

CRANFIELD UNIVERSITY

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Techno-Economic, Environmental and Risk Analysis (TERA) for Power
Generation

SCHOOL OF ENGINEERING
DEPARTMENT OF POWER AND PROPULSION

PhD
Academic Year: 2012 - 2013

Supervisor: Professor Pericles Pilidis
February, 2013

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This thesis is submitted for the requirements for the degree of PhD

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ABSTRACT

Gas turbines (GTs) are extensively used in many power generation applications. This project has close coupled advanced, economic diagnostics with the technology of prime movers using a Genetic Algorithm (GA) to optimise the economic performance of fleets of GTs for electricity production. The investigation has included comparative assessment of traditional and novel GT options, including the design and off-design performance of the engines. The originality of the work lies in the concurrent technical and economic optimisation of a fleet of GTs based on a GA using current and novel engine cycles in a wide range of climatic conditions.

The project has developed an effective model for optimising operational strategies for off-design conditions capable of optimising the economic performance of existing fleets of GT engines to meet power requirement while minimising environmental impact. It has also developed an approach able to simulate engine operating conditions with attendant costs under different scenarios based on the Techno-Economic, Environmental, and Risk Analysis (TERA) philosophy which allows for a broad and multidimensional analysis of the problem. By integrating the TERA model with in-house performance simulation software (Turbomatch) it has been possible to simulate the engine performances at design point and off-design conditions and maximise total power output at minimum cost to aid equipment selection and plant operation strategies for new plant.

This study simulated and accounted for the time value of money during the operational life of the power plant. The model includes a life cycle cost assessment including: capital cost, maintenance and operating costs, fuel cost and emission taxes. Using the Net Present Value (NPV) technique the model was able to make techno-economic comparisons between various modes of operation and variations in power demand.

Peak load operation requires GTs to operate at high firing temperatures with consequent reduction in component' useful life. The techno-economic analysis found the optimum condition between both operating condition and

corresponding strategies and thus includes a comparative lifing model, which performs stress and thermal analyses, and estimates the component's minimum creep life using the Larson Miller method.

A fleet of GT engine operating in a warm coastal environment have been modelled and investigated in this study. The results showed that the combined effect of the operating environment and the power demand can have significant impact on the blade creep life. The ability to predict this impact will aid GT users in the decision making process associated with GT operation.

The project has developed an emissions model which identifies the GT engine with smallest impact on global warming and lowest cost of ownership (including governmental taxation policies) and which will meet a variety of emission legislation.

ACKNOWLEDGEMENTS

This work is dedicated to my father; I am so proud being your son

..اهدي هذا العمل الي والدي..كم انا فخور جداً بأن اكون ابنك..

All praise to Allah (God), the most Merciful, the most Gracious, for all the uncountable bounties He has granted me and for helping me to successfully finish my study.

Completing my PhD degree is probably the most challenging activity of my last four years of my life. The best and worst moments of my doctoral journey have been shared with many people. It has been a great privilege to spend several years in the Department Power and Propulsion at the School of Engineering at Cranfield University, and its members will always remain dear to me. Special thanks go to Gill and Nicola.

My sincere debt of gratitude goes to my supervisor, Professor Pericles Pilidis. He patiently provided the vision, encouragement and advice necessary for me to precede through the doctoral program and complete my PhD.

Special thanks to Dr.Osama Lotfi, Dr.Samir Eshati, Dr .Bader Al-Abri Dr. Raja Khan, Dr. Stephen Ogaji, Dr. Khalifa Elshen, Dr. Ayad Gannan, Dr. Abdulmajid Addali, Dr. K.W.Ramsden and Mr Jonathan Haynes for their motivation and encouragement to achieve such work along with his continued input, support and enlightenment throughout the study. Your outstanding help will never be forgotten.

My friends in Libya, the UK and other parts of the World were sources of laughter, joy, and support. Special thanks go to Libyan and Islamic societies. I am very happy that, in many cases, my friendships with you have extended well beyond our shared time in Cranfield. Sincere thanks go to my colleagues at GECOL.

I wish to thank my father and my mother. Their love provided my inspiration and was my driving force. I owe them everything and wish I could show them just how much I love and appreciate them. My wife, sisters, brothers and my children (**AHMED, ASALA AND AMJED**), their love, support and encouragement allowed me to finish this journey. They already have my heart so I will just give them a heartfelt “thanks.”

PUBLICATIONS

- W. Mohamed, V. Sethi, P. Pilidis, A. Abu ,A.Nasir, Osama Lotfi “Evaluation of Electricity Cost in a Growing Market” in Proc. ASME Turbo Expo 2013: Power for Land, Sea and Air, Texas, June 03-07, 2013.
- A.O. Abu S. Eshati E.S. Najafi W. Mohammed P. Laskaridis A. Haslam, “Integrated approach for physics based life assessment of gas turbine blades” Proceedings of ASME Turbo Expo 2013 Gas Turbine Conference GT2013-95987 June 3-7, 2013, San Antonio, Texas, USA.
- A. Nasir, P. Pilidis, S. Ogaji and W. Mohamed “A study of the effect of gas turbine emissions on the economics of natural gas pipeline transportation” Proceedings of the 20th International Conference on Nuclear Engineering ICONE20 POWER2012-54273 July 30 - August 3, 2012, Anaheim, California, USA.
- W. Mohamed, V. Sethi, P. Pilidis, Hugo Pervier, Raja S.R. Khan, “A Method to Evaluate the Emissions of Gas Turbine for Power Generation”, Proceedings of ASME Turbo Expo 2012: Power for Land, Sea and Air GT2012 Copenhagen, GT2012-69491, June 11-15, 2012.
- W. Mohamed, B. Al-Abri ,P. Pilidis, A. Nasir “Economic Evaluation of Industrial Gas Turbines for Electrical Power Generation”, Proceedings of ASME Turbo Expo 2012: Power for Land, Sea and Air GT2012 Copenhagen, GT2012-69495, June 11-15, 2012.
- A.Nasir, P.Pilidis, S.Ogaji, and W.Mohamed “Some Economic Implications of Deploying Gas Turbine in Natural Gas Pipeline Networks” IJET 2012 Vol.5 (1):141-145 ISSN:1793-8244 10.7763/IJET.2013.V5.528.
- W. Mohamed, S. Eshati, P. Pillids, S. Ogaji, P. Laskaridis, A. Nasir A “Method to Evaluate the Impact of Power Demand on HPT Blade Creep Life”, Proceedings of ASME Turbo Expo 2011: Power for Land, Sea and Air GT2011 – 45092 June 06-10, 2011, Vancouver, Canada.
- W. Mohamed, S. Ogaji, R. Khan, P. Pilidis, B. Al-Abri, A. Nasir “Economic Optimisation of Industrial Gas Turbines for Electrical Power Generation: A Creep and Performance Based Study”, Proceedings of ASME Power 2011 Denver, July 12-14, 2011 POWER 2011-55283.
- A. Nasir, P. Pilidis, S. Ogaji, W. Mohamed “Economic Implications of Deploying Gas Turbine in Natural Gas Pipeline Networks”, Proceedings of ASME Power 2011 Denver, July 12-14, 2011 POWER 2011-55283.

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LIST OF ABBREVIATIONS

A_{AnSec}	<i>Blade section annulus area</i>
A_{cs}	<i>Blade section cross-section area</i>
AFT	<i>Adiabatic Flame Temperature</i>
APS	<i>American Physical Society</i>
b	<i>Axial chord m</i>
B	<i>Benefit stream</i>
BTU	<i>British Thermal Unit</i>
C	<i>LMP Parameter constant</i>
C12H23	<i>Engine fuel</i>
Ca_{In}	<i>Capital Investment</i>
CAE	<i>Computer Aided Engineering</i>
Capital_C	<i>Capital Cost</i>
CDP	<i>Compressor delivery pressure</i>
C_F	<i>Creep factor</i>
CFD	<i>Computational Fluid Dynamics</i>
C_{Fsec}	<i>Section's centrifugal forces</i>
CG	<i>Centre of gravity</i>
CH4	<i>Methane</i>
CO	<i>Carbon monoxide</i>
CO2	<i>Carbon dioxide</i>
COE	<i>Cost of Electricity</i>
C_p	<i>specific heat J/kg K</i>
CRF	<i>Capital Recovery Factor</i>
d_{CG}	<i>Distance between the rotation axis and the section CG</i>
DOC	<i>Direct operating costs</i>
DP	<i>Design point</i>
DPB	<i>Discounted Payback</i>
DT	<i>Destructive test</i>
E_C	<i>Emission Cost</i>
EA	<i>Evolutionary Algorithms</i>
eCO2	<i>Emissions of CO2 per unit mass of fuel</i>
EI	<i>Emission index</i>
EICO2	<i>Carbon dioxide index</i>
EINOx	<i>NOx emission index</i>
Em_cost	<i>Emissions Coast</i>
ES	<i>Evolutionary Strategies</i>
FAR	<i>Fuel-to-air ratio</i>
FE	<i>Finite element</i>
FEA	<i>Finite element analysis</i>
fpr	<i>Correction factor</i>
Fuel_C	<i>Fuel Cost</i>
func	<i>Function</i>
G	<i>Generator</i>
GA	<i>Genetic algorithms</i>
GECOL	<i>General Electrical company of Libya</i>
GJ	<i>Giga Joule</i>
GSP	<i>Goldhoof-Sherby parameter</i>
GT	<i>Gas turbine</i>
GWP	<i>Global warming potential</i>
h	<i>Blade Height m</i>

H	<i>Hydrogen</i>
H ₂ O	<i>water</i>
HC	<i>Hydro carbon</i>
HCF	<i>high cycle fatigue</i>
HP	<i>High Pressure</i>
HPC	<i>High pressure compressor</i>
HPT	<i>High pressure turbine</i>
HRSG	<i>Heat Recovery Steam Generator</i>
ICAO	<i>International Civil Aviation Organisation</i>
IEO	<i>International Energy Outlook</i>
IRR	<i>Internal Rate of Return</i>
ISO	<i>International system organisation</i>
J	<i>Joule</i>
K	<i>Kelvin</i>
kg	<i>Kilogram</i>
kg/s	<i>Kilogram/ Second</i>
kWh	<i>Kilowatt hours</i>
lb	<i>pound</i>
LCF	<i>low cycle fatigue</i>
LCOE	<i>Levelized Cost of Electricity</i>
LMP	<i>Larson-Miller parameter</i>
M	<i>Mach number</i>
M \$	<i>Millions of dollars</i>
M_C	<i>Maintenance Cost</i>
mCO ₂	<i>Mass of emitted CO₂</i>
MCSA	<i>Monte Carlo Simulated Annealing</i>
Mf	<i>Maintenance factor</i>
MHP	<i>Manson-Haferd parameter</i>
MJ/kg	<i>Mega Joule per kilogram</i>
mof	<i>mass fuel consumption</i>
MPa	<i>Mega Pascal</i>
MRMP	<i>Mandelson-Roberts-Manson parameter</i>
MSP	<i>Manson-Succop parameter</i>
MW	<i>Megawatt</i>
N	<i>Speed rpm</i>
n	<i>years</i>
<i>n</i>	<i>number of variables</i>
NDT	<i>Non-destructive test</i>
NGV	<i>Nozzle guide vane</i>
npop	<i>Number of population size</i>
NPV	<i>Net Present Value</i>
O&M	<i>Operating and Maintenance Cost</i>
O&M	<i>Operating and Maintenance cost</i>
O_H_yr	<i>Number of operating hours per year</i>
ODP	<i>Off-design point</i>
OPR	<i>Operating Pressure Ratio</i>
OSDP	<i>Orr-Sherby-Dorn parameter</i>
P	<i>Pressure MPa</i>
Pamb	<i>Ambient Pressure</i>
PCN	<i>Engine rotational speed</i>
R	<i>gas constant J/kg·K</i>
r	<i>Discount rate</i>

RPM	<i>Revolutions per minute</i>
RTDF	<i>Radial temperature distribution factor%</i>
SCC	<i>Society of Cosmetic Chemists</i>
sfc	<i>Specific fuel consumption</i>
SPB	<i>Simple Payback</i>
SRC	<i>Selective catalytic reduction</i>
T	<i>temperature k</i>
Ta	<i>Ambient temperature</i>
Tb	<i>Blade Metal Temperature</i>
T _{ci}	<i>Inlet coolant temperature</i>
TET	<i>Turbine entry temperature k</i>
t _f	<i>Time to failure</i>
T _g	<i>Section gas temperature</i>
TLCC	<i>total life cycle cost</i>
T _M	<i>Metal temperatures</i>
TMF	<i>thermal-mechanical fatigue</i>
TS	<i>Tabu Search</i>
TTF	<i>Time to Failure</i>
TTQ	<i>Temperature Transverse Quality</i>
LMP	<i>Larson-Miller parameter</i>
\$	<i>American Dollar</i>
°C	<i>Celsius degree</i>

Roman Characters

$f(\bar{x})$	<i>the objective function</i>
$\bar{x}$	<i>number of inequality and equality constraints</i>
j	<i>number of inequality and equality constraints</i>
k	<i>number of inequality and equality constraints</i>
$g_j(\bar{x})$	<i>are the j^{th} inequality equality constraints</i>
$h_k(\bar{x})$	<i>are the k^{th} equality constraints</i>
$[x_i^l, x_i^u]$	<i>variable x upper and lower limits</i>

Greek Characters

$\dot{\epsilon}_{CS}$	<i>secondary creep rate,</i>
σ_{CFSec}	<i>Centrifugal stress at each blade section</i>
ϵ_0	<i>plastic strain</i>
ϵ_C	<i>creep strain</i>
η_P	<i>polytrophic efficiency</i>
η_{ad}	<i>Adiabatic film effectiveness</i>
η_{con}	<i>Convection efficiency</i>
η_{ist}	<i>Turbine isentropic efficiency</i>
ρ	<i>Blade density</i>
σ	<i>Stress MPa</i>
ω	<i>Angular speed</i>
ϵ	<i>Cooling effectiveness</i>

Chapter one

1 INTRODUCTION

The demand for electricity is consistently growing throughout the world, particularly within developing countries. To meet this growing demand efficiently, it is necessary to improve both the usage patterns and technology of electricity generating equipment, and it is this which forms the motivation for this study. Because of the very great difficulties of storing electricity and increasing fuel costs there is a real need to operate generating systems more economically without compromising supply, stability and/or reliability. This must be achieved with a context of increasingly stringent constraints on the emissions from such engines.

Electrical power generation includes: wind, tidal, solar, nuclear, hydroelectric, coal fired plants and industrial turbines fired with gas or liquid fuel. Of these, gas turbines (GTs) are found in applications world-wide and there has been a continuous growth in demand for these engines as a means of power generation, because its fast start-up time and controllability mean it is able to react quickly to fluctuations in electricity demand. Research and development has ensured that these engines have an economically viable working life [34]. One sector in which GTs have found wide and increasing application for power generation is the oil and gas industries, and this increased popularity has raised the need to develop procurement methods that will optimise performance under any constraints imposed.

This study concentrates on industrial GT engines, and the primary aim is to develop an innovative tool for optimising co-ordinated power production from a number of gas turbines which generate electricity for sale in the market place. It is hoped that the optimisation processes developed will be applicable at least in part to any power producing process.

The optimisation algorithm must combine the separate tasks of meeting the load demand at any time, minimising cost, and satisfying any legal or contractual constraints (e.g. minimum up and down times). This study seeks to develop a genetic algorithm (GA) which will function as the optimisation tool and to present in an understandable form the analyses and results obtained; it is suggested that the Techno-economic and Environmental Risk Assessment (TERA) method integrated with a suitable optimiser will be suitable.

1.1 Background and Research Focus

To use and/or procure GTs for cost effective electrical power generation while simultaneously meeting environment constraints requires not only a good understanding of their economic viability but also a good understanding of the performance to be expected from the engines under various conditions. This is necessary to minimise cost and to ensure turbine availability, thus maximising user satisfaction. For example, it will often be necessary to choose between using multiple smaller power turbines or a single turbine of much larger capacity. To obtain an optimum solution, a number of different topics need to be investigated, these are summarised below.

1.1.1 Economic Issues

Global demand for electricity is growing at a rate higher than that of overall economic growth and, in many countries at almost 1.5–2 times that of the demand for primary energy sources. With existing technologies and applications the demand for electricity looks set for continuous growth and an ever higher share of the energy market [84].

Rigorous economic evaluation of electrical power generation plants is, therefore, of the utmost importance in today's financial environment. Such power plants often use GT engines and all aspects of performance and economics, including lifing need to be analysed in greater depth [84]. Tightening of economic constraints worldwide have stimulated research projects to minimise economic life cycle costs (operating and maintenance). These have included the development of integrated platforms including engineering,

financial and management features of the physical assets, with scenario based studies helping to quantify potential advantages and problems.

The economics of GT power generation has developed over the past 30 years from elementary calculations of generating cost per kWh to the immensely complex analysis of detailed operation and individual costs within large systems of generating units which requires that the economic analysis faithfully represents actual operations, technical as well as financial [100]. There has been a parallel development of increasing reliability and longevity of the power systems, because new turbines are expensive and the purpose is to maximise total profits.

For the power generation market the aim of research and development is to design a power plant that will run efficiently and profitably throughout its service life (over 20 years) [9]. Investment in GT power plant will be subject to the same considerations - economic return – as any other investment and so will compete with other projects that might prove more financially beneficial.

With power generation the greatest expenditure will be the initial capital cost and then when running the greatest operational costs will usually be fuel. But income comes after generation. Future income will occur under different conditions than during project evaluation and so there will be changes to the costs of fuel, etc. The choice of a proper discount rate (time value of money) is extremely important for capital intensive long-term projects with high operational costs, as with the electricity supply industry. In this project the Net Present Value method - a sophisticated discounting technique – is used to allow an initial assessment of whether a GT power plant is likely to be an attractive investment in a given situation and whether further investigation would be worthwhile.

1.1.2 Failure Mechanisms

Previous attempts to improve the efficiency of GTs means they now run at high turbine entry temperatures (TET) so the hot section components are exposed to higher temperatures and stresses. Thus, the components of the GT engine will

be subject to several failure mechanisms, such as low cycle fatigue, high cycle fatigue, thermal stress and creep [165].

In the case of stationary GT engines, creep is one of the most common failure mechanisms that reduce hot section component life. Creep failure mechanisms depend mainly on engine operating conditions, mode of operation, the design parameters and details of the critical hot section components in question [37]. Also, not only aerodynamic but also structural requirements determine the design parameters of such components. For economic reasons as well as for safety reasons, life assessment has always been an important concern to GT users. Overestimating actual blade life can lead to accidents and economic losses; however, underestimating the blade life will cause untimely removal of the components, hence wasted money. Unfortunately, the life limits provided by the original equipment manufacturer (OEM) are normally calculated on the basis of a design envelope of expected base load with associated mechanical and thermal stresses. These in turn are functions of the operating conditions and the capability of the materials within those conditions. The OEM guidelines do not always address specific operating environment and requirements of each operator. In view of this, knowing how an engine responds to changes in the operating and health conditions is essential as these changes will affect the engine performance parameters and hence alter the creep life [15]. By using a lifing module based on stresses and metal temperature variations and utilising the Larson-Miller Parameter (LMP) one can calculate the predicted time to failure [14; 15; 51; 52; 164].

1.1.3 Environmental Issues

Most power generation in the world still depends on burning fossil fuels which are a major source of air pollution, from poor air quality, to acid rain, to global warming. Increasing fuel costs worldwide poses serious economic problems for the continued use of this type of fuel. In addition, because electricity cannot easily be stored, generation must follow demand, which requires the start-up and shut down of power generating units. This adds further constraints; the need to operate non-continuous generating systems more economically and

environmentally friendly without compromising on supply stability and/or reliability.

In order to investigate methods whereby all these requirements can be satisfied and to develop and/or select engines which meet a wide range of emission legislation scenarios and mission taxation policies with minimum cost, a viable Techno-economic and Environmental Risk Assessment (TERA) model is required.

This study considers the impact of changes in operating and maintenance costs at different operating conditions based on cost of electricity and the net present value of the power plant. The purpose of this study is to quantify operating and maintenance (O&M) costs on a GT power plant for different operating conditions based on a specified profile of power demand. Accurately predicting this will help facilitate electricity producers take appropriate corrective actions or make changes in the mission profile and/or configuration of the power plants.

An in-house GT performance modelling tool called Turbomatch was used to develop and simulate representative thermodynamic models of the engine investigated [119; 154]. Data is generated from the Turbomatch simulations and used as an input for the multidisciplinary module, which is TERA. Ogaji et al., [133] have presented extensive descriptions of the modules incorporated in TERA, how the modules integrate and how optimisation can be obtained using this tool.

1.1.4 Optimisation

Because with commercial power generation an enormous number of interrelated factors are present there are a huge number of possible alternatives for the generation process. Automated optimisation techniques offer the possibility of achieving optimum decisions under these conditions [23] . An important example of such a problem is how best to meet the cyclically varying demand for electrical power (on a daily or seasonal basis). This is a problem faced by both generating and transmission companies.

This project has taken and enhanced a Genetic Algorithm (GA) as its preferred simulation tool for the study of portfolio optimisation. One outcome from the project will be to maintain the required output power of a number of generating units at minimum cost by selecting the best possible combination of units or, if an existing power station has to be re-equipped, specifying the necessary plant to meet demand for electricity at minimum cost over a specified time period.

Of course the cost of fuel and maintenance costs are essential to this study. However, the ambient temperature is a factor that impacts on GT performance. Thus, ambient conditions will be an essential part of any investigation into the sale price of electricity. Despite showing short term stochastic variations weather shows strong seasonal and daily trends and this allows it to be included.

1.1.5 Growth in World Electricity Generation

Figure 1-1 is from International Energy Outlook (IEO2011 [76]) and shows that electricity is expected to have an increasing share of the world's total energy demand. For the eighteen years from 1990 to 2008 growth in net electricity generation (3.0 % per annum) was nearly double the growth in delivered energy consumption (1.8 % per annum). Electricity consumption is expected to continue to grow more rapidly than liquid fuels, natural gas, or coal for all end-users except transportation.

It is expected that world demand for electricity will increase by about 2.3 % per annum from 2008, see Figure 1-1, and will continue to outpace growth in total energy use [77]. For the scenario shown in the figure world net electricity generation increases from 19.1×10^{12} kWh in 2008, to 25.5×10^{12} kWh in 2020 and 35.2×10^{12} kWh in 2035. Despite the 2008-2009 global recession worldwide electricity demand increased by an estimated 5.4 % in 2010.

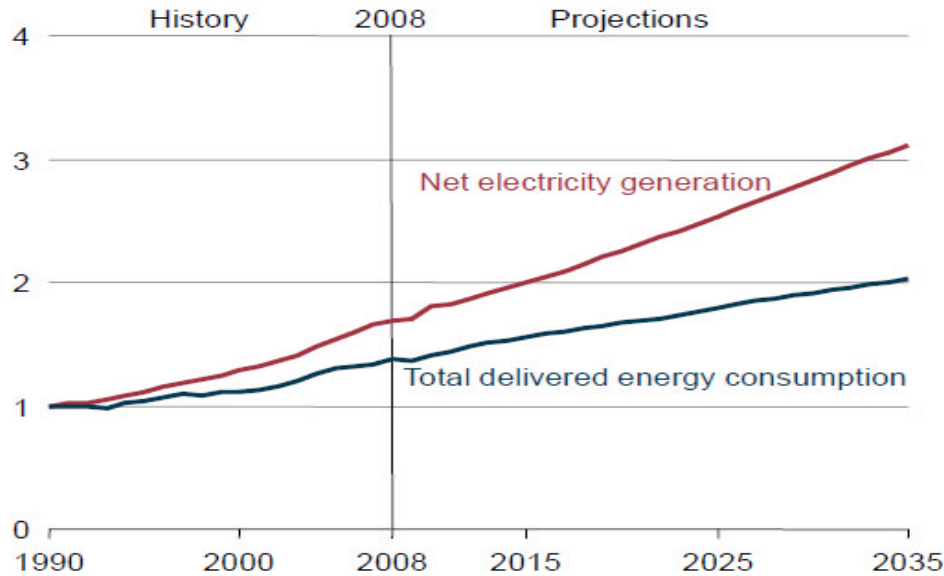


Figure 1-1: Growth in world electricity generation and total delivered energy consumption, 1990-2035 (index, 1990=1) [76]

1.1.6 Electricity Market

It is claimed that a major advantage of an open electric power market is the presence of more competition and reduced electricity costs, the move away from a monopoly supplier with consequent improvements in technological development, particularly increased efficiency of GT power plant [102] . In particular there would be considerable research effort put into forecasting of demand and supply, and fuel and electricity pricing [25; 34; 85; 99; 108; 114; 144].

The price of fuel and cost of electricity are supposedly stochastic in nature [76] but they certainly show long-term, seasonal and even daily trends. For example, consider the cost of electricity on a 24-hour basis, it is usually significantly lower between midnight and early morning, because the demand for electricity is much lower than during the day. In Libya the cost of electricity in the spring and autumn is lower than in the summer because the demand for electricity is higher in the summer [60].

The fuel cost, cost of electricity and maintenance cost will be major considerations for operational planning of power plant in a market based environment. However, this project considers that ambient temperature will also

have a measurable effect. A TERA model, able to capture the values of these variables on a daily basis to show their daily variability as well as longer-term trends has been created for this purpose.

1.2 The TERA Philosophy

Before introducing aims and objectives the concepts behind the model used in this thesis are presented. TERA (Techno-economic, Environmental and Risk Analysis) is a modelling approach which exploits the design space of engineering problems and identifies solutions which minimise overall design time and costs (such as design, construction, and running costs) and selects an optimum solution with reduced error in the decision making process as illustrated in Figure 1-2. Kyprianidis et al., [82] have claimed TERA to be: “an adaptable decision making support system for preliminary analysis of complex mechanical systems”. Others have described TERA as a multi-disciplinary tool for modelling of GTs and engine asset management [133; 136; 139; 140].

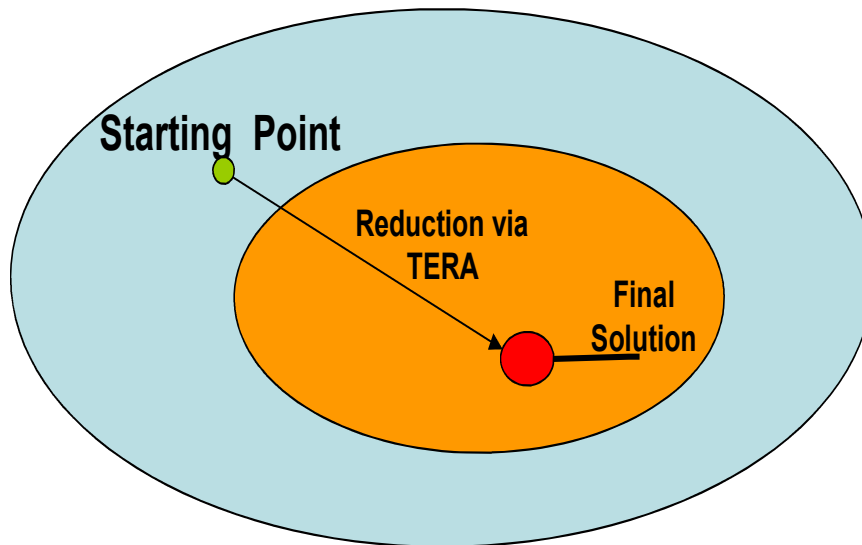


Figure 1-2: Role of TERA [133; 136]

Gayraud [59] was amongst the first at Cranfield University to study techno-economic assessment and selection of industrial GTs. His work later progressed to examine decision support within combined cycles. Whellens and Singh [96] have described how the TERA approach was used to model the design process to make traditional decision making easier. The author

presented an architecture and details of the lifing, economics, emissions, and performance modules [157-160] and the current architecture is an extension and final version of that (the architecture will be presented later).

1.3 A Brief History of Genetic Algorithms GA

In the 1950s and 1960s a number of computer scientists independently developed the concept that evolutionary systems could be used as a tool to optimise the solutions to engineering problems. The core idea was to allow a population of candidate solutions to a given problem to evolve in a manner inspired by genetic variation and natural selection but subject to certain imposed constraints [72].

Genetic algorithms (GAs) were first developed in the 1960s by Holland and colleagues at the University of Michigan [80]. Initially Holland studied adaptation as it occurs in nature with a view to develop ways whereby the mechanisms of natural adaptation might be used to improve the efficiency of computer modelling systems. Holland, in his book "Adaptation in Natural and Artificial Systems" [72; 73; 80] presented the GA as an abstraction of biological evolution and gave a theoretical framework for adaptation under the GA. Holland's GA is a method for developing from an initial population of approximate solutions (which in computer terms are simply strings of ones and zeros, and are called "chromosomes" to preserve the genetic similarities) to a new population which represents a better solution by using the kind of mechanisms present in natural selection at a genetic level; operators such as crossover, inversion and mutation. Each "chromosome" consists of "genes" (e.g., bits), each gene being an instance of a particular "allele" (e.g., 0 or 1). The operator governing selection contains a fitness test which selects those "chromosomes" to reproduce so that, on average, the fitter the "chromosome" the more offspring. Mutation is a process which interchanges the allele values at certain randomly selected locations in the "chromosome", inversion takes contiguous sections of the "chromosome" and reverses the order of the alleles, thus rearranging the order of the genes, crossover (also referred to as recombination) in GA creates

offspring by randomly exchanging sections of two parental “chromosomes”. Holland's [73] work was a major innovation.

Holland's work was the first to attempt to put computational evolution on a secure theoretical basis [80] and until recently was the basis of most subsequent theoretical work on GAs. Previous evolution strategies had been very limited and some commenced with a population of only two individuals, a parent and an offspring, with the offspring a mutated version of the parent [68]. Similarly, the evolutionary programming in [13] used only mutation to provide genetic variation. Populations of multiple individuals with crossover and inversion were not developed until later.

More recently there has been considerable development in the study of evolutionary computation methods, so that evolution strategies, programming and other approaches (including GAs) are coming together [106]. Thus today, the term "genetic algorithm" is often used to describe processes very distant from Holland's original notion.

1.4 Aim and Objectives

The aim of this work is to develop an optimisation tool based on a suitable GA and the TERA model which will allow optimum selection and operation of a fleet of GTs in order to maximise the required power output at minimum cost. Typical changes in both power demand and ambient conditions will be taken into account. It is considered that this work will be novel.

To achieve the above aim, the following objectives have been defined:

- To simulate engine performance by modelling a fleet of stationary GT engines using TURBOMATCH software: Design point (DP) and off-design point (ODP) calculations will be carried out to consider the variation of operating and ambient conditions.
- To develop an economic model.
- To develop and implement a generic component sizing model, a thermal and a stress model. The LMP time temperature approach will be used to

estimate the remaining life of hot section component at different design parameters and operating conditions.

- To develop a procedure to predict the emission characteristics of a gas turbine when generating power.
- To establish a new model for the solution of the optimisation problem by developing a Genetic Algorithm code (GA) to be adaptable to be integrated into the TERA model.
- To adapt a Genetic Algorithm (GA) code that is integrated with the TERA model in order to find an optimum solution to the objective function.

1.5 Contribution

This research project is expected to make the following contributions to knowledge:

- Developed an approach capable of simulating engine operating conditions and attendant cost under different scenarios based on the TERA philosophy.
- Developed an approach capable of optimising and hence determining suitable engine technologies (e.g. optimising operating strategies such as the size of GT, on/off times, best combination of suitable engines, etc.) firstly to optimise the existing fleet of engines for current requirements then to meet market growth requirements, while minimising cost and environmental effects.

1.6 Structure of Thesis

This thesis is split into 7 chapters. After giving a broad introduction to the increase of power demand and electricity trade, the thesis looks at the behaviour of the gas turbine engines at different operating and ambient conditions. These engines are analysed for their performance capabilities. Next, there are several chapters which look at the literature and methodology of each module within the optimisation code (TERA code & Genetic Algorithm GA). Finally, there is a section on scenarios which shows how the tool has been utilised.

Chapter One, “Introduction”:

Gives a general introduction and broad background about this thesis, includes a general overview followed by the aim for the study, objectives, methodology and then the contribution for this work.

Chapter Two, “Literature Review”:

Presents a literature review of the work undertaken previously in this field. It is focused on five key areas of interest, which were identified to be closely linked to the objectives of this work. These five areas are the Performance and Simulation for the Industrial Gas Turbines at Design Point and Off-Design Conditions, Gas Turbine Power Plant Economic and Power Generation, Failure Mechanism of Gas Turbine Engines, Environmental Issues and Optimisation Techniques.

Chapter Three, “Research Methodology”

The optimisation code (TERA & GA) methodology used in this study is explained in this chapter, which includes the TERA sub-models. The software model used in the performance simulation with the engine specification is presented. Also, the Economic model of the gas turbine power plant is presented. The creep life model is presented to investigate the effect of operating conditions, design parameters and working environment. The emission model is presented; the main objective is to estimate, through thermodynamic simulations, the range of CO₂ emissions of a typical power plant operation. Use this range to evaluate the impact of emission tax on the cost of electricity. Finally, interaction between the GA optimisation code and TERA modules acting as an external solver is presented in this chapter.

Chapter Four, “TERA Frame Work”

In this Chapter the TERA research methodology is explained and then the architecture of the proposed integrated framework is presented. Descriptions of the result of sub-models are given and the governing and required inputs are presented. Also, performs the economic analysis for each engine individually and for the whole power plant and this includes the capital cost, maintenance and operating cost, fuel cost, emission tax and net present value (NPV).

Chapter Five, “Genetic Algorithm (GA)”

Presents a brief description of genetic algorithm and its working mechanisms and the validation of the code used in the present study, the secure GA171. It also provides a study of the parameterization of the GA variables to efficiently search a highly multimodal parameter space for a global maximum.

Chapter six “Case Study”

Presents the optimisation scheme and its implementation; this chapter also discusses the application of the new code to a variety of case studies

Chapter Seven “Conclusion and Future Work”

Conclusions of the modelling and the case studies are summarised here as well as suggestions for further works in the areas studied

Chapter two

2 LITERATURE REVIEW

2.1 Industrial Gas Turbines Performance and Simulation

Engineers have achieved a more or less continuous increase in the efficiency and performance of GT engines. Simultaneously operators have been concerned with maximising both operational efficiency and the duration of the time periods between removing the engine from service for necessary maintenance. There still remain, however, a number of important issues such as GT off-design performance conditions and degradation of performance with time in service.

Degradation of performance is usually due to the day-to-day physical operating conditions of the GT. For example, fouling – which is due to a combination of the site where the GT is located and maintenance and operation – will cause component performance to deteriorate. Such considerations and their impacts on engine (and component) performance, life and other technical and economic matters are discussed in this chapter and Chapters 3 and 4.

Modelling of the GT and its operation is considered to provide useful information which helps with decision making and improved operation both in selection of GTs and the operation of the GT after it has been installed. There are many ways of simulating GT performance and operation and predicting possible consequential degradation and faults [14; 15].

This chapter reviews the literature on simulation and modelling of industrial GTs that has been performed especially for power generation applications.

2.1.1 Gas Turbine Performance Model

GT performance modelling is usually to provide performance parameters on the thermodynamic cycles for the industrial GT under investigation at those ODP conditions in which it will operate.

To simulate GT ODP performance Turbomatch was used. First the input files were constructed for each of the GTs under investigation their DP performance obtained (Appendix A). The second step was to obtain the ODP of each of the GTs required for the case studies. It was determined at the start of the project that the variables to be used to determine GT off-design conditions would be ambient pressure (P_{amb}), Turbine Entry Temperature (TET) and ambient temperature (T_{amb}).

2.1.1.1 Turbomatch Scheme Overview

Turbomatch is a FORTAN program developed at Cranfield University by the School of Engineering, Department of Power and Propulsion, to enable calculations of DP and ODP performance of existing and in-concept GT thermodynamic cycles [119; 154].

Turbomatch uses pre-programmed routines which are named “bricks” and with the use of interface “codewords” provides the ability to simulate the operational state of the engine’s different components and, as a result, the engine’s output power or thrust, fuel consumption, mass flow etc. Turbomatch assumes that the fuel used for the simulations is kerosene with a low calorific value of 43.165 MJ/kg.

Turbomatch also provides detailed information on the performance of every component, and also of the gas properties at every engine’s station. The results are presented not only in “.txt” files but also in a special “.xls” file which provides great flexibility if the engine’s (or component’s) performance parameters are to be tabulated and interpolated, and used as input data for other models such as in this study. The scheme is used in the majority of projects at Cranfield University that require GT performance calculations, either for aero, marine or stationary gas turbines.

2.1.1.2 Design Point Performance

Central to the concept of the engine design process is design point performance. A given specification for a given engine configuration will determine the component performance levels and cycle parameters. However, before analysis of any other operating conditions is possible the design point performance must be defined [163] . In this chapter the performance input, which cannot be divorced from component design, is described.

The condition at which the engine spends most of its operating life is usually chosen as the engine design point. For industrial units this would normally be the ISO base load. However an alternative that is sometimes used is to choose an important high power condition. Whichever is chosen as the design point, the engine will be designed for optimum performance under those conditions. This project assumes that the component design points are for the same operating condition as the engine design point in the concept design phase. Overall engine performance is defined by a number of key parameters which are used to assess how suitable a given engine design is for the given application. They may also be used to compare a number of possible alternative engine designs. These engine performance parameters include: Output power, specific power, exhaust gas power, specific fuel consumption, exhaust mass flow rate, exhaust temperature and thermal efficiency.

Brooks [27] has discussed cycle characteristics of several gas turbines including the thermodynamic principles of one and two shaft gas turbines, factors affecting performance and methods to enhance gas turbine output.

2.1.1.3 Off-Design Point Performance

Any movement away from design point is normally referred to off-design performance. This movement will be due to internal or external alteration. Internal alteration is caused by component degradation while external alteration is caused by deviation of ambient conditions. Here geometry is fixed and operating conditions are changing. Influence of the ambient condition in the gas turbine performance from ISO like pressure, temperature and altitude. To see

the effect of these changes on engine performance ambient temperature, the following procedure has been deliberated [163] :

External:

- ✓ Influence of ambient temperature
- ✓ Influence of altitude
- ✓ Influence of power setting

Internal:

- ✓ Influence of compressor efficiency degradation
- ✓ Influence of compressor flow capacity degradation
- ✓ Influence of turbine degradation

The operating condition is changing even in the same location from day to night. The off-design operation could be one or many combination of the above. This will help to know the output and efficiency of turbine in each operating condition.

2.1.1.4 The Influence of Ambient Temperature and Site Elevation

Change in the mass flow rate of air entering a GT will alter its performance. Factors affecting air density include pressure, temperature and humidity [54] . These inter-relate so that, for example, with increase in height above sea level both pressure and air temperature decrease with the net effect that air density decreases with height.

It can be understood that GT performance and efficiency decrease on hot days due to:

- Reduced air density.
- Reduced mass flow.
- Reduced pressure ratio.
- Increased Specific Fuel Consumption (SFC).

GT performance thus depends on ambient conditions which will vary from place to place and day to day [54]. The International Standards Organization (ISO) has established standard conditions which allow comparison between tests and these are now universally accepted and used.

Erdem and Sevilgen [50] have shown that seasonal temperature variations can cause a loss of power of between about 1.7% to about 7.2%, and that higher ambient temperatures decreased efficiency of electricity production. This means

higher ambient temperatures will increase fuel consumed per unit of electricity produced. Gorji and Fouladi [67] found that with an increase of ambient temperature from 5°C to 35°C (i.e. winter to summer), the cycle thermal efficiency decreased by 5.9% and the SFC increased by 5.7%.

2.2 Common Failure Mechanism in the Gas Turbine Hot Section

Failure of metal components will depend on what the metal is, degree of deformation, temperature, magnitude of the applied strain and the rate at which the strain is applied [122]. It is thus a very complex phenomenon. When a metal component breaks, it is necessary to determine the failure mode(s) and the origin of the damage in order to understand the event [110].

GT hot section components operate at extreme conditions and this will enhance the likelihood of occurrence of a number of damage mechanisms such as high temperature corrosion, fatigue, and creep deformation. These mechanisms, if sufficiently advanced, will stop the component functioning as intended and cause the component to fail prematurely.

2.2.1 Fatigue

Fatigue is often caused by repetitive forces that produce fluctuations in the components' stress (σ) which, if of sufficient magnitude, can lead to crack initiation, propagation and fracture. A fluctuating stress can cause a component to fail even if its magnitude is substantially less than that required for single load application failure [71; 124].

Both mechanical and thermal-mechanical fatigue (TMF) can be in this context. Mechanical fatigue is usually due to cyclic loading. This might be due to vibrational stress on GT blades during start-stop cycles or power change. It is often convenient to divide mechanical fatigue into: low cycle fatigue (LCF) and high cycle fatigue (HCF). The two are distinguished by where the repetitive application of load takes place [118; 124].

2.2.2 High Temperature Corrosion/Oxidation

Aggressive oxidising and corrosive conditions exist in both turbine and compressor. These may be due to the ambient air containing [142] sodium chloride from runway de-icing treatment or because the GT is near a marine environment, or atmospheric contaminants due to industrial pollution which often contain both sulphur and sodium, or even pollutants from volcanic activity which can generate high levels of sulphur. Within the GT itself gaseous combustion at high temperatures may produce sulphur, vanadium or even lead and bromine. Even though the blades are given a protective coating, oxidation and corrosive attacks are inevitable, especially when the blades are in aggressive environments and particulates damage the coatings.

2.2.3 Creep Deformation

Creep is a time-dependent deformation which takes place at high operating temperatures when the metal is subject to a mechanical stress which is less than the yield stress of the metal. Creep will cause an elongation of GT hot section components. Turbine blades, for example, will show a significant change in their shape with severe creep deformation, and will not function properly. If the deformation is an elongation of the blades there may be contact with the casing which would cause the blades to fracture. Figure 2-1 shows creep deformed turbine blades which have already lost their tips, indicating a severe creep attack [131].



Figure 2-1: Deformed turbine blades under creep attack [95]

Creep is reported to become significant when the homologous temperature (T_M , ratio between the material temperature and its melting temperature) is greater

than 0.4, and will become serious above a ratio of 0.6 (of course the actual value of the ratio will depend on the material) [55; 94]. Because the compressor operates at temperatures lower than the homologous temperature creep is not significant.

2.2.4 Competition among Damage Mechanisms

Table 2-2 and Table 2-2 show the relative importance of damage mechanisms for components under different conditions. For example, turbine blades are prone to oxidation, creep, LCF and HCF. Brun et al., [81] found that cold compressor surfaces can condense water in which chemicals such as salts or sulphur compounds have been absorbed to produce a corrosive, acidic, liquid which can generate wet corrosion.

Because land-based GT power generators are operated under uniform conditions with constant load for the majority of their time but in a high temperature environment, creep is usually dominant relative to fatigue and oxidation. This is not the case with aircraft GT engines, where frequent stop-start cycles and throttle changes means fatigue is more dominant than creep. For GT engines in marine environments the high concentration of sodium and chlorine present in the air ingested into the engine reacts with the fuel during combustion to form sodium sulphate which is then deposited on hot section components producing accelerated corrosion [58].

Table 2-1: Comparison of problems for gas turbine applications [143]

Gas Turbine Applications	Oxidations	Hot corrosion	Creep	Fatigue
Aircraft engines	Severe	Moderate	Moderate	Severe
Land-based power generation	Moderate	Severe	Severe	Light
Marine engines	Moderate	Severe	Moderate	Moderate

Table 2-2: Life expenditure effects on gas turbine components [12]

Design criteria and life expenditure effects						
	Time dependent life expenditure			Cyclic life expenditure		
Components	Oxidation, corrosion, erosion	Wet corrosion	Creep	LCF	HCF	Crack Propagation
Turbine blading	n	X	n	n	n	X
Compressor blading	X	n	X	n	n	X
Inner casing, mixing chamber, exhaust liner	n	X	n	n	o	X
Rotor parts (excluding blading)	X	X	X	n	X	n
Pressure-tight casing	X	X	X	n	X	X
Piping	X	o	X	n	n	X
n Significant contribution		o Affects only locally			X Irrelevant	

Figure 2-2 summarises in graphical form how the different damage mechanisms dominate at different temperatures. At metal temperatures below about 850°C, mechanical fatigue is dominant. Between about 850°C and 1000°C, thermal fatigue dominates and then above about 1000°C creep is the major threat.

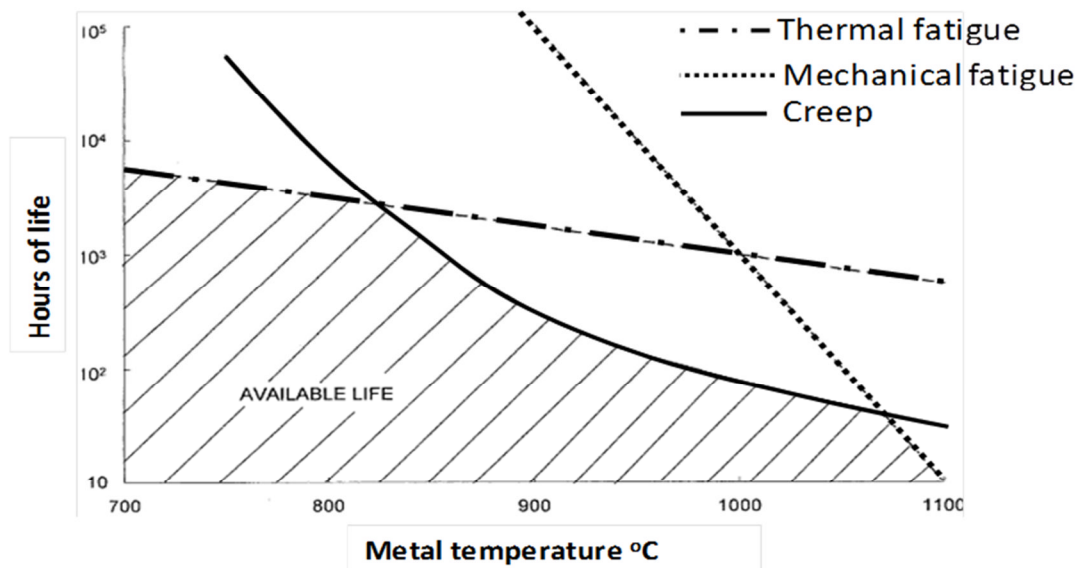


Figure 2-2: Factor influencing turbine-component life [113]

2.3 Understanding Creep

Creep, is a naturally progressive, permanent deformation that becomes significant and even substantial at higher temperatures and can end in rupture of the material. Creep strain is the progressive accumulation of plastic strain. Unfortunately, creep deformation can also occur at relatively low temperatures.

Figure 2-3 shows creep curves at two homologous temperatures and it can be seen that at the higher temperature ($T_M > 0.4$), the increase in length will be much greater than for the lower temperature ($T_M < 0.3$) and the metal will eventually undergo rapid extension followed by creep rupture. At the lower temperatures, the material undergoes less “stretching” and it is unusual for failure to take place.

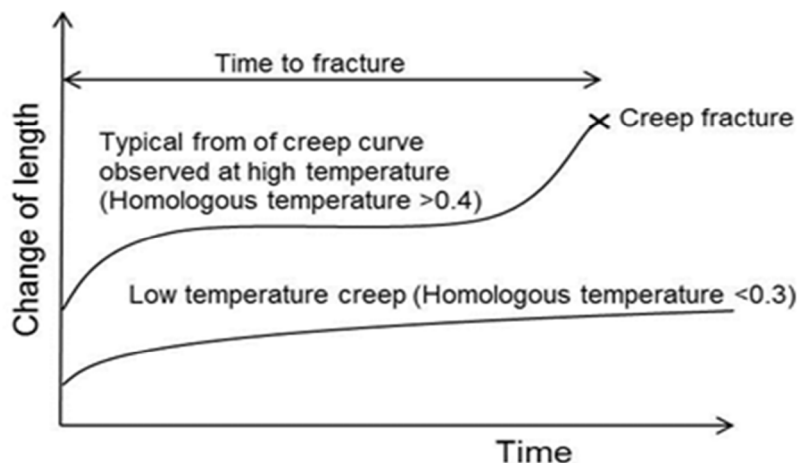


Figure 2-3: Creep curves at two homologous temperatures [125]

At higher values of T_M , there is greater dislocation mobility and the strength of the material decreases [56], it also means the material's slip system can change and an additional slip system may be created in certain circumstances. This additional slip system creates new 'paths' for the dislocation giving higher dislocation mobility. The result is that creep strain at higher values of T_M can be much more than at low values.

Webster and Ainsworth [55] have suggested that in polycrystalline materials creep is the result of grain boundary sliding, diffusion and dislocations. With increase in the temperature of the material, the atoms gain sufficient thermal energy to 'jump' from its original location to another, and in doing so transmits

energy to adjacent atoms. In time this diffusional process will change the polycrystalline atomic arrangement and the grain will extend with time.

2.3.1 Creep Curve and Stress Rupture Curve

In the laboratory creep behaviour is determined by the application of a constant uniaxial load or (σ) usually applied at a given temperature. The recorded curve for creep strain, (ϵ_c) is plotted a function of time, (t), see Figure 2-4.

Figure 2-4 shows that the initial application of the load causes an immediate initial plastic strain, (ϵ_0). Under the action of the load the plastic strain (ϵ_c) will continue to increase with time, (t). During Stage I(primary creep), the initial plastic strain/creep rate is high due to maximum dislocation taking place within the material, but the density of the dislocations increase until it becomes saturated and prevents more dislocation taking place, creating strain hardening that reduces the creep rate to a constant value (end of Stage I).

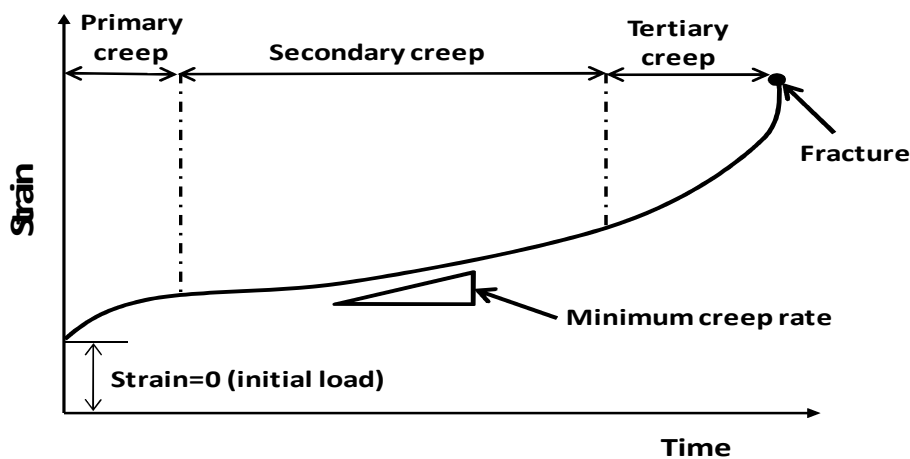


Figure 2-4: High temperature creep curve [131]

In Stage II (secondary creep), see Figure 2-4, creep rate is more or less constant and at its minimum value. This is known as secondary or steady-state creep and is due to a balance between the strain hardening rate and the deformation rate. Stage III is tertiary creep which ends in fracture due to any one of a number of factors [125] such as (i) mechanical instability, e.g. necking and localised reduction in cross-sectional area, (ii) microstructural instability, including grain growth or re-crystallisation with single-phase material or the

gradual loss of creep strength as over-ageing occurs during creep of precipitation-hardened alloys; and/or (iii) nucleation and growth of internal micro cracks which develop until the number and sizes of the micro cracks are sufficient to cause the creep rate to increase.

2.3.2 Factors Affecting Creep Deformation

Creep will be a function of such actors as applied loading, duration of exposure, metal properties and temperature [20; 57; 142]. The longer the component is subject to stress and to raised temperature the more deformed it will become.

Different materials have different creep resistances due to different grain size microstructural arrangement, vacancy concentration and activation energy. Figure 2-5 presents the stress-temperature patterns which produced creep rupture in different material in 100 hours. It can be seen that niobium alloys and tungsten have high temperature resistance but low stress resistance; on the other hand 12%CrMoV steels have a higher stress resistance but will fail at a lower temperature.

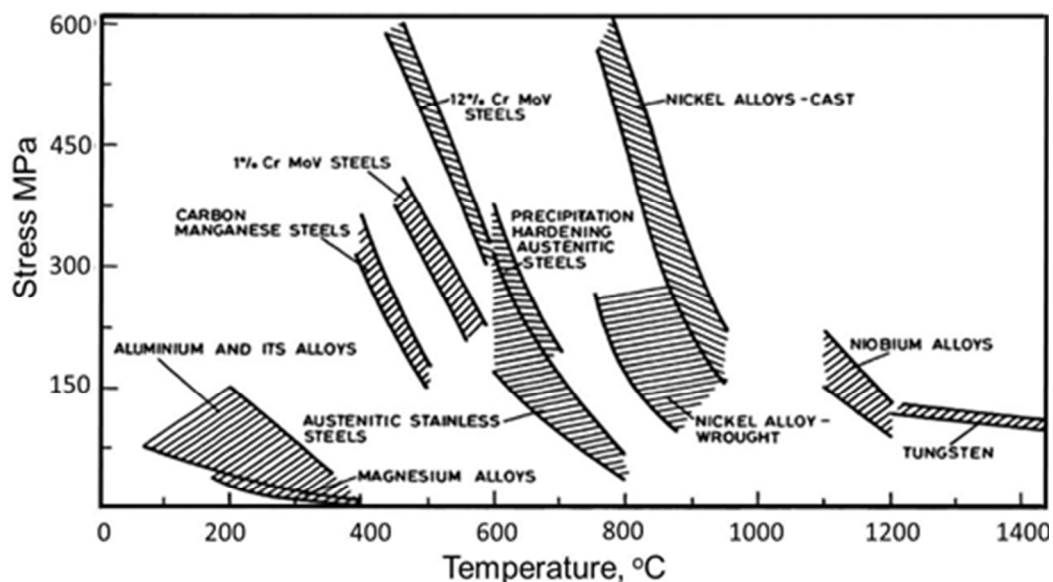


Figure 2-5: Stress and temperature to produce creep rupture in 100 hours in various alloys [55]

Elevated temperatures will weaken a material because of increased grain boundary sliding, dislocation, creep cavity nucleation, etc [78]. As a result the

creep rate will increase and this will shorten the time to failure(t_f). Figure 2-6 shows variation in creep when T_M is increased at a constant applied load. It can be seen that as T_M increases the time to failure (t_f) is shortened and the secondary creep rate, ($\dot{\epsilon}_{CS}$) increases. It can also be seen the 'stretching' of the material is greater at higher values of T_M .

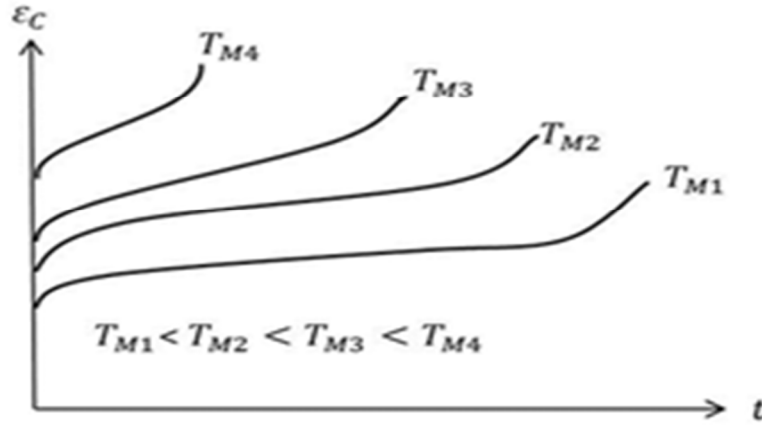


Figure 2-6: Schematic diagram of creep curves at different temperatures [14]

Creep rate, $\dot{\epsilon}_C$, depends on the magnitude of the applied load, σ . Figure 2-7 shows the creep rate at constant temperature for different applied loads. With increase in load, both primary and secondary creep stages shorten, and if the load is great enough are eliminated, hence reducing the time to failure. Similarly, the 'stretching' of the material is higher the higher the load but time of exposure is is shortened.

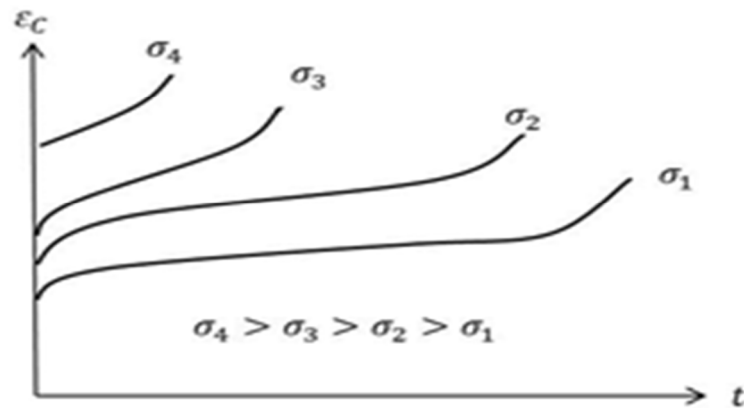


Figure 2-7: Schematic diagram creep curves at different levels of applied stress

[14]

2.4 Parametric Methods for Calculate Time to Failure

Unfortunately it is not always possible to make accurate component life estimation from data collected from creep curves and experimentally derived creep laws. Experiments can provide exact life estimation where the data collected accurately matches the practical conditions. However, in many situations the data available does not cover the temperatures and loads of interest and interpolation and/or extrapolation to the temperatures and stresses of interest need to be carried out. Creep laws contain empiric constants that need to be obtained experimentally before the model can be used. But often these constants are functions of temperature so the calculated life may not be accurate.

A large number of parametric techniques can be found in the literature such as those based on time and temperature. It is not beneficial to discuss every one; sufficient to say that the most widely accepted are the Goldhoof-Sherby parameter (GSP), Manson-Haferd parameter (MHP), Manson-Succop parameter (MSP), Orr-Sherby-Dorn parameter (OSDP) and Larson Miller parameter (LMP). The requirement for these models is that a full range of temperature and stress can be covered that may require extrapolation to high or low temperature and to high stresses beyond where test data exists. The melting point of the material sets a limit to the extrapolation of temperature (40% of melting temperature). The extrapolation of the stress is limited by the ultimate tensile strength at the temperature of interest which presents an upper limit to the applied load [21].

2.4.1 Larson Miller Parameter (LMP)

The LMP parameter has been useful in predicting long time rupture behaviour from low stress, creep rupture data; it is a useful analytical tool for evaluating the effects of stress on creep life over a range of temperatures. The LMP relies on the elimination of one of the two independent variables (temperature and applied stress) that are controlled during a creep test. The power of the LMP lies in the elimination of the temperature dependence and allows one to construct master rupture curves [47; 128].

$$LMP = \frac{T}{1000} (\log t_f + C) \quad 2-1$$

Where C is a constant for a given material, T is the Absolute temperature in K, t_f = time-to-failure, 1000 is a scaling constant.

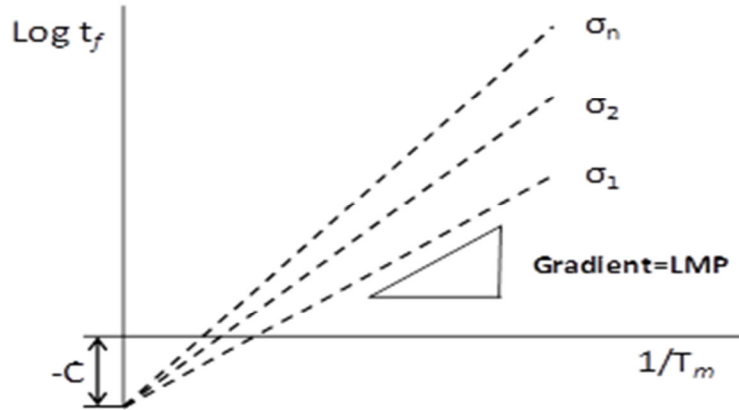


Figure 2-8: Schematic Illustration of plot of log tf vs 1/TM [131]

For industrial applications the constant C is usually given the value 20, but it will vary with application. The LMP approach assumes that if the lines of constant stress are extended back to cut the $\log t_f$ axis there is convergence at the point (0, -C) see Figure 2-8 [28; 49; 124; 156]. Any combination of temperature and time-to-failure will give equivalent values for LMP and for creep stress. The LMP has been expanded to include rupture and the time required to reach fracture due to either rupture or strain, depending on operating conditions. If the actual time of operation of a component is divided by the total life to failure, life fractions can be found [37].

2.5 Parameter Selection

It is necessary to discuss and compare the different parameters (see Section 1.4) used to fit creep data. It is critical for accurate life calculation to select the most appropriate assessment parameter which will be a function of, the type of material used, its temperature, relevant failure mechanisms and stress range.

Marahleh et al., [98] have stated that LMP is accurate for life prediction of materials subjected to extended periods at elevated temperatures where there

is no microstructural change. If microstructural change does occur the test results have lower values than the extrapolated values.

Bueno and Sordi [28] compared the performance of OSDP, GSP, MHP, MSP and LMP applied to creep data for Fe-Mn-Al steel. The best results were obtained from MSP but good results were also obtained from OSDP and LMP. Bueno and Sordi used the same five parameters to compare creep and hot tensile behaviour for Cr-Mo steel for different temperatures and stress levels. The best results were given by MHP followed by OSDP, and the worst results by GSP. The success of MHP was supposedly due to the fact that these were high temperature tests.

Eno et al., [49] appraised the same parameters except GSP was eliminated and the Mandelson-Roberts-Manson parameter (MRMP) included. The five parameters were judged by how well they fitted stress-temperature creep behaviour data for creep data obtained for nickel chromium alloy 617 and Haynes 230 alloy. In each case the best fit was obtained using MRMP, closely followed by MHP and LMP.

The two sets of results both concluded that LMP was a useful parameter because of its ease of use over a wide variety of applications and that the parameters should be considered as particular aspects of a common framework.

2.6 Creep Life Estimation Approaches

A lifing model defines the relation between loading level and component lifetime. It generally calculates total time to failure, and the major division in lifing models is between total life models and crack growth models [147]. In service the useful life of hot section components decreases progressively due to creep deformation because both deformation and fracture are time-dependent, see Figure 2-9. The rate at which useful life is consumed will be a function of the operating conditions of the specific GT and how well the material resists creep deformation. The material will degrade faster, and consume its useful life more quickly the more extreme the operating conditions. The material will

degrade progressively due to crack formation which begins even in the primary stage. Betten et al., [24].have described how micro-cracks begin on the surface and propagate until they link into macro-cracks and become visible at the tertiary stage of creep.

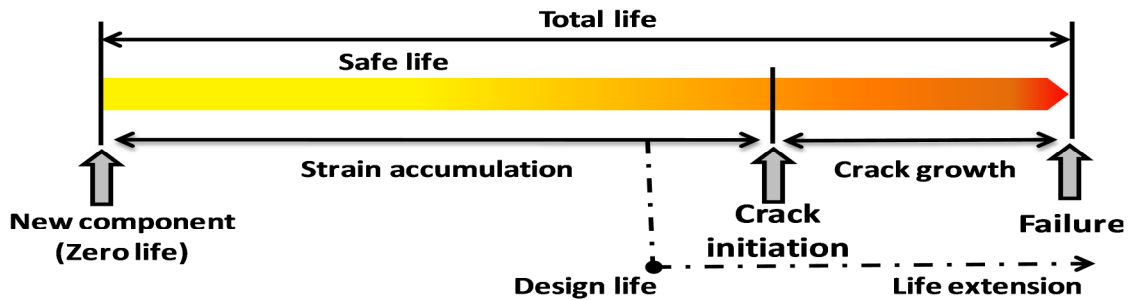


Figure 2-9: Creep life span of hot section components due to deformation [29; 33]

There are several methods for estimating creep life. In general, the life methodologies may be classed into three distinct approaches as shown in Figure 2-10 [51; 52] ;

- *Design approach*
- *Post-service approach*
- *Statistical/probabilistic approach*

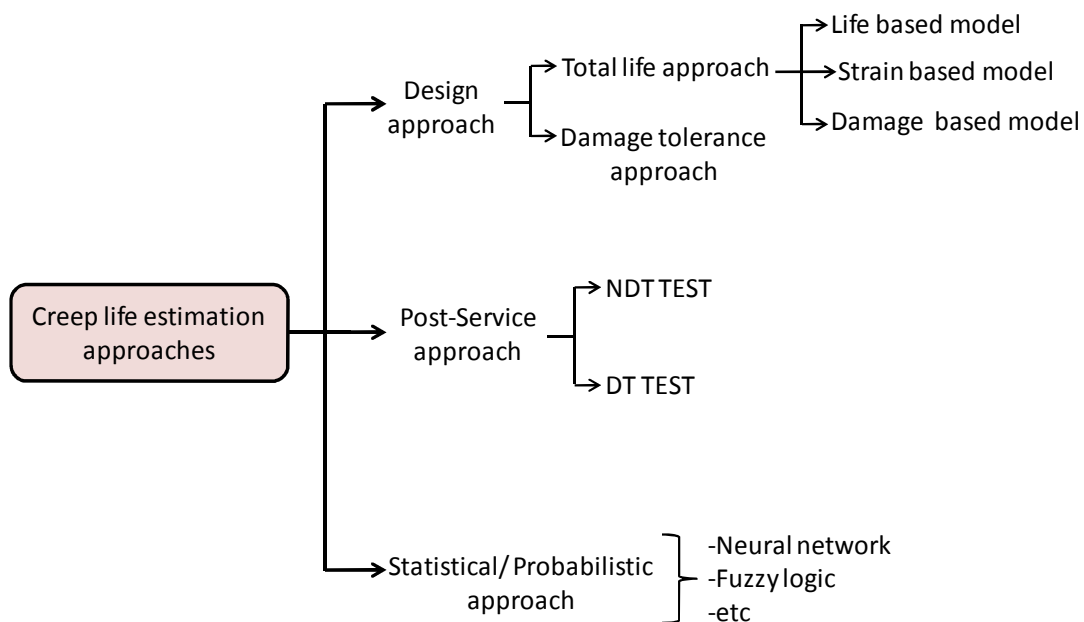


Figure 2-10 : Creep life estimation methodologies [51; 52]

Table 2-3: Lifting approaches[15; 51; 52]

	Design approach	Post-Service approach	Statistical approach
Methods	<ul style="list-style-type: none"> ✓ Analytical method ✓ Empirical method ✓ Numerical method 	<ul style="list-style-type: none"> ✓ Non-destructive inspection ✓ Destructive test 	<ul style="list-style-type: none"> ✓ Statistical tools ✓ Probabilistic tools ✓ Artificial intelligent methods
Advantages	<ul style="list-style-type: none"> ✓ Life estimation can be performed at design stage. ✓ Low cost if low fidelity model is used. 	<ul style="list-style-type: none"> ✓ Identify the components that need to be monitored. ✓ Offers different techniques for both destructive and non-destructive test. 	<ul style="list-style-type: none"> ✓ Reduce complexity ✓ Fast computing ✓ Identify driving factors ✓ Tackle the uncertainty
Disadvantages	<ul style="list-style-type: none"> ✓ Based on data to build the model. ✓ High complexity to achieve. ✓ High cost. 	<ul style="list-style-type: none"> ✓ Need prior techniques to estimate life at design stage. ✓ Time consume. ✓ Perform during maintenance. ✓ Inaccurate if uncelebrated device used. 	<ul style="list-style-type: none"> ✓ Requires prior models ✓ The factors may vary according to the nature of the research.

The techniques outlined in this section are used for different applications and at different stages of component failure so there can be no comparable accuracy and reliability.

Table 2-3, summarized the three lifting approaches and gives the general advantages and disadvantages of each technique.

2.6.1 Design Approach

The design approach calculates the component's remaining creep life using analytical and empirical data, and/or numerical models. Information such as component geometry, properties of the component material and likely engine operating conditions are required to estimate component life. Wood [167] has claimed that when the life fraction is greater than 0.5, conventional non-destructive testing (NDT) and destructive testing (DT) techniques should be carried out. Naeem [112]; Cerri [32]; Assoul et al., [19]; Eshati [51; 52]; Ghafir [15] and W. Mohamed [164] also developed creep life prediction models using the LMP. In each case the input data for stress and thermal analysis were supplied by a GT performance simulation model. In Assoul et al., [19] the gas

pressure and temperature pressure were found using the thermodynamics relations of a Brayton cycle. Simplified 0-D and 1-D models [15; 32; 52] were used to predict the bulk metal temperature of the individual components and temperature variations across the blade span. Naeem, [112]; Eshati, 88 and W. Mohamed [164] consider centrifugal stress as the main contributing factor, but Eshati, [52]; Abdul Ghafir, [15] include consideration of both bending moment and centrifugal stress.

2.6.2 Service-Based Approach

The service-based approach requires component damage evaluation and assessment of the remaining life of the component, both of which need direct access to the specific components. The status of the component (obtained either by directly measuring its material properties or assessing the extent of its damage as a result of actual service) is compared to standard scatter bands which provide a refined prediction [29]. Assessment of the remaining life will involve both non-destructive and destructive testing [153] [172].

2.6.3 Statistical/Probabilistic Approach

With this approach creep life is predicted using statistical methods, often through the application of artificial intelligence techniques. The objective is to construct a relationship between the driving factors and the resulting creep life. For example, Zhimin et al., [171] by limiting their work to the engine rotational speed and hot flow temperature were able, using the statistical response surface (RS) approach, to develop an explicit relationship between creep life and these two parameters. Later, Zhimin et al., [170] extended their investigation and added a further six parameters to the RS equation.

Wallace et al [162] extended the work of Zhimin to 16 parameters using FE and CFD techniques combined with the OSDP. More recently Zhao et al., [168] introduced a model to predict in-service creep rupture life based on the Z parameter [169].

2.7 Gas Turbine Power Plant Economic Evaluation

The value of a product or service is hard to measure and this is why in the stock market people value different shares differently. It is hard to ascertain when to value and what or who carries value. Similarly profit does not equal cash because cash has different values at different times. This is the main reason why cost is used in accounting and finance.

Another critical implication is risk in the sense that the future is uncertain and so there is no guarantee a certain level of return can be achieved. One can make an important observation here; that value is driven by factors, including time, risk and returns on the initial investment. Returns can be measured in terms of profits and cash, whilst risk is a measure of uncertainty and volatility of returns. The time factor denotes whether there is sustainability in an investment and looks at the entire life cycle of the returns.

Projects in industrial GTs can last for long periods of time, especially power generation plant which may well have a design plant life of more than 20 years. Hence, it is important to capture the value of the investment taking into account all three factors: returns on profits, risk taken when investing and the time value of money and resulting profits [16].

2.7.1 Economic Appraisal Method

The literature survey showed that various techniques are available for project assessment with respect to economic performance. These include Discounted Payback (DPB) and Simple Payback (SPB), Internal Rate of Return (IRR) and Net Present Value (NPV) methodologies [18] .

2.7.1.1 Discount Cash Flow Rate of Return Method

The Discount Cash Flow Rate of Return Method is a widely used evaluation model which examines every cash flow alternative for the duration of the evaluation. Different worth rates are used to discount each of the alternative cash flows.

The Discounted Cash Flow Rate of Return is the name given to the discount rate which results in the future cash flows equalling the initial investment. The best choice of project is the one with the highest discounted cash flow rate of return. However, if investment risks are ignored, all projects with a discounted cash flow rate of return that exceeds the cost of money are considered worthwhile [70] .

2.7.1.2 Investment Pay-Back Method

Investment Pay-Back Method is used by both utilities and free market enterprises for scoping analysis. The pay back method is calculated as the number of years required for the net benefit to equal the initial investment. Business enterprises in a free market system use this as a screening tool to examine a variety of alternatives. After narrowing down the pool of alternatives to a manageable size (typically 5 to 10) the enterprise may then conduct Discounted Cash Flow Rate of Return Analysis on the most promising candidates. In the regulated utility industry, the pay-back method is widely used on small discretionary investments, particularly for spare parts or retrofit activities of utility [70].

2.7.1.3 Minimum Revenue Requirements Method

The Minimum Revenue Requirements Method is the economic evaluation method most widely used by regulated utilities, because the rate of return on any investment is determined based on what the regulator allows. That return is a weighted average return on bonds, where the calculated interest is based on bond ratings and the equity return allowed by the regulating commission. It is possible to calculate the return to bond holders and return on equity as well as depreciation and taxes incurred for a number of alternative strategies. The best alternative is usually considered to be the one that necessitates the lowest revenue requirements. Thus, projects that have the lowest present worth revenue requirements are preferred [84][136] .

2.7.1.4 Net Present Value

The technique used to conduct the economic analysis is the Net Present Value Method which, essentially, tries to discount tomorrow's money in today's terms. Various costs are accounted for including maintenance costs, fuel costs and cost of acquisition of machinery. The Net Present Value formula can be seen in the following Equation:

$$NPV = \sum_n [B_n - C_n] / (1 + r)^n \quad \text{2-2}$$

Where C is capital and operational cost, B is benefit stream, r is discount rate and n is years.

Along the life of the project there will be two financial streams: one is the costs stream (which includes capital and operational cost (C)) and the other is the benefits stream (B). The two streams must contain all costs and benefits for the same estimated life frame of the project. The costs stream, being outward-flowing cash, is regarded as negative. The difference between the two streams is the cash flow – the 'net benefits stream'. The value of the net benefits in certain years can be negative, particularly during construction and the early years of the project. Discounting the net benefits stream into its present value, by multiplying each year's net benefits by that year's discount factor, will present the NPV of the project [48; 84].

2.7.1.5 Discount Rate

The life cycle costs of a project and its feasibility, for a given output, depend on three factors: (i) the investment cost, (ii) the operational costs, and (iii) the discount rate used. Many planners think that the discount rate is the most important of these three factors because it greatly affects the economics appraisal of the project and decision making, particularly in capital-intensive projects such as the electricity supply industry [97] .

Discount rate also greatly affects estimation of the net returns from the project (NPV) during the evaluation stage, the project's feasibility, and the decision to proceed with the investment or not.

To demonstrate the importance of discount rates, the cases for nuclear and coal power stations were compared. The results of the evaluation are shown in Figure 2-11, which presents the price per kWh of output and shows how the economics of each alternative changes with the discount rate. At low discount rates, less than 7%, the nuclear alternative is cheaper. However, at a discount rates of 9–10% or higher, coal has the lower cost per kWh, even at high coal prices. Obviously, the discount rate is crucial in such decision making between alternatives [48].

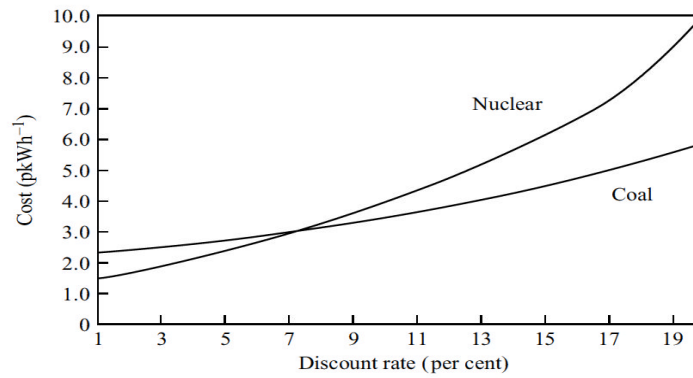


Figure 2-11 Sensitivity of nuclear and coal power stations costs to discount rate
[48]

2.7.2 Coast of Electricity

GTs are widely used to generate electricity so an accurate estimate of the absolute and comparative costs of generating electricity in this way is necessary for the effective initial valuation and later operation of such power plants [16].

$$COE \left(\frac{\$}{kWh} \right) = \text{capital Cost} + \text{fuel Cost} + \text{O\&M cost} + \text{emissions Cost} \quad \mathbf{2-3}$$

NPV uses *capital recovery factor* (CRF) whereby initial capital investment is changed into a sequence of equal annual payments. CRF is a simple formula which converts present value into equal annual payments over a definite time, at a given discount rate [84]. CRF is given by [16] :

$$CRF = \frac{1}{\left[\frac{1}{r} - \frac{1}{r(1+r)^n} \right]} \quad \mathbf{2-4}$$

The information necessary to evaluate the capital cost for GT power plants can be acquired from [2; 3; 5; 60]. These sources provide annually updated price lists of commercial GT packages from various manufactures, and other necessary cost data. The 2011 list (in \$/kW installed) was imported into the economic module. The required GT output in kW is input and the likely price is interpolated from the list. Data concerning fuel, O&M, and emission cost calculations are obtained from TERA.

2.7.3 Levelized Cost

A second indicator for economic evaluation of electricity generation is the *Levelized Cost of Electricity* (LCOE). If, over the analysis period, every unit of electricity produced by the GT system were sold at the LCOE the income would be equal to the total life cycle cost (TLCC) discounted back to the base year [2], i.e. if every unit of electricity produced were sold at the LCOE the project would break even and the NPV would be zero.

LCOE is found using a formula that includes all the operating costs of the project. In this project, the expression below is used and includes capital cost, fuel cost, maintenance costs, and emission cost.

$$LCOE = \frac{Capital_C + \sum_{i=1}^n \frac{Fuel_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{M_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{E_C}{(1+r_i)^n}}{\sum_{i=1}^n Power * Operating\ hours\ year} \quad \mathbf{2-5}$$

LCOE is constructed on two assumptions:

- The interest rate, r , used for discounting both costs and revenues does not change throughout the life of the project.
- The price of electricity price does not vary throughout the life of the project.

Despite these very serious shortcomings, LCOE is widely used for comparing the costs of different power generation technologies or different operating scenarios using the same technology.

2.8 Industrial Emissions Environmental Impact

The rationale behind conducting a study on emissions control and reduction is based on the Stern Report [141] and the Kyoto Protocol [150].

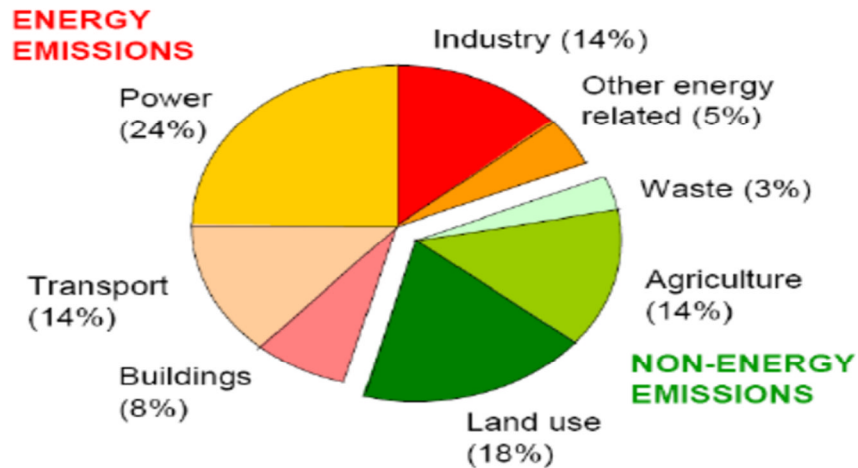


Figure 2-12: Contributions to emissions by industrial sector, with power production as the largest single group [141]

The Stern Report talks of the economics of climate change and highlights that there is a growing need to take timely action against increasing greenhouse gas emissions. The Kyoto protocol [150] sets government targets for 2012 and 2020 for levels of emission reduction targets. Figure 2-12 shows that almost a quarter of all emissions are due to power generation.

2.8.1 Carbon and Nitrogen Oxide Emissions

The two major pollutants from GTs are carbon and nitrogen based oxides. Carbon dioxide is the component which contributes most to global warming whilst nitrogen oxides are directly harmful to health since they promote photochemical smog. It is possible to solve the NO_x problem by low firing temperatures (and associated low power) but with an increase in the production of carbon dioxide and unburned hydrocarbons (UHC) such as carbon monoxide.

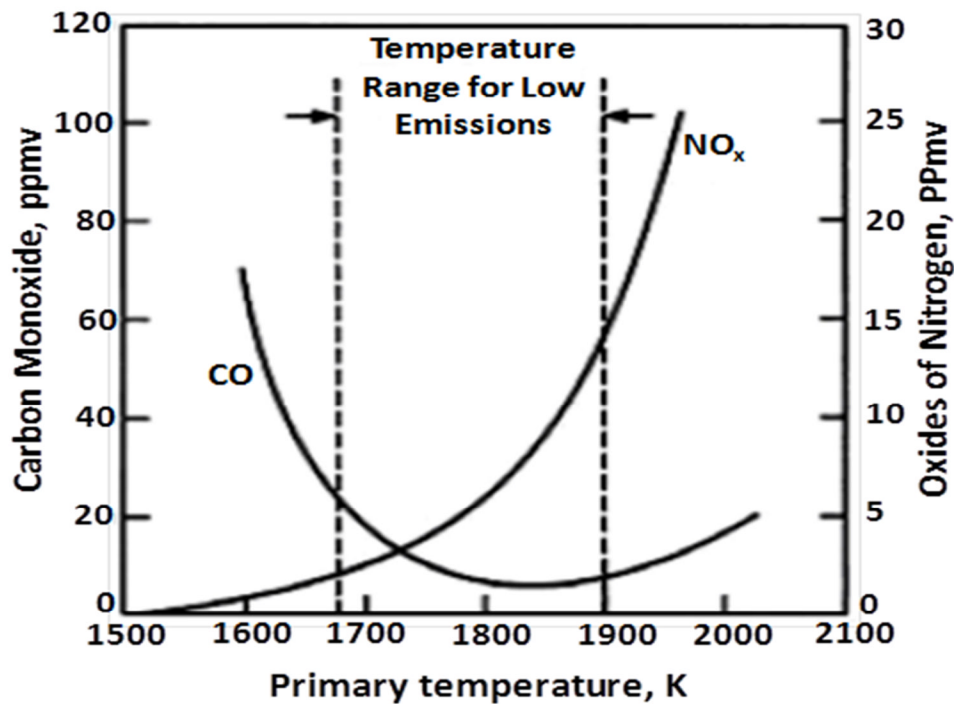


Figure 2-13: The trade-off between NOx and CO emissions [91]

At the other extreme high firing temperatures result in improved cycle efficiency and reduction in unburned hydrocarbons, but NOx production increases (NOx increases exponentially with combustor firing temperature) [69; 135]. This dilemma is pictured in Figure 2-13.

As can be seen from Figure 2-13, NOx emissions predominate at high combustion temperatures. High temperatures are related with high power outputs, and because compressor drivers work most of the time at base load, this EINOx has more importance than other emissions. Techniques such as DLE (Dry Low Emissions) have decreased the amount of NOx emissions but an important difficulty for this study has been the difference in engine firing temperatures between industrial and aero-derivative GTs.

As far as emissions estimation is concerned CO2 can be modelled using stoichiometric calculations assuming near to complete combustion; the balanced equations of the combustion reaction will give the amounts of CO2 produced. The NOx, CO and UHC on the other hand require more specialist treatment as will be discussed later.

2.8.2 Current Solutions

Cycle efficiency, combustor geometry and fuel type are all factors which affect the level of emissions and so design of the combustion system is key. Methods of emissions reduction include water injection and dry low NO_x systems for NO_x reduction and exhaust clean-up for carbon reduction.

2.8.2.1 Water Injection

Water injection into the combustor can reduce the flame temperature, and reductions of only 100K can lead to half the NO_x production [92]. However, a single 4MW GT can consume 4 million litres of water per annum. Thus, water and steam injection require huge amounts of water and this is not always available certainly not the Middle East where water scarcity can be a problem. In addition, the water must be treated to avoid corrosion to core components and incurring further costs.

2.8.2.2 Dry Low NO_x

Achieving low NO_x without the use of water is known as the dry system [69]. This involves lean or rich burn in the primary zone. Lean burn is most common with emphasis on pre-mixing of fuel and air to get the desired exhaust characteristics.

With industrial GTs, the magic point is 40% load [44]. Below this the combustion is restricted to the primary zone. At this point most new machines will burn only in the secondary zone whilst the pre-mixing will be happening in the primary, with fuel being introduced both in the primary and secondary zones [44]. Splitting the combustor burn in this way gives the flexibility for low and high power conditions and reduction in overall NO_x and carbon emissions.

Aero-derivative GTs on the other hand are inherently high NO_x producers simply due to high firing temperatures and water and steam injection are unlikely to be practical solutions. Some engines are retrofitted with different combustion units where, for example, the residence time may be increased by increased annulus depth for low carbon emissions. An example is the GE LM6000 [92]. Rolls Royce on the other hand have a radial arrangement which

increases volume for longer residence times [69]. However, the control for fuel introduction at different stages is difficult due to shaft speed relations to load in two-spool engines.

2.8.2.3 Exhaust Gas Clean-up

An example is selective catalytic reduction (SRC). Used when the requirements are for really low levels of NO_x. Ammonia converts the NO_x to N₂ and H₂O. Limited catalyst operating temperature range means that SRC is often only used with heat recovery steam generator (HRSG) systems.

2.8.2.4 Fuel Type

Turbines can use a multitude of fuels from gas to oil to coal in fluidised bed reactors. The majority of machines and plants around the world use gas. One major issue related to the combustion products of fuels, apart from levels of carbon and nitrogen oxide production, are sulphur components which produce acid rain. Unlike carbon and nitrogen oxides, which depend on firing temperatures, sulphur production depends solely on the amount of sulphur present in the fuel in the first place. Selection of the correct fuel is therefore very important but outside the direct line of this study.

2.8.3 Methods for Modelling Emissions

The emissions of a GT cannot be easily calculated for some pollutants since the chemical kinetics are not fully mapped by equilibrium based analysis. Because the systems are not in equilibrium estimations are required to ascertain the amount of pollutant being produced. This is true for pollutants such as NO_x and other quantities such as oxides of carbon, nitrogen and sulphur, as well as unburnt hydrocarbons. There are a number of options available to estimate the emissions.

2.8.3.1 CFD Based Approach

This is a method which involves looking at the emissions of a particular combustor design in great details by simulating the flow and its components and discretising the flow into small units so as to be able to sum or map the entire chemical kinetics for a given combustor. This is a time-consuming method and

is not fitted to the TERA philosophy since it goes into great detail and requires long computation times and model construction efforts. It also requires a lot of detail about combustor design which may or may not be readily available.

2.8.3.2 Physics Based Approach

This is an approach where the chemical kinetics are mapped makes use of the combustor geometry and understanding of the chemical kinetics to produce a detailed picture of the chemistry. It is useful for designing or evaluating new combustor types or design not in production. It goes into a high level of detail and again requires information which may only be found with the combustor manufacturer. All the main combustor units/sub-components are considered and the modelling is based on predefined mixing and understanding the flow in the turbulent phase.

2.8.3.3 Empirical and Semi-Empirical Methods

In the context of this research the most useful methods are the empirical methods which make use of already established trends in emissions from known combustor types and the empirical equations which relate these emissions to the thermodynamic conditions in the engine. This is a statistical treatment of already existing data for combustors. The limitations are that dry low NO_x combustors cannot be easily mapped using these techniques since the correlations are based on experimental data and are thus usually combustor specific.

Rizk and Mongia [130] described semi-empirical methods as ‘calculation approaches that simulate the combustion process by global expressions to account for reaction temperature, system pressures, evaporation and mixing and are used to provide insight about ignition, blowout and emission indices’.

In turn, the variables in these models include the combustor inlet and outlet temperatures and pressures, pressure loss across the liners and combustor, the fuel-air ratio, equivalence ratio, adiabatic flame temperatures, core mass flow and fuel flow, residence time, combustor volume, volume occupied by evaporated fuel and time required for fuel evaporation amongst others. This

makes this type of modelling more within reach of an analytical tool such as the TERA.

2.8.3.4 Emission Control Measures

The interest in GT emissions and the policies controlling their release to the environment has engendered considerable research on emission estimation methods and control measures. The GT is generally known to emit less pollutants than other prime movers because it admits sufficient air to complete combustion. However at part load, especially at minimum load condition or at start up more fuel is injected which increases the equivalence ratio.

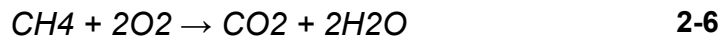
The design method for reducing pollutant emissions from combustors requires the consideration of the individual emission species involved. A great deal of compromise is required to attain the desired concentration of the individual pollutant species and performance indices such as: specific fuel consumption, temperature transverse quality (TTQ) or pattern factor and lean blow out limits. The emission species for NO_x, CO, UHC, CO₂ and smoke and their control techniques are shown in [151]:

Table 2-4: Emission species and their control techniques [151]

	Control Technique
NO _x	a. Lean-Head-End liner. b. Water & Steam Injection c. Dry-Low-Nox
CO	a. Combustor design b. Catalytic reduction
UHC & VOC	Combustor design
CO ₂	a. Combustor design b. Fuel choice
Smoke / particulate matter	a. Fuel atomization b. Air atomization c. Ash
Sox	Sulphur control in fuel.

2.8.4 Mapping the Emissions: Empirical Correlations

The first emissions module created for the TERA was an empirical correlation based on aircraft emissions and was adapted for industrial GTs usage [123]. The ideal combustion products from the exhaust of a GT for complete combustion would be CO₂ and H₂O with O₂, N₂ and other components which already exist in the ambient air. Of course this situation is near impossible with conventional combustor systems. The reaction will not be complete and thus some unwanted by-products will appear. It will be assumed here that GT drivers use only methane as fuel. The ideal reaction for pure combustion would be as follow:



The emissions produced by each engine need to be predicted in order for comparisons to be carried out. This analysis is needed since engine emissions are regulated and taxed and so ultimately it is an economic issue. It may be the case that one engine with better performance characteristics does not meet the emissions regulations and it will finally be less profitable because of the extra money spent on emissions taxes.

The emissions model is based on empirical correlation. It uses known values of emissions from a combustor of a given type which have either been charted by the OEM or are based on a reliable emissions database such as the International Civil Aviation Organisation (ICAO, 2005) [75] database which includes measured emissions at certain power settings for various engines (mostly aviation based). The database can then be used to calculate the emission in ODP operating conditions.

This method is an empirical method because the NO_x emissions, carbon emissions such as CO, CO₂ and UHCs are calculated using an emission index. The index denotes the rate of emission production at a given power setting, and thus a chemical equation of the simplified reaction can be derived. This will have a parent equation or trend (for example for NO_x emissions this will typically be the Lefebvre correlation) and then, based on the emissions

database or OEM supplied data, the Lefebvre correlation will be tuned to follow the trend of emissions for the particular combustor that is being studied [90]; [91]. In this way one can tune correlations by their exponents and then once the correlation is tuned it can be used to predict emissions at various power setting or operating conditions in off-design performance.

The charted NO_x trend for one of the GE Frame series of engines is shown in Figure 2-14. This was taken from a public domain document.

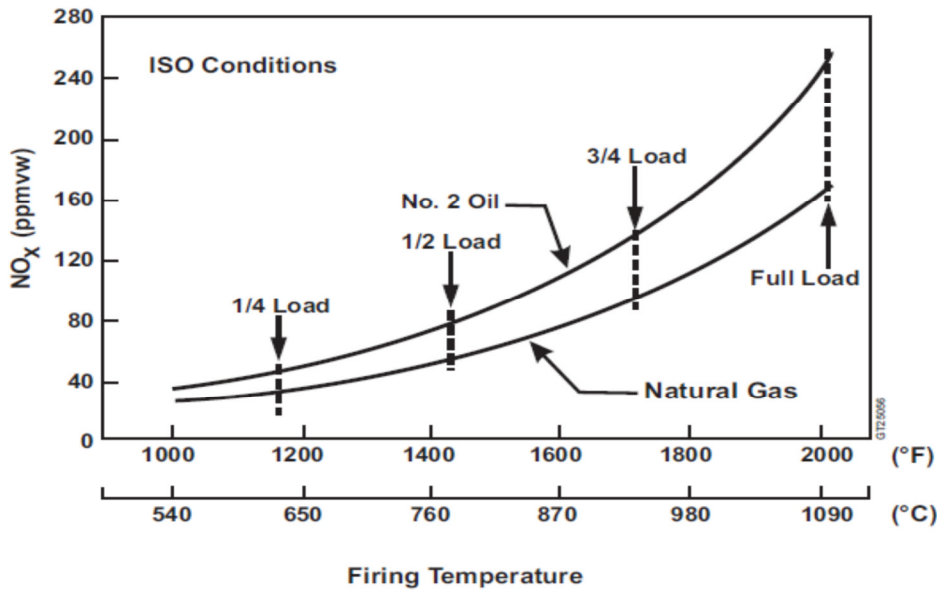


Figure 2-14: MS7001EA NO_x emissions trend [120]

2.8.5 Emission Indices

The definition of the emission Index of an emitted component produced during combustion of the fuel-air mixture is the mass in grams of the emitted component divided by the mass in kilograms of fuel flow, see Equation 2-8:

$$EI_{pollutant} = \frac{grams_{pollutant}}{kg_{fuel}} \quad 2-7$$

Alternatively, to find the amount of pollutant in grams, the specific fuel consumption can be multiplied by the time spent during that particular power setting and the emissions index;

$$grams_{pollutant} = EI_{pollutant}(time)(SFC) \quad 2-8$$

Emissions of oxides of sulphur and soot are not taken into account in this study. This omission does not change the results significantly because (i) natural gas quality standards are extremely high and the sulphur present in the fuel may be assumed to be negligible, (ii) the weight and size of industrial GTs are considerably greater than those of aviation GTs, which means a considerable increase in combustion chamber size is possible and therefore the fuel-air mixture and consequently the soot has more time to react and form CO₂ particles.

The Lefebvre correlation was used for the modelling here because it was defined for a fixed combustor with known geometry and the author felt this could be used, given that some of the key parameters were known for the engines [90]. The correlation is tuned to match the existing correlations as published by the OEM.

For predictions of CO emission the Lefebvre correlation was again used, while the Cranfield-Modified correlation was adopted for UHC emission. For details of how the emissions correlations were mapped from known trends refer to Courtinho [123].

2.8.6 Emission Calculation

A carbon tax that compensates for the Society of Cosmetic Chemists (SCC) varies by fuel source. The CO₂ production of the fuel source per unit mass or volume is multiplied by the SCC to obtain the tax. Based on the mean peer reviewed value (\$43/tC or \$12/tCO₂), the tableTable 2-5 below estimates the tax for various fuels [1; 4]:

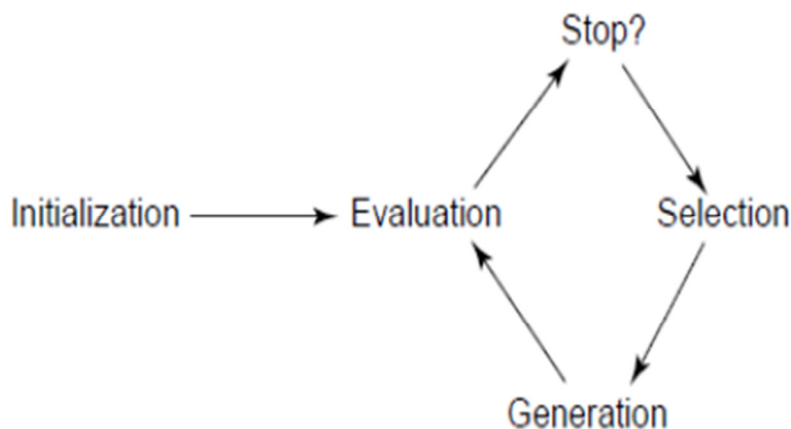
Note that the tax per kWh of electricity depends on the thermal efficiency of the generating power plant, which varies from power plant to power plant. The table follows the American Physical Society (APS) estimate of 10.3 BTU/Wh (33%) [7] The APS notes that "It is expected that future plants, especially those based on gas turbine systems, often will have higher efficiencies, in some cases exceeding 50%." A theoretical conversion rate of 100% is 3.412 BTU/Wh. A more practical limit for thermal power plants is Carnot's theorem.

Table 2-5: Estimation of CO2 TAX [1; 4]

Fuel	Tax	CO2 Emissions	Tax per kWh of electricity
	(per fuel unit)	(mass of CO2 produced)	
gasoline	\$0.11/US gal (\$0.028/L)	n/a	n/a
diesel fuel	\$0.12/US gal (\$0.032/L)	n/a	n/a
jet fuel	\$0.12/US gal (\$0.032/L)	n/a	n/a
natural gas	\$0.00066/cu ft (\$0.023/m ³)	117 lb/MBTU (181 g/kWh)	\$0.0066
coal (lignite)	n/a	215 lb/MBTU (333 g/kWh)	\$0.0121
coal (subbituminous)	n/a	213 lb/MBTU (330 g/kWh)	\$0.0119
coal (bituminous)	n/a	205 lb/MBTU (317 g/kWh)	\$0.0115
coal (anthracite)	n/a	227 lb/MBTU (351 g/kWh)	\$0.0127

2.9 Optimisation Method Review

Optimization is the process of finding the global maximum or minimum when a number of variables are involved, e.g. maximising profit or minimising cost. The performance of GT is a function of many variables, such as TET, air and fuel flow rates and pressure ratio. Often the correlations between these parameters and the engine's response function is not known, but tests can determine engine's response at certain values of the parameters. Such investigations are usually carried out iteratively, see Figure 2-15.

**Figure 2-15: The basic iterative optimization cycle [166].**

Practical tests start with a set of parameters selected according to a criterion such as they correspond to the DP. With modelling there is much greater freedom in selecting the initial set of parameters. The quality of the current 'solution' is assessed according to an evaluation criterion. A number of criteria may be used to stop the optimization, these might include maximum permitted temperature attained, quality of the solutions found, number of iterations [166].

If the iteration does not satisfy one of the stopping criteria the values obtained act as the start point for the next iteration. It is expected that such the optimization process will generate one or more solutions that meet the stopping criteria.

2.9.1 Local and Global Optimality

Figure 2-16 demonstrates the difference between local and global optima and minima. It can be seen that there are smaller and larger "mountains" in the figure, the smaller mountains represent local maxima (there are no higher places in its immediate neighbourhood) but the major peak represents the global maximum. Similarly the figure shows local and global minima. The challenge is to find the global optimum in the presence of local optima. A set of solutions called global optimizers have been developed to locate the highest peak, no matter from what point the search starts [166], while success is never guaranteed these methods will, in almost all cases, find good solutions.

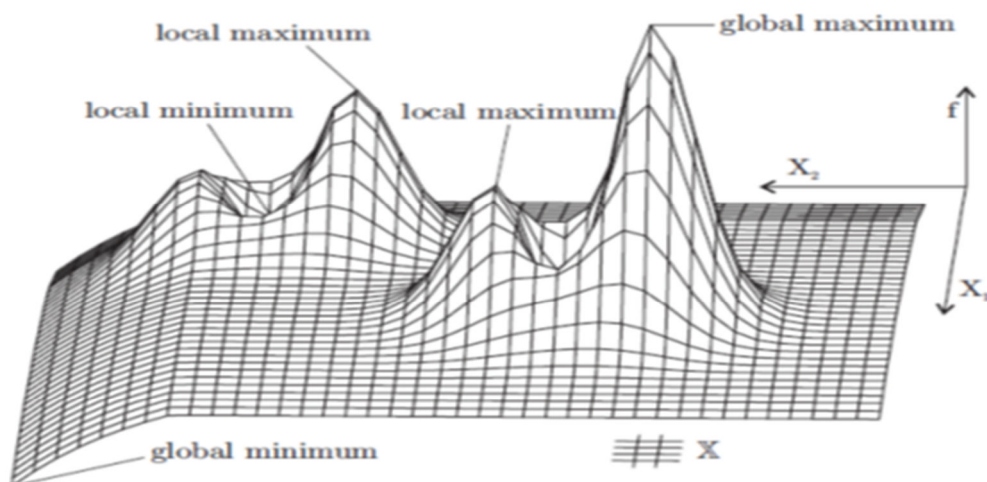


Figure 2-16: Global and local optima of a two-dimensional function [146]

2.9.2 Optimisation Methods

Figure 2-16 refers to a two-dimensional function, it is thus easy to understand how complicated the search process will be for multi-dimensional spaces. To cope with such complex problems stochastic methods have been developed, these contain a strong random component to avoid getting trapped in local optima.. The most important of these is the Monte Carlo Simulated Annealing (MCSA, or SA for short) [146], the principle behind this method is said to correspond to the cooling of a liquid, Other stochastic optimisation techniques are the Genetic Algorithm (GA), Tabu Search (TS) and Evolutionary Strategies (ES). The principle behind these latter methods corresponds to the Darwinian theory of evolution.

These methods were first developed in the 1960s but it not until the 1980s that they were applied to chemical kinetics. The results produced demonstrated very clearly that they had the potential to offer solutions not obtainable with classical optimization methods [166].

2.9.2.1 Monte Carlo Simulated Annealing

MCSA was popularised in the 1980s by Kirkpatrick et al., [132] who described how it could be used as a general optimisation technique. The method had been used thirty years previously by Metropolis et al., [111] and so is sometimes referred to as the Metropolis algorithm. MCSA is used in a very large number of commercial software packages and is often referred to as the standard method to be used for optimization problems [79].

The method is very simple. The algorithm performs a random walk in the search space. All moves that lead to a better solution are accepted according to the Boltzmann rule, all moves that lead to a worse solution are accepted but with a probability of value less than unity. The control parameter, T , (called the temperature – hence the annealing analogy) determines the probability of accepting a move that leads to a worse solution. The larger T the greater the probability of accepting a “bad” move and the more the search resembles a random walk. The process gradually “lowers the temperature” so that “bad” moves are rejected with increased probability.

2.9.2.2 Tabu Search

The TS optimises by avoiding re-evaluating solutions that are already known [53]. TS selects the best available move to generate a new state. Those states that appear on the Tabu list are excluded. Tabu is memory intensive and to prevent memory problems the Tabu list does not contain states but rather moves, or elements of moves that would reverse recent iterations. The Tabu list is updated continually and the overall result is that cycles with a length smaller than the length of the Tabu list are avoided.

Unfortunately it often requires expert knowledge to adequately define the separate components when applying the TS method as they are often very much problem dependent. TS has, as yet, only been applied to a limited number of problems in chemistry because the method is more suitable for sequential problems. Nevertheless a number of applications have been recently reported on assessing chemical similarity [152], molecular docking [42] and structure optimization problems [53].

2.9.2.3 Hybrid Methods

Hybrid techniques combine different optimisation methods and perform best when they combine the best features of their components. Figure 2-15 shows the basic optimisation cycle which will comprise elements from individual methods. Many methods differ in only one or two aspects. For example, between the steepest descent methods and TS there are two essential differences, the first occurs in the generation stage where the Tabu list forbids some solutions. The other difference is that the TS permits a worse solution if that is the best available, where the steepest descent technique would stop. One practical hybrid is of SA and GA. The SA controls selection by accepting all improving solutions (and worse solutions according to a probability determined by the Boltzmann distribution) while the GA maintains a pool of trial solutions and randomly generates possible new solutions (offspring). GA has the advantage that access to regions of the search space which are inadmissible to, say, a vintage SA is not a problem, whereas SA gives the advantage of the added control that the user may exercise through “temperature” control.

Table 2-6: Selection and generation characteristics for SA, TS, and GA [166]

Method	TS	GA
Selection	Accepts best of all admissible new solutions, even if it is worse than the previous solution	Accept solutions according to their relative quality in the population
Generation	Generates all solutions in neighbourhood	Uses random-based procedures such as cross-over and mutation to generate new solutions

Table 2-6 summarises typical strategies for selection and generation. Obviously there are two other possible hybrids. The first is GA/TS where the GA again maintains a pool of trial solutions and randomly generates possible new solutions (offspring) and the TS supervises the random reproduction mechanism, the second is SA/TS, this is a probabilistic TS in which a new solution is accepted with a probability governed by the SA Boltzmann distribution.

The strengths of these hybrid methods are also their weaknesses. Their versatility and adaptability has meant there are no standardised strategies for selecting and adapting these global search methods. Fortunately, there now exists in the literature many case studies which may contain analogous problems which can provide a suitable starting point [106]. If, however, one is not fortunate, no guidelines exist as to which of the million ways to tweak and alter the algorithms is best.

2.9.2.4 Evolutionary Optimization

The main characteristic of evolutionary algorithms such as EA and GA [41; 69, 91] is that they do not proceed from one trial solution to the next instead they use a population of trial solutions so that, generally, they find a more varied set of solutions. A major advantage of this is where there is interest in other good solutions not only in the global optimum. This can be important, for example, in chemistry optimisation of molecular structure will determine both the minimum molecular global energy and detect all the other molecular structures possible at

the specified temperature. An additional advantage of population-based methods is that they can prevent the same optimum being discovered again and again.

A second major advantage of this approach is that in EAs new solutions are obtained by standard operators such as cross-over and mutation, see below Sections 1.9.7 and 1.9.8. Good performance by EAs depends on successfully combining representation and evolutionary operators. Applications described in the literature include spectrum interpretation, molecular structure optimization, multivariate calibration, and selection of subsets for Quantitative Structure – Activity Relationship models [77; 127].

2.9.3 Comparison of Methods

Which of the methods described above is best suited for a given problem cannot be readily answered. Despite the name “global” these optimization methods give no guarantee that a truly global optimum will be found. For many practical problems it has been found that replicate runs produce very different solutions. This is because a different start point was used (affects all methods) or because of the random nature of the search (TS not affected). Thus many replicate runs need to be performed on a representative set of problems. However, these runs invariably take some time to complete, so comparisons between algorithms are rarely comprehensive.

It is difficult to test each algorithm with the same rigour and impartiality – one of the methods may already be known to those doing the testing, and this could give it a crucial advantage. Again, each algorithm comes with optimisation parameters that need to be fine-tuned which may be vital to the performance of the algorithm but which may constitute a complex meta-optimisation problem.

An advantage of GAs, when compared with e.g. gradient based optimisation techniques is their robustness and suitability for parallel computing. Finally, there is no clear-cut criterion with which to judge the performance of the optimization methods [42; 126].

2.9.4 Objective Functions

Objective functions are a way of ensuring a solution is optimal [109]. The optimum of a single criterion f , is either a maximum or minimum. Consider a manufacturing plant with incoming orders. These could be assigned to machines in such a way that minimizes the time needed to complete them. Alternatively, they could be assigned in a manner that maximized profit. It is conventional with global optimization that problems are defined so as to minimise a function, and if a criterion f is subject to maximization, we minimize $(-f)$.

2.9.5 General Overview on Genetic Algorithms

GAs are a subclass of EAs, Generally the elements of the GA search space are binary strings. Figure 2-17 shows that the genotypes (genetic makeup of the individuals) are used in reproduction while the values of the objective functions are calculated on basis of the phenotypes (e.g. physiological properties) in the problem space, which are found using genotype-phenotype mapping (GPM) [41; 72; 73; 89; 146].

Goldberg [66], considered how robust GAs were in determining the optimum solution compared with classical approaches, and concluded:

1. “They use an encoding of the parameters to the algorithm and not the parameters themselves,
2. They search from a population of points in a search space rather than a single point,
3. They use an objective or cost function, and not derivatives or some other problem-related knowledge, and

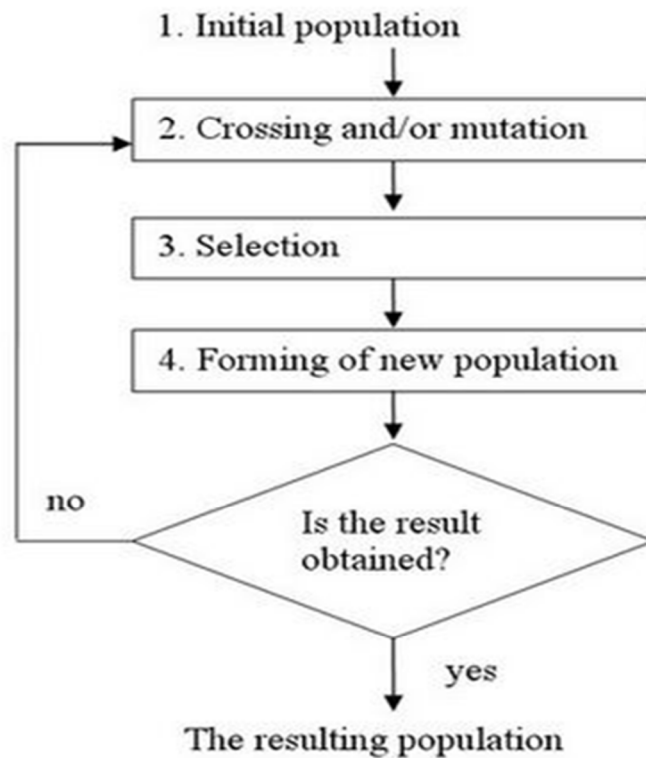


Figure 2-17: the basic cycle of a Genetic Algorithm [146]

4. They are stochastic rather than deterministic. Of course these differences, especially the latter, are not necessarily always strengths when applied to varying problem domains. However these features of GAs do free the algorithms from the constraints of “classical” methods, such as continuity, derivatives being available and unimodality.”

GAs are intrinsically suitable for parallel processing because they use a population of possible solutions. They also possess the capacity to consider more than one peak (or trough) simultaneously and thus are less likely to get stuck at local optima. Gen and Cheng [61] stated that the essential elements of GAs are:

- (i) “A genetic representation of solutions to the problem,
- (ii) A way to create an initial population of solutions,
- (iii) An evaluation function rating solutions in terms of their fitness,
- (iv) Genetic operators that alter the genetic composition of children during reproduction, and
- (v) Values for the parameters of genetic algorithms.”

Gen and Cheng [61] have declared that for solutions to be practically useful they must be both realistic and 'legal'. Realistic solutions must fall within the feasible region of the problem domain. 'Legal' solutions must represent a real potential solution.

The genotype may be presented as one- or multi-dimensional, depending upon the problem. Goldberg [66] and Holland [73] both used binary representation, strings of binary digits, to represent a potential solution where a given design variable has a state represented by a bit, see Section 1.9.6. However a potential solution can be implemented a number of ways. Gen and Cheng [61] considered limitations of the binary scheme such as Hamming Cliffs and discussed other representations:

- Real number encoding – good for function or constrained optimisations.
- Integer or literal permutation encoding – good for combinatorial optimisations.
- General data structure encoding (gene allele, n-ary) – good for real-world complex optimisations.

Goldberg [66] cites De Jong, [46] who says that, generally, the following metrics tended to give good results for GAs: (i) High crossover probability (ii) Low mutation probability (inversely proportional to population size) (iii) Moderate population size.

Holland [73] has pointed out that for both artificial and natural evolution the main driver of increasing fitness is recombination, and that mutation is of relatively low importance, its primary function being to sustain genetic diversity.

A memetic algorithm is a hybrid GA which incorporates local optimisation ("hill-climbing") by applying the local optimiser to each offspring before the GA computes the next generation [61]. In this way, a local optimiser acts as Lamarckian evolution, since the change to the offspring is not a result of genetic change, rather it is effectively epigenetic, and the algorithm is called memetic from the root of a "meme" [45], as a meme differs from a gene in that it may be changed (due to adaption) before being inherited.

Goldberg [66] has noted that when they are hybridised as “knowledge-directed”, GAs can improve algorithm performance by using non-objective function information with domain-specific knowledge. This class of hybrid GAs are considered relatively free from the worse than-random performance that can occasionally occur with general purpose optimisers because, essentially, they are no longer general purpose.

2.9.6 Penalty Function Methods for Constrained Optimisation

Constrained optimisation arises naturally in many practical engineering and scientific problems, but GAs have to be adapted to solve optimisation problems that include inequality constraints. A large number of methods have been proposed for dealing with constraints within GAs [35; 36; 103; 105; 137]. Most have severe disadvantages such as giving unfeasible solutions or requiring the additional of parameters, others are of very limited application having been specifically designed for a particular problem. This is usually done by introducing so-called penalty functions which apply a penalty to an unsuitable solution [104; 137]. Penalties are considered to transform constrained problems to unconstrained ones [64; 72] and these are usually written as non-linear programming problems [22], more details will be given in Chapter 3.

2.9.6.1 Constrained Optimisation

Constrained optimisation problems are of interest because they arise naturally in many situations in engineering and other science fields. In general, Genetic Algorithms are usually designed for the solution of unconstrained problems. They have therefore to be adapted to tackle the optimisation problems that involve inequality and/or equality constraints. The common form of implementation of constraint is based on the concept of penalty functions, which are set apply penalties to unfeasible solutions. A constrained optimisation problem is usually written as non-linear programming problem [22], more details will be given later in chapter three.

2.9.6.2 Penalty Functions

Penalty method transforms constrained problem to unconstrained one [64; 72]. Most of the problems in these fields are stated as constrained optimization problems. Since GAs are directly applicable also to unconstrained optimization, it is necessary to use some additional methods that will keep solutions in the feasible region.

During the past few years, several methods were proposed for handling constraints by GAs [35; 36; 103; 105; 137]; Most of these methods have serious drawbacks. While some of them may give infeasible solution or require many additional parameters, others are problem-dependent (i.e. specific algorithm has to be designed for each particular problem). The most popular approach in GA community to handle constraints is to use penalty functions that penalize infeasible solutions by reducing their fitness values in proportion to their degrees of constraint violation [104; 137]. In this part of literature review, we analyse these penalty-based methods

2.9.7 Chapter Conclusion

This literature review has described a number of technical, environmental and economic considerations linked to industrial GT power plant selection. Optimisation techniques have been reviewed to assess which one would be most suitable to minimise the total costs of electricity production.

During operation, industrial gas turbine components undergo various types of time-dependent degradation due to high temperatures and mechanical loading. These conditions make the components susceptible to such failure mechanisms as low cycle fatigue, high cycle fatigue, thermal fatigue, environmental attack and creep. In the case of stationary gas turbine engines creep is one of the most common failure mechanisms (under high stresses and temperatures) that significantly reduce component life. The effect of creep is highly dependent on the operating conditions of the engine.

A better understanding of the lifing factors of the failure mechanisms and their interactions will help designers in the trade-off between different design options and will also help operators to make wise maintenance decisions.

The economic appraisal method was described, which is used to carry out the financial calculations. The Net Present Value method is utilised to assess the time value of money and all other modules feed into this final module. A broad explanation of the methods used and how the assessment of total Electricity production, revenues and costs will be carried out.

It is concluded that GAs would be suitable to optimise (minimise) power plant costs and maximise profit. The GA would assist the user to define the properties of the most cost effective equipment to purchase, and then help determine the loads for existing units to meet demand at minimum life cycle cost.

The literature review makes it clear that there are many different interrelated aspects that need to be considered when attempting to optimise industrial GT power plants. In particular where optimisation must include off design conditions. The literature review has also shown that power plant optimisation is also looking to shorten the design time by minimising human interventions within the design process.

Chapter three

3 METHODOLOGICAL

3.1 Introduction

To operate a power plant to meet its power demand as efficiently as possible is challenging so the availability of an optimisation technique which selects the most appropriate running conditions while satisfying external regulatory constraints would be extremely beneficial.

If an optimiser were to be integrated into TERA this could automate the conceptual and preliminary design and operation processes. The available optimisers use a variety of techniques such as the GA to solve the problem of multiple local optima [23; 30; 31; 93]. Such an approach provides design time and cost reduction as well as a better solution, and can also be used to introduce economic and environmental factors into the optimal design. Such an approach would have the added benefit of providing guidance to the operator (or OEM) on future product specification.

One of the definitions of TERA is “*An adaptable decision making support system for preliminary analysis of complex mechanical systems*” [133; 138-140]. The governing equations of TERA arise from different disciplines, from different design considerations and/or operating areas such as performance, emissions, lifing, economics, etc. The coupling of these disciplines results in a multidisciplinary analysis tool of low fidelity and complexity producing shorter computational time. This chapter describes the development of a TERA/GA optimisation tool which allows selection and operation of industrial GTs to offer the required power demand at minimum cost based on five sub-models, see Figure 3-1:

- Gas turbine performance
- Hot section blade creep life

- Gas turbine emissions
- Gas turbine economics
- Genetic Algorithm (GA)

Each model is described by introducing its function in TERA and, where considered necessary, the preliminary development procedure is given in next sections. Modelling methodology is then analysed, this includes the mathematical expressions contained in the model and their range of applicability and limitations in this chapter and chapter four. As well as the model's inputs and outputs are described and an overview of previous work carried out in the creation and implementation of the models is given in chapter four. Finally any standards taken as reference (i.e. ISA) for the creation or operation of the model are given where the result is described.

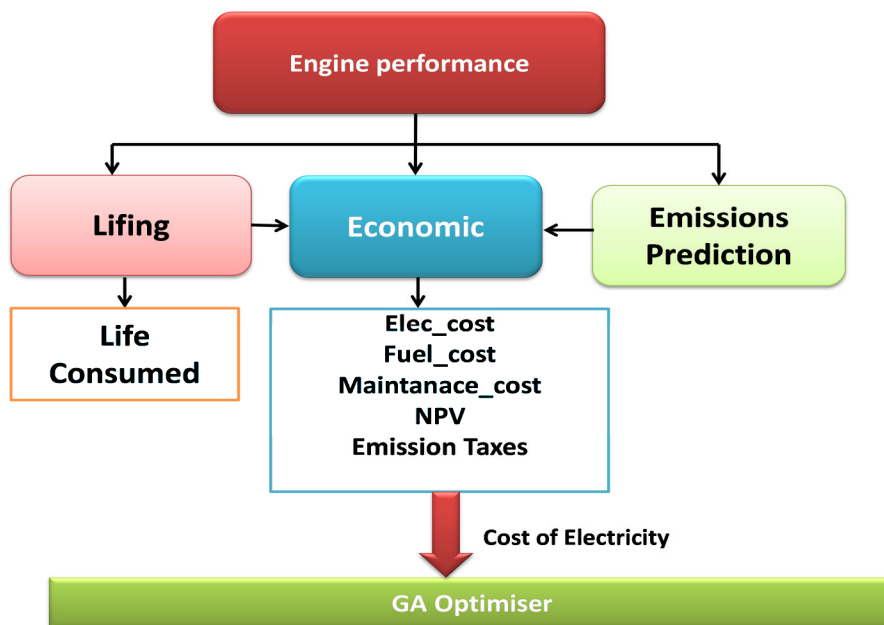


Figure 3-1: TERA and GA architecture

3.2 TERA for Power Generation

The developed framework consists of four simulation modules used to assess various aspects of GT design and performance as well as its environmental and economic impact. A set of simple FORTRAN subroutines were integrated with the In-house software (Turbomatch) to determine the engine performance, lifing

and economic aspects at different operating conditions. Figure 3-2 presents the TERA architecture created for the current study showing the logic of the coding structure. The developed sub-models are discussed in details in the following sections.

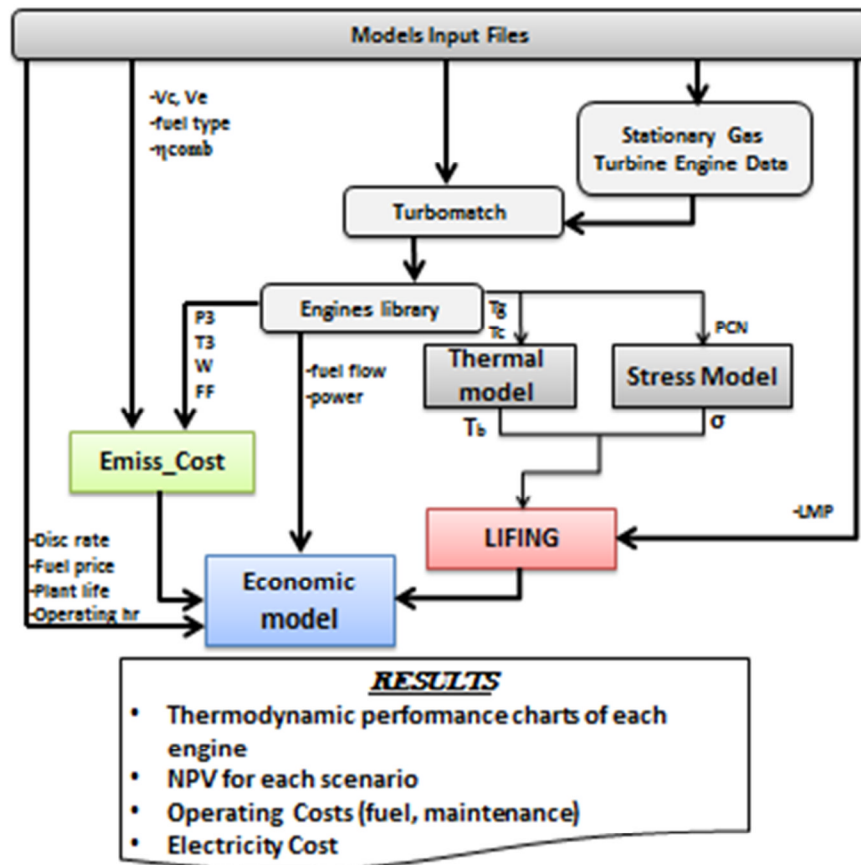


Figure 3-2: TERA architecture

3.2.1 GT Engine Performance Modelling

Using Turbomatch the GT performance parameters of the turbine under investigation were predicted for the design point (DP) conditions and a range of possible off-design point conditions (ODP) that could be experienced under operating conditions.

The initial step was to construct the input files and obtain the DP performance of each of the GTs being investigated (Appendix A). The next step was to obtain the ODP performance for each of the GTs as required by the given conditions

specified in the case study. It was initially decided that the variables used to determine GT ODP conditions would be ambient temperature (T_{amb}), turbine entry temperature (TET) and ambient pressure (P_{amb}). In fact ambient pressure was assumed constant and only the two temperatures were used as variables in the case studies.

To obtain predicted ODP operational parameters for each of the GTs being investigated their ODP performance parameters were obtained using Turbomatch which produced the performance parameters for each value of TET and T_{amb} . These were then tabulated in two dimensional look-up tables (Fortran file). Mass flow, fuel flow, power output, T_c , etc. could then be obtained linear interpolation and fed to other sub-models to give the values of the required output engine parameter.

3.2.1.1 Thermodynamic Performance Simulation

The thermodynamic performance simulation investigates the functioning of the GT driver in detail, based on the requirements of each turbine. Pressure, temperature and other thermodynamic parameters are calculated for each station (compressor, combustion, and turbine) of the engine. Figure 3-2 demonstrates the basic architecture of the performance code and shows where the performance module sits within TERA. Figure 3-3 shows how the subroutines within the module inter-relate.

The performance module, see Figure 3-3, is a code which extracts the relevant engine file from a database library of engine input files and writes to this file the ODP cases that are to be investigated as defined in the main input file. Once the ODP cases have been input to the basic template input file it is sent to Turbomatch which then performs the thermodynamic performance calculations, matching the compressor and turbine for each ODP condition using an iterative process [119]. The output is a large array of ODP data known as the Turbomatch Results File.

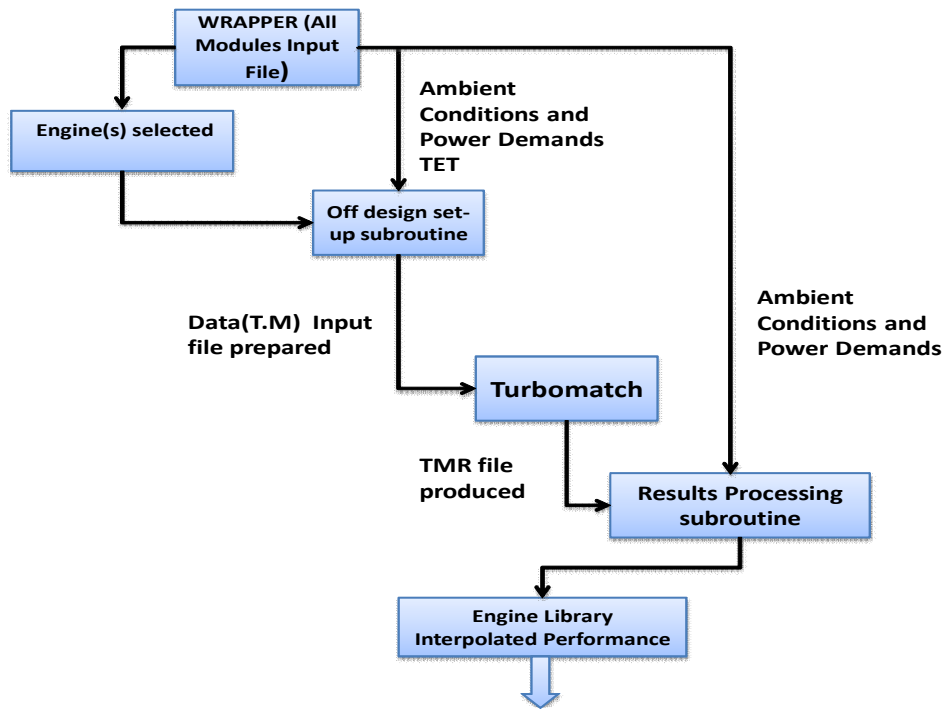
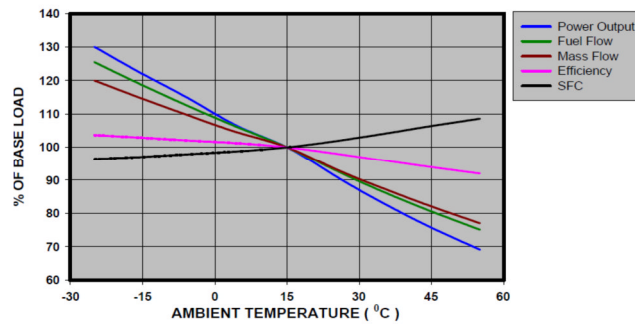


Figure 3-3: A schematic of the performance module

The Turbomatch Results File is then processed by the next subroutine (Engine Library Interpolated Performance) which generates a table of thermodynamic parameters obtained using linear interpolation to find the thermodynamic parameters (e.g. pressure and temperature) at each station for the desired power at the specified ambient temperature.

3.2.2 Lifting Model

The current study assumes that the high pressure turbine (HPT) blade can be used to represents the GT lifing. This study focuses on creep as the major failure mode and does not cover interactions between different failure modes. Using a physics-based model that includes thermal and mechanical stress,

analyses were performed on the HPT blades as shown in Figure 3-4. Gas turbine performance model output data was used as input data to the lifing sub-models.

In order to study the impact of operating and ambient conditions on the creep life of a gas turbine engine's hot section, a model single shaft engine was created. The Larson-Miller Parameter (LMP) was used to calculate the remaining blade creep life and the results are presented as creep factor.

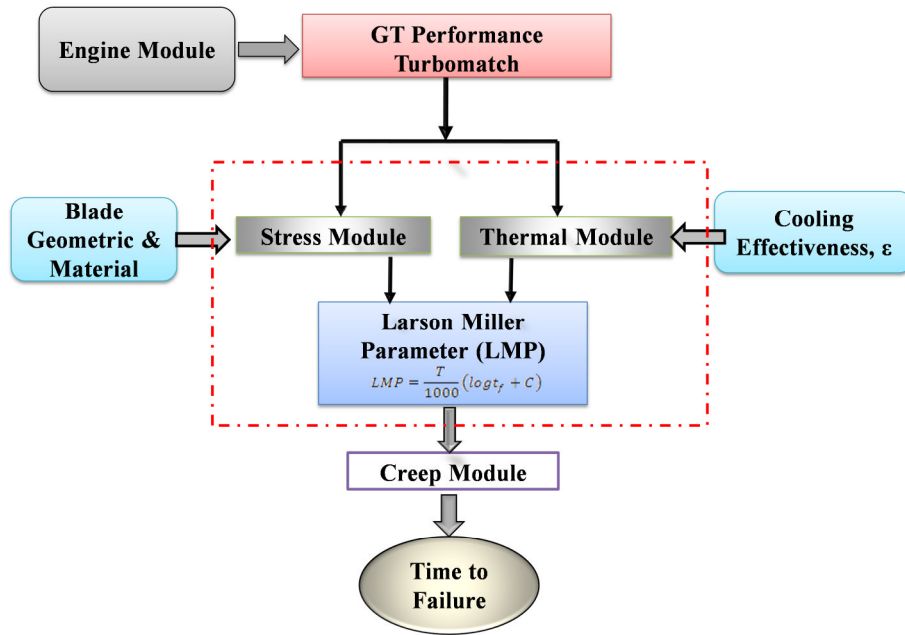


Figure 3-4: Creep life assessment model

3.2.2.1 Blade Creep Life Assessment Model

Here, a creep life model has been developed; see Figure 3-4, for use with the first stage rotor blade of a typical stationary HPT of the GT. The approach used for assessing HPT blade creep life was to develop a creep life model which consisted of sub-models for creep, thermal analysis, stress analysis and performance using Turbomatch. The results from the thermal and stress model are input in the creep model (LMP) which estimates the remaining creep life of the blade

3.2.2.2 Thermal Model

The model is intended, primarily, to calculate the temperature of the blade for the first stage of the HPT. The model starts from a value of overall effectiveness calculated by the designer and based on the cooling technology of the blade. The air coolant (T_{cin}) entering the blades, which comes from the last stage of the HP compressor, and the temperature of gas (T_g) surrounding the blades are both determined from the Turbomatch simulation. Also, the overall cooling effectiveness is assumed based on the technology of the blade and nozzle guide vane NGV outlet temperature as shown in Figure 3-5 [87].

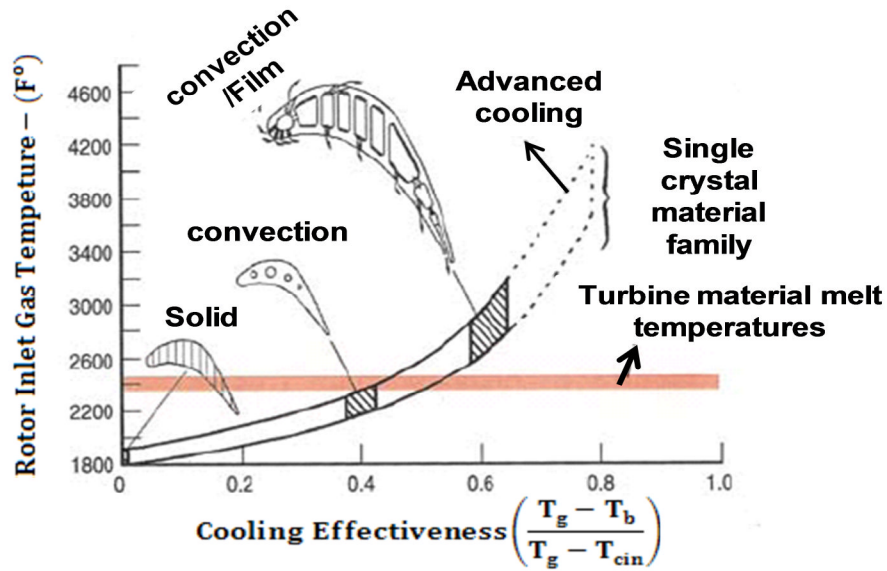


Figure 3-5: Cooling technology in turbine blades [87]

The model calculates the temperature of the blade metal (T_b) and as the temperatures change with operating conditions, the model is continuously updated and the new blade metal temperature is obtained. The creep model calculates component life according to (T_b) [148]:

$$\varepsilon = \frac{T_g - T_b}{T_g - T_{cin}} \quad 3-1$$

Where ε is cooling effectiveness, T_g gas stream temperature and T_{cin} inlet cooling temperature. Re-arranging Equation 3-1, the blade metal temperature (T_b) is obtained as in Equation 3-2:

3-2

$$T_b = T_g - \varepsilon(T_g - T_{cin})$$

3.2.2.3 Stress Model

While there are many different sources of stress to turbine blades, this section considers only direct centrifugal stresses which arise because of the mass of the blade. Operating in an inertia field, between 50 to 80 % of the blade material strength is used to overcome this stress [155].

For the creep life calculation, the centrifugal stresses on the blade were evaluated from root to tip. The data used in this model such as rotational speed was generated by Turbomatch. The blade was sub-divided into several sections, see Figure 3-6. It is assumed in the model that the axial velocity remains constant along the span of the blade and the centrifugal force acts at the blade section centre of gravity (CG). The centrifugal force on a rotating section is expressed as [155]:

3-3

$$CF_{sec} = \text{mass} \times \omega^2 \times d_{CG}$$

Where mass is the mass of the component, ω is the angular speed of the component, d_{CG} is the distance between the rotation axis and the section CG.

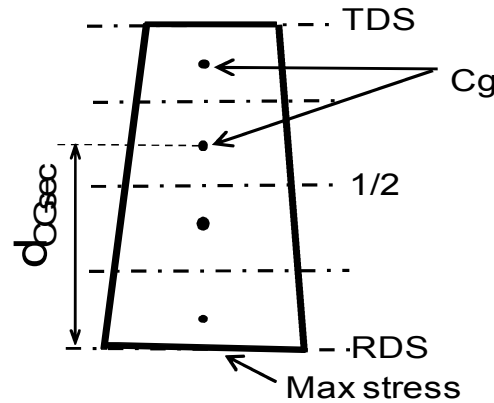


Figure 3-6: typical blade sections

Assuming the blade section has a rectangular shape its mass will be equal to density*average cross-sectional area*height, and the centrifugal force calculated using Equation 3-4:

$$CF_{sec} = \rho \times A_{AvCs} \times h_{sec} \times \omega^2 \times d_{CG} \quad 3-4$$

Where ρ is the density of the material, A_{AvCs} is the average cross-sectional area between the top and the bottom of the section, h_{sec} is the section height, and d_{CG} is the distance between the rotation axis and the section CG. Thus the centrifugal stress acting on a blade of constant cross-sectional area can be calculated using Equation 3-5:

$$\sigma_{sec} = \rho \times h_{sec} \times \omega^2 \times d_{CG} \quad 3-5$$

3.2.2.4 Creep Model

To obtain a reasonably conservative estimate of creep life, either at the current operating condition or the reference operating condition, the LMP approach was used. From Arrhenius's Law, the equation can be expressed as [10]:

$$LMP = \frac{T}{1000} (\log t_f + C) \quad 3-6$$

Re-arranging, t_f can be written as:

$$t_f = 10^{\left(\frac{1000 LMP}{T} - C\right)} \quad 3-7$$

Where T is the temperature of the material, t_f is the time to failure and C is a constant which is often generalised to 20 in industrial applications but it can vary somewhere between 13 and 27 depending on material used [83]. The stress will vary along the blade section, so creep life will be different for different blade sections. The minimum creep life calculated will be taken as the value which represents the blade's remnant life

3.2.3 Economic Model

To calculate the cost of electricity, this study considers major factors such as capital cost, emission tax and maintenance cost and also other major factors which are functions of the time of year such as ambient conditions and the price of fuel. This study also considers Net Present Value (NPV) and levelized cost of electricity (LCOE) as major factors when assessing the worth of a

project. Turbomatch was used to simulate the GT thermodynamic behaviour at OD and ODP conditions. This was linked with the lifing model used with the HPT blades. Figure 3-7 illustrates the power plant assessment model created to calculate levelized cost of electricity.

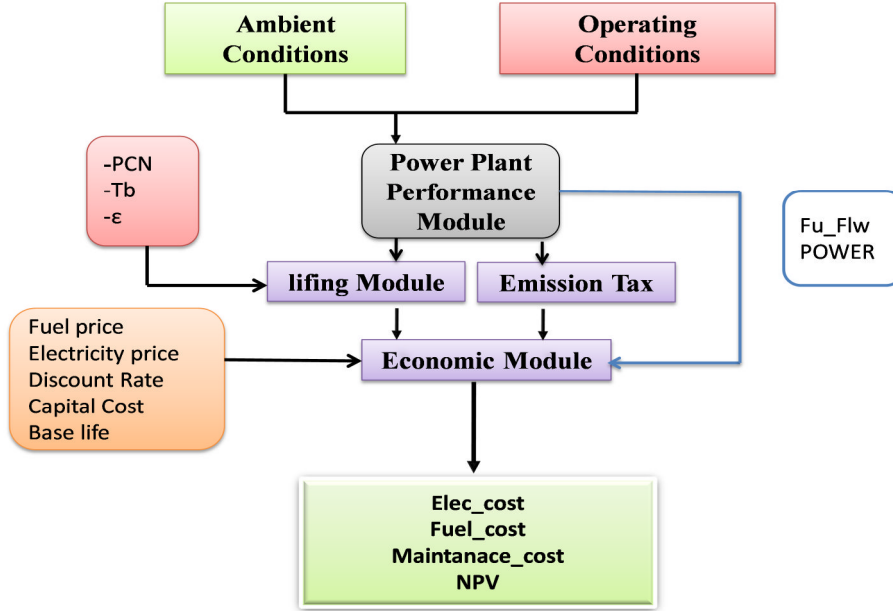


Figure 3-7: Power plant economic assessment module

3.2.3.1 Costs of Generating Electricity

Accurate estimation of the costs of generating electricity(COE) is vital to effective evaluation and later operation of power plant systems.

$$COE \left(\frac{\$}{kWh} \right) = Capital\ Cost + Fuel\ Cost + O\&M\ Cost + Emission\ Cost \quad 3-8$$

The up-front capital investment is converted into a stream of equal annual payments using the concept of capital recovery factor (CRF). CRF simply converts a present value into a stream of equal annual payments over a specified time, at a specified discount rate [84]. CRF is given by:

$$CRF = \frac{1}{\left[\frac{1}{r} - \frac{1}{r(1+r)^n} \right]} \quad 3-9$$

Where r is the specified discount rate and n is the duration in years of the project.

The data required to estimate the capital cost for GT power plants has been obtained from Energy Market 2004, Gas Turbine Handbook 2010 and GECOL [3; 6; 60]. The latter sources include an annually updated price list of commercial GT packages from different manufactures. The 2010 list is in \$/kW installed and into the economic module [8] . The price of the selected gas turbine is then interpolated from the list by inputting the gas turbine size in kW. Furthermore, parameters required for fuel, O&M, and emission costs calculations are obtained from the TURBOMACH [119][154] process simulator.

In addition, the cost of electricity (COE) is that cost that, if assigned to every unit of electricity produced by the system over the analysis period, will equal the total life cycle cost (TLCC) when discounted back to the base year [2]. In other words, if every unit of electricity produced is sold at the calculated COE, the project would precisely break even and the NPV would be zero.

Therefore, the formula that is used to calculate the COE should include all operating costs of the project under consideration. In this study, the following expression is used which is designed to include capital cost, fuel cost, maintenance costs, and emission cost (if there is any).

$$LCOE = \frac{Capital_C + \sum_{i=1}^n \frac{Fuel_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{M_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{E_C}{(1+r_i)^n}}{\sum_{i=1}^n Power * Ope_hour_yr} \quad 3-10$$

It is evident that maintenance costs account for a significant portion of total costs within a power plant of any sort and whilst these costs may be small compared to fuel, the cost of maintenance reflects another very important aspect; costs due to downtime or lost production. Whilst maintenance costs in terms of costs of components that need replacing may not be much, the costs of lost production due to downtime are of much greater significance. Hence it is vital to map the failure of a plant or machinery set and put it into the perspective of maintenance necessary and cost the components required and also to define how operations will affect the downtime of machinery.

Maintenance can represent between 15% and 60% of the operating costs [107].

$$Mf = Mf * \frac{[Unit\ Expected\ Life(hours)]}{[Time\ to\ Failure\ (hours)]} \quad 3-11$$

Where Mf is a maintenance factor = \$/kWh which depends on gas turbine technology, this is provided by the original engine manufacturer (OEM) [149].

$$M\ cost = Mf * power\ output * operating\ hours * availability \quad 3-12$$

Where $M\ cost$ is a maintenance cost per year

For CO_2 emission calculations, assuming complete combustion in the presence of excess air, which is reasonable, the CO_2 emissions will depend directly on the type, quality and quantity of the fuel used. The CO_2 emitted may be calculated using the following equation:

$$mCO_2 = eCO_2 * mof \quad 3-13$$

Where: mCO_2 is the mass of emitted CO_2 , in kg, eCO_2 is the emissions of CO_2 per unit mass of fuel (e.g. kg CO_2 /kg fuel), and mof - is the mass fuel consumption.

The tax liability for operating a gas turbine can be derived from the following equation:

$$Carbon\ Tax = m\ CO_2 * Tax\ Rate\ \$/kwh \quad 3-14$$

3.2.3.2 Net Present Value

During the life of the project there will be two financial streams: one is the costs stream (which includes capital and operational cost (C)) and the other is the benefits stream (B). The two streams must contain all costs and benefits for the same estimated life frame of the project. The costs stream, being outward-flowing cash, is regarded as negative. The difference between the two streams is the cash flow – the 'net benefits stream'. The value of the net benefits in certain years can be negative, particularly during construction and the early years of the project. Discounting the net benefits stream into its present value,

by multiplying each year's net benefits by that year's discount factor, will present the NPV of the project [16; 84].

$$NPV = \sum_{n=0}^{\infty} \frac{(B_n - C_n)}{(1 + r)^n} \quad 3-15$$

Where C is capital and operational cost, B is benefit stream, r is discount rate and n is year of operation.

3.2.4 Gas Turbine Exhaust Emissions Model

It was decided to change from the original theoretical emissions model to one which was semi-empirical on the grounds that not only was this a simpler method but would provide better estimates for the fixed combustor geometry that was being investigated. Both models require very similar inputs but the semi-empirical method would provide estimations for the aero-derivative combustors more easily given that the details of the industrial combustor were readily available. Cranfield University has developed a model to evaluate the amount of emissions produced by GTs in aviation. This model required some modifications (simplifications) to make it applicable to industrial GTs because they do not move and do not experience significant air pressure changes. Figure 3-8 shows the final model diagram.

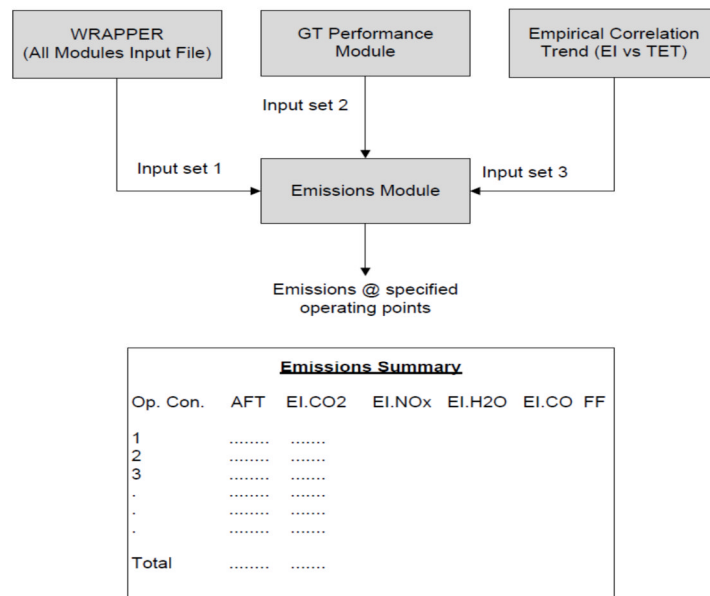


Figure 3-8: schematic of the structure of the emissions module

In this work predictions for CO emission use the Lefebvre correlation, and for unburned hydro carbon (UHC) emissions the Cranfield-Modified correlation was used. The Cranfield model which was modified for use with this study was initially developed by Courtinho [123].

- **Inputs Set 1** (User defined values for combustor):
 - ↳ Combustor volume (m^3).
 - ↳ Primary zone evaporation fuel volume (m^3).
 - ↳ Residence time (s).
 - ↳ Fraction of primary zone occupied by air (%).
 - ↳ Combustor efficiency (%).
 - ↳ Combustion mode (constant volume or constant pressure).
 - ↳ Fuel type (natural gas, kerosene, etc.).
 - ↳ Altitude (m).
 - ↳ Number of combustion chambers.
 - ↳ Switch between aero and industrial frame combustor types Input.
- **Inputs Set 2** (Thermodynamic parameters from performance results):
 - ↳ Compressor outlet temperature (K).
 - ↳ Firing temperature, TET (K).
 - ↳ P4, P3 - pressure before and after combustion chamber (kPa).
 - ↳ Mass flow rate (kg/s).
 - ↳ Fuel flow (kg/s).
- **Inputs Set 3:**
 - ↳ This is not a set input, but rather a correlation based on known combustor characteristics.
 - ↳ The known characteristic is mapped as an empirical equation in Excel and then that equation is converted to FORTRAN and hard coded.
 - ↳ Each engine type has its own empirical correlation.

- **General Procedure:**

1. The simplest combustor geometry is used and this, along with fuel type and residence time, combustor efficiency and primary zone information are inputs to set 1.
2. The output of the performance module provides information concerning the operating conditions, these are inputs to set 2 and include temperatures, pressures, fuel flow and core mass flow.
3. The adiabatic flame temperature (AFT) is estimated from the thermodynamic performance parameters: T_3 , P_3 , the heat enthalpy of the fuel and proportion of air in the primary zone.
4. The emissions indices are estimated from core mass flow, combustor volume, AFT, and pressures which enter into the Turbine (P_3).
5. For a given type of combustor the coefficients of the emission index equations are revised to fit known trends.
6. The correlations are then hard coded as inputs for set 3.
7. CO₂ emissions are based on stoichiometric relationships, while emissions NO_x, CO and UHC are calculated based on known correlations.

3.2.5 Optimisation Method

3.2.5.1 GA and TERA Integration

An automated optimisation environment has been developed to provide a continuous interaction between the GA optimisation code and TERA modules acting as an external solver as illustrated in Figure 3-9.

The GA code starts by randomly initialising the first population of individuals from the specified variables range listed in the input file. In the current study the variables are the running condition of each engine defined in this case by the TET. Each variable will be then coded with a fixed length character string composed of 0s and 1s. The control parameters for this function are already set in the input file.

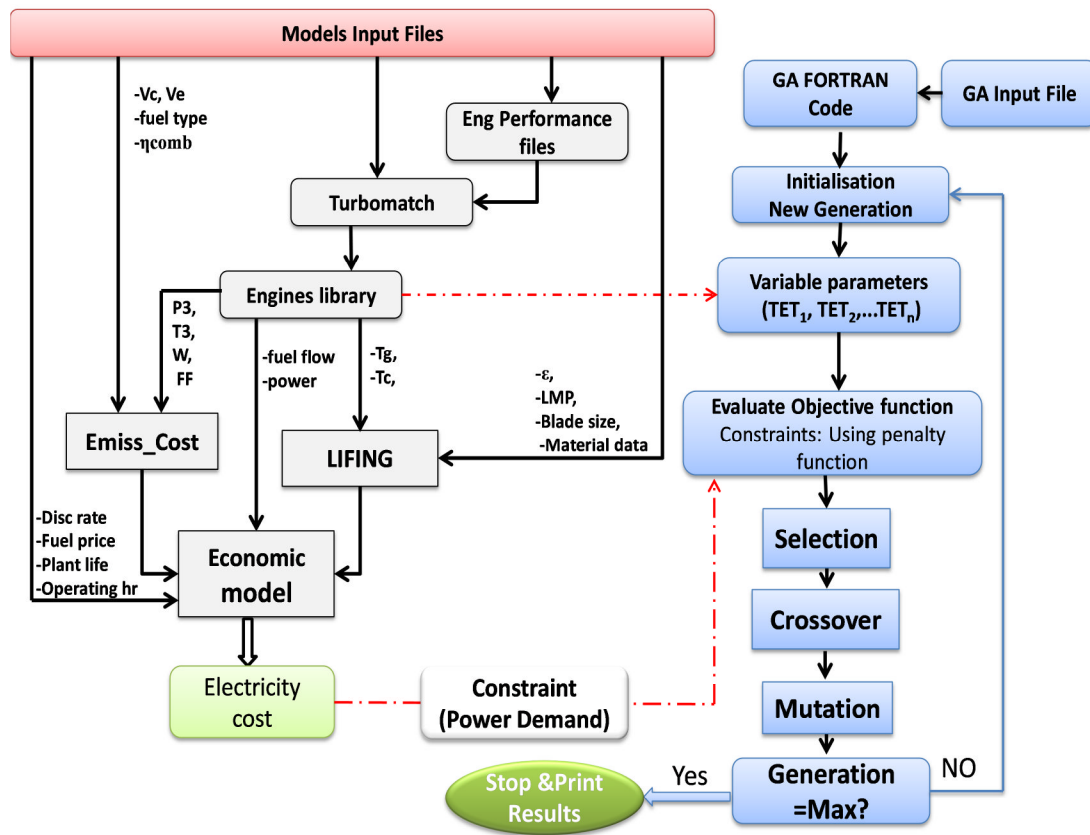


Figure 3-9: TERA & Optimisation architecture

The randomly selected variables together with the required settings will be provided to the external solver (TERA) which will be called automatically from the GA code. The output from Turbomatch analysis will be then redirected back to the GA code to serve as a fitness evaluator of each selected variable in the population. These will be in a form of objective function and constraints.

The GA routine will then create a new population of coded individuals (TET) using the crossover and mutation operators based on a given selection scheme. The selection probability of each generated variable will depend on its fitness value (objective function; electricity cost) and constraints (power demand).

Iteratively the GA code will perform these operations on the population of strings until the termination criterion has been satisfied.

3.2.5.2 Objective Function

In the power generation market the cost of electricity depends largely on the GT running conditions which affect operating and maintenance costs. In the current study the objective function was set as the cost of electricity as shown in Equation 9.

$$f(x) = \frac{C_I + \sum_{i=1}^n \frac{F_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{M_C}{(1+r_i)^n} + \sum_{i=1}^n \frac{Em_C}{(1+r_i)^n}}{P * T} \quad 3-16$$

Where: C_I = capital Investment, F_C = fuel cost, M_C = maintenance cost, Em_C = emission cost, T = operating hours per year and P = power output.

The objective function sub-routine within the GA code minimises the electricity cost for each running condition , which will be presented by chosen three typical days in year summer , winter ,and mid-season) each day divided into two hours to present the run condition at deferent operating and ambient condition (power demand ,and ambient temperature) . The latter would be the design variable defined as TET subject to satisfying the required constraints as described in the following section.

3.2.5.3 Constraint and Penalty Function

Constrained optimisation is of general interest because it arises quite naturally in many engineering, scientific, economic and social fields. Generally, GAs are designed to solve unconstrained problems and have to be adapted to be suitable to solve optimisation problems that include equality and/or inequality constraints. Usually the solution of constraint is based problems involves penalty functions, which are a set of penalties applied to unfeasible solutions. Constrained optimisation problems are often presented as one of a type of non-linear programming problems such as:

$$\text{Minimise } f(x)$$

Subject to:

$$\begin{cases} g_j(x) \geq 0, & j = 1, J \\ h_k(x) = 0, & k = 1, K \\ x_i^l \leq x_i \leq x_i^u, & i = 1, n \end{cases}$$

Where $f(x)$ is the objective function with n variables x ; J, K are number of inequality and equality constraints, respectively; $g_j(x)$ and $h_k(x)$ are the j^{th} inequality and k^{th} equality constraints, respectively. The parameter x varies in the range $[x_i^l, x_i^u]$.

When evolution algorithms employ constraint handling via penalty functions, the penalty function approach involves a number of penalty parameters, which must be correctly set in any problem to obtain viable solutions, typically:

$$eval f(x) = \begin{cases} f(x), & \text{feasible region} \\ f(x) + \text{penalty}(x), & \text{unfeasible region} \end{cases}$$

Where penalty $f(x)$ is zero, if no violation occurs, otherwise is negative.

In the current study the constraint was defined based on required power demand using above described technique.

3.3 Implementation of Methodology

One of the main objectives of the project was to develop and integrate methods of analysis, design and optimisation. Thus one goal of the automated design system was to enable the application of optimisation methods to the operational methodology of a power plant. The format therefore was based on the idea of linking an optimisation algorithm (GA), a TERA model and a set of routines interpolating results from the GT performance code (TurboMatch). This linking is necessary because one of the results from the TERA model is that the optimiser evaluator is used to calculate the fitness of each individual (variable). In addition, the performance parameters resulting from TurboMatch are used as inputs to the TERA routine. There must be a continuous automated interaction between the optimiser and other components of the optimisation system. The schematic representation of the operation is depicted in Figure 3-10.

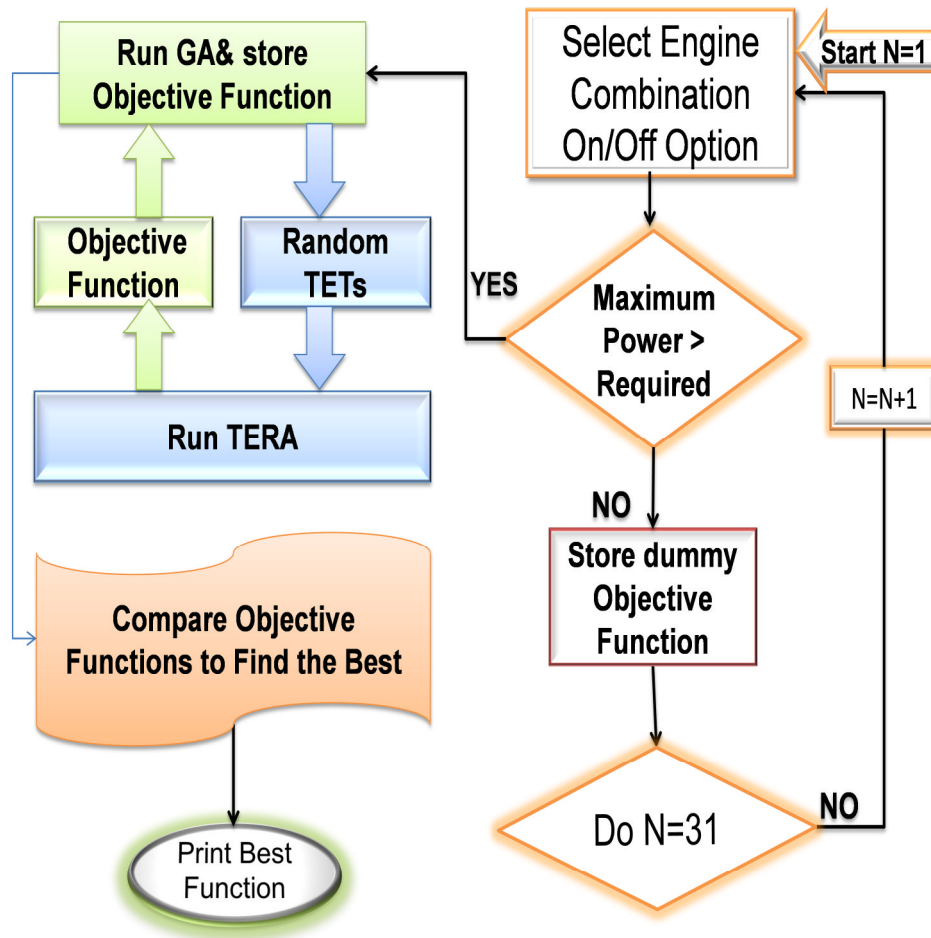


Figure 3-10: Implementation of methodology

Communication of the main components of the optimisation process is obtained through a FORTRAN routine, which is called from the GA optimiser. The process is initiated by calling the power demand routine that was created to evaluate which combinations of GT engines will meet the required load. It iterates through each combination of engines to work out the total power available from each combination (for example, for 5 engines, each can be on or off, giving 31 viable combinations - the combination where all 5 engines are off is obviously irrelevant). The selection method is based on satisfying the required power demand initially specified by the user. Therefore all possible combinations producing adequate power are taken through the optimisation process.

The GA code will then randomly select the TET for each engine within its combination. Then TERA routine is called to calculate the cost of electricity for each combination. The TERA routine has been modelled to allow input specification of each engine to be shut-down if there is no need to run the power plant (five engines) at full capacity and, if so, to return a single value based on shutdown cost, rather than calculated running cost.

The output results from the TERA model are then redirected back to the GA code. These include the total electricity cost together with the power output which will serve as input to the evaluator subroutine within the GA optimiser which will return the objective function that satisfies the required constraints (power demand).

After calculating the optimum values of cost of electricity for all combinations of operating engines that provide sufficient power, the GA code will select the combination that produces the optimum cost of electricity to re-run it and present the final result of minimum cost of electricity. A typical GA output results are shown in Appendix B.1.1 and B.1.2.

3.4 Optimisation process

Read input file (power demand) then iterate through the combinations of possibilities using a loop control variable:

- a. By turning the loop variable (1-31) into a binary number and treating each digit as one engine on or off all possible combinations are checked e.g. 29 = 11101 means engine 1,2,3,5 on and engine 4 off or 12 = 01100 means engine 2, 3 on and 1, 4, 5 off. This method makes it easy to define all possible combinations in a single loop.
- b. Then iterate using loop control variable for engines 1-5 to produce string for printing out showing whether each engine is on or off.
- c. Calculate maximum possible power output from current combination of engines (e.g. for loop variable 12 maximum power = maximum power from engine 2 + maximum power from engine

- 3). Uses loop (1-5 for each engine) and adds to running total variable PWRTTEST if engine is on.
- d. Check if maximum power greater than required power. If not store result as very large value and skip to end of loop (as this combination will not work). Then call TERA

TERA interpolates values from a 3-dimensional table library created from the performance model to feed the economic, lifing and emissions models contained within TERA. Each of these models requires additional inputs which are supplied from an input file for each model.

The parameters F for each engine are assigned or a suitable dummy value is used if the engine is switched off.

Then TERA is called. TERA calculates maintenance cost, fuel cost, and emissions cost for each engine and then calculate cost of electricity which is the objective function that GA is to minimise.

TERA was originally a separate program which has also been incorporated into a subroutine. Again, to minimise coding changes the TERA subroutine continues to write an output file which is then read within the objective function subroutine to obtain the electricity costs.

Objective function (**func**) used to calculate the total electricity costs by adding up costs for each engine which is on and including a shutdown cost for each engine which is off. A penalty function is then applied this and results in the final value supplied by objective function (**func**) back to the GA program for minimising.

Call GA program for this combination, which meet the power required as discussed above, (GA has been re-written as a subroutine) and stores the calculated objective function.

Loop 1-31 again, using loop control variable:

Compare objective functions for each combination and find the smallest objective function. Ignored combinations will have been assigned a very large

value so will never be counted (there is a separate check that at least one combination produced enough power)

Rerun GA for most efficient combination of engines. This run ensures that output files contain output for the most efficient run. Because GA was originally a separate program each run within the 31 creates output files that overwrite the previous ones.

It is easier coding to simply rerun GA again at the end to obtain correct output. To avoid this would require major rewriting of GA to store all data for each run and then only output the correct run. While this change would result in a more efficient program it is a major piece of coding and was not considered a good use of time. Each GA run is fairly short so the additional time for a 32nd run is not significant. Construct output string saying which engine is on and off using loop variable see appendix B.1.3.

3.5 Chapter Conclusion

This chapter reports the methodology used to carry out the research. The first part of the chapter discussed the idea regarding applicability of TERA to the research. The methodology has been designed so that the major tasks (GT performance, lifing, emission, and economic factors) involved in this research are clustered, specified and linked to each other. The optimization tool (GA) has been adapted to link with the TERA model, which include the impact analysis of different operating scenarios on the cost of electricity. Later, a description of each major task is given in chapter four for TERA model, and chapter five for a Genetic Algorithm GA.

Chapter four

4 Multidisciplinary Evaluation: Integrating TERA Modules in the Framework

4.1 Overview

The creation of TERA simulation tool was described in Chapter 3, how it was written in FORTRAN and how the user can exert control over the way different scenarios are run by calling on different modules integral to the tool, see also Figure 4-1. Later on TERA will be controlled by the Genetic Algorithm (GA) optimiser. The GA optimises the transfer of data between modules and execution imperatives. There is an initial input file which holds all the necessary information concerning the inputs to every module and on/off switches which control execution of engine module calculations. Thus the user is able to fully control the analytic process and execute whole TERA engine or run only those parts which are required. Manual transfer of data or files has been eliminated and many input files are ready prepared and it is often possible for the user to select the appropriate file. Of course the user may have to prepare bespoke input file for the TERA modules.

This chapter describes the development of an integrated and multidisciplinary model to improve decision-making when evaluating the efficiency of power generation projects. The model comprises:

- A Performance Module,
- A Lifting Module,
- An Economic Module, and
- An Emission Module.

The four modules when integrated form TERA, and can be used for evaluation of gas turbine (GT) power generation performance. The model is linked to a GA optimizer which will be referred as an external solver and this chapter presents the results obtained for each module separately before presenting results from

the integrated TERA model. Additional details will also be available in Appendix (A)and subsequent chapters where TERA is used in case studies.

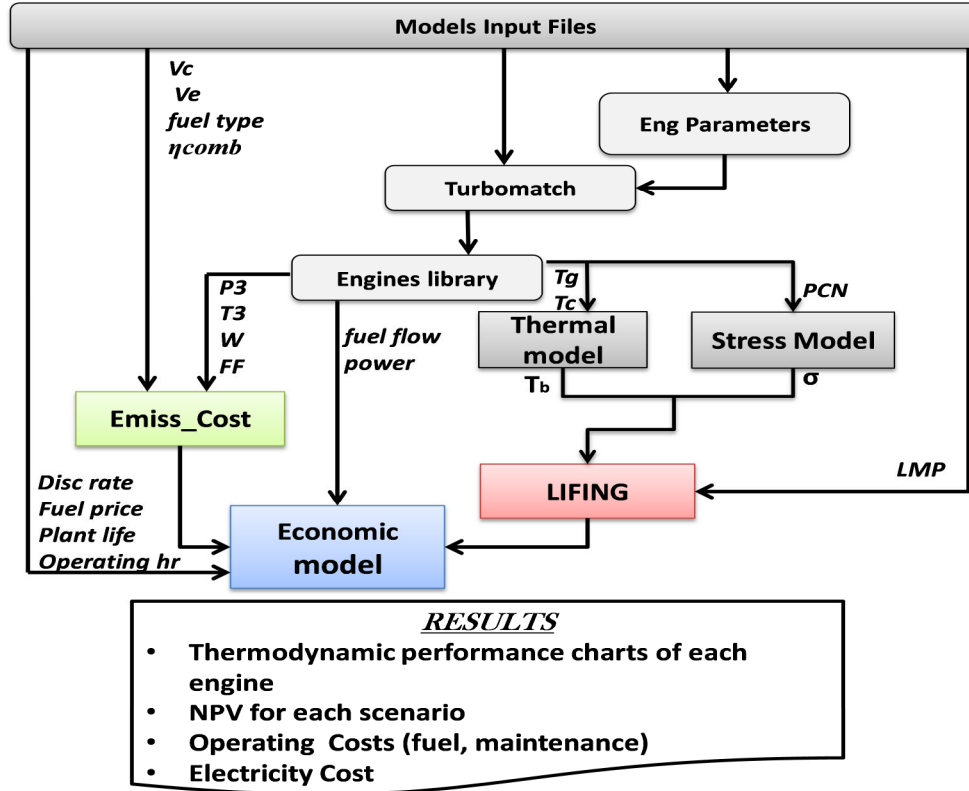


Figure 4-1: TERA model

The Turbomatch software package, developed at Cranfield University, [119; 154] was used to simulate GT engine performance and carry out performance analysis at design (OD) and off-design (OFD) points. As stated earlier Turbomatch is validated GT gas path analysis software able to provide the required engine health information for further analysis and decision making.

4.2 Gas Turbine Performance Model

Turbomatch with Pythia can simulate both steady state and transient GT diagnostics and perform gas path analysis, and can be linked with other software packages such as CFD and FE.

Turbomatch uses the component matching approach; at its simplest this means the values of parameters at the end of one stage/step are equal to their values

at the start of the next stage/step. Each component is determined using pre-programmed routines known as 'bricks'. These connect to each other to form an engine cycle. Figure 4-2 illustrates how the thermodynamic calculations are carried out using the data from the bricks; either as inputs by the user (brick data) and/or from other bricks (engine vector data). The final output is the engine shaft power or thrust, efficiency, specific fuel consumption, etc. It is also possible to obtain details of local gas properties and component performance at individual stations within the engine.

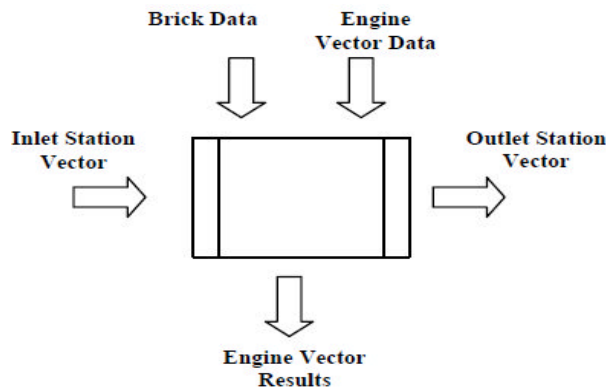


Figure 4-2: TURBOMATCH BRICK [121]

Before performing off-design (OFD) calculations, the design point has to be determined to fix the scaling factor for the turbine maps contained within Turbomatch. Then, the OFD can be computed using one of the following parameters: turbine entry temperature (TET), or fuel flow, or rotating component speed (PCN). There are five compressor and six turbine maps available in Turbomatch. There is also the capability to generate additional maps as required. This model generates the inputs required using the lifing, emissions, and economic modules in TERA, then feeds the required data to the optimiser GA. More details are given in Section 3.2.1.

4.3 Engine Model

Using Turbomatch, a single-shaft engines performance model, and 2 shaft aero-derivatives was developed based on the layout shown in Figure 4-3 and Figure 4-4. Figure 4-3 refers to single shaft industrial, this type of engine cycle can represent the engines one, three, four and five developed in this study.

Figure 4-4 refers to engine two, which represent the 2 shaft aero-derivative engine with free power turbine. The power turbine is linked to the gas generator aerodynamically and this gives benefits in terms of flexibility over shaft speeds and sensitivity to ambient conditions and control aspects of the engine.

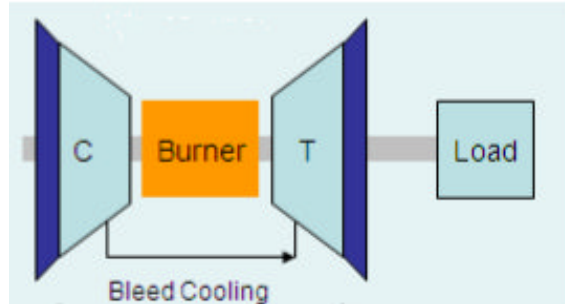


Figure 4-3: Schematic for a single shaft industrial engine

These configurations used to develop and run representative thermodynamic models of the engine to be investigated. The tool has the ability to simulate different thermodynamic cycles and processes whilst analysing the overall performance of the engine including among other things the effects of cooling flows, air and gas mixing, component degradation, variable geometry (including compressors, turbines and exhaust nozzles) as well as extraction of bleed air and shaft power off takes. Turbomatch can also calculate steady state engine performance at both design point and off-design point. In this study Turbomatch was used to develop and run a thermodynamic model of the engine and the cooling flows are extracted.

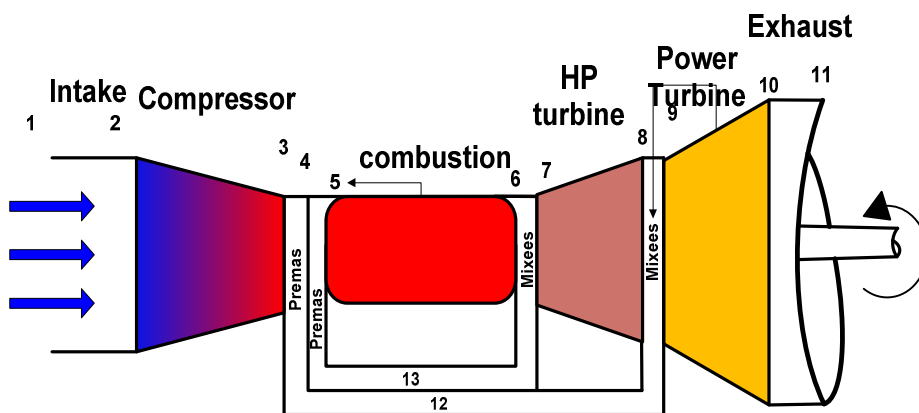


Figure 4-4: General layout of the gas turbine engine two Shaft

4.3.1 Engines in Context

The engine chosen for this study comprised a compressor, combustion chamber, HP turbine and free power turbine. Table 4-1 lists design point details of the five engines to be modelled.

Table 4-1: Engine Performance Parameters

Parameter	Unit	Engine_1	Engine_2	Engine_3	Engine_4	Engine_5
Power output	(MW)	165.1	30.012	130.12	42.003	240.1005
Mass Flow	(Kg/s)	533	82	410	141.1	541
TET	(K)	1387	1505	1400	1408	1525
Thermal Efficiency	%	0.362	0.42	0.3456	0.3384	0.3824
OPR		15:01	23:01	12.6:1	12:01	30:01:00
RPM	(rev/m)	3000	10050	3000	3000	3000
Fuel Flow	(kg/s)	10.6079	1.6691	8.7284	2.8989	14.6155

Engine performance was modelled using such output data as pressure, temperature, engine rotational speed and mass flow rate. These were determined for every component and each set of outlet values were then as the inputs to the next stage. This was the approach used for the blade creep, emission and economic models (all of which are within TERA), after which the optimizer GA was applied. Note that all the results shown are for the Engine 1 (single shaft 165MW). The results and Turbomatch input and output data for other Engines are shown in Appendixes C.

4.3.2 Performance Model Validation

An important point of discussion for this study is the accuracy of the calculated results, which obviously depend on the accuracy of the separate tools and integrated model. The model result has been validated against real data. This data was provided by the General Electrical Company of Libya (GECOL) [60]. To demonstrate the capabilities of performance model, Using Turbomatch a design point run has been carried out for the mechanical driver version of the

frame GT13E2 which is a 165MW single shaft industrial gas turbine machine with an overall thermal efficiency of 35.7% and design point TET of 1378K.

Table 4-2 Validation Results for Baseline Engine (1)

Parameters	Engine parameters	Simulation	Deviation Δ
Power (MW)	165	165.1	0.06
Mass flow(kg/s)	532	533	0.19
TET(k)	1378	1378	0
Efficiency (%)	37	36.2	2.16
OPR	15	14.9	0.67

The baseline configuration was validated against open literature. The validation results are shown in the Table 4-2 above. The pressure ratio OPR at design point condition is underestimated obtaining a difference of about 0.67%. However, the shaft power and inlet mass flow at the same condition were over predicted by almost 0.06% and 0.19% respectively. The worst case scenario was the engine thermal efficiency which gives a deviation of approximately 2.16% from the public data. The validation of the other engines was carried out using a public data (see the appendix D). In summary, the methodology is confirmed with a very good accuracy.

4.3.3 Operating and Ambient Condition

Engine thermodynamic performance simulation was based on a given site location with predefined ambient conditions. The ambient variations for the power plant [60] in its Libyan location are presented in Figure 4-5. The data was for typical days during winter, summer and mid-season. Thus, for each season, a single day was simulated and the results multiplied by the number of days in that season to get total amounts of fuel usage, emissions and so on. This method substantially reduces computation time. The unexpected fluctuations

seen for the mid-season line is because the mid-season is an average combination of spring and autumn.

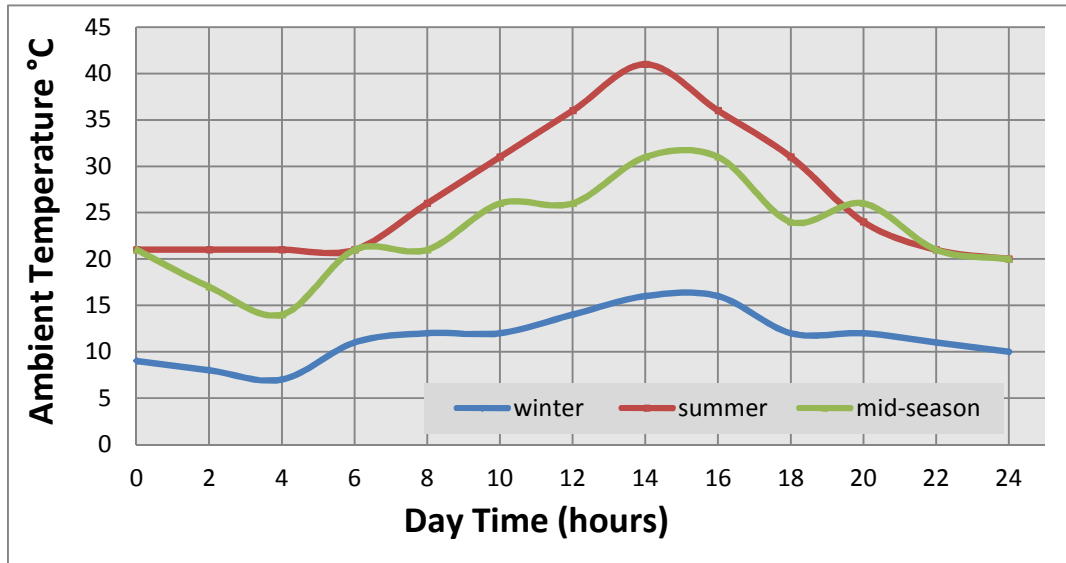


Figure 4-5: Daily ambient temperature variation at the plant location [60]

4.3.4 Effect of Ambient Temperature on Gas Turbine Inlet Mass Flow and Pressure

First some key performance results are presented. The variation of ambient temperature throughout the day for the three “typical days” at the location of the plant is illustrated in Figure 4-5. It can be seen that variation of ambient temperature was between +5 and +45 °C. This data was used in the TERA model to generate the results for the power plant over the whole year.

The effect of ambient temperature on the GT inlet mass flow and the compressor discharge pressure is shown in Figure 4-6. A 40 °C increase in ambient temperature (from 5 to 45 C) results in about a 16 % reduction in inlet mass flow i.e. 0.45 %approximate average(almost 2.3 kg/sec) reduction in mass flow for every degree centigrade increase in ambient temperature. Compressor discharge pressure has also dropped by 10 % for the same increase in ambient temperature. These two performance parameters are crucial because they affect the GT power output as well as overall thermal efficiency (η).

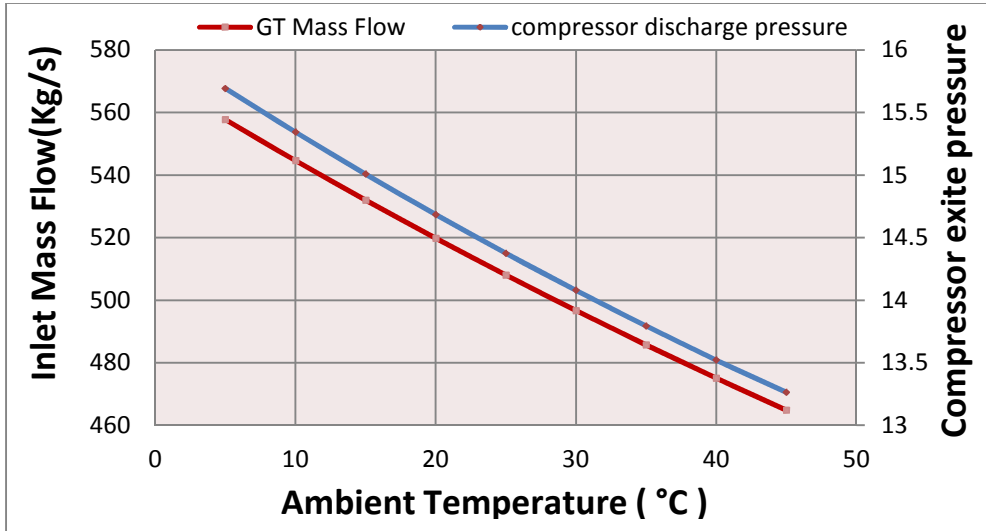


Figure 4-6: Effect of ambient temperature on gas turbine inlet mass flow and pressure

4.3.5 Effect of Ambient Temperature on Gas Turbine Output and Efficiency

Increasing TET will affect all downstream engine parameters, and the higher the TET the more obvious the effect. This is because component losses become relatively less important. When increasing the value of the TET care must always be taken not to exceed the upper thermal limit of the turbine components (rotors, blades, etc.). Above about 1300K a cooling system is generally necessary.

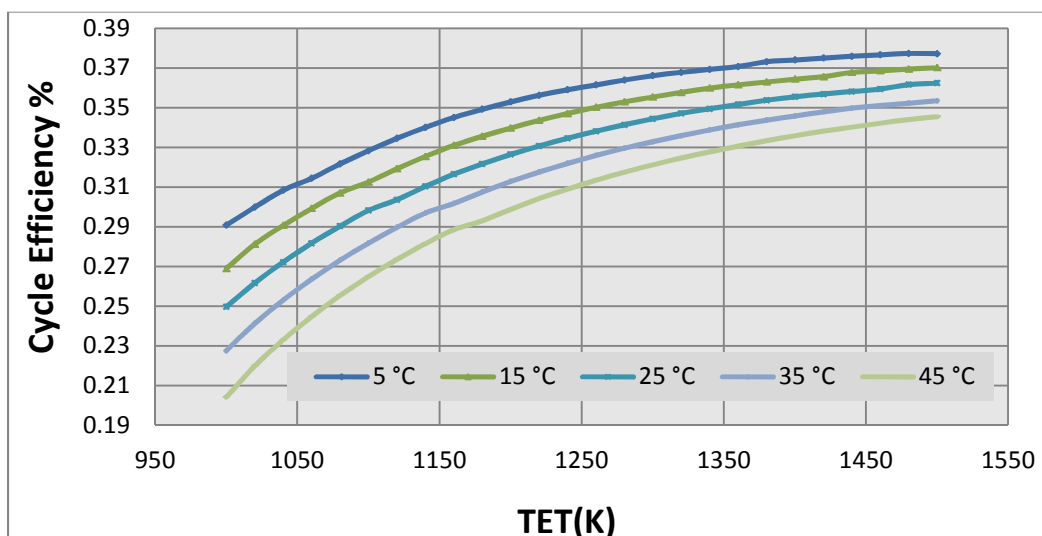


Figure 4-7: Thermal efficiency variation with TET

Figure 4-7 shows how the thermal efficiency varying with firing temperature (TET) for the simulated engine. It can be seen that there is a greater spread in cycle efficiency at lower TET temperatures. At a relatively low ambient temperature, 5°C, the engine is working with a cycle efficiency of about 29 % even for TET values as low as 1000 K. Under such conditions the curves suggest that increasing the TET would be expected to give only a marginal increase in power output. However, at ambient temperatures as high as 45°C the cycle efficiency will be 29 % for TET temperatures as high as 1200 K, and the curves suggest that increasing the TET would give a more noticeable improvement in cycle efficiency. It follows that, generally, a greater increase in thermal efficiency (and power output) is obtained from an increase in TET at higher ambient temperatures.

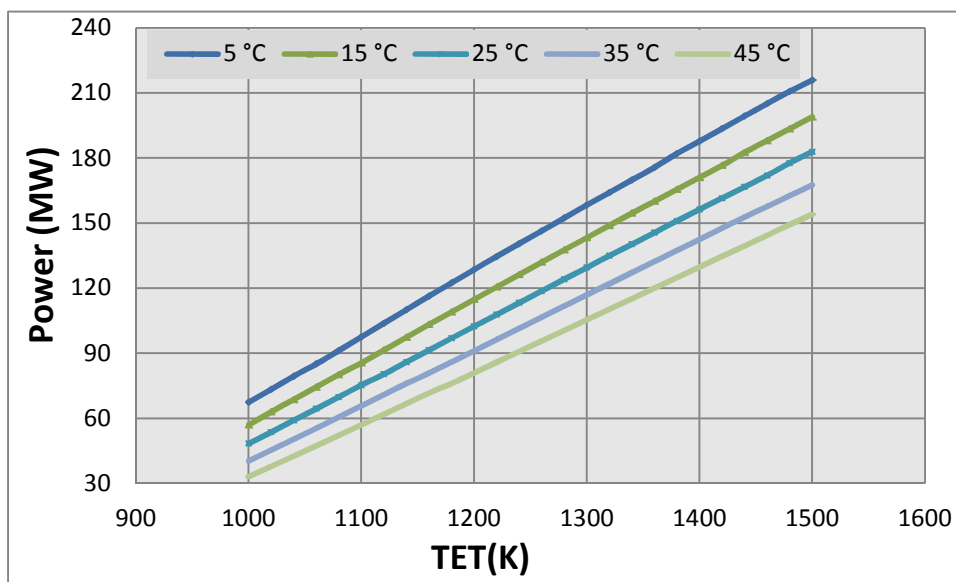


Figure 4-8: Power output variation with TET

Figure 4-8, shows the corresponding results to Figure 4-7 for shaft power output for the simulated engine as a function of TET. The curves appear to show a uniform increase in power with increase in TET for the range of ambient temperatures tested.

For both Figures 4-7 and 4-8 it can be seen efficiency and power output of GTs change with ambient conditions and the magnitude of these changes will have a substantial effect on fuel consumption, electricity production and plant

profitability. Ambient conditions are determined by location of the GT and cannot be changed.

4.4 Lifing Model

The data from the performance module is taken as input. The thermodynamic parameters used include the firing temperature, combustor inlet and outlet temperatures and pressures, and the rotational speed. The turbine creep lifing itself then splits into a two way analysis whereby the thermodynamic calculations are done in parallel with the stress calculations. The two then come together to conduct a parametric study based on the Larson-Miller Parameter (LMP). The LMP creep curve itself is a set of LMP values and stress values. This is generated from standard tests in which the material is tested under specified temperatures and loadings.

4.4.1 Lifing Model Layout

Based on the details given in Section 3.2.2 and Figure 3-4, the structures of the lifing model are:

Input set 1: (User Defined)

- Blade material
- Blade geometry data
- Number of segments into which blade is split
- Cooling effectiveness of blade (for thermal analysis model)

Input set 2: (From Performance Module)

- RPM
- Firing temperature at each operating condition
- Compressor exit temperature

Input set 3: (From Materials Database)

- Density of blade material
- LMP constant (C)
- LMP data (essentially test house data for the material)

4.4.2 Creep Factor

To perform an impact analysis comparison with a certain reference value is necessary. With blade creep life assessment, knowing the remnant creep life is, say, 20,000 hours, is not sufficient as it does not reflect how well the engine is being used. For example, if we could state that the 20,000 hours is actually 40% shorter than expected, this would indicate that the engine has been operating under severe thermal and mechanical loading. The value of 40% in this case is an indication of the magnitude of the impact of operating the engine away from its design point. Possessing this information allows the operators to better optimise mission profiles or establish an effective maintenance plan that will reduce operating and maintenance costs.

This study uses the Creep Factor approach (C_F) to measure the impact of actual operating conditions on creep life and quantify how quickly the creep life is being consumed relative to the specified operating condition desired by the operators. C_F is defined as a ratio between the calculated creep life remaining at the actual operating conditions and the remnant creep life calculated for the reference conditions [14; 15; 158]:

$$C_F = \frac{L_c}{L_{cRef}} \quad 4-1$$

- Where: L_c indicates the calculated remnant life for actual operating condition.
- L_{cRef} denotes the reference remnant life at user-defined reference operating conditions. This reference operating condition can be those of the design point, baseline operation and nominal operating conditions.

A realistic remnant life that is useful to the users will allow them to perform a realistic impact analysis, and the C_F value will help the user to assess changes in the remaining creep life of components operating at conditions which deviate from the normal user operating conditions. C_F will also help eliminate dependency on the OEM baseline operation which is not always achievable

when the user-defined normal operating conditions are far from the suggested baseline operation [15].

In general when:

- ✓ $C_F = 1$, the engine is being operated at the reference condition with $L_c = L_{cRef}$
- ✓ $C_F < 1$, the engine is being operated in a worse condition than its reference condition hence reducing the blades' remnant life.
- ✓ $C_F > 1$, the engine is being operated under better conditions than its reference conditions thus increasing the blades' remnant life.

4.4.3 Blade Geometry and Material Data

Here one engine (Engine 1) has been chosen as an example to illustrate the effect of operating and ambient conditions on engine life, further details of the other engines can be found in Appendix D.1. The component that most probably will require maintenance is the high pressure turbine (HPT) due to the combination of high operating temperature and high rotational speed (centrifugal force) on the HPT blades.

In this study, the blade geometry specifications were obtained from the industrial engine at the power plant during engine overhaul. The details of the first stage blade turbine geometry are presented in Table 4-3. The material used in this investigation is Nimonic alloy and its properties are shown in Table 4-3.

Table 4-3: First stage blade geometry fore engine (1) [60]

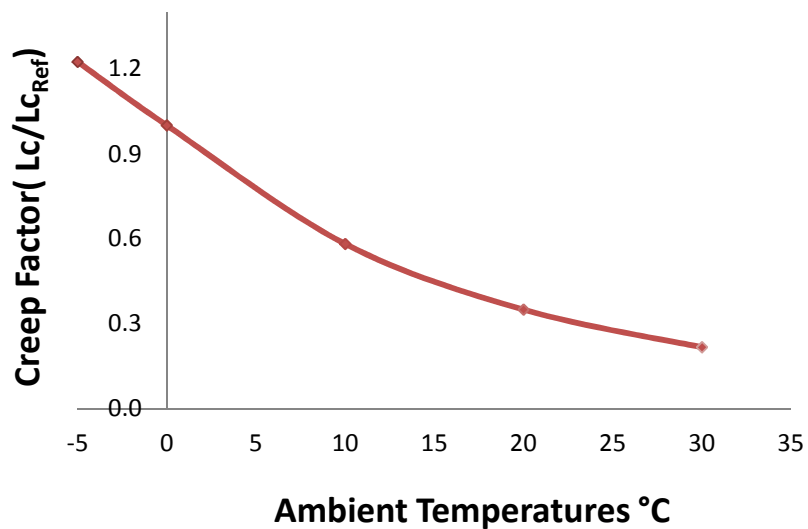
Geometrical Parameter	Values	Unit
Tip radius	0.95	m
Root radius	0.8	m
Blade height	0.2	m
Blade chord	0.08	m
Blade mass	6.32	kg

Table 4-4 Nimonic alloy material data

Density (Kg/m ³)	Melting range C°	Specific heat (J/Kg°C)
8180.00	1310	753

4.4.4 Effect of Ambient Temperature on Creep Life

Figure 4-9 shows the effect of ambient temperature on HP blade creep life. The design reference point was taken as (TET=1378 K, Ta= 288.15 K) equivalent to creep factor =1. It must be noted that the graph shows a scenario where there is a constant power demand with increasing ambient temperature and consequent increases in firing temperature. It can be seen that increasing ambient temperature results in a decrease in Creep Factor. This is expected due to a higher ambient temperature resulting in increased compressor delivery temperature, increased fuel flow requirement and thus an increase in firing temperature. It can be seen that the Creep Factor dropped almost linearly from its reference value to 0.22 when the ambient temperature is increased to 30°C. Further increase in the ambient temperature will definitely see further reduction in the blade's creep life.

**Figure 4-9: Blade creep life at different ambient temperatures**

As it would be expected, a decrease in ambient temperature from its reference value of 0 °C to -5°C results in an improved Creep Factor, from 1.0 to 1.3. This

is due to the fact that at lower ambient temperature, compressor delivery temperature is lower, resulting in a reduced fuel flow requirement and thus a reduction in firing temperature, as well as improved cooling capability since the inlet cooling temperature is also brought down (see Equation 3 in chapter three).

4.4.5 Effects of TET AND Power Demand on Creep LIFE

It is important to note that for both cases, the engine TET was chosen as a handle. The effect of changes in TET was investigated from 1280 K to 1400 K in steps of 20 K. The reason for choosing this range is to show the effect on the blade's creep life of having high and lower TET value relative to the design point which is 1378 K. An ambient temperature of 288.15 K, and $\varepsilon = 0.55$ were taken as reference values in this investigation. The increase in the creep factor indicates an increase in the blade's creep life.

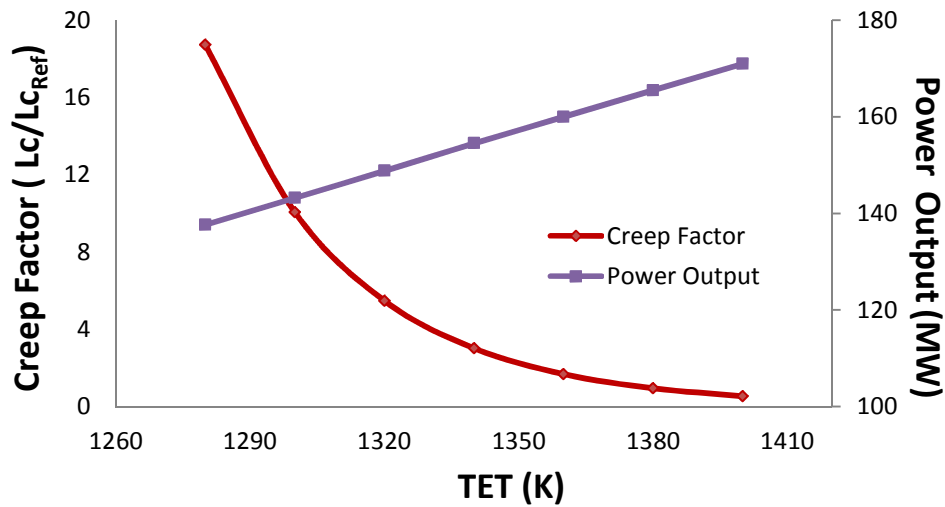


Figure 4-10: Blade creep life as a function of TET and power demand for clean engine

The variation of creep factor at different TET values and power settings has the detrimental effect of higher operating temperature for the engine, as can be seen in Figure 4-10. The Creep Factor was less than 1.0 when the TET was 1400K and increased to approximately 3.0 at 1340K. A similar effect can be seen with the change in power demand. The reduction in TET from 1400K to 1340K reduces power output from 170 MW to 150 MW. It follows that as the

shaft power reduces the blades creep life will increase, see discussion presented in Section 4.4.4. Figure 4-10 also shows that by increasing power output from 140 MW to 165 MW, with the associated increase in TET, the creep factor drops by 75%.

Figure 4-11 shows that a lower ambient temperature results in lower blade metal temperature. The consequent drop in metal temperature will increase the blade's remaining life (Figure 4-9). In Figure 4-11 shows that the stress in the figure remained unchanged during the investigation because the stress was a function of PCN (0.98%) which remains constant during this investigation.

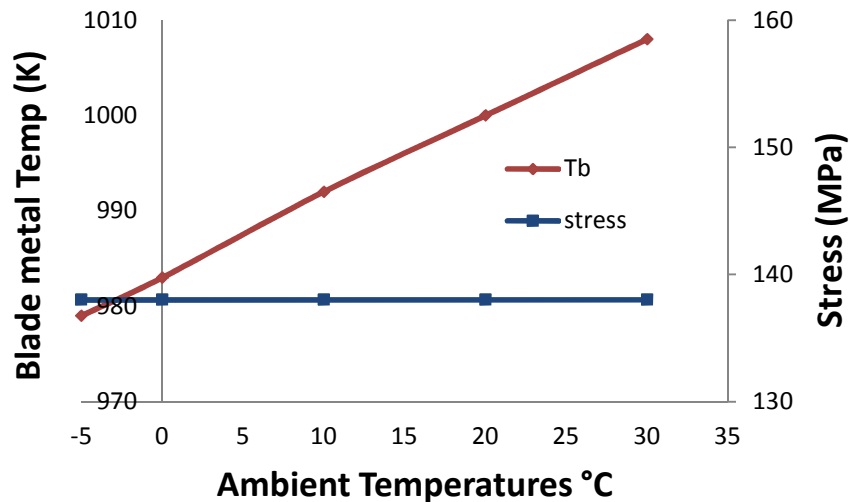


Figure 4-11: Change in ambient temperature and consequent change in blade metal temperature and stress

4.4.6 Effect of Compressor Degradation on Creep Life

Degradation in engine components, particularly the compressor, has some effects on engine life. Degradation in engine compressor (implemented here as equal levels of loss in compressor efficiency and flow capacity) results in higher compressor delivery temperature, as it is shown in Figure 4-12. An increase in compressor delivery means that cooling air would be delivered to the turbine blade at a higher temperature for the degraded case. This would be reflected in a higher blade metal temperature as shown in Figure 4-13.

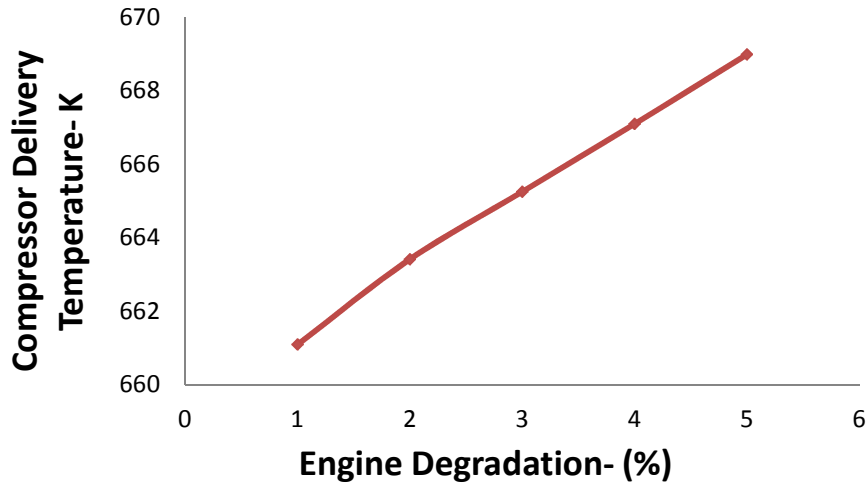


Figure 4-12: Compressor Delivery Temperature against Engine Degradation

The impact of engine degradation on blade metal temperature is shown in Figure 4-13. In this case, the firing temperature is maintained constant. A 5 K increase in blade metal temperature results in 20% reduction in the creep factor. The change in the metal temperature as shown in Figure 4-12 did not change very much (only from 1024 K to 1029 K) since for these case studies TET was kept constant. The small changes are due to the changes in the compressor delivery temperatures (Figure 4-12) as degradation magnitude increases. The increase in the compressor delivery temperatures is reflected as an increase in the coolant inlet temperature which reduces the air cooling capability and increases the blade metal temperature as shown in Figure 4-13.

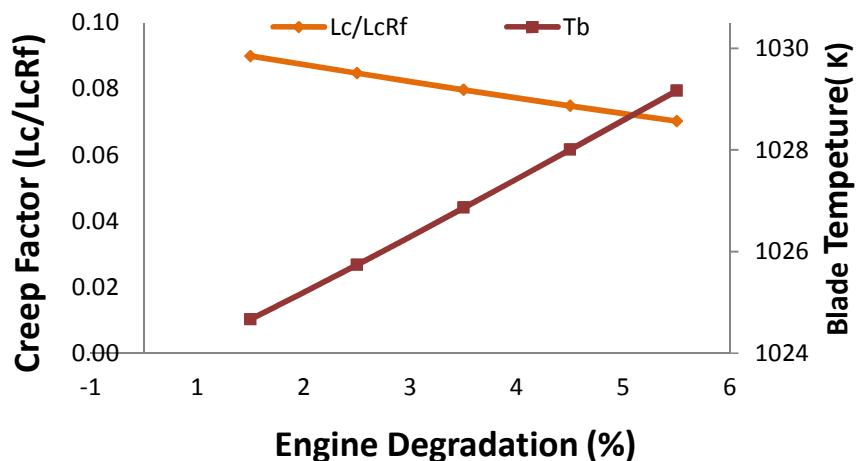


Figure 4-13: Blade creep life and metal temperature at different engine degradation levels ($T_{amb} = 318$ K)

Figure 4-14 shows that the temperature of the 5 % degraded engine has to be increased by 111 K (1378 K to 1489 K) above that of the clean engine to give the design point power output, substantially reducing the useful life of the engine. In other words, engine degradation results in a reduction in power output; if the engine is already being operated close to its base load the degraded engine has to be operated at higher TET to meet the power demand. This case is illustrated also in Figure 4-14.

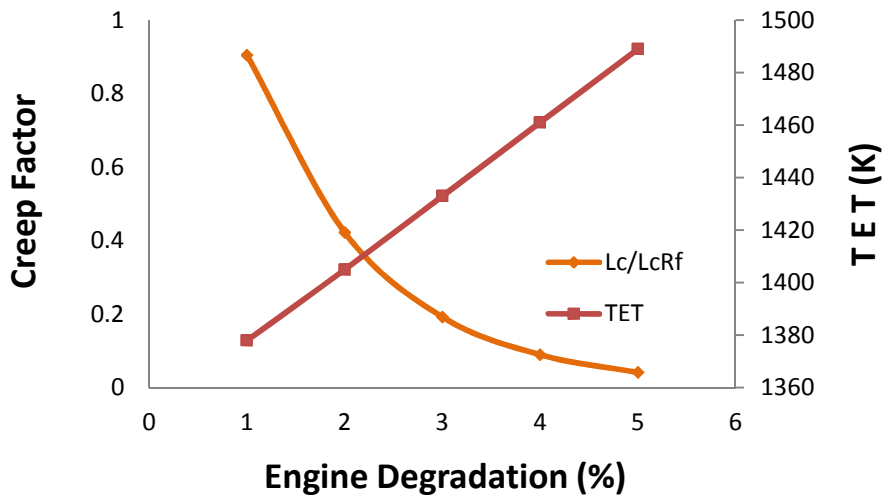


Figure 4-14: Blade creep life and TET with engine degradation

It is clear that over-firing of the engine significantly reduces the life of the hot section components and should be avoided if possible. Effective maintenance schemes or use of other engines with spare capacity is recommended in order to meet the required power demand.

4.5 Economic Model

Much research has been carried out on electricity pricing, forecasting the price of fuel, power demand and supply forecasting [26; 145]. Three major factors have emerged which are: the time of year (ambient conditions), the cost of electricity and the price of fuel. This project focuses on NPV and cost of electricity as the major factors to assess the worth of the project. Turbomatch was used to simulate GT thermodynamic behaviour at design and OFD conditions. This was linked with the lifing model used with the HP turbine blades

to calculate life consumed, and then maintenance cost. Also included was an emission model to evaluate likely emission tax. In order to study the impact of operating and ambient conditions on the NPV and electricity, and cost of a GT power plant, a model of gas turbine engines were created (result will be presented for only one engine, the result data from the remaining engines are in Appendix C). In addition, the operating environment of the GT power plant, which plays a major role in the performance of the turbine and the power plant, is described here.

An economic model has been developed; see Figure 4-15 in which the approach used for assessing power plant economy was also used to develop a creep life model using Turbomatch which consisted of sub-models for creep, thermal behaviour, stress analysis and thermal performance. The output from this model was combined with the data from the lifing and emission models. The results are then used to estimate the cost of electricity and NPV [11; 157; 159].

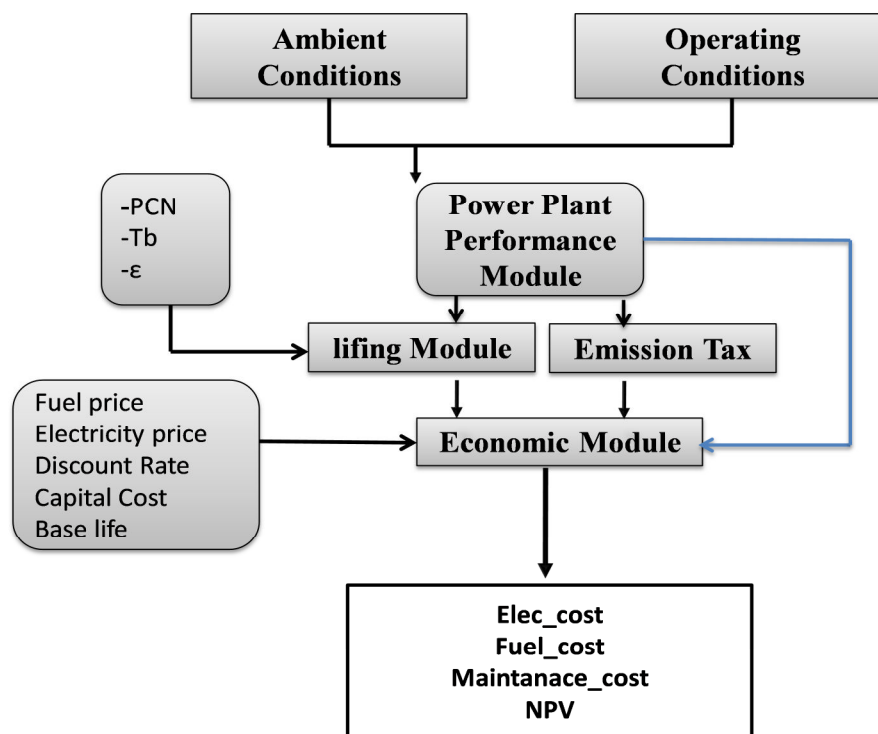


Figure 4-15: Economic model

4.5.1 Steps of Economic Model

Input Set 1 (User Defined):

- ✓ Discount rate (%)
- ✓ Design Plant life (years)
- ✓ Annual Operating hours
- ✓ Fuel heating value (MJ)
- ✓ Fuel Costs (\$/GJ)
- ✓ Emissions tax costs (\$/tonne)
- ✓ Electricity price (cents/kWh)
- ✓ Cost of GT (table from which cost is interpolated based on power)
- ✓ Degradation of engine (consequent increase in fuel consumption over the years)

Input Set 2 (Results of Lifting Module):

- ✓ Time to failure (life consumed).

4.5.2 Results and Discussion

In this section, a parametric analysis of the effect of power demand, discount rate, fuel price and engine degradation is presented. Both simulated base load and peak load have been investigated. During this investigation, the degradation in mass flow has also been considered. Costs of electricity and NPV at various operating conditions are shown in Figures 4-15 to 4-26.

4.5.2.1 Effect of Ambient Temperature on Power Output and NPV

To determine the actual variation in performance with change in ambient conditions three typical days have been chosen (winter, summer and mid-season) which are presented as 15°C, 30°C and 45°C respectively, see Figure 4-16.

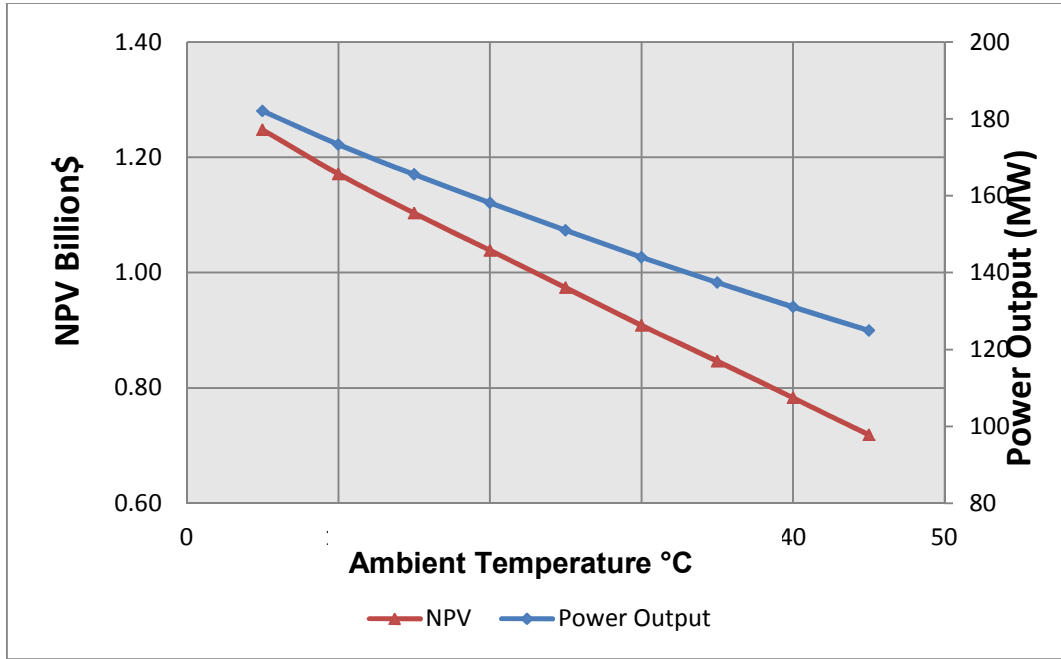


Figure 4-16: Influence of Ambient Temperature on Power Output and NPV

A typical discount rate 8% and 4.5\$/GJ have been assumed in this calculation. In Figure 4-16 the power output loss is about 12.7 % in mid-season and 24 % in the summer comparing with the reference point of 15°C. Also in Figure 4-16 the reduction in net present value can be seen clearly with increase in ambient temperature; 26 % in the mid-season and 50 % in the summer. In other words loss of power output and NPV occurs during periods when the temperature is above the 15°C standard ambient temperature.

4.5.2.2 Effect of Ambient Temperature on Fuel Consumption and COE

Figure 4-17 shows the impact of ambient temperature on fuel consumption. An increase in ambient temperature is coupled with decrease in fuel consumption at constant TET due the reduction that will occur in power output. This is will require a higher firing temperature to maintain the power output at the elevated ambient temperature. As would be expected, higher fuel consumption translates to higher operating cost as reflected in the COE, see Figure 4-17.

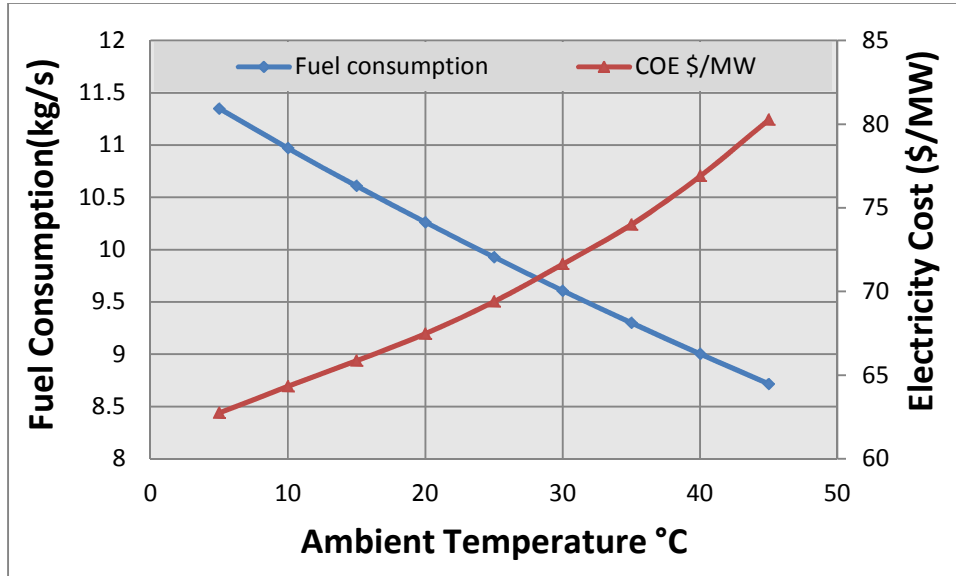


Figure 4-17: Effect of ambient temperature on fuel consumption and LCOE

4.5.2.3 Cost of Electricity at Different TETs

Running gas turbines at peak load for a prolonged period of time is not recommended by OEM as it drastically consumes the life of hot path components as it has been investigated in this thesis. Despite this fact, the high premium paid for the electricity dispatched at peak hours drives the power producers to investigate the feasibility of running their gas turbines at peak loads. However, a detailed knowledge of the impacts of peak operations on the units' maintenance costs becomes crucial so that power producers can compare the incremental revenues gained by dispatching at peaking hours with the additional maintenance costs. One novel aspect of this study is that it considers both fuel cost and maintenance costs in one platform so that an optimum decision making can be achieved.

4.5.2.4 Effect of TET on Fuel and Maintenance Costs

An interesting observation can be made from Figure 4-18 which clearly indicates the substantial increase in maintenance cost as the gas turbine is run beyond its rated TET. This is mainly due to the need for more frequent replacement of HPT due to the lower creep life resulted from running at higher firing temperature. It is also interesting to note the impact of higher firing temperature on the gas turbine thermal efficiency. Figure 4-18 clearly shows

that the thermal efficiency improves notably with higher firing temperature. This is reflected in lower fuel consumption and thus in reduced \$/MWh value.

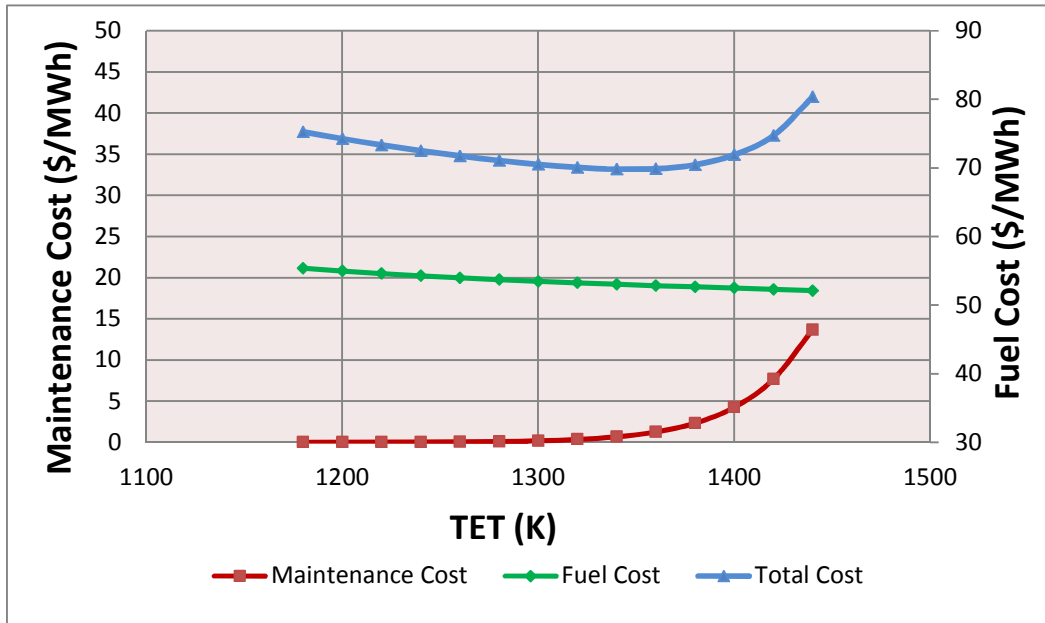


Figure 4-18: Effect of TET on fuel, maintenance, and total costs

4.5.2.5 Effect of Gas Price on Cost of Electricity

The dramatic increases in cost of electricity experienced in the past period have been attributed mainly to the increase in fuel cost price. This has clearly been demonstrated in figure 4-19. For example, an increase of gas price from 4 \$/GJ to 6 \$/GJ results in 37 increase in the cost of electricity.

The line rising intersecting electricity cost lines (marked in orange in **Figure 4-19**) is the line joining the points of minimum electricity cost at the various fuel prices considered. This line interestingly shows how the balance between fuel and maintenance costs changing causes the point of the minimum electricity cost to shift to higher TETs when higher fuel prices are considered. This can be attributed to the fact that at higher firing temperature, the impact of accelerated creep life consumption becomes a less dominant factor compared to the expected improvement in thermal efficiency, and thus resulting in an increase in the overall electricity cost. Such critical observation can only be made by incorporating dynamic and integrated models such as the one developed in this study.

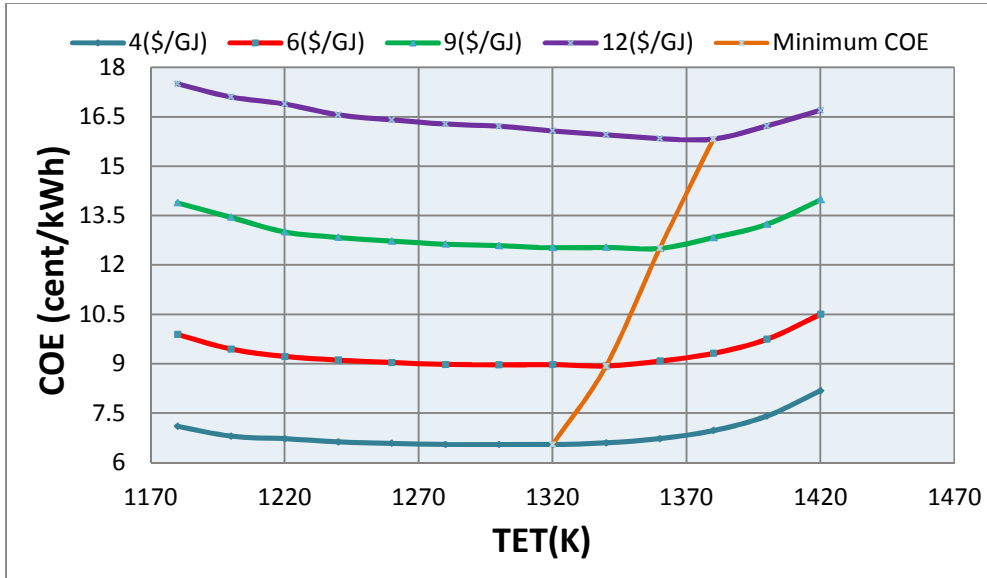


Figure 4-19: Cost of electricity at different gas prices

4.5.2.6 Influence of Variations of TET on Electricity Cost

Fuel cost and maintenance cost have traditionally be analysed separately and more weight has been typically given to fuel cost as it is believed to be the major operating cost for thermal power plants. This study has taken a step further and introduced a novel method of analysing the overall costs. This is clearly shown in Figure 4-20 which combines fuel cost and maintenance cost. Interestingly, Figure 4-20 indicates that the optimum COE does not coincide with the lowest TET as it would be expected. This is because although lower TET results in improved component life, it will also result in lower thermal efficiency which has a more pronounced impact on the overall electricity cost. In other word, the cost of electricity will increase as the TET is reduced below a certain optimum value due to reductions in thermal efficiency. The cost of electricity will also increase at high TETs due to reduced engine life and increased maintenance costs. This new method of analysing operating cost, which is pioneered in this study, is of utmost importance for power dispatcher to optimize their operation.

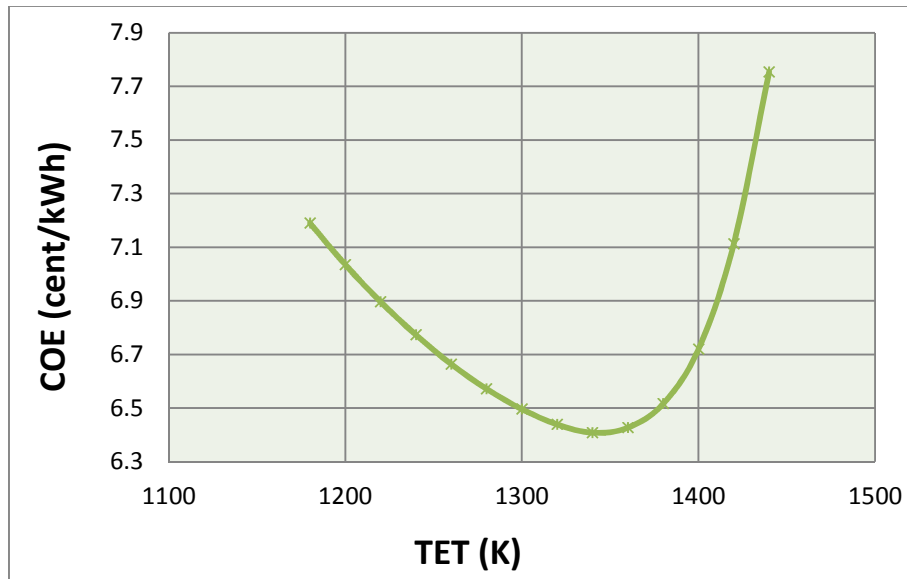


Figure 4-20: Cost of electricity at different TETs

4.5.2.7 Effect of Fuel Price and Discount Rate on NPV

The economics of plant operation have been quantified in terms of NPV, see Figure 4-21. The NPV technique normalises the value of investments in future years allowing one can see how the NPV varies for a given engine as a function of discount rate and fuel price. It must be noted that the discount rate is used as a measure of risk in finance. An increase in discount rate means a project with greater risk. The discount rate can be expected to change with geography from region to region depending on the varied risks that the operator takes on to produce the electricity.

The trend in Figure 4-21 shows that as discount rate increases, i.e. one is taking on more risk, the NPV value drops in an approximately inversely proportional relationship, as expected. It also shows that there is a drop in NPV for a reduction in gas price.

If one is to reduce the price of gas then it can be expected, of course, that there will be a decrease in NPV as revenues are reduced. What is interesting to see is that the reduction in gas price is not as imposing as is the change in discount rate, for example at the same gas price 4\$/GJ and change of discount rate from 5% to 15% the reduction in NPV will be 57.8%, whilst at a constant discount

rate of 5% a change in gas price from 4\$ /GJ to 9\$/GJ will give a reduction in NPV of only 25.9%.

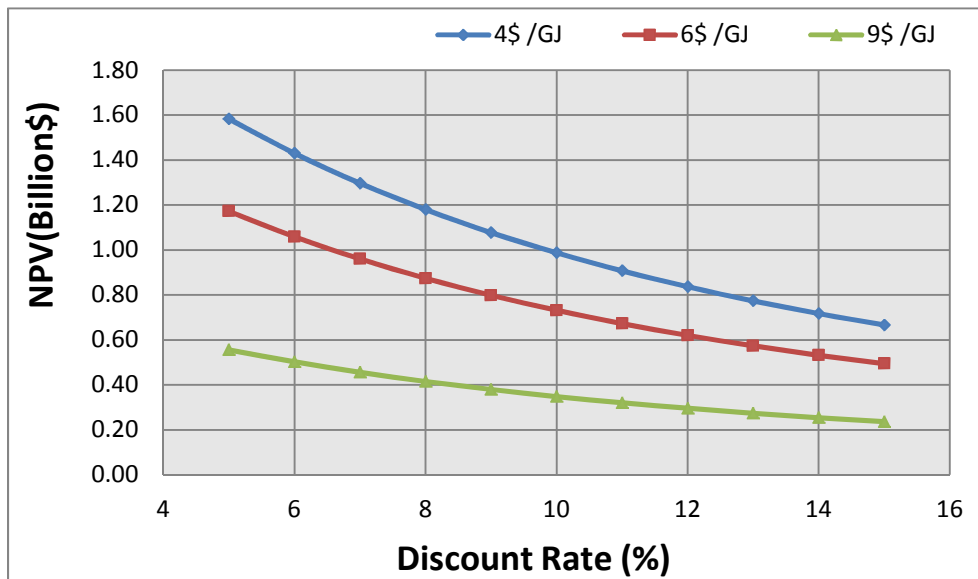


Figure 4-21: Change in NPV versus discount rate and fuel price

This is an important consideration when designing plant and selecting equipment because the value of the associated financial risk (the discount rate) appears to have a far greater effect on the projected profits than does the price of fuel gas used to run the plant. This will impact decisions on where the plant is located, and will also inform business decisions as to whether the operator should invest in a certain resource or project based on what an acceptable level of risk is. Certainly, for projects with higher associated risks, the operator will be looking for greater returns and this can be used as a bargaining chip when negotiating with the owner of the resource.

4.5.2.8 Effect of Discount Rate and Gas Price on NPV at Peak Load

Figure 4-22 presents the effect of gas price on discount rate and NPV when the power plant is operated at peak load. We see the NPV increases a bit faster than the base load, this is because of the increase in the amount of electricity that is produced and sold. However, the life of power plant will be affected. Although the NPV achieved during peak load operation is about twice for the base load, the life of the engine is reduced significantly. In this situation, optimum use of plant must consider whether to operate the power plant at peak

load to satisfy the demand, or to operate the plant at base load and look for another supply to meet the additional demand (for example building new power plant or buying from other providers).

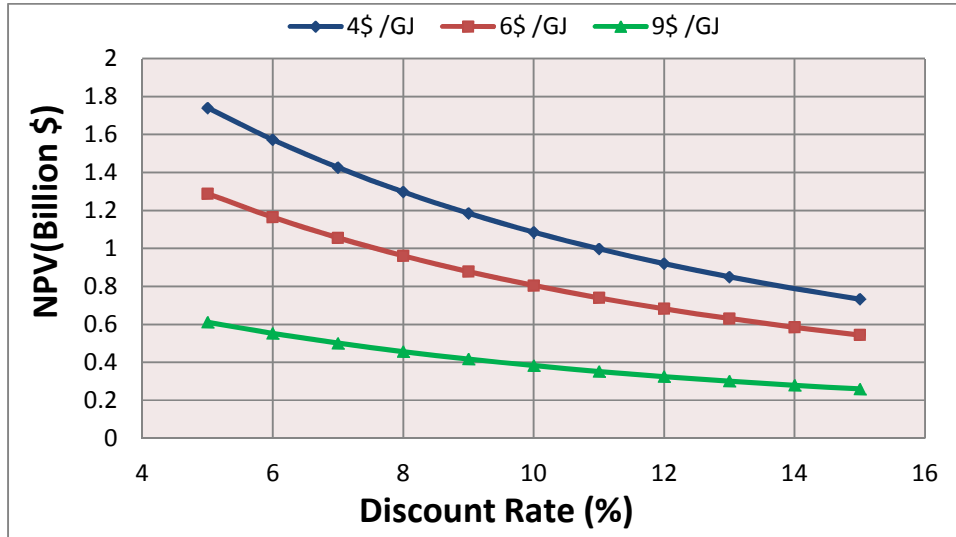


Figure 4-22: Change in NPV versus discount rate and fuel price at peak load

4.5.2.9 Effect of Gas Price on NPV and Electricity Price at Base and Peak Load

Figure 4-23 shows the relation between NPV and electricity price at different discount rates with same gas price for a power plant operating at base and peak loads. Comparison with the base load shows the cost of electricity rises although the NPV increases.

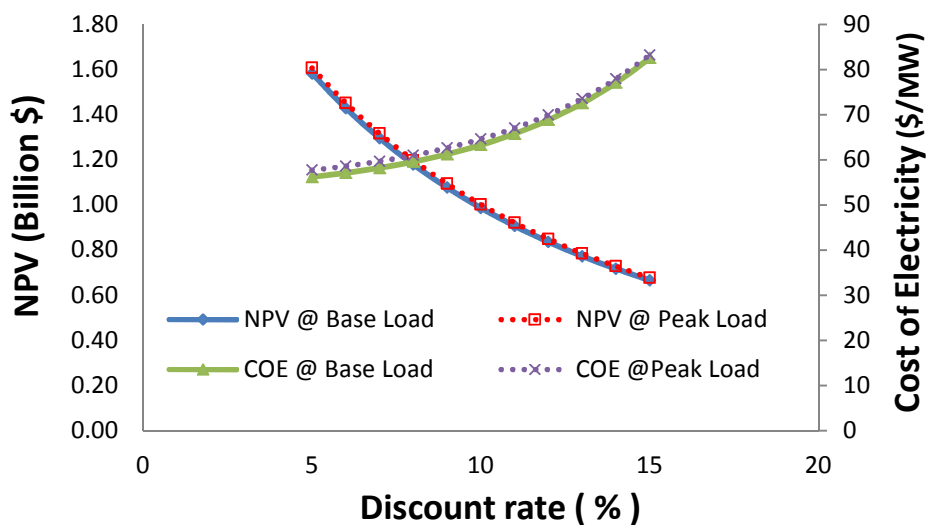


Figure 4-23: NPV Vs electricity price at peak load

The difference in electricity cost and NPV at base load with varying gas discount rate is not as high as when compared with the same situation at peak load. However this becomes a huge difference when the production is considered over the life of the project.

4.5.2.10 Influence of Emission Tax on NPV

Figure 4-24 assumes zero emission cost, that the NPV is limited to gas prices between 4 \$/GJ to 9 \$/GJ and the discount rates are between 5 % and 15 %. Under these conditions the NPV is lower when emission cost is added for the life span of the project. If the value of the NPV through the project life span with or without emission cost is positive then the project is profitable under the given conditions but is more profitable without the associated emission costs.

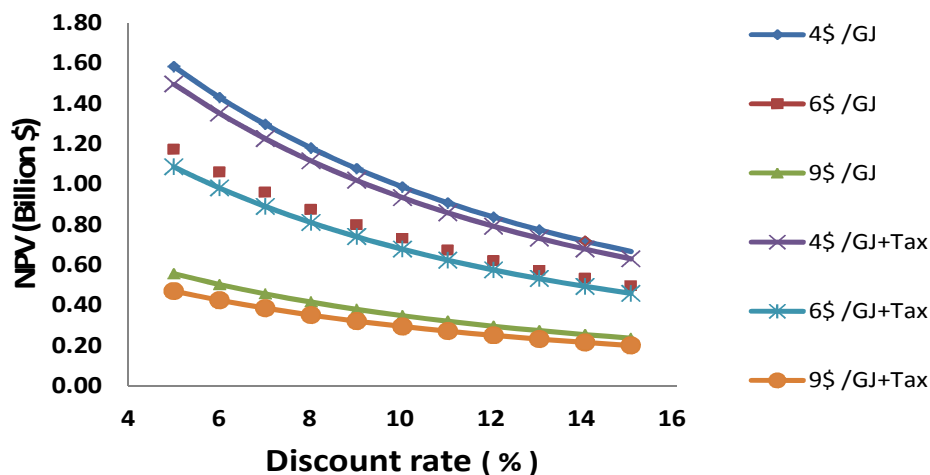


Figure 4-24: Change in NPV versus discount rate and fuel price with and without emission tax

4.5.2.11 Effect of Turbine Entry Temperature on CO₂ Emission

Figure 4-25 shows the effect of TET on total CO₂ emission cost. For any particular amount of TET, the emission cost increases with increase in TET. For a throughput of 1000 K the emission cost is about \$2 million per annum, while for 1400 K the emission cost sharply increases to just over \$6 million per annum.

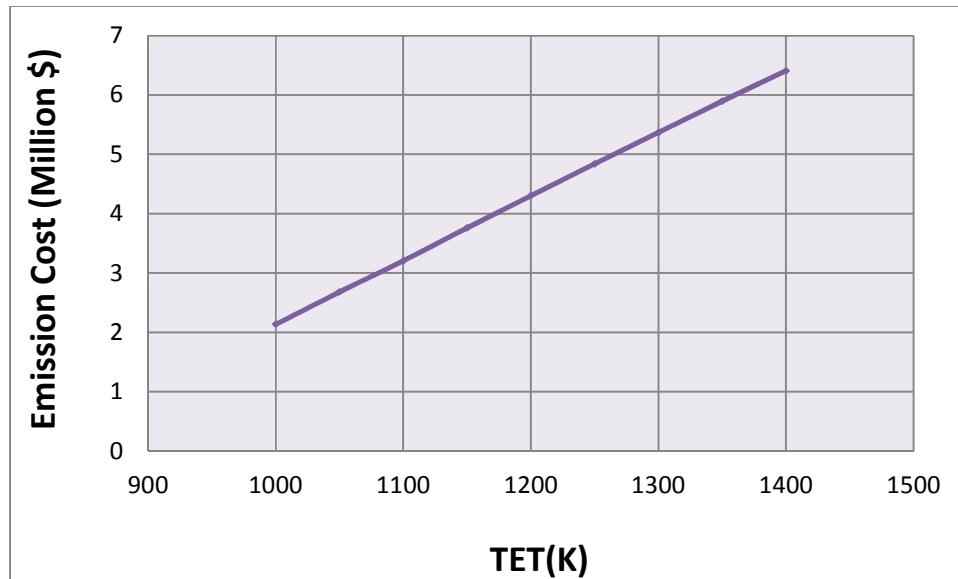


Figure 4-25: Emission Cost Against TET

4.5.2.12 Optimising Plant Life

Figure 4-26 shows how the designed plant life can affect the NPV. This can be used to find the optimum plant life for a given discount rate. Note that the range of plant life is greater at low discount rates and as the plant life is increased there is a smaller difference range of NPV values. This may be due to the fact that the plant has entered a phase where the failure rate has picked up and thus it is worth less to keep maintaining the plant rather than revamping it.

Figure 4-26 shows how the designed plant life can affect the NPV. This can be used to find the optimum plant life given a discount rate. Note that the plant life is more varied for low discount rates and as the plant life is increased there is a lesser difference between NPV values. This may be due to the fact that the plant has entered a phase where the failure rate has picked up and thus its worth lesser to keep maintaining as opposed to revamping the plant and that the maintenance aspects are coming to a normalised average value which is similar regardless the discount rate.

According to Figure 4-26, at lower discount rates there is significant worth in selecting the right plant design life, for example, at a discount rate of 5 %, there is substantial differences in the NPV values for the 20, 25 and 30 year design plant lives and it is worth designing for a longer plant life. However, with

increasing discount rate the differences in NPV decrease and the gain in return for longer design life seems to be diminish.

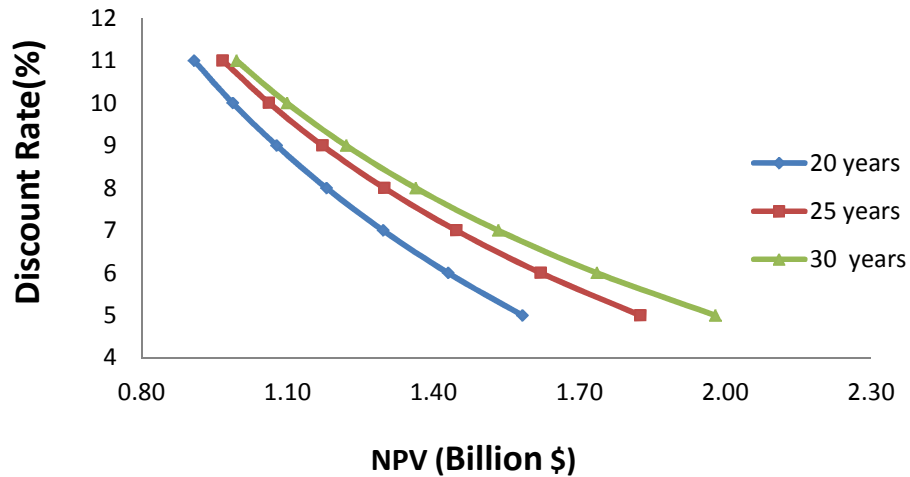


Figure 4-26: NPV vs discount rate for three projected plant lives

4.5.2.13 Effect of Compressor Degradation on LCOE and NPV

Degradation in engine components, particularly the compressor, affects engine power output. Degradation in engine compressor, implemented here as equal levels of loss in compressor efficiency and flow capacity, results in lower power output, as shown in Figure 4-27.

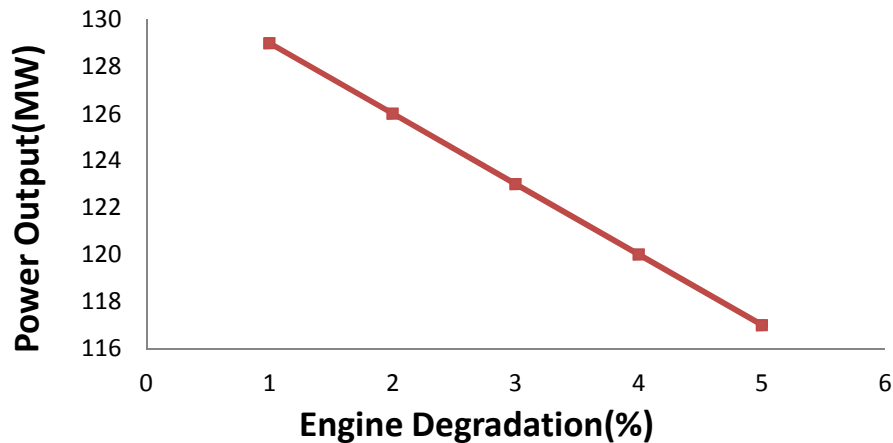


Figure 4-27: Engine degradation vs power output

4.5.2.14 Effect of Engine Degradation on NPV and Electricity Price at Peak Load

As mentioned earlier, as engine degradation percentage increases power output goes down. This means more fuel is needed for the same power output which leads to increased operating costs. Figure 4-28 gives us an idea about

this. The same figure shows that the COE increases as engine degradation rises.

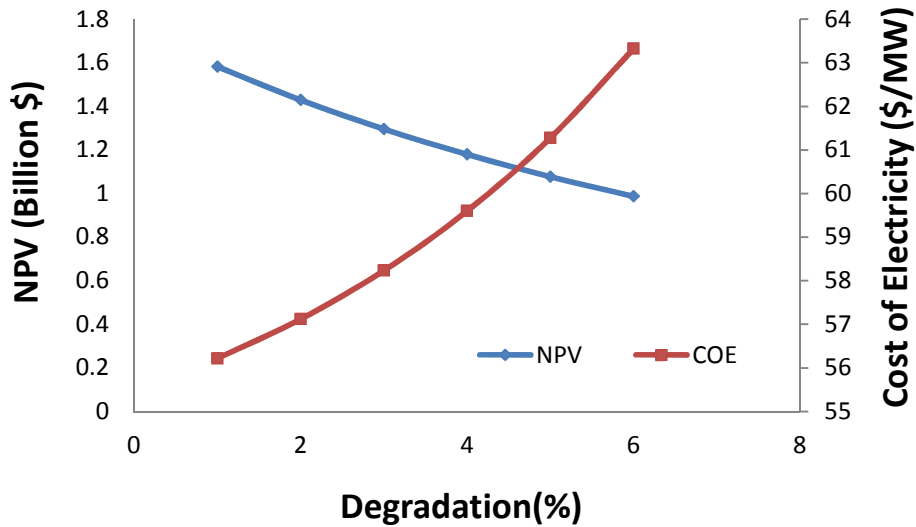


Figure 4-28: Cost of electricity and NPV at different engine degradation levels

4.6 Chapter Conclusion

A 165MW single shaft Industrial gas turbine has been simulated in this part as a model to investigate its behaviour at different operating conditions as shown in figures 4-5 to 4-28 and tables 4-1 and 4-2. For the engine design point performance some parameters have been assumed, some given and some calibrated as it is shown in table 4-1. The simulation showed that the key parameters for the ambient and the operating parameters that will effect on the performance and the efficiency of the gas turbine power plant are the ambient temperature and the power setting (TET).

Altitude has also a significant effect on the total performance in case if the power is in the stage of the location selection. For the ambient temperature as it is clear in this investigation, gas turbine likes cold wither and the choice is to reduce the temperature in hot times by using inlet cooling system which is will be a matter of economic to compare the benefit with the cost.

Figures 4-7 and 4-8 illustrated the effect of turbine entry temperature on the power and efficiency of the gas turbine and each engine has its own sensitivity to TET change. in most power plants which is include more than one engine,

the challenge is, when and how to operate the different units according to the power demand (TET) in order to minimise the Electricity cost from an operating point of view which is will be with the other aspects the main challenge for this study. It is has been shown that degradation due to compressor fouling plays a significant role in reducing the performance of the engine which will impact life cycle cost as will be discussed in detail later. Many other engines have been simulated by the same way using Turbomatch to establishing a library for wide type of engines and cycles.

Also this chapter has presented the effects of change in design parameters and operating conditions on the HP turbine blade creep life. Clean and deteriorated engines were considered. In addition, the section highlights how different operating conditions and design parameters can influence the blade's creep life.

A thermodynamic performance model of a stationary GT engine was developed to simulate both design and OFD conditions. The first stage turbine blade was sized in order to facilitate the estimation of creep life. Then the stress and temperature along the span of the blade were calculated to obtain the blade's remaining creep life. It was found that increasing the TET decreases the blade creep life along the span of the blade.

Blade metal temperature and ambient temperature have a strong influence on blade creep life, and these two factors will mainly determine that section of the blade with the lowest creep life. Emphasis should be given to the level of temperature and stress, and the locations of maxima along the blade, to better identify the location of minimum creep life. A deeper understanding of the relationship between operating conditions and design parameters will allow designers and users to obtain better trade-offs between different design options and maintenance decisions.

This analysis has strong economic implications because an understanding of creep life can lead to specialised maintenance in order to prolong the life of the hot gas path components. Depending on the way the engine is operated the maintenance costs will vary and the time before major overhaul will be affected

too. Estimates of creep life can be used to avoid unplanned shut downs and loss of production

Next, the chapter has presented the effects of operating conditions on the cost of electricity. In addition, the study has highlighted how different operating conditions and fuel price can influence the cost of electricity.

A thermodynamic performance model of a stationary GT engine was developed to simulate both design and OFD conditions. The discount rate, fuel price and the life of the power plant were estimated to facilitate the estimation of the cost of electricity. Moreover, lifing and emission model have developed to feed the economic model to better facilitate the cost of electricity.

The results show that increasing the discount rate and/or gas price increased the cost of electricity. Although both are out of the control of investors, emphasis should be placed on the level of the discount rate and gas price.

The effect of ambient temperature on thermal efficiency and fuel consumption has also been investigated. This study has also helped to establish the basis of a methodology for analysis of GTs used as plant for power generation, in particular it considers emissions.

Although lower TET results in improved component life, it will also result in lower thermal efficiency which has a more pronounce impact on the overall cost of electricity. In other words, the cost of electricity will increase at low TETs due to reduction in thermal efficiency, but the cost of electricity will increase at high TETs due to reduced engine life and increased maintenance costs.

The greater aim is to integrate these findings into a system which will act as optimiser for TERA based economic analysis. The study will emphasise assessment of performance of, and emissions from GT engines in the development of a suitable TERA framework which could be used for range of assessments including economic assessment.

A significant proportion of this chapter has been accepted for publication as:

Evaluation of Electricity Cost in a Growing Market in Proc. ASME Turbo Expo 2013: Power for Land, Sea and Air, Texas, June 03-07, 2013.

Also, the creep life model and the economic model with the results obtained in this study have been published in ASME. The title of the lifing paper is:

A method to evaluate the Impact of power demand on HPT blade creep life, GT2011-45092, Proceeding of ASME Turbo Expo 2011: Power for Land, Sea and Air.

The second one is 'A Method to Evaluate the Emissions of Gas Turbine for Power Generation GT2012-69491'' and ''Economic Evaluation of Industrial Gas Turbines for Electrical Power Generation GT2012-69495'' Proceedings of ASME Turbo Expo 2012: Power for Land, Sea and Air GT2012 Copenhagen, June 11-15, 2012)

The third one is a method to evaluate the Impact of power demand on HPT blade creep life GT2011-4509 proceedings of ASME Turbo Expo 2011: Power for Land, Sea and Air GT2011 June 06-10, 2011, Vancouver, Canada. [157-159]

The fourth one is Economic Optimisation of Industrial Gas Turbines for Electrical Power Generation: A Creep and Performance Based Study, Power2011-55283, Proceeding of ASME power 2011.

Chapter five

5 Genetic Algorithm

5.1 Introduction

In nature, biological structures that are more successful in grappling with their environment, survive more successfully. Biologists interpret the structures they observe in nature as the consequence of Darwinian natural selection operating in an environment. John Holland's pioneering book *Adaptation in Natural and Artificial Systems* (1975) provided a general framework for viewing all adaptive systems (whether natural or artificial) and then showed how the evolution process can be applied to artificial systems. Any problem in adaptation can generally be formulated in genetic terms and can often be solved by what is now commonly called a "Genetic Algorithm" (GA).

This chapter contains a description of the general features of Genetic Algorithms and of the particular implementation used in this study. The effects of the variation of the control parameters on the performance of the GA as an optimisation tool is presented and the Chapter concludes with a reference to the future perspectives of the method.

5.2 Genetic Algorithms

Genetic algorithms are search algorithms based on the mechanics of natural selection and natural genetics as shown in Figure 5-1. They transform a population of individual objects, each with an associated value of fitness, into a new generation of the population, using the Darwinian principle of survival and reproduction of the fittest and analogs of naturally occurring genetic operations such as crossover and mutation. When employed as part of an optimization routine, each possible point in the search space of a problem is encoded, using a problem specific representation scheme, as a fixed length character string (chromosomes) or other mathematical object, [66].

The genetic algorithm then attempts to find the best, or at least a very good solution to the problem, by genetically breeding the population of individuals over a number of generations. There are four major preparatory steps required to use the genetic algorithm on fixed-length strings to solve a problem. These consist of determining:

- The representation scheme
- The fitness measure
- The parameters and variables for controlling the algorithm
- A way of designating the result and a criterion for terminating a run.

In the conventional genetic algorithm, the individuals in the population are usually fixed length character strings. Specification of the representation scheme in the conventional genetic algorithm starts with a determination of the string length. The most important part of the representation scheme is the mapping that expresses each possible point in the search space of the problem. A precondition for solving a problem with the genetic algorithm is that the representation scheme satisfies the sufficiency requirement in the sense that is capable of expressing a solution to the problem.

The evolutionary process is then driven by the fitness measure. The fitness measure assigns a fitness value to each character string that encounters in the population. The fitness measure should satisfy the requirement of being fully defined in the sense that it is capable of evaluating any character string that it encounters in any generation of the population. The nature of the fitness measure varies with the problem.

The primary parameters for controlling the genetic algorithm are the population size and the number of generations to be run. The population size can consist of twenty, forty, hundred or more individuals. In addition there can be hundreds, thousands, or more generations in a run of the genetic algorithm.

Each run of the genetic algorithm requires specification of some termination criterion for deciding when to terminate the run and a method of result designation. The termination criterion for a run of the genetic algorithm usually consists of completing a specified maximum number of generations to be run. The present code includes a “restart” feature, as described below. Thus, if the

search has not found an optimum within the specified maximum number of generations, the process can be restarted without any loss of information.

There are three steps required to executing the genetic algorithm operating on fixed-length character strings:

- 1- Randomly create an initial population of individuals with fixed length character strings
- 2- Iteratively perform the following subsets on the population of strings until the termination criterion has been satisfied:
 - a- Assign a fitness value to each individual in the population using the fitness measure.
 - b- Create a new population of strings by applying the following three genetic operations. The genetic operations are applied to individual strings in the population selected with a probability based on fitness.
 - c- Reproduce an existing individual string by copying it into the new population.
 - d- Create two new strings from two existing strings by genetically recombining substrings using the crossover operation at a randomly chosen crossover point.
 - e- Create a new string from an existing string by randomly mutating the character at one randomly chosen position in the string.
- 3- Designate the string that is identified by the method of result designation (e.g., the best-so-far individual) as the result of the genetic algorithm for the run. This result may represent a solution or an approximate solution to the problem.

There are a number of characteristics that an optimization scheme should possess in order for it to be an “ideal” search technique for use with multi-dimensional engine modelling, for example.

In particular, a scheme should be able to handle:

- Multi-modal surfaces (i.e., many local extrema with only one global maximum or minimum)

- Ill-behaved surfaces (i.e., discontinuous or noisy)
- High-dimensionality and high parameter resolution

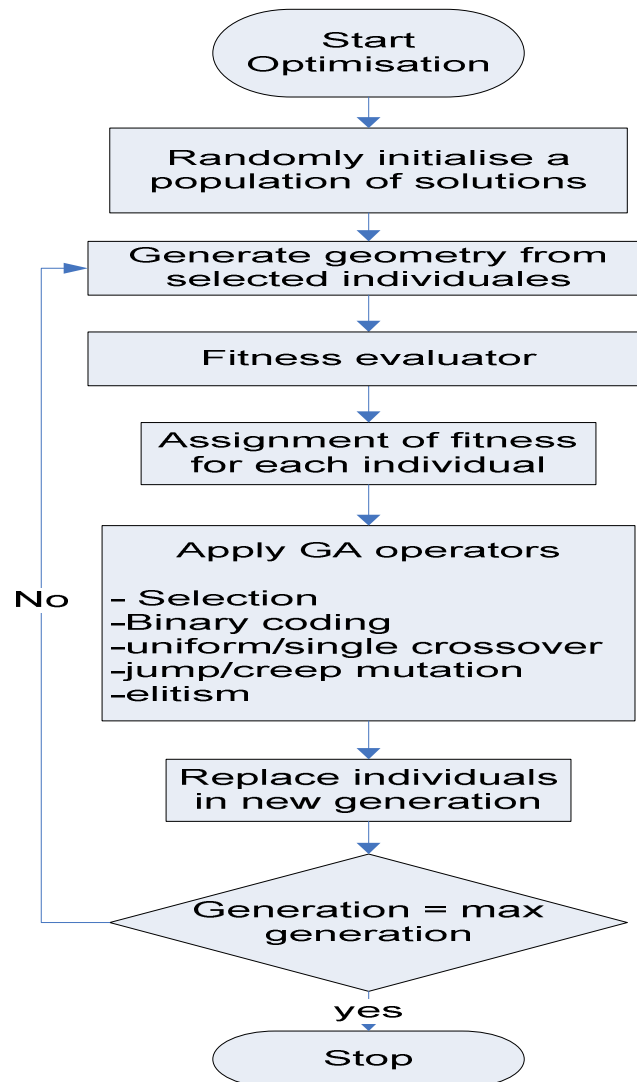


Figure 5-1 : Genetic algorithm flow chart

In addition, a few questions pertaining specifically to genetic algorithm search techniques must be addressed, including:

- How does the initial (random) population affect convergence?
- How many individuals should be included in a population?
- How many generations until convergence?

These questions have been addressed in the work of Senecal. P [134] . In this work it was shown that genetic algorithms are an excellent compromise among globality, flexibility and convergence. In addition, genetic algorithms have been successfully applied to applications ranging from design of pump impellers, [161], to analysis and multidisciplinary optimisation of internal coolant networks in turbine blades, [101] .

5.3 The Genetic Algorithms Method

This section presents details on the workings of Genetic Algorithms when applied to the solution of optimization problems. The features of Genetic Algorithm operators, binary coding, function evaluation, selection and crossover operators and elitism functions are explained and illustrated.

5.3.1 Genetic Algorithm Operators

In this theses Carroll's work [43] is the basis for the descriptions used for the GA operators and their impact on optimisation efficiency. For this research the initial GA code was adapted as shown in Figure 5-1, and several of alternatives were investigated to determine those that showed the most promise. Both a binary coding scheme and floating point were considered; different selection schemes and different types of crossover and mutation operators were also studied. A brief outline of the genetic operators is presented below.

5.3.1.1 Binary Coding

Binary string "chromosomes" are very much the popular choice in GA coding to represent a set of possible solutions [66]. This is the choice made here: a binary code is used to describe the GA and the operators, however to assess fitness for parenthood/procreation the actual values of the parameters are used.

The numbers of bits in the "chromosomes" will determine the precision with which the precision with which the design parameters are determined. If the number of bits is λ_i , the precision (π) of the parameter X_i is given by [74] :

$$\pi = \frac{X_{i.max} - X_{i.min}}{2^{\lambda_i} - 1} \quad 5-1$$

If m possible values of the parameter λ_i are required, its binary representation will need:

$$\lambda_i = \frac{\ln(m)}{\ln(2)} \text{ bits} \quad 5-2$$

For example the binary number 10001 in binary form is

$$1.2^4 + 0.2^3 + 0.2^2 + 0.2^1 + 1.2^0 = 16 + 0 + 0 + 0 + 1 = 17$$

5.3.1.2 Function Evaluation

Having a suitable fitness function becomes increasingly important in obtaining an optimal solution the more output variable the problem contains. Each separate “chromosome” is assessed by the fitness function and given a “figure of merit” The larger the value of this figure the closer the “chromosome” is to the optimum solution and the greater the likelihood it will be allowed to participate in reproduction, see below. Of course the fitness function and the final solution should correspond as closely as possible to give a truly optimal solution, but in addition the fitness function should occupy as little computer time as possible..

5.3.1.3 Selection Operator (Or Reproduction)

The genetic operation of reproduction is based on the Darwinian principle of reproduction and survival of the fittest. A reproduction operator combines the relative fitness of a generation's chromosomes with some randomness in order to determine parents of the following generation. The so-called “roulette wheel strategy” is one technique that is often used for reproduction as shown in Figure 5-2. This method calculates the ratio $f_i / \sum_i f_i$ for each chromosome i , which is considered its probability of survival into the next generation. As explained by Ansari and Hou [17], this approach gives strings with higher fitness values f_i a greater probability of survival. In addition, since the number of strings in a population is held constant over time, the reproduction operator will generate a new population of the same size. This implies that chromosomes with higher fitness values will eventually dominate the population.

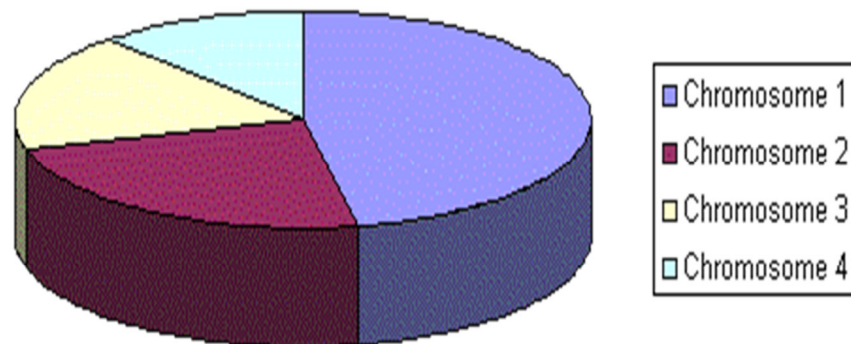


Figure 5-2: Selection process using roulette wheel [93]

The basic implementation of a roulette wheel selection assigns each string a “slot” on a wheel, with the slot size proportional to the fitness value of the string. To select a chromosome for reproduction, the roulette wheel is “spun”, and the string corresponding to the slot that the wheel stops on is chosen.

In an alternative reproduction strategy, the so-called “tournament selection,” randomly selected pairs of strings “fight” to become parents in the mating pool through their fitness function value[66] . It was found by Goldberg and Deb [65] that tournament selection is generally an improved selection technique compared to the roulette wheel selection.

Tournament selection can be summarized in the following way:

1. The present generation is first “mixed up” such that the order of individuals is completely random.
2. The fitness of individual 1 is compared with the fitness of individual 2. The individual with the higher fitness is chosen as “parent 1.”
3. The fitness of individual 3 is compared with the fitness of individual 4. The individual with the higher fitness is chosen as “parent 2.”
4. Parents 1 and 2 are used in the crossover and mutation operations described below.

The above process is repeated until the desired number of children is produced.

5.3.2 Crossover Operator

Human reproduction is biological crossover. Crossover in GAs begins with Parent A and parent B chosen by, say, Tournament selection. These two

parents will produce two children who are a part of the next generation of possible solutions in the search space. These will be subject to selection and testing in their turn. Each child will contain genetic material from both parents which may result in fitter individual “chromosomes” (better solutions). Listed below are three ways of performing crossover:

5.3.2.1 Single Point Crossover

In each “chromosome” the same single point is identified as the crossover point. In Figure 5-3 this is the point in each “chromosome” where the colour changes. The offspring takes from parent A, the binary string that stretches from the beginning of the “chromosome” to the crossover point, and the remainder of the offspring is copied from parent B, see Figure 5-3.

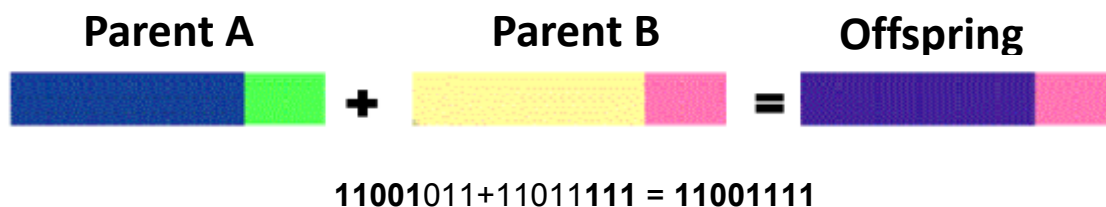


Figure 5-3: Single point crossover

5.3.2.2 Two Points Crossover

This is directly analogous to single point crossover except two points are set, see Figure 5-4. From parent A, the offspring takes the binary string stretching from the start of the “chromosome” to the first crossover point. From parent B, the offspring receives that part of the “chromosome” between the first and second crossover points. The remainder of the offspring’s “chromosome” is copied from parent A, see Figure 5-4.

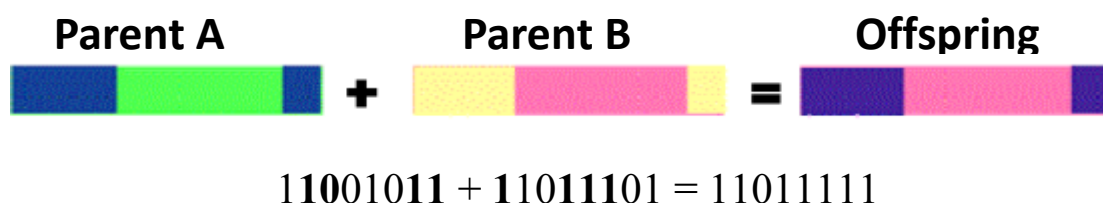


Figure 5-4: Two point crossover

5.3.2.3 Uniform Crossover

Binary strings of random length are copied from parent A and parent B and combined in order in the offspring, see Figure 5-5.

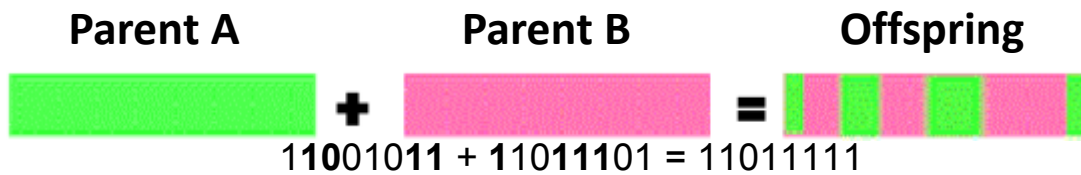


Figure 5-5: Uniform point crossover

5.3.3 Mutation Operator

Unfortunately crossover has a major limitation it can home in on a local maximum or minimum, which is thought of as a population losing genetic diversity. Mutation is a mechanism commonly used to maintain this diversity and prevent a too early loss of important aspects [30]. Mutation has to balance two contradictory tasks, to maintain diversity but not to hinder the search for the optimum solution. It does this by randomly changing the binary code in a “chromosome”, occasionally and randomly changing a 0 into 1 and vice versa, this process has to be done with very low probability because otherwise the GA would be reduced to a random search. Figure 5-6 demonstrates one such low probability even. The initial string is 10111001 position 3 is chosen for mutation. The new string is 10011001.

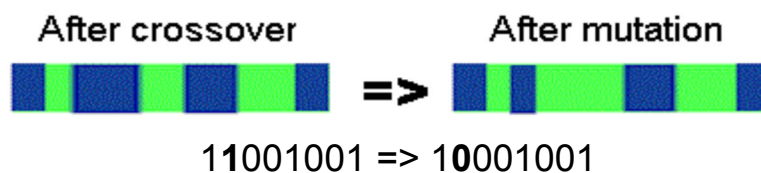


Figure 5-6: Mutation operators

5.3.4 Elitism Operator

If the GA selection process were truly random then crossover and mutation could reduce the fitness of the best “chromosomes”. Elitism is the process of preferentially copying the best chromosome(s) unchanged into the next generation. It has been found that elitism significantly speeds up the performance of GAs and protects good solutions once found [93].

5.3.5 Constraint Handling

Using GAs to solve constrained optimization problems can be difficult because of the presence of the constraints. Penalty functions are now commonly used method of dealing with constraints. More details are given in chapter three.

5.3.6 Areas Applications of Genetic Algorithm

Today, there are many applications in science, economy, and research and development [40] that can be tackled with genetic algorithms. Some example areas of application of genetic algorithms are [146]:

- Scheduling
- Chemistry, Chemical Engineering
- Medicine
- Data Mining and Data Analysis
- Geometry and Physics
- Economics and Finance
- Networking and Communication
- Electrical Engineering and Circuit Design
- Image Processing
- Combinatorial Optimization

5.3.7 Applications of Genetic Algorithms to Turbo-Machinery

GAs are being widely applied in such fields as data mining, economics, engineering, image processing, medicine, networking and communications, science, etc., [39; 40][146]. However, this section concentrates on the applications of GAs to turbo-machinery even though there have been only a small number of relevant publications

Oyama and Liou [115; 116], attempted to redesign a four stage compressor using a a multi-objective EA. The objective function attempted to maximise total pressure ratio and overall adiabatic efficiency. The design parameters were taken to be the total pressure, the flow angles at the stator trailing edges and solidities at the stator and rotor trailing edges. Using an SGI work station it took four hours to number crunch a solution which outperformed the original with a

theoretical 1% improvement in efficiency while maintaining the same pressure ratio.

Oksuz et al., [117] and Giannakoglou [62] have presented 2-D studies on the optimisation of turbomachinery which were intended to be exploited in the design of more efficient algorithms for 3-D problems. Oksuz et al., [117] used a GA linked with the very fast Euler/boundary-layer coupled algorithm of Giles and Drela [63] within an automated optimisation loop to optimise the aerodynamic performance of a turbine cascade. The MISES software package carried out the fitness tests of the population used in the optimisation process and investigated the effects of various sizes of population, crossover procedures, etc., on the performance of the GA. The authors claim significant improvements were achieved.

Wahba [161] used a GA with fixed population number to optimise viscous flows governed by the Navier-Stokes equations [88] to produce a new design of the impeller blade profiles of a centrifugal pump. Linking CFD and a GA produced a general design tool for shape optimisation. The interaction of pump blade curvature and flow separation was also investigated and it was found that the GA was able to produce good results with a minimum of user expertise. 200 generations were used but the major gains had been achieved by about the 100th generation. The vast majority of the computational time (days) required to produce a solution was due to the Navier-Stokes computations. The GA code took less than 1 second per generation.

Osama Lotfi [93] has presented a computational method for optimising the design of an industrial axial fan using a GA. His method started with a Navier-Stokes flow solver (which included the necessary grid generator to produce the appropriate computational meshes), he then developed specific interfaces to link with a FORTRAN GA optimisation code, all within an automated design loop.

Fujita et al., [86] have applied a simple GA to optimise the planning of energy plant configurations, number of machines, type of machines, etc., to satisfy the

specified energy demand, to minimise the capital cost of plant facilities and on-going energy cost.

Knight et al., [129] developed an optimisation tool for economic optimisation of GT power generation based on a GA, case studies reported in their paper suggest significant financial benefits are achievable. However, the economic gains depend on the specific application: the plant configuration, the economic circumstances chosen for plant operation, and accuracy of the simulations used for modelling e.g. GT operation.

To test the efficacy of the optimisation, the GA was applied to a system simple enough for the optimum configuration to be found by inspection. Comparison of results confirmed a good performance of the method [38] .

5.4 GA Code Employed in the Study

The Genetic Algorithm code used in the current study is the secure GA171, a Fortran version of a genetic algorithm driver, developed by David Carroll from CU Aerospace [30; 31]. An extensive manual and associated set of example applications make this code user friendly. The program includes tools for using genetic algorithms to carry out optimisation in FORTRAN code using any genetic operators. The GA171 code initializes a random sample of individuals with different parameters to be optimized using the genetic algorithm approach, i.e. evolution via survival of the fittest. The selection scheme used is tournament selection with a shuffling technique for choosing random pairs for mating. The routine includes binary coding for the individuals, jump mutation, creep mutation, and the option for single-point or uniform crossover. Niching (sharing) and an option for the number of children per pair of parents is included. More recently, an option for the use of a micro-GA has been added.

In order to better understand the GA operation technique, and to investigate the effects of the variation of the solution parameters, a number of trials were run where different population sizes, crossover and mutation types were tried. The effect of adding elitism and niching to the GA were also tested

5.4.1 Test Function

One of the challenging aspects of using genetic algorithm is to choose the appropriate configuration parameter setting. Discussion of GA theory provides surprisingly little guidance for proper selection of these settings. In order to better understand the GA operation technique, and to investigate the effects of the variation of the solution parameters, a number of trials were run where different population sizes, crossover and mutation types were tried. The effect of adding elitism and niching to the GA were also tested.

Multimodal functions are functions which have multiple optimum solutions, i.e. local optimal solutions. Multimodality in a search and optimisation problem can therefore be the cause of difficulties for an optimisation algorithm not capable of searching for global solutions as it risks getting “stuck” on a local optimum. This is because in these problems there exist many attractors in which an algorithm can become directed to. The test employed in the investigation of the different GA parameters described above makes therefore use of a multimodal function (equation 5-3) which will be used as an objective function to test the efficiency of the GA code and to study the effects of different GAs techniques.

$$f(x) = (\sin(5.1 * \pi * x + 0.5))^{nvalley} * \exp(-4 * \log(2) * \frac{(x - 0.0667)^2}{0.64}) \quad 5-3$$

Equation 51 is an N-dimensional version of the multimodal function with decreasing peaks used by Goldberg and Richardson (1987). The above function is defined on [0, 1] and consists of five unequally spaced peaks of non uniform height. Maxima are located at approximate values of 0.080, 0.247, 0.451, 0.681, and 0.934. Maxima are of approximate height 1.000, 0.948, 0.770, 0.503 and 0.250 respectively. It is deemed to be a reasonably tough problem for the GA, especially for higher dimensions and larger values of n valley. It is also illustrative of the non-linear type of problems faced in aerodynamic optimization situations. A plot of the function is shown in Figure 5-7.

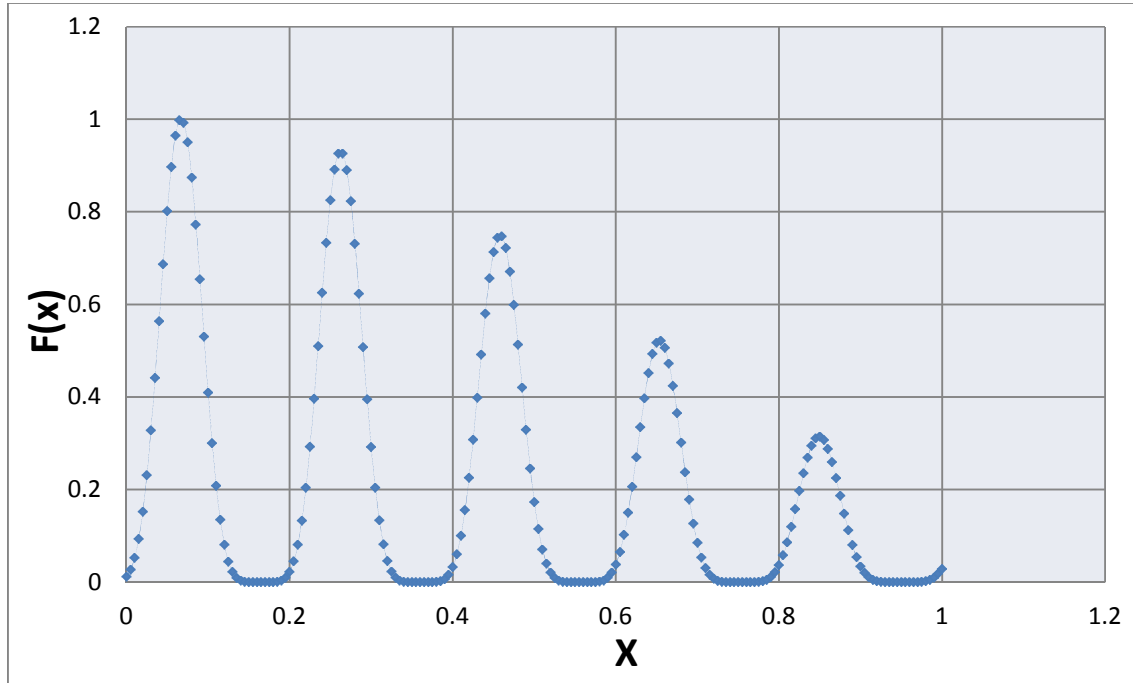


Figure 5-7: The multimodal function

5.4.2 Effect of Population Size

In general it is reasonable to expect that larger populations should find the optimal individual for a particular environment in fewer generations than when employing smaller populations. At the same time, larger populations take a longer amount of time to compute their progress. For quick function evaluations which take considerably less than a CPU second, it may be acceptable to run large populations. However, for function evaluations which are represented by running a CFD code (which may take 3-6 CPU hours for a single calculation), total run time for many generations can be between a week and more than a month depending on the population size and number of processors used (parallel GA) .

The effect of population size versus the number of generations required to locate the global maximum, or the same is to say time taken by the optimisation routine to achieve its task, was investigated through the evaluation of five population sizes corresponding to 20, 50, 100, 150 and 200 individuals. As expected, Figure 5-8 shows that the larger the population size (*npop*) parameter, the fewer the number of generations are required to find the optimal

solution. A more important question is how many function evaluations (calls to Multimodal function) were made to find the optimal power for the different populations. To find the optimal solution there were 1600 function evaluations made for $n_{pop}=200$, 1200 function evaluations for $n_{pop}=100$, and only 600 function evaluations for $n_{pop}=50$. Seen from this perspective therefore the $n_{pop}=50$ case had the better performance in terms of computational cost.

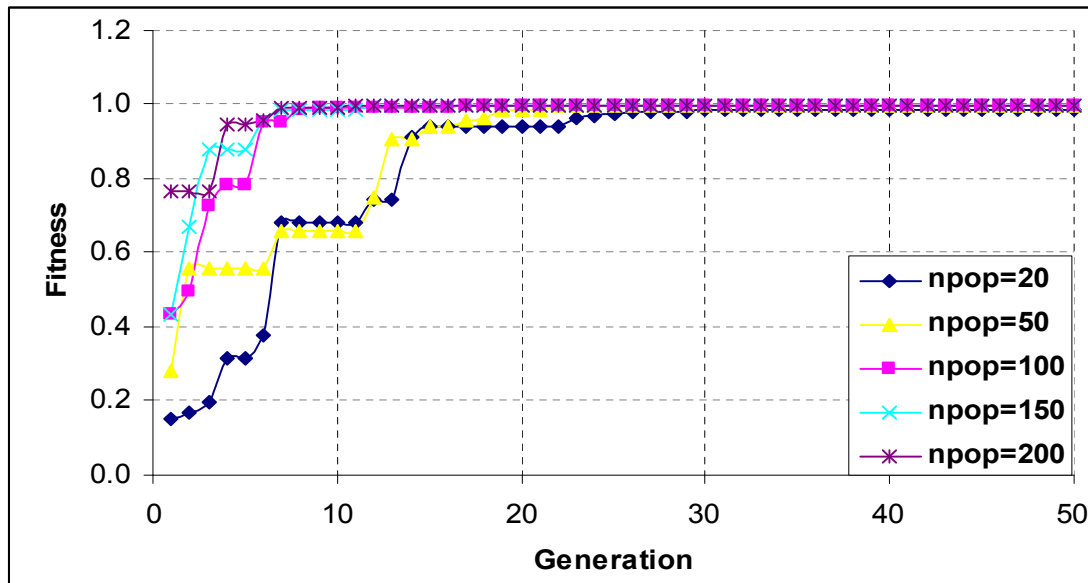


Figure 5-8: GA performance versus population size

5.4.3 Effect of Crossover

The effect of crossover was also investigated employing the multimodal function described above. Carroll [30], as mentioned above, found that uniform crossover tended to preserve more individuals than single-point crossover. For that reason, uniform crossover was the preferred choice in Carroll's work. However a question requiring answer is whether or not there is a significant difference between the two crossover choices for the present application. In order to investigate this effect runs were carried out using single-point and uniform crossovers. The plot of Figure 5-9, depicting GA performance versus crossover and niching scheme, shows that the uniform crossover case ($i_{uniform}=1$, $i_{niche}=1$) approaches the optimal solution more rapidly than the single-point crossover case ($i_{uniform}=0$, $i_{niche}=1$). Since the uniform crossover

case initially reach the optimal solution more rapidly, there is a preference for uniform over single-point crossover.

5.4.4 Effect of Uniform Sharing

One of the important attributes of uniform crossover and sharing (niching) is that both of these GA techniques tend to preserve variety in the genetic pool. Figure 5-9 shows that when both uniform crossover and niching are turned off, the GA performance slows down. In fact, without uniform sharing ($i_{\text{uniform}}=0$, $i_{\text{niche}}=0$), the optimum solution was not found until generation 29 (whereas with uniform sharing the optimum solution was found at generation 13). Thus, it appears that uniform crossover and niching supplement each other slightly and it is important to have at least one of these techniques in the GA for better performance.

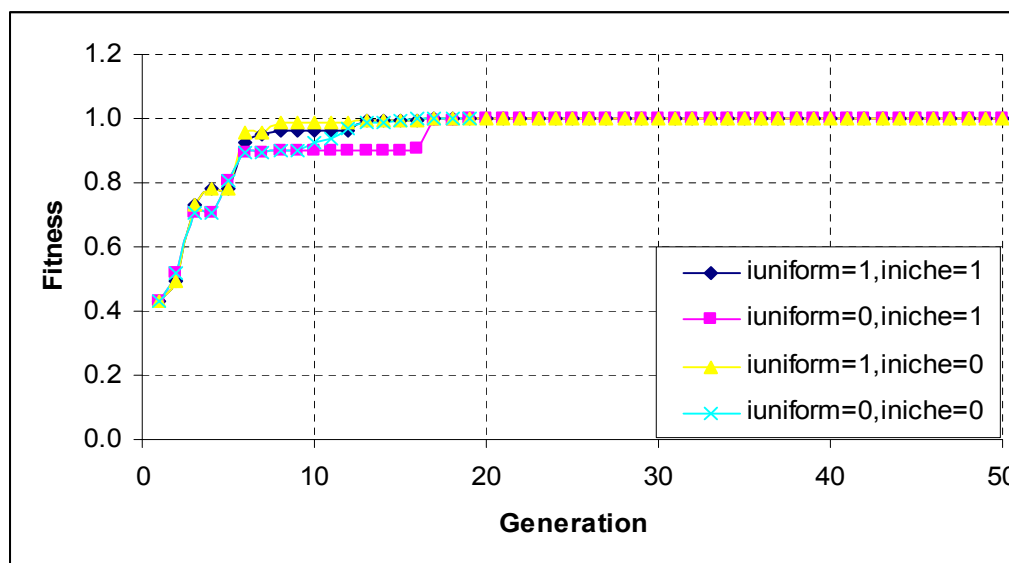


Figure 5-9: GA performance versus crossover and niching scheme

5.4.4.1 Effect of Creep Mutation

Creep mutation can be useful in the sense that it can help slide the population of individuals towards the optimal solution rather than just having to jump towards it. Figure 5-10 compares the non-uniform, non-niching, creeping case ($i_{\text{uniform}}=0$, $i_{\text{niche}}=0$, $i_{\text{creep}}=1$, $i_{\text{elite}}=1$) with the non-uniform, non-niching, non-creeping case ($i_{\text{uniform}}=0$, $i_{\text{niche}}=0$, $i_{\text{creep}}=0$, $i_{\text{elite}}=1$). With creep mutations removed, the GA did not find the optimal solution until generation 18.

Since the addition of the creep mutations found the optimum solution sooner than without them, creep mutations appear to be of benefit to the GA.

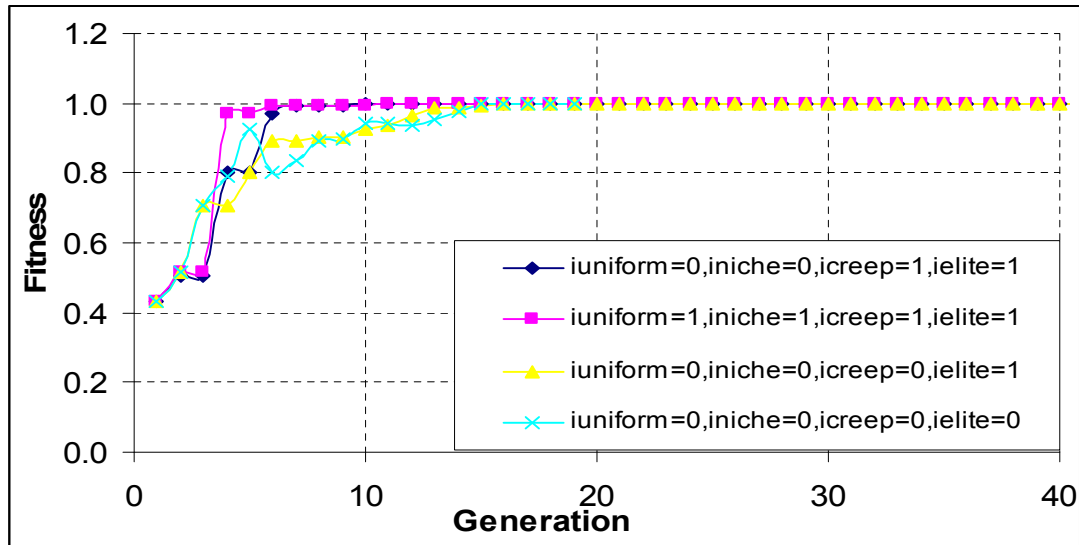


Figure 5-10: GA performance versus creep mutations and elitism

5.5 Chapter Conclusion

This chapter contains a description of the general features of Genetic Algorithms and of the particular implementation used in this study. The effects of the variation of the control parameters on the performance of the GA as an optimisation tool is presented and the Chapter concludes with a reference to the future perspectives of the method.

In order to better understand the GA operation technique, and to investigate the effects of the variation of the solution parameters, a number of trials were run where different population sizes, crossover and mutation types were tried. The effect of adding elitism and niching to the GA were also tested.

The tournament selection, uniform crossover, creep mutation scheme with elitism appears to work the best of this application. Overall, the GA technique worked well for this multimodal function and it is extremely fast at finding the global optimum.

Chapter six

6 Case Studies

6.1 Introduction

This chapter describes the development of an automated optimisation process which was developed to optimise a fleet of an existing electrical power plant based on the required load. The optimisation process employs a genetic algorithm (GA) for global optimisation purposes and is coupled to an external solver (TERA) developed as described in detail in Chapter 3.

The selected power plant for the current study is owned by the General Electrical Company of Libya (GECOL) which is the only supplier of electricity in Libya. The current power plant offers a good example for the optimisation of operational cost because of the surrounding environment and operating conditions. The chapter starts with a brief description of the automated design optimisation environment and the method developed for the power plant optimisation. This is followed by a detailed discussion on the handling of constraints and the management of design variables and objective functions. The chapter also includes the optimisation results and a discussion on operating the power plant efficiently based on electrical cost during the various seasons.

6.2 Implementation of Optimisation strategy

An automated optimization environment has been developed, which simplifies the implementation and testing of optimisation and evaluation schemes, see Figure 6-1. The optimisation environment also provides a generic interface to the external solver (TERA), which can be easily changed to compute different cost functions.

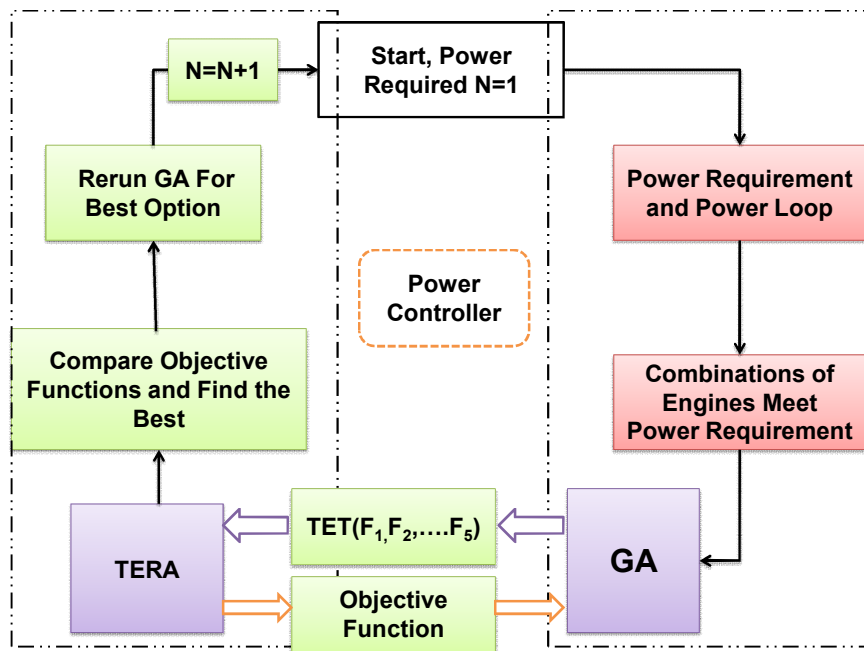


Figure 6-1: Design logic of optimisation flow chart

In the current electrical power plant optimization, the developed model TERA is used as external solver to evaluate the cost of electricity at various operating conditions.

The optimisation process starts by calling the power demand routing to work out which combination of engines will satisfy the specified required load. A switch was set to turn on or off the selected or deselected engines based on the maximum total power output. The chosen combination of engines that meet the required power demand will be considered for the optimisation process. The TERA model routine will be called to assess the randomly selected running condition for the chosen engines and calculate the cost of electricity for each engine. In the case of deselected engines, a shutdown cost in the form of a maintenance cost is added to the final total electricity cost.

The output provided by TERA model is used by the GA objective function routine together with the specified constraints to satisfy the required power demand.

The GA evaluator finally evaluates the objective functions and constraints by computing fitness values with respect to particular assessment schemes. A controller supervises all components of the optimization loop in order to initiate the optimization process, to manage its running and to terminate the process when an appropriate stopping criteria are fulfilled. The controller sequentially executes succeeding tasks through a number of tools, as soon as the results from the preceding ones are available.

6.3 Case Study 1: Power plant operation optimisation

The selected power plant as a case study to deploy the developed automated optimisation process consists of five gas turbine engines that vary in size and output power and should operate efficiently when satisfying the required power demand. For the operational power range of each of the engines see Table 6-3. The main objectives of the current optimisation are to minimise the total electricity cost, meet the required load and select operating engines to run the plant as efficient as possible.

It is worth noting that the required power demand varies with time of day and season of the year as shown in Figure 6-2. Therefore a set of optimisation cases were performed covering different hours of the day and seasons.

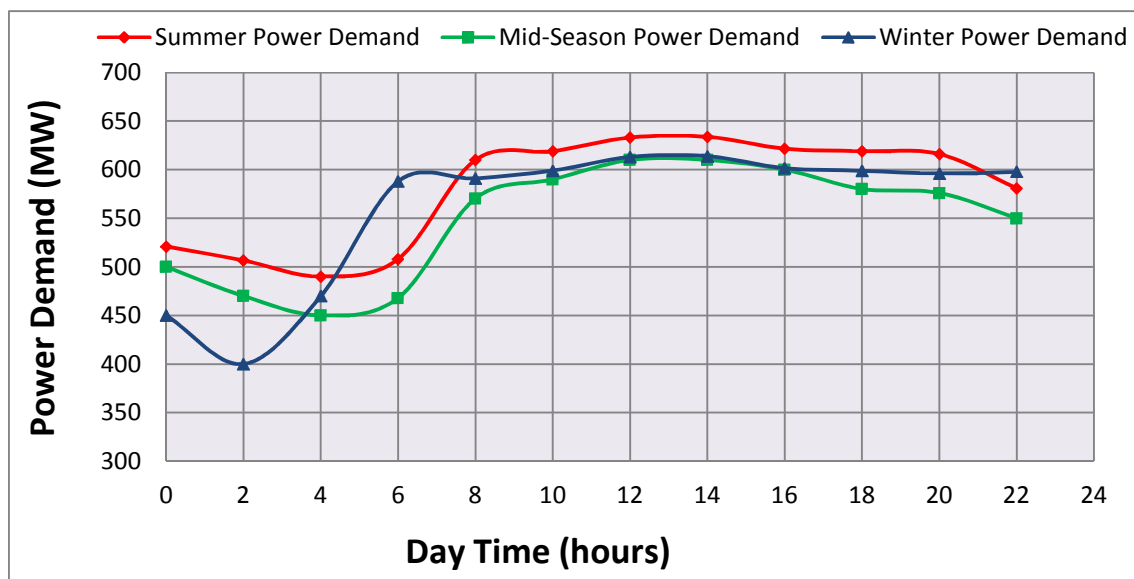


Figure 6-2: Variation of daily power demand for different seasons

6.3.1 Design Variables

Although they are a number of parameters that contribute to define the gas turbine power output, in the current optimisation process the Turbine Entry Temperature (TET) was used as a main design variable to minimise the electricity cost while satisfying the required power demand. The variation of ambient temperature was also taken into account when optimising for different times and seasons. Other important parameters in the external solver TERA that define the cost of electricity were also included with the design variables.

The range of the design variables was set so that the optimizer would be able to explore a wide variety of different power outputs. Table shows the optimised range of the TET for the five engines and Table 6-2 shows the key assumptions made regarding costs

Table 6-1: Design variables parameters (TETs) at (15 °C)

Engine NO	Min (TET)K	Max (TET)K
Engine 1	1000	1500
Engine 2	1100	1600
Engine 3	1000	1500
Engine 4	1000	1488
Engine 5	1105	1605

Table 6-2: Key assumptions

Parameter	Unit	Baseline Value
Discount rate	%	8
Natural gas price	\$/GJ	4
Grid electricity tariff	cents/kWh	8
CO2 tax	\$/ton	16
GT Maintenance Cost	(cent/Kwh)	45
GTs Load	%	85

6.3.2 Objective Function and Constraint

The main challenge in operating any power plant is to meet the required power demand at minimum cost taking into account gas turbine (GT) lifing and environmental issues. Thus the objective function for the current optimisation was set as, minimising the cost of electricity produced while the constraint was to satisfy the required power demand. Therefore, the main tasks are to operate the power plant economically and environmentally friendly.

The objective function is defined by Equation 6-1:

To Minimise $f(x)$;

$$f(x) = \frac{C_I + \sum_{i=1}^n \frac{F_Cost}{(1+r_i)^n} + \sum_{i=1}^n \frac{M_Cost}{(1+r_i)^n} + \sum_{i=1}^n \frac{Em_Cost}{(1+r_i)^n}}{P * T} \quad 6-1$$

Where: $f(x)$ = Electricity cost, C_I = Capital cost Investment, F_Cost = Fuel cost, M_Cost = Maintenance cost, Em_Cost = Emission cost, T = Operating hours per year, P = Power output, r = Discount rate and n = Number of years (project age).

The constraints were incorporated in the objective function via a penalty method using the technique described in Section 3.6.3. These are defined as the required power demand for each time and period of the day and year respectively.

$$Power\ Min \leq power\ Demand \leq Power\ Max$$

Table 6-3 presents the power output range for the listed TET performance parameters described in the design variables section.

Table 6-3: Engines operational power range

Engine NO	Minimum TET(K)	Maximum TET(K)	Minimum Power(MW)	Maximum Power(MW)
Engine 1	1000	1500	57	199
Engine 2	1100	1600	5	32
Engine 3	1000	1500	53	149
Engine 4	1000	1488	17	47
Engine 5	1105	1605	211	246

Other parameters required for electricity costs such as fuel price, and discount rate were assumed to be constant during the life time of the project.

6.3.3 Optimised Operating Condition at Winter Season

The optimisation process was set for each season of the year and time of the day based on the required power demand. The variation of ambient temperature and required power demand for a winter day is shown in Figure 6-3.

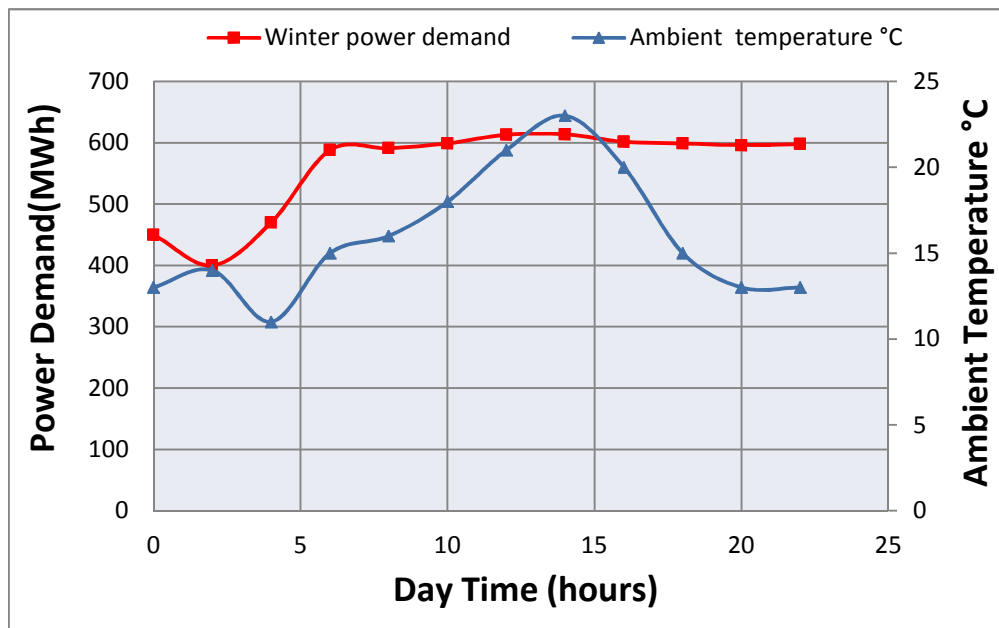


Figure 6-3: Typical variation of required power demand and ambient temperature for a winter day

During the optimisation run a population size of 20 individuals evolved for a total run of 600 generations. The overall turnaround time was between 15 to 25 minutes for each case. The optimisation process was regarded as converged when the variation of the objective function was seen to have plateaued.

A statistical report produced by the GA171 code for the optimisation run of single time during a winter day is presented in Table 6-4. The optimiser employed 600 generations to move the solution to a level considered to be representative of the best possible solution for the case. This was established from the analysis of the convergence history which is discussed below. Other

entries in Table 6-4 are the Minimum function value, which was the objective function for this run, the Average function value of a generation which denotes the typical level of fitness of that particular generation and the Number of crossovers. Finally the Elitist reproduction on individuals describes the number of instances where fittest chromosomes of a given generation were expressly preserved to take part in the following generations. This approach is taken since it is well established that elitism can have a marked influence in the performance of GA codes.

Table 6-4 : Power plant optimization - GA global statistical report for a winter day

Population size	20
Current generation	600
Minimum function value	219.104
Average function value of generation	219.118
Number of crossovers	206
Number of creep mutations	8
Number of jump mutations	0
Elitist reproduction on individuals	3
Number of evaluations	12000

As described in the design logic section the optimisation code starts by working out the combination of engines switched on or off based on the required power demand for the specified time during a typical winter day. The selected engine condition combinations together with the maximum guaranteed total power that can be produced is presented in Table 6-5. Other combination lists for the rest of the day are presented in Appendix (E.1).

The GA code then optimises the operating condition for each combination based on; variation of the TETs, the output provided by the external solver TERA, and satisfying the required power demand.

Table 6-5: possibility of combinations that give power requirement 450 MW from 00:00am to 2:00 am and 13 °C (winter day)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	OFF	1475	1335	1336	1409	474.5
Combination 2	1339	OFF	OFF	1368	1417	492.0
Combination 3	1340	OFF	1336	OFF	1355	594.0
Combination 4	1339	OFF	1335	1368	1410	641.3
Combination 5	1339	1475	OFF	OFF	1418	476.7
Combination 6	1344	1475	OFF	1337	1418	524.0
Combination 7	1250	1475	1336	OFF	1410	626.0
Combination 8	1250	1475	1336	1368	1418	673.4

The best possible lowest electricity cost for the listed combinations is presented in Table 6-6. This shows that combination 5 achieved the lowest electricity cost. This combination is then selected by the GA code to plot the convergence history as shown in Figure 6-4.

Table 6-6 : Optimum achieved lowest electricity cost for the selected combinations (winter day)

Number of combinations	Optimum COE (\$/MWh)
Combination 1	282.6499
Combination 2	283.6499
Combination 3	221.5122
Combination 4	279.4936
Combination 5	219.1043
Combination 6	277.9357
Combination 7	279.2152
Combination 8	337.4902

A typical convergence history for three selected periods in the day (00:00 - 02:00, 04:00 - 06:00 and 12-02:00am check against figure) are shown Figures 6-4, 6-5 and 6-6 respectively. This presents the how variation of the electricity cost evolved throughout the GA generations. The plots show a fairly continuous

line indicative of a smooth design space. This characteristic is due to the use of an elitism operator whereby the best individuals of a given generation are guaranteed replication in the following generation. It is worth noting that each of the optimised periods requires a set of combinations as a starting point, while the graphs in the Figures below only plot the convergence histories of the best achieved solutions. Appendix (E.1) presents the results of other periods of the day together with combination tables.

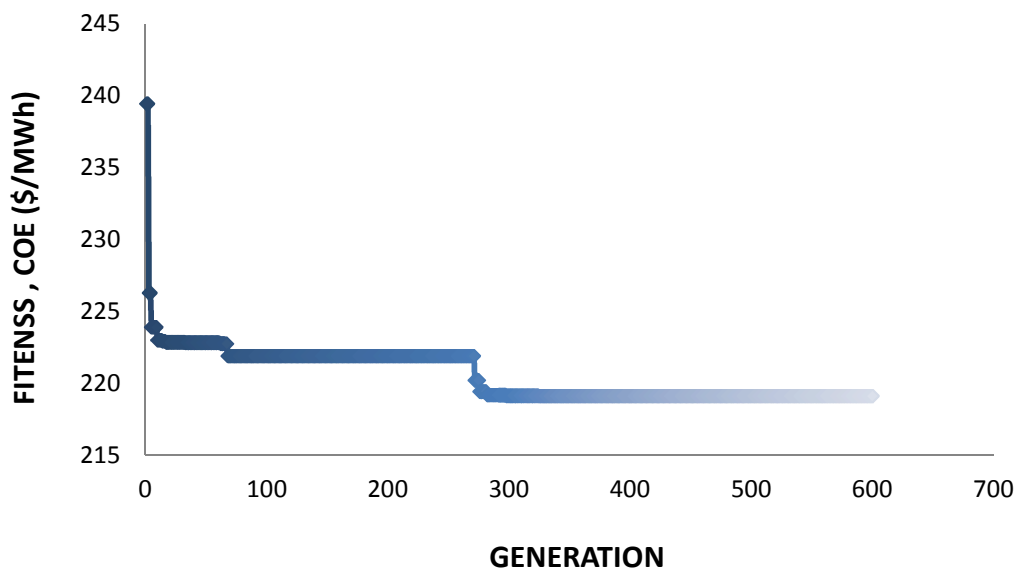


Figure 6-4: GA Cost of Electricity (COE) convergence history at winter day (00:00 to 02:00)

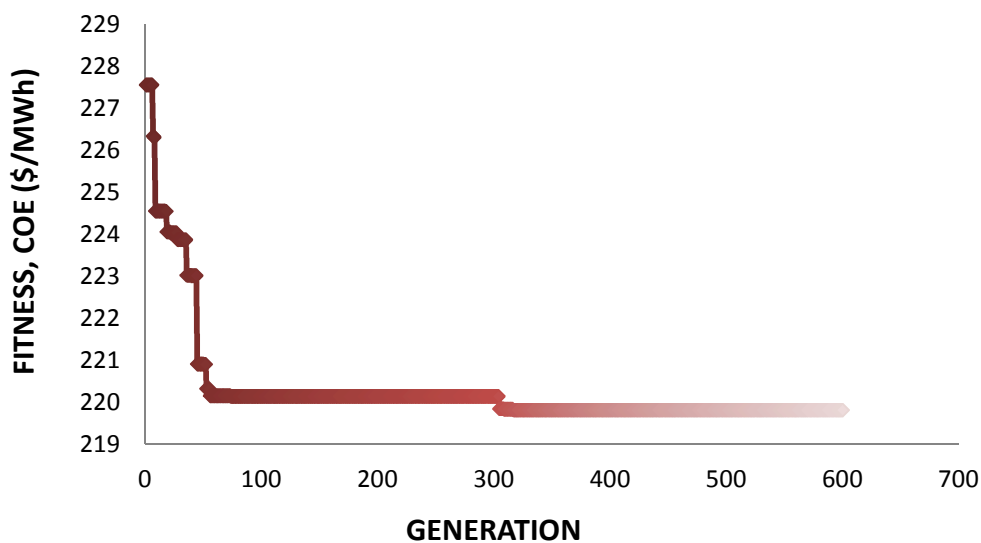
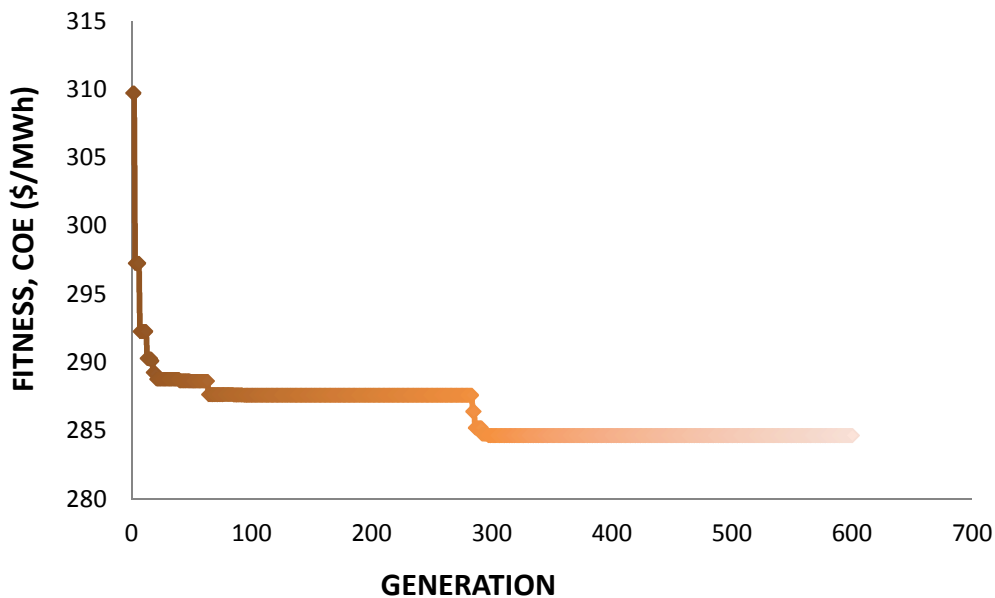


Figure 6-5: GA Cost of Electricity (COE) convergence history at winter day (04:00 to 06:00)**Figure 6-6 GA Cost of Electricity (COE) convergence history at winter day (12:00 to 14:00)**

The complete optimised typical winter day operating condition results are presented in Table 6-7. This include the required power demand for each time interval of two hours throughout the day together with a comparison between the optimised total electricity cost for a selected engines combination and the total COE for all engines running. It is clear that adopting the developed automated optimisation technique to optimise the operational strategy for the existing power plant has resulted in a significant saving. As for the current operating condition where all engines running, the total electricity cost was around \$3745. This is reduced to a total cost of around \$278 over the winter season using the optimisation method. Accordingly, for each season, a single day's worth of simulation is carried out and then multiplied by the number of days in that season to get total amounts of fuel usage and emissions and so on. This method reduces computation time.

Table 6-7: Optimisation of Operational Procedure (Existing & Proposed) for Typical winter Day

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	13	450	337.4902	219.1043	118.38
2	14	400	335.9654	164.4526	116.86
4	11	470	335.012	219.8102	115.9
6	15	588	337.2345	222.9448	118.13
8	16	591	339.1177	223.7183	120.01
10	18	599	341.9148	281.937	122.81
12	21	613	344.9519	284.6719	125.84
14	23	613.8	346.2355	285.6252	127.13
16	20	601.5	344.3619	284.298	125.25
18	15	598.9	337.2345	278.5387	118.13
20	13	596	337.4899	279.2152	118.38
22	13	597.8	337.4899	279.2152	118.38

6.3.4 Optimised Operating Condition at Summer Season

The developed optimisation tool was also deployed for the summer season using the same methodology as presented in the previous section. The summer season is characterised by having higher ambient temperatures, which consequently leads to higher power demand as shown in Figure 6-7. This creates an additional load on the engines which already faces harsher operating conditions due to the higher inlet temperature. This in turn will affect the life of engine and result in an additional cost due to extra maintenance requirements.

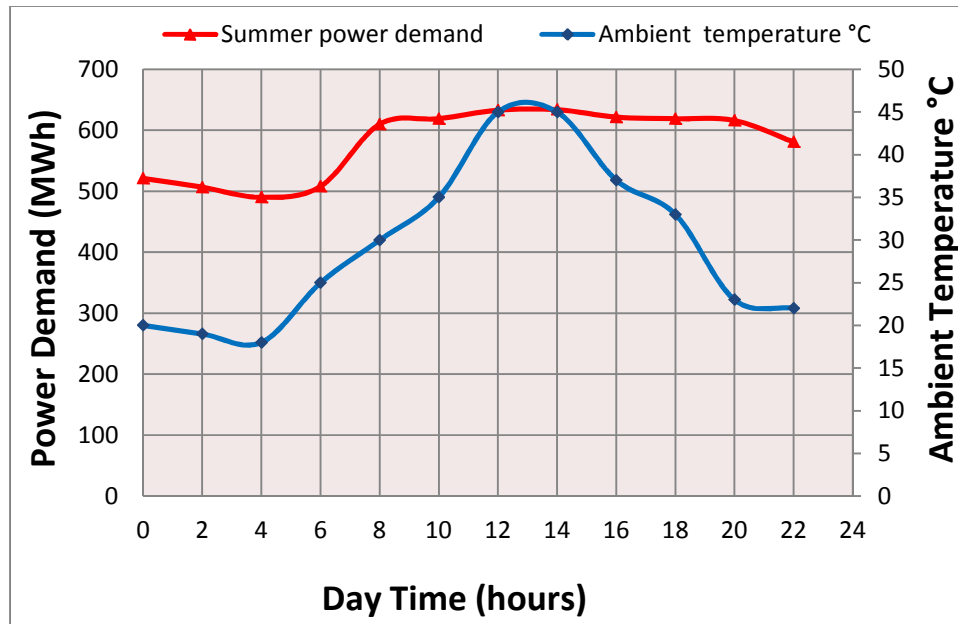


Figure 6-7: Variation of required power demand and ambient temperature for a summer day

Table 6-8 presents the selected engine condition combinations together with the maximum guaranteed total power the selected engines can produce. The current selection was based on the first two hours of a summer day with power requirements of 521MW at an ambient temperature of 20 °C. Combinations for the rest of the day together with the optimisation results are presented in Appendix (E.2).

Table 6-8: Possibility of combinations that give power requirement from 00:00 to 02:00 and 20 oC

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1333	OFF	1330	OFF	1354.99	594
Combination 2	1332	OFF	1330	1337	1355	641
Combination 3	1333	1475	OFF	1337	1386	524
Combination 4	1333	1475	1330	OFF	1389	626
Combination 5	1344	1475	1328	1366	1386	673

6.3.4.1 GA Global Statistical Report for A Summer Day

Table 6-9 shows a statistical report produced by the GA171 code for the optimisation run of single time during a summer day for the above combinations. To provide a consistent optimisation comparison, the same number of generations and population size was adopted. This resulting in 12000 objective function evaluations. It is clear from the table that the minimum function value and average value of the last generation are very close, which explains why all individuals in the population almost converged.

Table 6-9: power plant optimization - GA global statistical report for a summer day

Population size	20
Current generation	600
Minimum function value	226.96
Average function value of generation	227.11
Number of crossovers	205
Number of creep mutations	8
Number of jump mutations	0
Elitist reproduction on individuals	2
Number of evaluations	12000

The optimisation results of the selected combinations are presented in Table 6-10. It shows the lowest achieved total cost of electricity for each combination where the highlighted result indicates the optimum solution. This combination is then selected by the GA code to plot the convergence history as shown in Figure 6-8.

Table 6-10: Optimum achieved lowest electricity cost for the selected combinations (summer day)

Number of Combination	Optimum COE (\$/MWh)
Combination 1	226.9649
Combination 2	287.4664
Combination 3	285.9058
Combination 4	284.298
Combination 5	344.3619

The objective function solution history for three periods in the day (00:00 - 02:00, 02:00 - 04:00 and 14:00 - 16:00) are shown Figures 6-7, 6-8 and 6-9, respectively. These plots report minimum fitness, and hence the minimum cost of electricity of the population for each generation in the selected summer day.

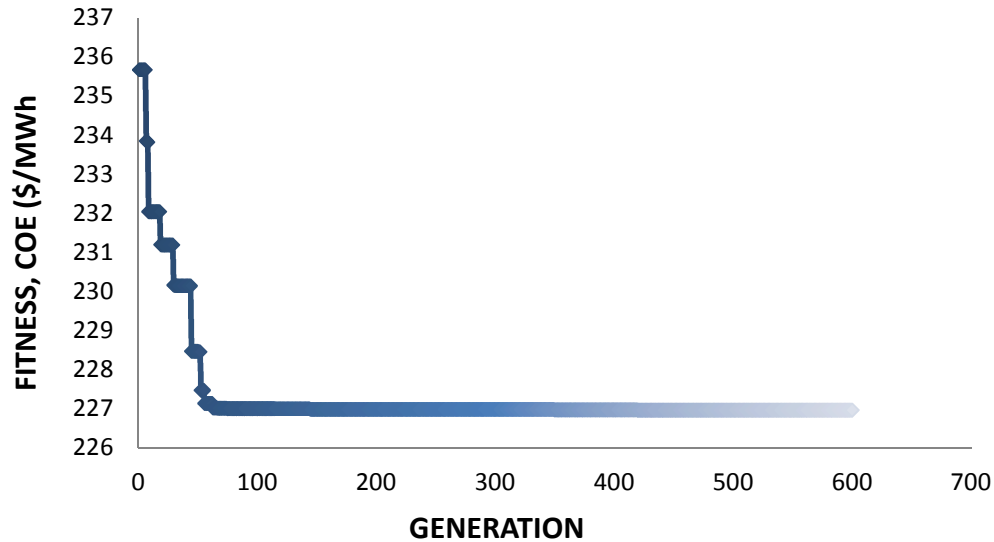


Figure 6-8: GA Cost of Electricity (COE) convergence history at summer day (00:00 to 02:00)

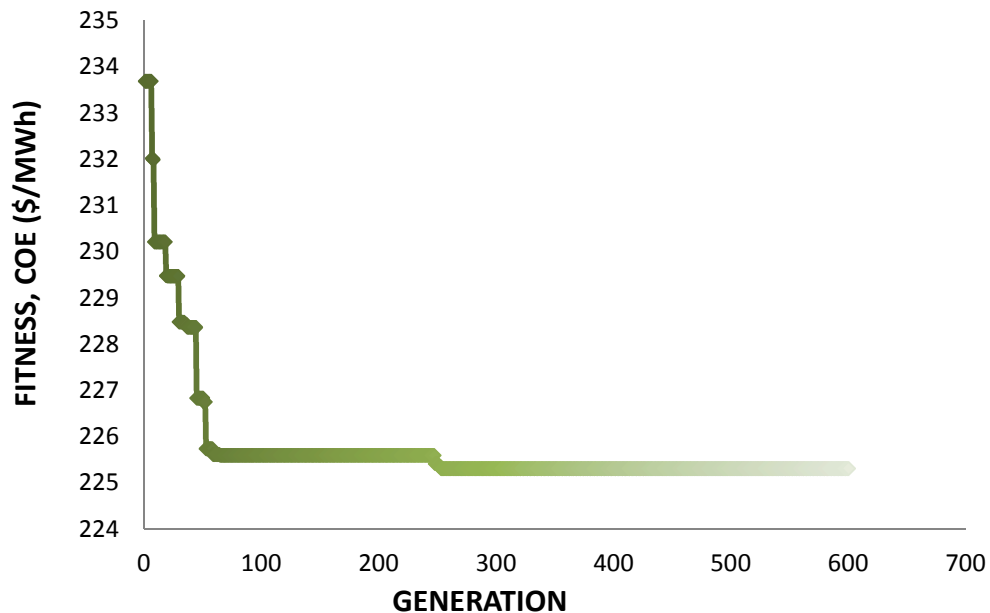


Figure 6-9: GA Cost of Electricity (COE) convergence history at summer day (02:00 to 04:00)

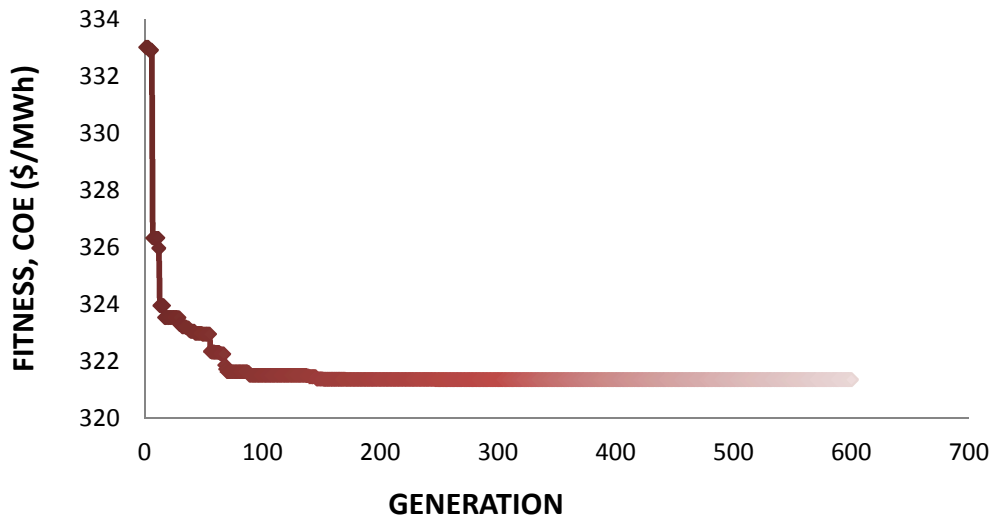


Figure 6-10: GA cost of electricity (COE) convergence history at summer day (14:00 to 16:00)

Table 6-11: Optimisation of operational procedure (Existing and Proposed) for typical summer day

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	20	521	344.3619	226.9649	117.4
2	19	506.6	342.8325	226.1297	115.87
4	18	490	341.9148	226.2015	114.95
6	25	508	347.6756	234.1737	120.71
8	30	610	362.8959	298.8548	135.93
10	35	620	371.0349	308.0985	144.07
12	45	633	388.804	321.3498	161.84
14	45	633.8	388.804	321.3498	161.84
16	37	621.5	374.3978	306.8987	147.43
18	33	618.9	367.6822	304.0849	140.72
20	20	616	344.3619	284.298	117.4
22	22	580.8	345.5742	231.545	118.61

The optimised operating condition for a typical summer day are presented in Table 6-11. This includes the required power demand for two hour intervals throughout the day together with a comparison between the optimised total electricity cost for a selected engine combination and the total COE for all engines running. The application of the optimisation tool to the operational strategy for the existing units shows a significant reduction in electricity cost. The total cost of the current operational strategy is about \$397,471, while the optimised engine configuration shows a reduction in the total cost of about \$302,675 over the summer season, a saving of about \$94,796 in total cost for one season over the expected useful life of the plant.

6.3.5 Optimised Operating Condition at Mid-Season

Mid-season operation was used to represent both spring and autumn. Thus the cost of electricity was calculated for 180 days to achieve the cost for both seasons rather than 90 days per season as used in the previous optimisations (winter and summer). The average ambient temperature and power demand for mid-season are shown in Figure 6-11.

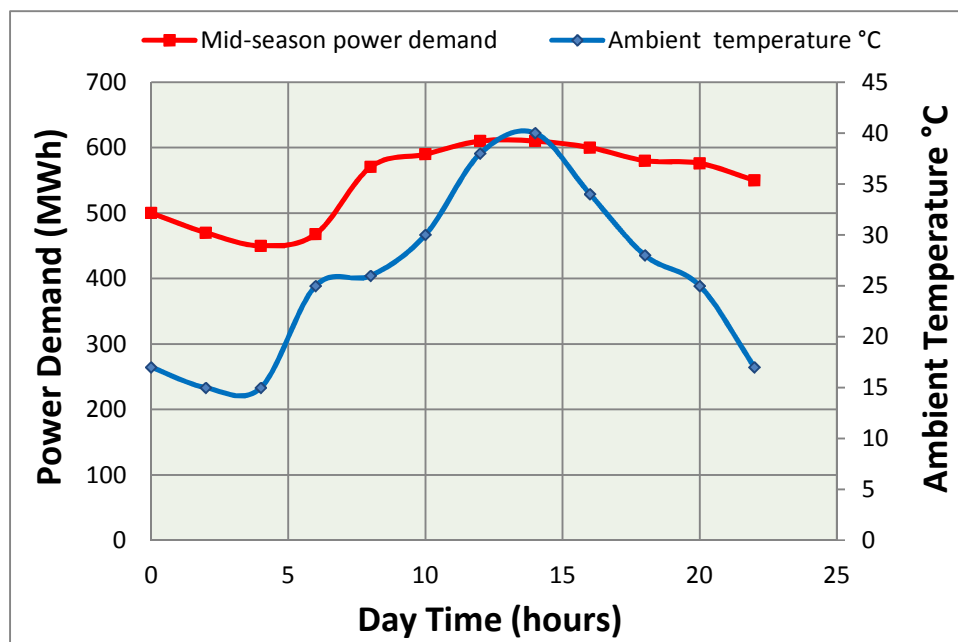


Figure 6-11: Variation of required power demand and ambient temperature for a Mid- season day (hours)

Again the optimisation code starts by working out the combination of engines switched on or off based on the required power demand for the specified time during a typical day. The selected engine condition combinations together with the maximum guaranteed total power are presented in Table 6-12.

Table 6-13 shows the lowest possible electricity cost for the listed combinations. This shows that first combination achieved the lowest electricity cost. This combination is then selected by the GA code to plot the convergence history as shown in Figure 6-12. For the rest of the day together with the optimisation results are presented in Appendix (E.3).

Table 6-12: possibility of combinations that give power requirement from 00:00 to 02:00 and 17 °C

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1335.902	OFF	1332	011 OFF	1354.99	594
Combination 2	1336	OFF	1332	011 1364.647	1402	641
Combination 3	1336	1475	OFF	1368	1418	524
Combination 4	1336	1475	1331	950 OFF	1405	626
Combination 5	1336	1475	1332	591 1336.597	1404	673

Table 6-13: Optimum achieved lowest electricity cost for the selected combinations (mid-season day)

Number of Combination	Optimum COE \$/MWh
Combination 1	224.51
Combination 2	283.52
Combination 3	281.86
Combination 4	280.78
Combination 5	340.50

The convergence histories of three selected time periods for a mid-season day (00:00 to 02:00, 06 to 06 am, and 22:00 pm to 24:00) are shown in Figures 6-12, 6-13, and Figure 6-14 respectively. These present the variation of electricity cost as it evolves throughout the GA generations. The plots show a fairly continuous line indicative of a smooth design space.

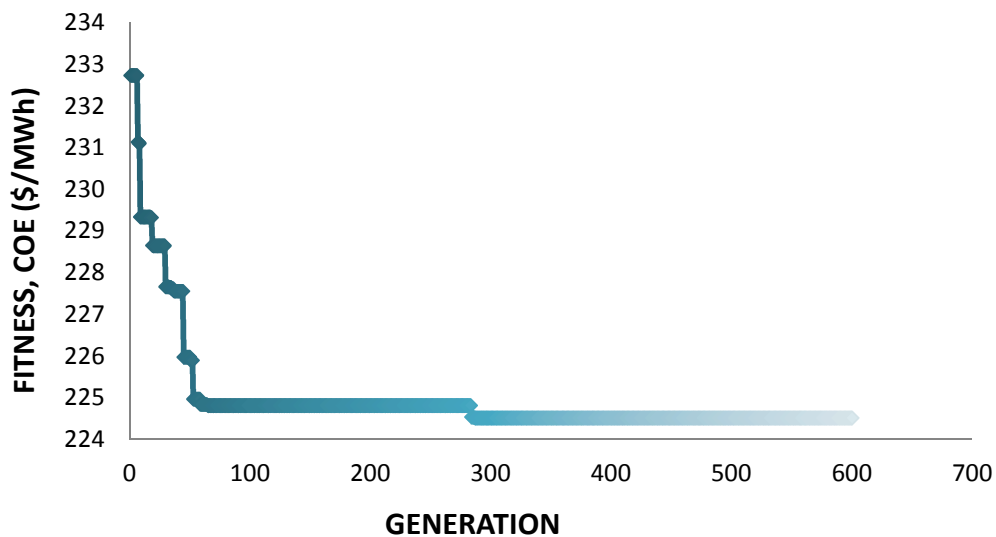


Figure 6-12: GA Cost of Electricity (COE) convergence history mid-season (00:00 to 02:00)

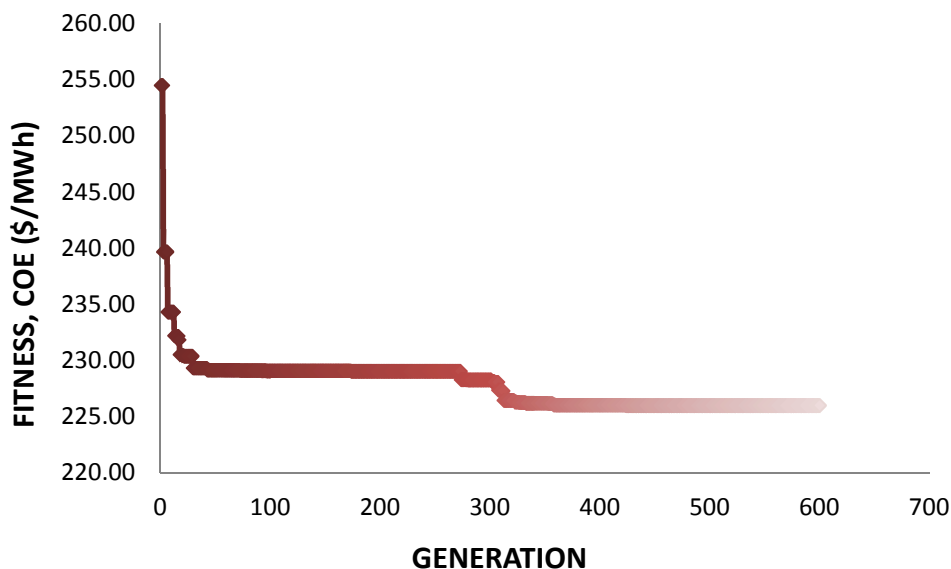


Figure 6-13: GA Cost of Electricity (COE) convergence history mid-season (06:00 to 08:00)

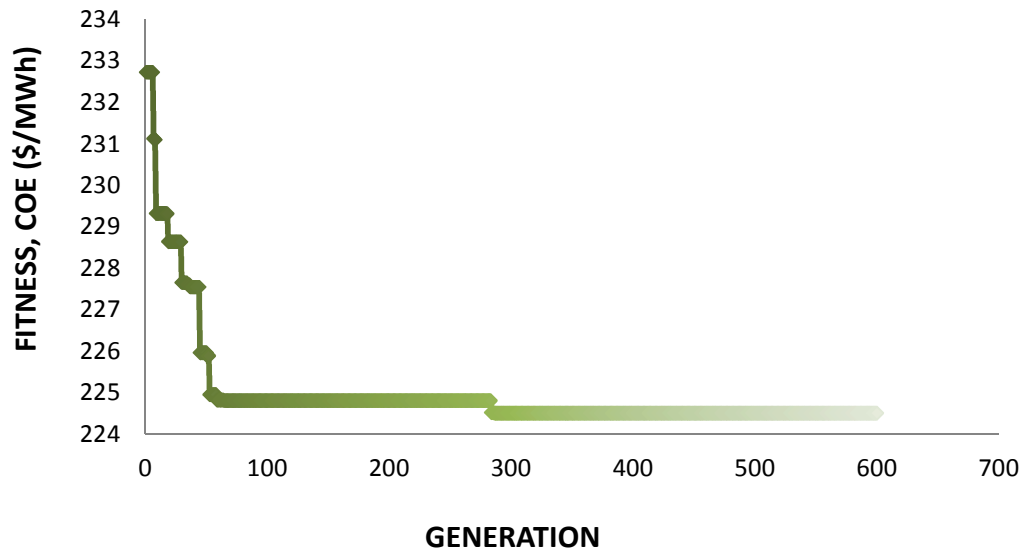


Figure 6-14: GA Cost of Electricity (COE) convergence history mid-season (22:00 to 24:00)

Table 6-14: Optimisation of operational procedure (Existing and Proposed) for typical mid-season day

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	17	500	340.5043	224.5072	115.997
2	15	470	337.2345	220.8482	116.386
4	15	450	337.2345	220.8482	116.386
6	25	468	347.6756	225.9934	121.682
8	26	570.4	349.8781	232.0014	117.876
10	30	590	362.8959	238.7789	124.117
12	38	610	373.4531	308.463	64.9901
14	40	610	379.7199	310.9959	68.724
16	34	600	369.3417	305.4509	63.8908
18	28	580	354.7729	233.9555	120.814
20	25	576	347.6756	234.1737	113.501
22	17	550	340.5043	224.5072	115.997

Table 6-14 presents the overall statistical report for a typical mid-season day produced by GA for the optimised total electricity cost. It shows significant electricity cost reduction from the current operational strategy at \$763,360 to the optimised combination of engines at \$536,494. This result is a saving of \$26,866 in total electricity cost over the whole mid-season.

To conclude, Table 6-15 presents all the electricity cost during the year (current and proposed). It is shown that a 27% reduction in the total cost of electricity can be achieved by optimising the engines' combined power profiles during the year while considering the total power demand constraint.

Table 6-15: Current and proposed COE with seasonal savings

Seasons	Original COE(\$/MWh)	Proposed COE(\$/MWh)	saving(\$per season)	saving (%)
Winter	374,854	278,165	96,689	0.26
Summer	397,471	302,675	94,796	0.24
Mid-Season	763,360	536,494	26,866	0.30

In general this research shows that GA is a powerful optimisation tool that can be applied to gas turbine power plant operational optimisation. The overall results have shown a significant saving in the total cost of electricity when using the automated optimisation method.

6.4 Case Study 2: Risk Evaluation of Increasing Fuel Price

One of the riskier aspects in evaluating the profitability of investing in the electrical supply industry is the likely fluctuations in fuel prices. Uncertainties and subsequent errors between estimated and actual fuel prices will cause cost overruns, not only significantly increasing electricity costs but substantially reducing expected benefits.

The first case study discussed above assumed stable fuel prices but prices will, in reality, almost certainly not be stable and may deviate wildly from that assumption, possibly due to a sudden real or threatened reduction in supply.

Thus, this case study makes the assumption of high fuel cost with the aim of investigating the effects of changes of fuel price (see Figure 6-15) on the objective function of the optimisation method used here.

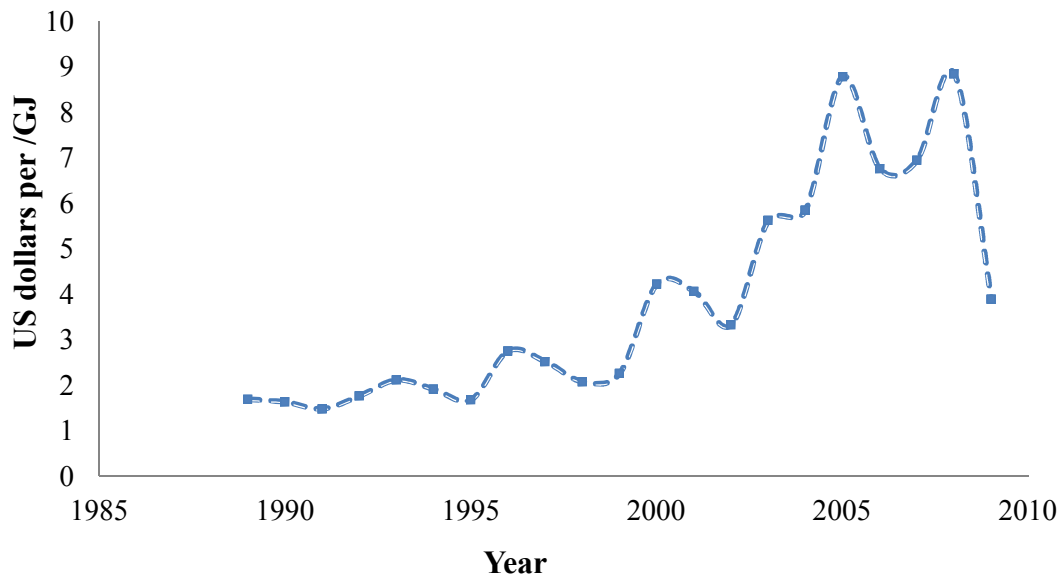


Figure 6-15 Historical of natural gas prices (BP, 2010)

US dollars per /GJ

6.4.1 Optimised Operating Conditions for Winter, Summer, and Mid-Season for Fuel Cost \$6/GJ

Optimisation analysis for this new case study was carried out to investigate the effect of increase of fuel price on the optimum operational condition of the power plant. The current case study assumes the higher gas price of \$6/GJ and the results were compared to the baseline as presented in Section 6.3 where the gas price was taken to be \$4/GJ.

The same optimisation procedure as used in the baseline study was adopted for the current study. This includes the same objective function, constraints, ambient temperatures and required power demand for each period.

Figures 6-16 and 6-17 represents the GA optimisation convergence history of the current case and the baseline respectively for the winter season. The time period was 00:00 to 02:00 and was selected for all the comparisons presented here.

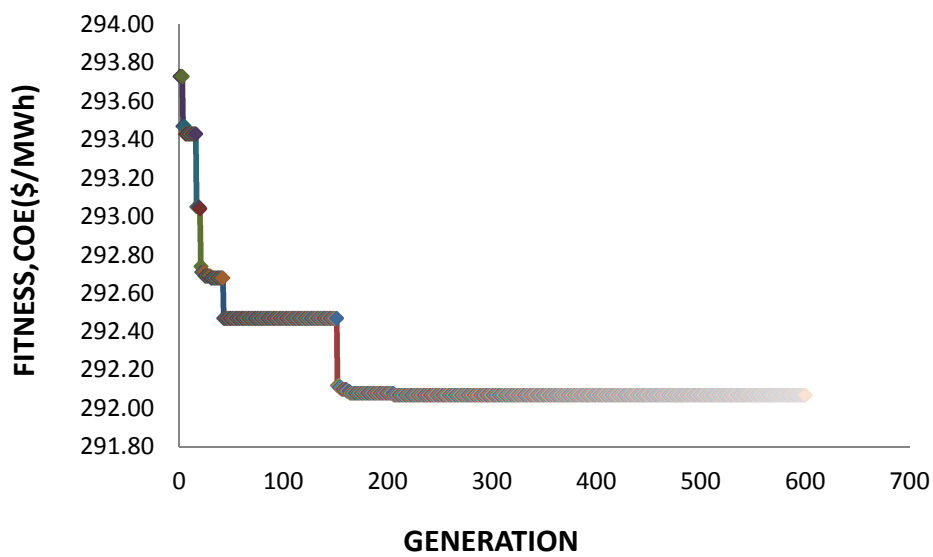


Figure 6-16: Convergence history for 00:00 to 02:00 on a winter day at (\$6/GJ)

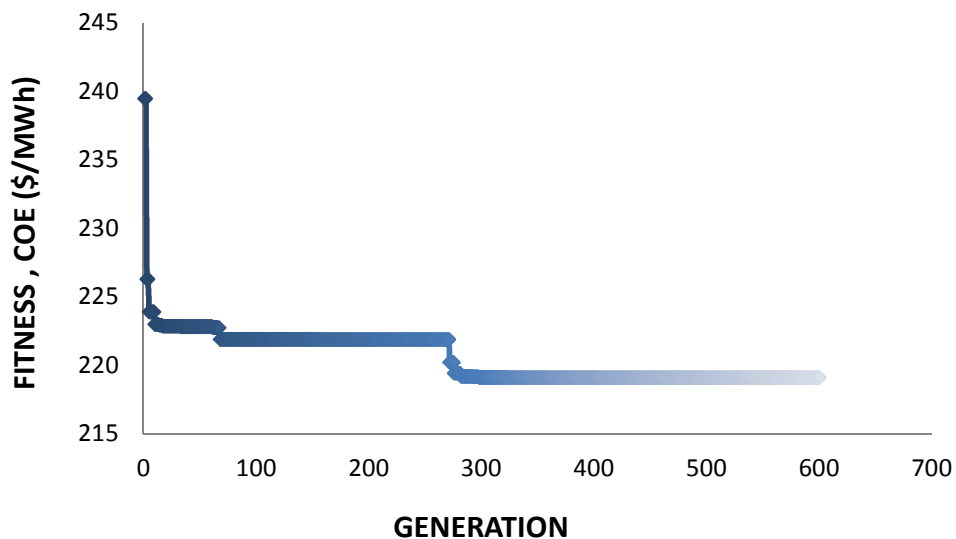


Figure 6-17: Convergence history for 00:00 to 02:00 on a winter day at (\$4/GJ)

The effect of increasing the gas price can be seen clearly from the GA convergence history comparison. The current case study demonstrates that the gas price has a major effect on the cost of electricity. Further comparisons were made for summer and mid-season, see Figures 6-18 to 6-21. These confirm the effect of increase of gas price on the electricity cost. However, the variation in the optimum electricity cost, objective function, for each season is related the ambient condition and required power demand.

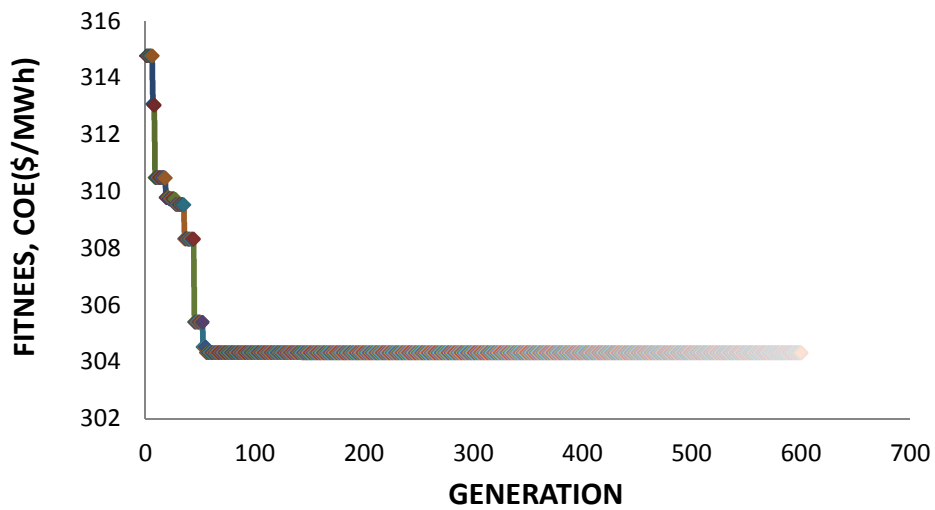


Figure 6-17: Convergence history for 00:00 to 02:00 on a summer day at (\$6/GJ)

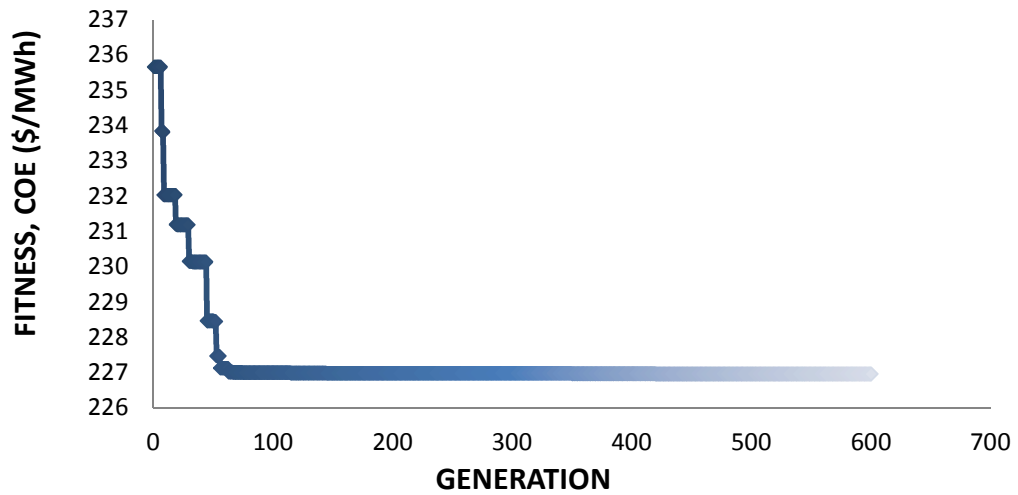


Figure 6-18: Convergence history for 00:00 to 02:00 on a summer day at (\$4/GJ)

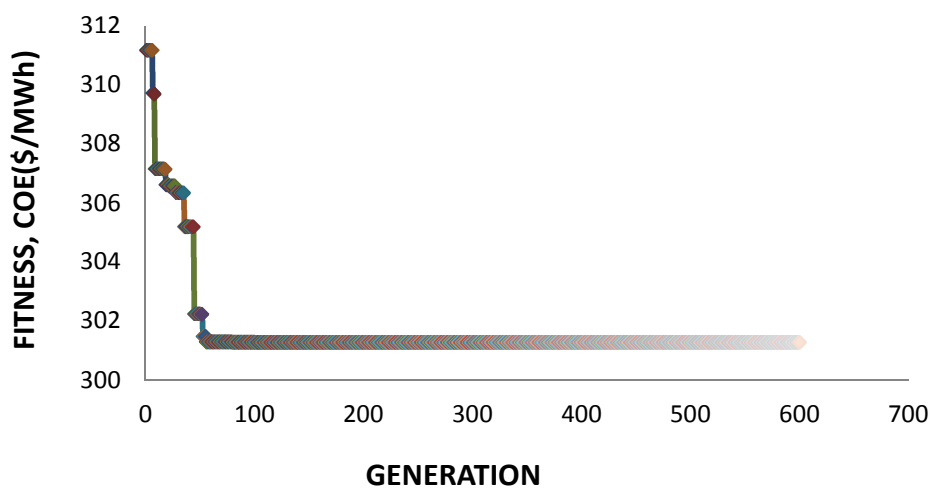


Figure 6-19: Convergence history for 00:00 to 02:00 on a winter day at (\$6/GJ)

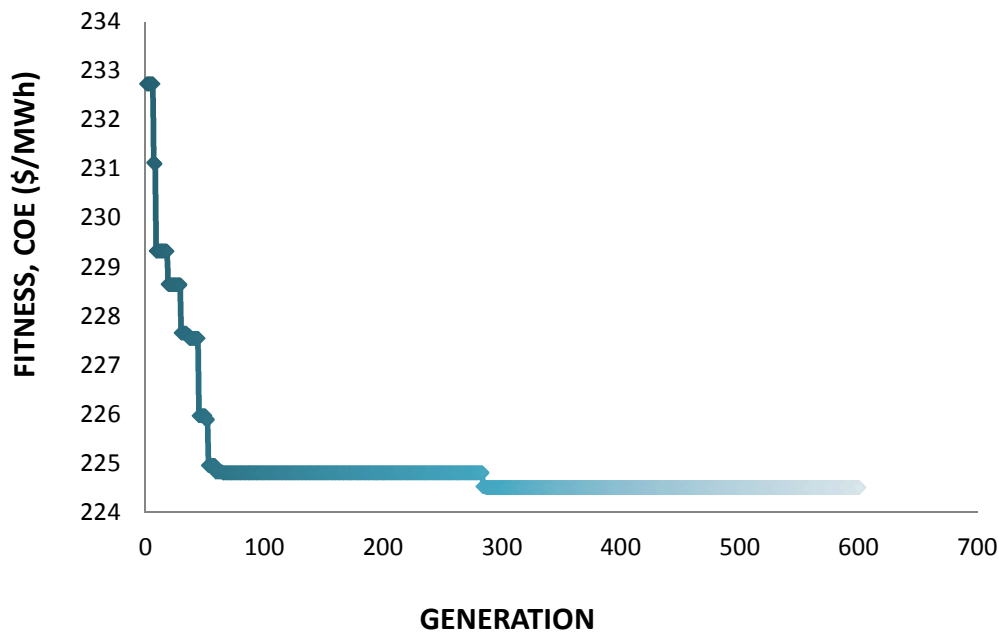


Figure 6-20: Convergence history for 00:00 to 02:00 on a winter day at (\$4/GJ)

A complete optimised electricity cost comparison between the current case study and the baseline is presented in Table 6-16. This represents a whole year operation: winter, summer and mid-season. It is clear that the effect of fuel cost has a negative effect on the optimised electricity cost which tends to be sensitive to the fuel price. There is approximately a 37% increase in the overall cost of electricity for each season in the current case study with a 50% higher fuel price. The complete Optimisation result of Operational Procedure (Existing & Proposed) for three typical days winter, summer and mid-season will be presented in Appendix (E.4).

Table 6-16: Comparison between the baseline and the current case

Seasons	COE at Base line Case (\$4/GJ)	COE at Optimised Base line Case	COE at Current Case (\$6/GJ)	COE at Optimised Current Case	$\Delta\%$
Winter	\$ 374,853	\$278,164	\$ 515,157	\$ 374,320	0.0008
Summer	\$ 397,471	\$ 302,675	\$543,398	\$ 406,212	0.0047
Mid-Season	\$ 763,360	\$ 536,494	\$ 1,045,907	\$ 716,518	0.0023

It is worth noting that the GA optimiser has performed well in reducing the total electricity cost by approximately 28% at current case study compared to 25% at the base line case study.

In general, what is needed is to represent risk in a measurable way. There are various parameters of operation like downtime, availability, reliability, fuel price, and they all have a risk aspect attached to them. One feels the need to measure the risk in a quantitative way and give the risk a numerical value for comparison purposes.

6.5 Case Study 3: Effect of Maintenance Cost on COE

Maintenance costs are a significant proportion of total costs for all power generation plants. While maintenance may cost very much less than fuel, this cost can be very important in reducing the costs incurred by downtime and lost production. Thus it is essential to map plant and/or machinery failures and set these against maintenance and component costs and how these affect downtime of plant and machinery.

In the baseline case presented in Section 6.3 the factor for GT maintenance cost was set at 0.45 \$/KWh. In the current case study this factor was increased to 0.50 \$/KWh to investigate the effect of this parameter on the operational cost of the power plant. The optimisation procedure and other assumptions were the same in both the baseline and the current optimisation study.

The engine condition combinations that satisfy the required power demand for winter, summer and mid-season are presented in Tables 6-17, 6-18 and 6-19, respectively. The same time period (00:00 to 02:00) was used throughout. It is noticeable that the combinations of engines which meet the required power demand is vary for whole year operation due to the difference in the ambient conditions and required power demand.

Table 6-17: Possible combinations that meet power requirement 00:00 to 02:00 winter

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	OFF	1474	1328	1337	1402	474
Combination 2	1328	OFF	OFF	1365	1418	492
Combination 3	1333	OFF	1330	OFF	1355	594
Combination 4	1334	OFF	1327	1337	1418	641
Combination 5	1334	1474	OFF	OFF	1418	477
Combination 6	1336	1474	OFF	1337	1405	524
Combination 7	1334	1474	1330	OFF	1418	626
Combination 8	1328	1474	1330	1365	1402	673

Table 6-18: Possible combinations that meet power requirement 00:00 to 02:00 summer

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1312	OFF	1328	OFF	1355	594
Combination 2	1327	OFF	1324	1362	1355	641
Combination 3	1312	1471	OFF	1337	1386	524
Combination 4	1312	1471	1324	OFF	1386	626
Combination 5	1328	1471	1324	1362	1386	673

Table 6-19: Possible combinations that meet power requirement 00:00 to 02:00 mid-season

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1250	OFF	1328	OFF	1355	594
Combination 2	1312	OFF	1328	1337	1355	641
Combination 3	1330	1473	OFF	1337	1386	524
Combination 4	1250	1473	1328	OFF	1395	626
Combination 5	1312	1473	1327	1363	1395	673

The effect of increasing the maintenance cost factor on the optimised objective function and electricity cost is presented in Table 6-20. It is clear to see that the difference between the baseline and the optimised current case is very small. This was mainly due, as explained before, to the fact that maintenance costs are very much less than fuel costs. However, the long term effect can have a negative impact on the total electricity cost as the current study was assumed for only one year operational cost. For the rest of the day together with the optimisation results are presented in Appendix (E.5).

Table 6-20: comparison between reference case and assumed case at variation of season days

Seasons	Base line case	Optimisation of base line case	Current case	Optimisation of Current case
winter	337.49	219.10	337.77	219.79
summer	344.36	226.96	346.00	227.50
mid-season	340.50	224.51	341.30	227.65

The convergence history for the current and baseline cases for the selected period of the day (00:00-02:00) are both presented in Figure 6-19. This plot reports the minimum fitness value, cost of electricity, of the population for each generation in the whole search space. Although the optimum solution tends to vary between the two compared cases the convergence trend is almost identical because maintenance costs are relatively so small.

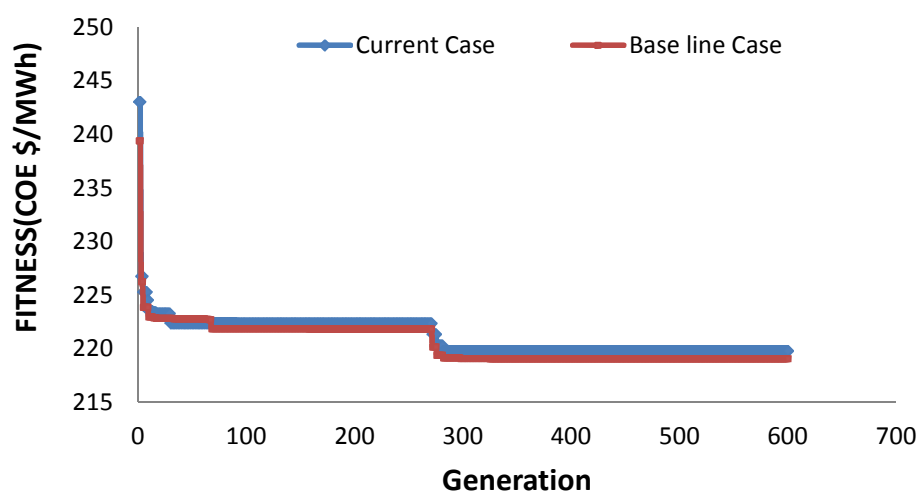


Figure 6-21: GA Cost of Electricity (COE) convergence history at winter day (at reference and assumed case)

6.6 Case Study 4: Measure of Risk by Varying Discount Rate

Three factors determine the feasibility of a specific project: (i) investment required, (ii) operational costs, and (iii) discount rate, where the discount rate may be most important. Discount rate is particularly important for capital projects such as those in the electricity supply industry.

The greater the risk the greater, usually, will be the discount rate. Indeed the discount rate is considered as a measure of financial risk [84]. Thus the discount rate will vary with the siting of the project – some countries are considered high risk, others are more stable – and other factors such as whether the operator will produce oil, gas or electricity, see Chapter Four for more details. Figure 6-20 shows The effect of discount rate on net present value.

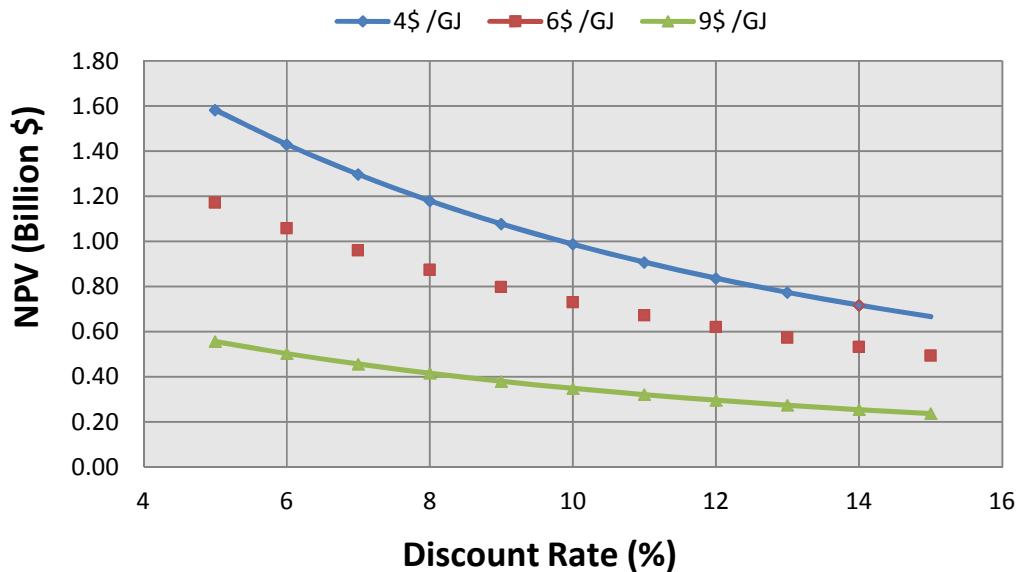


Figure 6-22: Change in NPV versus discount rate and fuel price

The discount rate for the baseline case in Section 6.3 was 8%, and in the current case study was increased to 10%.

Because the discount rate is independent of any variation in ambient conditions, only one operating period was required (00:00 – 02:00 on a typical winter day) to carry out optimisation with the new discount rate. Of course, the same

optimisation process used for the baseline case as is adopted in the current study.

The optimisation results of the selected combinations that meet the required power demand are presented in Table 6-21. It shows the best achieved lowest total cost of electricity for each combination for both the baseline and recent updated discount rate.

Table 6-21: Comparison of optimum COE between base line and current case Studies

Number of Combination	Base line Case Optimum COE(\$/MWh)	Current Case Optimum COE(\$/MWh)
Combination 1	282.65	286.03
Combination 2	222.16	224.51
Combination 3	221.51	223.31
Combination 4	279.49	282.90
Combination 5	219.10	221.94
Combination 6	277.94	281.22
Combination 7	279.22	280.01
Combination 8	237.49	339.36

A comparison of the convergence history for reference and present study is presented in Figure 6-21 and Figure 6-22. The optimisations were both run for 600 iterations where one could notice the variation in the search space which is due the random selection by the GA code. It is noticeable that increasing the discount rate has resulted in a small increase in cost of electricity. As was expected the optimum result for the new assumed discount rate is slightly higher when compared to the baseline case.

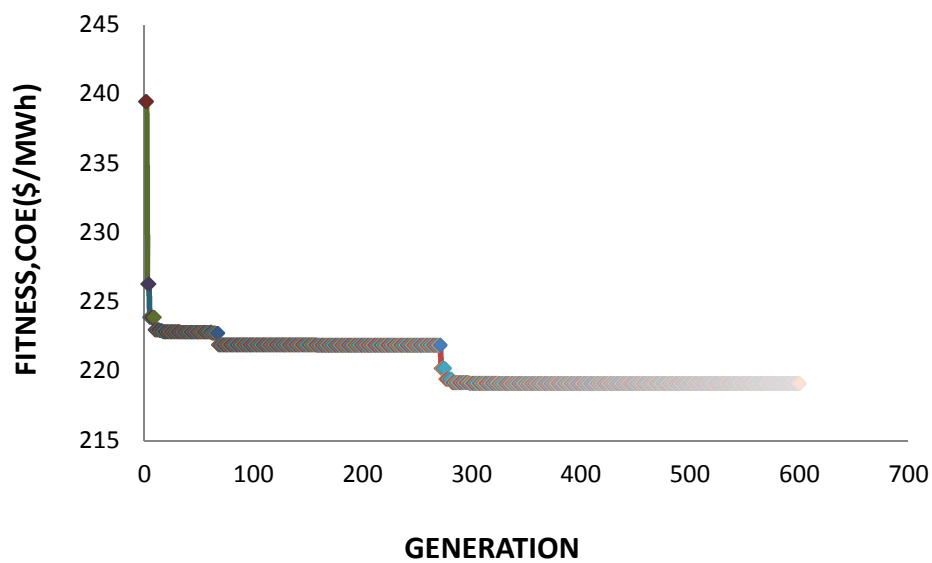


Figure 6-23: GA Cost of Electricity (COE) convergence history at Base line case (8% Discount Rate)

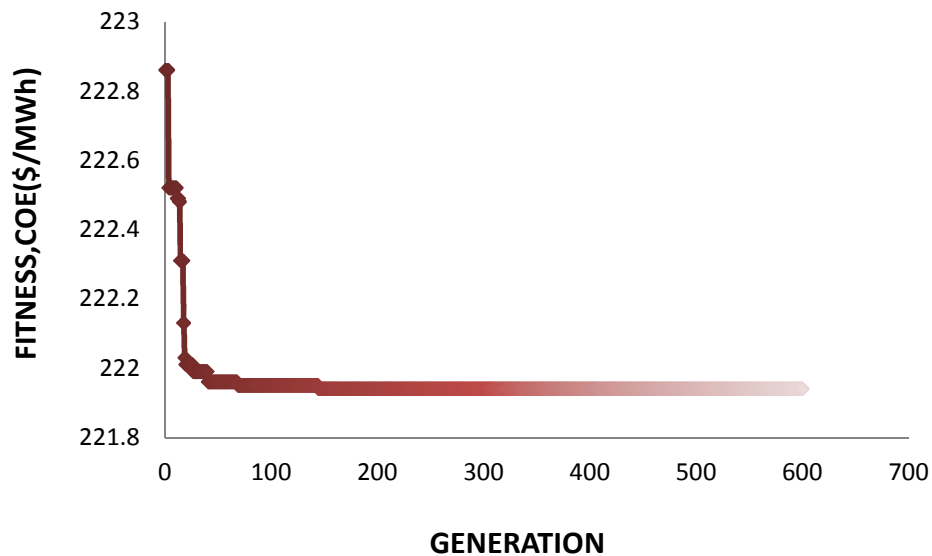


Figure 6-24: GA Cost of electricity (COE) convergence history at Current case (10% Discount Rate)

A detailed comparison between the current case study and the baseline for the complete time intervals of the day are presented in Table 6-22. It can be seen that the GA code performed well in reducing the electricity cost for each case and for all periods of the day. In addition, the effect of maintenance cost on the objective function, cost of electricity, is quite small compared to the first case study. This effect was noticed for all the time intervals of the day. For the rest of the day together with the optimisation results are presented in Appendix (E.6).

Table 6-22: Comparison between the current case study and baseline for the complete day

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	COE at Base Line case (\$/MWh)	Optimised Base Line case (\$/MWh)	COE at Current case (\$/MWh)	Optimised Current case (\$/MWh)
0	13	450	337.49	219.10	339.36	221.9
2	14	400	335.97	164.45	340.31	165.8
4	11	470	335.01	219.81	339.37	219.9
6	15	588	337.23	222.94	344.56	225.1
8	16	591	339.12	223.72	343.59	225.9
10	18	599	341.91	281.94	346.47	285.4
12	21	613	344.95	284.67	349.56	288.5
14	23	613.8	346.24	285.63	354.06	292.2
16	20	601.5	344.36	284.30	348.87	290.9
18	15	598.9	337.23	278.54	344.56	284.9
20	13	596	337.49	279.22	339.02	282.6
22	13	597.8	337.49	279.22	339.02	282.6

6.7 Chapter Conclusions

This study has been carried out for a very warm environment with a wide swing in ambient temperature during the day with consequential and similar variation in power demand over the day. Such variations mean that the optimum GT engine combination for electricity production will also vary with time of day.

The investigation revealed that for the power plant studied, the whole GT engine fleet was run away from the design point most of the time. The study showed that even when demand was relatively low, all of the gas turbines in the power plant were being run. This has a significant impact on the cost of electricity because the engines are operating at part load, which is very inefficient. The reason that this was allowed to happen is because no study into optimising the cost of electricity had been carried out prior to this research project. This optimisation study shows that considerable savings can be made

to the cost of electricity by operating fewer engines closer to design load and hence peak efficiency.

This research project has shown that GA can be a powerful optimisation tool when applied to optimise GT power plant usage. The results obtained demonstrate a noticeable reduction in electricity generation costs after using the GA optimiser. This investigation has also shown that the TETs for the GTs are the most important variables determining maintenance and operating costs. The optimisation code has been validated using the two case studies described above and confirms that the profitability of a GT power plant is very sensitive to both ambient conditions and external power demand.

This chapter has reported the testing of an optimisation method based on a GA which can minimise electricity cost for a typical industrial GT power plant for different power demands while taking into account changes in the local ambient conditions.

Chapter seven

7 Conclusions and Recommendations for Further Work

This chapter summarises the key results of the research and highlights possible further work to continue this work. This study was motivated by the growth in demand for electrical power in Libya, and the lack of an authoritative optimisation tool that enables the producer to select and generate power most cost-effectively.

The main contribution of this research has been to effectively simulate engine operating conditions and attendant costs under different scenarios based on the Techno-Economic, Environmental, and Risk Analysis (TERA) philosophy. This approach is capable of optimising (and hence determining) appropriate engine parameters to optimise of existing fleets of engines to better meet current power requirements and to present a novel means of meeting market growth demands, while minimising cost and environmental impact.

The objective function and constraints of the software package are evaluated with respect to the ambient and operating conditions. In the case of repowering an existing power plant the objective of the optimisation process is to minimise electricity cost over the expected remaining life for the plant by varying the TET (power setting).

7.1 Method Implementation

The initial objective of this project was to develop an automated optimisation system for operational methodology of power plants. The approach used was to link a genetic optimisation algorithm, the TERA model/routine and GT performance data from Turbomatch (a code for determining GT performance). The GT performance data produced by Turbomatch are used as an input to TERA. This linking enables the results produced by the TERA model to be used

directly by the optimiser to determine the fitness of each individual parameter (TET). The method requires a continuous interaction between the optimiser and other components.

The GA optimiser is a FORTRAN routine which is started by calling the power demand routine that evaluates which combinations of GT engine parameters are required to meet the required load. The optimiser searches through each and every combination of engines to and calculates the total power generated by each combination and determines which of the combinations satisfy the power demand required by the user.

The GA code operates by randomly selecting a TET for each GT in the combination. Then TERA determines the cost of electricity for each combination (based on TET). TERA is structured to allow any one or combination of engines to be shut-down if power plant is not to be run full capacity. In which case TERA returns a single cost value which includes a so-called “shutdown cost” which presented here by maintenance cost.

The cost output by TERA is then fed back to the GA code. The output from TERA is not only total electricity cost but also the power output (this is the combination of GTs which is most cost effective for the given output). The latter is input to the GA optimiser subroutine which returns an objective function that meets the necessary constraints (power demand).

The GA optimiser code calculates the cost of electricity for all combinations of GT engines that can provide the required power and selects the combination that gives optimum (minimum) cost of electricity to re-run it and present the final result of minimum cost of electricity.

7.2 TERA Codings

The framework that has been developed consists of four simulation modules to assess different aspects of GT design and performance as well as its environmental and economic impact. The framework comprises:

- A Performance Module,
- A Lifting Module,

- An Economic Module, and
- An Emission Module.

A set of FORTRAN subroutines were integrated with the Turbomatch in-house software to determine the engine performance, lifing and economic aspects at different operating conditions.

- The effect of TET on thermal efficiency and fuel consumption has been investigated. Lower TET results in improved component life, but it also results in lower thermal efficiency which has a more pronounced impact on the overall electricity cost. The overall effect is that the cost of electricity increases at low TETs.
- This study has presented the effects of the design parameters (e.g TET, ϵ , etc) and operating conditions (T_{amb}) on the HP turbine blade creep life. Clean and deteriorated engines were considered. The study highlighted how these operating conditions and design parameters influenced blade creep life. Similarly with behaviour of the material was investigated as a function of TET and it was found that increasing TET decreased blade creep life.
- This study has investigated that, blade metal temperature and ambient temperature have a strong influence on blade creep life, and these two factors will mainly determine the section of the blade with the lowest creep life. Emphasis should be given to the level of temperature and stress, and the locations of maxima along the blade, to better identify the location of minimum creep life. A deeper understanding of the relationship between operating conditions and design parameters will allow designers and users to obtain better trade-offs between different design options and maintenance decisions.
- This analysis has strong economic implications because an understanding of creep life can lead to specialised maintenance in order to prolong the life of the hot gas path components. Depending on the way the engine is operated the maintenance costs will vary and the time between major overhaul will also be affected too. Estimates of creep life can be used to avoid unplanned shut downs and loss of production.

- The study has also presented the effects of operating conditions on the cost of electricity and highlights how different operating conditions (including fuel prices) influence the cost of electricity. The discount rate, fuel price and the life of power plant were estimated to facilitate better estimation of cost of electricity.
- The relevant elements in cost of electricity will increase at high TETs due to reduced engine life and increased maintenance costs. Lifting and emission models were developed to feed the economic model to facilitate more accurate calculation of the cost of electricity.
- Variations in discount rate and/or gas price change the cost of electricity. Although both these factors are outside the control of investors it needs to be emphasised that these are important factors in determining the cost of electricity. Recent history has shown how increase in fuel prices has certainly played a role in the escalating cost of electricity.
- Electricity cost and NPV are limited in this study to gas prices between \$4/GJ to \$9/GJ and the discount rates limited to between 5% to 15%. Under these conditions the cost of electricity higher and NPV is lower when emission cost is added for the life span of the project. If the value of the NPV through the project life span with or without emission cost is positive then the project is profitable under the given conditions but is more profitable without the associated emission costs.

7.3 Optimisation Method

This project has developed a computational software package that minimises the total cost of electricity produced by combinations of GT engines. The package includes consideration of variation in ambient and operating conditions at the given geographic location of the GT fleet (the power plant).

The GA was first parameterised and this was followed by a specific code written to link the GA optimisation algorithm with TERA in such a way that all the codes were linked to run as a single package. TERA runs with the GA working as an external solver to optimise the solution, a large number of subroutines already existed inside the code including economics, power demand, lifting, and

emission tax. This task was made possible by creating a library of power plant engines that includes at least five different engines sizes (the GECOL site has five different GT engines).

Different subroutines (economic, lifing, and emission) were added to the code and used to calculate the different cost functions. There was flexibility to add other cost subroutines without having to significantly change the code.

- The method developed has been applied to optimise power plant configuration with the aim of achieving minimum electricity cost subject to the constraint of a given total power demand. The code has been tested for four case studies (see Sections 6.3, 6.4, 6.5 and 6.6).
- The base line case study has been applied to minimise electricity cost for an existing power plant by repowering the existing engines. It has been shown that a 27% reduction in the total cost of electricity could be achieved by optimising the engines' combined power profiles over a year subject to the total power demand constraint.
- The second hypothetical case study related the risk of an increase in fuel price to the base line study. The results showed that, as expected, the overall cost of electricity is very sensitive to the price of fuel. A \$2 (50%) increase in the price of fuel above the reference value generated approximately 37% increase in the overall cost of electricity, independent of season. Thus the price of fuel, and the risk of fuel price increases must be factored into the baseline cost of electricity.
- The third case study investigated an increase of maintenance costs (11 %) on minimum cost of electricity when comparing to the base line case study. The result shown the resultant increase in cost of electricity was minimal, and could be ignored compared to effect of increase of fuel costs. However the cost of maintenance reflects on another very important aspect; such as the cost of lost production.
- The fourth case study was to assess the effect of increase of discount rate compare to the base line. It was shown that as the discount rate increases - which may be likened to taking on more risk - the cost of electricity value increase in a parallel and proportional relationship. An

increase of discount rate by 2% leads to almost 1.3% increase in objective function cost.

In conclusion this project has confirmed that the GA is a powerful optimisation tool that can be successfully applied to GT power plant usage. Use of the GA optimiser achieved a substantial reduction (27%) in the cost of electricity for a real and typical power plant consisting of 5 GTs. An important part of the optimisation process was allowing for changes in demand on the power plant and consideration of changes in local ambient conditions.

7.4 Recommendations for Further Work

The optimisation model developed achieved excellent results when applied to the GECOL power plant at the north cost in Libya. This strongly suggests that this thesis is a good basis for a more advanced and wider study.

Areas worthy of further research are:

- On-site comparison of model predictions against live power plants,
- A search of in-house and public domain data results to allow comparisons with model predictions,
- An investigation of the heat production of GT power plant as a possible source of useful energy in addition to electrical,
- To investigate in more detail the cost of shutting down and restarting power plant GTs,
- Inclusion of a sub-routine to predict NO_x and CO emissions from GTs as well as CO₂, this would include the effects of any resulting adverse pollution tax on cost of electricity production,
- Investigate the usability and possible beneficial economic consequences of using different types of fuel, including heavy oil, bio-diesel and even hydrogen, and
- A more detailed examination of how additional failure mechanisms in GT power plant (corrosion, fatigue, oxidation, etc.) can be simulated and included into the model.

It is to be expected that energy costs will rise in the near, and not so near, future making the modelling and simulation of GT power plants even more necessary. At the same time it is expected that the increasing demand for energy particularly in the so-called developing countries will continue unabated, so that the benefit of more efficient electricity production will not only be cost beneficial but also environmentally friendly.

REFERENCES

- [1] "The calculation is: $A \text{ lb CO}_2/\text{million BTU} \times (1 \text{ million BTU}/1000000 \text{ BTU}) \times (10.3 \text{ BTU/Wh}) \times (1 \text{ tonne}/2205 \text{ lb}) \times (\$12/\text{tonne CO}_2) = B \text{ \$/kWh}$. See "Special topics relating to electricity" in the *Energy Units* document from the American Physical Society, accessed 2010-07-1.
- [2] *NREL.A Manual for the Economic Evaluation of Energy Efficiency and Renewable Energy Technologies*, (1995.), National Renewable Energy Laboratory.
- [3] *Energy Market Authority . "Long Run Marginal Cost (LRMC) Parameters for 1 January 2005 to 31 December 2006*.
- [4] *Fuel and Energy Source Codes and Emission Coefficients". Voluntary Reporting of Greenhouse Gases Program. U.S. Department of Energy (DOE), Energy Information Administration (EIA). Retrieved (2008-04-15.), available at: <http://www.eia.doe.gov/oiaf/1605/coefficients.html>. (accessed 17/10/2012).*
- [5] *OECD. Projected Costs of Generating Electricity*. (2010.), , Organisation for Economic Co-operation and Development.
- [6] *Gas Turbine World Handbook . Vol. 28. Pequot Publishing, Inc., (2010.), .*
- [7] *Energy Units". American Physical Society. 2011.(2011-05-05.), available at: <http://www.aps.org/policy/reports/popa-reports/energy/units.cfm>.*
- [8] *Forecast International Power System Group, "The market for gas turbine electrical power generation," (Sep. 2010.), F646, Forecast International, Newtown, CT.*
- [9] A , P. and G , M. (2011), *The Future Role of Fossil Power Generation*, E50001-G220-A137-X-4A00, Siemens AG Energy Sector, Erlangen, Germany.
- [10] A. (2005), *Mechanical Design of Turbomachinery* (unpublished MSc course notes), Cranfield University.
- [11] A, N., P, P., S, O. and W, M. (2012), "A STUDY OF THE EFFECT OF GAS TURBINE EMISSIONS ON THE ECONOMICS OF NUTURL GASPIPLINE TRANSPORTATION", *Proceedings of the 20th International Conference on Nuclear Engineering ICONE20* , July30 - August 3, 2012, Anaheim, California, USA, ASME, USA, .
- [12] A. Dibbert, (2006), "Extending Gas Turbine Life", *Turbomachinery International*, vol. 47, no. 2, pp. 36-37.

- [13] A.J. Owens, and M.J. Walsh. Wiley (1966,), *Artificial Intelligence Through Simulated Evolution*, New York.
- [14] Abdul Ghafir, M. F. (2010-2011), *PERFORMANCE BASED CREEP LIFE ESTIMATION FOR GAS TURBINES APPLICATION* (pHD thesis), School of Engineering, Cranfield University.
- [15] Abdul Ghafir, M. F., Li, Y. G., Sing, R., Huang, K. and Feng, X. (2010), "Impact of Operating and Health Conditions on Aero Gas Turbine hot Section Creep Factor Approach", *ASME, Turbo Expo*, June 14- 18, 2010, Glasgow .
- [16] Al-Abri , B. (2011), *A Surface-Subsurface Model for the Techno-Economic and Risk Evaluation of Thermal EOR Projects* (PhD thesis), School of Engineering ,Department of Power and Propulsion, Cranfield University.
- [17] Ansari. Hou. and McKenzie. A, B. "Axial Flow Fans and Compressors; Aerodynamic Design and Performance". Cranfield Series on Turbomachinery Technology, 1997." .
- [18] Arnold, G. ((2005)), *Corporate Financial Management'* Third Edition ed, Pearson Education Ltd.
- [19] Assoul, Y., Benbelaid, S., Zeravcic, V. S., Bakic, G. and Dukic, M. (2008), "Life Estimation of First Stage High Pressure Gas Turbine Blades", *Scientific Technical Review*, vol. LVIII, no. 2, pp. 8-13.
- [20] B. Weber, J. Huitang, R. Pistor and P. Lowden. (2005.), "Application of an integrated engineering approach for LM1600 blade life on-line assessment (05-IAGT-2.2), in *16th Symposium on Industrial Application of Gas Turbine, Alberta, Canada*.
- [21] Bagnall, S. ((2008), *Fatiuge Life Prediction in Turbine Components* 52.
- [22] Bazaraa, M. S., Sherali H.D. and Shetty, C. M. (1993.), *Nonlinear programming: theory and algorithms*, 2nd edition ed, John Wily and Sons.
- [23] Ben Hariz, H. (2010),*The Optimisation of the Usage of Gas Turbine Generation Sets for Oil and Gas Production Using Genetic Algorithms* (PhD Thesis thesis), Cranfield University.
- [24] Betten, J., Sklepus, S. and Zolochovsky, A. (1999), "A Microcrack Description of Creep Damage in Crystalline Solids with Different Behaviour in Tension and Compression", *International Journal of Damage Mechanics*, vol. 8, no. 3, pp. 197-232.

- [25] Breipohl, A. M. (2002), "Electricity price forecasting models," Power Engineering Society Winter Meeting, 2002. *IEEE*, vol. 2, pp. 27-31.
- [26] Breipohl, A. M. (2002), "Electricity price forecasting models", *Power Engineering Society Winter Meeting*, vol. 2.
- [27] Brooks, F. J. ((2000)), *GE Gas Turbine Performance Characteristics*, GE Report.
- [28] Bueno, L. O. and Sordi, V. L. (2008), "Creep behaviour of Fe–Mn–Al steel from 500 °C to 800 °C: Part 2: Aspects of rupture strength and parametric analysis", *Materials Science and Engineering*., vol. A, pp. 483-484 - 560-563.
- [29] Cane, B. J. and Aplin, P. F. (1994), "Creep Life Assessment Methods", *Journal of Strain Analysis*, vol. 29, no. 3, pp. 225-232.
- [30] Carroll, D. L. "Genetic Algorithms and Optimizing Chemical Oxygen-Iodine Lasers," *Developments in Theoretical and Applied Mechanics*, Vol. XVIII, eds. H.B. Wilson, R.C. Batra, C.W. Bert, A.M.J. Davis, R.A. Schapery, D.S. Stewart, and F.F. Swinson, School of Engineering, The University of Alabama, 1996, pp.411-424." .
- [31] Carroll, D. L. (1996), "Chemical Laser Modeling with Genetic Algorithms," , *AIAA J*, vol. 34, no. 2, pp. 338-346.
- [32] Cerri, G., Gazzino, M. and Borghetti, S. (2006), "Hot Section Life Assessment by a Creep Model to Plan Gas Turbine Based Power Plant Electricity Production", Brussels, Belgium. ", *3rd international conference, The Future of Gas Turbine technology*, 11-12-2006.
- [33] Chaboche, J. L. (1987), "Continuum damage mechanics: Present state and future trends", *Nuclear Engineering and Design*, vol. 105, no. 1, pp. 1933.
- [34] Chen, H. (2005), *A Multi-scale Forecasting Methodology for Power Plant Fleet Management*, (PhD dissertation, thesis), Georgia Institute of Technology, Georgia.
- [35] Coello, C. A. C. (1999), *A Survey of constraint handling techniques used with evolutionary algorithms*, Technical Report, Lania-RI-99-04, Laboratorio de Informatica Avanzada, Veracruz, , available from <http://www.cs.cinvestav.mx/~constraint/> , Mexico.
- [36] Coello, C. A. C. (2002.), "Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: A survey of the state of the art. ", *Computer Methods in Applied Mechanics and Engineering*, vol. 191, pp. 1245-1287.

- [37] Cookson and Haslam, A. S. (2008), *Mechanical Design of Turbomachinery* (unpublished unpublished MSc Lecture Notes), Cranfield University.
- [38] Corneliu Popescu, Daniela E. Popescu, (Sept. 2003)], " International Geothermal Conference ", Reykjavík .
- [39] Cravero, C. and Dawes, W. (1997.), "Throughflow Design Using an Automatic Optimisation Geometry", *ASME Paper 97-GT-294*. .
- [40] D. Quagliarella, , J. P´eriaux, , C. Poloni. and G. Winter. (1997), *Genetic Algorithms and Evolution Strategy in Engineering and Computer Science: Recent Advances and Industrial Applications – EUROGEN 1997 Recent Advances in Industrial Applications*. Wiley & Sons., Triest, Italy.
- [41] D.E. Goldberg. (1989.), *Genetic Algorithms in Search, Optimization and Machine Learning* Addison-Wesley, Canada.
- [42] D.R. Westhead, D.E. Clark, C.W. Murray. (1997), "A Comparison of Heuristic Search Algorithms for Molecular Docking", *J. Comput.-Aided Mol*, vol. Des 11, no. 209–228.
- [43] David L. Carroll. (1996), " Chemical Laser Modeling with Genetic Algorithms," *AIAA Journal*, vol. 34, no. 2.
- [44] Davis L.B. and Washam. R.M. (1989), "*Development of a Dry Low NOx Combustor*", *American Society of Mechanical Engineers, paper 89-GT-255*.
- [45] Dawkins, R. (2006,), *The Selfish Gene*, 30th Anniversary Edition edn ed, Oxford University Press, Oxford, UK.
- [46] De Jong, K. A. (1975), *An analysis of the behavior of a class of genetic adaptive systems* , University of Michigan.
- [47] DiMelfi, R. J. (1978), " "Understanding the Larson-Miller parameter", by F. T. Furillo, S. Purushothaman and J. K. Tien (1)", *Scripta Metallurgica*, ", vol. 12, no. 4, pp. 327-329.
- [48] DIMSON, E. (1989), "The discount rate for a power station", *Energy Economics*, no. 11, pp. 13.
- [49] Eno, D. R., Young, G. A. and Sham, T. L. (2008), "A Unified View of Engineering Creep Parameters ", *Proceedings of PVP2008, ASME Pressure Vessels and Piping Division Conference*, July 21-31, Chicago, Illinois, pp. 1.
- [50] Erdam H A & Sevilgen H S, (2006), " Case study: effect off ambient temperature on the electricity production and fuel consumption of simple cycle gas turbine, applied thermal engineering ", Vol. 26, pp. 230-236.

- [51] Eshati, S., ABU, A., LASKARIDIS, P. and HASLAM, A. (2011), "Investigation into the Effects of Operating Conditions and Design Parameters on the Creep Life of High Pressure Turbine Blades in A Stationary Gas Turbine Engine ", *10th International Symposium on Compressor and Turbine Flow Systems-Theory and Application Areas Lodz*, 26 - 28 October.
- [52] Eshati, S., Abdul Ghafir, M. F., Laskaridis, P. and Li, Y. G. (2010), "Impact of operating conditions and design parameters on gas turbine hot section creep life.", *ASME, Turbo Expo*, 14-18-JUNE 2010, Glasgow .
- [53] F. Glover, M. L., (1997.), *Tabu Search*, Kluwer, Boston.
- [54] Frank, J. B., *Gas turbine performance characteristics*, , GER-3567H, GE Power Systems, Schenectady, New York.
- [55] G. A. Webster and R. A. Ainsworth (1994.), "*High Temperature Component Life Assessment*", *Chapman & Hall, London*, vol. 1.
- [56] G. E. Dieter (ed.) (1989.), *Mechanical Metallurgy, SI Metric*, 3rd ed, McGraw-Hill Higher Education.
- [57] G. Parthasarathy. (2008), "Neural Network Models for Usage Based Remaining Life Computation," *Journal of Engineering for Gas Turbines and Power*, vol. 130.
- [58] G. Y. Lai (2007.), " *High-temperature corrosion and materials applications*. , ", *ASM International* .
- [59] Gayraud, S., (1996), *Technical and Economical Assessment for Industrial Gas Turbine Selection* (MSc Thesis thesis), Cranfield University, United Kingdom.
- [60] GECOL (2010), *General Electrical Company of Libya (GECOL): Annual report*, , Libya.
- [61] Gen, M. & Cheng, R. (2000.), *Genetic Algorithms & Engineering Optimization*, . , Wiley, New York.
- [62] Giannakoglou, K. C. (1999.), "Designing Turbomachinery Blades Using Evolutionary Methods", *ASME Paper 99-GT-181* .
- [63] Giles, M. B. and Drela, M. (1987), "A two-dimensional transonic aerodynamic design method", *AIAA Journal*, vol. 25, no. (9), pp. 1199-1206.
- [64] Goldberg D. E. and Deb K. (1992), " Genetic Algorithms, Nois, and the Sizing of Populations", *Complex System*, ", vol. 6, pp. pp. 333-362.

- [65] Goldberg, D. E. and Deb, K., (1991), "A Comparative Analysis of Selection Schemes used in Genetic Algorithms," in: *Foundations of Genetic Algorithms*, Morgan Kauffmann Publishers, San Mateo, CA, . ", .
- [66] Goldberg, D. E. (1989,), *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley, Reading, MA. .
- [67] Gorji .M and Fouladi. F. *Ambient temperature effects on gas turbine power plant: a case stud* , Department of mechanical engineering, faculty of engineering, university of Mazandaran Babol, Iran.
- [68] H, G., Beyer. and H-Paul, S. (2002), " Evolution strategies A comprehensive introduction , *Natural Computing*, vol. 1, pp. 3–52.
- [69] H.I.H. Saravanamuttoo and G.F.C. Rogers, H. C. (2001), *Gas Turbine Theory*, Fifth Edition. ed, .
- [70] Harry, G. S. (1989), "Least cost electric utility planning", in John Wiley & Sons, USA .
- [71] Haslam and Cookson, R. A. (2007), *Mechanical Design of Turbomachinery* (unpublished MSc Lecture Notes), CranfieldUniversity.
- [72] Holland, J. H. (1975), *Adaptation in naturel and artificial systems*, MIT Press, Cambridge.
- [73] Holland, J. H. (1992,), *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence* , 2nd, MIT Press, Massachusetts.
- [74] Homaifar A., Lai S. H. V. and Qi X. ((1994),), " Constrained Optimisation Via Genetic Algorithms" *Simulation*, vol. 62, no. (4), pp. 242-254.
- [75] ICAO Journal (2006), "The magazine of the International Civil Aviation Organization", *The magazine of the International Civil Aviation Organization*, vol. 61, no. 5.
- [76] IEO2011 (2011), *International Energy Outlook 2011*, DOE/EIA-0484, U.S. Energy Information Administration, USA.
- [77] J. DeVillers. (1996.), *Genetic Algorithms in Molecular Modeling, Principles of QSAR and Drug Design*, Academic Press.
- [78] J. Li and A. Dasgupta. (Sep. 1993), "Failure-mechanism models for creep and creep rupture," *IEEE Transactions on Reliability*, vol. 42, no. 3, pp. 339-353.

- [79] J.H. Kalivas (1995), "Adaption of Simulated Annealing to Chemical Optimization Problems: Data Handling in Science and Technology .", Elsevier Science, vol. 15.
- [80] John Henry Holland. (1975), *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*. The Uni-versity of Michigan Press, Ann Arbor.
- [81] K. Brun and R. Kurz (2010), "GAS TURBINE CORROSION -. [Online]. Available, available at: http://findarticles.com/p/articles/mi_qa5385/is_201003/ai_n53928165/ (accessed [Accessed: 13-Sep-2011].).
- [82] K.G. Kyprianidis, R.F.C. Quintero, D.S. Pascovici, S.O.T. Ogaji, P. P. and A.I. Kalfas. (2008), "EVA- A Tool for Environmental Assessment of Novel Propulsion Cycles", *ASME Paper GT2008-50602*, June 9-13, Berlin, Germany, ASME TURBO EXPO 2008 Power for Land Sea and Air,., Germany.
- [83] Kaufman, J. G., Long, Z. and Ningileri, S. (2007), "Application of Time-Temperature-Stress Parameters to High Temperature Performance of Aluminium Alloys", Warrendale, PA .
- [84] khatib, H. (2008), *Economic Evaluation of Projects in the Electricity Supply Industry*, The Institution of Engineering and Technology, London, UK.
- [85] Kian, A., Keyhani, A. (2001), "Stochastic price modeling of electricity in deregulated energy markets," , in Hawaii International Conference, *System Sciences, 2001. Proceedings of the 34th Annual*, 3-6 Jan.
- [86] Kikuo Fujita et al. (1996) "Genetic Algorithms Based Optimal Planning Method of Energy Plant Configurations" Conferences", *The 1996 ASME Design Engineering Technical*, September 18-22, Irvine, California, .
- [87] Koff, B. L. (2003), "Gas Turbine Technology Evolution-A Designer's Perspective", 14-17 July, Dayton, Ohio.
- [88] Kundu, P. K. and Cohen, I. M. (2008), *Fluid Mechanics, fourth edition*. QA901 .K86 2008, previous edition as electronic resource: QA901 .K86, Academic Press, New York.
- [89] L. Darell Whitley. "A genetic algorithm tutorial. Statistics and Computing, 4 (2):65–85, June 1994. ISSN: 0960-3174 (Print) 1573-1375 (On-line). doi:10.1007/BF00175354. [accessed 2012-10-25]. Also published as technical report [2207][Online], available at: Online available at http://samizdat.mines.edu/ga_tutorial/ga_tutorial.ps and <http://www.citeulike.org/user/Bc91/article/1449453>.

- [90] Lefebvre, A. H. (1984), "Fuel Effects on Gas Turbine Combustion—Liner Temperature, Pattern Factor, and Pollutant Emissions", *Journal of Aircraft*, vol. 21, no. 11, pp. 887–98.
- [91] Lefebvre, A. H. (1998), *Gas Turbine Combustion*, 2nd ed, Taylor and Francis, London, UK.
- [92] Leonard, G. and Stegmaier, J. (1993), "Development of an Aeroderivative Gas Turbine Dry Low Emissions Combustion System", *American Society of Mechanical Engineers, paper 93-GT-288*.
- [93] Lotfi, O. (2006), *Aerodynamic optimisation of an industrial axial fan blade* (Ph.D. thesis), Cranfield University, School of Engineering, 2006.
- [94] M. E. Kassner and M.-T. Peres-Prado (2004), *Fundamentals of creep in metals and alloys*, Elsevier Science Ltd, Oxford.
- [95] M. T. Naeem, S. A. Jazayeri and N. Razamahdi (2008), "Failure Analysis of Gas Turbine Blades", *IJAC-IJME International Conference 2008*, vol. Nashville, Tennessee.
- [96] M.W, W. and R. Singh. (2002), " Propulsion System Optimisation for Minimum Global Warming Potential.", *Proceeding of the 23rd ICAS Congress*, Toronto, Canada .
- [97] MACKERRON, G. (1992), "Nuclear Costs: Why do they keep rising?", *Energy Policy*, , no. 20, pp. 641-652.
- [98] Marahleh, G., Kheder, A. R. I. and Hamad, H. F. (2006), "Creep-Life Prediction of Service-Exposed Turbine Blades", *Materials Science*, vol. 42, pp. 476-481.
- [99] Marquez, L., Hill, T. O'Connor, M., and Remus, W. (1992), "Neural network models for forecast: a review," *System Sciences, Proceedings of the Twenty- Fifth Hawaii International Conference on*, vol. iv, no. 1992, pp. 7-10.
- [100] Marsh, D. W. (1980), *Economic of electric utility power generation*, , Oxford University.
- [101] Martin.J. (2002), " Analysis and Multidisciplinary Optimisation of Internal Coolant Networks in Turbine Blades", *Journal of Propulsion and Power*, vol. 18, no. 4.
- [102] McGovern. T and Hicks, C. (2004), "Deregulation and restructuring of the global electricity supply industry and its impact upon power plant suppliers", *International Journal of Production Economics*, no. 89, pp. 321-337.

- [103] Michalewicz, Z. A. (1995), "Survey of constraint handling techniques in evolutionary computation methods", *Proceedings of the 4th Annual Conference on Evolutionary Programming*, pp. 135-155.
- [104] Michalewicz, Z., Dasgupta, D., Le Riche, R. and Schoenauer, M. (1996), "Evolutionary algorithms for constrained engineering problems ", *Computers & Industrial Engineering Journal*, vol. 30, pp. 851-870.
- [105] Michalewicz, Z. and Fogel, D. B. (2000), *How to solve it: Modern Heuristics* , Springer Verlag, , Berlin.
- [106] Mitchell Melanie (1999), *An Introduction to Genetic Algorithms*, Fifth ed, Massachusetts Institute of Technology, UK.
- [107] Mobley, R. K. (2002), *An Introduction to Predictive Maintenance*, 2nd Edition ed, Maryland Heights, MO, Elsevier Science.
- [108] Mori, H., Urano, S., (1996), "Short-term load forecasting with chaos time series analysis," Intelligent Systems Applications to Power Systems, 1996. ", *Proceedings, ISAP '96., International Conference on*, 28 Jan.-2 Feb .
- [109] N, M. (1979), " COMBINATORIAL OPTIMIZATION WITH RATIONAL OBJECTIVE FUNCTIONS", *MATHEMATICS OF OPERATIONS RESEARCH USA.*, vol. 4, no. 4.
- [110] N. Boutarek, D. S., M. A. Acheheb, M. Iggui and S. Bouterfaïa (2008), "Competition between three damaging mechanisms in the fractured surface of an Inconel 713 superalloy," *Materials Characterization*", vol. 59, no. 7, pp. 951-956.
- [111] N. Metropolis., A.W. Rosenbluth., M.N. Rosenbluth. and A.H. (1953), " Equation for State Calculation by Fast Computing Machines ", *J. Chem. Phys*, vol. 21, pp. 1087–1091.
- [112] Naeem, M. (2009), "Implications of Day Temperature Variation for an Aero-Engine's HP Turbine-Blade's Creep Life-Consumption", *Aerospace Science and Technology*, vol. 13, pp. 27-35.
- [113] Naeem, M., Singh, R. and Probert, D. (2001), "Consequences of Aero-Engine Deteriorations for Military Aircraft", *Applied Energy*, vol. 70, pp. 103-133.
- [114] Obradovic, Z., Tomsovic, K. (1999), "Time series methods for forecasting electricity market pricing," *Power Engineering Society Summer Meeting, 1999. IEEE*, vol. 2, pp. 18-22.

- [115] Oyama, A. and Liou, M. S. (2002.), "Multiobjective Optimisation of a Multistage Compressor Using Evolutionary Algorithm", *AIAA Paper 2002-3535*.
- [116] Oyama, A., Liou, M. S. and Obayashi, S., (2002), "Transonic Axial-Flow Blade Shape Optimisation Using Evolutionary Algorithm and Three-Dimensional Navie-Stokes Solver", *AIAA Paper 2002-5642*.
- [117] Ozhan Oksuz, , Sinan Akmandor and Mehmet S. Kavsaoglu. (2002), "Aerodynamic Optimization of Turbomachinery Cascades Using Euler/Boundary-Layer Coupled Genetic Algorithms", *JOURNAL OF PROPULSION AND POWER*, vol. Vol. 18, no. No. 3.
- [118] P. Mestaneck. (2008), "Low cycle fatigue analysis of a last stage steam turbine blade," *Applied and Computational Mechanics*, vol. 2, pp. 71-82.
- [119] Palmer. (1999), *The TURBOMATCH Scheme for Gas-Turbine Performance Calculations* (unpublished User's Guide), Cranfield University, Cranfield, UK.
- [120] Pavri. R. and Moore.G, D. (2003), "*Gas Turbine Emissions and Control*," Atlanta, US : GE Power Systems, GER-4211.
- [121] Quintero, R. F. C. (2008),*Techno-Economic and Environmental Risk Assessment of Innovative Propulsion Systems for Short Range Civil Aircraft* (unpublished PhD thesis), Cranfield University.
- [122] R. P. Y. Wei and R. P. Gangloff (1989), "*Fracture Mechanics: Perspectives and Directions*", *Philadelphia: ASTM International*, vol. 1.
- [123] R. QUINTERO (2009), *Techno-Economic and Environmental Risk Assessment of Innovative Propulsion Systems for Short-Range Civil* (PhD thesis), School of Engineering ,Department of Power and Propulsion, Cranfield University.
- [124] R. Viswanathan (1989), "*Damage mechanisms and life assessment of high-temperature components*", *ASM International*.
- [125] R. W. Evans and B. Wilshire (1999), *Introduction to Creep*, , IOM Communication Ltd, London.
- [126] R. Wehrens, , E. Pretsch, and L.M.C. Buydens (1998), 'Quality Criteria of Genetic Algorithms for Structure Optimization', *J.Chem. Inf. Comput. Sci*, vol. 38, pp. 151–157.
- [127] R.S. Judson (1997), "Genetic Algorithms and Their use in Chemistry", in K.B. Lipkowitz, D. B. B. (ed.) *Reviews in Computational Chemistry* , pp. VCH1–73.

- [128] Razak, A. M. Y. (2007), *Industrial Gas Turbine: Performance and Operability*, Woodhead Publishing Limited, Abington Hall Cambridge, England.
- [129] Richard Knight et al. (2006), " GTPOM: Thermo-Economic Optimization of Whole Gas Turbine Plant", *Journal of Engineering for Gas Turbines and Power*, vol. 12, pp. 535.
- [130] Rizk, N. K., and Mongia, H. C. (1994), "*Emissions Predictions of Different Gas Turbine Combustors*", *AIAA*, vol. 94-0118.
- [131] Eshati, S. (2012), *AN EVALUATION OF OPERATION AND CREEP LIFE OF STATIONARY GAS TURBINE ENGINE* (PhD thesis), SCHOOL OF ENGINEERING ,DEPARTMENT OF POWER AND PROPULSION, CRANFIELD UNIVERSITY.
- [132] S.Kirkpatrick,C.D. Gelatt, and M.P. Vecchi. (1983)," Optimization by Simulated Annealing", *Science*, vol. 220, pp. 671–680.
- [133] S.O.T. Ogaji, P. Pilidis and R. Hales. (2007), " TERA - ATool for Aero-engine Modelling and Management.", *Second World Congress on Engineering Asset Management and the Fourth International Conference on Condition Monitoring*, 11-14 June,2007, Harrogate,UK, Harrogate,UK.
- [134] Senecal P. K. " Development of a Methodology for Internal Combustion Engine Design Using Multi-Dimensional Modeling with Validation Through Experiments," Ph.D. Dissertation, University of Wisconsin-Madison, 2000.
- [135] Singh. (2007), *Gas Turbine Applications* (unpublished Course Notes), Department of Power and Propulsion, Cranfield University.
- [136] Sirag, A. (2011), *A TERA Approach to Aero Engine Performance Assessment* (MSc thesis), CRANFIELD UNIVERSITY.
- [137] Smith, A. E. and Coit, D. W. (1997), "Constraint handling techniques-penalty functions", in *Handbook of Evolutionary Computation*, Oxford University Press and Institute of Physics Publishing, UK, pp. chapter C 5.2.
- [138] Sobieszczanski-Sobieski.J and .Haftka. R, T. (1996), " Multidisciplinary Aerospace Design Optimization: Survey of Recent Developments, 96-0711, Jan1996. ", *AIAA Paper* .
- [139] Stephen, O. (2010), *TERA for Aircraft Engines*, available at: <http://www.cranfield.ac.uk/environment/research/envhealth/page26938.html> (accessed October, 2009).

- [140] Stephen, O., Pericles, P. and Vishal, S. (2009), "Power Plant Selection in a Carbon Constrained World: The TERA (Technoeconomic Environmental Risk Analysis)", *Journal of Aerospace Power*, vol. 24, no. 4, pp. 1.
- [141] Stern, N. (2006), *Stern Review: The Economics of Climate Change*, Her Majesty's Treasury .
- [142] T. J. Carter (2005), ""Common failures in gas turbine blades," *Engineering Failure Analysis*", vol. 12, no. 2, pp. 237-247.
- [143] T. Sourmail (2009), "Coatings for Turbine Blades," [Online]. Available, available at: <http://www.msm.cam.ac.uk/phase-trans/2003/Superalloys/coatings/index.html> (accessed 04/07/2012).
- [144] Temraz, H.K., Salama, M.M.A., and Chikhani, A.Y., (1997), "Review of electric load forecasting methods, Electrical and Computer Engineering," , *IEEE 1997 Canadian Conference*, vol. 1, no. 1997, pp. 25-28.
- [145] Temraz, H. K., Salama, M. M. A. and Chikhani, A. Y. (1997), "Review of electric load forecasting methods", *Electrical and Computer Engineering*, vol. 1, pp. 25-28.
- [146] Thomas , W. (2009), " Global Optimization Algorithms Theory and Application", [Online], . 10/2012 available at: Newest Version: <http://www.it-weise.de/>.
- [147] Tinga, T., De Wolf, W. B., Visser, W. P. J. and Woldendorp, S. (2001), "Integrated Lifting Analysis of a Film-Cooled Turbine Blade", *RTO-AVT Symposium on Monitoring and Management of Gas Turbine Fleets for Extended Life and Reduced Costs* NATO Research and Technology, Manchester, UK .
- [148] Torbidoni, L. and Horlock, J. H. (2005), "A new method to calculate the coolant requirements of a high-temperature", *Journal of Turbomachinery*, ASME, vol. 127, no. 1, pp. 191-199.
- [149] U. S. Energy Information Administration. (2010), *Updated Capital Cost Estimates for Electricity Generation Plants*, DC 20585, U.S. Department of Energy, Washington.
- [150] United Nations, (1998), *The Kyoto Protocol* .
- [151] Uwakwe, D. (2011), *Industrial Gas Turbine Emission Assessment and Modelling for LNG Application* (MSc Thesis thesis), School of Engineering, Cranfield University, UK.

- [152] V. Kvasnicka, J. P., (1994), "Fast Evaluation of Chemical Distance by Tabu Search Algorithm", *J. Chem. Inf. Comput. Sci*, vol. 34, pp. 1109–1112.
- [153] Vagn, H. J. (1998), "Non-destructive metallography used on-site, possibilities and experience", *7th European Conference on Non-Destructive Testing*, Copenhagen .
- [154] Vassilios. (Turbomatch Manual), *Gas Turbine Performance Simulation and Diagnostics* (unpublished Course Notes), Cranfield University, School of Engineering.
- [155] Vigna, S. O. (2006), *A Flexible Lifting Model for Gas Turbines: Creep and Low Fatigue Approach* (MSc thesis), Cranfield University.
- [156] Viswanathan, R. and Stringer, J. (2000), "Failure Mechanisms of High Temperature Components in Power Plants", *Journal of Engineering Materials*, vol. 122, pp. 246-255.
- [157] Wanis, Mohamed., B. Al-Abri., P. Pilidis. and A. Nasir. (2012), "Economic Evaluation of Industrial Gas Turbines for Electrical Power Generation, GT2012-69495", *Proceedings of ASME TurboExpo2012: Power for Land, Sea and Air*, GT2012 June 11-15, Copenhagen .
- [158] Wanis, Mohamed., S. Eshati., P. Pilidis., S. Ogaji., P. Laskaridis. and A. Nasir (2011), "A Method to Evaluate the Impact of Power Demand on HPT Blade Creep Life", *Proceedings of ASME Turbo Expo 2011: Power for Land, Sea and Air GT2011 – 45092*, June 06-10, Vancouver, Canada .
- [159] Wanis, Mohamed., S. Ogaji., R. Khan., P. Pilidis., B. Al-Abri. and A. Nasir. (2011), "Economic Optimisation of Industrial Gas Turbines for Electrical Power Generation: A Creep and Performance Based Study", *Proceedings of ASME Power2011*, July 12-14, Denve .
- [160] Wanis, Mohamed., V. Sethi., P. Pilidis., Hugo Pervier. and Raja S.R. Khan. (2012.), " A Method to Evaluate the Emissions of Gas Turbine for Power Generation,GT2012-69491 ", *ProceedingsofASMETurboExpo2012: Power for Land, Sea and Air GT2012* June 11-15, Copenhagen .
- [161] Wahba, W. (2001), *Design Optimisation of Centrifugal Pump Impellers Using a Parallel Genetic Algorithm* (PhD Thesis thesis), Cranfield University., Cranfield University.
- [162] Wallace, J. M. and Dimitri, N. M. (2003), "Creep Life Uncertainty Assessment of a Gas Turbine Airfoil", *Proceeding of 4th AIAA Non-Deterministic Approaches Forum*, 7-10, April, Norfolk Virginia.
- [163] Walsh, P. P. and Fletcher, P. (2004), *Gas Turbine Performance*, 2nd, Black well Science Ltd.

- [164] Wanis, Mohamed, S. Eshati, P. Pilidis, S. Ogaji and P. Laskaridis. (2011), "A Method to Evaluate the Impact of Power Demand on HPT Blade Creep Life", *Proceedings of ASME Turbo Expo 2011: Power for Land, Sea and Air GT2011*, Vancouver, Canada .
- [165] Weber, B., Huitang, J., Pistor, R. and Lowden, P. (2005), "Application of An Integrated Engineering Approach for LM1600 Blade Life On-Line Assessment", 12- 14 October 2005, Banff, Alberta, Canada .
- [166] Wehrens.Ron. and L.M, C.,Buydens. (2000), "Classical and Nonclassical Optimiazation Methods", in *Encyclopedia of Analytical Chemistry*, John Wiley & Sons Ltd, Chichester, pp. 9678-9689.
- [167] Wood, M. I. (1999), "Gas Turbine Hot Section Components: the challenge of "residual life" assessment", *Journal of Power and Energy*, vol. 214, pp. 193-201.
- [168] Zhao, J., Li, D., Zhang, J., Feng, W. and Fang, Y. (2009), "Introduction of SCRI model for creep rupture life assessment", *International Journal of Pressure Vessels and Piping*, vol. 86, no. 9, pp. 599-603.
- [169] Zhao, J., Han, S., Gao, H. and Wang, L. (2004), "Remaining Life Assessment of a CrMoV Steel Using the Z-Parameter Method", *International Journal of Pressure Vessels and Piping*, vol. 81, pp. 757-760.
- [170] Zhimin, L., Vitali, V. and Dimitri, N. M. (2002), "Probabilistic Remaining Creep Life Assessment for Gas Turbine Components under Varying Operating conditions", *43rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference*, 22-25, April, Denver, Colorado .
- [171] Zhimin, L., Mavris, D. N. and Volovoi, V. V. (2001), "Creep Life Prediction of Gas Turbine Components Under Varying Operating Conditions", june 4-7, Louisiana, USA.
- [172] Zuljan, D. and Grum, J. (2005), "Non-destructive metallographic analysis of surface and microstructures by means of replicas, in *The 8th International Conference of the Slovenian Society for Non-Destructive Testing*", *The 8th International Conference of the Slovenian Society for Non-Destructive Testing*, September 1-3, Slovenia .

APPENDICES

Appendix A : Engines Input Files

A.1 Engine (1) Input File Turbomatch Design Point Performance Calculations

```
DP SI KE CT FP
-1
-1
INTAKE S1-2 D1-4 R300
COMPRES S2-3 D5-11 R301 V5 V6
PREMAS S3,4,9 D12-15
BURNER S4-5 D16-18 R303
MIXEES S5,9,6
TURBIN S6-7 D19-26,301,27 V19 V20
NOZCON S7-8,1 D28 R305
PERFOR S1,0,0 D19,29-31,305,300,303,0,0,0,0,0,0,0
CODEND
BRICK DATA ITEMS
! INTAKE
1 0.0 ! ALTITUDE
2 0.0 ! ISA DEVIATION:Tamb=288.15 K, Pamb=1.01325 bar
3 0.0 ! MACH NUMBER
4 0.9951 ! PRESSURE RECOVERY
! COMPRESSOR
5 -1.0 ! SURGE MARGIN
6 0.98 ! DESIGN SPEED
7 15 ! DESIGN PRESSURE RATIO
8 0.885 ! ISENTROPIC EFFICIENCY
9 1.0 ! ERROR SELECTION
10 3.0 ! COMPRESSOR MAP NUMBER
11 0.0 ! RELATIV TO DP VARIABLE STATOR ANGLE
! SPLITTER
12 0.96 ! LAMBDA (W)
13 0.0 ! DELTA (W)
14 1.0 ! LAMBDA (P)
15 0.0 ! DELTA (P)
! BURNER
16 0.07 ! PRESSURE LOSS 0%
17 0.998 ! EFFICIENCY
18 -1.0 ! FUEL FLOW (-1 = TET SPECIFIED. SEE SV DATA)
! POWER TURBINE
19 165100000.0 ! AUXILLARY POWER REQUIRED
20 0.8 ! NON DIMENTIONAL MASS FLOW
21 0.6 ! NON DIMENTIONAL SPEED
22 0.90 ! ISENTROPIC EFFICIENCY
23 -1.0 ! RELATIV ROTATIONAL SPEED
24 1.0 ! COMPRESSOR NUMBER
25 3.0 ! TURBINE MAP NUMBER
26 1000.0 ! POWER INDEX N
27 0.0 ! ANGLE
! NOZCON
28 -1.0 ! AREA FIXED
! PERFORMANCE
```

29 1.0 ! PROPELLER EFFICIENCY
 30 0.0 ! SCALLING INDEX
 31 0.0 ! REQUIRED DP NET THRUST OR POWER OUTPUT FOR PT

-1
 1 2 532.00 ! MASS FLOW
 5 6 1378.0 ! TURBINE ENTRY TEMPERATURE
 -1
 -3

A.2 Engine (2) Input File Turbomatch Design Point Performance Calculations

DP SI KE CT FP

-1

-1

INTAKE S1-2 D1-4 R100
 COMPRE S2-3 D5-10 R101 V5 V6
 PREMAS S3,12,4 D11-14
 PREMAS S4,13,5 D15-18
 BURNER S5-6 D19-21 R102
 MIXEES S6,13,7
 TURBIN S7-8 D22-29,101 V23
 MIXEES S8,12,9
 TURBIN S9-10 D30-38 V30 V31
 NOZCON S10-11,1 D39 R107
 PERFOR S1,0,0 D30,40-42,107,100,102,0,0,0,0,0
 CODEND

DATA ITEMS

!INTAKE

1 0.0 ! INTAKE ALTITUDE
 2 0.0 ! ISA DEVIATION
 3 0.0 ! MACH NO
 4 0.9951 ! PRESSURE RECOVERY

!COMPRESSOR

5 -1.0 ! Z PARAMETER
 6 -1.0 ! ROTATIONAL SPEED N
 7 23.1 ! PRESSURE RATIO
 8 0.8825 ! ISENTROPIC EFFICIENCY
 9 0.0 ! ERROR SELECTION
 10 4.0 ! MAP NUMBER

!PREMAS

11 0.025 ! BLEED AIR
 12 0.00 ! FLOW LOSS
 13 1.0 ! PRESSURE RECOVERY
 14 0.0 ! PRESSURE DROP

!PREMAS

15 0.075 ! BLEED AIR
 16 0.0 ! FLOW LOSS
 17 1.0 ! PRESSURE RECOVERY
 18 0.0 ! PRESSURE DROP

!BURNER

19 0.075 ! FRACTIONAL PRESSURE LOSS DP/P
 20 1.0 ! COMBUSTION EFFICIENCY

```

21 -1.0      ! FUEL FLOW
!HP TURBINE
22 0.0       ! AUXILIARY WORK
23 -1.0      ! NDMF
24 -1.0      ! NDSPEED CN
25 0.885     ! ISENTROPIC EFFICIENCY
26 -1.0      ! PCN
27 1.0       ! COMPRESSOR NUMBER
28 4.0       ! TURBINE MAP NUMBER
29 -1.0      ! POWER LOW INDEX
!POWER TURBINE
30 27600000.00 ! AUXILIARY WORK
31 -1.0      ! NDMF
32 -1.0      ! NDSPEED CN
33 0.885     ! ISENTROPIC EFFICIENCY
34 -1.0      ! PCN
35 0.0       ! COMPRESSOR NUMBER
36 4.0       ! MAP NUMBER
37 -1.       ! POWER LOW INDEX
38 -1.       ! COMWORK
!NOZCON
39 -1.       ! THROAT AREA
!PERFOR
40 1.00      ! PROPELLER EFFICIENCY
41 0.0       ! SCALING INDEX
42 0.0       ! REQUIRED THRUST
-1
1 2 82.5
6 6 1505
-1

```

A.3 Engine (3) Input File Turbomatch Design Point Performance Calculations

```

DP SI KE CT FP
-1
-1
INTAKE S1-2  D1-4      R300
COMPRES S2-3  D5-11    R301 V5 V6
PREMAS S3,4,9 D12-15
BURNER S4-5   D16-18    R302
MIXEES S5,9,6
TURBIN S6-7   D19-26,301,27 V20
NOZCON S7-8,1 D28
PERFOR S1,0,0 D19,29-32,300,302,0,0,0,0,0,0,0,0
CODEND

```

DATA ITEMS

```

1  0.0      ! INTAKE ALTITUDE
2  0.0      ! ISA DEVIATION
3  0.0      ! MACH NO
4  1.0      ! PRESSURE RECOVERY
!COMPRESSOR
5  -1.0     ! Z PARAMETER
6  -1.0     ! ROTATIONAL SPEED N

```

```

7 12.6 ! PRESSURE RATIO
8 0.88 ! ISENTROPIC EFFICIENCY
9 1.0 ! ERROR SELECTION
10 4.0 ! MAP NUMBER
11 0.0 ! ANGLE
!PREMAS
12 0.95 ! BLEED AIR
13 0.0 ! FLOW LOSS
14 1.0 ! PRESSURE RECOVERY
15 0.0 ! PRESSURE DROP
!BURNER
16 0.05 ! FRACTIONAL PRESSURE LOSS DP/P
17 0.99 ! COMBUSTION EFFICIENCY
18 -1.0 ! FUEL FLOW
!TURBINE
19 130100000.0! AUXILIARY WORK
20 -1.0 ! NDMF
21 -1.0 ! NDSPEED CN
22 0.89 ! ISENTROPIC EFFICIENCY
23 -1.0 ! PCN
24 1.0 ! COMPRESSOR NUMBER
25 4.0 ! TURBINE MAP NUMBER
26 1000.0 ! POWER LOW INDEX
27 0.0 ! NGV ANGLE RELATIVE TO D.P.
!NOZCON
28 -1.0 ! THROAT AREA
!PERFOR
29 1.00 ! PROPELLER EFFICIENCY
30 0.0 ! SCALING INDEX
31 0.0 ! REQUIRED THRUST
32 0.0 !NOZZLE GROSS THRUST
-1
1 2 410.0 ! INLET MASS FLOW (kg/s)
5 6 1400.0 ! COMBUSTION OUTLET TEMPERATURE (K)
-1

```

A.4 Engine (4) Input File Turbomatch Design Point Performance Calculations

```

DP SI KE CT FP
-1
-1
INTAKE S1,2 D1-4 R300
COMPRES S2,3 D5-11 R301 V5 V6
PREMAS S3,4,9 D12-15
BURNER S4,5 D16-18 R302
MIXEES S5,9,6
TURBIN S6,7 D19-26,301,27 V20
NOZCON S7,8,1 D28
PERFOR S1,0,0 D19,29-32,300,302,0,0,0,0,0,0,0,0
CODEND

DATA ITEMS
1 0.0 ! INTAKE ALTITUDE
2 0.0 ! ISA DEVIATION
3 0.0 ! MACH NO
4 1.0 ! PRESSURE RECOVERY
!COMPRESSOR

```

```

5 -1.0 ! Z PARAMETER
6 -1.0 ! ROTATIONAL SPEED N
7 12.2 ! PRESSURE RATIO
8 0.88 ! ISENTROPIC EFFICIENCY
9 0.0 ! ERROR SELECTION
10 4.0 ! MAP NUMBER
11 0.0 ! STATOR ANGLE REL. TO DP
!PREMAS
12 0.90 ! BLEED AIR
13 0.0 ! FLOW LOSS
14 1.0 ! PRESSURE RECOVERY
15 0.0 ! PRESSURE DROP
!BURNER
16 0.06 ! FRACTIONAL PRESSURE LOSS DP/P
17 0.99 ! COMBUSTION EFFICIENCY
18 -1.0 ! FUEL FLOW
!TURBINE
19 42300000.0! AUXILIARY WORK
20 -1.0 ! NDMF
21 -1.0 ! NDSPEED CN
22 0.89 ! ISENTROPIC EFFICIENCY
23 -1.0 ! PCN
24 1.0 ! COMPRESSOR NUMBER
25 4.0 ! TURBINE MAP NUMBER
26 1000.0 ! POWER LAW INDEX
27 0.0 ! NGV ANGLE REL. TO DP
!NOZCON
28 -1.0 ! THROAT AREA
!PERFOR
29 1.0 ! PROPELLER EFFICIENCY
30 0.0 ! SCALING INDEX
31 0.0 ! REQUIRED THRUST
32 0.0 !NOZZLE GROSS THRUST
-1
1 2 141.1 ! INLET MASS FLOW (kg/s)
5 6 1408.0 ! COMBUSTION OUTLET TEMPERATURE; TET (K)
-1

```

A.5 Engine (5) Input File Turbomatch Design Point Performance Calculations

```

DP SI KE CT FP
-1
-1
INTAKE S1-2 D1-4 R300
COMPRES S2-3 D5-11 R301 V5 V6
PREMAS S3,4,12 D12-15
PREMAS S12,13,14 D16-19
BURNER S4-5 D20-22 R303
MIXEES S5,13,6
TURBIN S6-7 D23-30 V23 V24
MIXEES S7,14,8
DUCTER S8-9 D31-34 R304
TURBIN S9-10 D35-42,301 V36
ARITHY D43-49
NOZCON S10-11,1 D50 R305
PERFOR S1,0,0 D100,52-54,305,300,303,0,0,304
CODEND

```

BRICK DATA ITEMS

! INTAKE

1 0.0 ! ALTITUDE
 2 0.0 ! ISA DEVIATION:Tamb=288.15 K, Pamb=1.01325 bar
 3 0.0 ! MACH NUMBER
 4 -1.0 ! PRESSURE RECOVERY

! COMPRESSOR

5 -1.0 ! SURGE MARGIN
 6 .98 ! DESIGN SPEED
 7 30.0 ! DESIGN PRESSURE RATIO
 8 0.86 ! ISENTROPIC EFFICIENCY
 9 0.0 ! ERROR SELECTION
 10 4.0 ! COMPRESSOR MAP NUMBER
 11 0.0 ! RELATIV TO DP VARIABLE STATOR ANGLE

! SPLITTER

12 0.74 ! LAMBDA (W)
 13 0.0 ! DELTA (W)
 14 1.0 ! LAMBDA (P)
 15 0.0 ! DELTA (P)

! SPLITTER

16 0.025 ! LAMBDA (W)
 17 0.0 ! DELTA (W)
 18 1.0 ! LAMBDA (P)
 19 0.0 ! DELTA (P)

! BURNER

20 0.0 ! PRESSURE LOSS 0%
 21 0.998 ! EFFICIENCY
 22 -1.0 ! FUEL FLOW (-1 = TET SPECIFIED. SEE SV DATA)

! POWER TURBINE

23 116000000.0 ! AUXILLARY POWER REQUIRED
 24 0.8 ! NON DIMENTIONAL MASS FLOW
 25 0.7 ! NON DIMENTIONAL SPEED
 26 0.89 ! ISENTROPIC EFFICIENCY
 27 -1.0 ! RELATIV ROTATIONAL SPEED
 28 0.0 ! COMPRESSOR NUMBER
 29 2.0 ! TURBINE MAP NUMBER
 30 1000.0 ! POWER INDEX N

! DUCTER

31 2.0 ! REHEAT
 32 0.0 ! PRESSURE LOSS 0%
 33 0.97 ! EFFICIENCY
 34 -1.0 ! FUEL FLOW LIMIT

! COMPRESSOR POWER TURBINE

35 125000000.0 ! AUXILLARY POWER REQUIRED
 36 -1.0 ! NON DIMENTIONAL MASS FLOW
 37 -1.0 ! NON DIMENTIONAL SPEED
 38 0.89 ! ISENTROPIC EFFICIENCY
 39 -1.0 ! RELATIV ROTATIONAL SPEED
 40 1.0 ! COMPRESSOR NUMBER
 41 1.0 ! TURBINE MAP NUMBER
 42 1000.0 ! POWER INDEX N

! ARITHY

43 1.0 ! ADDITION
 44 -1.0
 45 100.0 ! POWER OUTPUT (RESULT)
 46 -1.0
 47 23.0 ! POWER OF TURBINE 1

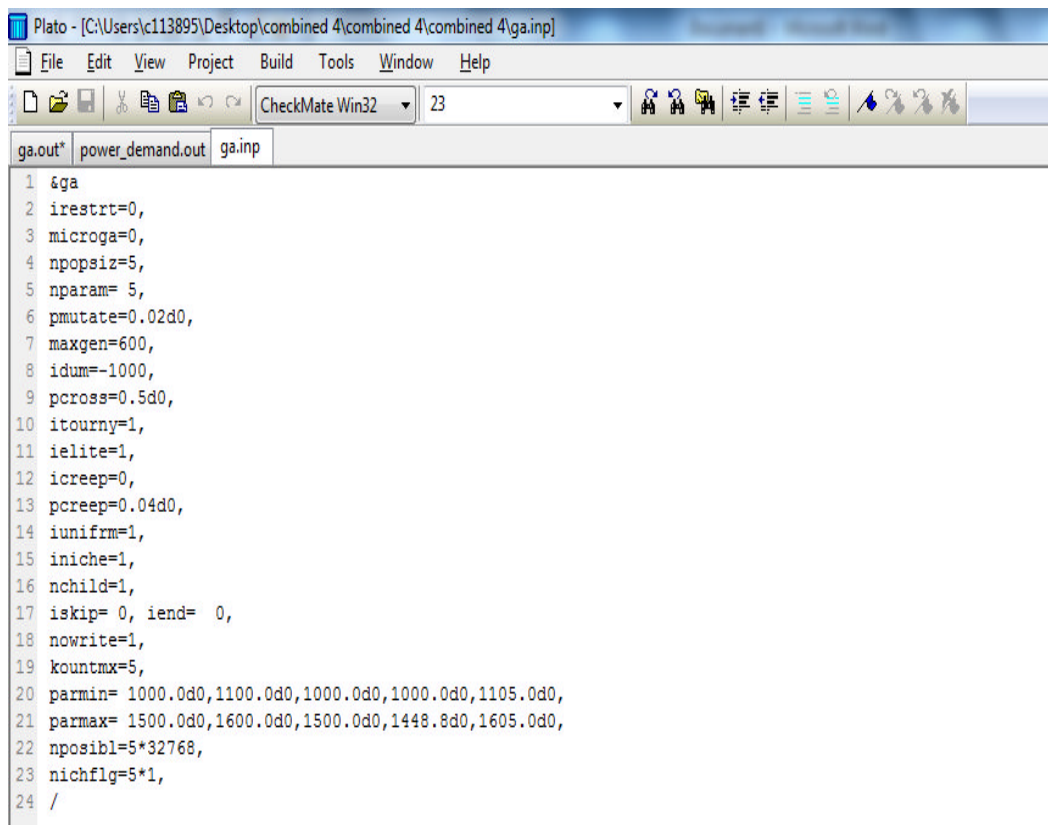
```

48 -1.0
49 35.0      ! POWER OF TURBINE 2
! NOZCON
50 -1.0      ! AREA FIXED
! PERFORMANCE
51 241000000.0 ! POWER TURBINE
52 1.0       ! PROPELLER EFFICIENCY
53 0.0       ! SCALLING INDEX
54 0.0       ! REQUIRED DP NET THRUST OR POWER OUTPUT FOR PT
-1
1 2 541.00   ! MASS FLOW
5 6 1535.0   ! TURBINE ENTRY TEMPERATURE 1
9 6 1525.0   ! TURBINE ENTRY TEMPERATURE 2

```

Appendix B Genetic Algorithm typical output and input files

B.1.1 GA Input file



The screenshot shows a text editor window titled 'Plato - [C:\Users\c113895\Desktop\combined 4\combined 4\combined 4\ga.inp]'. The window has a menu bar (File, Edit, View, Project, Build, Tools, Window, Help) and a toolbar. Below the toolbar, there are tabs for 'ga.out*', 'power_demand.out', and 'ga.inp'. The 'ga.inp' tab is active, displaying the following text:

```

1  &ga
2  irestrt=0,
3  microga=0,
4  npopsiz=5,
5  nparam= 5,
6  pmutate=0.02d0,
7  maxgen=600,
8  idum=-1000,
9  pcross=0.5d0,
10 itourny=1,
11 ielite=1,
12 icreep=0,
13 pcreep=0.04d0,
14 iunifrm=1,
15 iniche=1,
16 nchild=1,
17 iskip= 0, iend= 0,
18 nowrite=1,
19 kountmx=5,
20 parmin= 1000.0d0,1100.0d0,1000.0d0,1000.0d0,1105.0d0,
21 parmax= 1500.0d0,1600.0d0,1500.0d0,1448.8d0,1605.0d0,
22 nposibl=5*32768,
23 nichflg=5*1,
24 /

```

B.1.2 : Typical GA output

```

Plato - [E:\GA_3\GA_5\Updated-Originalga.out]
File Edit View Project Build Tools Window Help
CheckMate Win32 23
ga.out*
821 ##### Generation 40 #####
822 # Binary Code Param1 Param2 Param3 Param4 Param5 Fitness
823 1 111111010100000110000111010011111 1419.493 1471.194 1385.578 1382.617 1504.636 -431.96270 (Penalty applied - original power 608275.40000)
824 2 110110101110001010001010101011111 1405.528 1477.438 1388.679 1390.923 1505.515 -431.47200 (Penalty applied - original power 605980.00000)
825 3 111110101010010100001100011110101111 1417.931 1471.194 1385.481 1382.617 1504.636 -431.86770 (Penalty applied - original power 607825.40000)
826 4 111110101010010100001100011110101111 1417.931 1471.218 1391.047 1382.420 1517.918 -431.59940 (Penalty applied - original power 609850.50000)
827 5 11111100000100011111101010010001010101 1419.298 1471.243 1385.578 1376.317 1504.636 -432.08090 (Penalty applied - original power 607829.70000)
828
829
830 Average Values: 1416.03626 1472.45750 1387.27256 1382.97899 1507.46834 -431.79654
831
832 Average Function Value of Generation= -431.79654
833 Maximum Function Value = -431.47200
834
835
836 Number of Crossovers = 185
837
838 Number of Jump Mutations = 5
839 Number of Creep Mutations = 0
840 Elitist Reproduction on Individual 4
841
842
843 Summary of Output
844 Generation Evaluations Avg.Fitness Best Fitness
845 0.1000E+01 0.5000E+01 -4406E+03 -43484E+03
846 0.2000E+01 0.1000E+02 -4384E+03 -43163E+03
847 0.3000E+01 0.1500E+02 -4366E+03 -43163E+03
848 0.4000E+01 0.2000E+02 -4341E+03 -43163E+03
849 0.5000E+01 0.2500E+02 -4342E+03 -43163E+03
850 0.6000E+01 0.3000E+02 -4351E+03 -43163E+03
851 0.7000E+01 0.3500E+02 -4341E+03 -43163E+03
852 0.8000E+01 0.4000E+02 -4343E+03 -43163E+03
853 0.9000E+01 0.4500E+02 -4344E+03 -43163E+03
854 0.1000E+02 0.5000E+02 -4346E+03 -43163E+03
855 0.1100E+02 0.5500E+02 -4346E+03 -43163E+03
856 0.1200E+02 0.6000E+02 -4345E+03 -43163E+03
857 0.1300E+02 0.6500E+02 -4342E+03 -43163E+03
858 0.1400E+02 0.7000E+02 -4343E+03 -43163E+03
859 0.1500E+02 0.7500E+02 -4362E+03 -43163E+03
860 0.1600E+02 0.8000E+02 -4351E+03 -43163E+03
861 0.1700E+02 0.8500E+02 -4335E+03 -43155E+03
862 0.1800E+02 0.9000E+02 -4327E+03 -43155E+03
863 0.1900E+02 0.9500E+02 -4321E+03 -43155E+03
864 0.2000E+02 0.1000E+03 -4316E+03 -43155E+03
865 0.2100E+02 0.1050E+03 -4316E+03 -43154E+03
866 0.2200E+02 0.1100E+03 -4321E+03 -43154E+03
867 0.2300E+02 0.1150E+03 -4328E+03 -43154E+03
868 0.2400E+02 0.1200E+03 -4331E+03 -43154E+03
869 0.2500E+02 0.1250E+03 -4317E+03 -43154E+03
870 0.2600E+02 0.1300E+03 -4317E+03 -43154E+03
871 0.2700E+02 0.1350E+03 -4315E+03 -43147E+03
872 0.2800E+02 0.1400E+03 -4316E+03 -43147E+03
873 0.2900E+02 0.1450E+03 -4327E+03 -43147E+03
874 0.3000E+02 0.1500E+03 -4316E+03 -43147E+03
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1000

```

B.1.3 Output for a combinations which meet power demand required

```

Plato - [C:\Users\c113895\Desktop\case_s_winter\power_demand_00]
File Edit View Project Build Tools Window Help
CheckMate Win32 23
ga.out* power_demand.out ga.inp power_demand.out power_demand_00
1
2
3
4 Required power = 450000.00
5
6 ENGINE Maximum power Best
7 1 2 3 4 5
8
9 OFF OFF OFF OFF ON 245660.00 Insufficient power
10 OFF OFF OFF ON OFF 47361.00 Insufficient power
11 OFF OFF OFF ON ON 293021.00 Insufficient power
12 OFF OFF ON OFF OFF 149960.00 Insufficient power
13 OFF OFF ON OFF ON 395020.00 Insufficient power
14 OFF OFF ON ON OFF 196721.00 Insufficient power
15 OFF OFF ON ON ON 442381.00 Insufficient power
16 OFF ON OFF OFF OFF 32078.00 Insufficient power
17 OFF ON OFF OFF ON 277738.00 Insufficient power
18 OFF ON OFF ON OFF 79439.00 Insufficient power
19 OFF ON OFF ON ON 325099.00 Insufficient power
20 OFF ON ON OFF OFF 181438.00 Insufficient power
21 OFF ON ON OFF ON 427098.00 Insufficient power
22 OFF ON ON ON OFF 228799.00 Insufficient power
23 OFF ON ON ON ON 474459.00 -282.64990
24 ON OFF OFF OFF OFF 198950.00 Insufficient power
25 ON OFF OFF OFF ON 444610.00 Insufficient power
26 ON OFF OFF ON OFF 246311.00 Insufficient power
27 ON OFF OFF ON ON 491971.00 -222.16130
28 ON OFF ON OFF OFF 348310.00 Insufficient power
29 ON OFF ON OFF ON 593970.00 -221.51220
30 ON OFF ON ON OFF 395671.00 Insufficient power
31 ON OFF ON ON ON 641331.00 -279.49360
32 ON ON OFF OFF OFF 231028.00 Insufficient power
33 ON ON OFF OFF ON 476688.00 -219.10430
34 ON ON OFF ON OFF 278389.00 Insufficient power
35 ON ON OFF ON ON 524049.00 -277.93570
36 ON ON ON OFF OFF 380388.00 Insufficient power
37 ON ON ON OFF ON 626048.00 -279.21520
38 ON ON ON ON OFF 427749.00 Insufficient power
39 ON ON ON ON ON 673409.00 -337.49020
40
41
42 Optimum solution Engine 1 ON Engine 2 ON Engine 3 OFF Engine 4 OFF Engine 5 ON
43

```

Appendix C :Some Results Obtained For Each Engine Module Separately Before Integrated TERA Model.

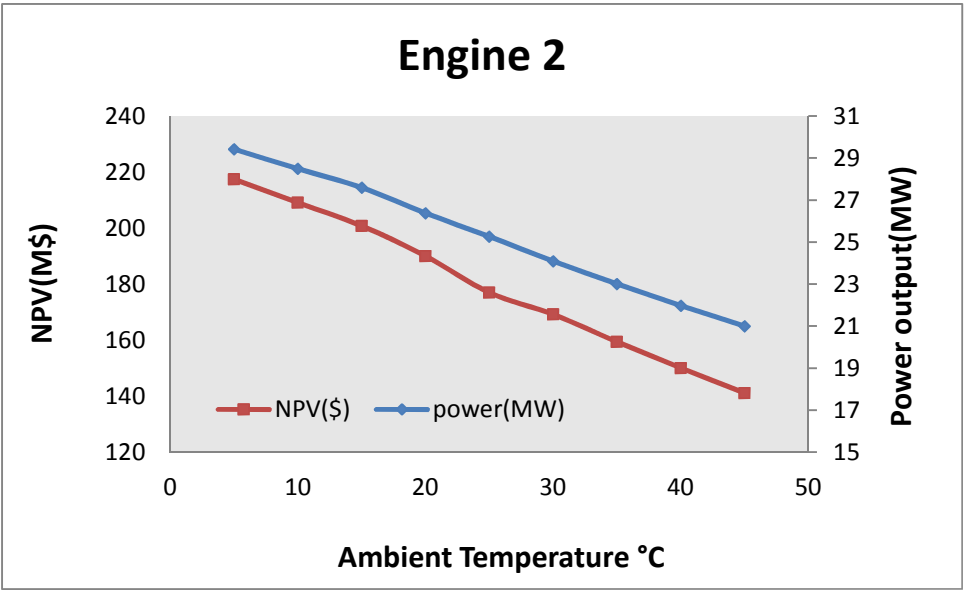
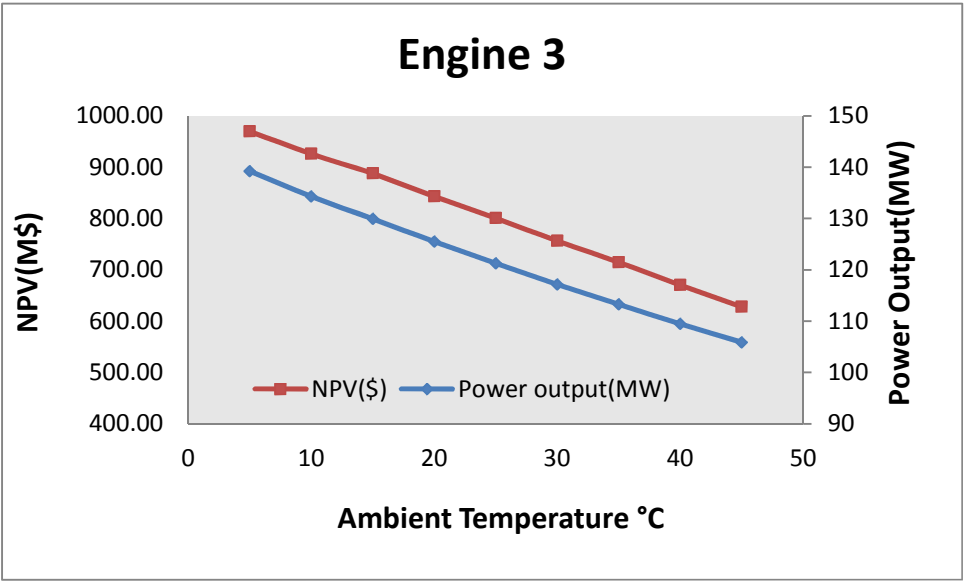
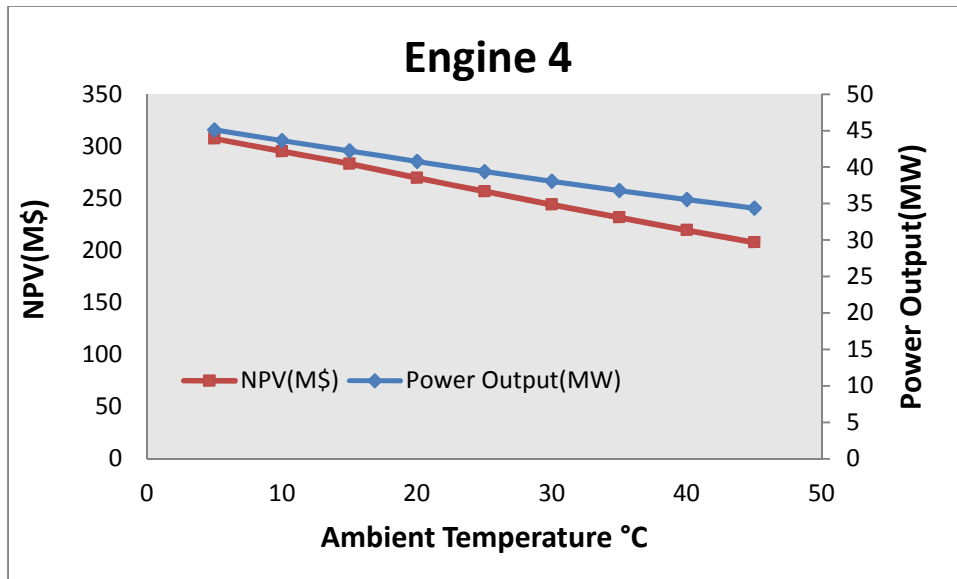


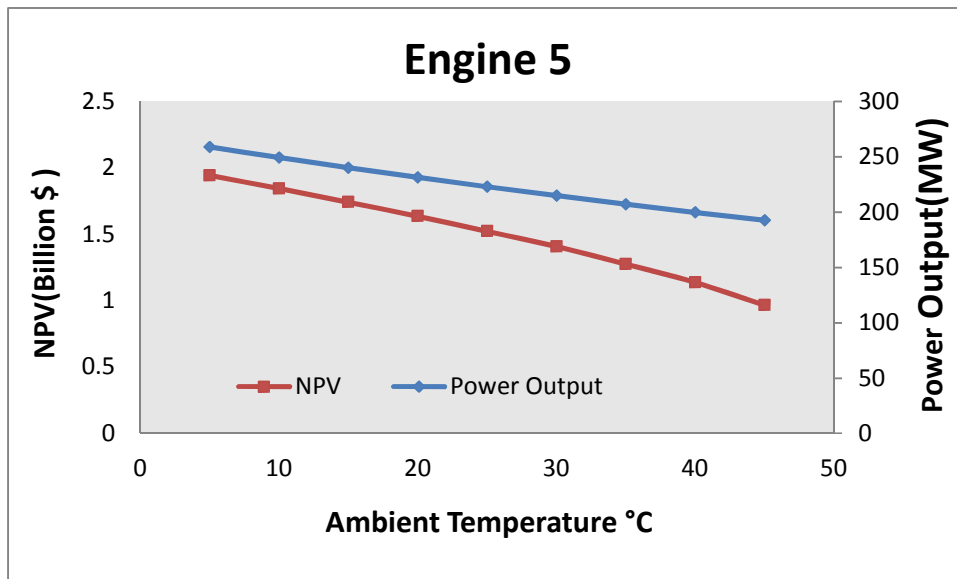
Figure C.1 : Influence of Ambient Temperature on Power Output and NPV



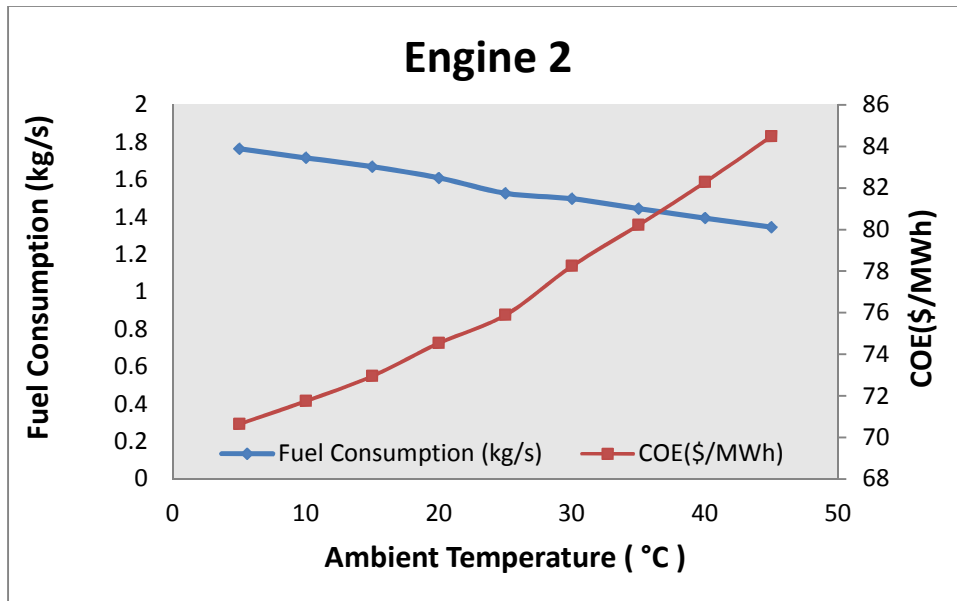
FigureC.2: Engine Influence of Ambient Temperature on Power Output and NPV



FigureC.3: Engine Influence of Ambient Temperature on Power Output and NPV



FigureC.4: Engine Influence of Ambient Temperature on Power Output and NPV



FigureC.5: Effect of Ambient Temperature on Fuel Consumption and LCOE

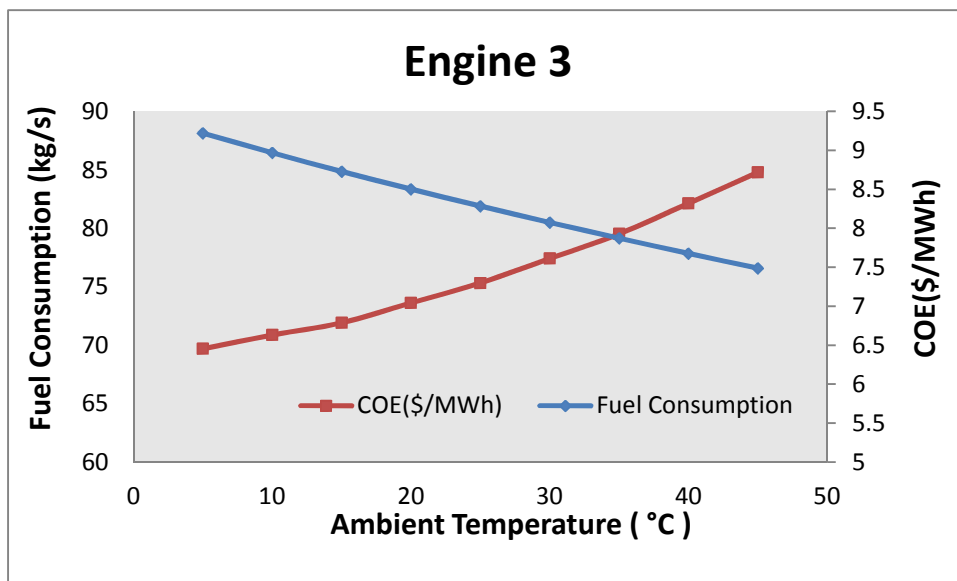
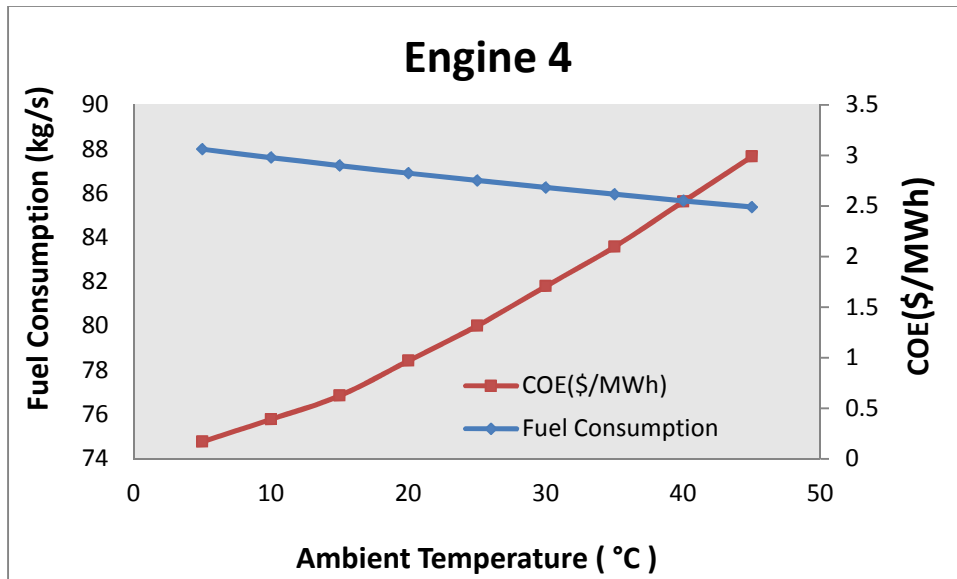
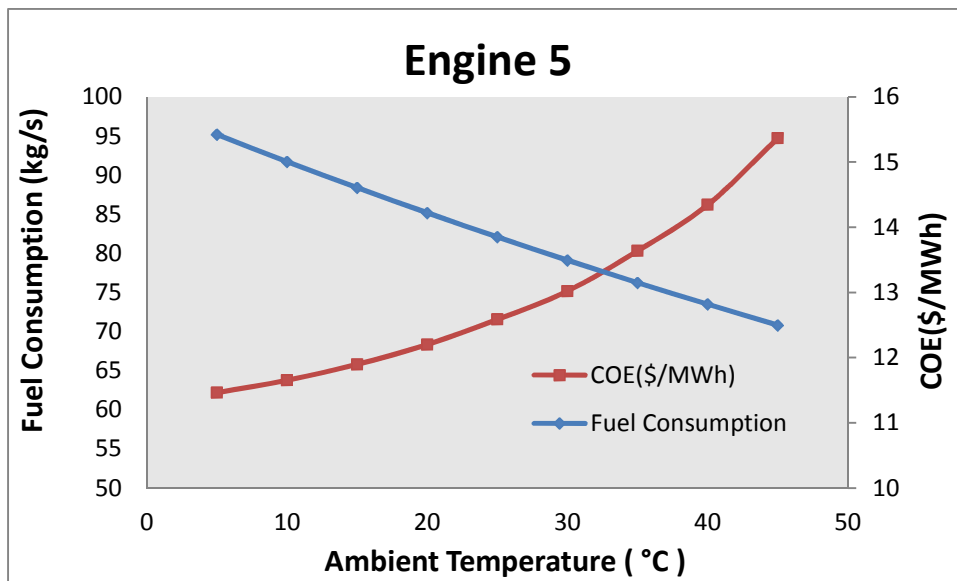


Figure: C.6 Effect of Ambient Temperature on Fuel Consumption and LCOE



FigureC.7 Effect of Ambient Temperature on Fuel Consumption and LCOE



FigureC.8: Effect of Ambient Temperature on Fuel Consumption and LCOE

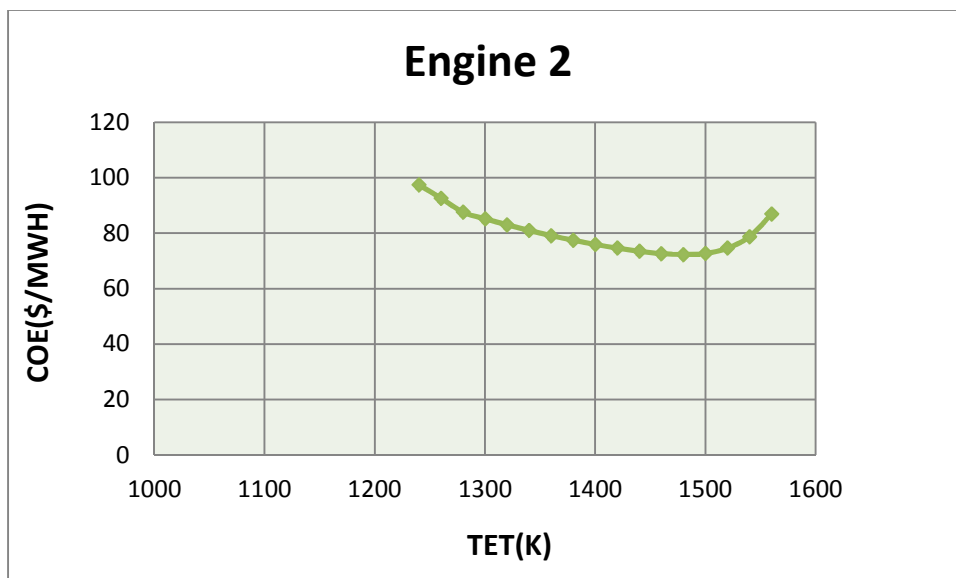


Figure C.9: Cost of electricity at different TETs

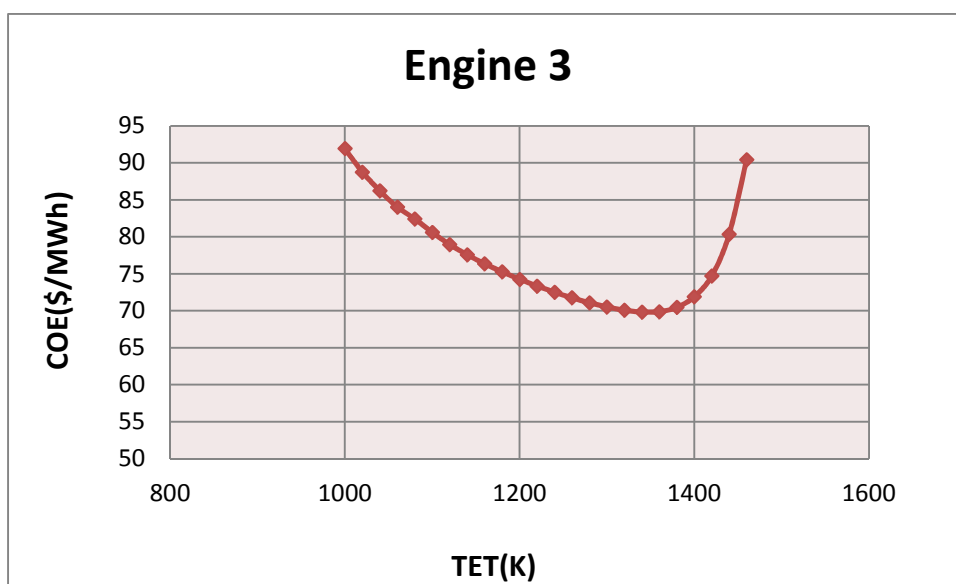


Figure C.10: Cost of electricity at different TETs

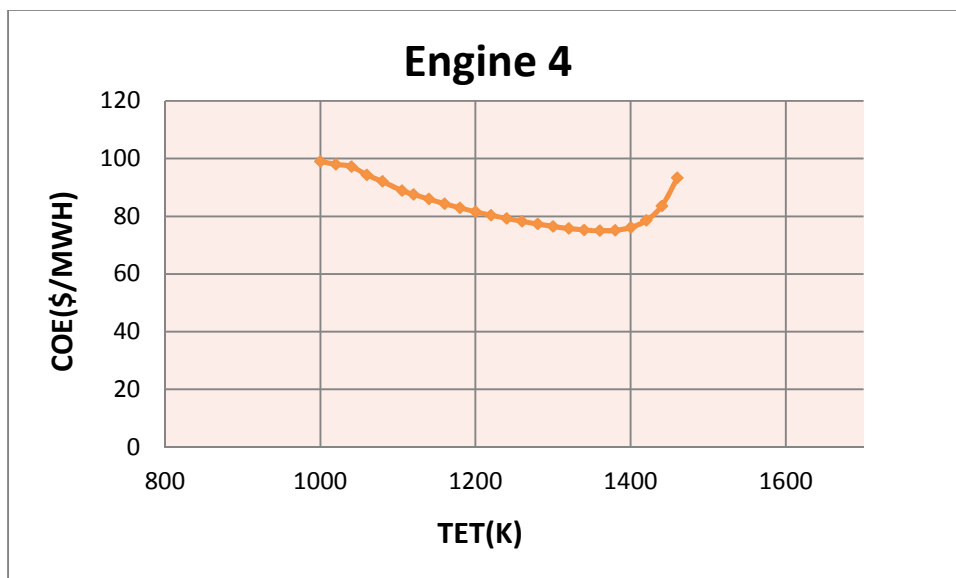


Figure C.11: Cost of electricity at different TETs

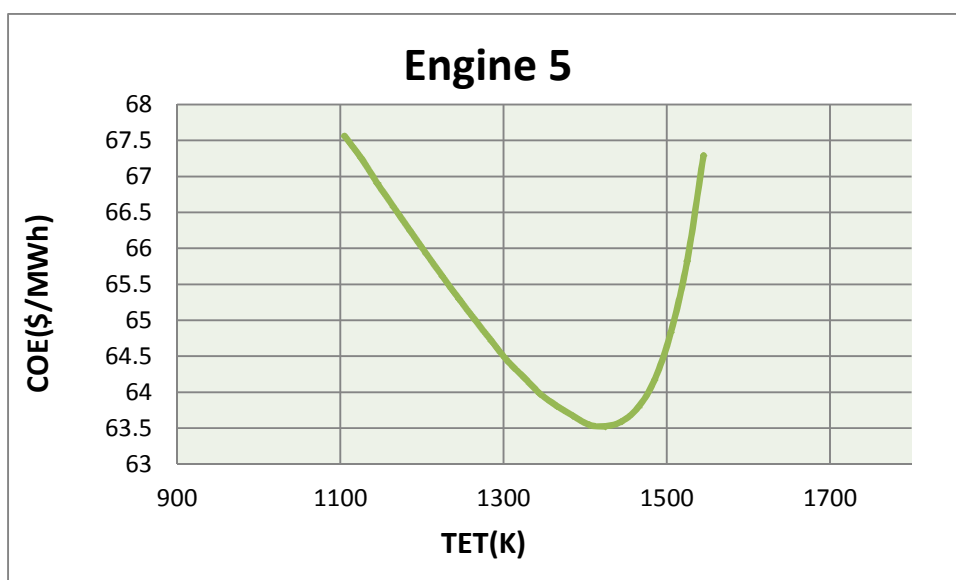


Figure C.12: Cost of electricity at different TETs

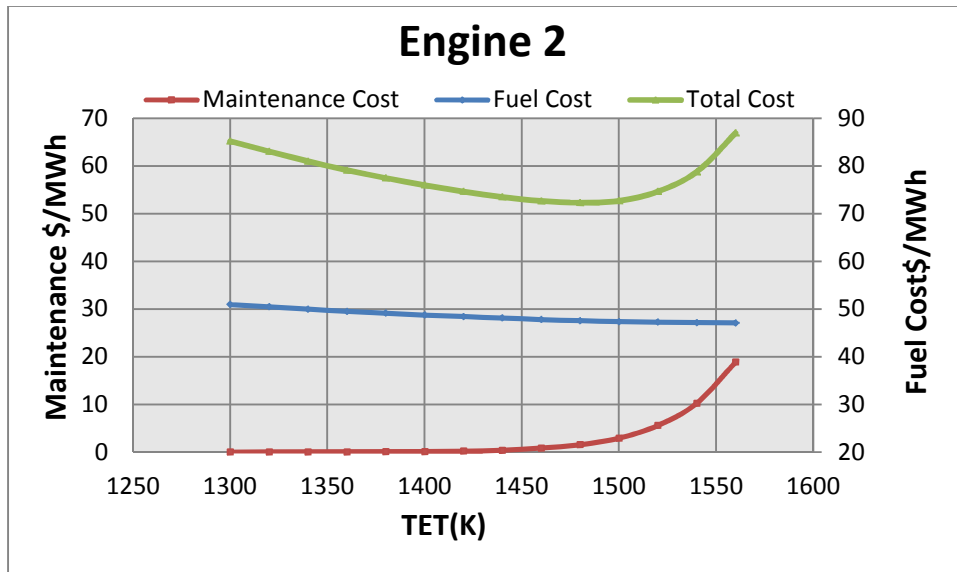


Figure C.13: Effect of TET on Fuel, Maintenance, and Total Costs

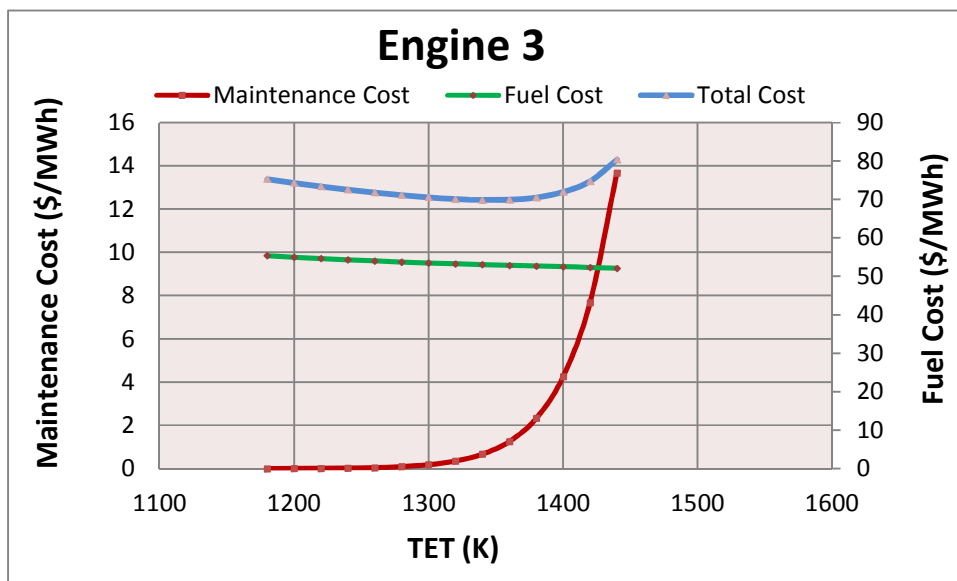


Figure C.14: Effect of TET on Fuel, Maintenance, and Total Costs

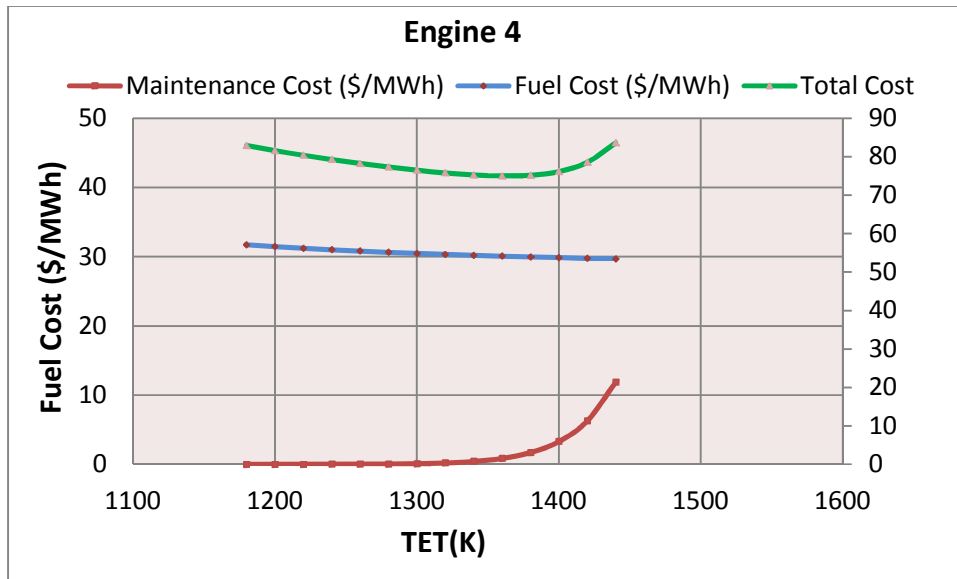


Figure C.15: Effect of TET on Fuel, Maintenance, and Total Costs

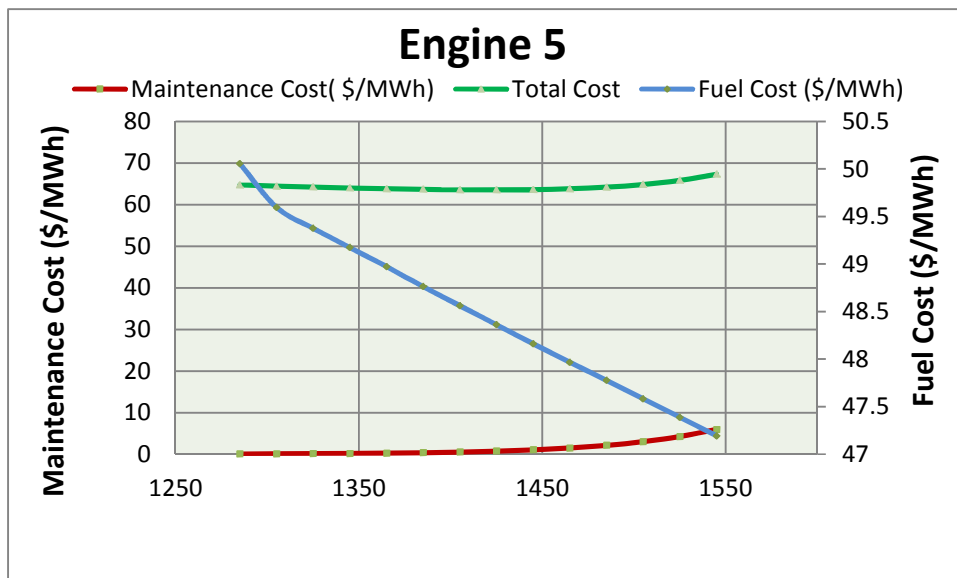


Figure C.16: Effect of TET on Fuel, Maintenance, and Total Costs

Appendix D : Design parameters validation for the other engines

Table D.1 Validation Results for Baseline load (Engine 2)

parameters	Engine parameters	simulation	Deviation %
Power (MW)	28	27.6	0.014
Mas Flow(kg/sec)	82	80.438	0.019
TET (k)	1505	1505	0
Thermal Efficiency (%)	38	0.3835	0.989
OPR	23	22.98	0.00086

Table D.2: Validation Results for Baseline load (Engine 3)

parameters	Engine parameters	simulation	Deviation
Power (MW)	130	1301	0.00076
Mas Flow(kg/sec)	390	389.500	0.00128
TET (k)	1400	1400.00	0
Thermal Efficiency (%)	0.34	0.3456	0.01647
OPR	12	12.6	0.05

Table D.3: Validation Results for Baseline load (Engine 4)

parameters	Engine parameters	simulation	Deviation
Power (MW)	42	4230	0.0071
Mas Flow(kg/sec)	125	126	0.008
TET (k)	1408	1408	0
Thermal Efficiency (%)	0.38	0.3384	0.1094
OPR	12	12.2	0.0166

Table D.4: Validation Results for Baseline load (Engine 5)

parameters	Engine parameters	simulation	Deviation
Power (MW)	240	241	0.004
Mas Flow(kg/sec)	540	541.000	0.0018
TET (k)	1525	1525	0
Thermal Efficiency (%)	0.38	0.3824	0.0063
OPR	30	30	0

D.1 Blade Geometry Data

Table D.1.1: First Stage Blade Geometry fore Engine (2)

Geometrical Parameters	values
Tip Radius (m)	0.4
Root Radius(m)	0.3677
Blade Height(m)	0.042

Table D.1.2: First Stage Blade Geometry fore Engine (3)

Geometrical Parameters	values
Tip Radius (m)	0.8
Root Radius(m)	0.72
Blade Height(m)	0.21

Table D.1.3: First Stage Blade Geometry fore Engine (4)

Geometrical Parameters	values
Tip Radius (m)	0.5
Root Radius(m)	0.45
Blade Height(m)	0.08

TableD.1.4: First Stage Blade Geometry fore Engine (5)

Geometrical Parameters	values
Tip Radius (m)	0.8
Root Radius(m)	0.92
Blade Height (m)	0.22

Appendix E : The Combinations for the three typical days together with the optimisation results for the case study 1

E.1 Typical winter day at base line case study

Table E.1.1: possibility of combinations that give power requirement from 04:00 to 06:00 (winter day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	OFF	1475	1336	1364	1415	474
Combination 2	1340	OFF	OFF	1365	1418	492
Combination 3	1340	OFF	1336	OFF	1416	594
Combination 4	1344	OFF	1344	1369	1418	641
Combination 5	1250	1475	OFF	OFF	1418	477
Combination 6	1344	1475	OFF	1337	1418	524
Combination 7	1340	1475	1336	OFF	1415	626
Combination 8	1250	1475	1336	1365	1418	673

Table E.1.2: Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	280.30
Combination 2	220.69
Combination 3	219.81
Combination 4	277.72
Combination 5	220.15
Combination 6	275.85
Combination 7	274.42
Combination 8	335.01

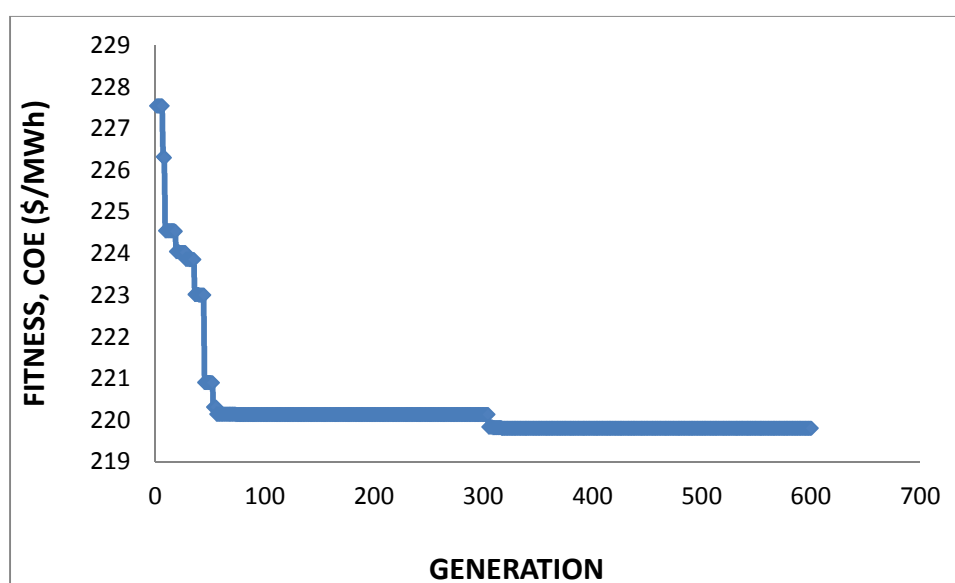


Figure E.1.1: Convergence history for 04:00 to 06:00 on winter day at base line case study

Table E.1.3: possibility of combinations that give power requirement from 10:00am to 12:00pm (winter day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1344	OFF	1331	1366	1347	641
Combination 2	1336	1475	1332	OFF	1399	626
Combination 3	1336	1475	1331	1337	1399	673

Table E.1.4: Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	284.87
Combination 2	281.94
Combination 3	342

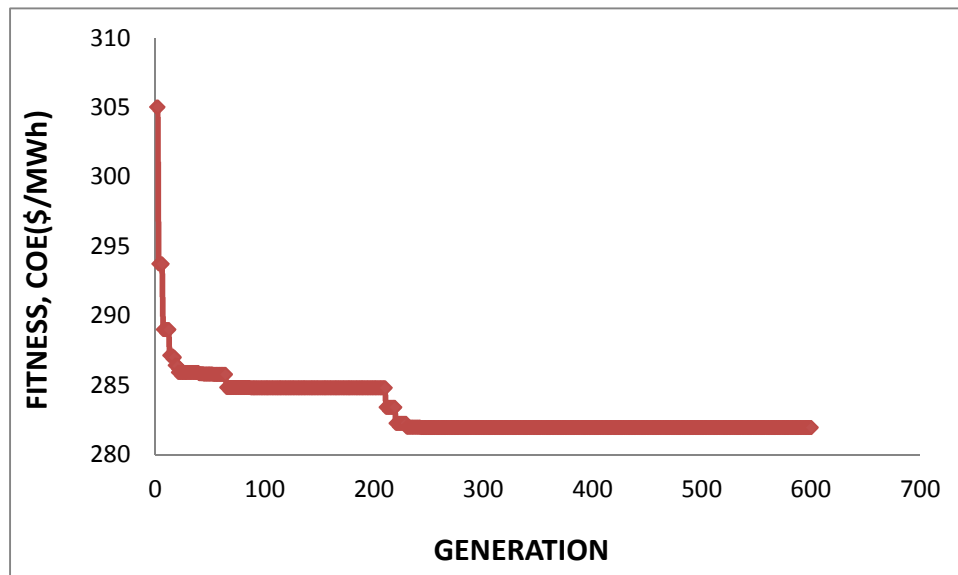


Figure E.1.2: Convergence history for 10:00am to 12:00pm on winter day at base line case study

Table E.1.5: possibility of combinations that give power requirement from 20:00pm to 22:00pm (winter day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1339	OFF	1334	1368.14	1410	641.33
Combination 2	1250	1475	1335	OFF	1410	626.05
Combination 3	1250	1475	1335	1368	1418	673.41

Table E.1.6: Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	279.49
Combination 2	279.22
Combination 3	337.49

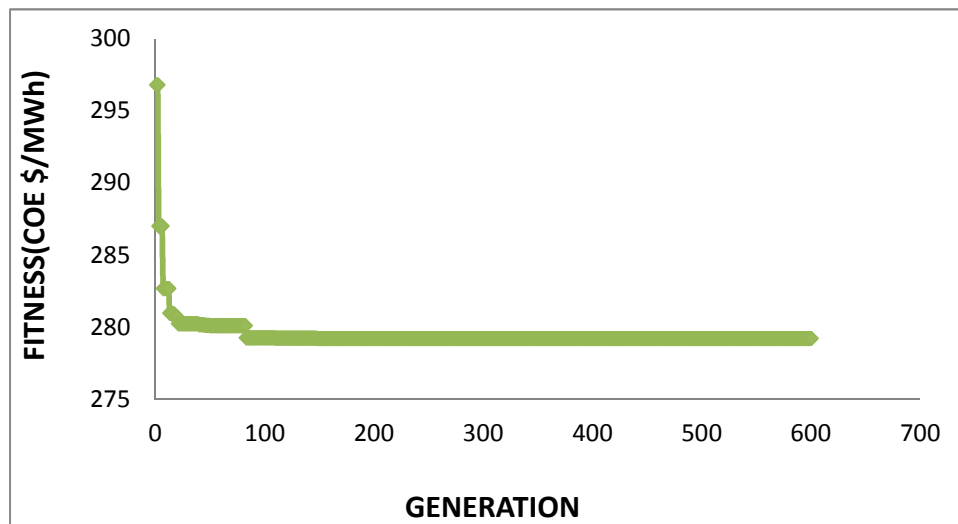


Figure E.1.3: Convergence history for 20:00pm to 22:00pm on winter day at base line case study

E.2 Typical summer day at base line case study

Table E.2.1: possibility of combinations that give power requirement from 04:00 to 06:00 (summer day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1335	OFF	OFF	1367	1399	492
Combination 2	1335	OFF	1331	OFF	1355	594
Combination 3	1344	OFF	1331	1366	1347	641
Combination 4	1336	1475	OFF	1367	1399	524
Combination 5	1336	1475	1332	OFF	1399	626
Combination 6	1336	1475	1331	1337	1399	673

Table E.2.2 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	226.20
Combination 2	225.31
Combination 3	284.87
Combination 4	282.99
Combination 5	282
Combination 6	341.92

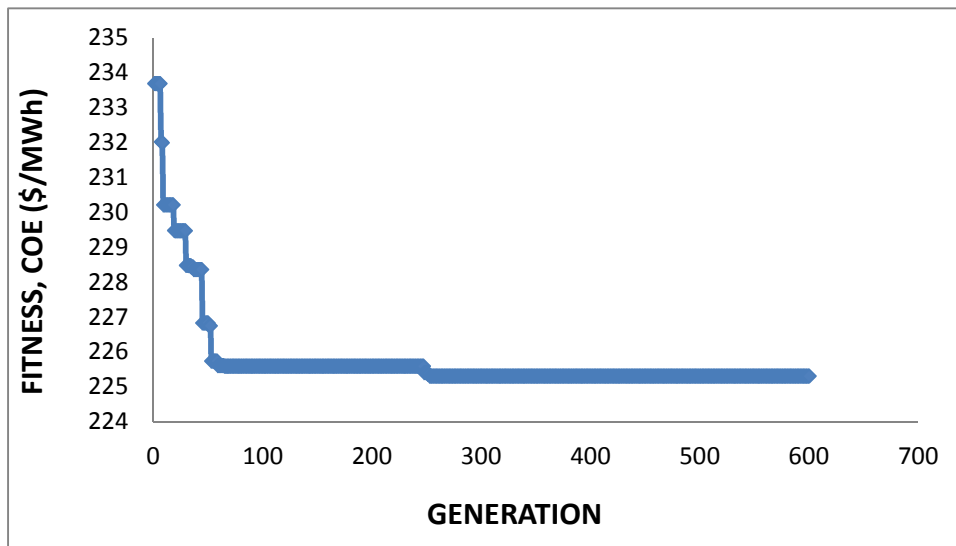


Figure E.2.1: Convergence history for 04:00pm to 06:00am on summer day at base line case study

Table E.2.3: possibility of combinations that give power requirement from 12:00 pm to 14:00 pm (summer day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1250	OFF	1312	1337	1314	641.33
Combination 2	1250	1473	1312	1337	1314	673.41

Table E.2.4 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	321.35
Combination 2	388.80

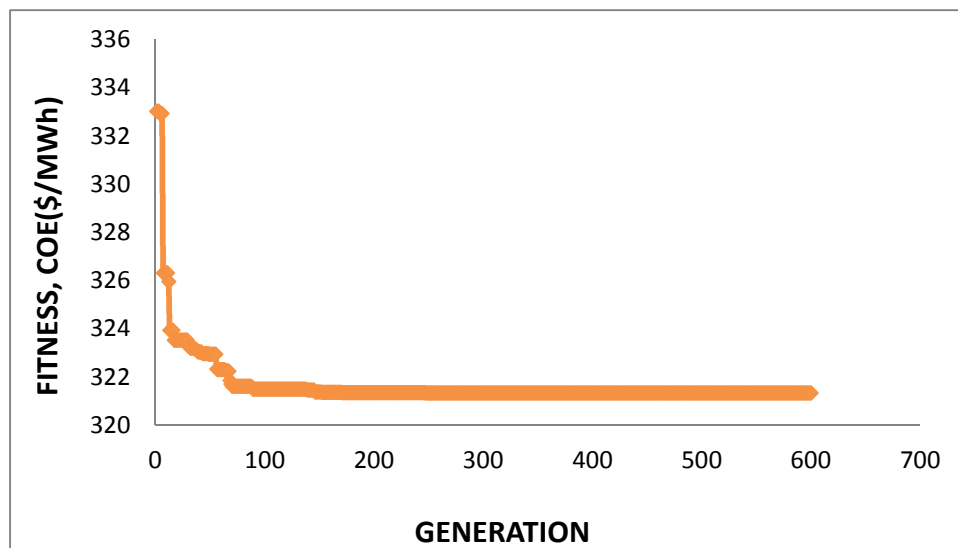


Figure E.2.2: Convergence history for 12:00pm to 14:00am on summer day at base line case study

Table E.2.4: possibility of combinations that give power requirement from 14:00 pm to 16:00 pm (summer day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1250	OFF	1312	1337	1314	641.00
Combination 2	1250	1473	1312	1337	1314	673.00

Table E.2.5 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	321
Combination 2	389

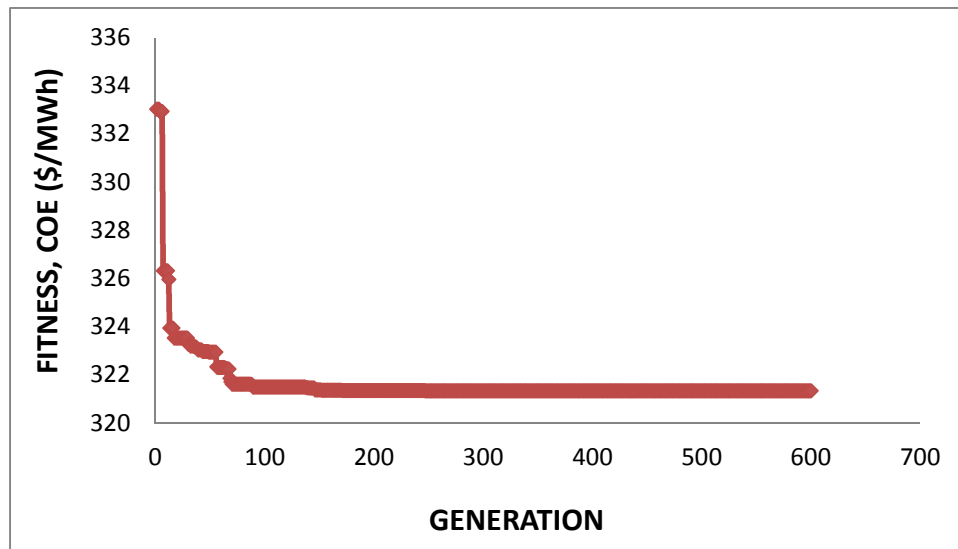


Figure E.2.3: Convergence history for 14:00pm to 16:00pm on summer day at base line case study

E.3 Typical Mid-season day at base line case study

Table E.3.1: possibility of combinations that give power requirement from 06:00 to 08m:00 (Mid-season day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	OFF	1467	1327	1337	1369	474
Combination 2	1328	OFF	OFF	1337	1371	492
Combination 3	1250	OFF	1328	OFF	1355	594
Combination 4	1328	OFF	1327	1337	1355	641
Combination 5	1329	1465	OFF	OFF	1370	477
Combination 6	1329	1465	OFF	1337	1371	524
Combination 7	1250	1467	1328	OFF	1369	626
Combination 8	1344	1467	1327	1368	1369	673

Table E.3.2 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	291.26
Combination 2	232.82
Combination 3	234
Combination 4	292.95
Combination 5	225.99
Combination 6	287.82
Combination 7	289.15
Combination 8	347.68

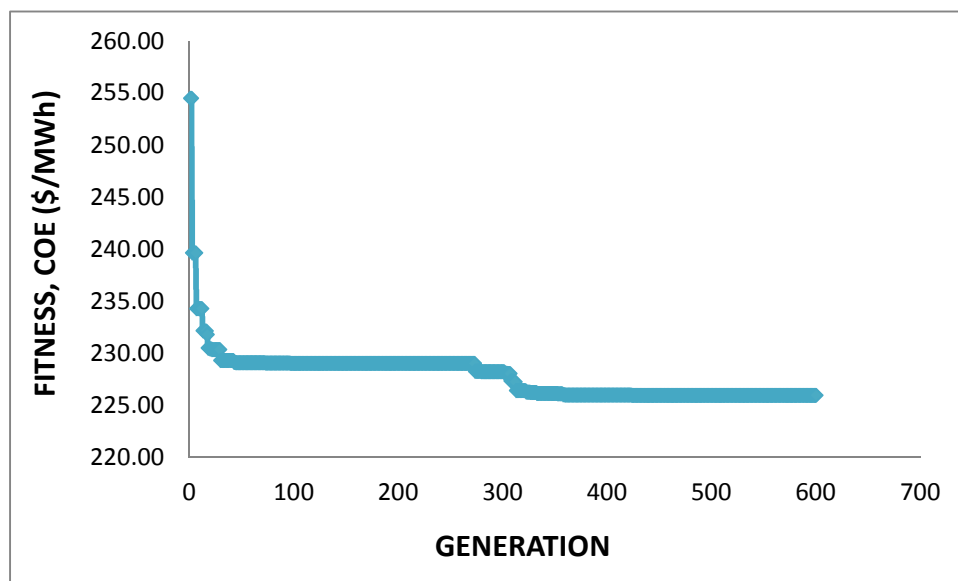


Figure E.3.1: Convergence history for 06:00am to 08:00am on Mid-season day at base line case study

Table E.3.3: possibility of combinations that give power requirement from 14:00pm to 16:00pm (Mid-season day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1250	OFF	1316	1337	1325	641.33
Combination 2	1316	1475	1316	OFF	1355	626.05
Combination 3	1250	1475	1316	1358	1355	673.41

Table E.3.4 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	314.55
Combination 2	311.00
Combination 3	379.72

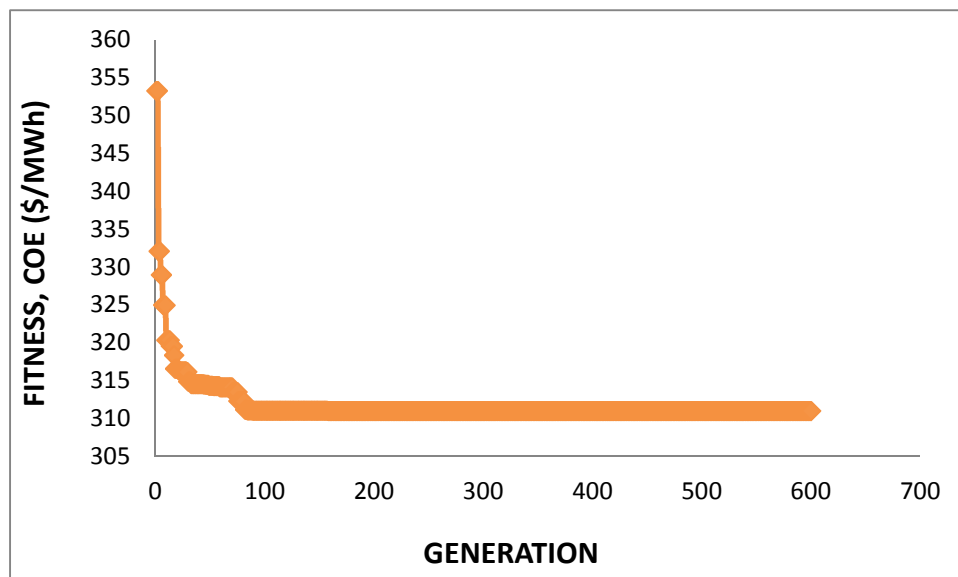


Figure E.3.2: Convergence history for 14:00pm to 16:00pm on Mid-season day at base line case study

Table E.3.5: possibility of combinations that give power requirement from 22:00 to 24:00 (Mid-season day at base line case study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	1336	OFF	1332	OFF	1355	593.97
Combination 2	1336	OFF	1332	1365	1402	641.33
Combination 3	1336	1475	1331	OFF	1405	626.05
Combination 4	1336	1475	1332	1337	1404	673.41

Table E.3.6 Optimum achieved lowest electricity cost for the above selected combinations

Number of Combination	Optimum COE (\$/MWh)
Combination 1	224.51
Combination 2	284
Combination 3	281
Combination 4	340.50

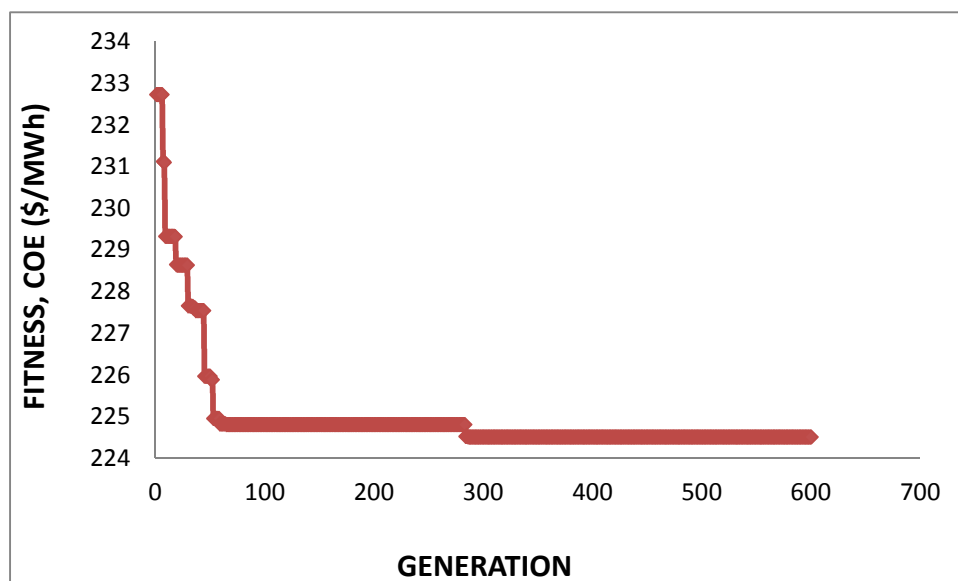


Figure E.3.3: Convergence history for 14:00pm to 16:00pm on Mid-season day at base line case study

E.4 Case study 2 Risk Evaluation of Increasing Fuel Price

E.4.1 Winter day

Table E.4.1: Optimisation of Operational Procedure (Existing & Proposed) for Typical winter Day (gas price \$6/GJ)

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	13	450	461.130	292.0706	169.06
2	14	400	466.216	213.88	174.145
4	11	470	458.254	290.039	166.183
6	15	588	464.1512	298.8156	172.081
8	16	591	465.7859	300.3077	173.715
10	18	599	472.902	382.5445	180.831
12	21	613	473.2503	385.6336	181.18
14	23	613.8	474.9366	386.0394	182.866
16	20	601.5	476.505	385.4118	184.434
18	15	598.9	464.1512	382.0894	172.081
20	13	596	461.1302	375.9322	169.06
22	13	597.8	461.1302	375.9322	169.06

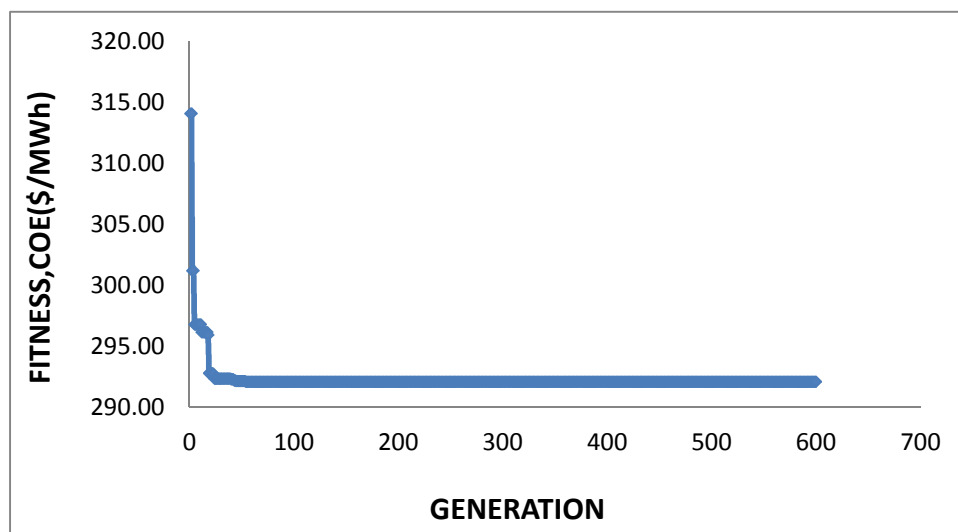


Figure E.4.1: Convergence history for 00:00am to 02:00am on winter day at gas price (\$6/GJ)

Table E.4.2: possibility of combinations that give power requirement 450 MW from 0:00Am to 2:00am and 13 °C (winter day at gas price \$6/GJ)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	OFF	1475	1340	1372	1429	474.459
Combination 2	1342	OFF	OFF	1372	1429	491.971
Combination 3	1342	OFF	1340	OFF	1355	593.97
Combination 4	1342	OFF	1344	1337	1429	641.331
Combination 5	1344	1481	OFF	OFF	1429	476.688
Combination 6	1344	1475	OFF	1372	1429	524.049
Combination 7	1344	1475	1344	OFF	1429	626.048
Combination 8	1344	1475	1339	1373	1429	673.409

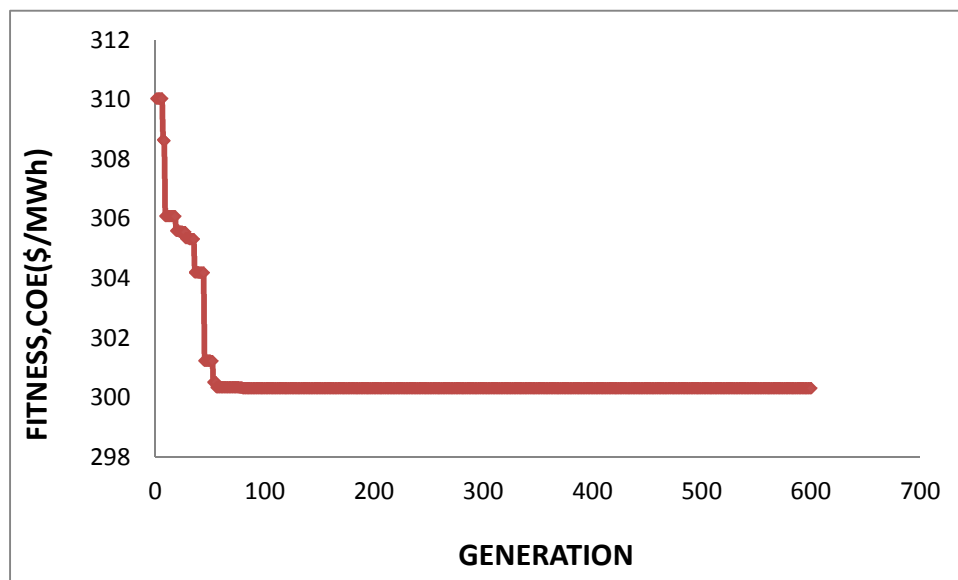


Figure E.4.2: Convergence history for 08:00am to 10:00am on winter day at gas price (\$6/GJ)

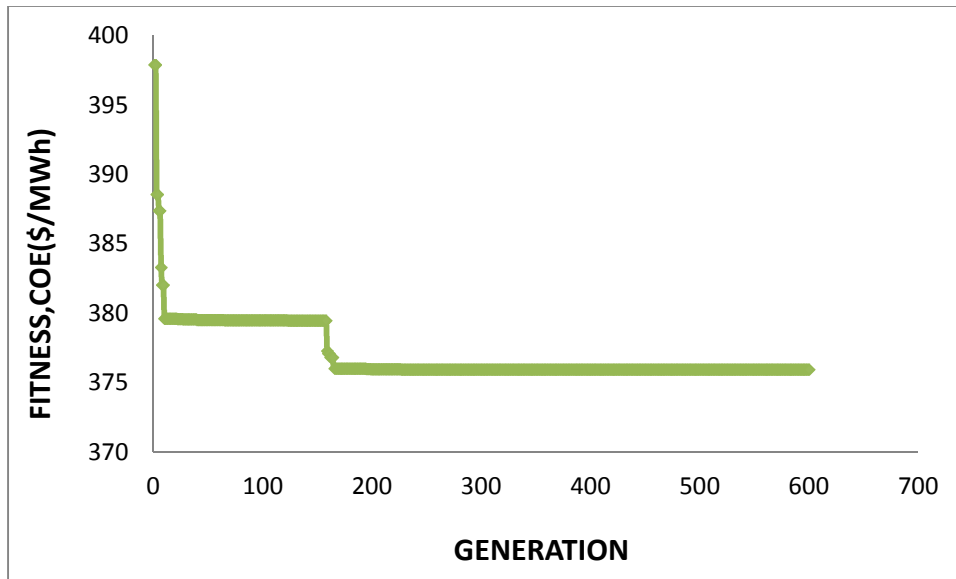


Figure E.4.3: Convergence history for 22:00pm to 24:00am on winter day at gas price (\$6/GJ)

E.4.2 Summer day

Table E.4.2.1: possibility of combinations that give power requirement 521 MW from 0:00Am to 2:00am and 20 °C (summer day at fuel price \$6/GJ)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1338	OFF	1334	OFF	1355	593.97
Combination 2	1338	OFF	1335	1365	1406	641.331
Combination 3	1339	1479	OFF	1370	1418	524.049
Combination 4	1339	1475	1334	OFF	1402	626.048
Combination 5	1250	1475	1328	1365	1402	673.409

Table E.4.2.2: Optimisation of Operational Procedure (Existing & Proposed) for typical summer day at fuel price \$6/GJ

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	20	521	476.505	304.3178	172
2	19	506.6	474.7038	303.2853	170
4	18	490	472.902	302.2723	169
6	25	508	475.258	309.454	171
8	30	610	495.5295	404.9835	191
10	35	620	501.209	408.978	197
12	45	633	526.681	434.142	222
14	45	633.8	526.681	434.142	222
16	37	621.5	509.361	416.411	205
18	33	618.9	497.423	405.639	193
20	20	616	476.505	385.412	172
22	22	580.8	473.749	306.315	169

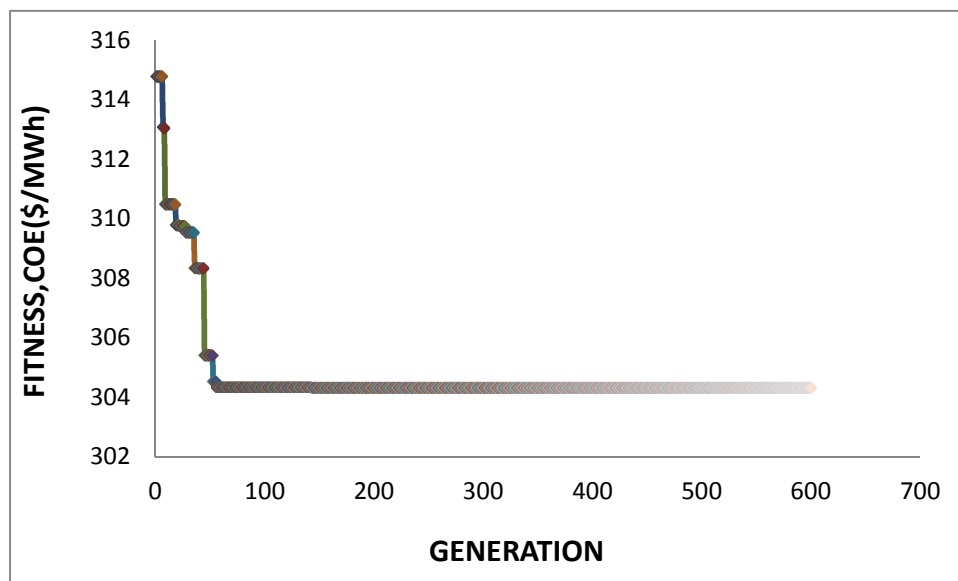


Figure E.4.2.1: Convergence history for 00:00pm to 02:00pm on summer day at gas price (\$6/GJ)

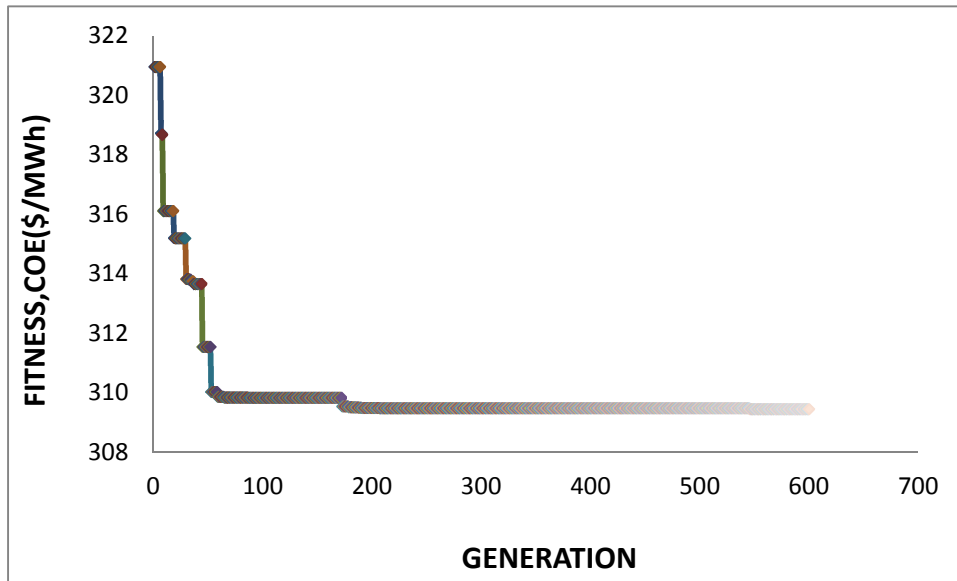


Figure E.4.2.2: Convergence history for 06:00pm to 08:00pm on summer day at gas price (\$6/GJ)

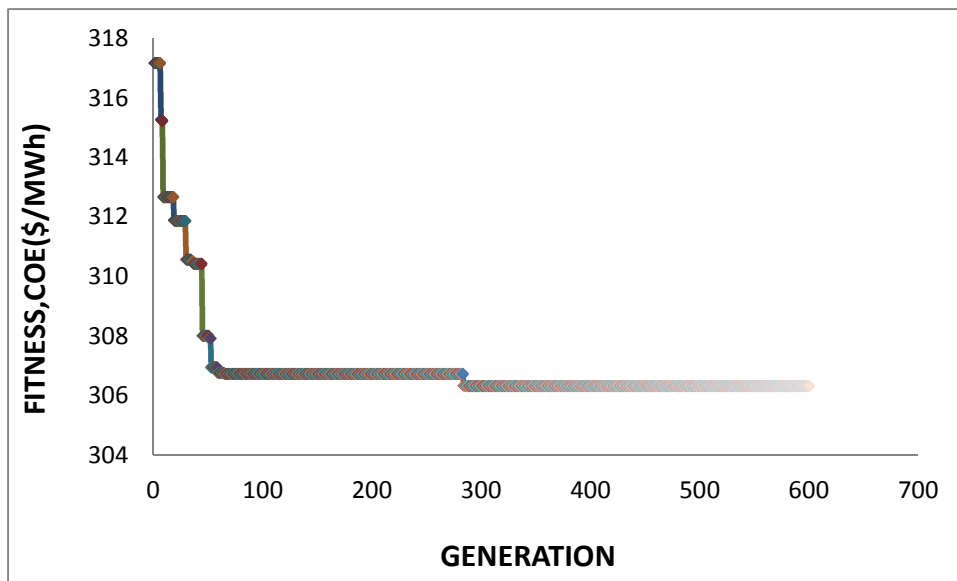


Figure E.4.2.3: Convergence history for 22:00pm to 24:00am on summer day at gas price (\$6/GJ)

E.4.3 Mid-season

Table E.4.3.1: possibility of combinations that give power requirement 500 MW from 0:00Am to 2:00am and 17 °C (mid-season day at fuel price \$6/GJ)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1340	OFF	1336	OFF	1355	593.97
Combination 2	1341	OFF	1336	1336	1418	641.331
Combination 3	1340	1480	OFF	1337	1418	524.049
Combination 4	1341	1475	1335	OFF	1418	626.048
Combination 5	1250	1475	1336	1372	1418	673.409

Table E.4.3.2: Optimisation of Operational Procedure (Existing & Proposed) for typical mid-season day at fuel price \$6/GJ

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	17	500	471.1621	301	170
2	15	470	464.151	294.226	163
4	15	450	464.151	294.226	163
6	25	468	475.258	299.222	174
8	26	570.4	482.453	310.518	181
10	30	590	495.53	315.017	195
12	38	610	511.444	414.012	210
14	40	610	515.737	421.692	215
16	34	600	499.435	407.278	198
18	28	580	484.857	312.731	184
20	25	576	475.258	309.454	174
22	17	550	471.162	301.28	170

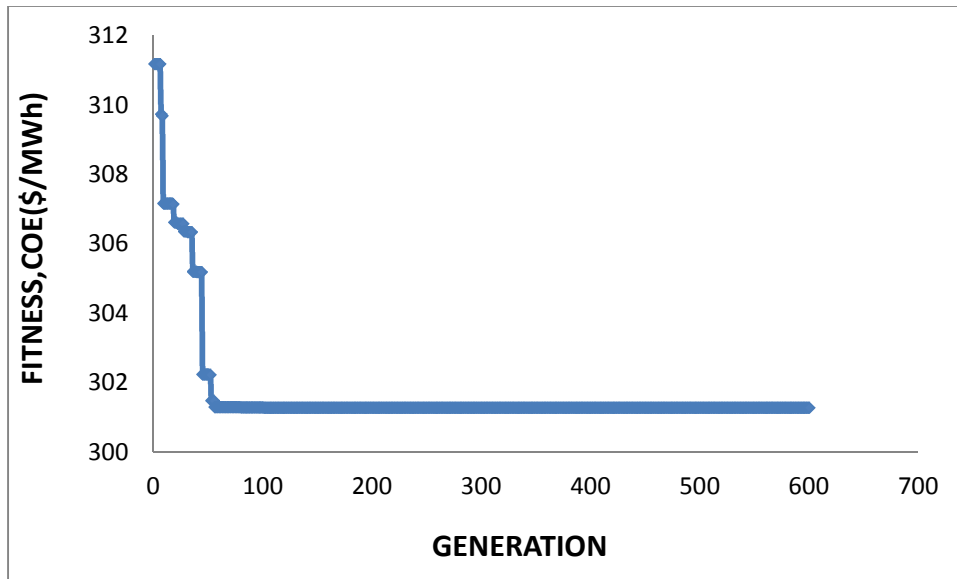


Figure E.4.3.1: Convergence history for 00:00pm to 02:00pm on mid-season day at gas price (\$6/GJ)

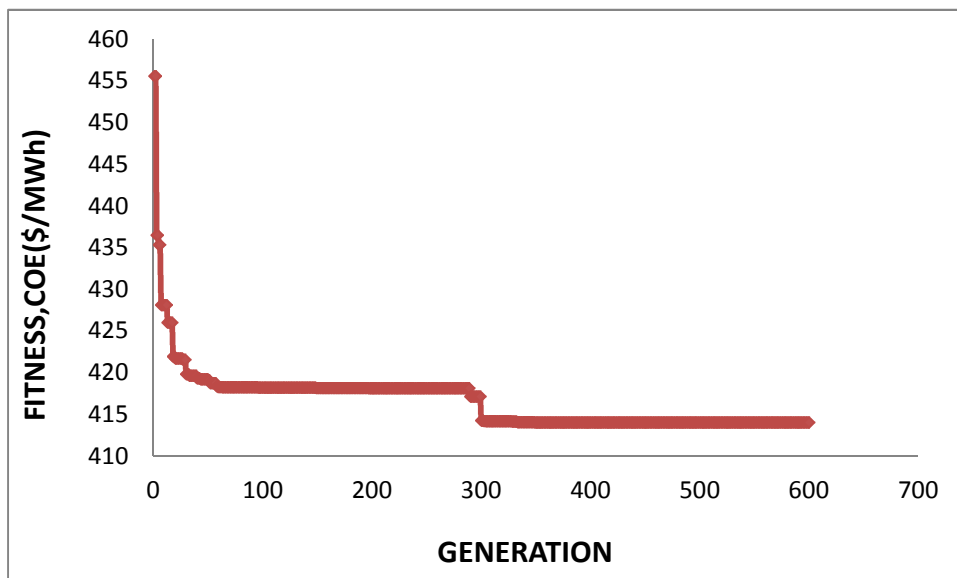


Figure E.4.3.2: Convergence history for 12:00pm to 14:00pm on mid-season day at gas price (\$6/GJ)

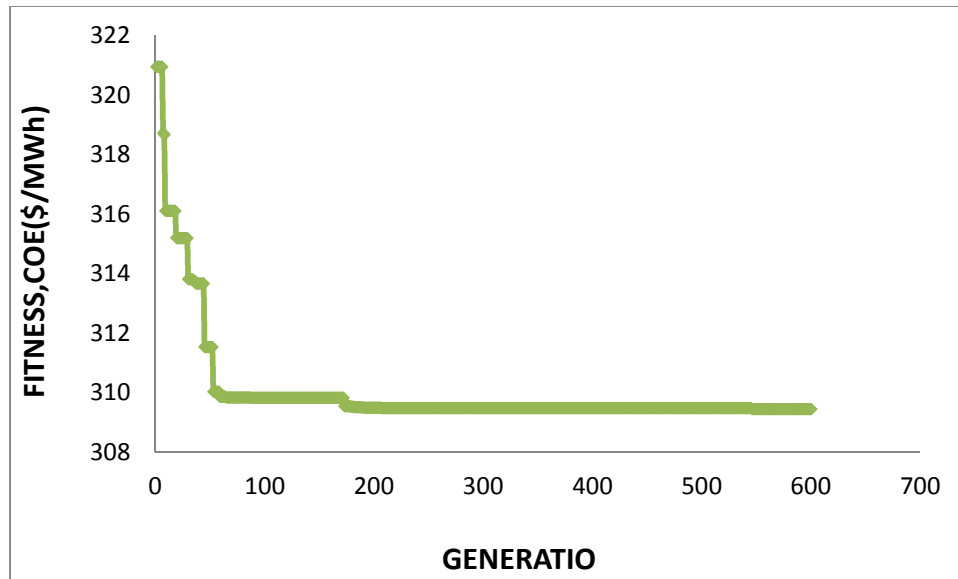


Figure E.4.3.3: Convergence history for 20:00pm to 22:00pm on mid-season day at gas price (\$6/GJ)

E.5 Case study 3: Effect of Maintenance Cost on COE

E.5.1 Winter

Table E.5.1.1: possibility of combinations that give power requirement 450 MW from 0:00Am to 2:00am and 13 °C (winter day at current study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	OFF	1474	1328	1337	1402	474459
Combination 2	1328	OFF	OFF	1365	1418	491971
Combination 3	1333	OFF	1330	OFF	1355	593970
Combination 4	1334	OFF	1327	1337	1418	641331
Combination 5	1334	1474	OFF	OFF	1418	476688
Combination 6	1336	1474	OFF	1337	1405	524049
Combination 7	1334	1474	1330	OFF	1418	626048
Combination 8	1328	1474	1330	1365	1402	673409

Table E.5.1.2: Optimisation of Operational Procedure (Existing & Proposed) for typical winter day

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	13	450	337.765	219.7898	118
2	14	400	339.617	164.799	120
4	11	470	335.275	219.962	115
6	15	588	338.32	226.042	119
8	16	591	340.036	224.08	120
10	18	599	342.709	282.963	123
12	21	613	346.226	285.613	126
14	23	613.8	350.119	289.073	130
16	20	601.5	345.462	285.385	126
18	15	598.9	338.32	279.429	119
20	13	596	337.765	280.313	118
22	13	597.8	337.765	280.313	118

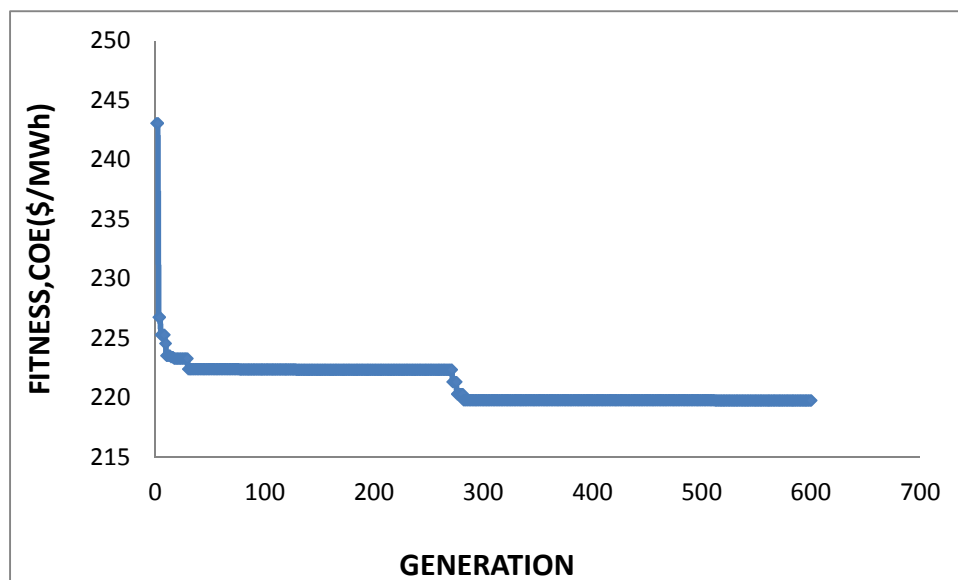


Figure E.5.1.1: Convergence history for 00:00am to 02:00pm on winter day

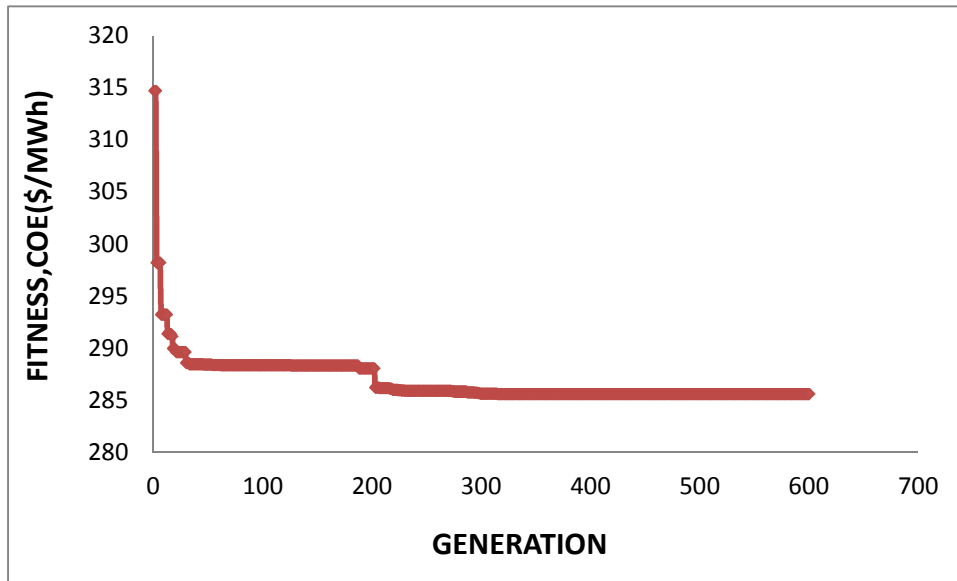


Figure E.5.1.2: Convergence history for 12:00pm to 14:00pm on winter day

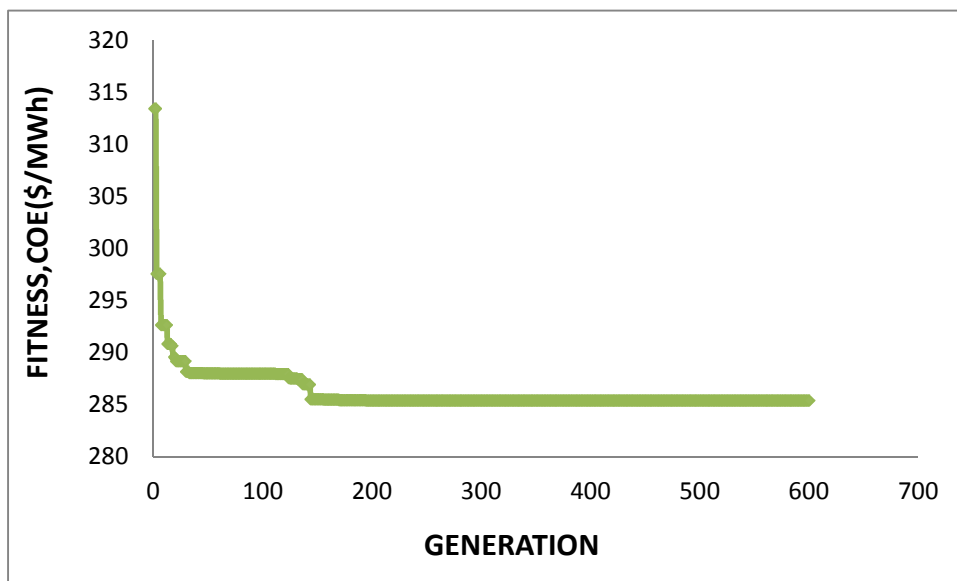


Figure E.5.1.3: Convergence history for 16:00pm to 18:00pm on winter day

E.5.2 Summer

Table E.5.2.1: possibility of combinations that give power requirement 521 MW from 0:00Am to 2:00am and 20 °C (summer day at current study)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1312	OFF	1328	OFF	1355	593.97
Combination 2	1327	OFF	1324	1362	1355	641.331
Combination 3	1312	1471	OFF	1337	1386	524.049
Combination 4	1312	1471	1324	OFF	1386	626.048
Combination 5	1328	1471	1324	1362	1386	673.409

Table E.5.2.2: Optimisation of Operational Procedure (Existing & Proposed) for typical summer day current study

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	20	521	345.462	227.644	118
2	19	506.6	346.659	226.81	119
4	18	490	342.709	225.827	115
6	25	508	351.443	231.792	124
8	30	610	364.021	301.027	136
10	35	620	372.569	307.851	145
12	45	633	390.136	321.92	162
14	45	633.8	390.136	321.92	162
16	37	621.5	375.985	310.7	148
18	33	618.9	366.141	305.051	138
20	20	616	345.462	285.385	118
22	22	580.8	346.855	232.27	119

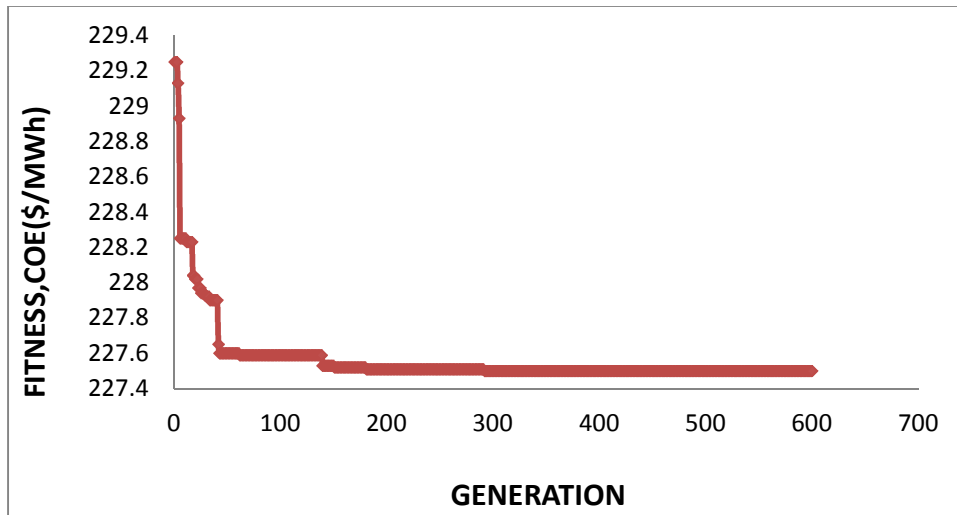


Figure E.5.2.1: Convergence history for 00:00pm to 02:00am on summer day

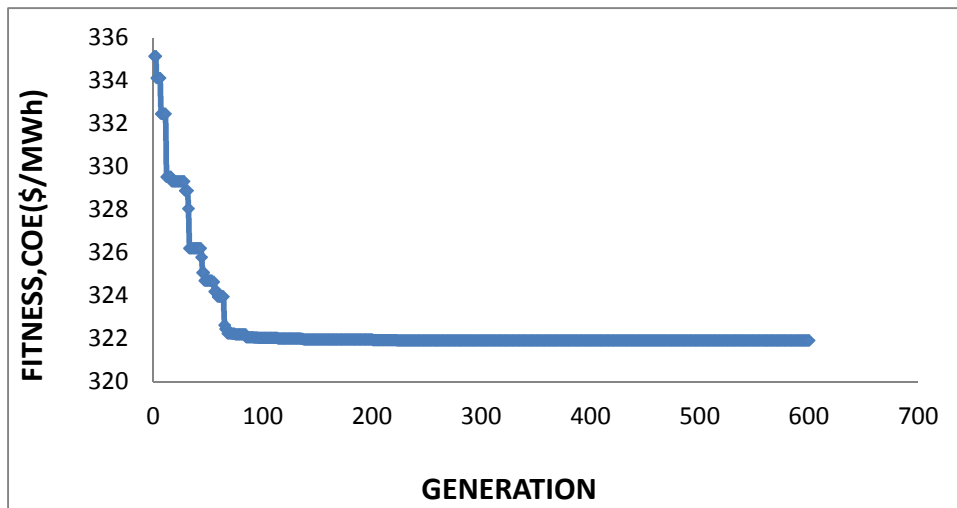


Figure E.5.2.1: Convergence history for 14:00pm to 16:00pm on summer day

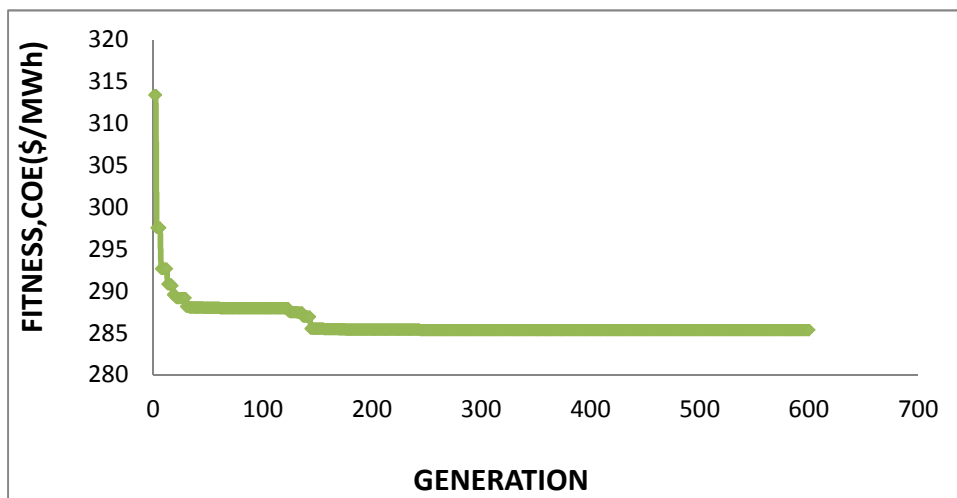


Figure E.5.2.1: Convergence history for 20:00pm to 22:00pm on summer day

E.5.3 Mid- season

Table E.5.3.1: possibility of combinations that give power requirement 500 MW from 0:00Am to 2:00am and 17 °C (mid-season day)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power
Combination 1	1250	OFF	1328	OFF	1355	593970
Combination 2	1312	OFF	1328	1337	1355	641331
Combination 3	1330	1473	OFF	1337	1386	524049
Combination 4	1250	1473	1328	150 OFF	1395	626048
Combination 5	1312	1473	1327	1363	1395	673409

Table E.5.3.2: Optimisation of Operational Procedure (Existing & Proposed) for typical mid-season day at fuel price \$6/GJ

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)	Δ
0	17	500	341.295	227.65	114
2	15	470	338.32	221.537	111
4	15	450	338.32	221.537	111
6	25	468	351.443	226.826	124
8	26	570.4	353.979	235.426	126
10	30	590	364.021	239.173	136
12	38	610	377.49	312.173	150
14	40	610	381.015	315.222	153
16	34	600	370.59	306.439	143
18	28	580	358.928	237.272	131
20	25	576	351.443	231.792	124
22	17	550	341.295	227.65	114

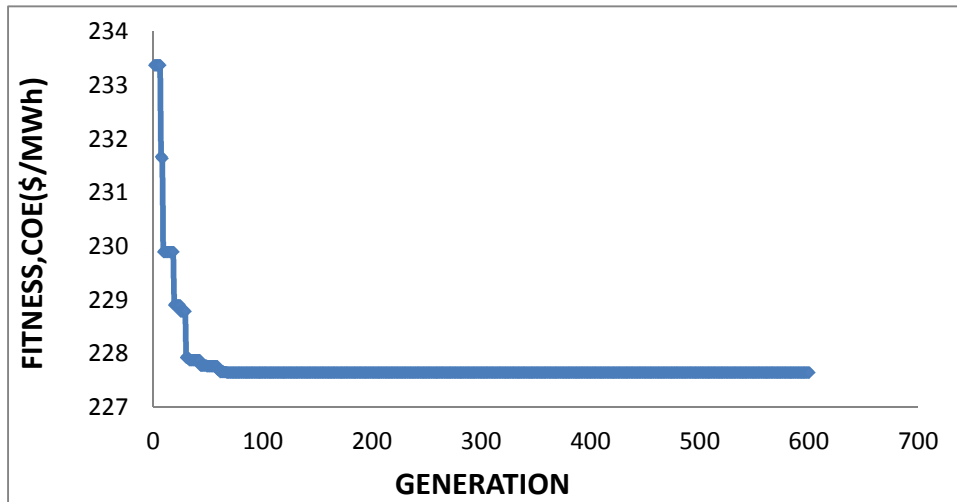


Figure E.5.3.1: Convergence history for 00:00am to 02:00am on mid-season day

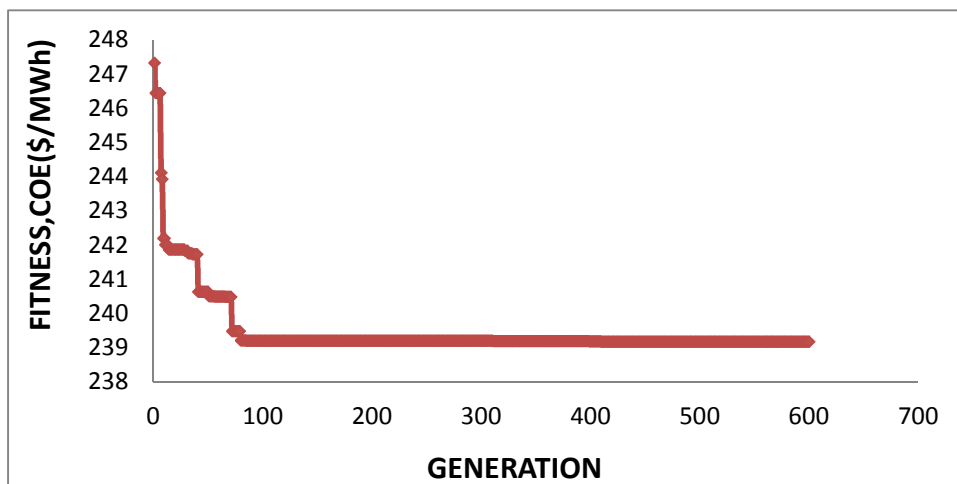


Figure E.5.3.2: Convergence history for 10:00am to 12:00pm on mid-season day

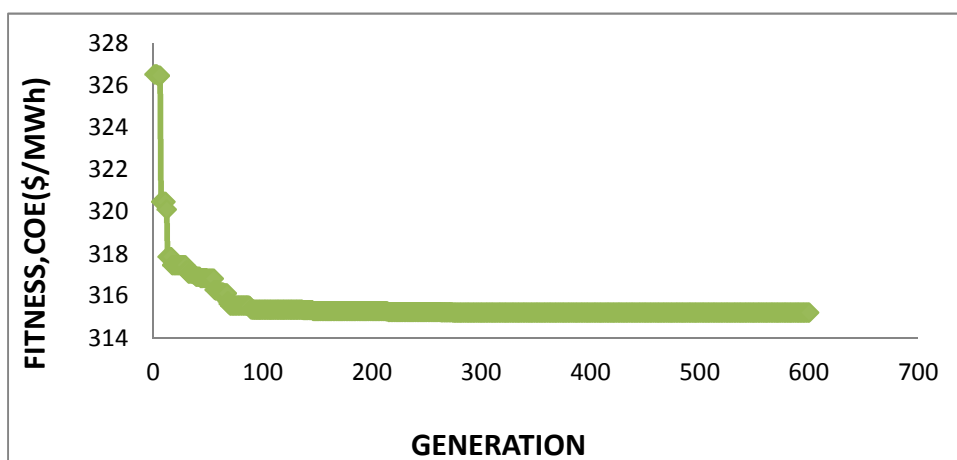


Figure E.5.3.3: Convergence history for 14:00pm to 16:00pm on mid-season day

E.6 Measure of Risk by Varying Discount Rate

Table E.6.1.1: possibility of combinations that give power requirement 450 MW from 0:00Am to 2:00am and 13 oC (winter day at 10% discount rate)

Number of Combination	Engine1 (Optimum TET)	Engine2 (Optimum TET)	Engine 3 (Optimum TET)	Engine 4 (Optimum TET)	Engine 5 (Optimum TET)	Maximum Power(MW)
Combination 1	OFF	1475	1336	1365	1355	474459
Combination 2	1344	OFF	OFF	1370	1410	491971
Combination 3	1340	OFF	1336	OFF	1410	593970
Combination 4	1344	OFF	1336	1370	1355	641331
Combination 5	1344	1475	OFF	OFF	1355	476688
Combination 6	1344	1475	OFF	1372	1355	524049
Combination 7	1344	1481	1336	OFF	1355	626048
Combination 8	1346	1475	1339	1364	1355	673409

Table E.6.1.2: Optimisation of Operational Procedure (Existing & Proposed) for typical mid-season day at discount rate 10%

Time Interval Hours of Day	Ambient Temperature °C	Power Demand (MW)	Total Electricity Cost All Engines Running(\$/MWh)	Optimised Total Electricity Cost Selected Engines Combination(\$/MWh)
0	13	450	339.36	221.9
2	14	400	340.31	165.8
4	11	470	339.37	219.9
6	15	588	344.56	225.1
8	16	591	343.59	225.9
10	18	599	346.47	285.4
12	21	613	349.56	288.5
14	23	613.8	354.06	292.2
16	20	601.5	348.87	290.9
18	15	598.9	344.56	284.9
20	13	596	339.02	282.6
22	13	597.8	339.02	282.6

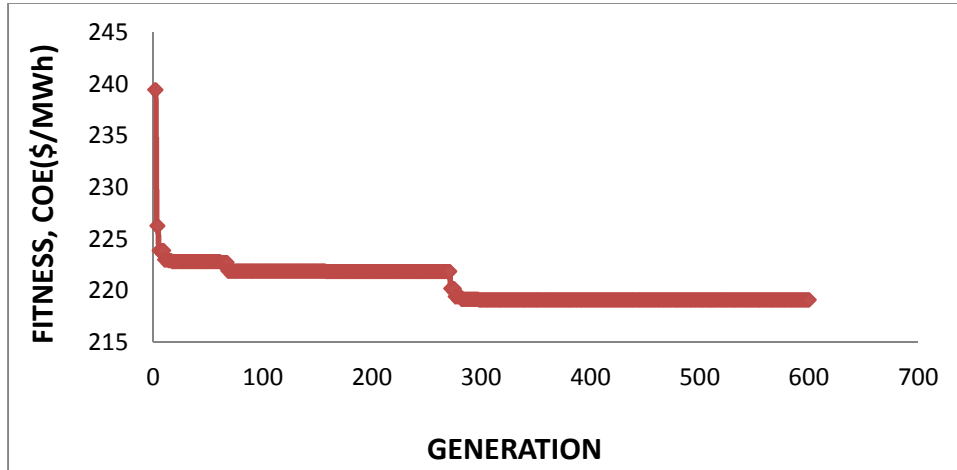


Figure E.6.1.1: Convergence history for 00:00am to 02:00pm on winter day at current case study 10%discount rate

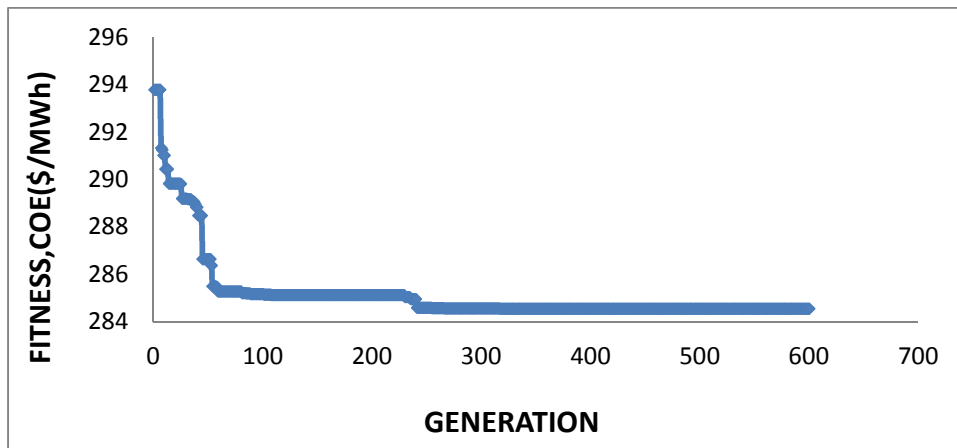


Figure E.6.1.2: Convergence history for 18:00pm to 20:00pm on winter day at current case study 10%discount rate

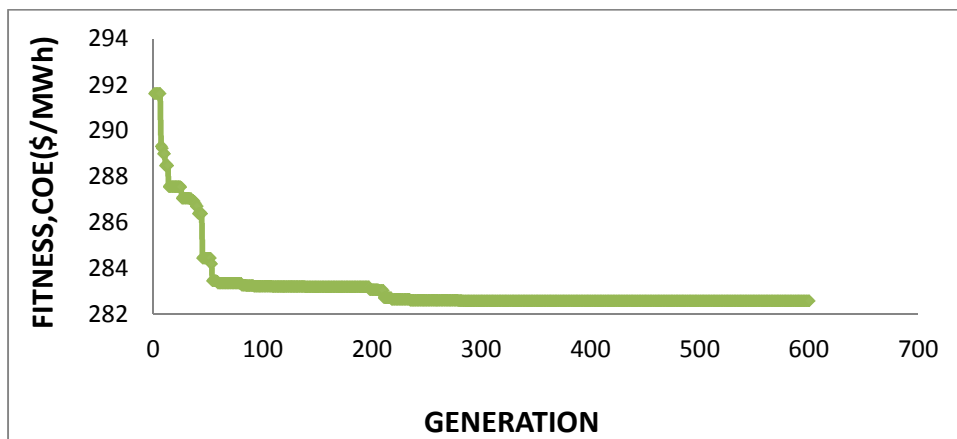


Figure E.6.1.3: Convergence history for 22:00pm to 24:00am on winter day at current case study 10%discount rate

