.00	0.00	55.8923	54.4678	110.3601	-
FC-14	HPC	I/C	-1.00	1.00	-0.00	0.00	46.7782	47.7968	94.5750	-
FC-15	HPC	HPT	-1.00	-1.00	-1.00	3.00	14.9094	13.1645	28.0739	✓
FC-16	HPC	LPT	-0.00	-1.00	-3.00	1.00	53.4924	54.7816	108.2740	-
FC-17	HPC	FPT	-0.00	-1.00	-2.00	-1.00	40.3781	44.2582	84.6363	-
FC-18	HPC	R/C	-1.00	1.00	-0.00	0.00	46.7782	47.7968	94.5750	-
FC-19	I/C	HPT	-0.00	0.00	-2.00	3.00	14.8092	15.0571	29.8663	✓
FC-20	I/C	LPT	-0.00	1.33	-0.00	1.00	48.6583	50.5195	99.1778	-
FC-21	I/C	FPT	-0.00	2.00	-3.00	-3.00	28.9364	34.5901	63.5265	-
FC-22	I/C	R/C	-2.00	2.00	-0.00	0.00	52.2449	48.5493	100.7943	-
FC-23	HPT	LPT	-0.00	3.00	-2.00	1.00	17.4032	15.4847	32.8879	✓
FC-24	HPT	FPT	-0.00	3.00	-0.00	-1.00	25.9708	23.4875	48.4583	-
FC-25	HPT	R/C	-2.00	3.00	-0.00	0.00	24.8092	15.0571	39.8663	-
FC-26	LPT	FPT	-3.00	-1.00	-3.00	-3.00	22.2214	24.5871	46.8085	-
FC-27	LPT	R/C	-0.00	1.00	-0.00	1.33	48.6583	50.5195	99.1778	-
FC-28	FPT	R/C	-3.00	-3.00	-2.00	2.00	26.6699	33.6049	60.2749	-

The Fault Class Analysis Indicates that Fault is in - Fault Class: 10

Additionally the following Fault Classes should be investigated:
Fault Class:- 4
Fault Class:- 15
Fault Class:- 19
Fault Class:- 23

Table 7.9: A typical Fault Class analysis

7.7.1.2 Results from Integrated Fault Diagnostics Model

The effect of using the response surface model as part of the IFDM has been shown earlier. It has the advantage of reducing the time taken in earlier generations. The results obtained from the IFDM with all the three constituent modules enabled in shown in table 7.10.

The fault case chosen for study is a multiple component fault and is the same which was examined in fault case-2 in the simple MOPA based diagnostics in section 7.4.2. The same fault case has been deliberately considered for easy comparison of the results obtained by different methods.

It can be observed from the results that, the faulty components have been identified correctly and faults quantified accurately. The diagnostics starts with a randomly generated population and evaluates the population to obtain the fitness values. The first 25 generations obtain the objective functions directly from the response surface thereby avoiding calls to engine performance code. This process eliminates the weak individuals in the beginning of the search process. In the second stage, the master takes over the optimisation process and monitors the various critical parameters like the diversity factor, fitness improvement etc. and passes it on to the built-in logic which is in the form of a rule based expert system. The master receives instructions from the expert system and accordingly controls the slave by controlling the population size, mutation size etc. A comparison of minimum objective functions for fault classes is shown in figure 7.18. It can be noticed that the minimum objective function indicating the fault (FC-10) is distinctly the lowest when compared with others. If we compare the results for the same fault condition with the simple MOPA based diagnosis model, it can be seen that the competing fault classes condition shown in figure 7.18 has been eliminated to a large extent. The elitist model used in the IFDM retains the best solutions from a given population in an elite pool over a number of generations. When there is no significant fitness improvement in the population the strings from the elite pool are transferred to the main population, and more strings in the vicinity of the elite strings are generated for better local tuning. This improves the accuracy and prevents competing fault classes to a large extent.

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 242 TIME/DATE: 15:57:50 [20-Apr-03]

Fault Class Analysis

FC	MOF	Time	Efficiency Change (Δη) - Percentage				Flow Capacity (ΔΓ)- Percentage			
		(Min)	Component-1		Component-2		Component-1		Component-2	
			Δη	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID	ΔΓ	Comp-ID
FC-1	52.7738	17	-0.0752	LPC	-	-	-1.7356	LPC	-	-
FC-2	63.0423	23	-0.0038	ICL	-	-	-1.2786	ICL	-	-
FC-3	50.0108	10	-1.9932	HPC	-	-	1.0823	HPC	-	-
FC-4	26.0000	34	-0.1252	HPT	-	-	2.9741	HPT	-	-
FC-5	54.3175	16	-2.7564	LPT	-	-	0.2546	LPT	-	-
FC-6	47.6799	12	-1.4799	FPT	-	-	0.7612	FPT	-	-
FC-7	53.7400	17	-0.3458	RCP	-	-	0.6016	RCP	-	-
FC-8	47.0787	13	-1.0674	LPC	-1.5024	ICL	-2.6404	LPC	-1.1501	ICL
FC-9	49.9649	10	-0.6971	LPC	-1.8458	HPC	-1.1007	LPC	0.2326	HPC
FC-10	12.3000	38	-1.0581	LPC	-2.1608	HPT	-2.9999	LPC	3.7949	HPT
FC-11	51.5208	18	-1.1198	LPC	-2.0922	LPT	-2.0841	LPC	0.8320	LPT
FC-12	29.7490	30	-2.9304	LPC	-2.7364	FPT	-2.9386	LPC	-2.5350	FPT
FC-13	53.2599	17	-0.0018	LPC	-0.0272	RCP	-1.1449	LPC	0.2150	RCP
FC-14	48.8336	15	-0.3104	ICL	-1.9324	HPC	2.7241	ICL	1.4415	HPC
FC-15	26.4160	24	-0.0612	ICL	-0.4017	HPT	3.0000	ICL	3.0000	HPT
FC-16	51.6143	18	-1.8131	ICL	-0.4787	LPT	0.6932	ICL	-0.8197	LPT
FC-17	47.9465	22	-0.1277	ICL	-2.3249	FPT	-2.2380	ICL	0.3417	FPT
FC-18	48.9250	20	-1.0156	ICL	-0.2994	RCP	-0.2181	ICL	1.2257	RCP
FC-19	19.7000	36	-0.8843	HPC	-1.7081	HPT	1.6484	HPC	2.9686	HPT
FC-20	50.7463	18	-1.6553	HPC	-1.1424	LPT	1.8760	HPC	0.6753	LPT
FC-21	35.7157	24	-0.6231	HPC	-2.0140	FPT	1.9992	HPC	-0.7355	FPT
FC-22	51.0805	17	-1.7831	HPC	-0.1613	RCP	1.9862	HPC	0.9934	RCP
FC-23	28.0414	32	-1.8774	HPT	-2.8195	LPT	2.8966	HPT	-0.2002	LPT
FC-24	20.9000	39	-0.8066	HPT	-2.1006	FPT	2.8803	HPT	0.7303	FPT
FC-25	17.1000	43	-1.9646	HPT	-1.1486	RCP	2.9948	HPT	1.6857	RCP
FC-26	20.7000	39	-0.0535	LPT	-2.6623	FPT	-2.1645	LPT	-2.9856	FPT
FC-27	53.6178	15	-2.6627	LPT	-1.3727	RCP	1.0588	LPT	1.7646	RCP
FC-28	32.3382	23	-2.7457	FPT	-1.9999	RCP	-0.6532	FPT	1.9561	RCP
		640								

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26426.3906	308.2079	1.0003	23992.2910	308.2154	1.0012

Fault Detected (Change in Component Performance Parameters)

Component-1				Component-2			
Δη	Comp-ID	ΔΓ	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID
-0.9267	LPC	-3.2561	LPC	-2.1364	HPT	3.8972	HPT

Sensor fault Detection

Faulty Sensor -1		Faulty Sensor-2	
Sensor ID	Sensor Type	Sensor ID	Sensor Type
HPC (Exit)	Temperature	-	-

Table 7.10: Results from the Integrated Diagnostics Model (IFDM)

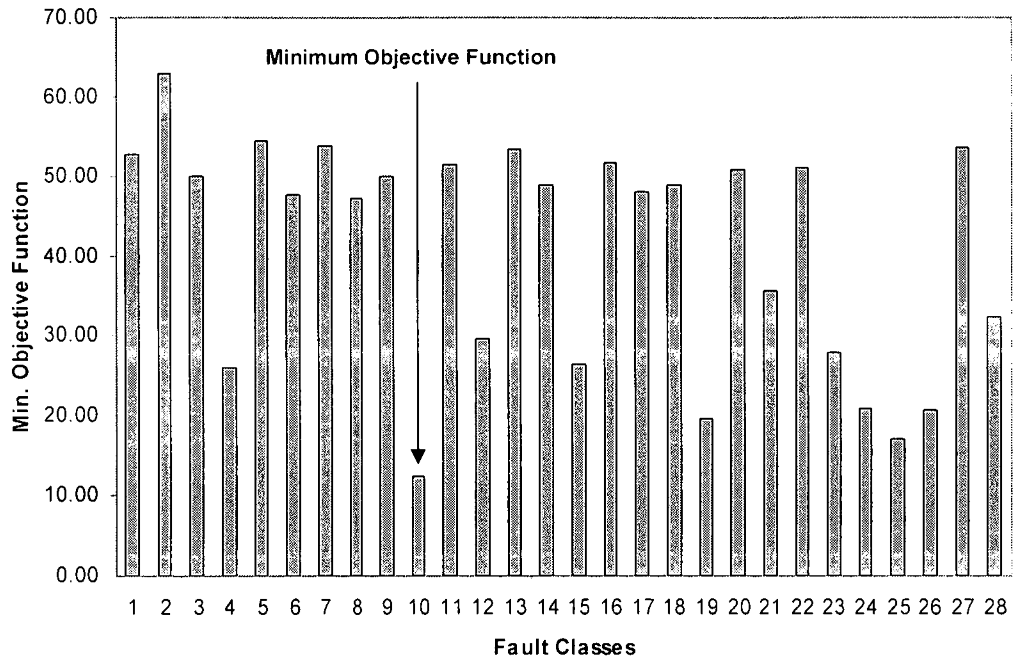

Figure 7.18: Comparison of Minimum Objective Functions in IFDM

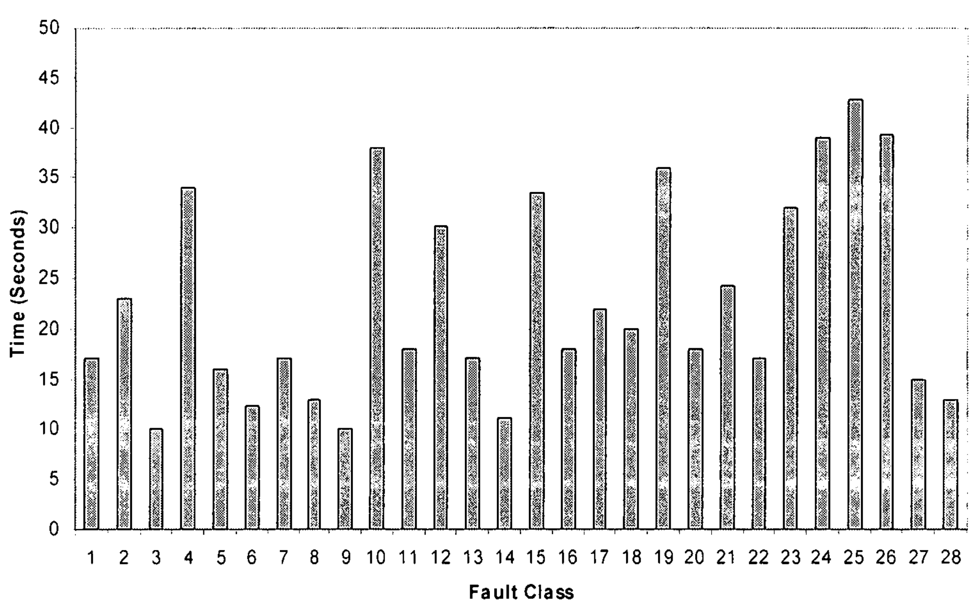

Figure 7.19: Time taken for fault classes in IFDM

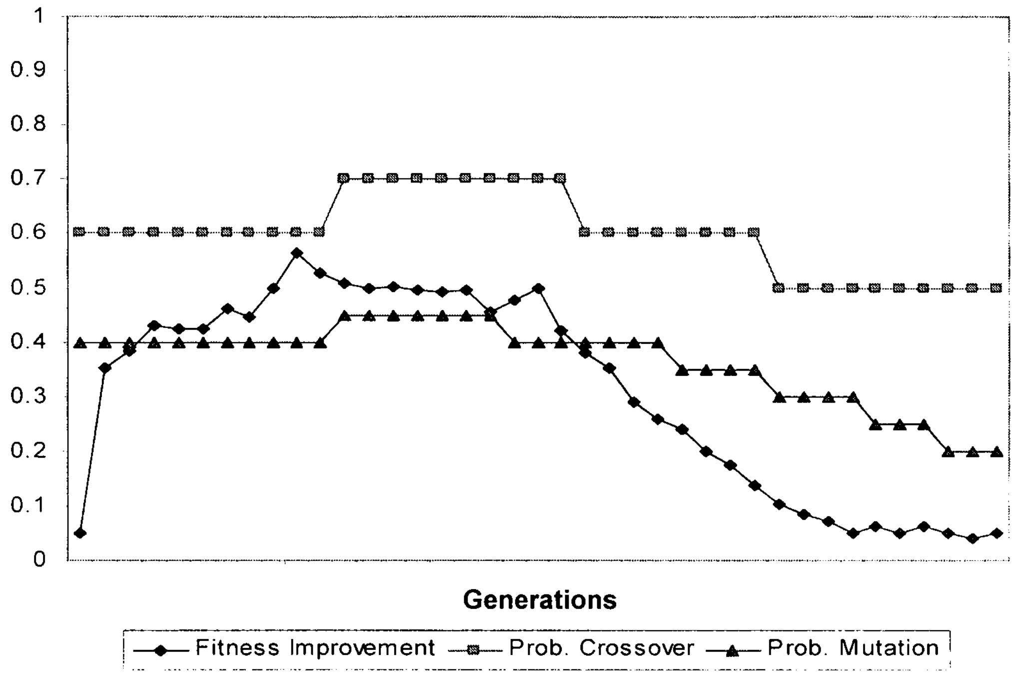

Figure 7.20: Variation in GA parameters in the IDM

Unlike the MOPA based the diagnostics technique, in which the number of strings and generations are fixed before the commencement of the diagnostics process, in the IFDM the critical GA parameters are varied during the search process depending on the prevailing situation. The search is stopped based on the termination condition issued by the master and therefore the time taken for each fault class is different. Figure 7.19 shows the time taken by each fault class during the search process. It can be observed that the time taken for fault classes with lower magnitudes of minimum objective function is more compared to the others. In the example considered, the fault classes with higher magnitudes of minimum objective functions have been terminated early. In the IFDM the input from the fault class analysis model has been used for managing the search more effectively. It can be seen that the time taken for the fault classes suggested by the FCA are high compared to the others which means that those fault classes have been searched more thoroughly. Figure 7.20 shows an example of the variation of P_C and P_M with the change in population fitness value.

7.7.2 Results from Hybrid Diagnostics Model

The development of a hybrid model for engine fault diagnostics has been described in detail in chapter-6. Essentially this concept involves a Nested Neural Network (NNN) being used as a pre-processor to reduce the number of fault classes to be searched by the GA diagnostics model. Neural networks are very good at classifying data and widely used for pattern recognition problems. In the context of engine fault diagnostics, training a single neural network to detect a fault and accurately quantify the fault is a difficult task and requires enormous amount of training patterns. Also, the confidence in the output from the network may not be very high. Instead a network is assigned the task of classifying the data into one or more logical subgroups and this process continues till the classification leads to a small group (of fault classes) which can be analyzed by the GA diagnostics model. The HDM is distinctly partitioned into two parts: IFDM and NNN classifier. Results from the IFDM have already been discussed in the previous section. A brief discussion of results from NNN is presented in the following section:

7.7.2.1 Discussion of Results from NNN

The process starts with a node classifying the input data into having a component fault or a sensor fault. If it is identified as a sensor fault, the data is forwarded to an Auto-Associative Neural Network (AANN) for isolation of faulty sensor(s) as well as assessment of the fault magnitudes. On the other hand, if a pattern is identified as a component fault by the node, it is then passed to the next node which classifies it as a single component or multiple components fault. If it is identified as a single component fault then the input data is passed onto to a node which further classifies into appropriate category (fault class). If it is classified as a multiple components fault, then it forwarded to nodes for classification to appropriate subgroups and finally classified into fault classes. A brief description of the constituent nodes is presented:

NODE L1NI – the test measurements are introduced to this node which is trained to accomplish an important task of classifying the data into: component fault or sensor. The node was subjected to series of rigorous tests with randomly simulated test patterns as follows-

- data with only sensor faults
- data with only component faults
- data with component and sensor faults (not occurring simultaneously)

The break down of the classification by L1N1 is shown in figure- 7.21. Data set-1 has patterns only from component faults and Data set-2 has patterns only form sensor faults

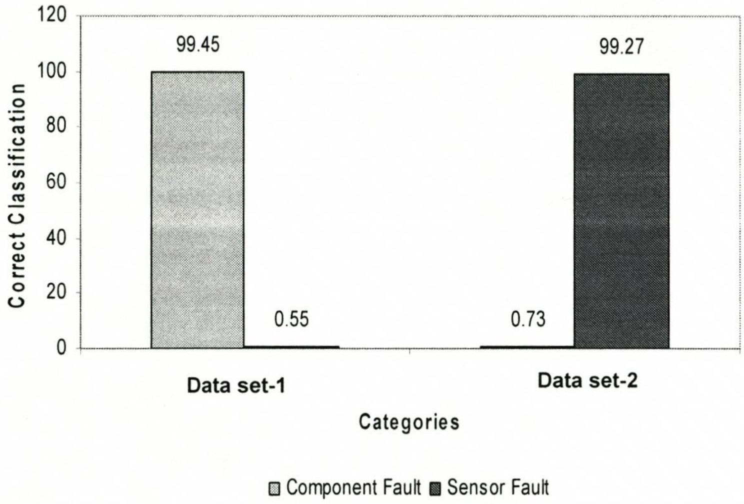

Figure-7.21: Classification Accuracy for L1N1 Node

The accuracy achieved by the network was over 99%. Investigation of the misclassified data revealed that some input data with low levels of sensor faults were classified as having component faults or input data with low levels of component faults were classified as having sensor faults. The levels of faults involved were very small and therefore the patterns were indistinguishable. It practical sense, such faults would not significantly impact on the performance of the engine or endanger the safe operation of the engine. It should be noted that the data from 28 fault classes are involved and therefore the network is subjected to a large amount of data and needs good generalisation capability.

NODE-L2N1 – this node is required to classify the input data as having a single component fault or multiple component fault (restricted to a maximum of two components simultaneously faulty). The node was subjected to a series of test with randomly generated fault data. The classification accuracy or the overall confidence factor achieved was 94%. The individual break down of classification is shown in figure 7.22. Data set-1 consists of only single component faults and data set-2 consists of only multiple component faults.

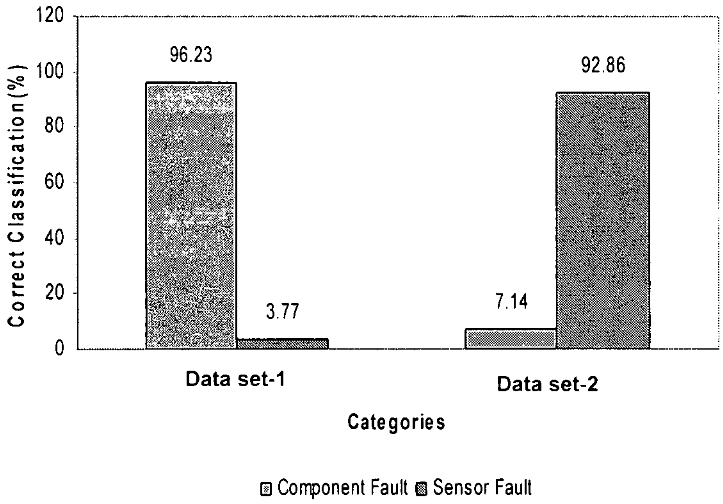

Figure-7.22: Classification Accuracy for L2N1 Node

The network achieved low accuracy due to the large variety of data involved in the training. The training data involved patterns from 28 fault classes, which implies various combinations of components and different fault levels. Therefore the network generalisation capability was poor. Many cases of overlaps in classification among the two categories were found. Further investigation revealed that single component fault with high fault levels were classified as multiple component faults and multiple component faults with very low fault levels were classified as single component faults. however, the misclassification does not seriously affect the diagnostics process, as closer examination showed that a single component fault misclassified as a multiple component fault normally detects the fault class which has one component same the actual faulty component (single component fault) and "smears" as small amount of the fault to the other component. When multiple component faults are classified as single component faults, it is normally observed that one of the component has a low level fault and the other which has higher level fault can be identified by the nest level.

NODE-L3N1- is a TERMINAL node and is required to provide the fault classes for further examination by the GA module. This node exhibits high level of classification accuracy as the patterns produced by the faults in the components are distinguishable by the network. The task of classification can be carried out by a network smaller than the ones used for the above two networks i.e. L1N1 and L2N1. In general, if the confidence rating of the network is very high, it would identify only one fault class to be examined by the GA module. However, in order to make the NNN robust, a simple logic is incorporated, which considers the individual fault class classification levels before deciding the fault class(es) to be examined.

Table 7.11 shows the classification of L3N1 node for a scenario where the classification accuracy is not very high. The network was trained with 6720 patterns for identifying a single component fault. The result is obtained from simulation of the node with 3360 random test patterns. The overall network CF is 98.06% and the classification accuracy of the individual fault class is shown in the table 7.11. The ability of the node to classify a fault as FC-1 is 97.50% and the remaining 2.5% of the data was classified as the fault in other fault classes. Under these circumstances the node will identify more than one fault class to reduce the probability of misclassification.

CAT.	CODE	TP	INCORRECT CLASSIFICATION								TOTAL	CC	CF
			Cat-1	Cat-2	Cat-3	Cat-4	Cat-5	Cat-6	Cat-7	UKN	Total		(%)
Cat-1	**FC-1**	**480**	**x**	**x**	**4**	**x**	**1**	**x**	**3**	**x**	**8**	**468**	**97.50**
Cat-2	FC-2	480	3	x	1	2	x	3	1	x	10	476	99.17
Cat-3	FC-3	480	1	x	3	x	x	x	2	x	6	465	96.88
Cat-4	FC-4	480	2	3	x	x	6	x	x	x	11	473	98.54
Cat-5	FC-5	480	6	x	x	4	2	4	x	x	16	470	97.92
Cat-6	FC-6	480	x	x	x	1	1	3	x	x	5	469	97.71
Cat-7	FC-7	480	x	1	7	x	x	1	x	x	9	474	98.75
Total		3360	12	4	15	7	10	11	6		65	3295	**98.06**

Overall Network CF (%)- 98.06
Categories to be investigated: Cat-1, Cat-3, Cat-7

Table 7.11: Typical Classification status for a single component fault

It can be noted, that some faults in FC-3, FC5 and FC-7 are also categorised as fault in FC-1. therefore , in the event that the network classification accuracy is not very high, a fault identified in FC-1 could actually be a fault in any one of the other fault classes. To take into account the network has identified three fault classes to be optimised by the GA module. It has omitted FC-5 as the percentage of FC-5s classified as FC-1 is much less compared to the others.

NODE	CLASSIFICATION OF CATEGORIES (%)							CF(%)
LIN1	SF		CF					99.36
	99.45		99.27					
L2N1	SCMPF		MCMPF					94.54
	96.23		92.86					
L3N1	FC-1	FC-2	FC-3	FC-4	FC-5	FC-6	FC-7	99.74
	99.90	99.97	99.88	99.54	99.92	99.71	99.25	
L3N2	GROUP-1		GROUP-2		GROUP-3			98.87
	99.83		99.52		97.12			
L4N1	LPC-GP		HPC-GP					99.80
	100.00		99.60					
L4N2	HPT-GP		LPT-GP		FPT-GP			99.80
	98.44		98.87		99.26			
L4N3	ICL-GP		RCR-GP					98.95
	99.79		98.92					
L5N1	FC-8	FC-9	FC-10	FC-11	FC-12	FC-13		98.62
	98.50	99.17	97.88	98.54	98.92	98.71		
L5N2	FC-14	FC-15	FC-16	FC-17	FC-18	FC-8		98.47
	97.62	99.23	98.38	97.94	99.12	98.54		
L5N3	FC-23	FC-24	FC-25	FC-19	FC-15	FC-10		98.67
	98.49	99.56	98.67	98.89	97.84	98.59		
L5N4	FC-26	FC-27	FC-23	FC-20	FC-16	FC-11		98.34
	97.68	98.64	99.33	98.21	9872	97.48		
L5N5	FC-28	FC-26	FC-24	FC-21	FC-17	FC-12		98.01
	97.29	99.09	97.78	98.67	97.37	97.88		
L5N6	FC-19	FC-20	FC-21	FC-22	FC-14	FC-9		98.43
	97.56	99.27	98.59	98.74	97.92	98.51		
L5N7	FC-28	FC-27	FC-25	FC-22	FC-18	FC-13		98.03
	97.34	99.21	96.73	98.67	97.45	98.78		

Table-7.12: Confidence Rating of Nodes in a NNN

The classification accuracy of the all the nodes in five layers of NNN is shown in table 7.12.It can seen observed, that the classification accuracy of nodes are quite high and the network is capable of identifying the correct fault classes, but the possibility of occasional misclassification cannot be ruled out. Therefore, the provision for identifying more than one class is made and this flexibility is provided only in the TERMINAL nodes. The arrangement of the nodes in the NNN and the fault classes used for training has been done is such a way that, if a particular fault is misclassified by a BRANCH node, there is still chance that the fault may be captured at by another node.

FAULT CASE	FAULT IMPLANTED	FCs IDENTIFIED
CASE-1	FC-1 (SCMF)	FC-1
CASE-2	FC-2 (SCMF)	FC-2
CASE-3	FC-4 (SCMF)	FC-4
CASE-4	FC-6 (SCMF)	FC-6
CASE-5	FC-8 (MCMF)	FC-8,FC-10
CASE-6	FC-10 (MCMF)	FC-10,FC-19,FC-23,FC-25
CASE-7	FC-16 (MCMF)	FC-16
CASE-8	FC-18 (MCMF)	FC-18, FC-13
CASE-9	FC-25 (MCMF)	FC-25,FC-19
CASE-10	FC-28 (MCMF)	FC-28

Table-7.13: Classification of component faults

The network was subjected to tests with simulated faulty data and results of ten sample test cases are presented in table 7.13. The faults have been shown only up to fault class levels. It can be observed that, in the case of single component faults the NNN has identified the correct fault classes and also suggested only one fault class to the GA module. In the case of multiple component faults, the NNN has been able to identify a single fault class in case-7 and 10. In some the cases the NNN has identified more than one fault class. This depends on the accuracy of the node and also the fault levels and noise levels in the input data play an important role. It should be noted that the fault classes in the TERMINAL nodes, especially at level-5 are potential competing fault classes and they have been grouped together for ease of classification.

Test case-6 presents an interesting scenario. The implanted fault is in FC-10, which comprises of LPC and HPT. In an ideal situation, the input data should have been expected to be pass through the node L4N1 (GROUP-1), which is trained with data from FC-8 to FC-18. Then it would have branched to L5N1 (LPC-GP), which contains all fault classes with LPC as one of the components. But it was misclassified by L3N2(MCMPF) and passed to L4N2 (GROUP-2), which has been trained using data from FC-23 to FC-28 and finally ends up at L5N3 (HPT-GP) which comprises of all fault classes having HPT as common component. However, it should be noted that FC-10 is part of the HPT group also and it appears in the list of fault classes suggested by the NNN. This shows the flexibility and high factor of safety available in the NNN.

NODE L2N2 (Sensor Fault Diagnosis): Once the L1N1 node identifies the data as having sensor fault, the input data is forwarded to the node identifying the sensor faults. The Auto-Associative Neural Network (AANN) is found to be most appropriate for the sensor fault diagnostics. AANN basically consists of several layers of nodes which form symmetrical structure with a bottleneck. The number and configuration of nodes on either side of the bottleneck layer are identical. The key point is to understand the number of bottleneck neurons required and their meaning. In general, it can be said that the number of neurons in the bottle neck is inversely proportional to the number of faulty sensor being sought. A large number of faulty sensors being sought would require a more constricted bottleneck. Additionally large number of neurons in the hidden layers do not actually produce improvements in the performance (Zedda, 1999c). The activation functions are the identity function for input and output layers and the hyperbolic tangent function for hidden layers. Input and output are expressed by relative values with respect to the un-deteriorated off-design condition as defined by the noisy environment and power setting parameters.

Fault classes are created for generating data and the number of fault classes depends on the number of faulty sensors being considered. For every fault class, a database is created by using the performance simulation code in synthesis mode: give performance parameters the measurements are calculated and then noised. White noise with Gaussian distribution was added to all the data used for training and testing. The noise values used are up to 3σ.

Several test were carried out to validate the performance of the node in isolating the faulty sensors. Bias ranging from 4σ to 15σ for respective instruments were used to generate faulty sensor data. A sample of a bias implanted in the HPC (Exit) pressure sensor is shown in figure 7.24. The bias levels have been correctly identified by the network in all the cases. The small deviations in the identified values are mainly due to the measurement noise. It was observed that, small levels of bias which are close to noise levels are more difficult to isolate.

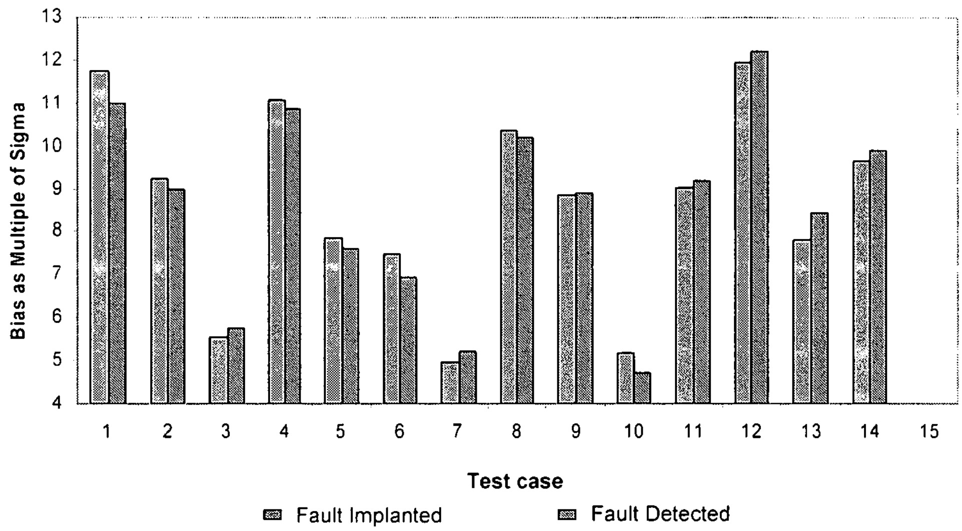

Figure 7.23: Sensor fault detection for HPC (Exit) pressure sensor

7.7.2.2 Discussion of Results from HDM

First, a single component fault is considered in which FC-2 (HPC) is considered faulty ($\Delta\eta$ = -2.0% and $\Delta\Gamma$= -4.0%). The data was introduced to the NNN and was classified has having a component fault. the data traversed through the NNN and was suggested to be associated with FC-2. The results from the hybrid diagnostics system for a single component fault is shown in table- 7.12. The task of identifying a single faulty component is fairly simple for a NNN. The GA optimiser has searched for fault in FC-2 only. The overall time taken is only 27 minutes. The time could go up if the fault classes to be examined are more depending on the classification ability of the NNN pre-processor. The time taken has also reduced as the master terminated the process after 72 generations. The other parameters like P_C,P_M and population size are variable and depend on the directions from the master. The elite pool consists of best 10% strings of the total population and preserves the best solution.

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 289 TIME/DATE: 09:28:16 [27-Oct-02]
Neural Pre-processor Output

Fault Class-2
Fault Class Analysis

FC	MOF	Gen	Time	Efficiency Change (Δη) - Percentage				Flow Capacity (ΔΓ)- Percentage			
			Mins	Component-1		Component-2		Component-1		Component-2	
				Δη	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID	ΔΓ	Comp-ID
FC-2	5.7256	72	27	-1.9634	HPC	-	-	-4.0101	HPC	-	-
			27								

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure
26424.4414	308.2270	1.0002	23997.6289	308.1990	1.0001

Fault Detected (Change in Component Performance Parameters)

Component-1				Component-2			
Δη	Comp-ID	ΔΓ	Comp-ID	Δη	Comp-ID	ΔΓ	Comp-ID
-1.9634	HPC	-4.0101	HPC	-	-	-	-

Sensor fault Detection

Faulty Sensor -1		Faulty Sensor-2	
Sensor ID	Sensor Type	Sensor ID	Sensor Type
		-	-

Table 7.14: Results from Hybrid system for single component fault

The hybrid system developed has reduced the total run time of the fault diagnostics model significantly. The reduction in the run time gives the opportunity for the diagnostics model to be run several times to ascertain the fault identified. The GA based IFDM was run 100 times and the distribution of the component faults obtained (quantification of efficiency & flow capacity changes) where plotted as shown in figures 7.24 & 7.25. It can be observed that on most occasions the faults quantified was very close to the implanted fault. It can be seen that the average of the distribution is very close to the implanted faults and the values falling on the extremes are also within normally acceptable limits. The spread of the results obtained is very less. This gives more confidence in the results particularly with GAs which follows stochastic transition rules and the results are a true representation of a global minimum.

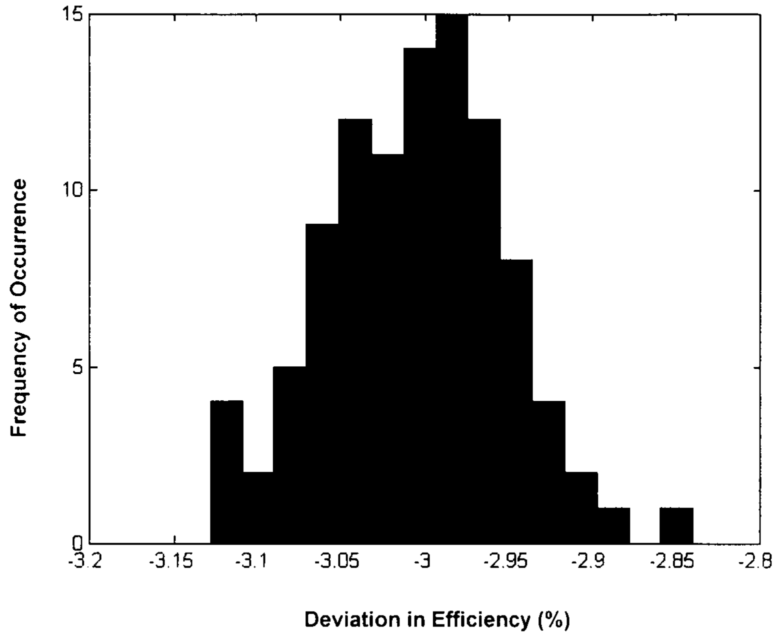

Figure 7.24: Quantification of Fault (efficiency-case-1)

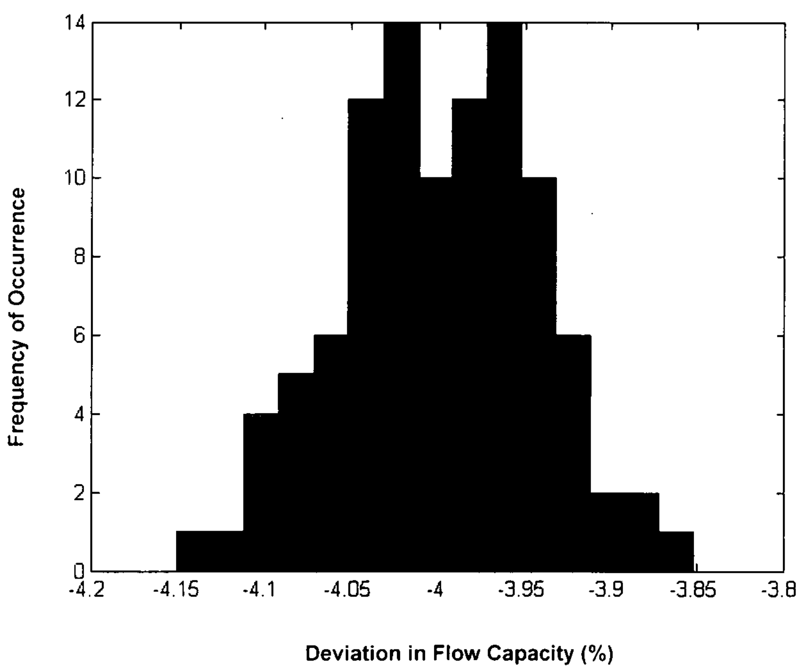

Figure 7.25: Quantification of Fault (flow capacity-case-1)

In the second test case, a multiple component fault has been considered. The same case which was considered for the simple MOPA based and IFDM based model has been considered for ease of drawing a comparison. The result from the Hybrid diagnostics model is shown in table 7.15. In the case of multiple components fault, the neural pre-processor (NNN) has identified four fault classes which are mostly likely to contain the fault. the GA optimizer has identified the correct fault class and identified the deviations correctly. The total time taken was 1 hour and 59 minutes which is a significant improvement over the traditional GA optimisation method.

Several test cases were run and it was found the diagnostics accuracy achieved was high and results were consistent. In addition, there is a significant improvement in the overall diagnostics time. The saving in time gives the opportunity to run the model several times to have more confidence in the results obtained. The test case was run many times to ascertain the faulty components and quantification of the deviation in performance parameters. A distribution of component performance deviations calculated are shown in figure 7.26 and 7.27 for LPC and HPT. It can been seen that the average of the deviations are close to the implanted values and also the extreme values are within acceptable limits. It can also be seen that the spread for LPC efficiency values is more. This is because the magnitude of fault implanted was small. However, the average is close to the implanted value.

The GA diagnostics model uses probabilistic transition rules and therefore it is also possible that occasionally the model detects the faults in other fault classes erroneously, especially the competing fault classes, this is attributable mainly to randomness in the application of GA operators coupled with measurement noise and model inaccuracies. Figure 7.28 shows the results from running the diagnostics model 56 times. The algorithm has detected FC-10 on 53 occasions .The advantage of HDM is that, the system can be run many times to build a statistical base. The more number of times a fault is detected in a trial set, the more consistent the method is and the more confidence the user can have in the fault diagnostics capability.

INTERCOOLED RECUPERATED-WR21 DIAGNOSIS REPORT

Performance Engineering Group, Cranfield University
Test Case: WR21/DIAG/ 269 TIME/DATE: 11:30:43 [29-Jun-03]

Neural Pre-processor Output

Fault Class-10
Fault Class-19
Fault Class-23
Fault Class-25

Fault Class Analysis

FC	MOF	Gen	Tim	Efficiency Change ($\Delta\eta$) - Percentage				Flow Capacity ($\Delta\Gamma$)- Percentage			
				Component-1		Component-2		Component-1		Component-2	
				$\Delta\eta$	Comp-ID	$\Delta\eta$	Comp-ID	$\Delta\Gamma$	Comp-ID	$\Delta\Gamma$	Comp-ID
FC-10	11.342	74	32	-1.1012	LPC	-1.9763	HPT	-3.1421	LPC	3.9874	HPT
FC-19	14.881	67	25	1.8629	HPC	1.8714	HPT	0.0603	HPC	0.6850	HPT
FC-23	18.386	78	34	2.9356	HPT	1.0407	LPT	2.1277	HPT	0.1555	LPT
FC-25	16.032	64	28	2.5467	HPT	1.1781	RCR	0.2712	HPT	-0.0702	RCR
			119								

Estimated Environment & Power Setting Parameters

Operating Point-1			Operating Point-2		
Power/Fuel	Temperature	Pressure	Power/Fuel	Temperature	Pressure

Fault Detected (Change in Component Performance Parameters)

Component-1				Component-2			
$\Delta\eta$	Comp-ID	$\Delta\Gamma$	Comp-ID	$\Delta\eta$	Comp-ID	$\Delta\Gamma$	Comp-ID
-1.1012	LPC	-3.1421	LPC	-1.9763	HPT	3.9874	HPT

Sensor fault Detection

Faulty Sensor -1		Faulty Sensor-2	
Sensor ID	Sensor Type	Sensor ID	Sensor Type
		-	-

Table – 7.15: Test Result for multiple component faults

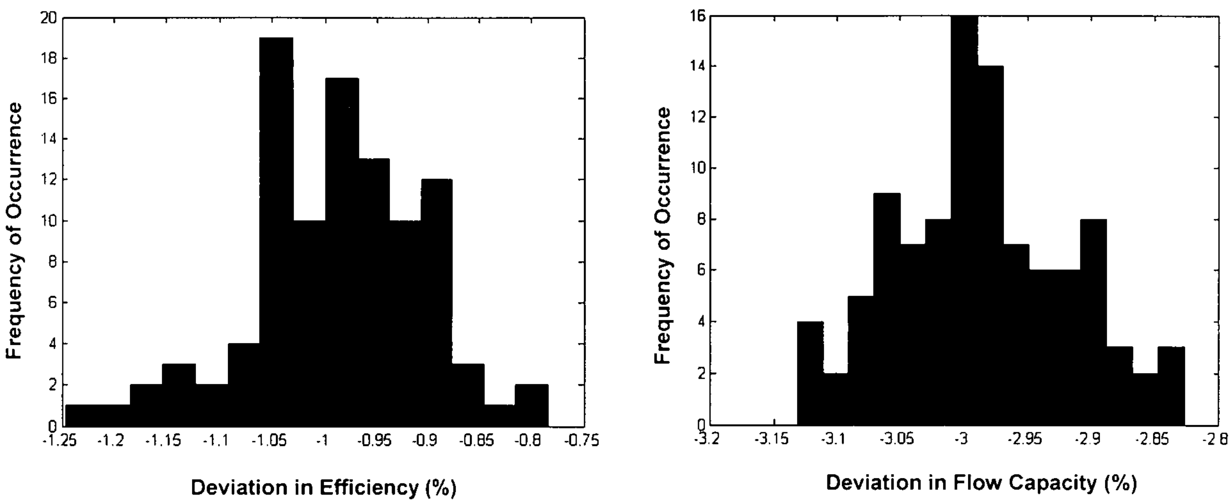

Figure 7.26: Distribution of Fault Quantification in LPC

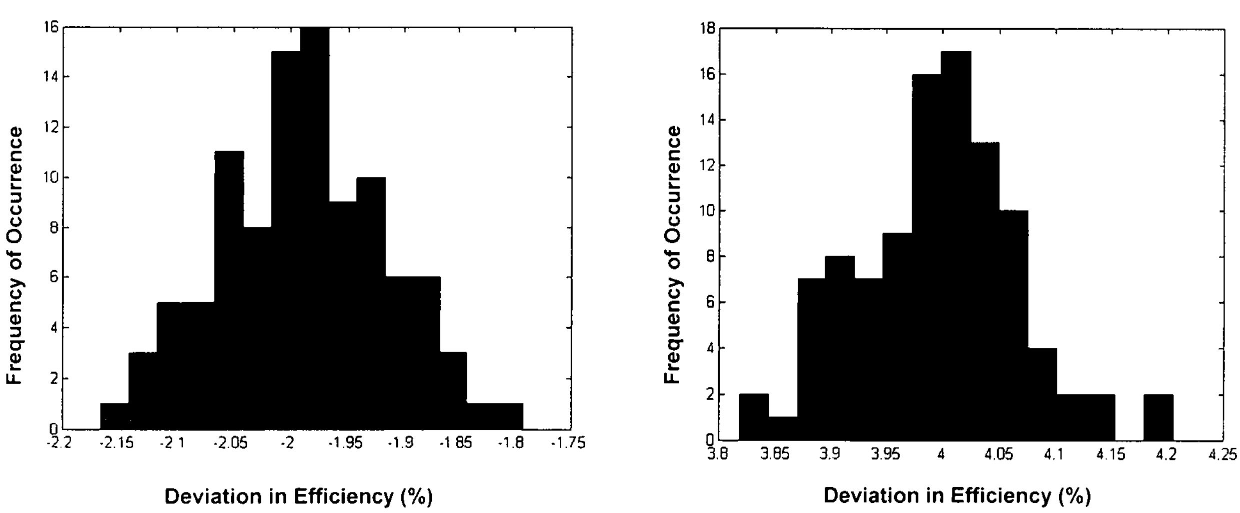

Figure 7.27: Distribution of Fault Quantification in HPT

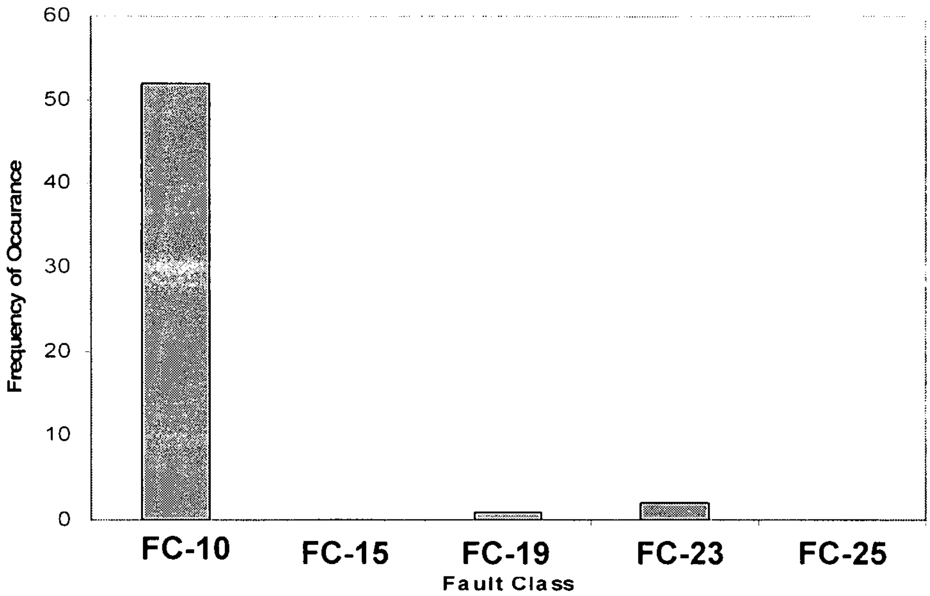

Figure 7.28: Results from multiple runs of diagnostics model

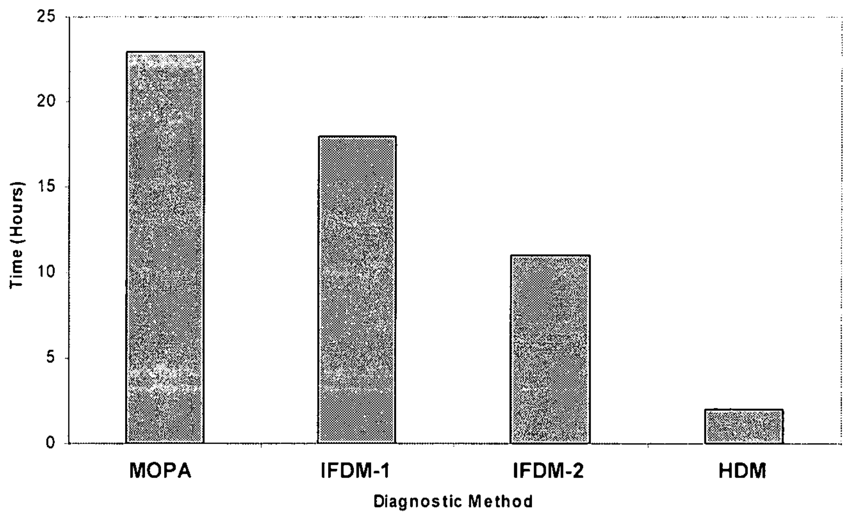

Figure 7.29: Comparison of different fault diagnostics schemes

A comparison of the different scheme of GA diagnostics process is shown in figure 7.29. Case-1 shows the diagnostics using the MOPA method and takes the longest time. Case-2 shows the IFDM-1 with only the response surface model enabled. Case-3 shows the time taken by IFDM-2 method and Case-4 shows the hybrid method. It is evident from the result that the hybrid method is the fastest method. The speed of the Hybrid model depends on the number of fault classes to be examined. The fewer fault classes, the faster the method is. However, there is limitation in the application of the HDM. Since the NNN are capable of distinguishing between faults which are exclusively component or sensor faults, a case of simultaneous component and sensor faults cannot be handled by the HDM though the IFDM is capable of doing it independently. Attempts to train nodes for distinguishing faults in component, sensors or both poses complex scenarios, requires prohibitively large amount of data and the accuracy achieved was not encouraging and therefore the present study is limited to faults associated with components are sensors only.

7.7.2.3 Discussions on No-Fault Conditions

In practice, all the engine parameters (measurable) are monitored and logged at regular intervals and assessed for trend shifts. A gradual trend shift indicates normal degradation attributable to various factors. Abrupt shifts in trend is a cause for concern and requires the attention of a fault diagnostics engineer. Keeping this in mind, the NNN has not been trained for distinguishing between fault and no-fault condition. This reduces the number of nodes and also the training time for such a network which will require a large amount of training data.

A set of clean data with noise was introduced to the NNN and it was found that it identified fault classes arbitrarily depending on the noise levels. These fault classes were subjected to GA optmisation and the results showed that the diagnostics system identified faults which were of insignificant magnitude. Such small deviations do not warrant any action and normally can be considered as no fault. In fact, some researchers (Ogaji, 2003c) consider fault levels below 0.7% as clean condition or affected by noise. Table 7.16 shows the results from a few test cases where clean data with noise was subjected to fault diagnostics.

CASE	FC BY NNN	FAULT IDENTIFIED					
		Component -1			Component-2		
		$\Delta\eta$	$\Delta\Gamma$	Comp-ID	$\Delta\eta$	$\Delta\Gamma$	Comp-ID
Case-1	FC-3	-0.0012	0.1921	ICL	-	-	
Case-2	FC-2	-0.0026	-0.0019	HPC	-	-	
Case-3	FC-8	-0.0148	0.2028	LPC	-0.0128	-0.1142	HPC
Case-4	FC-6	-0.0467	0.0540	FPT	-	-	
Case-5	FC-21	-0.0575	-0.2169	HPC	-0.0076	0.1836	FPT

Table 7.16: Results for no-fault conditions

7.7.2.4 Results with Different Sets of Operating Points

The importance of choice of operating points has been discussed earlier in the chapter. It was shown that the power setting values falling within 6-10% gave the best results. While all results presented were at the operating points mentioned in chapter-5, other sets of operating points were also examined. This exercise required the NNN to be trained with data from different operating points (separate NNN for each set). The results showed similar diagnostics capability and it is difficult to make a choice of the best set. In the practical application the choice of operating points would be dictated by the operational requirements of the ship. Results from a few test cases for different sets of operating point is placed at appendix-H.

7.8 Summary

A detailed discussion of the results obtained from the enhanced diagnostics model has been presented with supporting results from the diagnostics model. The various aspects which need to be addressed in the development of the model have been described in the earlier part of the chapter . The development of the IFDM demonstrated the utilisation advanced concepts in genetic algorithm for fault diagnostics of gas turbine engines. The combination of NNN with IFDM to form a HDM demonstrated the effective utilization of the strengths two different fault diagnostics technique to overcome the limitations of each other.

Since the NNN are classifying only at fault class level, the network are small in size and can be set up and trained quickly. Their generalisation capability is good as they are expected to make only a broad classification without having to quantify. The reduced diagnostics time can be utilised to run the system more number of times to ascertain the final results. An improvement in any of the technique can result in the improved output of the combined system, on the other hand the limitation of one technique becomes the limitation of the whole system.

The next chapter concludes the work and suggests some recommendation for future work.

CHAPTER-8

CONCLUSIONS AND RECOMMENDATIONS

8.1 Literature Review

The first part of the present work aimed at analysing the various performance analysis based diagnostics techniques available in the public domain. From the extensive literature survey conducted, it emerged that the there is an array of conventional and artificial intelligence techniques available for the purpose of engine fault diagnostics. Conventional Kalman filter based techniques have long been the back bone of most gas turbine fault diagnostics method. Poor knowledge of the probability of fault occurrence and evolution, need for tuning, "smearing" effect, divergence due to modelling errors and linearization are common problems associated with Kalman filter based methods. Analysis of the pertinent literature also indicates that a wide range of applications based on ANN have been investigated. The large variety of ANN architectures makes it difficult to select the best for diagnostics purposes. The results from the use of genetic algorithm in engine fault diagnostics has been encouraging: The method has the advantage of taking into account the measurement noise and sensor bias but, this method has the disadvantage of long run-times.

8.2 Development of IFDM and HDM

The present work aimed at developing a GA based diagnostics model and validating it against the advanced cycle WR21 engine. The research work commenced with development of a performance model for the WR21 engine. Extensive modifications have been incorporated into the model to make it compatible with the fault diagnostics model. The Integrated Fault Diagnostics Model (IFDM), which has been developed for gas turbine engines has a much wider applicability in fault detection. It is essentially a mathematical-model based technique in which various permutations of faults are implanted in the model to obtain simulated measurements and these are compared with those obtained with a nominally-simulated real engine (clean engine).

This relation between the component property and the measured parameters are the essence of this diagnostics model. The fundamental requirement for the successful use of such a technique is the ability to measure the desired parameters, which indicate the present condition of an equipment/system at that operating condition. The second important requirement is to define the relationship between the measurements and the constituent component characteristics/properties, such that any deviation in the component property is appropriately reflected as changes in measurement linearly or non-linearly. However, if the fault does not directly or indirectly relate to the measurements then it would not be possible to detect or a different model would be required.

The response surface approach in IFDM is essentially a type of ANN mapping of the performance model to and therefore uses the same performance model for data generation. The other concepts like the "master-slave" model and "elitist" model are associated with string manipulation techniques to improve the accuracy of the diagnostics model. The NNN pre-processor used in the HDM largely depend on the quality of the training data and type of training employed. The training data is obtained from the model by implanting suitable faults in the model.

The results from the HDM have been shown to be more accurate, reliable and consistent. Additionally, they have been obtained in a much shorter period than the basic model. The significant reduction in the total run time makes it possible for the model to be run several times to build a statistical base of the faults diagnosed to have more confidence in the results obtained.

Several publications in refereed journals and conferences have arisen from the current research work, few of which are with collaborating researchers and are included amongst the references. In addition, the sponsor has also applied for a patent for the research conducted (Patent ref: GB 0301707.6. dated 24 Jan 2003).

8.2.1 Wider Applicability of Diagnostics Model

Application of IFDS is not necessarily limited to gas turbine fault diagnostics but the applicability of the method can be extended to many other systems. A prerequisite in the use of such methodology is that a mathematical model for simulation of the system under consideration is available and is able to represent a clean and degraded state of the system with the desired accuracy. Some of the areas where the IFDM has potential applications are:

- Reciprocating engines (Petrol/Diesel etc.).
- Combined cycle plants.
- Auxiliary machineries like compressors, pumps, electric motors etc.
- Engine control systems.
- Chemical processes and plants.

The list mentioned above is indicative rather than exhaustive.

8.3 Summary of Contributions

The development of a fault diagnostics model using advanced feature in genetic algorithm has been discussed in chapter-6. A thorough analysis of the method with supporting results has been presented in this chapter-7. The method has its advantages, particularly in dealing with noisy and biased measurements. It also preserves the non linearity of the engine performance model. The research work presented in this thesis has given an insight into the working of the GAs and the application ANN. The technique developed opens new avenues for the use of intelligent systems and hybrid systems in the application of the engine fault diagnostics. The methodology developed also effectively addresses some of the shortcomings of the MOPA based research work. The contributions made by this research work is summarised as follows:

- The development of a diagnostics model using advanced concepts like a heuristics modifications of genetic parameters in the master-slave configuration, and elitist model for more reliable and consistent diagnostics underpins the novelty of the work.
- The development of a hybrid model using the NNN and IFDM has improved the convergence time of the algorithm significantly. This makes it possible for the user to run the model several times to have more confidence in the output.

The integration of the ANN and GA for improved performance of the diagnostics and the manner in which they have been used is a novel feature.

- The fault diagnostics model has been validated against an advanced cycle engine like the WR21, whose configuration and behaviour are unique. This implies that such fault diagnostics systems can be explored for more complex configuration and with a possibility of applying these techniques on combined cycle plants. The method is generic and can be used for any engine with minimal modification.

8.4 Potential Applications of the Diagnostics Model Developed

The aftermarket for gas turbines has undergone significant changes and is set to see more profound changes in the future. Advanced engine fault diagnostics systems will play an important role in defining the various aspects of the engine operation, maintenance, repairs & manpower planning. The techniques which has been developed will have the following potential areas of application in industry-

- Improved safety in operating gas turbine engines due to accurate prediction of the potential faults. This will facilitate timely withdrawal of the engine from service before any catastrophe occurs.
- Life extension, based on individual engine/component condition and usage profile leading to reduced overall life cycle cost. This is an important activity to reduce the overall maintenance costs. A method for managing the maintenance of gas turbine propelled naval ships by estimating the creep life for a gas turbine fitted on board naval ship has been studied by Sampath & Singh (2003). Such techniques can provide engineering justification for scheduling maintenance and optimise maintenance interval.
- Training personnel on importance of good maintenance practice by simulating fault conditions.

8.5 Limitations of the Research work

The research work has explored the possibility of applying sophisticated intelligent systems and hybrid methodologies for engine gas path fault diagnostics. The results obtained have been very encouraging and opened new avenue for engine fault diagnostics. However, the technique developed has certain limitations which are as follows:

- Engine simulation code – the diagnostics model heavily relies on the engine performance model, which is one of the contributors to the occasional discrepancies, and are attributable to the inconsistencies at some points in the component maps. However, this rectifiable by the use of more sophisticated simulation models.
- The NNN used in the pre-processor and response surface need adequate training which necessitate the generation of a large amount of training data and long training times. The networks are trained for a particular operating point and require the engine measurements to be taken at same operating point. Measurements taken at different operating points will require the networks to retrained, which is time consuming process.
- While the hybrid model tries to overcome the limitation of one technique with strength of the other, the limitation of one of the them becomes the limitation of the whole system. e.g. the GA module relies on the NNN to suggest the fault classes for optimisation. The NNN is limited in its ability in identifying correctly faults, where component and sensor faults occur simultaneously. Though independently, the GA module is capable of identifying such faults but the limitation of the NNN places the restriction of the whole diagnostics system.

8.6 Recommendations for Future Work

An advanced fault diagnostics system has been developed, which has effectively overcome some of the limitations of the previous methods. However, efforts must continue to overcome the limitations in the present model and the increase its applicability. Some of the recommendations of future work are as follows:

- Parallel processing

  The use of HDM has significantly reduced the total diagnostics time. However, the total time still depends on the number of fault classes to be optimized. Fortunately, the optimisation of one fault class does not affect the other and therefore it is an ideal candidate for parallel processing. Each fault class could be optimized by a different node and then the final results could be compared by one master node. In this way the total time close to the time taken for one fault class.

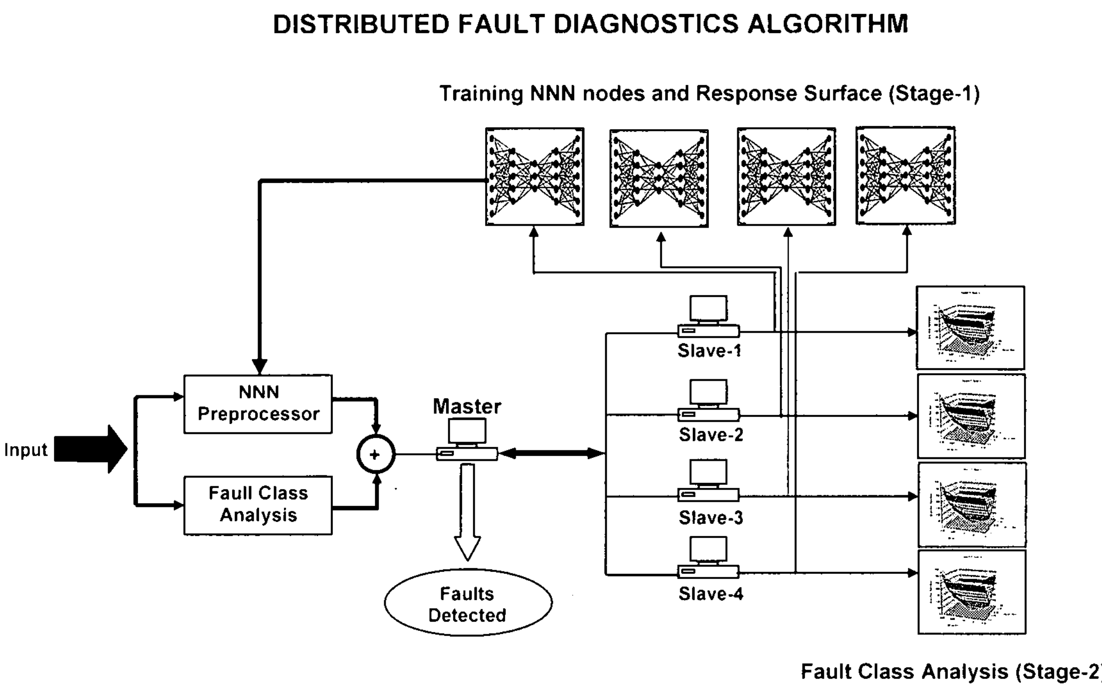

Figure 8.1: Concept of Parallel Processing

The concept is shown is figure 8.1. the same architecture can be used to train the ANN for response surface and NNN. The concept was taken up as a pilot project during the course of this research and has been successfully tested with two computers.

- Expert system with Diagnostics Model

  The use of an expert system to infer the results from the diagnostics model is another interesting application and needs to be explored. This is particularly important for user level interaction with the diagnostics model. The output of the diagnostics model indicating a reduction in compressor efficiency is hardly of any importance to a user, unless the consequence of a particular fault on the operation of engine is explained.

- Transient diagnostics

  The use of information from the engine transients have been used for fault diagnostics by several researcher like Sampath et al (2003), Ogaji et al (2003) and have reported success. These works were limited to noise free measurements and single component faults. The use of measurements during transients has shown much promise in diagnostics and need to be explored for more complex scenarios like multiple component faults, sensors faults etc. However, one should bear in mind that the transients are very complex conditions due to accompanying phenomenon like heat soakage, tip clearance , blade growth etc. and are different for different situations. e.g the transients of a cold engine is different from a transient of a hot engine or there could slow transients and fast transients etc. These conditions have to be given due consideration in a diagnostics model.

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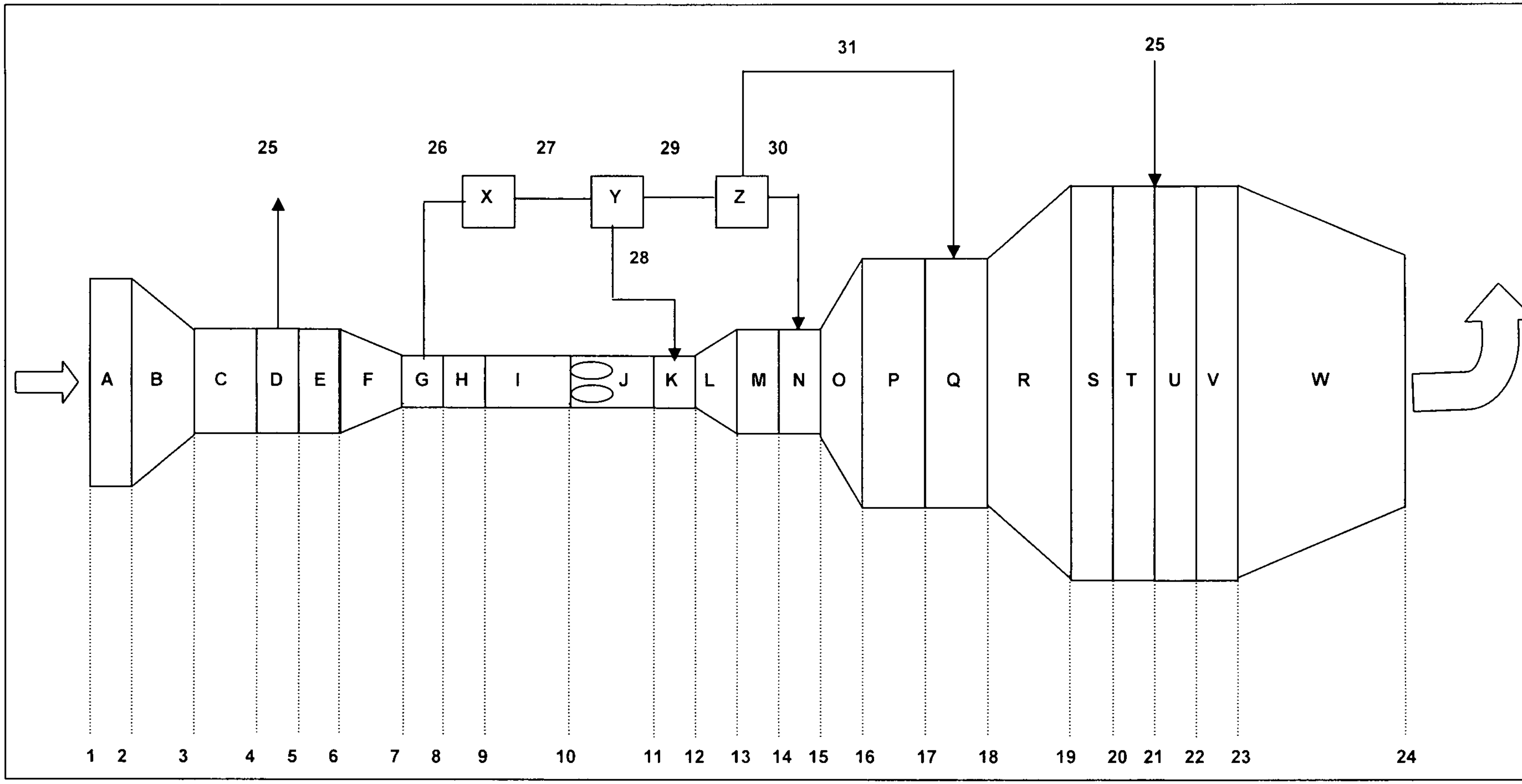
APPENDIX-A



A – Intake
B – LP Compressor
C – Intercooler
D – Splitter
E – Duct

F – HP Compressor
G – Splitter- Coolant
H – Duct
I – Heat Exchanger (cold side)
J – Burner

K – Intake
L – LP Compressor
M – Intercooler
N – Splitter
O – Duct

P – HP Compressor
Q – Splitter- Coolant
R – Duct
S– Heat Exchanger (cold side)
T – Burner

U – Intake
V – LP Compressor
W – Intercooler
X – Splitter
Y – Duct

Z – HP Compressor

Figure- G-1: Block diagram of ICR WR21 (TURBOMATCH Model BRICK arrangement)

Turbomatch Input File for WR21 (MODE-1)

APPENDIX-B

```
OD IM KE VA FP
-1
-1
INTAKE          S1,2 D1,2,3,4 R300
COMPRE          S2,3 D10,11,12,13,14,15,16 R301 V10 V11
INTCLR          S3,4 D24,25,26,27,28 R303
PREMAS          S4,25,5 D30,31,32,33
DUCTER          S5,6 D34,35,36,37 R304
COMPRE          S6,7 D40,41,42,43,44,45,46 R305 V40 V41
PREMAS          S7,26,8 D50,51,52,53
DUCTER          S26,27 D54,55,56,57 R306
PREMAS          S27,29,28 D60,61,62,63
PREMAS          S29,31,30 D70,71,72,73
DUCTER          S8,9 D80,81,82,83 R308
HETCOL          S9,10 D84,85,86,87,88
BURNER          S10,11 D89,90,91 R309
MIXEES          S11,28,12                                          Shaft Power is Variable
TURBIN          S12,13 D92,93,94,95,96,97,98,99,305,100 V93
DUCTER          S13,14 D101,102,103,104 R310
MIXEES          S14,30,15
TURBIN          S15,16 D110,111,112,113,114,115,116,117,301,118 V111
MIXEES          S16,31,17
DUCTER          S17,18 D120,121,122,123 R311
TURBIN          S18,19 D130,131,132,133,134,135,136,137,138,139 V130 V131
DUCTER          S19,20 D140,141,142,143 R312
HETHOT          S9,20,21 D144,145,146,147
MIXEES          S21,25,22
DUCTER          S22,23 D148,149,150,151 R313
NOZCON          S23,24,1 D152 R314
ARITHY          D170,171,172,173,174,0,0,0,0
PERFOR          S1,0,0 D330,153,154,155,0,0,309,0,0,0,0,0,0
CODEND
Turbomatch simulation////
```

Brick No	Brick data		Brick No	Brick data		Brick No	Brick data		Brick No	Brick data
1	0.0000		46	0.0000		93	-1.0000		135	0.0000
2	20.0000		50	0.1600		94	-1.0000		136	4.0000
3	0.0000		51	0.0000		95	0.8900		137	1.0000
4	0.9900		52	1.0000		96	-1.0000		138	-1.0000
10	-1.0000		53	0.0000		97	1.0000		139	0.0000
11	-1.0000		54	0.0000		98	4.0000		140	0.0000
12	0.4000		55	0.0100		99	1.0000		141	0.0100
13	0.8850		56	0.0000		100	0.0000		142	0.0000
14	0.0000		57	100000.0000		101	0.0000		143	100000.000
15	4.0000		60	0.1000		102	0.0000		144	0.0100
16	0.0000		61	0.0000		103	0.0000		145	0.8450
24	0.8500		62	1.0000		104	100000.00		146	0.0010
25	0.0200		63	0.0000		110	5.0000		147	0.0000
26	20.0000		70	0.0000		111	-1.0000		148	0.0000
27	0.0000		71	0.0000		112	-1.0000		149	0.0150
28	0.0000		72	1.0000		113	0.8800		150	0.0000
30	0.0200		73	0.0000		114	-1.0000		151	100000.00
31	0.0000		80	0.0000		115	1.0000		152	-1.0000
32	1.0000		81	0.0050		116	4.0000		170	5.0000
33	0.0000		82	0.0000		117	1.0000		171	-1.0000
34	0.0000		83	100000.0000		118	0.0000		172	330.0000
35	0.0100		84	0.0250		120	0.0000		173	-1.0000
36	0.0000		85	0.8450		121	0.0050		174	130.0000
37	100000.0000		86	0.0050		122	0.0000		153	1.0000
40	-1.0000		87	0.0000		123	100000.00		154	0.0000
41	-1.0000		88	0.0000		130	20000.00		155	0.0000
42	4.3000		89	0.0400		131	1.0000			
43	0.8850		90	0.9510		132	-1.0000			
44	1.0000		91	-1.0000		133	0.8900			
45	5.0000		92	0.0000		134	1.0000			

Station Vector Data

Station No	Item	Data
1	2	126.00
11	6	1360.00

Turbomatch Input File for WR21 (MODE-2)

```
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-1
INTAKE      S1,2 D1,2,3,4 R300
COMPRE      S2,3 D10,11,12,13,14,15,16 R301 V10 V11
INTCLR      S3,4 D24,25,26,27,28 R303
PREMAS      S4,25,5 D30,31,32,33
DUCTER      S5,6 D34,35,36,37 R304
COMPRE      S6,7 D40,41,42,43,44,45,46 R305 V40 V41
PREMAS      S7,26,8 D50,51,52,53
DUCTER      S26,27 D54,55,56,57 R306
PREMAS      S27,29,28 D60,61,62,63
PREMAS      S29,31,30 D70,71,72,73
DUCTER      S8,9 D80,81,82,83 R308                  TET is Variable
HETCOL      S9,10 D84,85,86,87,88
BURNER      S10,11 D89,90,91 R309 W11,6
MIXEES      S11,28,12
TURBIN      S12,13 D92,93,94,95,96,97,98,99,305,100 V93
DUCTER      S13,14 D101,102,103,104 R310
MIXEES      S14,30,15
TURBIN      S15,16 D110,111,112,113,114,115,116,117,301,118 V111
MIXEES      S16,31,17
DUCTER      S17,18 D120,121,122,123 R311
TURBIN      S18,19 D130,131,132,133,134,135,136,137,138,139  V131
DUCTER      S19,20 D140,141,142,143 R312
HETHOT      S9,20,21 D144,145,146,147
MIXEES      S21,25,22
DUCTER      S22,23 D148,149,150,151 R313
NOZCON      S23,24,1 D152 R314
ARITHY      D170,171,172,173,174,0,0,0,0
PERFOR      S1,0,0 D330,153,154,155,0,0,309,0,0,0,0,0,0
CODEND
Turbomatch simulation////
```

Brick No	Brick data	Brick No	Brick data	Brick No	Brick data	Brick No	Brick data
1	0.0000	46	0.0000	93	-1.0000	135	0.0000
2	20.0000	50	0.1600	94	-1.0000	136	4.0000
3	0.0000	51	0.0000	95	0.8900	137	1.0000
4	0.9900	52	1.0000	96	-1.0000	138	-1.0000
10	-1.0000	53	0.0000	97	1.0000	139	0.0000
11	-1.0000	54	0.0000	98	4.0000	140	0.0000
12	0.4000	55	0.0100	99	1.0000	141	0.0100
13	0.8850	56	0.0000	100	0.0000	142	0.0000
14	0.0000	57	100000.0000	101	0.0000	143	100000.000
15	4.0000	60	0.1000	102	0.0000	144	0.0100
16	0.0000	61	0.0000	103	0.0000	145	0.8450
24	0.8500	62	1.0000	104	100000.00	146	0.0010
25	0.0200	63	0.0000	110	5.0000	147	0.0000
26	20.0000	70	0.0000	111	-1.0000	148	0.0000
27	0.0000	71	0.0000	112	-1.0000	149	0.0150
28	0.0000	72	1.0000	113	0.8800	150	0.0000
30	0.0200	73	0.0000	114	-1.0000	151	100000.00
31	0.0000	80	0.0000	115	1.0000	152	-1.0000
32	1.0000	81	0.0050	116	4.0000	170	5.0000
33	0.0000	82	0.0000	117	1.0000	171	-1.0000
34	0.0000	83	100000.0000	118	0.0000	172	330.0000
35	0.0100	84	0.0250	120	0.0000	173	-1.0000
36	0.0000	85	0.8450	121	0.0050	174	130.0000
37	100000.0000	86	0.0050	122	0.0000	153	1.0000
40	-1.0000	87	0.0000	123	100000.00	154	0.0000
41	-1.0000	88	0.0000	130	20000.00	155	0.0000
42	4.3000	89	0.0400	131	1.0000		
43	0.8850	90	0.9510	132	-1.0000		
44	1.0000	91	-1.0000	133	0.8900		
45	5.0000	92	0.0000	134	1.0000		

Station Vector Data

Station No	Item	Data
1	2	126.00
11	6	1363.00

APPENDIX-C

INTERCOOLED RECUPERATED-WR21 DATA SHEET (DESIGN POINT PERFORMANCE)

Complete Set of Available Instrumentation from Engine Model

Sl No	Station- Description	Total Temperature (deg Kelvin)	Total Pressure (Atm)
1	Intake(In)	308.14999	1.00000
2	LP Compressor(In)	308.14999	0.99000
3	LP Compressor(Exit)	406.6911	2.37600
4	Intercooler(Exit)	310.05365	2.32848
5	HP Compressor(In)	310.05365	2.32848
6	HP Compressor(Exit)	489.33997	9.91234
7	Heat Exchanger(Cold)(In)	489.33997	9.86278
8	Heat Exchanger(Cold)(Exit)	730.48419	9.66552
9	Burner(Exit)	1363.00000	9.27890
10	HP Turbine(In)	1247.86853	9.27890
11	HP Turbine(Exit)	1096.86487	5.02774
12	LP Turbine(In)	1088.05542	5.02774
13	LP Turbine(Exit)	1003.45563	5.02774
14	Power Turbine(In)	1003.45563	3.41962
15	Power Turbine(Exit)	774.92010	1.05090
16	Heat Exchanger(Hot)(In)	774.92010	1.04039
17	Heat Exchanger(Hot)(Exit)	582.95325	1.02999
18	Exhaust	577.81250	1.01454

WR21 Design Point Performance Data

Sl No	Parameter description	Value	Units
1	Shaft Power	20000.00	HP
2	Inlet Mass Flow	126.00	lb/s
3	Fuel Flow	1.99	lb/sec
4	S.F.C	0.3582	lb/hp-hr
5	E.S.F.C	0.3582	lb/hp-hr
6	Sp. Shaft Power	158.7302	hp/lb/sec
7	Thermal Efficiency	0.3831	Percent
8	HP Shaft Speed	7905	RPM
9	LP Shaft Speed	5872	RPM
10	PT Shaft Speed	3281	RPM

Instrumentation Set Fitted on Test Engine:

Sl No	Parameter description	Value	Unit	Type of sensor
1	HP Compressor(In)	2.328	Atm.	(Pressure)
2	HP Compressor(Exit	9.912	Atm.	(Pressure)
3	IC Differential	0.048	Atm.	(Pressure)
4	HP Compressor(In)	310.101	Deg Kelvin	(Temperature)
5	HP Compressor(Exit)	489.323	Deg Kelvin	(Temperature)
6	Combustor Entry	730.5	Deg Kelvin	(Temperature)
7	Power Turbine(In)	1003.00	Deg Kelvin	(Temperature)
8	Power Turbine(Exit)	774.90	Deg Kelvin	(Temperature)
9	HP Shaft Speed(RPM)	7905	RPM	(Tachometer)
10	LP Shaft Speed(RPM)	5872	RPM	(Tachometer)
11	PT Shaft Speed(RPM)	3281	RPM	(Tachometer)
12	VAN Position	0	Degree	(Position)

APPENDIX-D

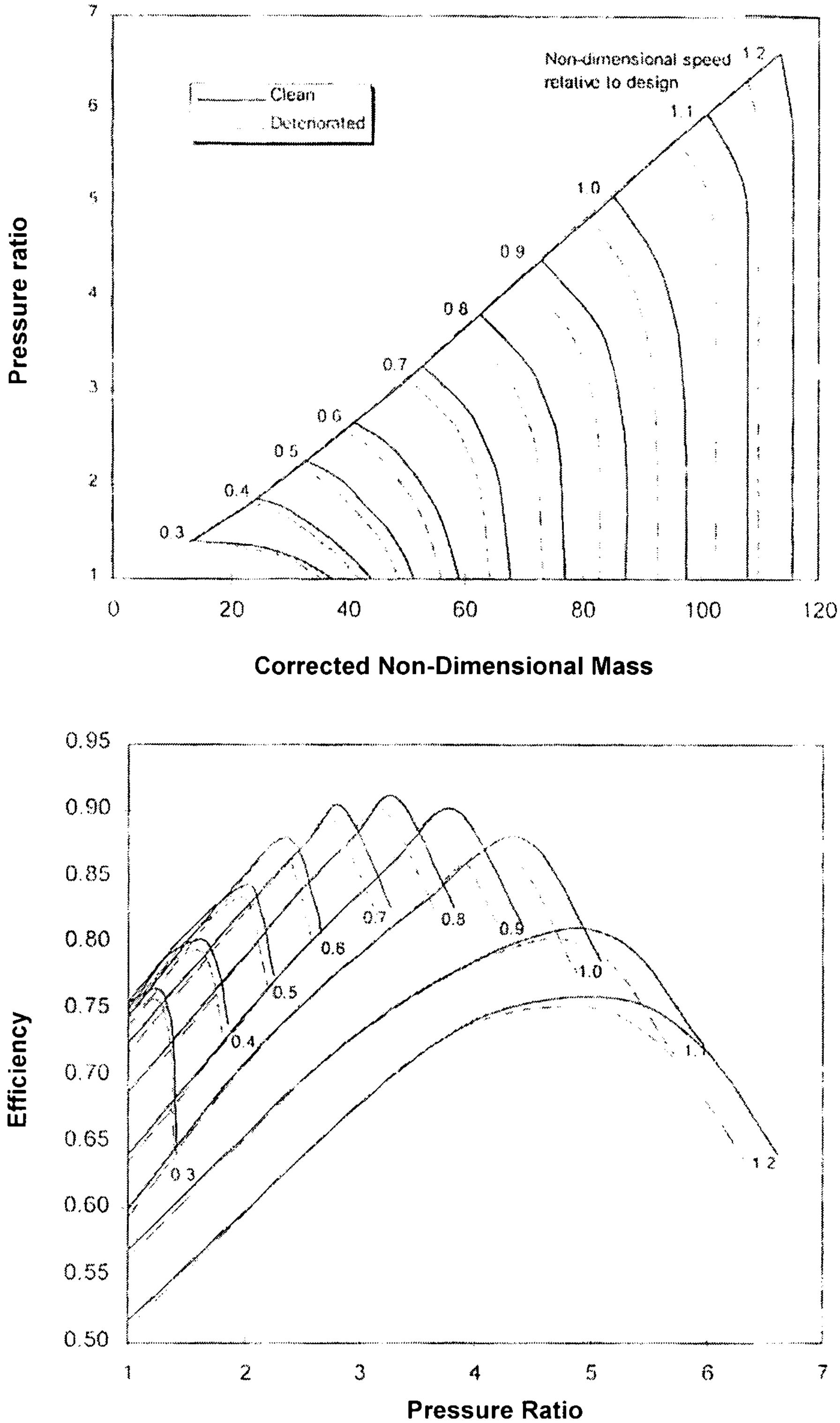

Figure D-1 : Compressor Fouling

APPENDIX-E

Performance of the ICR WR21 (TURBOMATCH Model)

A detailed description of the development of the TURBOMATCH model has been presented in chapter-4. The engine bears thermodynamically semblance to the actual engine. A comparison of the engine with actual has not been provided in this thesis. However, the performance of the model is in close agreement with the actual engine. The performance of the engine model used in the diagnostics model has been briefly described. The performance of the engine is discussed in two modes: VAN enabled and VAN disabled. The aim is to show that, the model developed is in conformity with the theory (for improving part efficiency) discussed in chapter-4. Figure F.1 shows the FPT inlet temperature plotted against the shaft power. It can be seen that, for the engine with the VAN disabled, the FPT inlet temperature increases with increase in power whereas, the temperature can be kept almost constant by manipulating the VAN. This is a special feature of the ICR WR21.

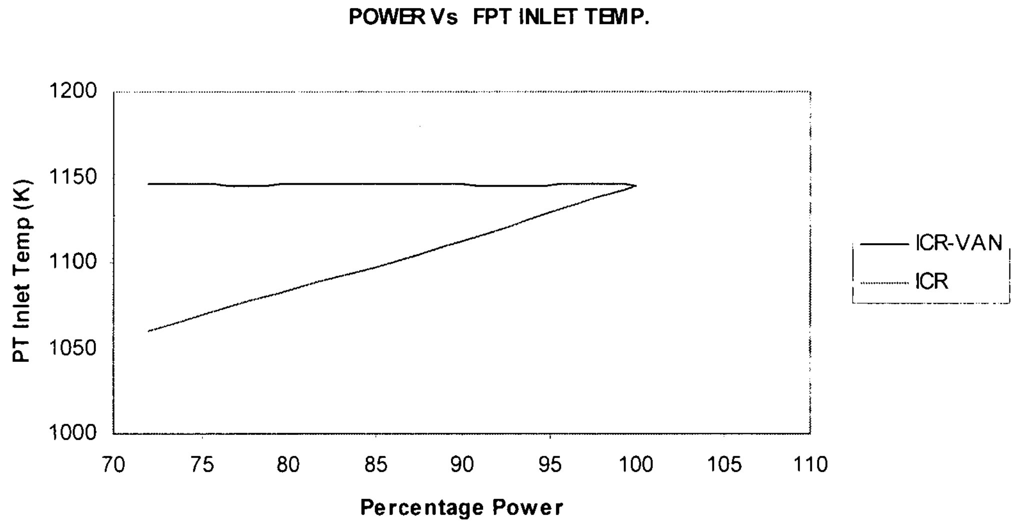

Figure F.1: Comparison of FPT inlet temperature

The VAN scheduling is an important feature of the WR21 engine and is linked to the fuel control system. The VAN is in fully closed position at 40% power and fully open at full power. Due to high FPT inlet temperatures at low powers, the heat is recovered through the recuperator and hence a reduction in SFC when compared to an engine without the VAN. Due to confidentiality reason the actual scheduling cannot be discussed here. However, figure F.2 shows the VAN schedule for the WR21 engine using TURBOMATCH. The VAN angles are plotted against percentage power. The engine model of WR21 (TURBOMATCH) has certain limitations and therefore VAN scheduling below 72% power does not give stable results.

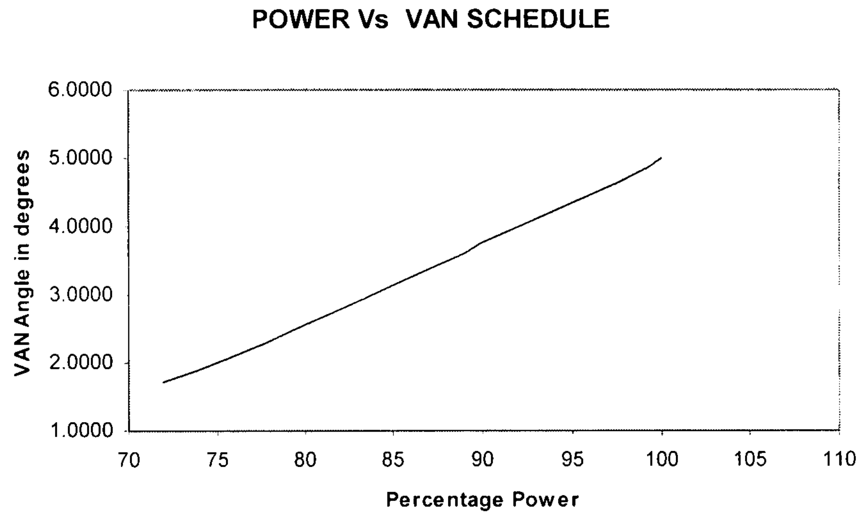

Figure F.2: VAN Scheduling with Variation in Power

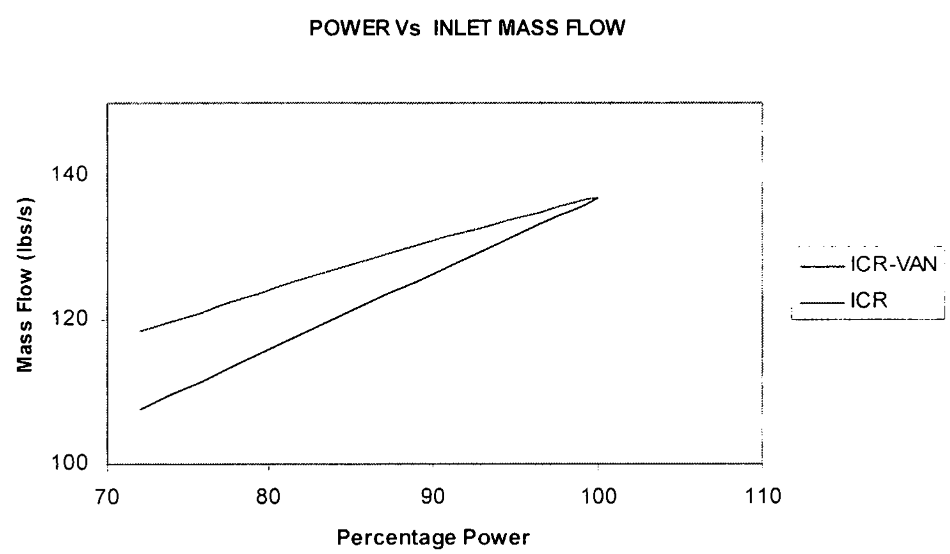

Figure F.3: Variation in Engine Mass Flow with Change In Power

Figure F.3 shows the inlet mass flow plotted against the percentage power. The van operation has effect on the mass flow upstream. The mass flow for the engine with VAN is less at all power levels (except max. power). Figure F.4 shows the TET of both modes plotted against the power. It is clear that the engine with the VAN in operation runs hotter. This is beneficial in obtaining better s.f.c at lower powers. However, from engine life point of view, it is detrimental as it consumes more creep life of hot section components.

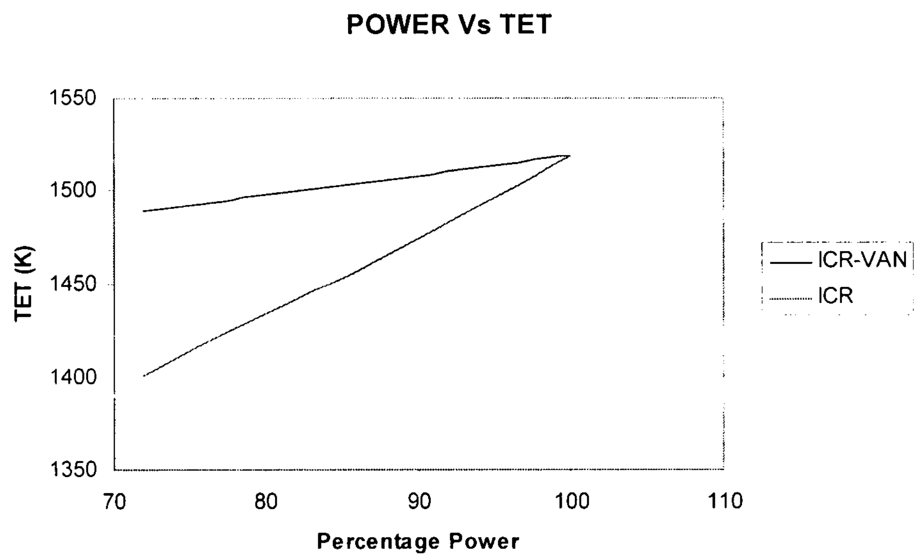

Figure F.4: Variation in TET with Power

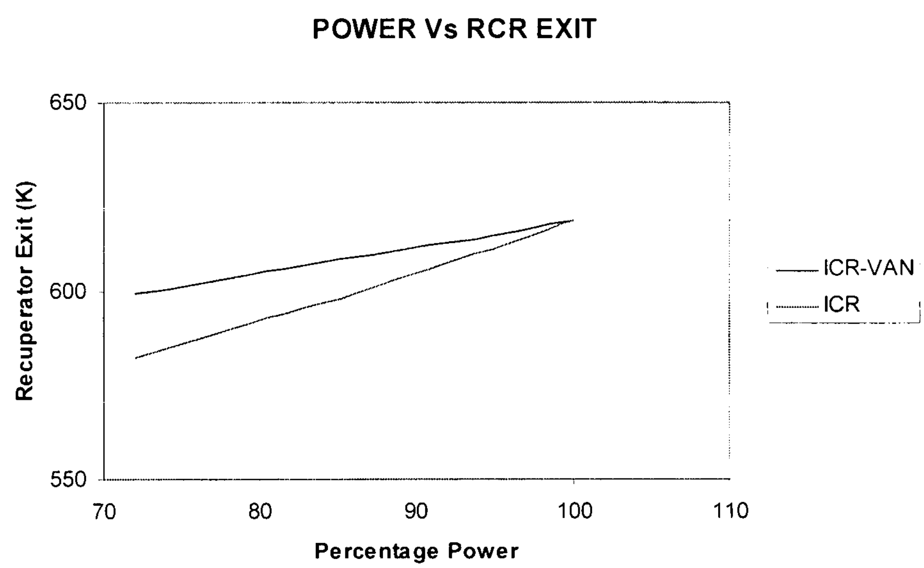

Figure F.5: Variation in RCR exit temperature with power

Figure F.5 shows the recuperator exit temperature plotted against the power. It is clear that the recuperator exit temperature is more in the case of engine with VAN enabled. The FPT inlet temperature is kept by the increasing the TET at lower powers and since the work output of the FPT has reduced for the same inlet temperature; the temperature at recuperator inlet is high. This is the reason for the recuperator outlet to be high.

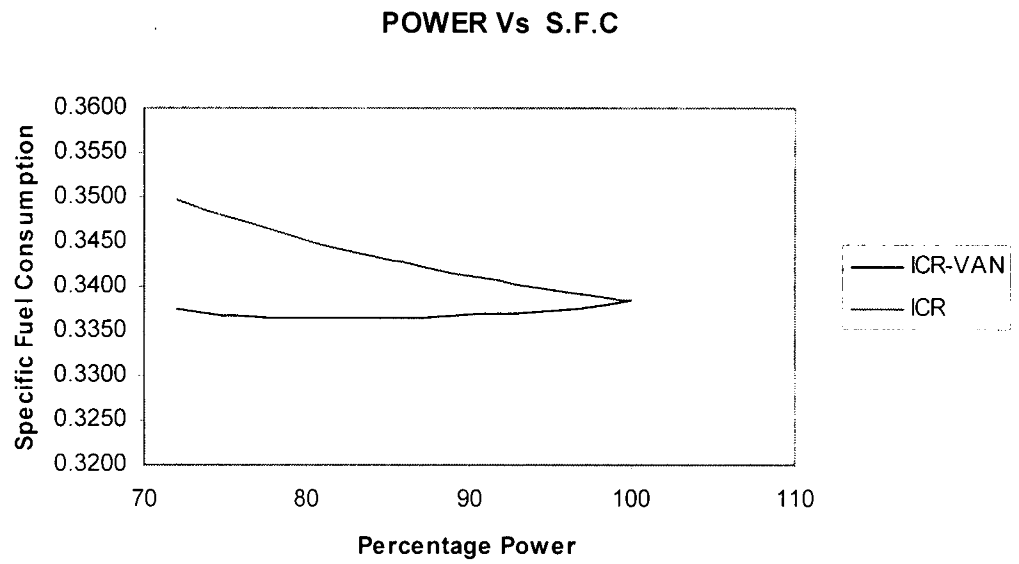

Figure F.6: Difference in Specific fuel consumption

Figure F.6 show the s.f.c of the engine plotted against power for two modes. The s.f.c of the engine either VAN enables is almost flat for lower powers when compared with the engine without VAN. This shows the importance of the role played by the VAN but the improvement in s.f.c with a price i.e. the engine hot always running hot.

As mentioned earlier, the engine parameters are broadly in agreement with the actual engine data. Figure F.7 shows a comparison between the s.f.c from the actual WR21 engine and performance model developed using TURBOMATCH. It can be seen that the performance is reasonably close. It is pertinent to mention that the diagnostics model will use the deviation between the measurements. The consistency of the model is more important and therefore the model proved adequate for the purpose of research.

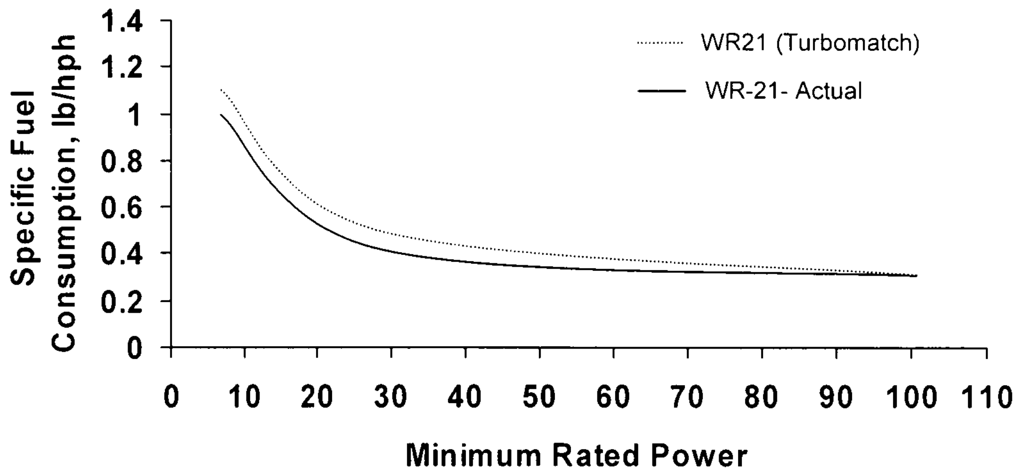

Figure F.7: Comparison of s.f.c between actual and TM-Model for WR21

APPENDIX-F

INTERCOOLED RECUPERATED WR-21 TEST DATA REPORT

Values of Sigmas of Measured Parameters

1	0.0667	(HP Compressor(In))
2	0.1000	(HP Compressor(Exit))
3	0.1333	(IC Differential)
4	0.1333	(HP Compressor(In))
5	0.1000	(HP Compressor(Exit))
6	0.3333	(Combustor Entry)
7	1.0000	(Power Turbine(In))
8	0.6667	(Power Turbine(Exit))
9	1.0000	(HP Shaft Speed(RPM))
10	1.0000	(LP Shaft Speed(RPM))

Instrumentation Bias Detail:

No of Instruments Biased: 1
Instrument Bias Type : Multiple of Sigma
Biased Instrument- 1 : SI-1 1.3333 HP Compressor(In)

Environment & Power Setting Parameters Bias Details

No of Instruments Biased: 3

	Actual	Biased	Sigma
Flow/Power	26400.00	26410.95	0.1
Amb. Press	1.00	0.99	0.1
Amb. Temp.	308.15	308.57	0.1
Flow/Power	24000.00	23987.06	0.1
Amb. Press	1.00	0.99	0.1
Amb. Temp.	308.15	307.93	0.1

Component Fault Details

Deterioration for Fault Class: 10

Sl No.	Cmp/ID	Component	Effy(%)	Flow Cap.(%)
1	1	Compressor(LP)	-2.00	-3.00
2	4	Turbine(HP)	-1.00	4.00

ENGINE MEASUREMENTS

Sl No	Engine Measurement	Operating Point-1	Operating Point-2	Units
1	HP Compressor(In)	2.461395	2.402424	Atm.
2	HP Compressor(Exit	11.783918	11.181908	Atm.
3	IC Differential	0.050233	0.049029	Atm
4	HP Compressor(In)	313.519165	312.218109	Deg K
5	HP Compressor(Exit)	524.768066	514.605957	Deg K
6	Combustor Entry	800.755066	775.583923	Deg K
7	Power Turbine(In)	1125.822021	1081.373291	Deg K
8	Power Turbine(Exit)	857.458740	827.117981	Deg K
9	HP Shaft Speed(RPM)	8197.160156	8116.459473	RPM
10	LP Shaft Speed(RPM)	6395.008789	6236.973633	RPM

APPENDIX-G

GRAPHICAL USER INTERFACE FOR WR21 DIADNSTICS MODEL

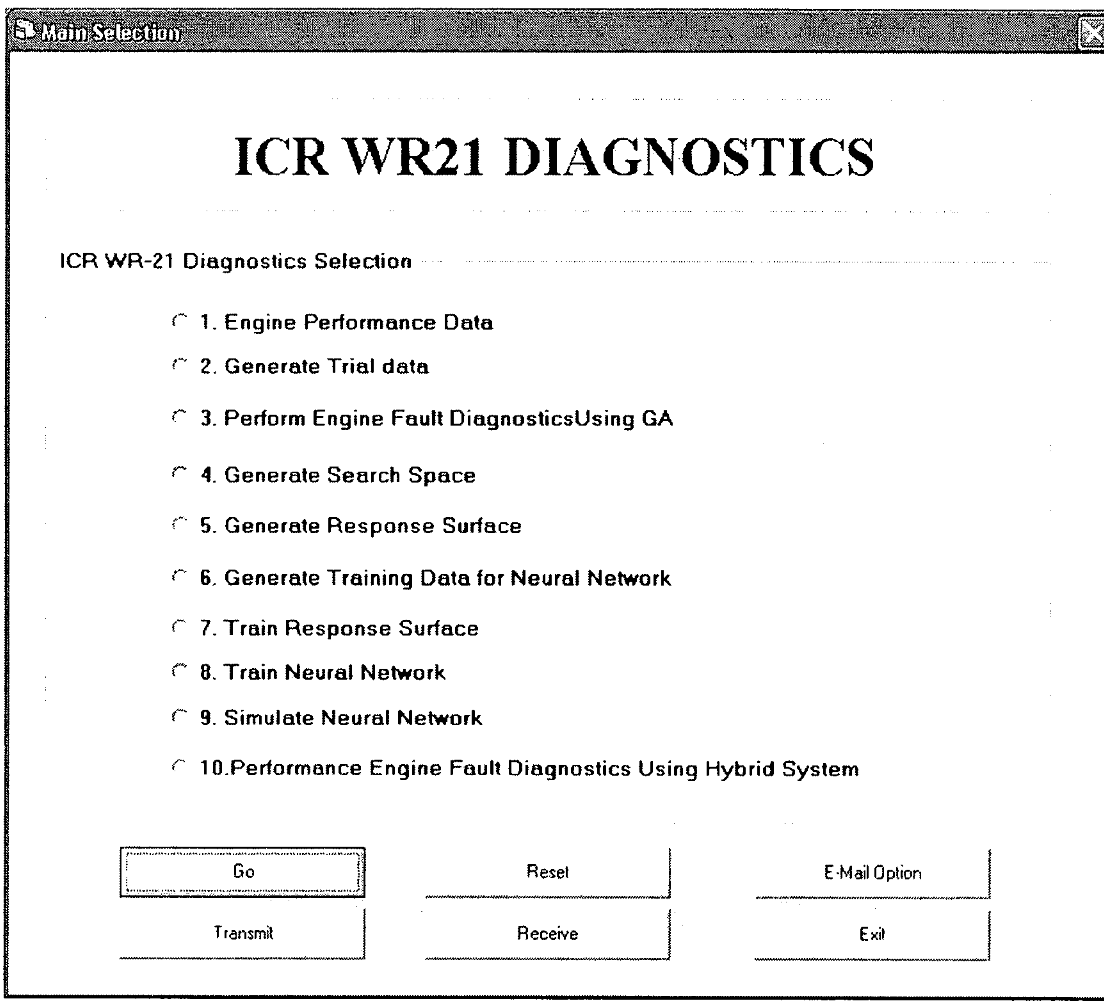

Figure G-1: GUI for ICR WR21 Diagnostics Model

A user friendly GUI has been developed for the ICR WR21. the front end of the software is shown in figure G-1. The program has various options from generating search spaces to performing diagnostics in the HDM mode.

APPENDIX-H

RESULTS FROM DIFFERENT SETS OF OPERATING POINTS

CASE	**FC**	**COMPONENTS**		**FAULT IMPLANTED(%)**				**FC BY NNN**	**PREDICTED FAULT (%)**				
		COMP- 1	**COMP-2**	**COMP-1**		**COMP-2**			FC	**COMP-1**		**COMP-2**	
				$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$			$\Delta\eta$	$\Delta\Gamma$	$\Delta\eta$	$\Delta\Gamma$
CASE-1	FC-1	LPC	-	-0.5	-2.0	-	-	FC-1	FC-1	-0.48	-2.09	-	-
CASE-2	FC-2	HPC	-	-1.0	-4.0	-	-	FC-2	FC-2	-1.11	-3.83	-	-
CASE-3	FC-9	LPC	ICL	-0.8	-2.5	4	2	FC-9,FC-14	FC-9	-0.76	-2.81	2.98	1.82
CASE-4	FC-23	HPT	LPT	-2.0	4.0	-1.0	3.0	FC23, FC-24	FC-23	-1.87	4.21	-1.13	2.79
CASE-5	FC-26	LPT	FPT	-3.0	6.0	-2.0	5.0	FCs : 21,24,26	FC-26	-2.91	5.76	-2.09	4.84

ENVIRONMENT AND POWER SETTING PARAMETERS	
Operating Point -1	
Power (hp)	22000.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0
Operating Point -2	
Power (hp)	20000.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0

Table H-1: Results from different sets of operating points –(Case-1)

CASE	FC	COMPONENTS		FAULT IMPLANTED(%)				FC BY NNN	PREDICTED FAULT (%)				
		COMP- 1	COMP-2	COMP-1		COMP-2			FC	COMP-1		COMP-2	
				Δη	ΔΓ	Δη	ΔΓ			Δη	ΔΓ	Δη	ΔΓ
CASE-1	FC-4	HPT	-	-1.5	4.5	-	-	FC-4	FC-4	-1.38	4.22	-	-
CASE-2	FC-6	FPT	-	0.2	1.0	-	-	FC-6	FC-6	-0.21	1.09	-	-
CASE-3	FC-12	LPC	FPT	-2.5	-5.0	3.0	6.0	FC-12	FC-12	-2.28	-4.53	2.61	4.89
CASE-4	FC-19	ICL	HPT	6.0	2.0	-1.0	3.0	FC-19,FC-23	FC-19	6.23	2.40	-0.87	2.97
CASE-5	FC-25	HPT	RCR	-0.5	2.5	8.0	3.0	FCs: 21,25,28	FC-25	-0.37	2.74	6.65	2.43

ENVIRONMENT AND POWER SETTING PARAMETERS	
Operating Point -1	
Power (hp)	24000.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0
Operating Point -2	
Power (hp)	22000.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0

Table H-2: Results from different sets of operating points – (Case-2)

CASE	FC	COMPONENTS		FAULT IMPLANTED(%)				FC BY NNN	PREDICTED FAULT (%)				
		COMP- 1	COMP-2	COMP-1		COMP-2			FC	COMP-1		COMP-2	
				Δη	ΔΓ	Δη	ΔΓ			Δη	ΔΓ	Δη	ΔΓ
CASE-1	FC-3	ICL	-	5.0	1.0	-	-	FC-3	FC-3	3.8	0.56	-	-
CASE-2	FC-5	LPT	-	-1.0	4.0	-	-	FC-5	FC-5	-1.06	3.96	-	-
CASE-3	FC-8	LPC	HPC	-0.7	-3.0	0.5	-2.0	FC-8,FC-10	FC-8	-0.52	-2.69	-0.23	-1.87
CASE-4	FC-14	HPC	ICL	-3.0	-6.0	6	1	FC-14	FC-4	-3.14	-5.39	4.99	0.64
CASE-5	FC-28	FPT	RCR	-2.0	4.0	3.0	1.0	FC-21,FC-28	FC-28	-1.83	4.24	3.17	0.67

ENVIRONMENT AND POWER SETTING PARAMETERS	
Operating Point -1	
Power (hp)	26400.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0
Operating Point -2	
Power (hp)	24000.00
Ambient Temperature (T_0) (Deg. Kelvin)	308.15
Ambient Pressure (P_0) (atm)	1.0

Table H-3: Results from different sets of operating points – (Case-3)