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JUDUL : LOAD DISPATCH OPTIMIZATION OF OPEN CYCLE INDUSTRIAL GAS TURBINE PLANT INCORPORATING OPERATIONAL, MAINTENANCE AND ENVIRONMENTAL PARAMETERS

SESI PENGAJIAN : 2005/2006

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LOAD DISPATCH OPTIMIZATION OF OPEN CYCLE INDUSTRIAL GAS TURBINE PLANT INCORPORATING OPERATIONAL, MAINTENANCE AND ENVIRONMENTAL PARAMETERS

FONG YEOW HEANG

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Mechanical)

Faculty of Mechanical Engineering
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FEBRUARY 2006

"I declare that this thesis entitled "load dispatch optimization of open cycle industrial gas turbine plant incorporating operational, maintenance and environmental parameters" is the result of my own research except as cited in references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any degree".

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ABSTRACT

Power generation fuel cost, unit availability and environmental rules and regulations are important parameters in power generation load dispatch optimization. Previous optimization work has not considered the later two in their formulations. The objective of this work is to develop a multi-objective optimization model and optimization algorithm for load dispatching optimization of open cycle gas turbine plant that not only consider operational parameters, but also incorporates maintenance and environmental parameters. Gas turbine performance parameters with reference to ASME PTC 22-1985 were developed and validated against an installed performance monitoring system (PMS9000) and plant performance test report. A gas turbine input-output model and emission were defined mathematically into the optimization multi-objectives function. Maintenance parameters of Equivalent Operating Hours (EOH) constraints and environmental parameters of allowable emission (NOx, CO and SO2) limits constraints were also included. The Extended Priority List and Particle Swarm Optimization (EPL-PSO) method was successfully implemented to solve the model. Four simulation tests were conducted to study and test the develop optimization software. Simulation results successfully demonstrated that multi-objectives total production cost (TPC) objective functions, the proposed EOH constraint, emissions model and constraints algorithm could be incorporated into the EPL-PSO method which provided optimum results, without violating any of the constraints as defined. A cost saving of 0.685% and 0.1157% could be obtained based on simulations conducted on actual plant condition and against benchmark problem respectively. The results of this work can be used for actual plant application and future development work for new gas turbine model or to include additional operational constraints.

ABSTRAK

Kos bahan api untuk kuasa penjanaan, kesediaan mesin untuk diguna dan undang-undang alam sekitar adalah merupakan faktor-faktor yang penting dalam kajian pengagihan beban optimum untuk kuasa penjanaan. Objektif kajian ini ialah mencipta model optimasi pelbagai objektif dan optimasi algorithm bagi pengagihan beban optimum untuk tarbin gas kitar terbuka. Ini bukan saja mengambil kira operasi parameter, tetapi juga untuk parameter penyelenggaraan dan alam sekitar yang belum pernah dikaji sebelum ini. Parameter prestasi formula untuk tarbin gas yang berdasarkan kepada ASME PTC 22-1985 telah dihasilkan serta disahkan berbanding dengan sistem prestasi pemantauan (PMS9000) dan laporan ujian prestasi dari stesen. Model tarbin gas dan penghasilan ezkos telah dihasilkan serta dikenalpasti secara matematik ke dalam fungsi optimasi pelbagai objektif. Parameter penyelenggaraan *Equivalent Operating Hours (EOH)* dan parameter alam sekitar bagi had limit pembebasan NOx, CO dan SO2 yang dibenarkan juga diambil kira dalam kajian tersebut. Gabungan kedua-dua kaedah optimasi Extended Priority List dan Particle Swarm Optimization (EPL-PSO) telah digunakan dengan berjaya untuk menyelesaikan model dalam kajian ini. Sebanyak empat simulasi telah dilaksanakan untuk mangaji dan menguji optimasi perisian yang dicipta. Hasil simulasi dalan laporan ini telah berjaya menunjukan bahawa fungsi Kos Jumlah Pengeluaran (TPC) optimasi pelbagai objektif, EOH *constraint*, ekzos gas model dan *constraint* lain telah berfungsi dengan baik bersamaan kaedah optimasi EPL-PSO. Keputusan simulasi juga telah berjaya menunjukkan bahawa keputusan optima dapat dicapai tanpa melampaui sebarang *constraints*. Penjimatan kos sebanyak 0.685% dan 0.1157% telah didapati jika keputusan simulasi dibandingkan dengan data dari stesen dan masalah *benchmark* dari kajian kesusteraan. Hasil usaha kerja ini boleh digunakan untuk applikasi sebenar oleh stesen janakuasa dan kajian masa depan bagi tarbin gas model yang baru, termasuk penglibatan *constraints* yang baru.

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LIST OF SYMBOLS

α	-	thermal time constant for the unit start up (hour)
$a_{i,(1,2,..10)}$	-	Unit *i* input output model polynomial coefficient
β	-	Emissions relative weight
$b_{i,(1,2,..10)}$	-	Unit *i* NOx emission model polynomial coefficient
$c_{i,(1,2,..10)}$	-	Unit *i* CO emission model polynomial coefficient
C_1, C_2	-	Objective function constant parameters
C_c	-	Cold start cost (GJ)
C_F	-	Fixed start-up cost ($)
CO	-	Carbon monoxide emission (ppm)
$d_{i,(1,2,..10)}$	-	Unit *i* SO2 emission model polynomial coefficient
D	-	Dimensional vector $X_{i,d}$ ($X_{i,1}$, $X_{i,2}$, …, $X_{i,D}$)
DCS	-	Distribution control system
DDE	-	Dynamic Data Exchange
EOH	-	Equivalent operating hour (hour)
EOH_{allow}	-	Allowable EOH_{diff} (hour) between units
EOHdiff	-	Remaining EOH before next maintenance work, EOH_N – EOH
EOH_n	-	Next maintenance work equivalent operating hour (hour)
EP	-	Evolutionary Programming
EPL	-	Extended Priority List
EPL-PSO	-	Extended Priority List – Particle Swarm Optimization
E_p	-	Total emissions (ppm)
FC	-	Fuel cost ($/GJ)
$f()$	-	Objective function
f_2	-	NOx emission objective function

f_3	-	CO emission objective function
f_4	-	SO2 emission objective function
f_{ei}	-	Emission objective function for unit i
g	-	Constraint function
gbest	-	PSO global best particle
GA	-	Genetic Algorithm
Ho	-	Initial unit status
HPSO	-	Hybrid Particle Swarm Optimization
HR	-	Heat rate (kJ/kWh)
HMI	-	Human Machine Interface
IHR	-	Incremental heat rate (GJ/h)
i	-	i^{th} unit
IO	-	Input output
j	-	j^{th} emission type
KPI	-	Key Performance Indicators
lbest	-	PSO local best particle
LC	-	Load cost ($/kWh)
LC'	-	Differential of LC function / Incremental heat rate (GJ/h)
LCO	-	Allowable CO emission (ppm)
LNOx	-	Allowable NOx emission (ppm)
LSO2	-	Allowable SO2 emission (ppm)
L_T	-	Electrical load / Power demand (MW)
M	-	Total types of emissions
MinDown	-	Minimum down time
MinDownAllow	-	Allowable minimum down time
MinUp	-	Minimum up time
MinUpAllow	-	Allowable minimum up time
N	-	Total unit or U_{max}
NOx	-	Nitride oxide emission (ppm)
OnOffStatus	-	Unit operation status {0,1}
P_i	-	Power output of unit i (MW)
Pbest	-	PSO best particle
PL	-	Priority / Sequence

Pmin	-	Unit minimum power output (MW)
Pmax	-	Unit maximum power output (MW)
ppm	-	Particle per million
PSO	-	Particle Swarm Optimization
$\rho 1$, $\rho 2$	-	PSO constant parameters
R	-	Total spinning reserve
RM	-	Ringgit Malaysia
s	-	PSO penalty factor
s_0	-	PSO initial penalty factor
$S(V_i)$	-	PSO sigmoid function
SdC	-	Shut down cost ($)
StC	-	Start up cost ($)
SO2	-	Sulfur dioxide emission (ppm)
t	-	Time interval
t_{cool}	-	Time in hours the unit has been cooled
T_{max}	-	Total time interval
TPC	-	Total production cost ($)
TPCWE	-	Total production cost with emission ($)
$U_{i,t}$	-	Unit commitment {0, 1} for unit *i* at *t* interval
U_{max}	-	Total unit or N
V	-	PSO particle velocity
V_{max}	-	PSO particle maximum velocity
W	-	Relative weight assigned to the total production cost
w	-	PSO initial weight
$X_{i,d}$	-	PSO particle position for i^{th} particle and d dimension

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The supply of natural energy resources such as natural gas, diesel and coal is decreasing year by year. Malaysia's petroleum resources can only meet the national requirement for another 20 to 30 years (Bernama, 1998). Unless there is an alternative energy source which is cheaper, cost based on fossils fuel would become an even more important consideration. From statistics provided by Department of Electricity and Gas Supply Malaysia, the generation plants in Malaysia mainly 63.4% consist of combined cycle blocks with gas turbine. Approximately 75% of energy generated in the country uses natural gas as fuel, making it the most important fuel in electricity production.

The power generation fuel cost is therefore has become a very sensitive and important parameter to the power generation plant as they cannot effort to waste or inefficiently utilize any energy resources. With reference to Ng (2001), 1% drop of the gas turbine thermal efficiency would lead to 0.065sen/kwh increase of power generation fuel cost (on the basis of the gas turbine running at 30% thermal efficiency). There is therefore a need to ensure the gas turbine always operate at its optimal performance.

On the other hand, the contribution of the gas turbine to environmental pollution raises questions concerning environmental protection and methods of eliminating or reducing pollution either by design or by operational strategies. Pollution affects not only humans, but also other life-forms (such as animals, birds, fish, and plants). It also causes damage to materials, reducing visibility, as well as causing global warming. These effects may be interpreted as costs because it affects life in one way or another. The damage caused by a pollutant depends on its type, meteorological conditions and on our exposure to it. This suggests that each pollutant should be treated on its own merit in assigning cost values (usually referred to as valuing environmental externalities). This represents the potential harm or damage created. The main subtances of the emmisions are Nitrogen Monoxide (NOx), Sulfida Dioxide (SO2) and Carbon Monoxide (CO). Environmental rules and regulations for power generation industries has been implemented extensively and has become an important considerations and even as a regulation. Such regulation are being implemented in developing countries and even in Malaysia that is working towards global environment protection and perservation.

Gas turbine or other electric power plants are currently operating on the traditional basis of least fuel cost strategies (economic dispatch or optimal power flow) without considering the pollutants produced. In order to consider the pollution in the cost function, it is necessary to know the types of pollution produced from power plants, its effects and also requirements of the relevant laws. One of the method to reduce emissions is to dispatch the power generation to minimize emissions or as a supplement to the usual cost objective of economic dispatch. This method requires only minor modification of dispatching programmes to include emissions. Emission dispatching is an attractive short-term alternative in which the primary objective is to minimize the overall emissions by loading the cleaner generating units as much as possible while forcing those with higher emission rates to generate less.

Maintenance parameter such as Equivalent Operating Hours (EOH) are also not currently included to the load dispatch optimization to avoid two or more machines being sent for maintenance at the same time. Insufficient capacity to deliver power as demanded might happen, if wrong decision had been made in manual scheduling.

Industrial gas turbine in most plants do not always operate at their optimum operating conditions to achieve the objectives of minimum cost and minimum emissions, since dependent variables condition like atmospheric pressure, temperature of working fluid, production targets, equipment efficiency, etc. are always fluctuating. Besides, the gas turbine performance degradation may lead to changes of optimal operating points. From time to time, engineers are faced with problem of determining the optimum operating regimes or ways to run a particular machine quickly and accurately in order to obtain maximum benefit from the machine, at all times and under every set of circumstances. It can be very complex and time consuming to generate an accurate mathematical model that represent the machine which optimizes the objective function using suitable optimization techniques.

The primary objective of power dispatch optimization in the past has been concentrated on the minimization of generation cost in meeting the demand on power system – economic dispatch. Few proven mathematical optimization method such as, Extensive Enumeration, Dynamic Programming and Lagrange Relaxation had been used widely in solving such economic dispatch problem. However, the first two methods only work efficiently with small and moderate size system, while Lagrange method suffers from convergence problem, and always trap into a local optimum. Several artificial intelligence (AI) method also had been carried out to solve such optimization problem. Although AI method such as evolutionary computation techniques and genetic algorithm can provide a near-global solution but it takes a very long computation time.

Research work that involves economic load dispatch optimization which includes environmental impact of power generation are very limited. One of the approaches to reduce the emission from thermal power plants is the minimum emission dispatch based on the efficient weight estimation technique as described in El-Keib et al. (1994) and Ramnathan (1994).

This research work therefore attempted to solve the above problems of production scheduling which relates to the determination of the generating units to be service and to meet system demand, while satisfy all the operational and maintenance constraints with minimum cost and minimum emissions. This optimization problem is also commonly known as an economic environmental unit commitment optimization.

1.2 Problem Statement

A direct inference from the previous work reported in the literature review (Chapter 2) showed several evident shortcomings, which are summarized as follows:

a. Maintenance parameter such as Equivalent Operating Hours (EOH) is not included to the load dispatch optimization in preventing two or more machines being sent for maintenance at a time. Insufficient capacity to deliver power as demand might happen if incorrect decision had been made in manual scheduling.

b. Environmental parameters is not included as part of the objective functions in current load dispatch optimization. No load dispatching guidelines at present in meeting environmental regulations (if implemented) in Malaysia

1.3 Objective and Scope

The objectives of this work were:

a. to develop a model for optimizing cost-effective distribution of load demand across units of open cycle gas turbine, incorporating machine operating conditions, maintenance and environmental parameters.

b. to develop a software to validate the developed model and optimization method

The model described in this project aims to provide a flexible framework to evaluate various operational planning options for emission compliance. It can be used to determine the optimum unit commitment and loading levels of each affected unit so as to meet the emission targets. Moreover, it performs multi-objective dispatch considering both the cost and emissions.

This current work was confined to offline optimization. The developed software could honour be upgradeable or scalable for open loop real-time optimization or closed loop real time optimization. No experimental work was done in this work. This means that all experimental data employed for model validation and optimization studies in Chapter 6 and 8, were obtained from existing plant performance monitoring system.

1.4 Methodology

This project was undertaken with an industrial partner TNB Connaught Bridge Power Station, where four of their open cycle ABB 13E gas turbines were studied in this research work. Gas turbine performance parameters in quantify gas turbine performance and its computation technique in accordance to ASME standard was identified before developing the gas turbine efficiency and emissions model. The model that provided a complete representation of the machine behavior could be obtained within the parameters of interest based on a combination of physical principles (thermodynamic) and performance curves. The machine model was then validated against the data acquired from the plant via the installed performance monitoring system (PMS9000), and Gas Turbine Manufacturer's Performance Test Reports.

The cost-based objective functions which represents profit, operating cost energy, yield, etc was developed such that optimization studies could be formulated and make recommendations on operation and maintenance strategy that lead to optimal performance, with considering machine operating conditions, maintenance and environmental parameters. Suitable optimization algorithm was identified to determine the optimal distribution of load demand across the various operating units.

Software coding of above subroutines (both model and optimization) was then undertaken for further studies and validation. Four case studies were carried out to test the program against the benchmark problem and actual field measurement data. Finally, the simulation results were then studied and reported.

1.5 Significance of Research Work

The result of this work will be an essential tool to the plant operation in order to make a plant operate more effectively and competitively. With the development of low price and high performance computer, such software can easily be implemented and routinely applied to improve day-by-day performance of most of the plant operation, typically petrochemical, power generation and water treatment plant with offline simulation and optimization.

It has often been noted that processing facilities are data rich but knowledge poor. The plant DCS system generates an enormous amount of information about the process. This offers scope for such software to be utilized. It is anticipated that the simulation and optimization software can be upgraded to on-line or real-time optimization which leverages the wealth of the information into a range of other benefits. It could convert pure data to information, to knowledge and ultimately, to wisdom, providing the engineers with access to an off-line model which reflects the current plant condition at any point in time and equipment performance indicators.

Recent advances in development of new technology of Advanced Process Control (APC) such as model-based predictive control, shows the potential of the need of simulation and optimization software. In future, the software will incorporate with APC and be implemented to a much greater extent than real-time optimization.

1.6 Thesis Outline

The main body of this thesis begins with a literature study in Chapter 2 that reviews the gas turbine performance calculations and its maintenance practices in general, optimization theory and application, previous work on economic load dispatch problem and selective optimization techniques namely particle swarm optimization. Thereafter, in Chapter 3, the overall methodology of this research is presented.

The formulation of objective function is the one of the crucial steps in the application of optimization to a practical problem and this is illustrated in Chapter 4. The incorporation of both environmental and maintenance parameters into the general objective function is discussed in details. With the developed objective function in Chapter 4, the gas turbine performance and emission model are formulated in Chapter 5. Subsequently, in Chapter 6, the model is validated against actual plant data from the performance monitoring system PMS9000 and machine performance test report.

In Chapter 7, the advanced and recent artificial intelligence technique, namely particle swarm optimization (PSO) is enhanced and tested as the optimization techniques in solving the optimization problem as presented in the previous chapters. The reasons of implementing particle swarm optimization to this problem and comparisons among other techniques are reviewed.

An optimization for load dispatch is of little value unless it is demonstrated that it can give accurate results for known cases. Therefore, in Chapter 8, simulation case studies are made. First, based on the benchmark problem from the literature, the behaviour of the optimization result is validated. Thereafter it is shown that a close agreement was obtained and with the best computation time. After the test with benchmark problem was completed, various studies (by removing some aspects) are carried out with actual plant data for further validation. Finally, the full procedure was implemented on the actual plant model and the resulting optimum solution is found to be superior to the existing solutions used by the plant. After this, general conclusions of the work are drawn in Chapter 9, where also some possible ideas for future work are presented.

CHAPTER 2

LITERATURE REVIEW OF RELATED WORK

2.1 Introduction

This chapter relates to the previous work on load dispatch optimization of open cycle gas turbine in the literature. Related work on gas turbine modeling, optimization and commercial load dispatch software are also reviewed.

2.2 Gas Turbine Model and Performance Calculations

Common cycle analyses for simple gas turbine were presented by Saravanamutto (1996) and Wilson (1997). The most common cycle of the gas turbine is the Brayton cycle, which has several assumptions of ideal conditions as stated below:

i. Compression and expansion processes are reversible and adiabatic
ii. The change of kinetic energy of the working fluid between inlet and outlet of each component is negligible
iii. No pressure losses in inlet ducting, combustion chambers, heat exchanger, intercoolers, exhaust ducting, and ducts connecting the components
iv. The working fluid has the same composition throughout the cycle and is a perfect gas with constant specific heats

v. The mass flow of gas is constant throughout the cycle.

Further improvements to this cycle have been done, which components losses are taken into account. Several predictions of components losses and pressure losses were presented by Saravanamutto (1996) and Wilson (1997) with the components' efficiency provided. A model for predicting the performance of a Brayton Cycle gas turbine was developed by Wilson and Korakianitis (1994). The working fluid properties such as mean heat capacity or air, fuel-air mixture, and of products of combustion, are evaluated as analytical-polynomial functions of temperature and fuel-air ratio using the method described by Wilson (1997).

Performance computational methods have generally been standardized; and industrial test standards universally used are the ASME PTC 22-1985 and ISO 2314-1989. These international standards specify standards guidelines, procedures and rules for the conduct and report of test for gas turbine power plants or gas turbine engines. Formulation is provided to determine and verify the power, thermal efficiency and other performance characteristics of gas turbine power plants. It applies to open cycle gas turbine power plants using normal combustion and also includes closed cycle and semi-closed cycle gas turbine.

The standard that is most commonly used to perform performance test for gas turbine is ASME PTC 22-1985. This Code can be applied not only to gaseous fuel but also liquid fuels. This Code is however not applicable to gas turbines used for aircraft propulsion or to free-piston power plants. The object and scope of this Code are as follows:

a. Defining procedures for testing gas turbines to determine efficiency and power output specified operating conditions.
b. Defining standard conditions and provides for procedure for adjusting results, obtained under test conditions, to specified or standard conditions.

2.3 Common Plant Maintenance Practices

In general, any equipment that is running at base-load could operate to a recommended number of hours before maintenance action is required or its operating life is used up and required replacement. These hours are termed its Normal Operating Hours. If the equipment is put under additional strain by being run at higher loads, or cycled frequently (machine startup and shut down) then its time before overhaul/replacement will be consumed faster, and its value will be significantly reduced.

Equivalent Number of Operating Hours (EOH) is determined based on the normal operating hours with taking into considerations of the operating conditions of the machines [Azlisham (2002)]. EOH has been employed by most of the gas turbine manufacturer as guidelines to determine the maintenance interval of the machines. EOH is a determination of the effect of the start cycle and running hours of the machines.

For most of the time, the plant would not want two machines or more to have same EOH. This is due several reasons, which are:

a. the plant may not able to supply sufficient power as contracted due to more machines are unavailable for that period

b. lack of man power to complete the maintenance work and restore back the machine as soon as possible

Currently, the production scheduling within the few units of open cycle gas turbine in Connaught Bridge Power Station was determined manually, with considering EOH factor as well as other factors such as operating cost and power demand.

At this moment, unit commitment and load dispatch optimization application inclusive of these maintenance parameters (EOH) had not yet been reported.

2.4 Optimization Theory and Application

Optimization is the act of obtaining the best result under given circumstances. In design, construction, and maintenance of any engineering system, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation could be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions that give the maximum or minimum value of a function.

The optimum seeking methods are also known as mathematical programming techniques and are generally studied as a part of operations research. The areas of operation research mainly classified to 3 main areas, which are mathematical programming techniques, stochastic process techniques and statistical method as describe in Pike (1986).

Mathematical programming techniques are useful in finding the minimum of a function of several variables under a prescribed set of constraints. Stochastic process techniques can be used to analyze problems described by a set of random variables having known probability distributions. Statistical methods enable one to analyze the experimental data and build empirical models to obtain the most accurate representation of the physical situation. Table 2.1 lists various mathematical programming techniques together with other areas of operations research.

The conventional optimization techniques or method used is basically based on the formulation of the optimization problem (equation or objective function involved), while advanced method such as neural networks, genetic algorithms and particle swarm method is more non-deterministic solution where it is not formulation dependent.

Table 2.1: Methods of operations research

Mathematical programming techniques	Stochastic process techniques	Statistical methods
Calculus methods Calculus of variations Nonlinear programming Geometric programming Quadratic programming Linear programming Dynamic programming Integer programming Stochastic programming Separable programming Multi objective programming **Network methods: CPM** and PERT Game theory Simulated annealing Genetic algorithms Neural networks Particle Swarm	**Statistical decision** theory Markov processes Queuing theory Renewal theory Simulation methods Reliability theory	Regression analysis Cluster analysis Pattern recognition Design of experiments Discriminate analysis (factor analysis)

Source: Pike (1986)

2.5 Economic Environmental Unit Commitment (EEUC)

The primary objective of power dispatch in the past has been concentrated on the minimization of generation cost in meeting the demand on power system – economic dispatch. The cost incurred however has ignored the environmental impact of power generation due to emission of various harmful pollutants such as such as sulfur oxides (SO_2), nitrogen oxides (NO_x) and emission particles. With the increasing concern for the environment and the introduction of environmental regulations, the effect of emission have to be taken into account in generation dispatch. Reducing atmospheric pollution is deemed to be one of the major challenges for utilities over the next few decades, as highlighted by IEEE Current Operating Problems Working Group (1995). This could be achieved by incorporating the emission considerations into the economic dispatch algorithm, thus expanding existing problem to an Economic-environmental unit-commitment (EEUC) optimization problem. Economic-environmental unit-commitment (EEUC) optimization problem is a highly constrained problem and, as such, it poses a special challenge to conventional or artificial inteligence techniques.

Limited research works in this field are reported. One of the approaches to reduce the emission from thermal power plants is the minimum emission dispatch based on the efficient weight estimation technique as described in El-Keib et al. (1994) and Ramnathan (1994). Kullor et al. (1992) described a method of solving the UC including all of the emission considerations in the unit commitment objective function. Emissions are considered as a second objective function and are added to the main objective function with a weighting factor. The UC is solved based on Lagrangian relaxation with multiple decomposition.

Gijengedal (1996) suggested an emission-constrained approach using an LR-based algorithm that identified the least-cost action for achieving daily or weekly emissions targets. His problem formulation included all standard system constraints and explicit addresses variable emission during start-up, operation and shut down of units.

Similar weighting concept as mentioned above was used later in this work for the development of the optimization objective function.

2.6 Load Dispatching and Unit Commitment Optimization Techniques

Information gathered on the optimization techniques application in load dispatching and unit commitment is summarized in this section. A more complete review of optimization algorithm used and the trend of optimal thermal generating unit commitment or load dispatching can be found in Subir Sen et al. (1998).

The unit commitment (UC) and load dispatch is an important problem in production scheduling which relates to determination of the generating units to be in service during each interval of the scheduling period (a day or a week), to meet system demand and reserve requirement at minimum cost for the total scheduling period, subject to variety of equipment, system, operation, environmental and maintenance constraints. This is a mixed-integer nonlinear time-dependent optimization problem. Since this problem was introduced, several methods have been applied to solve this problem. With reference to Subir Sen et al. (1998), those techniques can be widely classified as follows:

1. Extensive enumeration
2. Priority list
3. Dynamic programming (DP)
4. Lagrangian Relaxation (LR)
5. Branch-and-bound method
6. Decommitted method
7. Expert systems/artificial neural networks
8. Evolutionary computation
9. Other approaches
10. Combined techniques

An extensive enumeration method finds a solution by enumerating all possible combinations of generating units, and then selects the combination that yields the least cost operation and satisfies all constraints. This method works well with small and moderate sized system. However, it takes long time to find a solution and become not practical when comes to a large system.

Priority list method is the simplest technique for solving UC problem. This method arranges generating units in a startup/shutdown rules heuristically with increasing/ decreasing order by operation cost, including state transition cost. The pre-determined order is then used to commit the units such that the system load and reserve requirements are satisfied. Its result, however, is not a general one because this method bases on many assumptions.

The Dynamic Programming technique (DP) finds a solution by building and evaluating the decision tree that consists of the units' status for an optimal solution.

The search can be carried out in the forward or backward direction. The time periods of the study horizon are known as the stages of the problem. This method has many advantages such as its ability to maintain solution feasibility. Nevertheless, this method has dimensionality problem with a large power system because the problem size increases rapidly with the number of generating units to be committed, which results in an unacceptable solution time.

The Lagrange Relaxation (LR) method decomposes the UC problem into many sub-problems, which are easily to be solved separately. The sub-problems are linked by Lagrangian multipliers that are added to the master problem to yield a dual problem. The dual problem has lower dimensions than the primal problem and is easier to solve. The difference between the two functions yields the duality gap for which the primal function is an upper bound. This gap is generally used as a measurement of near-optimality of the solution. Sasaki et .al (1992) showed the mathematical formulation of LR technique and its practical computational steps. Viramani et al. (1989), Takriti et al. (2000) and Bakistzis et al. (2000) proposed other approaches based on LR. The LR technique has emerged as an effective method of solving the UC problem because it is easily to handle various constraints, this method does not need a priority list and it can provide a fast solution. Nevertheless, this method sometime suffers from numerical convergence especially when the problem is non-convex. Besides, the quality of solution from LR strongly depends on the method to update Lagrangian multipliers. Most of researches dealing with LR use gradient method to achieve this task. However, solution obtained from gradient-based method suffers from convergence problem, and always trap into a local optimum.

The branching and bounding is comparable to DP, as both constitute intelligently structured searches over the space of feasible solutions. The branch-and-bound approach determines a lower bound to the solution, and then finds a near-optimal feasible commitment schedule. This lower bound can be determined from the dual optimization problem that uses the LR technique. Information obtained from the dual problem is instrumental in producing dynamic priority lists. These lists are useful in the determination of a feasible solution, and help in the computation of an upper bound of the solution. With reference to Subir Sen et al. (1998), this approach can be extended to allow a probabilistic reserve constraint that included the effect on reserve of random unit forced outages and uncertain demands over and above deterministic reserve constraint. However, Li C. A. et al. (1997) mentioned that this method is also practically intractable due to the large storage size require to implement them on a computer.

The decommitment method uses the concept that the most disadvantageous unit is decommitted first, then the next, and so on. This process is called optimal ordered unit decommitment. The unit decommitment procedure continues until no further reduction in total cost are possible or the UC schedules of two consecutive iterations remain unchanged without violation of spinning reserve requirement at any hour of the study time period. Li C. A. et al. (1997) shows the example of this method.

An expert system improved the UC solution by adjusting the program's parameters through interaction with the system operator. Tong S. K. et al. (1991) combines the UC algorithm and the knowledge of experienced power system operators and UC experts, to assist operators in scheduling generating unit and create a rule-based expert system. As for artificial neural networks (ANN), it can handle the inequality constraints, which exist a lot in UC problem, easily and efficiently by using the sigmoid characteristic. The inability to accurately predict system load demand and to account for the effects of unit forced outages makes the UC problem stochastic. The ANN also can handle this stochastic nature by means of the Hopfield ANN. Sasaki (1992) showed the application of ANN to UC problem.

Nowadays, the evolutionary computation techniques, such as Simulated Annealing (SA), Genetic Algorithm (GA) and Evolutionary Programming (EP) have been given much attention in power system optimization including UC problem. Using SA, UC problem is compared to the annealing of a metal. When a metal is cooled slowly (annealed), its energy tends to assume a globally minimal value. The state temperature of the metal, correspond to the various feasible solutions of the problem to minimize and the energy of a state is analogous to the objective function, the cost of a feasible solution. The SA generates a near-optimal and feasible solution. The convergence time (speed) of UC by SA, however, is a limiting factor. Zhuang and Galiana (1990) first presented the application of SA in UC problem; then the test systems of up to 100 units was simulated. In Mantaway et al. (1998), the new rules for randomly generating feasible solutions are introduced. Then the problem was classified into 2 sub-problems: a combination optimization problem and a nonlinear programming problem. The former was solved using the SA while the latter problem was solved using a quadratic programming routine. Another example is Wong S.Y (1998), where an enhanced version of SA was presented.

The GA represents a class of general purpose stochastic adaptive search techniques while simulate natural inheritance by genetics and the Darwinian "survival of the fittest" principal. The basic advantage of the GA solution is the flexibility. It provides in modeling both time-dependent and coupling constraints. Another advantage is that it can be very easily converted to work on parallel computers. In general, the GA is a good global-search technique, but a poor local-search technique. Dasgupta et al. (1994) and Kazarlis et al. (1996) presented the application of GA to UC problem. Results have been compared with other techniques, such as LR and DP.

The EP is also one of the evolutionary computation techniques. It shares a common conceptual base with GA and other evolutionary techniques, which simulate the evolution of individual structures through processes of selection, mutation and recombination. The example of application of EP to UC problem can be found in Juste et al. (1999). In addition to the method mentioned above, some techniques, such as Interior-Point technique and Tabu search were employed to solve UC problem.

Up until now, several techniques, described above, have been used to solve UC problem. Each method has its own advantage and disadvantage for example; evolutionary computation techniques can provide a near-global solution but takes a long computation time. The LR can provide a fast solution but sometime suffers from numerical convergence. In order to obtain a better solution within a reasonable time, recently, the combined techniques are attractive to many researchers. In Liang et al. (2000), an extended mean field annealing neural network was proposed. The method used the property of SA, which can find good solution, and a rapid convergence property of ANN to solve UC problem. The other GA-based hybrid methods can be found in Orero et al. (1997), Huang S. J. et al. (1997), Mantaway et al. (1999), Padhy (2001) and Aldridge et al. (2001). In Cheng C. P. et al. (2000), GA was used to update the multipliers in traditional LR. Simulation results show that it provided a better solution within a shorter time compared with GA and LR.

2.7 Evolutionary Programming Techniques in Economic Load Dispatch

Evolutionary Algorithms (EA) is computer-based problem-solving systems based on principles of evolution theory, which is similar to Genetic Algorithm. A variety of EA have been developed and they all share a common conceptual base of simulating the evolution of individual structures via processes of Selection, Mutation and Recombination. The processes depend on the perceived performance of the individual structures as defined by an environment. The interest in these algorithms has been rising fast for they provide robust and powerful adaptive search mechanisms. The interesting biological concepts on which EA are based also contribute to their attractiveness.

There has been a great interest in the use of EA in Power Systems because these approaches are very well suited to deal with all those kinds of problems that usually represent nightmares for researchers and developers: integer variables, non convex functions, non differentiable functions, domains not connected, badly-behaved functions, multiple local optima, multiple objectives, etc. (L.M. Proenca, J, etl, 1999). Furthermore, they are not necessarily restricted to deal with numerical models, allowing the natural building of hybrid models including knowledge, under the forms of rules or other. This complexity is what is required, in order to build larger Power System models with more adherences to reality. In very complex situations, they seem to be the only practical tool available.

Evolutionary Programming algorithms in Economic Dispatch (ED) have clear advantages over traditional methods due to their robustness, but also provide an edge over Genetic Algorithms, mainly because:

They do not need any special coding of individuals. In the case of ED, since the desired outcome is the operating point of each of the dispatched units (a real number), each of the individuals can be directly presented as a set of real numbers, each one being the produced power of the unit it concerns.

Since each of the individuals codes within itself its own mutation rate, and since it is itself mutated, the algorithms provide themselves a self-regulating adaptive scheme.
On the other hand, no special requirements are made regarding the objective function and constraints, which is a very interesting feature of Evolutionary Programming algorithms (and also of Genetic Algorithms) as compared to traditional methods.

2.8 Particle Swarm Optimization (PSO)

2.8.1 Basic Concept of PSO (Source: Kennedy and Eberhart (1995a) & (1995b))

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The technique was developed based on several concepts of the nature.

Natural creatures sometimes behave as a swarm. One of the main streams of artificial life research is to examine how natural creatures behave as a swarm and reconfigure the swarm model inside a computer. Bird flocking and fish schooling could be modeled with such simple models. Even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can however be complicated. The behavior of each agent inside the swarm could be modeled with simple vectors and following rules:

a. to step away from the nearest agent;
b. to go toward the destination

c. to go to the center of the swarm.

Another concept of PSO is from the examination of the human beings decision making process, which is the “individual learning and cultural transmission”. Human beings use their own experience and the experience of others in its decision process. They would know which choices of their neighbors have found are most positive so far, and how positive the best pattern of choices was. Each agent then decides his or her decision using his or her own experiences and other people’s experiences.

According to the background mentioned above, the PSO was then developed. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and is inspired by particles moving around in the search space for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is represented by *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called local best, *lbest*. When a particle takes all the population as its topological neighbors, the best value becomes a global best and is represented by *gbest*.

The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations. The final *gbest* at the end of the generations is taken as the optima results.

2.8.2 Particle Swarm Optimization Techniques in Economic Load Dispatch

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The PSO technique has ever since turned out to be a competitor in the field of numerical optimization.

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). PSO consists of a population refining their knowledge of the given search space in search for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Details explanation on the concept, theory and algorithm are discussed in later chapter.

In past several years, PSO has been successfully applied in many research and application areas. It is demonstrated that PSO gets better results in a faster, cheaper way compared with other methods. Another reason that PSO is attractive is that there are few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

Only little known work that focus on the application of PSO in economic dispatch is found. The recent work on swarm intelligence for hybrid cost dispatch problem had been published by El-Gallad et al. (2001), El-Gallad et al. (2002) and Naka et al. (2002). The paper presents a modified particle swarm optimizer to solve the economic power dispatch problem with piecewise quadratic cost function. The proposed algorithm finds combination of power generation that minimized the total cost function while exactly satisfying the total demand. The maintenance, environmental and time dependent constraints are not taken into considerations in this work. Specifically, a modification is applied to both velocity and the way each individual in the population updates its position inside the problem space. The proposed technique is designed to prevent constraints region and to reduce the chances that the algorithm ends up being trapped in a local minimum. Several case studies had been carried to compare with existing numerical method as written in Allen et al. (1996). The results obtained had showed the easiness of implementation and accuracy of the proposed techniques as compared to numerical method – hierarchical approach.

Another similar application of PSO is published by Naka et.al (2002) and Kennedy (2001) who had applied the hybrid PSO techniques for distribution state estimation that is similar to economic load dispatch problem. The authors propose a hybrid particle swarm optimization (HPSO) for a practical distribution state estimation. The proposed method considers nonlinear characteristics of the practical equipment and actual limited measurements in distribution system. The proposed method able to handle the non-differential and noncontiguous objective function that is caused by the nonlinear characteristics. The method had estimated load and distributed generation output values at each node by minimizing the difference between measured and calculated voltages and currents. The results of the numerical simulations indicate that the proposed method can estimate the target system conditions more accurately that the original PSO. The results had indicated the applicability of PSO in such optimization problems.

Recent research in using Hybrid Particle Swarm Optimization (HPSO) to solve unit commitment problem had been conducted by Tiew-On, et al (2003). Its problem formulation took into consideration of minimum up and down time constraints, start up cost and spinning reserve, which and was defined as the minimization of the total objective function. The simulation results, which were performed with the benchmark problem of 10 generator scheduling problem, had demonstrated well that the HPSO is a competent method to solve UC problem. However, the computational time was still considered high as similar to genetic algorithm or evolutionary programming.

2.9 Commercial Optimization Software and Solutions

2.9.1 RTO+® from MDC Technology

In the commercial market, one of the leading providers of Production Optimisation and Performance Monitoring software solutions is MDC Technology of Emerson Process Management. The software product for real-time optimisation software packages from MDC is called RTO+®. RTO+ is a unique modular system, which meets the specific requirements of application in a single, highly integrated package. RTO+® is specifically designed for real-time on-line applications. An integrated suite of tools enables the engineer to configure applications for a range of tasks.

There are a wide variety of optimisation algorithms. Every algorithm or technique is, in effect, a compromise between the non-linearity of the objective function and constraints, and the ease with which the sub problem can be solved. RTO does not use only single method and embed it deeply in their model solution techniques, even though most commercial RTO systems select a single method (usually SQP based). Instead, RTO+® has a library of optimisation routines enables optimisation both of equipment set points and mixed integer, equipment selection optimisation. This provides significant benefits in being able to choose the most appropriate optimisation method for each particular problem.

The components of RTO+ include data reconciliation, performance monitoring, real-time optimisation (both open and closed loop), What-if studies, multi-time period co-ordinated optimisation and mixed integer equipment selection optimisation. Based on information from the internet, the load dispatch optimisation is not one of the product provided by MDC so far.

The implementation of RTO+ has been claims had increased profits by 3 - 5% typically. (Source: http://www.mdctech.com/products/rto.htm) by improving the operating margins with fast response to changing conditions. This has help the plant to achieve maximum throughput.

2.9.2 *SmartProcess* Optimization Software from Westinghouse Process Control (Source: www.westinghousepc.com/smartprocess/introduction.cfm)

For more than a century now Westinghouse Process Control (now known as Emerson Process Management Power & Water Solutions) has been developing innovative solutions to help power plants improve performance and increase profit margins. SmartProcess™ -- is the plant optimisation software from this company. It delivers increased efficiency and tremendous cost savings.

SmartProcess™ is using both neural network and linear technology to constructs a customized plant model that simulates a variety of plant variables under changing conditions and load levels, and then identifies precise control settings for continuous optimal performance.

The success of SmartProcess™ has been dramatic. Initial installations have reported savings of up to $300,000 per year. According to EPRI, at a 500 MW plant, even a moderate performance improvement of only .5% can result in a cost savings of well over $200,000 per year.
(Source: http://www.westinghousepc.com/smartprocess/introduction.cfm)

Each SmartProcess™ module targets a specific area, improving efficiencies throughout the process. SmartProcess Modules are Boiler Efficiency Optimizer, Low NOx Optimizer, Opacity Optimizer, Steam Temperature Optimizer, Sootblower Optimizer, Sootblower Cleanliness Advisor, Economic Dispatch Optimizerand Global Performance Advisor

The Economic Dispatch Optimiser optimises the distribution of load demands across multiple units or unit components through a cost-based function. However, the module does not take any environmental and maintenance parameters but only generate efficiency curves, operating costs and emissions to improve profitability.

2.9.3 ABB Optimax – PowerFit

OPTIMAX PowerFit is an application designed for utilities with complex generation portfolios, be it electrical or a combination of electrical and thermal energy, which are seeking to optimize their costs and power production. By using their existing state of the art numerical solver, OPTIMAX PowerFit helps to minimize the generation costs of any power company in the dynamically changing power sector by optimizing the energy distribution between generated power and purchased power in order to satisfy the load demands and ensure profitable and safe operation. However, the module does not take any maintenance parameters and emissions into considerations.

2.9.4 Others

Other products that also provide an optimisation solution for economic load dispatch S2000P Economic Load Dispatch from SE-ACE Innovations. S2000P Economic Load Dispatch from SE-ACE Innovations using the same techniques as described by Allen J. Wood and Bruce F. Wollenberg (1996), which is based on the incremental heat rate and lambda search method. The consideration taken for the modules are the cost of starting up a unit, the maintenance costs and the fuel costs.

2.10 Concluding Remarks

Various related work had been highlighted and discussed in this chapter. Several ideas and methods from this literature review had been used for the following development work. The idea of weighting concept used in economic environmental unit commitment problem formulation, as mentioned in Section 2.5

was used and enhanced in this work. The details of the objective functions formulation can be found in Chapter 4.

There is quite substantial research works that had been completed in the development of optimization techniques, as elaborated in Section 2.4. These techniques was studied and discussed in Chapter 7, where the latest enhanced particle swarm optimization method was used and implemented in solving the developed optimization problem above.

The few literature review of current commercial optimization software and solutions in Section 2.9 had again indicated the needs of such research work and ultimately the potential of commercializing it in future.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The overall research methodology is illustrated in Figure 3.1. The research required a problem formulation identifying the essential elements of a conceptual or verbal statement of a given application, and organizing them into a prescribed mathematical form, namely the system model, objective function (economic criterion) and the process model (constraints).

3.2 System Boundaries

Before undertaking any optimization study, it was important to clearly define the boundaries of the system under investigation. In the context a system is the restricted portion of the universe under consideration. The system boundaries are simply the limits that separate the system from its surroundings, because, for purposes of analysis, all interactions between the system and its surroundings are assumed to be frozen at selected representative levels.

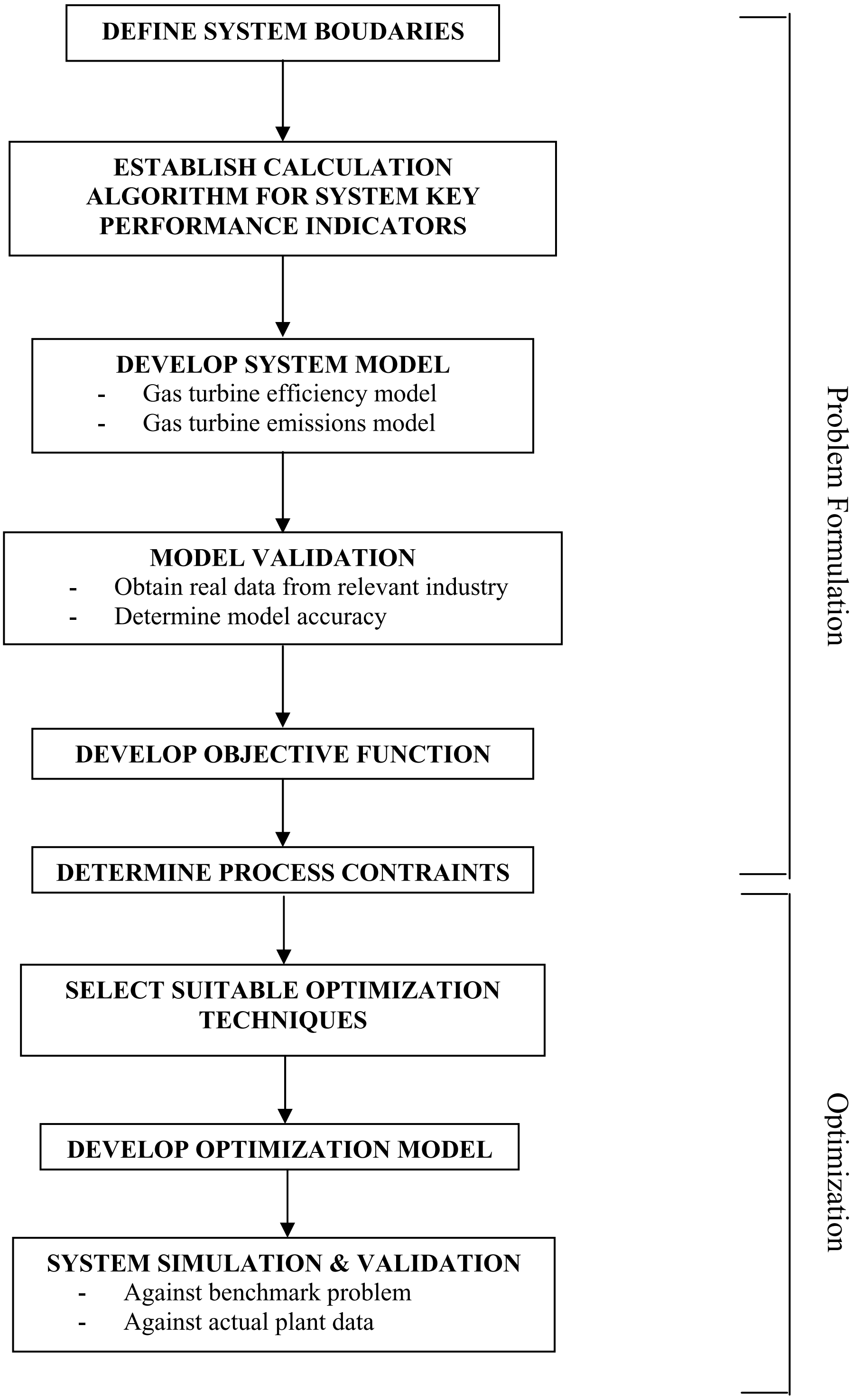

Figure 3.1: Research methodology

Since this project was undertaken with an industrial partner TNB Connaught Bridge Power Station, the machine under investigation was a ABB Gas Turbine 13E dual fuel in an open cycle plant. The development of the model was based on a simple single shaft gas turbine, with the boundaries illustrated in Figure 3.2.

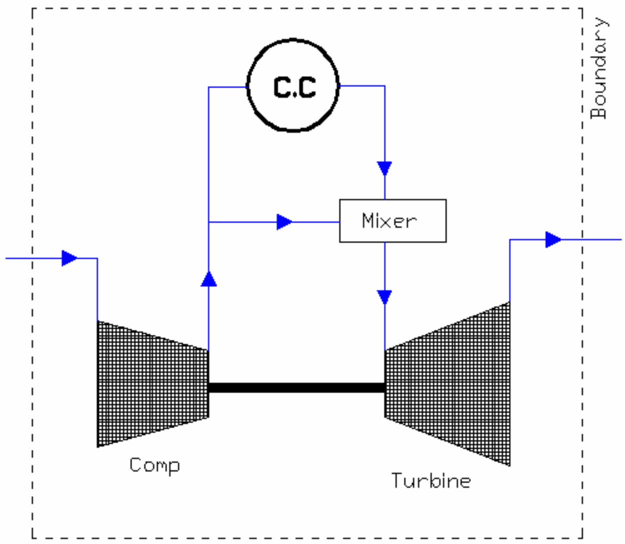

Figure 3.2: Simple gas turbine schematic

3.3 Establishing Calculation Algorithm for System Key Performance Indicators

The performance parameters or key performance indicators of a gas turbine are important to be identified as they show the existing machine condition. These key performance indicators could be used as a baseline to compare with, for model validation and optimization. The performance computation methods used were mainly based on ASME PTC 22 – 1985 industrial standard and industrial standards of gas turbine manufacturer (ABB).

3.4 System Modeling

Once the system of interest was selected and its boundaries defined, the next step required the formulation of a performance and emission model. The model was developed via mathematical expressions that relate the input-output variables of the process and associated coefficients, include both equality and inequality constraints. In this project, well-known physical principles (mass balances, energy balances) and empirical relations was used. Mathematical model was then simplified as much as possible without losing the essence of the problem so that a mathematical optimization process could be achieved.

3.5 Data Collection and Data Acquisition System

Data acquisition for performance monitoring was setup to obtain plant real-time process data from the Digital Control System (DCS) at Connought Bridge Power Station. The design, installation and implementation of the system were completed with the cooperation of Machinery Performance Monitoring Group Sdn. Bhd. The performance calculation program was incorporated to the system to perform real-time performance calculations. The system was designed on HMI software, namely Wonderware InTouch 7.11. All retrieved real-time data and calculated performance data was logged to the system and was used for model validation and optimization study. Details setup of the system is elaborated in later chapter.

3.6 Model Validation

After the system model had been developed, the mathematical was programmed in Visual Basic Programming Language, and the validation of the model was then carried out. In this respect, a set of actual field measurement data and data obtained during generation of machine performance test report were taken from the plant to validate the model. Heat rate and power output of the gas turbine were used as comparison parameters since they were documented in the plant hand over test report by the manufacturer. The model accuracy would then be determined at design and off design conditions. The measurement data would be used to modify the various model performance parameters (tuning factors) such that the model reflects the actual state of the equipment prior to optimization calculations.

3.7 Development of Objective Functions

Once the models were validated, the criterion and objective function were determined on the basis of which the performance of the system can be evaluated so that the "best" set of operating conditions can be identified. The objective functions represented profit, cost energy, yield, etc. in terms of the key variables of the process being analyzed. Since this work involved environmental parameters, the problem became a multi-objectives function optimization, where the emissions objective functions was determined.

3.8 Determining Process Constraints

Every constraints of the process either controllable or uncontrollable variables were identified and apply to the optimization process latter. The constraints include the production targets, allowable EOH between machines, allowable emissions contents, machines characteristics and other uncontrollable independent variables such as ambient conditions was also be considered.

3.9 Selecting Suitable Optimization Techniques

Optimization could be defined as the process of finding the conditions that give the maximum or minimum value of a function. The optimum seeking methods are also known as mathematical programming techniques are mainly classified to 3 main areas, which are mathematical programming techniques, stochastic process techniques and statistical method.

The optimization techniques or method used was basically based on the formulation of the optimization problem (equation or objective function involved). In this project a suitable optimization algorithm was identified when the objective functions and its prescribed set of constraints were determined. Enhancement or modification of identified suitable optimization algorithm was carried out in order to solve the complicated multi-objectives functions.

3.10 System Simulation and Validation

3.10.1 Against Benchmark Problem

The developed optimization model was validated against benchmark simulation data to check its reliabilities, accuracy and performance, with particular reference to Cheng, Liu, and Liu (2000) and Kazarlis, Bakirtzis, and Petridis (1996). The standard Unit Commitment optimization model was used instead of the developed optimization model in this simulation, because the benchmark problem is only available for standard Unit Commitment problem, which excludes emissions and EOH constraints.

3.10.2 Against Actual Plant Data

In principles, optimization studies may be performed by experimenting directly with the system. Thus, the independent variables of the system or process may be set to selected values, the system operated under those conditions, and the system performance index evaluated using the plant actual measurement performance data. The identified suitable optimization methodology was used to predict improved choices of the independent variable values, and the experiments continued in this fashion. Comparisons were made between the calculated results and the actual plant data. The parameters used for this comparison were the power distribution and total emissions contents among the gas turbines.

EOH parameter could not be tested in normal operating conditions as EOH of the current running machine in the plant was not close to each other. Additional case would be generated experimentally to test on the effect of allowable EOH and emissions parameters. The case was created with very close allowable EOH among the machines, while the second case was created with very tight allowable emissions limits. This exercise therefore not only validated the accuracy and reliability of this work, but also the viability of the developed software for gas turbine load dispatch optimization.

CHAPTER 4

FORMULATION OF OBJECTIVE FUNCTIONS AND CONTRAINTS

4.1 Introduction

The formulation of objective function is the one of the crucial steps in the application of optimization to a practical problem. In this chapter, objective functions of the open cycle industrial gas turbine are formulated. The essential elements of a conceptual or verbal statement of a given application were identified and organized into a prescribed mathematical form, namely the objective function (economic criterion) and the process model (constraints).

The formulated objective function represented profit, cost energy, yield, etc. in terms of the key variables of the process being analyzed. Besides, additional objective functions considering the environmental impact have been formulated and incorporate to the optimization problem. The process model and constraints described the interrelationships of the key variables. The process models were built and explained in this chapter. Special attention on developing mathematical models, particularly empirical models of input-output curve and the emission model for gas turbine, by fitting empirical data by least squares, are presented in the next chapter.

The identified system constraints are the machines' allowable maximum and minimum power generation, load-power balance, system spinning reserve, and maintenance parameters (based on plant EOH practices). Details of implementation of the maintenance parameter are discussed in detail in this chapter.

4.2 Development of Objective Functions

According to Himmelblau (1988), three categories of objective functions are considered that included operating and capital cost. The first category of objective functions involved no capital costs at all but just operating costs and revenues. Such cases are often referred to as "supervisory control" problems and arise when capital costs are a fixed sum (the equipment is already in place). These costs are not influence by optimizing the operating variables. A second category is optimization of capital equipment in circumstances where no operating costs are involved. Many mechanical design problems fall in this category. The third category of objective functions includes both capital costs operating costs. Such problems usually involve some capital expenditure in order to reduce operating costs or manufacture additional product.

In this project, the objective of the research was to develop software based multi-objective optimization solution of load dispatching for open cycle industrial gas turbine plant, which the equipment or machine is already in place. The objective function formulated as below is therefore considered as the first category as described by Himmelblau (1988), which involves no capital costs at all but just operating costs and revenues.

Besides the cost, the environmental impact of power generation due to emission of various harmful pollutants such as sulfur oxides (SO_2), nitrogen oxides (NO_x) and emission particles are taken into account into the generation dispatch problem formulation of this project. This is achieved by incorporating the emission considerations into the economic dispatch algorithm, thus expanding existing problem to an economic-environmental unit-commitment optimization problem.

Therefore, the objective functions are formulated based on the goal to minimize the total production cost and minimize emissions generation, subject to variety of constraints and it is expressed in units of currency ($).

4.2.1 Problem Definition

The most efficient generator in the system does not guarantee minimum cost and minimum emission generation as it may be operated with different fuel cost, maximum capacity, spinning reserve, Equivalent Operating Hours (EOH) and emissions model among other alternative generator. Hence the problem is to determine the generation of different units such that the total operating cost and total emissions released are minimum, without violating the constraints of power demand, machines' capacity, minimum start-up time, minimum shut down time, power reserve, emission limits, and allowable EOH between units.

Figures 4.1 show the configuration that was developed in this research. This system consists of U_{max} gas turbine to serve a received electrical load, L_T. Each unit's use different of fuel, with different start-up cost, shut down cost, Input-Output curve, equivalent operating hour and emission models. The output of each unit, P_i, is the electrical power generated by that particular unit.

Mathematically speaking the problem may be stated very concisely. That is objective function, $f(\mathbf{P})$, is equal to the total cost and total emissions generated for supplying the indicated load. The problem is to minimize $f(\mathbf{P})$ subject to the constraints that the sum of the powers generated must equal the received load, the load does not exceed the specific design power generation limits, full fill sufficient spinning reserve, maintain specific interval of EOH between units and does not exceed the specific environmental emissions limitation of each pollutants.

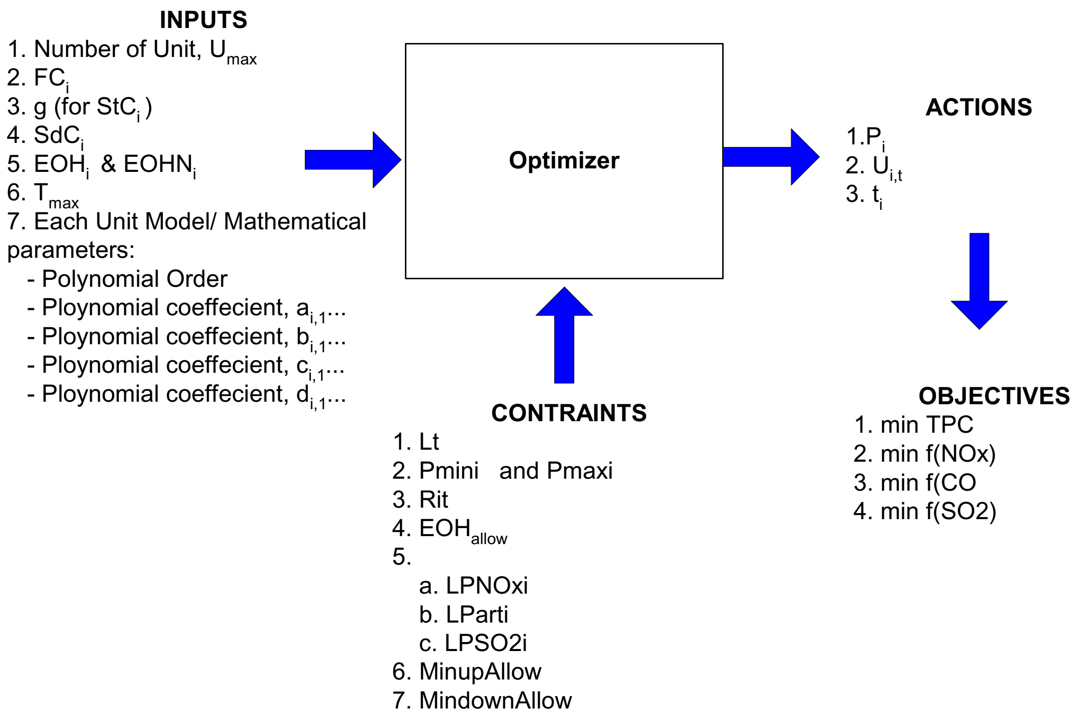

Figure 4.1: Problem definition

4.2.2 Objective Function 1: Total Production Cost

The method and formulation of the total production cost was determined and taken based on the reference Allen J W ood and Bruce F. Wollenberg (1996), with the considerations of unit power generation cost, unit start-up cost and unit shut-down cost.

a. Unit power generation cost

The model of a unit to represent its power generation cost could be obtained from unit's input output (IO) curve. The detailed modeling of the unit's IO curve is discussed in the next chapter. This curve can be obtained from the manufacturer or any performance test report conducted on the unit.

The input to the unit was usually measured in GJ/h, and the output measured in MW. A simplified input-output curve of the thermal unit, known as heat rate (HR) curve is more commonly obtained either from the manufacturer specification or from the performance test report. A sample of the HR curve is given in Figure 4.2. Converting the ordinate of HR curve from kJ/kWh to GJ/h results in the input-output curve shown in Figure 4.3. In all practical cases, the input-output model of generator *i* will be represented as a polynomial function of real power generation

$$LC = a_{i1} + a_{i2} \cdot P_i + a_{i3} \cdot P_i^2 + \ldots + a_{i11} \cdot P_i^{10} \qquad \text{(Eq 4.1)}$$

,in kJ/kWh

And the fuel cost of the generation in $/kWh is

$$\text{Fuel Cost} = FC_i [a_{i1} + a_{i2} \cdot P_i + a_{i3} \cdot P_i^2 + \ldots + a_{i11} \cdot P_i^{10}] \qquad \text{(Eq 4.2)}$$

An incremental heat rate (IHR) must be generated in order to determine the incremental cost for a unit. The incremental heat rate is defined as a derivative of the input-output function;the incremental heat rate curve plots this derivative versus load, as shown in Figure 4.4.

$$LC_i^{'} = \frac{dLC_i}{dP_i} = a_{i2} + 2a_{i3} \cdot P_i + 3a_{i4} \cdot P_i^2 + \ldots + 10a_{i11} \cdot P_i^9 \qquad \text{(Eq 4.3)}$$

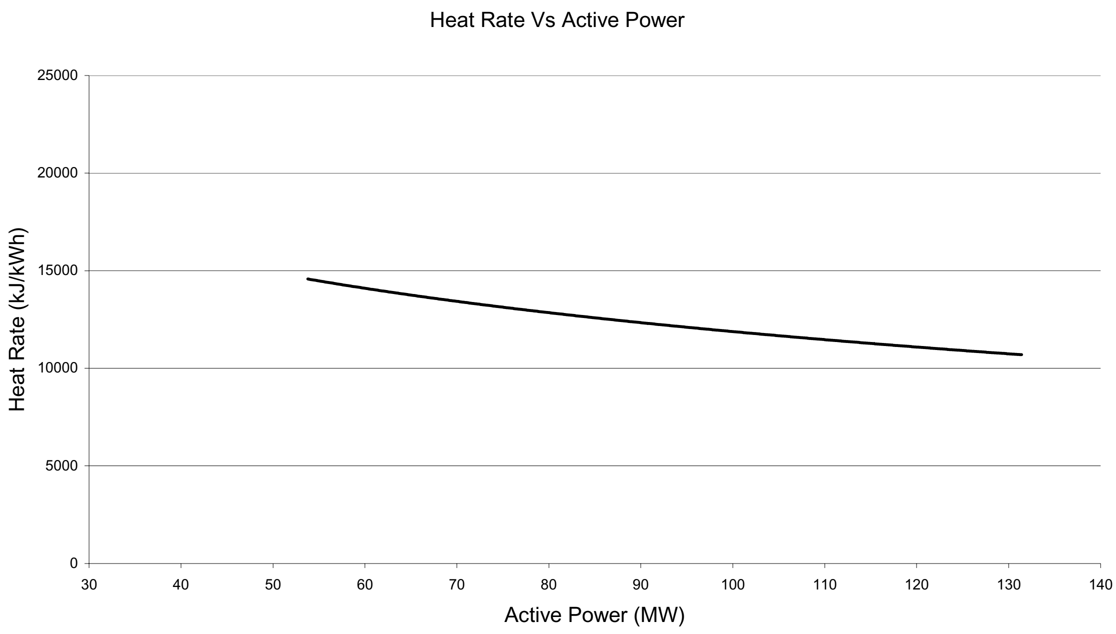

Figure 4.2: Unit's heat rate curve

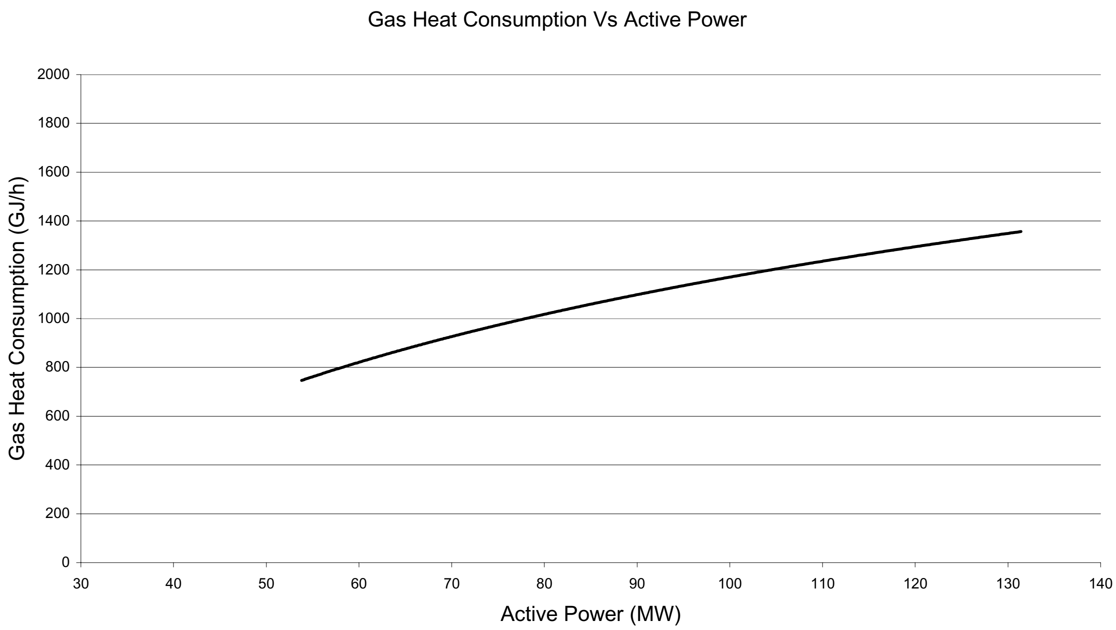

Figure 4.3: Unit's input-output curve

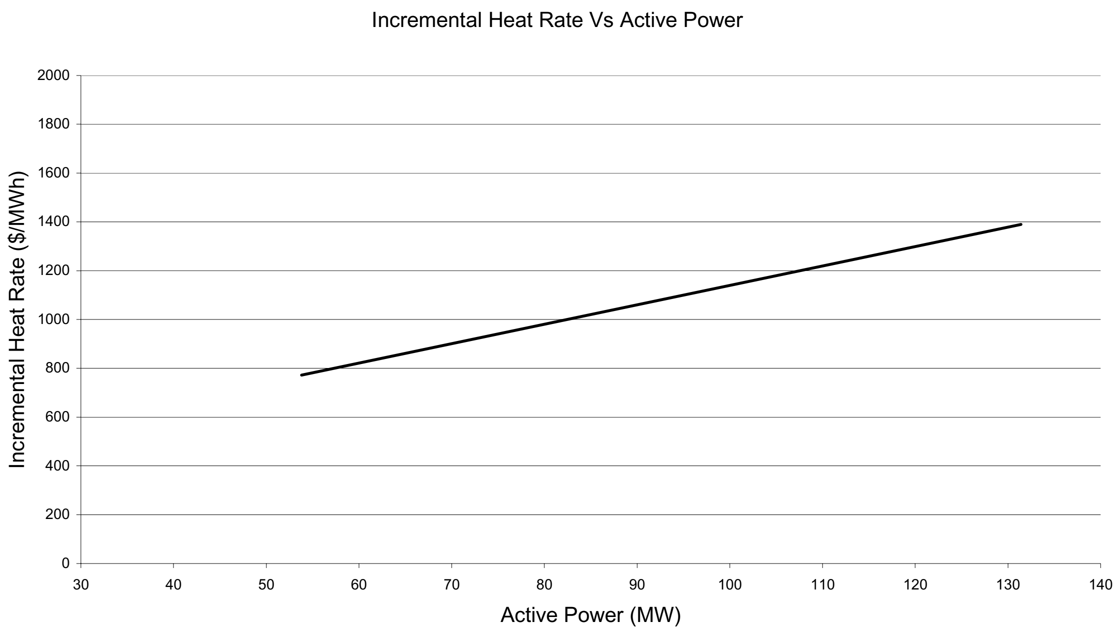

Figure 4.4: Unit's incremental heat-rate Curve

The incremental fuel cost curve is a measure of how costly it will be to produce the next increment of power. The total operating cost includes the fuel cost, and the cost of labor, supplies and maintenance. These costs are assumed to be fixed percentage of the fuel cost and are generally included in the incremental fuel-cost curve. The equation below represents the total production cost,

$$\text{TPC} = \sum_{t=1}^{T_{\max}} \sum_{i=1}^{U_{\max}} \left[u_{i,t} \cdot FC_i \times (LC_i^{'}) + u_{i,t} \cdot (1 - u_{i,t-1}) StC_i (Ho_{i,t}) + u_{i,t-1} \cdot (1 - u_{i,t}) SdC_i \right] \quad \text{(Eq 4.4)}$$

Where,

T_{max} = Total time interval (h)

U_{max} = Total unit

$t \rightarrow time\ (1 \leq \mathrm{t} \leq \mathrm{T}_{\max})$, discrete integer variable that represent the time from the beginning of the commitment analysis

$i \rightarrow unit\ (1 \leq i \leq \mathrm{U}_{\max})$, discrete integer variable that represent unit i^{th}

LC_i' = Incremental Heat Rate (GJ/h) of unit i

FC_i = Fuel Cost ($/GJ) of unit i

$u_i^t \in \{0,1\}$ state of unit *i* at time *t*

Ho_i^t = number of hours unit *i* has been shutdown

Hence, the objective function

$$f(\mathbf{P}) = \text{Min } \{TC\} \qquad \text{(Eq 4.5)}$$

with design vector,

$$\mathbf{P} = (P_i, t_i) \qquad \text{(Eq 4.6)}$$

b. Unit start-up cost, StC:

Since the temperature and pressure of the machine must be changed slowly, a certain amount of energy must be expanded to bring the unit on line. This energy does note result in any MW generation from the unit and is brought into the unit commitment problem as a start-up cost.

The start –up cost can vary from a maximum 'cold-start' value to a much smaller value if the unit was only turned off recently and is still relatively close to normal temperature. For industrial gas turbine in this case, it is considered as a function of the number of hours (Ho_i^t) the unit has been down:

$$StC = C_c(1-\varepsilon^{-t_{cool}/\alpha}) \cdot FC + C_F \qquad \text{(Eq 4.7)}$$

where,

C_c = cold-start cost (GJ)

FC = Fuel Cost ($/GJ)

C_F = fixed start-up cost

(includes crew expenses, maintenance expenses), ($)

α = thermal time constant for the unit

t_{cool} = time in hours the unit has been cooled

c. Unit shut down cost, SdC:

It is considered as a fixed amount for each unit per shut-down.

4.2.3 Other Objective Functions – Emissions Cost

Three most common substances generated by a gas turbine included in this study are namely nitrogen dioxide (NO_x), particle and sulfur dioxide (SO_2). These emissions objective functions are formulated as below, where each of the emission models is represented in polynomial function.

a. Objective Function 2 – Nitrogen Oxide emission (NOx)

$$f_2 = \min \sum_{t=1}^{T_{max}} \sum_{i=1}^{U_{max}} u_{i,t} (PNOx)_{i,t} \qquad \text{(Eq 4.8)}$$

Where

$$PNOx_{i,t} = f(P_i) = b_{i,1} + b_{i,2} \cdot P_i + b_{i,3} \cdot P_i^2 + ... + b_{i,10} \cdot P_i^{10} \qquad \text{(Eq 4.9)}$$

$b_{i,(1,2,..10)}$ = Unit i NOx emission model polynomial coefficient

b. Objective Function 3 – Carbon Monoxide emission (CO)

$$f_3 = \min \sum_{t=1}^{T_{max}} \sum_{i=1}^{U_{max}} u_{i,t} (CO)_{i,t} \qquad \text{(Eq 4.10)}$$

Where

$$CO_{i,t} = f(P_i) = c_{i,1} + c_{i,2} \cdot P_i + c_{i,3} \cdot P_i^2 + ... + c_{i,10} \cdot P_i^{10} \qquad \text{(Eq 4.11)}$$

$c_{i,(1,2,..10)}$ = Unit i CO emission model polynomial coefficient

c. Objective Function 4 – Sulfur Dioxide emission (SO_2)

$$f_4 = \min \sum_{t=1}^{T_{\max}} \sum_{i=1}^{U_{\max}} u_{i,t} (SO2)_{i,t} \qquad \text{(Eq 4.12)}$$

`

where

$$SO2_{i,t} = f(P_i) = d_{i,1} + d_{i,2} \cdot P_i + d_{i,3} \cdot P_i^2 + ... + d_{i,10} \cdot P_i^{10} \qquad \text{(Eq 4.13)}$$

$d_{i,(1,2,..10)}$ = Unit i SO2 emission model polynomial coefficient

4.2.4 Multi-objectives Problem Formulation

Multi-objectives problem was formulated in order to generate the efficient set of commitment schedules and dispatch plans, that was, the group of plans from which a best compromise plan should be selected, regardless preferences and value trade-offs between cost and emission attributes. A commonly used procedure by Tiew-On Ting and Loo C.K. (2003) for generating the efficient set of operation plans was *the weighting method*, which converts the multi-objective criterion function into *the weighting problem*.

In the process of electric power generation, more than one pollutant are emitted depending on the type of fuels being used. The total emission of a single pollutant from generation, E_p, is given by

$$E_p = f_{e1}(P_1) + f_{e2}(P_2) + \cdots f_{ei}(P_{U\max}) \qquad \text{(Eq 4.14)}$$

where E_p is the total pollutant emission and $f_{ei}(P_i)$ is the amount of emission from i^{th} generator at power level P_i MW. Considering M types of pollutants, the problem becomes a multi-objective function with total fuel cost and emission of m pollutants being minimized simultaneously. In order to reduce the dimension of the problem while reflecting the relative degree of damage caused by individual pollutant, the minimization of multiple pollutants can be combined into a single criterion by assigning weight to each of the pollutants. Thus, the total weighted emission of m types of pollutants, E_M, is given by

$$E_M = \beta_1 \cdot E_{p1} + \beta_2 \cdot E_{p2} + \cdots \beta_M \cdot E_{pM} \qquad \text{(Eq 4.15)}$$

where E_{pj} is the total emission of the j^{th} emission and β_j is the relative weight of j^{th} emission representing its relative degree of harmfulness. The weights of all emissions must have the following relation:

$$\sum_{j=1}^{M} \beta_j = 1 \qquad \text{(Eq 4.16)}$$

with the simplified expression of the total emission, the problem is reduced to a bi-criterion optimization problem with two conflicting objectives. Although the environmental impact of emission cannot be described in monetary terms, the trade-off between the fuel cost and the total weighted emission can be evaluated by minimizing the following expression:

$$TPCWE = W \cdot TPC_N + (1-W) \cdot E_M \qquad 0 \le W \le 1 \qquad \text{(Eq 4.17)}$$

where,

W = relative weight (constant value) assigned to the total production cost

It represents the relative weight assigned to the total production cost and consequently (1-W) is the relative weight assigned to the emission. Equation (4.17) can be rewritten as

$$TPCWE = W \cdot \left(TPC_N + \left(\frac{1-W}{W} \right) \cdot E_M \right) \qquad \text{(Eq 4.18)}$$

the minimization of which is identical to the minimization of the following expression in the context of optimization.

$$TPCWE' = TPC + \left(\frac{1-W}{W} \right) \cdot E_M \qquad \text{(Eq 4.19)}$$

The term $\left(\frac{1-W}{W}\right)$ in equation (4.19) has the unit of $/mass and is here referred to the *pseudo environmental cost* (P.E.C.) of the total weighted emission. The trade-off curve between the total fuel cost and the total weighted emissions can be traced out by minimizing equation (4.19) at successive intervals of P.E.C. from zero to infinity, representing economic and emission dispatch respectively.

4.3 System Constraints

System constraints in practice usually include several factors. These include the following:

i. Load power balance

$$\sum_{i=1}^{N} P_i^t \geq L^t \qquad \text{(Eq 4.20)}$$

From equation (4.20), the constraints is formulated as below

$$g_1(P) = L^t - \sum_{i=1}^{N} P_i^t \leq 0 \qquad \text{(Eq 4.21)}$$

ii. Spinning reserve

Spinning reserve is the term used to describe the total amount of generation available from all units synchronized on the system minus the present load plus losses being supplied. Spinning reserve must be carried so that the loss of one or more units does not cause too far a drop in system frequency. Qite simply, if one unit is lost, there must be ample reserve on the other units to make up for the loss in a specified time period.

Spinning reserve must be allocated to obey certain rules, usually set by regional reliability council (in the United States) that specifies how the reserve is to be allocated to various units. Typical rules specify that reserve must be a given percentage of forecasted peak demand, or that reserve must be capable of making up the loss of the mostly heavily loaded unit in a given time, or such. Others calculate reserve requirements as a function of the probability of not having sufficient generation to meet the load.

$$\sum_{i=1}^{N} R_i^{\,t} \geq R^t \quad \text{being } R_i^t = p_{\max i}^{\ t} - p_i^t \qquad \text{(Eq 4.22)}$$

where,

R_i^t =Unit spinning reserves for unit i

R^t =Total spinning reserve

From equation (4.10), the constraints is formulated as below

$$g_2(P) = R^t - \sum_{i=1}^{N} R_i^{\,t} \leq 0 \qquad \text{(Eq 4.23)}$$

iii.Unit minimum and maximum capacity

Unit minimum capacity is the design minimum MW can be generated by the unit, while unit maximum capacity is the design maximum MW can be generated by the unit. The constraints can be represented as below equation:

$$P_{\min_i} \leq P_i \leq P_{\max_i} \qquad \text{(Eq 4.24)}$$

where,

$P_{\min_i}$ =minimum capacity for unit i

$P_{\max_i}$ =maximum capacity for unit I

iv.Minimum up time

Minimum time that a unit must stay online after a startup

$$\min up_i \geq \min upAllow_i \qquad \text{(Eq 4.25)}$$

where, $$\min \mathrm{up_i} = \sum_{t \text{ where } u_{i,t}=0}^{u_{i,t}=1} (1) \qquad \text{(Eq 4.26)}$$

v.Minimum shutdown time

The minimum time a unit must stay offline after shutdown

$$\min down_i \geq \min downAllow_i \qquad \text{(Eq 4.27)}$$

where, $$\min \mathrm{down_i} = \sum_{t \text{ where } u_{i,t}=1}^{u_{i,t}=0} (1) \qquad \text{(Eq 4.28)}$$

vi.Interval time of Equivalent Operating Hour (EOH) between Units

In general, any equipment that is running at base-load is likely to operate without failures for an expected number of hours before it needs a maintenance action or its useful life is used up and required replacing. These hours are Normal Operating Hours. If the equipment is put under additional strain by being run at higher loads, or cycled frequently (many stops &starts) then its time before overhaul/replacement will be consumed faster, and its value will be significantly reduced.

Laboratory study shown that rapid startups and shutdowns cause high stresses on the hot gas path components. The worst effects were caused by machine trip, especially full load. A full load trip is not catastrophic in itself, but the resultant life reduction is equivalent to that of about 10 normal shutdown. Because of this fact, gas turbine maintenance practices are dependent on the counts of starts and operating hours. Whichever criterion limit is first reached determines the maintenance interval. Table below illustrate the method recommend by ABB in calculating the EOH for the ABB 13E gas turbine at Connaught Bridge Power Station. Since this gas turbine model provides a variable inlet guide vane (IGB), it will automatically prevent sudden cooling to the turbine when the machine is trip or shutdown.

Table 4.1: Table of unit's additional equivalent operating hour of different operating condition

Operating Condition	Additional EOH
Start	20
Shutdown	Nil
Trip	Nil

Equivalent Number of Operating Hours (EOH) has been employed by most of the gas turbine manufacturer as guidelines to determine the maintenance interval of the machines. EOH, which is based on the equivalent hours count, is a determination of the effect of the start cycle and running hours of the machines. Details of this guideline are attached in Appendix A.

Table 4.2 shows an example of EOH table for maintenance planning for ABB 13E gas turbine at Connaught Bridge Power Station. The plant currently used this practice to carry out their periodical maintenance work.

Table 4.2: Example of EOH table

Maintenance Type	Total EOH (hour)	Time required for repair (days)
A - Inspection	6000	6
B- Inspection	12000	8
A - Inspection	18000	6
C – Inspection (Overhaul)	24000	45

Based on the table above, the maintenance is carried out based on unit EOH, which depends on total operating hour and start cycle of the unit. Once the unit's EOH reach certain value as specified by the manufacturer (as shown Table above), particular maintenance work need to be done. For example, the Table above shows that if a machine has 12000 of EOH, the machine need to be sent for B-Inspection maintenance work.

For most of the time, the plant would not want have two machines or more to have same remaining EOH before next maintenance work, *EOHDiff*. Due to the reasons specified in Literature Review (section 2.2), an interval of EOH between machines has to been determined and considered as a constraint to the objective function. The flowchart to determine this constraint for all units is illustrated in the flow chart of Figure 4.5.

$$\left| EOHDiff_m - EOHDiff_{m+1} \right| \geq \mathrm{EOH_{allow}} \qquad \text{(Eq 4.29)}$$

where,

$EOHDiff_m$ = Remaining EOH before next maintenance work

= $EOH_{N} - EOH$

$EOH_{i,N}$ = Next maintenance work equivalent operating hour

EOH_i = Current equivalent operating hour

$(EOH_{allow})_i$ = Allowable interval of EOH

The program coding in Visual Basic language for the above constraints, is given as below,

For i = 1 to (U_{max} – 1)

For j = (i + 1) to U_{max}

$$\left| EOHDiff_i - EOHDiff_j \right| \geq EOH_{allow}$$

Next

Next

vii.Unit's Allowable Emissions

Unit's allowable emission constraint is the permitable emission of each pollutant that are generated or caused by the operational of the unit generator. These constraints are represented as below:

$$NOx_{i,t} \leq LNOx_i \qquad \text{(Eq 4.30)}$$

$$CO_{i,t} \leq LCO_i \qquad \text{(Eq 4.31)}$$

$$SO2_{i,t} \leq LSO2_i \qquad \text{(Eq 4.32)}$$

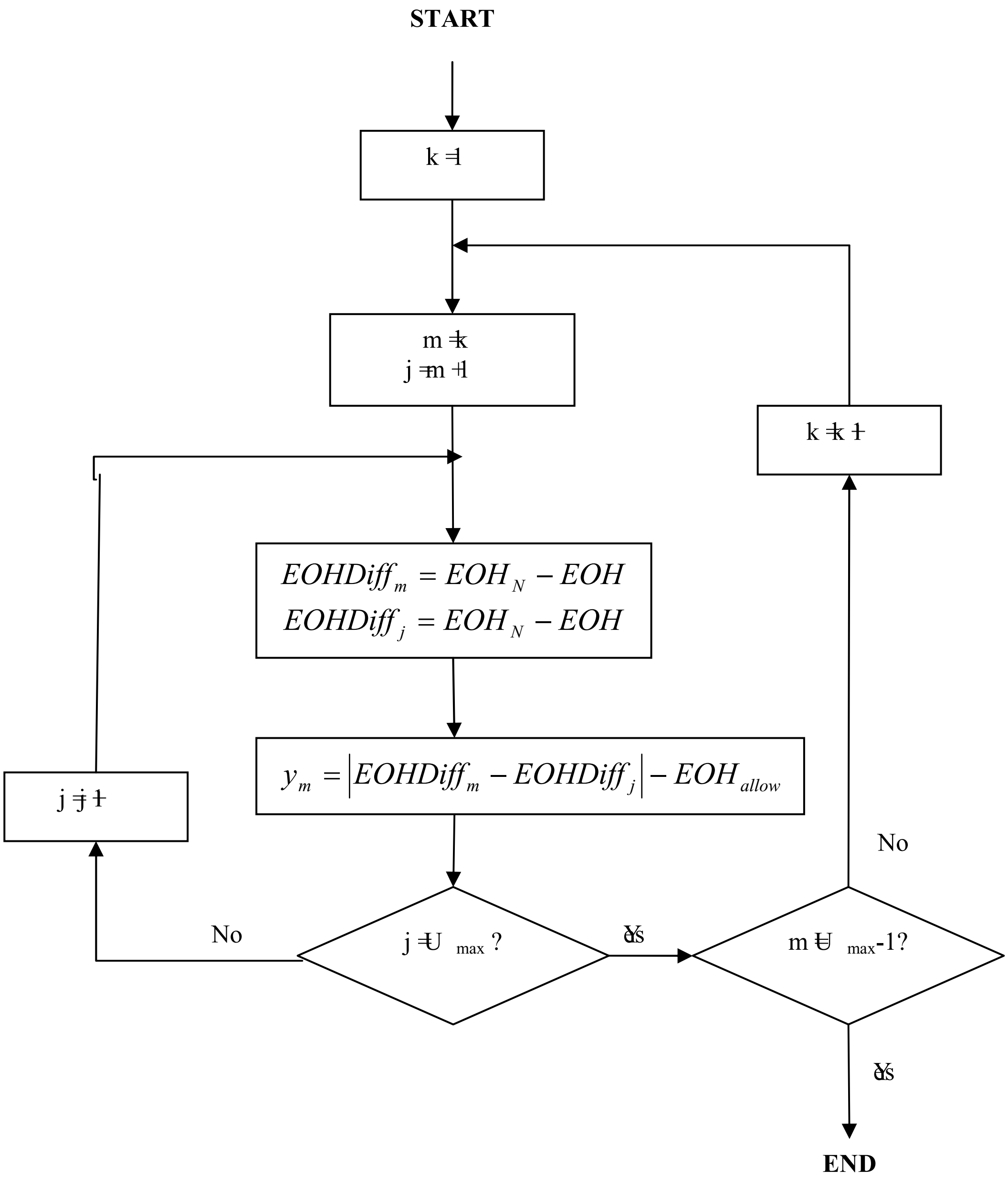

Figure 4.5: Data flow to determine constraints of interval of EOH between units

4.4 Concluding Remarks

The mathematical optimization problem of this work had been developed. With the combination of Equation 4.4, 4.15 and 4.19, the objective function, which represented the production cost and the environmental impact, can be summarized in below equation.

$$TPCWE = \left[\sum_{t=1}^{T_{max}} \sum_{i=1}^{U_{max}} \left[u_{i,t} \cdot FC_i \times (LC_i^{'}) + u_{i,t} \cdot (1 - u_{i,t-1}) StC_i (Ho_{i,t}) + u_{i,t-1} \cdot (1 - u_{i,t}) SdC_i \right] \right]$$

$$+ \left(\frac{1-W}{W} \right) \cdot (\beta_{NO} \cdot E_{pNO} + \beta_{CO} \cdot E_{pCO} + \beta_{SO2} \cdot E_{pSO2}) \qquad \text{(Eq 4.33)}$$

The summary of all identified optimization constraints of this objective function is tabulated in Table 4.3

Table 4.3: Summary of Optimization Constraints

	Constraints	Equation
a	Load power balance	4.21
b	Spinning reserve / power reserve	4.23
c	Machines' allowable minimum and maximum power generation	4.24
d	Machines' allowable minimum up time	4.26
e	Machines' allowable minimum down time	4.28
f	Maintenance parameters (EOH practices)	4.29
g	Emissions limits	4.30 4.31 4.32

CHAPTER 5

PERFORMANCE CALCULATIONS AND MATHEMATICAL MODELING

5.1 Introduction

In analyzing the problems associated with the controlled operation of power system, there are several parameters of interest. Fundamental to the economic operating problem here was the set of input-output characteristics of an open cycle industrial gas turbine.

A brief description on the operation of an open cycle gas turbine plant was discussed based on Connaught Bridge Power Station, Klang. The description explained the identification of the controllable variable and the output parameter of the model. The gas turbine key performance was also identified and its computation method for a gas turbine was determined and explained, which required for the unit model development.

The process models were built and as elaborated in this chapter. Since loading is the only controllable variable for the operation; the model was developed based on the machine's input-output curve provided by the manufacturer or from any of the performance test report. Special attention on developing mathematical models, particularly empirical models of input-output curve for gas turbine, by fitting empirical data by least squares method, are also explained.

The computational coding for the modeling algorithm are explained and included in this chapter. This allows the software able to be reused for any new machines added to the system in future, or input-output curve of the machines to be edited, which changed dynamically due to tear and wear, or degradation of the machines.

The model as well as the software coding were simulated and validated against calculated (from model). Detailed measured data from the performance test report as well as real-time value were obtained from the plant.

5.2 Description of Open Cycle Gas Turbine Operation

There are four ABB 13E open cycle gas turbines in Connaught Bridge Power Station, using gaseous fuels. Because gas turbine can start-up and generating power very quickly, this open-cycle plant has been used as a peaking plant to support other full load operation plant such as Jana Manjung Power Station, Connaught Bridge Combined Cycle Power Station, Paka Power Station and other low cost operating plant.

The operation of the gas turbine is mainly controlled by the variable inlet guide vane (V-IGV). Under the V-IGV control, fuel firing rate would automatically increase when load demand increase. It would also allow more mass flow to balance the increase of the fuel flow rate. It would automatically prevent sudden cooling to the turbine when the machine is trip or shutdown.

Due to these reasons, the power output or parameter associated with “loading” is the only controllable variable for the operation. The model for this optimization was therefore developed based on the machine’s input-output curve provided by the manufacturer or from any of the performance test report.

5.3 Gas Turbine Performance Computation Method

Performance computational methods in general were based on ASME standards, and most current technical papers published in the literature. Actual power stations field performance test report were used as the basis for the formulation and verification of computation equations employed in the present industrial. This was obtained from the OEM (ABB) performance test report for Connaught Bridge Power Station, Klang. The performance test report for ABB gas turbine was further used for calculations guidelines as the information provided was more complete.

Similar method had been used for performance monitoring software development by Oon, K.P. (2000). Some modification to the formulation, especially to the machine correction factor was done and incorporated to the software performance monitoring system (PMS9000), where had been installed and implemented at Connaught Bridge Power Station for the four open cycle gas turbines.

Equations used to calculate the corrected heat rate and corrected power output were obtained from the test report, whereas other formulas used to calculate unit thermal efficiencies and heat rate were adapted from ASME PTC-22 (1985), reference test from REMACO (1996a), REMACO (1996b), and published paper in the literature Gill (1984), Tyler (1998) and Walsh et al. (1998).

5.3.1 Gas Turbine Key Performance Indicators

The main key performance indicators required for this project of economic operation optimization are corrected heat rate and corrected power output, which is normally represented by the Unit Heat Rate Curve. The following process parameter and constants are required in the calculations of gas turbine performance indicators:

Rated Parameters

Rated ambient temperature, RTamb (Deg C)

Rated ambient pressure, PBAmb (bar)

Rated ambient humidity, HBAmb (%)

Rated turbine speed, SBTurbine (rpm)

Rated Power Output,WBGenOut (MW)

Rated Power Factor, WBFactor

<u>Constant parameters:</u>

Fuel low heating value, LHV

<u>Measured parameter:</u>

Ambient temperature, TIAmb (Deg C)

Ambient pressure, PIAmb (bar)

Ambient humidity, HIAmb (%)

Fuel gas temperature, Tgas (Deg C)

Actual fuel gas flow, ACFH (kg/s)

Exciter voltage and current (V,A)

Turbine Speed, SIShaft (rpm)

Power generator output, Ps (MW)

Power Factor, *powerfactor*

Auxiliaries power, WIAuxil (kW)

Following shows the formulation of the key performance indicator for a gas turbine.

<u>Combustor</u>

a. Ambient gas density (kg/m^3)

   ρgas = SGgas * ρair28

b. Corrected K Factor at operating condition

   $$\mathrm{Kt} = \mathrm{K59} \times \left[1 - (2.672 \times 10^{-5} \times (Tgas - 59))\right]$$

c. Fuel gas flow (m^3/h)

   $$\mathrm{ACFH} = \frac{Freq \times 36000}{Kt \times 7.481}$$

d. Corrected fuel gas flow (Sm^3/h)

$$\text{SCFH} = \left(ACFH \times \frac{Pgas}{14.73} \times \frac{520}{Tgas} \times \frac{Fpv^2}{zb} \right) \times \rho gas$$

<u>Overall unit</u>

a. Excitation power (MW)

$$Excit = \frac{Volt \times Current}{1000 \times 0.975}$$

b. Net generator power output (MW)

Pact = Ps - Excit

c. Net heat rate (kJ/kwh)

$$NHR = \frac{HC}{Pact}$$

d. Thermal Efficiency (%)

$$Eff = \frac{3600}{HR} \times 100$$

5.3.2 Correction to Key Performance Indicators

Performance of gas turbine is sensitive to the variation of atmospheric pressure, temperature and humidity. The calculated performance needs to be corrected with standard correction factors supplied by the manufacturer's to rated atmospheric conditions for comparison. Examples of correction curves supplied by the manufacturer are appended in Appendix B. Two important performances that were corrected as such were generator power output and heat rate. The heat rate and power output must be adjusted to correspond to the selected exhaust temperature, turbine speed, and compressor inlet temperature using the correction factors supplied by the manufacturer.

5.4 Unit Heat Rate Model

5.4.1 Problem definition

As mentioned in Section 5.2.1, the model of a gas turbine to represent its power generation cost could be obtained from machine's input-output (IO) curve. This curve could be obtained from the manufacturer or field performance test report conducted on the machine. The objective here then was to determine the input-output model of generator *i,* which was an empirical based model. From the observation of curve pattern of the IO curve as shown in previous chapter, Figure 5.3, the model could be represented as a polynomial function of real power generation. The most suitable regression technique was the polynomial least square method.

5.4.2 Polynomial Least Square Regression Technique

Least square regression is one of the mathematical procedures for finding the best fitting curve to a given set of points by minimizing the sum of the squares of the offsets ("the residuals") of the points from the curve. The sum of the squares of the offsets is used instead of the offset absolute values because this allows the residuals to be treated as a continuous differentiable quantity.

The least squares fitting technique is the simplest and most commonly applied form of linear regression and provides a solution to the problem of finding the best fitting line through a set of points (Lancaster, 1986). An explanation of this technique is presented in this section. Details development of the formulation could be found in Appendix C or in reference Lancaster (1986).

Generalizing from a straight line (i.e., first-degree polynomial) to a 10th degree polynomial, the input-output model could be represented as follows,

$$LC = a_{i,1} + a_{i,2} \cdot P_i + a_{i,3} \cdot P_i^2 + ... + a_{i,11} \cdot P_i^{10} \qquad \text{Eq (5.1)}$$

where

$a_{i,1}$, $a_{,i2}$, $a_{i,3}$ = polynomial coefficient for unit i .

With reference to Eq (C.9), Eq(5.1) is transformed to matrix form as

$$\begin{bmatrix} Tn & \sum P_i & . & . & \sum P_i^{10} \\ \sum P_i & \sum P_i^2 & . & . & \sum P_i^{11} \\ . & . & . & . & \\ . & . & . & . & \\ \sum P_i^{10} & \sum P_i^{11} & . & . & \sum P_i^{20} \end{bmatrix} \cdot \begin{bmatrix} a_{i,1} \\ a_{i,2} \\ . \\ . \\ a_{i,10} \end{bmatrix} = \begin{bmatrix} \sum LC \\ \sum P_i LC \\ . \\ . \\ \sum P_i^{10} LC \end{bmatrix} \qquad \text{Eq (5. 1)}$$

where,

Tn = Total sets of data being used

In matrix notation, the equation for a polynomial fit is given by

$$A \cdot x = B \qquad \text{Eq (5.2)}$$

This matrix equation can be solved numerically, or can be inverted directly if it is well formed. The method used to solve this linear equation will be the Gauss Elimination method for faster solution.

5.4.3 Gauss Elimination Method

In this section, the above linear matrix equation (Equation 5.2) is interpreted to this method and solution is mathematically formulated for computational coding in Visual Basic. A detail formulation of Gauss Elimination method can be found in Appendix D.

5.5 Unit Emissions Model

There are several emission substances that can be generated by a gas turbine. Three most common substances generated by a gas turbine considered in this study were namely nitrogen dioxide (NO_x), carbon dioxide (CO) and sulfur dioxide (SO_2). The unit emissions model for these substances could be obtained from unit emissions test data which is represented in graphs Emissions Content (%) versus Power Output. The trend of the data is model with a polynomial function empirical model. The method and software developed and described in Section 5.4 would be used to generate the unit emissions model.

The polynomial functions for the three types of emissions model were represented as below:

$$NOx_{i,t} = f(P_i) = b_{i,1} + b_{i,2} \cdot P_i + b_{i,3} \cdot P_i^2 + ... + b_{i,10} \cdot P_i^{10} \qquad \text{Eq (5.3)}$$

$$CO_{i,t} = f(P_i) = c_{i,1} + c_{i,2} \cdot P_i + c_{i,3} \cdot P_i^2 + ... + c_{i,10} \cdot P_i^{10} \qquad \text{Eq (5.4)}$$

$$SO2_{i,t} = f(P_i) = d_{i,1} + d_{i,2} \cdot P_i + d_{i,3} \cdot P_i^2 + ... + d_{i,10} \cdot P_i^{10} \qquad \text{Eq (5.5)}$$

CHAPTER 6

MODEL VALIDATION

6.1 Introduction

In this chapter, the developed model as well as the software coding in the previous chapter to calculate and predict the machine input-output behavior would be simulated and validated against real case data. Two types of data were taken for the model validation, namely the plant real-time data obtained from the installed on-line performance monitoring software (PMS) and the data from the performance test report.

The performance calculation and correction as explained in Section 4 are incorporated into a performance monitoring system (PMS). The installation of the on-line performance monitoring software (PMS) in order to provide real-time data of machine current health is briefly discussed in this chapter. This includes the system setup which covers the hardware layout and system communication architecture with the plant Distributed Control System (DCS).

6.2 Performance Monitoring System

For the performance monitoring aspect of this project, PMS was installed at the plant as one of the requirement of the plant. This opportunity has been taken to validate the performance calculation as required in this optimization development.

PMS90 is a Windows-based application software developed by Machinery Performance Monitoring Group Sdn.Bhd. for real-time equipment performance monitoring. The HMI-software platform that it sat on is called Wonderware InTouch, where it makes it easier for retrieving and logging of real-time process data. The PMS90 provides fast and accurate information on the current performance of the machine for informed economic decisions related to maintenance and operations.

6.3 System Setup

6.3.1 Hardware Layout

The schematic in figure below shows the hardware component layout for the PMS90 system installation at Connaught Bridge Power Station, for the four open cycle ABB 13E gas turbines.

The PMS90 server components acquired real-time data from the Siemens Teleperm ME DCS and then process it into key performance indicators (KPI). Both the measured and KPI will be stored into 'lgh' file format. Since Siemens Teleperm ME is connected to the ABB control system, the installed system will able to read all the data required from the ABB control system.

Teleperm ME I/O Server (DDE) was used to communicate with the plant DCS via CS275 bus. The DDE Server allowed DDE clients to exchange data via Standard- or Fast-DDE to and from other TELEPERM M participants. DDE - *Dynamic Data Exchange* - was established by Microsoft as a protocol to control data exchange between programs. Data interchange between plant Teleperm ME Automation Systems (AS220EA device) and DDE-Server work by using bus system CS275 from Siemens. The DDE-Server was connected to the bussystem via Siemens's interface card N-AT PCI.

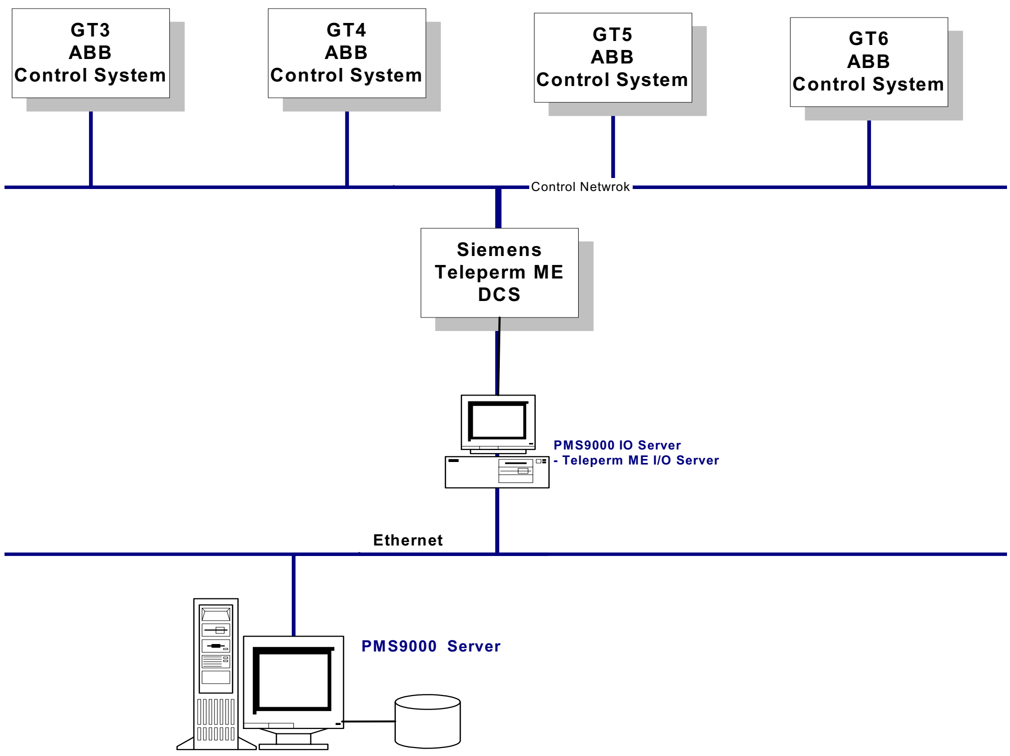

Figure 6.1: System hardware layout

A workstation was installed with a N-AT /PCI interface card. It was connected to plant Teleperm ME (AS220EA) device through bus interface adapter S8 to read and write data. The supported data or signals were ASK analog values, BSK Binary values and MSK binary values.

6.3.2 Communication Protocol

PMS9000 communicates with the I/O servers by using standard communication protocols DDE (Dynamic Data Exchange) and NetDDE (Network DDE). Dynamic Data Exchange (DDE) is a communication protocol developed by Microsoft to allow applications in the Windows environment to send/receive data and instructions to/from each other. It implements a client-server relationship between two concurrently running applications. The *server* application provides the data and accepts requests from any other application interested in its data. Requesting applications are called *clients*. Some applications such as InTouch and Microsoft Excel can simultaneously be both a *client* and a *server*.

6.4 Model Validation Results

The developed modeling software is tested and validated with two types of data, namely plant real-time data and unit's performance test report.

6.4.1 Comparison with PMS9000 Performance Calculations

Real-time data is obtained via a performance monitoring system (PMS9000), which had been installed and commission in Connaught Bridge power station, Kang to communicate with the plant Distributed Control System (DCS). All the performance calculations as stated in section 3 is coded into the PMS9000 in order to obtain corrected key performance indicators.

Four gas turbines (Unit 3,4,5&6) operational real-time data is obtained for the period when the machine is starting up and until the machines is shutdown. This is used to model the relationships of machine's heat consumption (GJ/h) and power output (MW). All process parameters and calculated key performance indicators for a day of 3rd of January 2009 are obtained.

All data captured by PMS9000 under the Wonderware InTouch HMI platform is stored in 'lgh' format. A program in Excel VBA is written in order to extract the data into CSV format, which is readable in Excel. The data is edited in the format such that it can be executed by the modeling software. The empirical fitting of the data for four gas turbines are shown in the figure below. The calculated machine model polynomial function with the highest accuracy is determined by the software and is shown as below.

Table 6.1: Unit Input-Output model polynomial coefficient (from actual plant data)

Unit	Poly. Order	$a_{i,1}$	$a_{i,2}$	$a_{i,3}$	$a_{i,4}$	$a_{i,5}$	$a_{i,6}$	$a_{i,7}$
3	2nd	3.89573 E+02	7.06073 E+00	7.97689 E-03				
4	3rd	6.10368 E+02	-6.63739 E-01	9.64947 E-02	-3.35093 E-04			
5	6th	-3.17497 E+03	2.90055 E+02	-9.15362 E+00	1.55762 E-01	-1.47268 E-03	7.35777 E-06	-1.51928 E-08
6	2nd	4.21764 E+02	6.44591 E+00	1.05805 E-02				

The following figure illustrates the best polynomial curve fitted model of the four gas turbines.

Comparison of the estimated machine's heat consumption based on the modeling program with the plant actual real-time data had been made in this project. The details numeric data is tabulated in Appendix E. The figures below show graphically the percentage of errors of these comparisons for the four gas turbines.

In an overall perspective, the model provided fairly good accurate results. The model for unit 3 and unit 4 gave the most accurate results, where the errors were within ±1.5%. For unit 5 and 6, the errors averaged in within ±4% region.

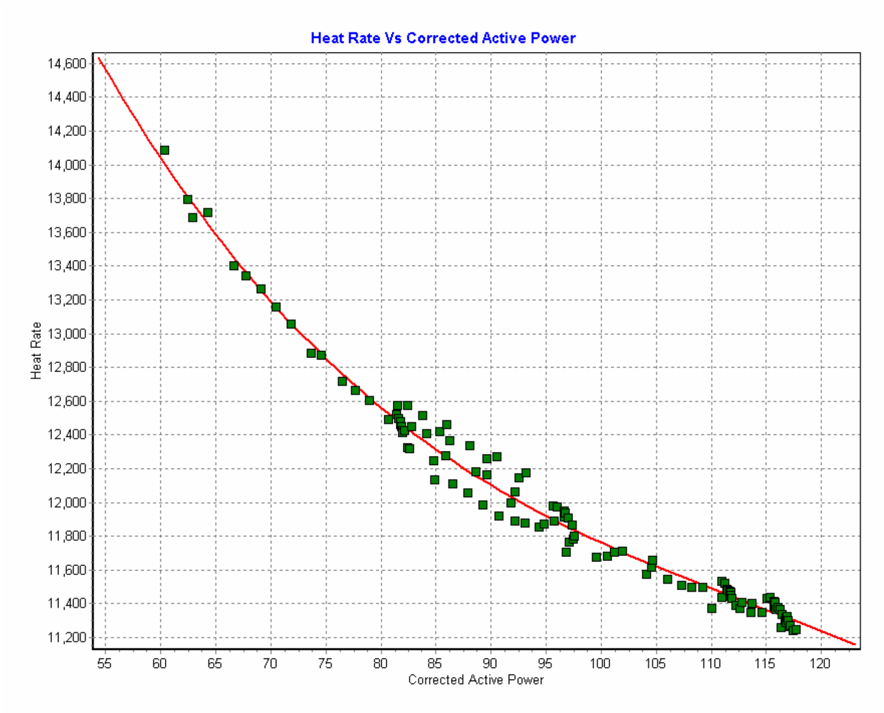

Figure 6.2: Unit 3 - Corrected heat rate versus corrected active power

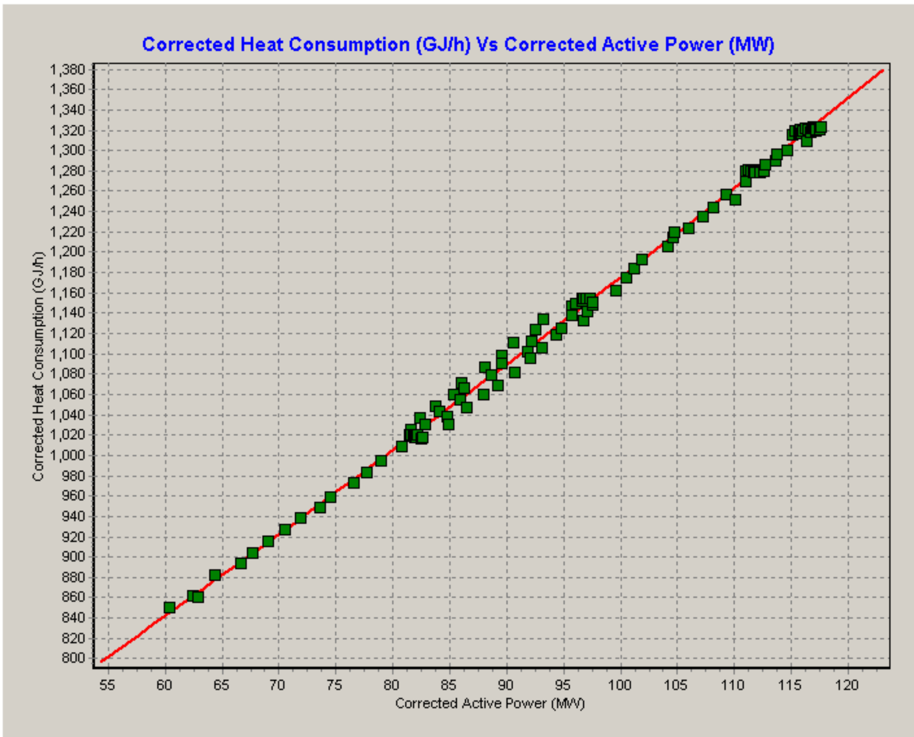

Figure 6.3: Unit 3 - Corrected heat consumption versus corrected active power

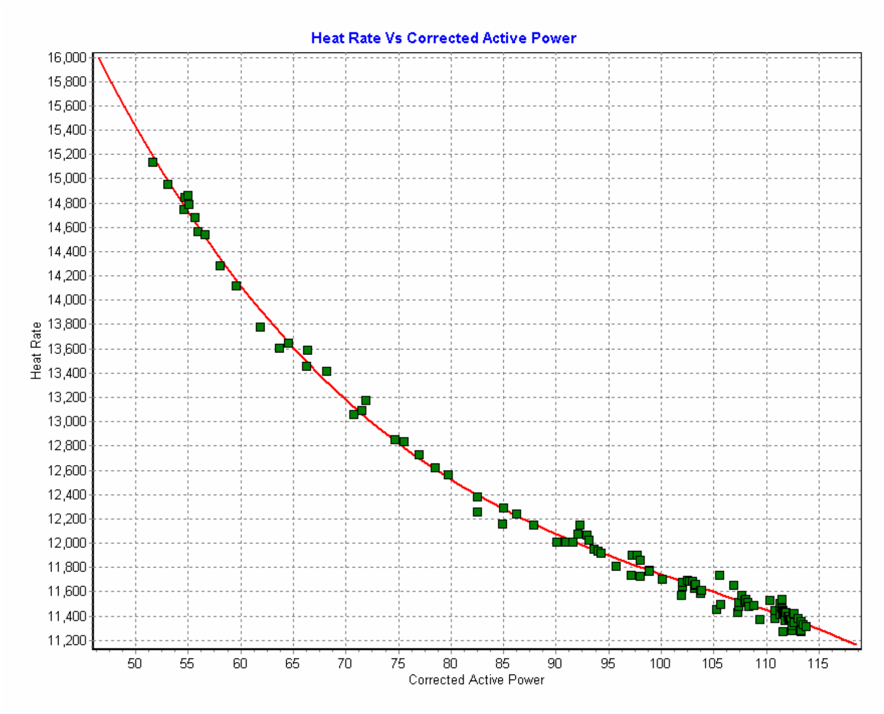

Figure 6.4: Unit 4 - Corrected heat rate versus corrected active power

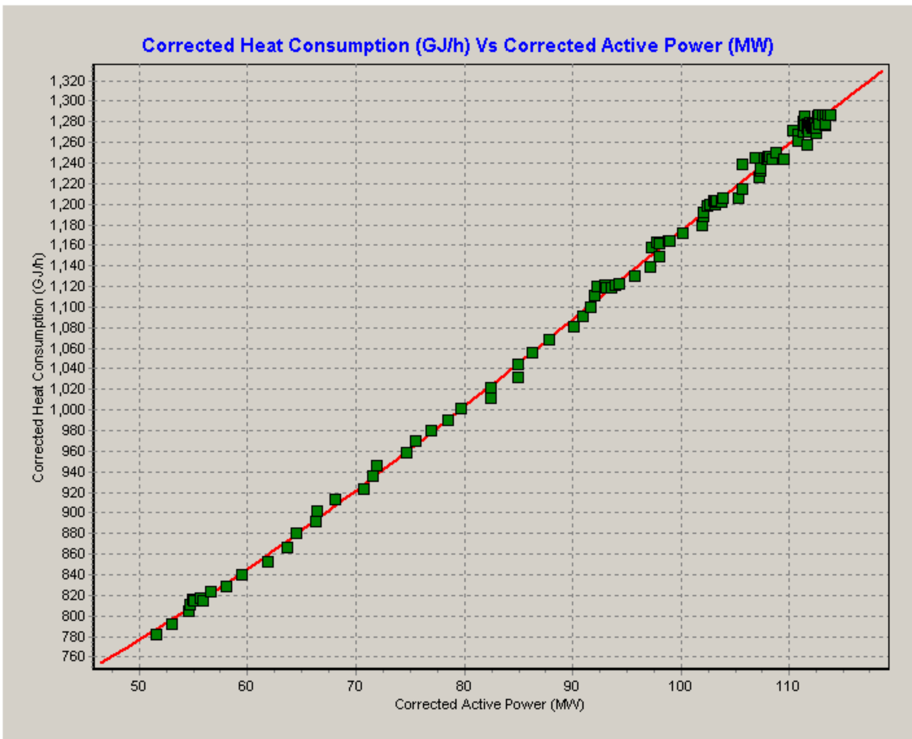

Figure 6.5: Unit 4 - Corrected heat consumption versus corrected active power

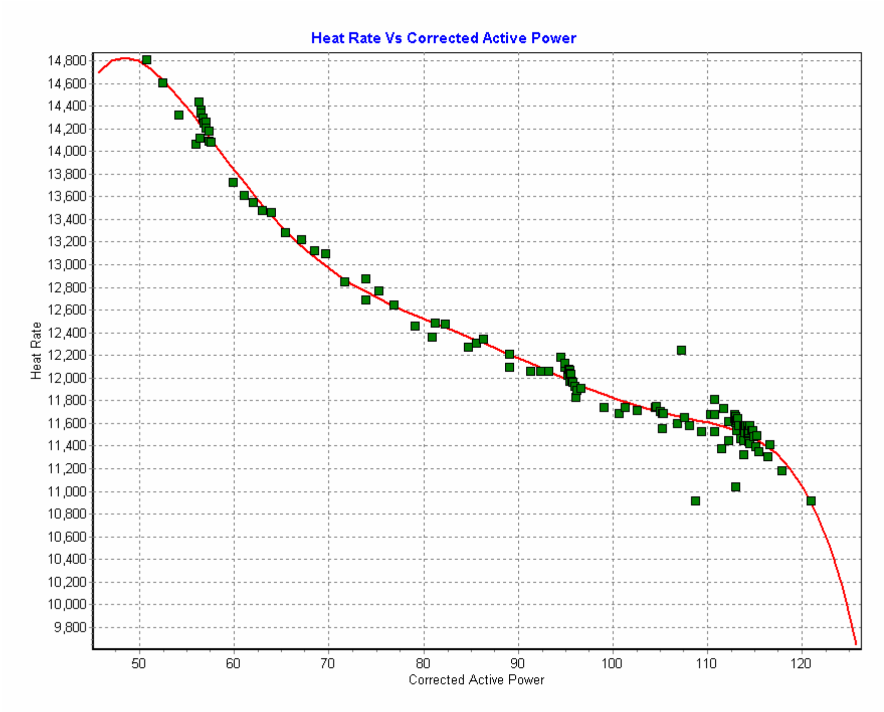

Figure 6.6: Unit 5 - Corrected heat rate versus corrected active power

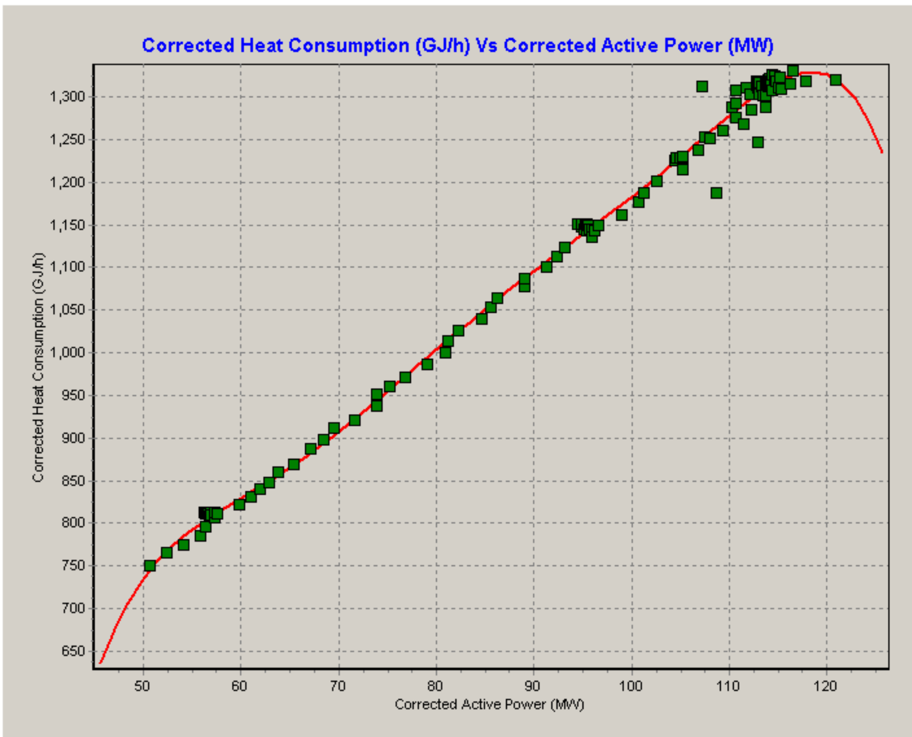

Figure 6.7: Unit 5 - Corrected heat consumption versus corrected active power

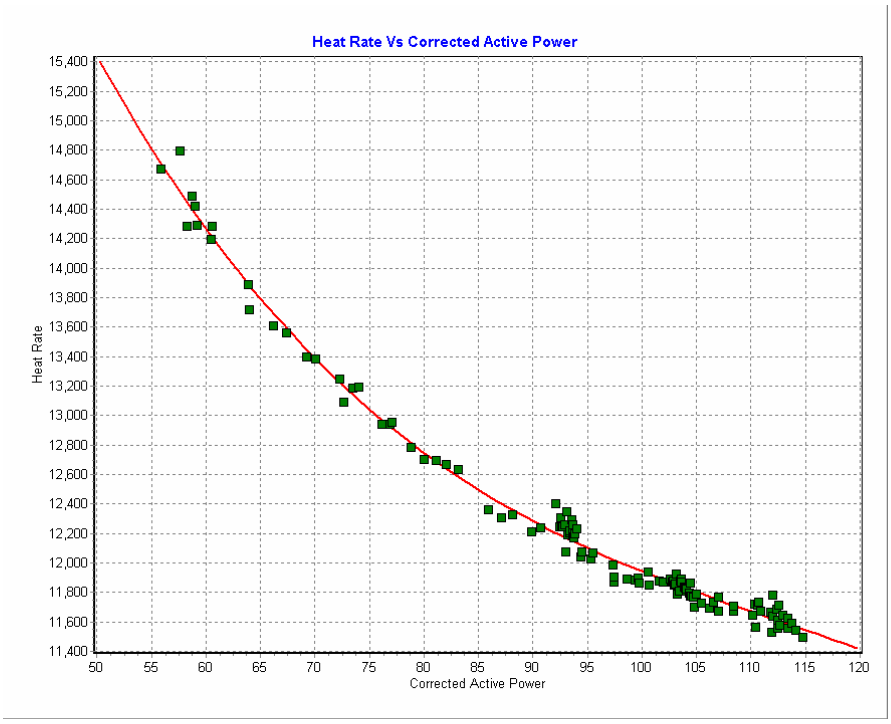

Figure 6.8: Unit 6 - Corrected heat rate versus corrected active power

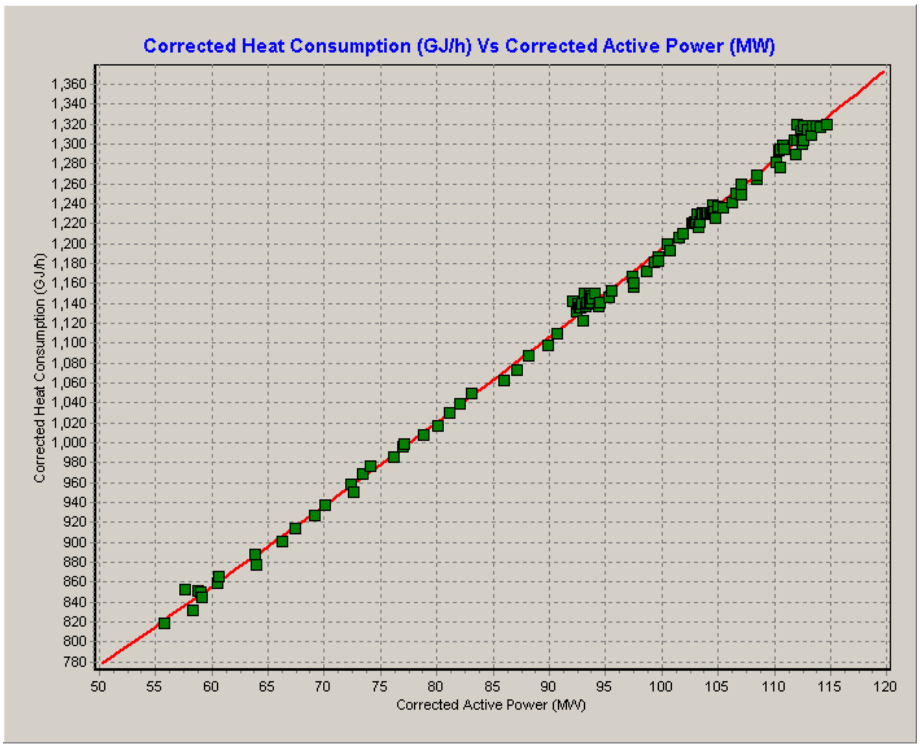

Figure 6.9: Unit 6 - Corrected heat consumption versus corrected active power

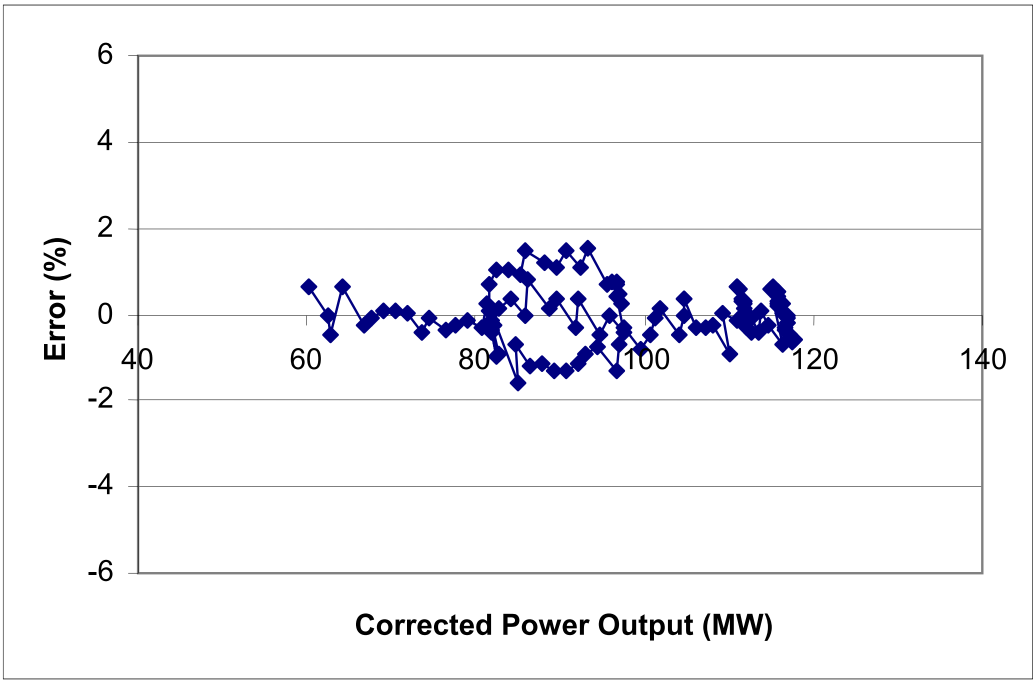

Figure 6.10: Unit 3 – Error (%) versus corrected active power (MW)

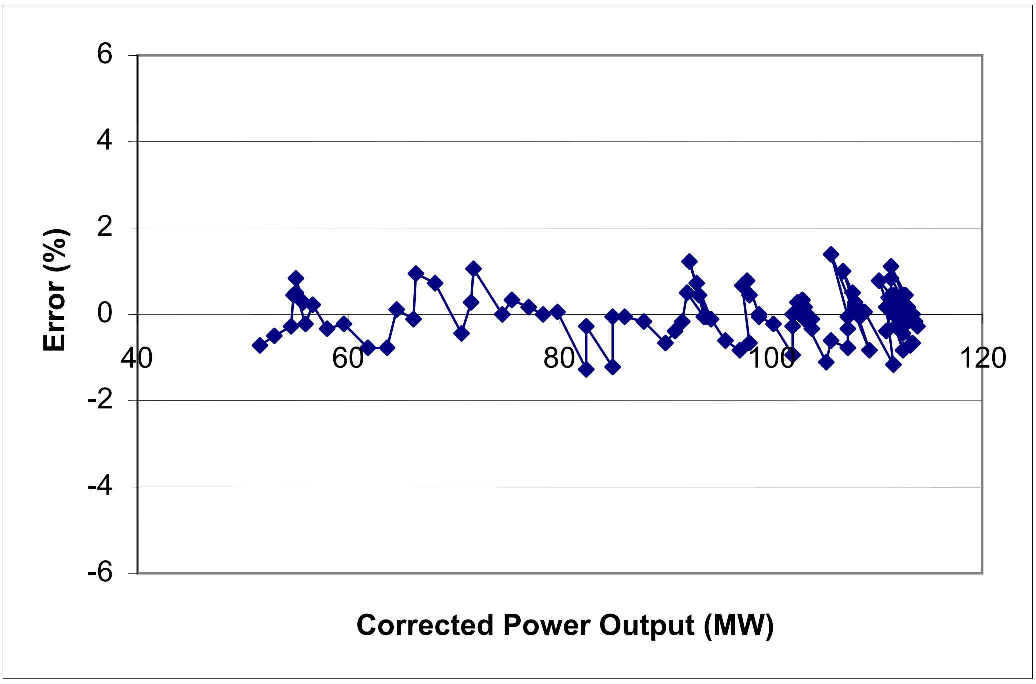

Figure 6.11: Unit 4 – Error (%) versus corrected active power (MW)

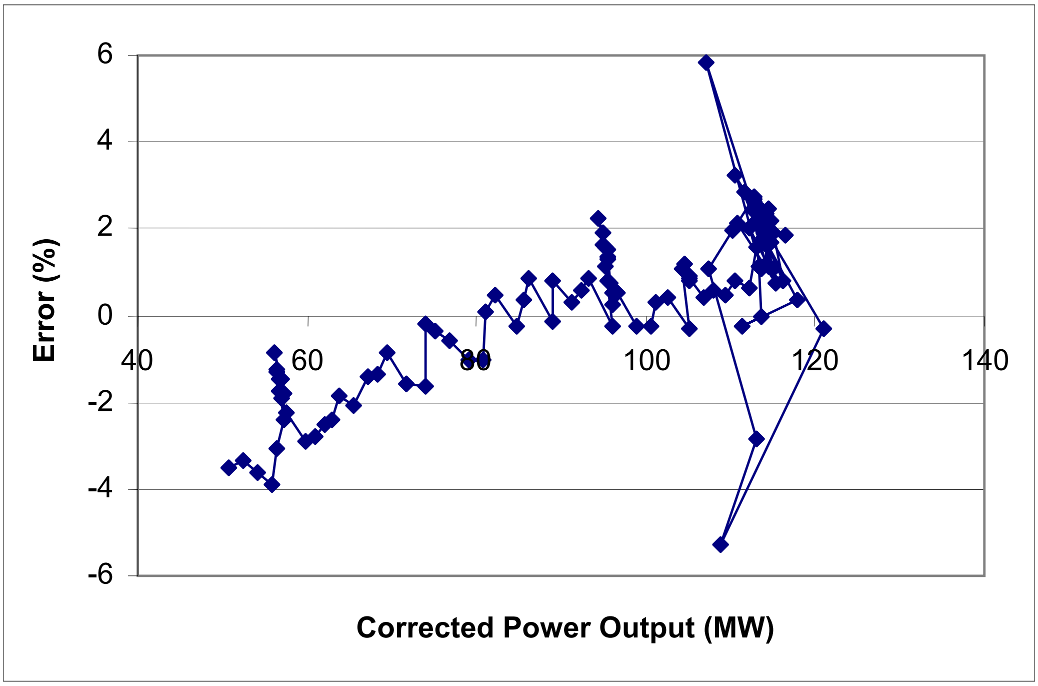

Figure 6.12: Unit 5 – Error (%) versus corrected active power (MW)

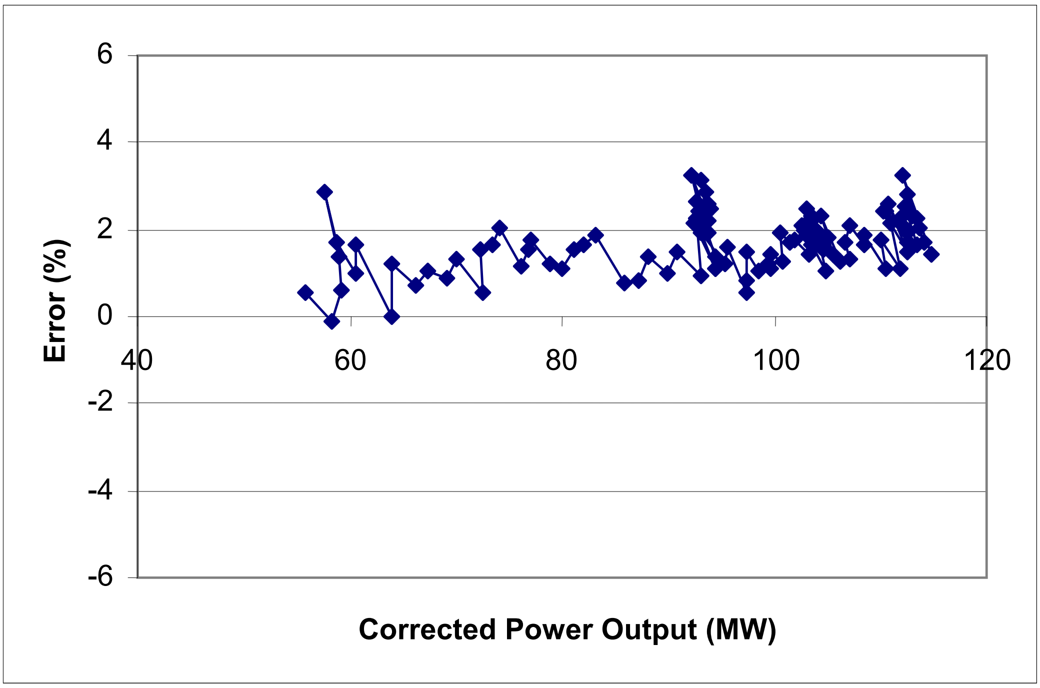

Figure 6.13: Unit 6 – Error (%) versus corrected active power (MW)

6.4.2 Comparison with Unit's Performance Test Report

Two performance test reports as conducted by TNB's Maintenance and Testing Company in REMACO (19) and (19) for unit 3 and 4 were provided by the plant to use in this model validation. The empirical fitting of the data for the gas turbines are shown in figure below. The calculated machine model polynomial function with the highest accuracy determined by the software is tabulated as below.

Table 6.2: Unit Input-Output model polynomial coefficient (against performance test report)

Unit	Poly Order	a1	a2	a3
3	2nd	8.86347E+02	6.07776E+00	-5.51626E-03
4	2nd	5.03373E+02	6.24708E+00	1.47206E-02

Comparison of the estimated machine's heat consumption based on the modeling program with the performance test report data had been made in this project. The details numeric data is tabulated in Appendix F. The figures below show graphically the percentage of errors of these comparisons for the two gas turbines.

In conclusion, the model provided fairly accurate result. The model for unit 3 and unit 4 gave more accurate results, where the errors were in the region within ± 0.5%

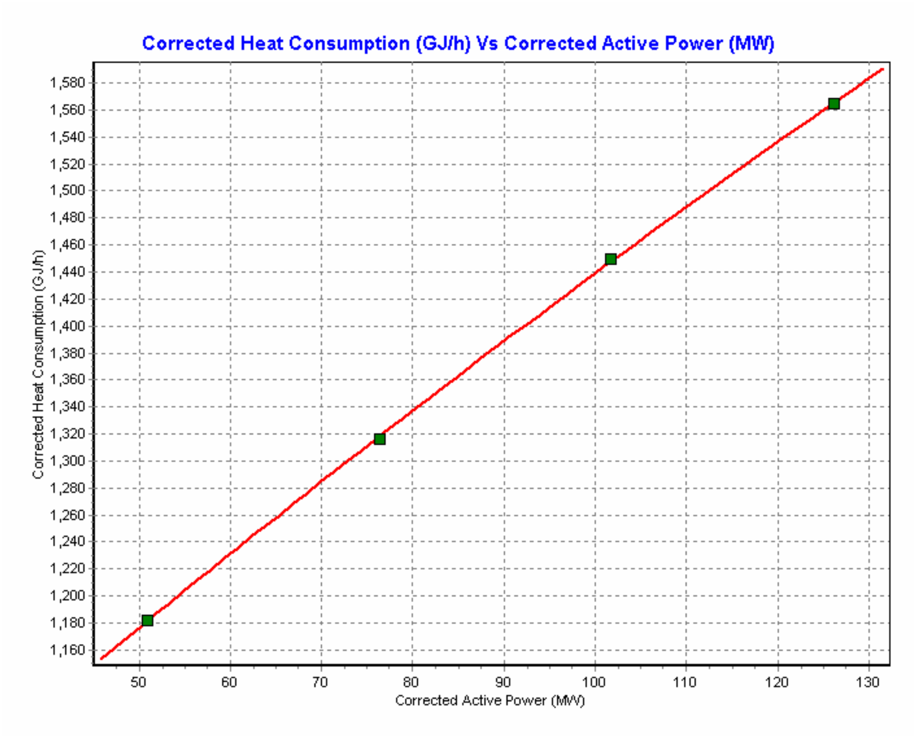

Figure 6.14: Unit 3 – Corrected heat consumption (GJ/h) versus corrected active power (MW) (against performance test report)

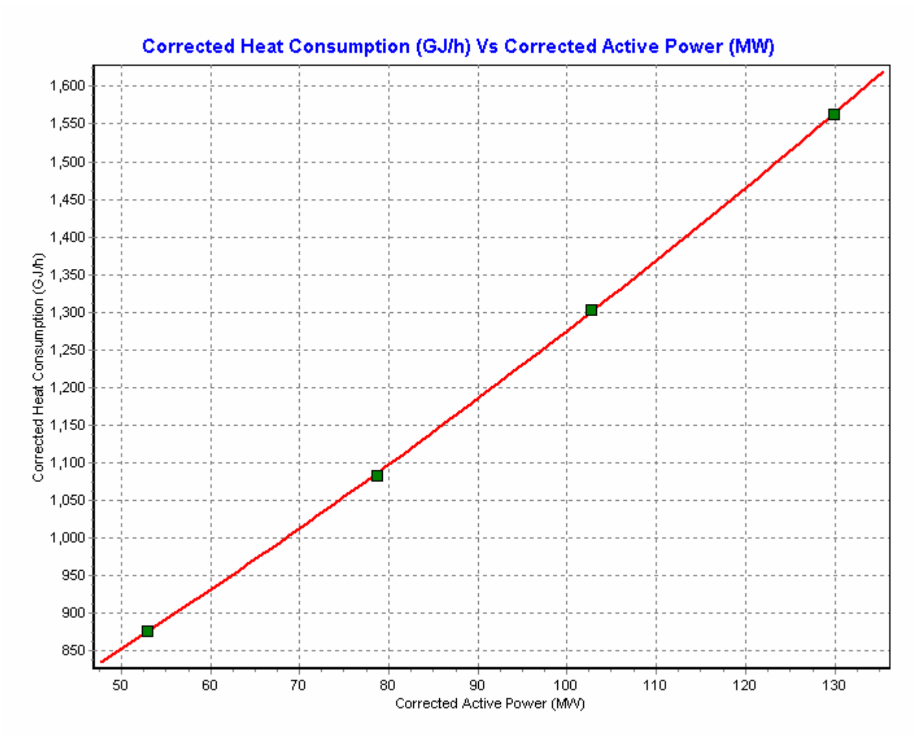

Figure 6.15: Unit 4 – Corrected heat consumption (GJ/h) versus corrected active power (MW) (against performance test report)

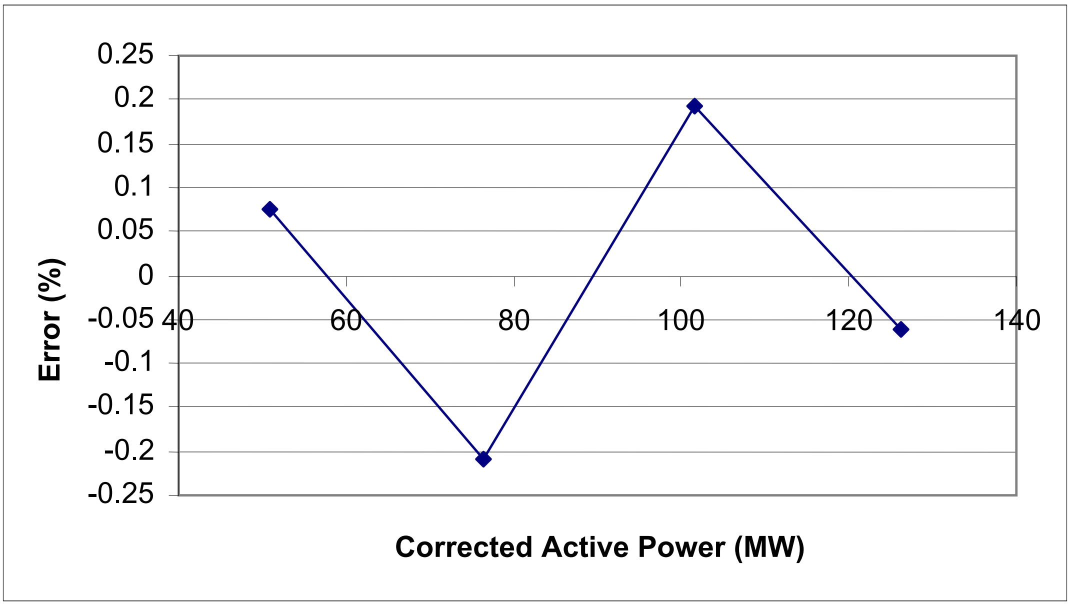

Figure 6.16: Unit 3 - Error (%) versus active power (MW) (against performance test report)

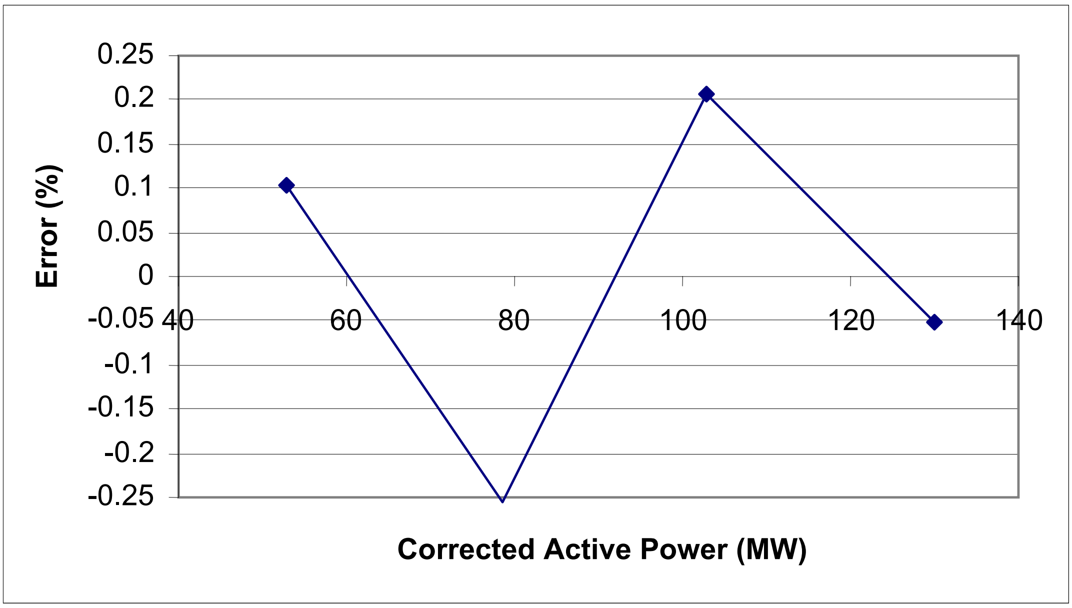

Figure 6.17: Unit 4 - Error (%) versus active power (MW) (against performance test report)

6.5 Concluding Remarks

Both of the model validation results had showed the correctness of model, where the developed software predicted accurately the behavior of the input-output of the machines. The error of ±4% generated from Unit 5 when compared against real-time data may not necessarily be due to the error of the model. This could be in fact due to other factors as the real-time data was not taken at steady state conditions. When the model was compared against performance test report, it only gave a ±2% error. In conclusion, the model had showed acceptable and accurate results to model the behavior of the machines. This model was used for the subsequent optimization algorithm study and analysis.

CHAPTER 7

OPTIMIZATION ALGORITHM

7.1 Introduction

Optimization is a process of finding the conditions that give the maximum or minimum value of a function. There are several optimum seeking methods, also known as mathematical programming techniques, that had been developed for solving engineering problems. Conventional or traditional method had shown reliable and deterministic results for the past decade. Most of these methods were however dependent on the formulation of the optimization problem (equation or objective function involved), resulting in computational difficulties when used for complex problems. Recent research on artificial intelligence techniques such as neural network, genetic algorithm (GA), evolutionary programming (EP) and particle swarm optimization (PSO) had good response from the industries, mainly due to its capabilities in solving complex problems.

In this work, an advanced and recent artificial intelligence technique, namely particle swarm optimization (PSO) was used and tested as the optimization techniques in solving the optimization problem as presented in the previous chapters. In this chapter, the reasons of implementing particle swarm optimization to this problem and comparisons among other techniques are discussed. The details implementation and modification of the algorithm with extended priority list (EPL) method to the optimization problem and the software coding are also elaborated in detail.

7.2 Identification of Suitable Optimization Algorithm

Several optimization techniques and its application in load dispatching and unit commitment were summarized in Section 2.4 and 2.6. As discussed in Section 2.4, the overall techniques in mathematical programming could be classified into two categories, which are:

a. Conventional mathematical programming optimization techniques;
b. Artificial intelligence (AI) techniques, which is usually termed as stochastic techniques or advanced techniques.

The optimization problem defined in this work was a fairly complicated multi-objectives optimization problem with the presence of time-dependent constraints such as start-up cost, minimum up and down times, and equivalent operating hours (EOH). From the system operation viewpoint, the introduction of environmental and EOH constraints introduced a series of difficult questions. Even though emission constraints are not new to the industry, requirements imposed on air quality by the authorities as well as the tightening of emission limits had greatly complicated the operations scheduling process.

During recent years, extensive and productive research had focused on different methods for solving standard UC problem as mentioned in Section 2.6. There appeared to be a lack of work reported on environmental effects into this problem. Any significant research was reviewed in Section 2.5. An artificial intelligence or advanced method was therefore used in this research to solve this complex optimization problem.

Particle swarm optimization (PSO) based techniques with incorporation of Extended Priority List (EPL) was selected and used in solving this research's problems. The reasons of this selection among other advanced techniques are discussed and summarized below.

PSO is an extremely simple algorithm that had been reported to be effective for optimization for a wide range of application, as reported in Kennedy and Eberhart (1995a). It comprises a very simple concept and paradigms that can be implemented in a few lines of computer code. It requires only primitive mathematical operators and is therefore computationally undemanding in terms of both memory requirements and speed as compared to other techniques. PSO had also been demonstrated to perform well on genetic algorithm (GA) test functions, and it appeared to be promising approach for robot task learning.

As mentioned by Kennedy and Eberhart (1995a), PSO can be used to solve many of the same kinds of problems as genetic algorithm (GAs). This optimization technique does not have difficulties associated with GA, such as interaction in the group that enhances rather than detracts from progress toward the solution. The particle swarm system also has memory functionality, which GA does not have. In the PSO algorithm, individual values (particle) that drift away from the optimum point (optima) are drawn back to converge towards the optimum point. Knowledge of good solutions is thus retained by all particles in PSO as compared to GA which results in the loss of such previous knowledge of the problem when change in genetics populations, except when elitism is employed, in which case usually one or a small number of individuals retain their “identities” (Source: Kennedy and Eberhart (1995a) & (1995b)).

One of the major advantages of PSO is its ability to provide a global optimum result. The PSO was compared to a benchmark for genetic algorithms in “Handbook of Genetic Algorithm” by Davis (1991) against the extremely nonlinear Schaffer f6 function as in Kennedy and Eberhart (1995a). This function is extremely difficult to optimize, as the highly discontinuous data surface features many local optima. PSO paradigm found the global optimum in each run, and appears to approximate the results reported for elementary genetic algorithms in terms of the number of evaluations required to reach certain performance levels.

Another reason that PSO is attractive is that there are few parameters to adjust as mentioned in Kennedy and Eberhart (2001), Shi and Eberhart (1998b) and Trelea (2003). One version, with slight variations, works well in a wide variety of applications. Particle swarm optimization has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on a specific requirement.

Because of its simplicity, performance and reliability as stated above, the promising optimization method was used and worth to be implemented in this research, even tough little known related application with this research was reported at this moment.

The computation speed and performance of AI techniques was still one of the main disadvantages of PSO. Therefore, improvements of PSO with incorporation of other methods as reported by C.K. Loo and Tiew-On Ting (2003) was enhanced and carried out in this research. Extended Priority List (EPL) was used to leverage its advantages of fast searching, and repair its main disadvantage of local optimum focus.

7.3 PSO Algorithm and Implementation

7.3.1 PSO Algorithm

As already mentioned, PSO is different from other evolutionary algorithms. Indeed, in PSO the population dynamics simulates a bird flock's behavior where social sharing of information takes place and individuals can profit from the discoveries and previous experience of all other companions during the search for food. With reference to Kennedy and Eberhart (1995), each companion is called *particle* in the population, which is now also called *swarm*, is assumed to "fly" over the search space in order to find promising regions of the landscape. Each particle is treated as a point in a *D*–dimensional space which adjusts its own "flying" according to its flying experience as well as the flying experience of other particles (companions).

There were many variants of the PSO proposed so far, after Eberhart and Kennedy introduced this technique in Kennedy and Eberhart (1995a) and (1995b). In this research project, we used a new version of this algorithm, which was derived by adding a new inertia weight to the original PSO dynamics as reported by Shi and Eberhart (1998a). This version is described in the following paragraphs.

The individuals or particles in a PSO have their own positions and velocities. These individuals are denoted as particles. The PSO traditionally has no crossover between individuals, has no mutation and particles are never substituted by other individuals during the run. Instead the PSO refines its search by attracting the particles to positions with good solutions. With reference to Shi and Eberhart (1998a), each particle remembers its own best position found so far in the exploration. This position is called personal best and is denoted by *pbest* in equation (7.1). Additionally among these personal bests, there is only one which has the best fitness. The best among *pbest* is called the global best and is denoted by *gbest* in equation (7.1).

$$V_i = wV_{i,d} + \rho_1 \cdot rand(\ ) \cdot (gbest_d - X_{i,d}) + \rho_2 \cdot rand(\ ) \cdot (pbest_{i,d} - X_{i,d}) \quad \text{(Eq 7.1)}$$

where w is known as the inertia weight. Other notation adopted in this equation is defined as below:

N = the size of the population

D = dimensional vector $X_{i,d}$ ($X_{i,1}$, $X_{i,2}$, …, $X_{i,D}$)

V = particle velocity

i = particle number, where i = 1,2,…, N

The best found position for the given particle is denoted by *pbest* and *gbest* is the best position known for all particles. The parameters ρ1 and ρ2 are set to a constant value whereas rand() is randomly generated value between 0 and 1. The position of each particle is updated every iteration. This is done by adding the velocity vector to the position vector, as described in Kennedy et al. (2001) and Shi et al. (1998a), as in below equation (7.2):

$$X_{i,d} = X_{i,d} + V_{i,d} \quad \text{(Eq 7.2)}$$

It has been noticed that members of the group seem to share information between them, a fact that leads to increased cohesion or efficiency (e.g., in search of food) of the group. Some scientists suggest that knowledge is optimized by social interaction and thinking is not private but also interpersonal. Therefore, particle swarms have not only individual, but also a collective intelligence, simply by their social interactions.

The pseudo code of the procedure as reported by Kennedy et al. (2001) and Shi et al. (1998a) is as follows:

For each particle

Initialize particle

END

Do While maximum iterations or minimum error criteria is not attained

For each particle

Calculate fitness value

If the fitness value is better than the best fitness value (pbest) in history

set current value as the new pbest

End

Choose the particle with the best fitness value of all the particles as the gbest

For each particle

Calculate particle velocity

Update particle position

End

Loop

Particles' velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user, then the velocity on that dimension is limited to Vmax.

The searching is a repeat process, and the stop criteria are that the maximum iteration number is reached or the minimum error condition is satisfied.

7.3.1.1 Extended Priority List (EPL) - Particle Swarm Optimization (PSO) Approach

New approach of using Hybrid Particle Swarm Optimization (HPSO) to solve unit commitment problem had been conducted by Tiew-On Ting et al. (2003). The simulation results, which were performed with the benchmark problem of 10 generator scheduling problem, had demonstrated well that the HPSO was a competent method to solve UC problem. However, the computational time was still considered as high as genetic algorithm or evolutionary programming.

Extended Priority List (EPL) method as described in Section 2.6, although provides fast solution, but it relied on too many assumptions. In order to utilize EPL advantages, EPL was incorporated into PSO to provide a close initial solution to enable PSO to perform faster. In this work, the proposed Extended Priority List (EPL) and PSO as reported by Tiew-On Ting and Loo (2003) was used and further enhanced to improve its competency especially its computation time and accuracies. The priority list function was therefore performed first before proceed to the PSO algorithm as illustrated in Figure 7.1. The priority list sub function is shown as follow:

'Calculate power generation cost in RM/MW by assuming operating in Pmax
*U(i).P = (a(i, 1) + a(i, 2) * Pmax(i) + a(i, 3) * Pmax(i) ^ 2 + a(i, 4) * Pmax(i) ^ 3 + a(i, 5) * Pmax(i) ^ 4 + a(i, 6) * Pmax(i) ^ 5 + a(i, 7) * Pmax(i)*

*^ 6 + a(i, 8) * Pmax(i) ^ 7 + a(i, 9) * Pmax(i) ^ 8 + a(i, 10) * Pmax(i) ^ 9) / Pmax(i)*

```
'Priority List arrangement
For i = 1 To Umax
        For j = i + 1 To Umax
        If U(j).P < U(i).P Then    'Swap the values
                temp = U(j)  'Swap P
                U(j) = U(i)
                U(i) = temp
        End If
        Next j
Next i

For i = 1 To Umax
        PL(i) = U(i).x
Next i
```

The original version of particle swarm optimization (PSO) operates on real values. However, with a simple modification the particle swarm algorithm could be made to operate on binary problems, such as those traditionally optimized by genetic algorithm, and this method is called Hybrid Particle Swarm Optimization (HPSO). The HPSO was also incorporated to the EPL-PSO method above to provide better global optimum.

In binary particle swarm, Xi and pbest can take on values of 0 or 1 only. The velocity, V_i will determine a probability threshold. If V_i is higher, the individual is more likely to choose 1, and lower values favor the 0 choice. Such a threshold needs to stay in the range [0, 1]. The function is called sigmoid function derived as follows:

$$s(V_i) = \frac{1}{1 + \exp^{-V_i}} \qquad \text{(Eq 7.3)}$$

The function squashes its input into the requisite range and has properties that make it agreeable to be used as probability threshold. A random number (drawn from a uniform distribution between 0 and 1) is then generated, whereby X_i is set to 1 if the random number less than the value from the sigmoid function as illustrated below,

$$If\ rand(\ ) < s(V_i)\ then\ u_i = 1\ else\ u_i = 0 \qquad \text{(Eq 7.4)}$$

where u_i represents the on or off state of generator i. In order to ensure that there is always possibility of a bit flipping (on and off of generators); a constant velocity maximum, $V_{\max}$ was set at the start of a trial to limit the range of V_i. In practice, $V_{\max}$ was often set at ±4.0, so that there is always at least chance that a bit will change state. This is to limit V_i so that $s(V_i)$ does not approach too closely to 0 or 1. In solving the unit commitment problem, the real valued PSO and binary PSO were run in parallel, with each updated according to Equation (7.3) and Equation (7.4) separately. The real valued PSO would optimize the generated power, p_i in the vicinity of the on and off status, u_i, which was changed and optimized by binary PSO.

The overall data flow diagram of the application of the complete EPL-PSO optimization algorithm to this research optimization problem could be summarized in the figure below. Other functions were discussed in the next section of this chapter.

7.3.1.2 Satisfying Power Demand and Reserve constraints

With reference to Shi and Eberhar (1999), the objective of the unit commitment problem was formulated with a combination of total production cost as the main objective, with power balance and spinning reserve as inequality constraints. Whereby $Z_f(x) = TPC_N$ (Equation (4.4)) and $Z_u(x)$ was equivalent to the blend of power balance and spinning reserve constraints. Subsequently, the formulation of the objective function is shown below:

$$Z(x) = Z_f(x) + sZ_u(x) \qquad \text{(Eq 7.5)}$$

$$Z(x) = TPC_N + \frac{s}{2}\left[C_1(PowD_t - \sum_{i=1}^{N} P_{i,t}U_{i,t})^2 + C_2(PowD_t + R_t - \sum_{i=1}^{N} P_{i(\max)}U_{i,t})^2 \right]$$

(Eq 7.6)

s is the penalty factor which is computed at the *i-th* generation defined as $s = s_0 + \log(t+1)$ determined the accuracy and speed of convergence. From the experiment, greater value of *s* increased its speed and convergence rate. Due to this reason, a value of 100 for s_0 was chosen. There are several methods for choosing *s* and each method establishes a family of intervals for every constraint that determined the appropriate values for *s*. The pressure on the infeasible solution could be increased with the number of generations as discussed in Kuhn-Tucker optimality theorem and penalty function theorem provided guidelines to choose the penalty term. In Equation (7.5), C_1 was set to 1 if constraint Equation (4.20) was violated and $C_1 = 0$ whenever it was not violated. Likewise, C_2 was also set to 1 whenever violation of Equation (4.22) was detected, and it remained 0 otherwise. The second term in the penalty factor is the reserve constraint, where R_t is the reserved power. Thus, Equation (7.6) could also be written as:

$$Z(x) = TPC_N + \frac{s}{2}\left[C_1(L_t - \sum_{i=1}^{N} P_{i,t}U_{i,t})^2 + C_2(1.1L_t - \sum_{i=1}^{N} P_{i(\max)}U_{i,t})^2 \right] \qquad \text{(Eq 7.7)}$$

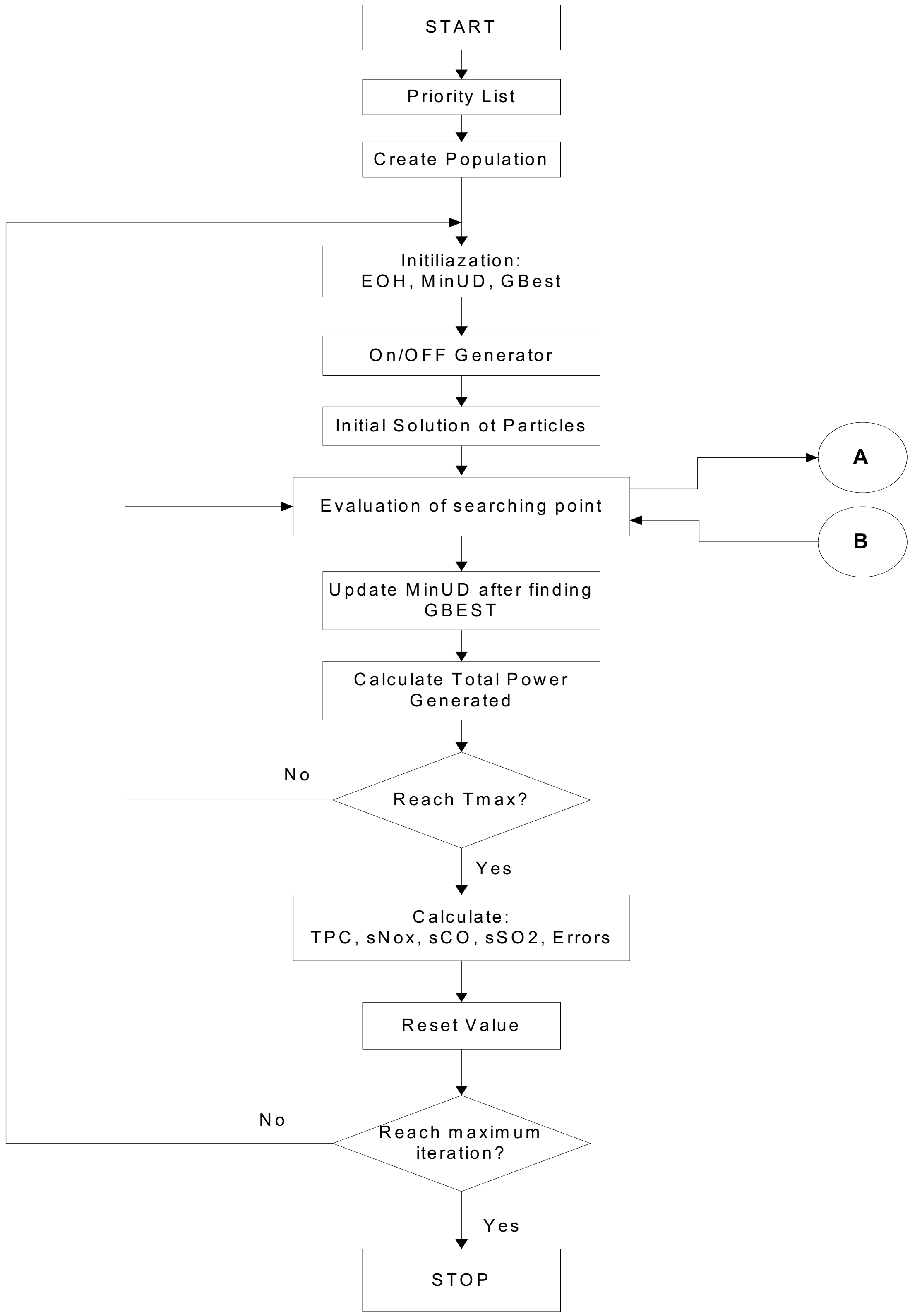

Figure 7.1: Overall EPL-PSO algorithm data flow diagram

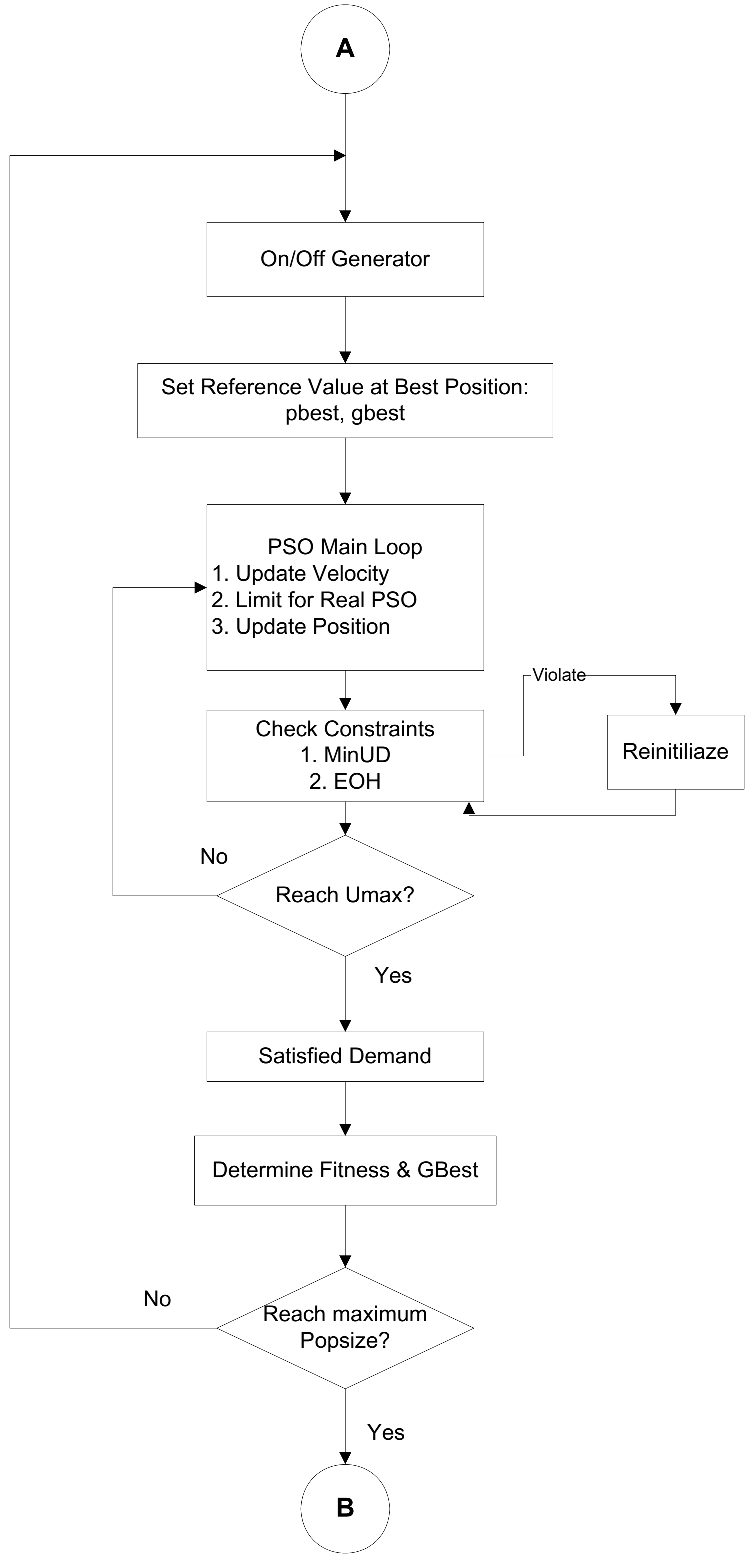

Figure 7.2: PSO – Evaluation of searching points algorithm data flow diagram

By substituting Equation (4.4) into (7.7),

$$Z(x)=\sum_{i=1}^{N}\left[FC_i(P_{i,t})+StC_i(1-X_{i(t-1)})\right]U_{i,t}+\frac{s}{2}\left[C_1(L_t-\sum_{i=1}^{N}P_{i,t}U_{i,t})^2+C_2(1.1L_t-\sum_{i=1}^{N}P_{i(\max)}U_{i,t})^2\right]$$

(Eq 7.8)

Equation (4.24) is the fitness function for evaluating every particle in the population of PSO for an hour. For H hours, Equation (7.8) is redefined as below.

$$Z(x)=\sum_{k=1}^{H}\left\{\sum_{i=1}^{N}\left[FC_i(P_{i,t})+StC_i(1-X_{i(t-1)})\right]U_{i,t}+\frac{s}{2}\left[C_1(L_t-\sum_{i=1}^{N}P_{i,t}U_{i,t})^2+C_2(1.1L_t-\sum_{i=1}^{N}P_{i(\max)}U_{i,t})^2\right]\right\}$$

(Eq 7.9)

In order to decrease the pressure of constraint violation error on the fitness function, $Z(x)$, a set of major feasible solutions that satisfy the power demand was generated before evaluation using Equation (7.9) was considered. The pseudocode is given as below (Source: Tiew-Ong Ting and C.K.Loo (2003)).

Do while ((P_g < L_{Ti}) and (k < 100))

    $k = k + 1$
    i = (kt **modulus** N) + 1
        If generator i is off **then** on it
            Update total generated power, $P_g = P_g + P_i$
        End if
        Else if generator i if on **then**
            (1) Minus the relevant power of unit i, $P_g = P_g - P_i$
            (2) Reinitialize, $P_i = P_i + rand() * (P_{i(max)} - P_i)$
            (3) Update total generated power, P_g, $P_g = P_g + P_i$
        End if

Loop

Where,

P_g	total power generated, $P_g = P_i + P_{i+2} + P_{i+3} \ldots P_N$.
P_i	power generated by generator i
P_i(max)	maximum limit of P_i

N	total number of operating generator.
L_t	power demand to be satisfied
rand( )	random number generator between 0 to 1.

7.3.1.3 Satisfying Generation Limit Constraints

As particles explored the searching space which was bounded by power limit as derived in Equation (4.24), they did encounter cases whereby the power generated exceeded the boundary and therefore violated the constraint in Equation (4.24). The PSO general method for constraints as in Kennedy et al. (2001) and Shi et al. (1998a), was also been used in Tiew-Ong Ting and C.K.Loo (2003) and in this work to avoid this. The value would be reinitialized whenever it is greater than the maximum or smaller than the minimum. The pseudocode is shown as follows:

If $P_i > P_{i(max)}$ then
reinitialize, $P_i = P_{i(min)} + rand(\,) * (P_{i(max)} - P_{i(min)})$
End if

If $P_i < P_{i(min)}$ then
reinitialize, $P_i = P_{i(min)} + rand(\,) * (P_{i(max)} - P_{i(min)})$
End if

7.3.1.4 Satisfying Minimum Up and Down Time Constraints, EOH Constraints and Emissions (NOx, CO and SO2) Limit Constraints

The technique used to satisfy the minimum up and down time in this experiment was simply based on the recommendation as reported in Tiew-On Ting and Loo (2003). As the solution was based upon the best particle (*gbest*) in the history of the entire population, constraints were taken care off by forcing the binary value in *gbest* to change its state whenever either $MinUP_i$ or $MinDown_i$ constraint was violated. However this could change the fitness value evaluated using Equation (7.9). It implied that the current *gbest* might no longer be the best among all the other particles. To correct this error, the *gbest* would be reevaluated using the same Equation (7.9). The pseudocode to satisfy minimum up and down time constraints is shown below:

```
For i = 1 To Umax

j = PL(i)
'Determine that EOH is not violated before turning on
If OnOffStatus(j) = True Then
        If TPmax < LT(t) * (1 + R) Then
                If MinUD(j) < 0 And Abs(MinUD(j)) < minDownAllow(j)
        Then
                        u(j).x = 0
                Else
                        u(j).x = 1
                        'TPmax storing total of Pmax
                        TPmax = TPmax + Pmax(j)
                End If

        ElseIf TPmax > LT (t) * (1 + R) Then
                If MinUD(j) > 0 And Abs(MinUD(j)) < minUpAllow(j) Then
                        u(j).x = 1
                        'TPmax storing total of Pmax
                        TPmax = TPmax + Pmax(j)
                End If
        End If
End If
Next i
```

where,

PL = Priority list order determined by the “PriorityList” Function

The technique used to satisfy the EOH constraints as presented in Equation 4.29 and the data flow in Figure 5.5, was similar to the technique described above. The pseudocode that satisfied EOH constraint is shown as follows:

```
For i = 1 to (U_max – 1)
    For j = (i + 1) to U_max
        temp = PL(j)
        IF |EOHDiff_i – EOHDiff_j| ≥ EOH_allow Then
            OnOffStatus(Temp) = True
        End if
    Next
Next
```

where,

PL = Priority list order determined by the “PriorityList” Function

Same technique applies for satisfying emission limits constraints (NOx, CO and SO2). The pseudocode for this constraint is shown below:

If $NOx_i > LNOx_i$ or $CO_i > LCO_i$ or $SO2_i > LSO2_i$ then

reinitialize, $P_i = P_{i(min)} + rand() * (P_{i(max)} - P_{i(min)})$

End if

7.3.1.5 Parameters Selection and Convergence Enhancements

There are only few parameters need to be tuned in PSO, which greatly influence the PSO algorithm performance, often stated as the exploration-exploitation tradeoff. Exploration is the ability to test curious regions in the problem in order to locate a good optimum. As defined in Shi and Eberhart (1998b) and

Trelea (2003), exploitation is the ability to concentrate the search method around a promising candidate solution in order to locate the optimum precisely. The PSO parameters are:

a. population size
b. cognitive / social ratio/ learning factor
c. inertia weight
d. maximum velocity

The population size or number of particles is in the typical range of 20 - 40. For most of the problems, 10 particles were large enough to get good results, but for some difficult problems, 100 or 200 particles were required and tried before. As reported in Shi and Eberhart (1999), PSO was not sensitive to the population size. However, the recent work by Carlisle and Dozier (2001) shown that it was generally true in terms of performance, but not in terms of costs. A population size of 20 appeared to be a better choice, which was small enough to be efficient, yet large enough to produce reliable results. Therefore, the population sizes of 20 particles were used in this work.

Kennedy (1998) asserted that the sum of the values of the cognitive and social components of the PSO (or terms as the learning factors), ρ1 and ρ2 should be about 4.0, and common usage was to set each equal to 2.05. However, other settings were also used in different papers. But usually ρ1 equaled to ρ2 and ranged from [0, 4]. The values used in this work was based on the recent work by Carlisle Carlisle and Dozier (2001), who had come to a conclusion that the reasonable compromise for the cognitive and social component values appear to be 2.8 and 1.3 respectively.

With reference to Shi and Eberhart (1998a), the role of the inertia weight *w* was considered very important in PSO convergence behavior, which was employed to control the impact of the previous history of velocities on the current velocity. In this way, the parameter *w* regulated the trade between the global (wide–ranging) and local (nearby) exploration abilities of the swarm. A large inertia weight facilitated global exploration (searching new areas); while a small one tended to facilitate local exploration, such as fine–tuning the current search area. A suitable value for the inertia weight *w* usually provided balance between global and local exploration abilities and consequently a reduction on the number of iterations required to locate the optimum solution. A general rule of thumb suggests that it was better to initially set the inertia to a large value, in order to make better global exploration of the search space, and gradually decrease it to get more refined solutions, thus a time decreasing inertia weight value was used as in Shi and Eberhart (1998a). As recommended above, the medium range of inertia weight value 0.5 was used in the following case study and analysis.

Velocity maximum, Vmax determined the maximum change for one particle could take during each iteration. Vmax usually was set according to the range of the particle, for example, the particle X1 of (x1, x2, x3) which belongs [-10, 10] will have Vmax = 20. With reference to Carlisle and Dozier (2001), when the particle reached Xmax, the Vmax would then be set to zero.

Finally the stop condition of PSO algorithm would be the maximum number of iterations the PSO had executed or the minimum error requirement it had achieved. The minimum error requirement for this analysis were where global best value of each particle remains within the defined error compare to 500 of previous iteration.

CHAPTER 8

SIMULATION AND CASE STUDIES

8.1 Introduction

Four case studies and test cases were performed in this work. The difference of each test case is tabulated in table below.

Table 8.1: Test cases

No.	Test	Benchmark Data	Benchmark Model	Plant Data	Actual Model	With EOH	With Emissions
1.	Test 1	X	X				
2.	Test 2		X	X			
3.	Test 3			X	X	X	
4.	Test 4			X	X	X	X

The first test case was carried out to check reliabilities, accuracy and performance of the Extended Priority List –Particle Swarm Optimization (EPL-PSO) algorithm against benchmark simulation data, with particular reference to Cheng, Liu, and Liu (2000) and Kazarlis, Bakirtzis, and Petridis (1996). The standard Unit Commitment optimization model was used instead of the developed optimization model in this simulation, because the benchmark problem is only available for standard Unit Commitment problem, which excludes emissions and EOH constraints.

After the EPL-PSO was tested, the standard model from Test One was used again in Test Two. In order to test with real plant data, real-time data obtained from the DCS and PMS9000 system as mentioned in Section 6.3 was used. The simulation results were then compared against current plant operations.

The remaining two test cases were carried out based on the optimization model mentioned in Section 4.24. The model was tested with EOH constraints but without the emissions constraints in Test Three. The complete optimization model, which includes EOH constraint, emissions model and constraints, was then tested in the final test (Test Four).

The simulations were carried out on a DELL Inspiron 8200 notebook with Pentium M 2.4 GHz processor and 512MB RAM memory. The EPL-PSO algorithm was programmed in Visual Basic language and the parameters for EPL-PSO with reference to Section 7.3.2.6 are as follows:

Table 8.2: EPL-PSO parameters

Population size	20
Maximum iteration	2000
Maximum velocity, *V*max	*Pi*(max) - *Pi*(min)
Inertia weight, *w*	0.5

The test results were then compared against current plant operations and discussed in this chapter.

8.2 Test One: Against Benchmark Simulation Data

The objective of Test One is to test the developed optimization algorithm's (EPL-PSO) reliabilities, accuracy and performance against benchmark test case. The same benchmark had been used to test with different optimization methods such as Lagrange Relaxation, Dynamic Programming, Evolution Programming and Genetic Algorithm as reported by Cheng, Liu, and Liu (2000) and Kazarlis, Bakirtzis, and Petridis (1996). However, the benchmark only involves standard Unit Commitment optimization constraints of power balance, spinning reserve, generator power limit and minimum up/down time, which excludes the emissions and EOH constraints. Therefore, the developed optimization model in this project was slightly modified to accommodate to this benchmark test case simulation.

The modifications were as follows:

1. Modification of start up cost and shut down cost formulation to constant parameters:

```
If Abs(MinUD(i)) >= minDownAllow(i) And
    Abs(MinUD(i)) <= (minDownAllow(i) + g(i, 3)) Then
    StC(i) = g(i, 2)
ElseIf Abs(MinUD(i)) > (minDownAllow(i) + g(i, 3)) Then
    StC(i) = g(i, 1)
End If
```

2. Excludes all emissions and EOH constraints:

    a. Total Production Cost

    TPC = sumLC

    b. Errors

    ```
    ER = (100 + Log(psocount + 1) / 2) * (C1 * (PowerSum - PowD(t)) ^ 2 _
      + C2 * (Res - (1 + R) * PowD(t)) ^ 2)
    ```

    c. Excludes CheckEOH function in the Main function

8.2.1 Benchmark Simulation Data

Simulations were conducted on a UC problem reported by Kazarlis et al. (1996). Ten units of generators (10-unit based problem) were used in this simulation and its system operator data and the load demand for 24 hours are tabulated in Table 8.3 and Table 8.4 respectively. In Table 8.3, "Initial Status" indicates how long the unit has been committed or decommitted. If the value is positive, it indicates the numbed of hours the unit has been committed, while if negative, it indicate the number of hours the unit has been decommited.

The results reported here represent the average of the entire population across 20 runs in order to stochastic nature of PSO. Total of seven test run were performed to investigate the characteristics of the EPL-PSO method, each with 25, 50, 100, 250, 500, 750 and 1000 generations. Adaptation of Particle Swarm parameters are shown in Table 8.2, as determined in Section 7.3.2.6.

8.2.2 Test One: Simulation Results and Discussions

The simulation results are tabulated in Table 8.5 through Table 8.7. In each case the difference between the average best and the average worst runs was calculated to indicate the likelihood that the EPL-PSO will reproduce the same range of solution.

The best total production cost of $565,163 was obtained for 1000 generations run and this suggested cost savings of 0.1157%, which is equivalent to $662, as compared to the optimum benchmark results of $565,825. The worst simulated results also suggested savings of 0.01142% or $646. Besides, the results also showed no errors or no violation of any of the constraints defined, such as reserve constraints, power demand, and minimum up and minimum down time.

Table 8.3: Generator system operator data (Kazarlis et al. (1996))

Unit	EU	1	2	3	4	5	6	7	8	9	10
Pmax	MW	455	455	130	130	162	80	85	55	55	55
Pmin	MW	150	150	20	20	25	20	25	10	10	10
A	\$/h	1000	970	700	680	450	370	480	660	665	670
β	\$/MWh	16.19	17.26	16.6	16.5	19.7	22.26	27.74	25.92	27.27	27.79
γ	\$/MWh^2	0.00048	0.00031	0.002	0.00211	0.00398	0.00712	0.0079	0.00413	0.00222	0.00173
Min Up	h	8	8	5	5	6	3	3	1	1	1
Min Down	h	8	8	5	5	6	3	3	1	1	1
Hot Start Cost	\$	4500	5000	550	560	900	170	260	30	30	30
Cold Start Cost	\$	9000	10000	1100	1120	1800	340	520	60	60	60
Cold Start Hours	h	5	5	4	4	4	2	2	0	0	0
Initial Status	h	8	8	-5	-5	-6	-3	-3	-1	-1	-1

Table 8.4: Load demand for 24 hours (Kazarlis et al. (1996))

Hour	Load	Hour	Load	Hour	Load
1	700	9	1300	17	1000
2	750	10	1400	18	1100
3	850	11	1450	19	1200
4	950	12	1500	20	1400
5	1000	13	1400	21	1300
6	1100	14	1300	22	1100
7	1150	15	1200	23	900
8	1200	16	1050	24	800

As shown in Table 8.5, the proposed method gave the better solution in comparison with other methods, except GA method as reported by Senjyu et al. (2002). EPL-PSO method obtained $1193 higher total production cost (TPC at best case) as compared to the results as reported in Senjyu et al. (2002), which gave $563,977. However, Senjyu et al. (2002)'s GA achievement had provided a lower stability solution with difference between the best and worst case by $1629, while EPL-PSO provides better stability with only $25 or 0.0045% difference.

Besides, the proposed method, EPL-PSO algorithm also indicated good reliabilities and consistencies as shown in Table 8.5, which gave 100% success rates in all the simulations and less than 0.02% difference between the best and the worst case. The proposed method also shows good performance with the best computation time of only 31.5 seconds for 500 generations as compared to other artificial intelligence methods such as EP and GA, which required more than twice the computational time than EPL-PSO algorithm.

When further test were performed with different generations, it appears that the EPL-PSO algorithm performs better global optimum results and success rates with higher number of generations. As illustrated in Figure 8.1 and Figure 8.2, it shows that EPL-PSO algorithm have very good success rate (100%) in all simulations. The total production cost obtained however was relatively insensitive to the number of generation when the number of generation is more than 250. Figure 8.2 indicates that the execution time increases in a quadratic manner with the increase of generations.

As a conclusion, the simulation results above shows that the proposed EPL-PSO method provides better optimum, consistent and reliable results, and satisfying all the constraints with the best computation time.

Table 8.5: Simulation results comparison (Total production cost, $ for 10 units)

Final Gen.	Optimization Solution											
	D.P.	Lagr. Relax.	EP Juste et al. (1999)	GA Kazarlis et al. (1996)		GA Senjyu et al. (2002)		EPL-PSO				
				Best	Worst	Best	Worst	Success (%)	Average	Best	Worst	Difference (%)
500	565,825	565,825	0	565,825	570,032	563,977	565,606	100	565,181	565,170	565,195	0.0045
1000	565,825	565,825						100	565,170	565,163	565,179	0.0029

Table 8.6: Simulation computation time comparison (Average time, seconds for 10 units)

Units	Final Generation	Optimization Solution					
		D.P.	Lagr. Relax.	EP Juste et al. (1999)	GA Kazarlis et al. (1996)	GA Senjyu et al. (2002)	EPL-PSO
10	500	-	-	100	221	85	31.5
10	1000	-	-	-	-	-	67

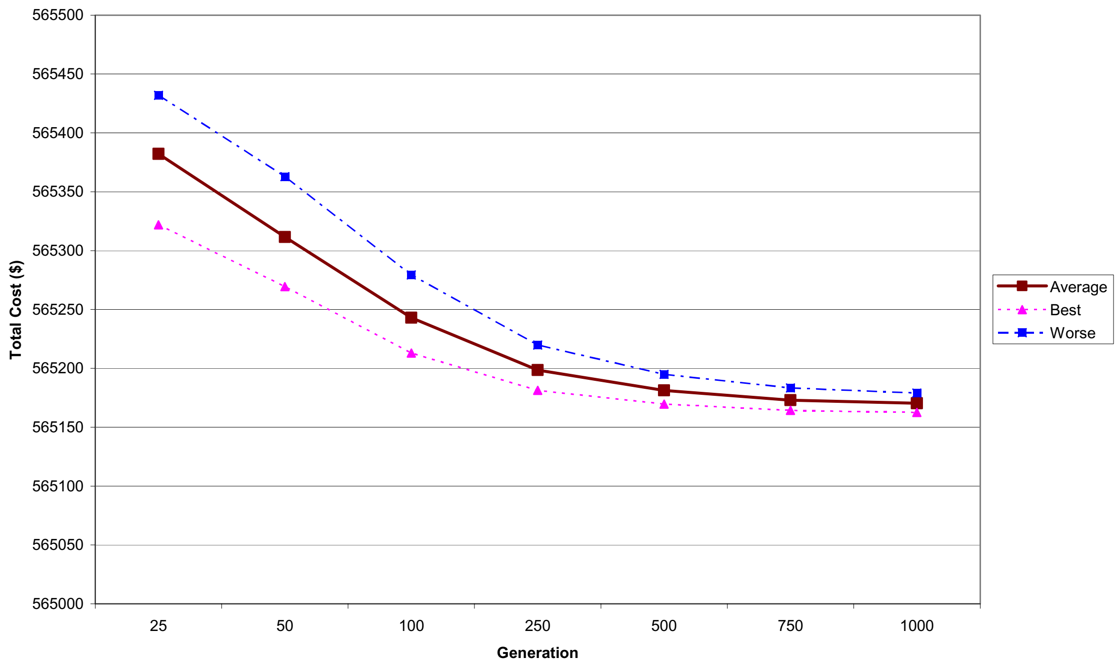

Figure 8.1: EPL-PSO average results from 20 runs with increase number of generations

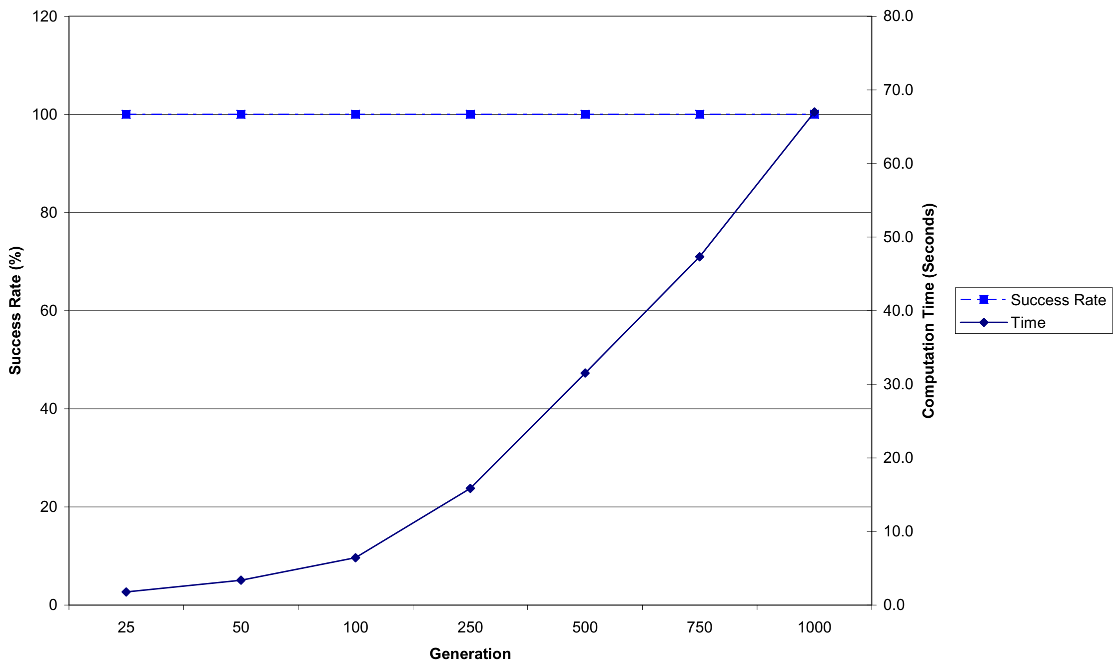

Figure 8.2: EPL-PSO performance with increase number of generations

Table 8.7: Test one commitment schedule (Total cost: $ 565,163)

Time	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10	Error
1	1	1	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0	0
3	1	1	0	1	0	0	0	0	0	0	0
4	1	1	1	1	0	0	0	0	0	0	0
5	1	1	1	1	0	0	0	0	0	0	0
6	1	1	1	1	1	0	0	0	0	0	0
7	1	1	1	1	1	0	0	0	0	0	0
8	1	1	1	1	1	0	0	0	0	0	0
9	1	1	1	1	1	1	1	0	0	0	0
10	1	1	1	1	1	1	1	1	0	0	0
11	1	1	1	1	1	1	1	1	1	0	0
12	1	1	1	1	1	1	1	1	1	1	0
13	1	1	1	1	1	1	1	1	0	0	0
14	1	1	1	1	1	1	1	0	0	0	0
15	1	1	1	1	1	0	0	0	0	0	0
16	1	1	1	1	1	0	0	0	0	0	0
17	1	1	1	1	1	0	0	0	0	0	0
18	1	1	1	1	1	0	0	0	0	0	0
19	1	1	1	1	1	0	0	0	0	0	0
20	1	1	1	1	1	1	1	1	0	0	0
21	1	1	1	1	1	1	1	0	0	0	0
22	1	1	1	1	1	1	1	0	0	0	0
23	1	1	0	1	1	0	0	0	0	0	0
24	1	1	0	0	0	0	0	0	0	0	0

Table 8.8: EPL-PSO performance with increase number of generations

Final Gen.	Optimization Solution							
	D.P.	PL-HPSO						
		Success (%)	Computation Time (s)	Average	Best	Worst	Dif (%)	Savings (%)
25		100	1.8	565382	565322	565432	0.0195	0.0782
50		100	3.4	565312	565269	565363	0.0165	0.0907
100	565825	100	6.4	565243	565213	565279	0.0117	0.1029
250	-	100	15.8	565199	565181	565220	0.0068	0.1107
500	-	100	31.5	565181	565170	565195	0.0045	0.1138
750	-	100	47.3	565173	565164	565183	0.0034	0.1152
1000	-	100	67.0	565170	565163	565179	0.0029	0.1157

8.3 Test Two

After the EPL-PSO algorithm was tested and validated against the benchmark data in Test One, the standard model, which excludes emissions and EOH constraints, was used again in Test Two. The objective of Test Two was to test with real-time data obtained from the DCS and PMS9000 system as mentioned in Section 6.3. The simulation results were then compared against current plant operations.

Due to the fact that gas turbine model developed was a heat consumption model instead of input-output model, with units GJ/h, slight modification was performed to include the fuel cost (RM/GJ) constant back to the total production cost function. The modification to Fitness function was as follows:

$$sumLC = (.x * FC(i) * LC(i) + StSdC(i)) + sumLC$$

8.3.1 Test Two: Test Conditions

Simulations were conducted on data acquired from the plant DCS and PMS9000 system on 3rd of January 2003 from 07:00 till 23:00. Four units of ABB 13E gas turbines of the open cycle plants were used in this simulation. Its system operator data and the load demand were tabulated in Table 8.9 and Table 8.10 respectively. Due to some unavailable information, several assumptions had been made in this simulation. The hot startup and cold startup cost were assumed to be the same for all the gas turbines and were estimated to be $5,000 and $10,000 respectively. Meanwhile the shutdown cost was assumed to be zero and power reserve for the open cycle was set to 5%.

The test was performed with 2000 iterations for the solution to convergence. Adaptation of Particle Swarm parameters are tabulated in Table 8.2, as determined in Section 7.3.2.6.

Table 8.9: ABB-13E gas turbine generator system operator data

Unit	EU	1	2	3	4
Pmax	MW	130	130	130	130
Pmin	MW	60	60	60	60
A1	GJ/h	389.57	610.37	-32917	412.13
A2	GJ/MWh	7.06	-0.6637	2574.1	6.7555
A3	GJ/MWh^2	0.00797	0.096495	-81.004	0.010618
A4	GJ/MWh^3	0	-0.00033509	1.3399	0
A5	GJ/MWh^4	0	0	-0.012258	0
A6	GJ/MWh^5	0	0	5.8876 E-5	0
A7	GJ/MWh^6	0	0	-1.1612 E-7	0
Fuel Cost	sen/GJ	6.07	6.07	6.07	6.07
Min Up	H	5	5	5	5
Min Down	H	5	5	5	1
*Hot Start Cost	$	5000	5000	5000	5000
*Cold Start Cost	$	10000	10000	10000	10000
Cold Start Hours	H	1	1	1	1
Initial Status	h	-5	-5	-5	-5

* *Assumption – data not available from plant*

Table 8.10: Load demand data (acquired from Siemens Teleperm ME DCS)

t	Date	Time	Power Demand (MW)
1	3/1/2003	7:00:00	0
2	3/1/2003	8:00:00	260.50
3	3/1/2003	9:00:00	449.68
4	3/1/2003	10:00:00	480.68
5	3/1/2003	11:00:00	471.81
6	3/1/2003	12:00:00	369.74
7	3/1/2003	13:00:00	326.51
8	3/1/2003	14:00:00	449.30
9	3/1/2003	15:00:00	470.59
10	3/1/2003	16:00:00	451.90
11	3/1/2003	17:00:00	423.45
12	3/1/2003	18:00:00	383.19
13	3/1/2003	19:00:00	423.95
14	3/1/2003	20:00:00	422.77
15	3/1/2003	21:00:00	397.43
16	3/1/2003	22:00:00	346.09
17	3/1/2003	23:00:00	379.71

8.3.2 Test Two: Simulation Results and Discussions

The simulation results of Test Two are tabulated in Table 8.11. The total production cost of $44,228 was obtained for 2000 generations run. This indicated savings of $405 as compared to the actual measurement of operating cost, which was equivalent to 0.9074% savings. EPL-PSO provided different unit commitment scheduling as compared to the actual measurement, where GT6 was not selected as the cheapest unit to start and operate instead of GT3. Besides, GT4 and GT5 were prioritized to operate as full load as possible.

The results as shown in Table 8.11 also shows that all the constraints defined, namely reserve constraints, power demand, minimum up / down time and generator power limits were satisfied.

Figure 8.3 illustrates the EPL-PSO performance with increase number of generation. As shown in the figure, EPL-PSO again had shown its great stabilities in searching of the optimum results within just few iteration as found in Test One.

As discussed above, the proposed EPL-PSO method provides better optimum unit commitment and load dispatch solution as compared to the current plant operating practices. The simulation results obtained in this study was however still subject to other unavailable or unknown information of actual plant conditions and constraints, such as maintenance, resources, other plant conditions, etc, which lead to plant different operational method and decision. One such example is when the gas turbine may not able to operate at full load of 130 MW as designed, due to actual operating constraints.

Table 8.11: Simulation results comparison with actual plant operation data

	Actual (MW)					EPL-PSO (MW)				
T	GT3	GT4	GT5	GT6	Total	GT3	GT4	GT5	GT6	Total
1	0	0	0	0	0	0	0	0	0	0
2	0	112.52	61.08	86.90	259.83	60.00	70.50	130.00	0	260.50
3	113.88	113.29	113.83	108.68	449.68	99.67	130.00	130.00	90.01	449.68
4	121.25	119.15	122.03	118.25	480.68	117.85	130.00	130.00	102.83	480.68
5	121.12	116.50	117.69	116.51	471.81	112.72	130.00	130.00	99.09	471.81
6	120.52	67.50	67.54	114.18	369.74	82.45	81.12	130.00	76.17	369.74
7	96.71	68.05	66.59	95.17	326.51	62.44	72.77	130.00	61.30	326.51
8	120.00	98.30	118.86	112.14	449.30	99.85	130.00	130.00	89.45	449.30
9	120.68	117.39	117.51	115.01	470.59	112.01	130.00	130.00	98.58	470.59
10	111.09	118.58	116.66	105.56	451.90	101.46	130.00	130.00	90.44	451.90
11	97.58	117.01	115.44	93.42	423.45	85.20	130.00	130.00	78.25	423.45
12	78.33	116.68	115.57	72.61	383.19	88.07	84.52	130.00	80.60	383.19
13	98.49	113.34	112.63	99.49	423.95	85.48	130.00	130.00	78.47	423.95
14	100.27	113.31	113.73	95.47	422.77	84.73	130.00	130.00	78.04	422.77
15	89.86	112.20	111.77	83.60	397.43	70.36	130.00	130.00	67.07	397.43
16	80.86	92.54	91.95	80.73	346.09	71.67	76.19	130.00	68.22	346.09
17	101.08	92.95	93.97	91.70	379.71	86.67	83.56	130.00	79.48	379.71
	Total Cost ($)				**44,633**					**44,228**
	Savings ($)									**+405**
	Savings (%)									**0.9074%**

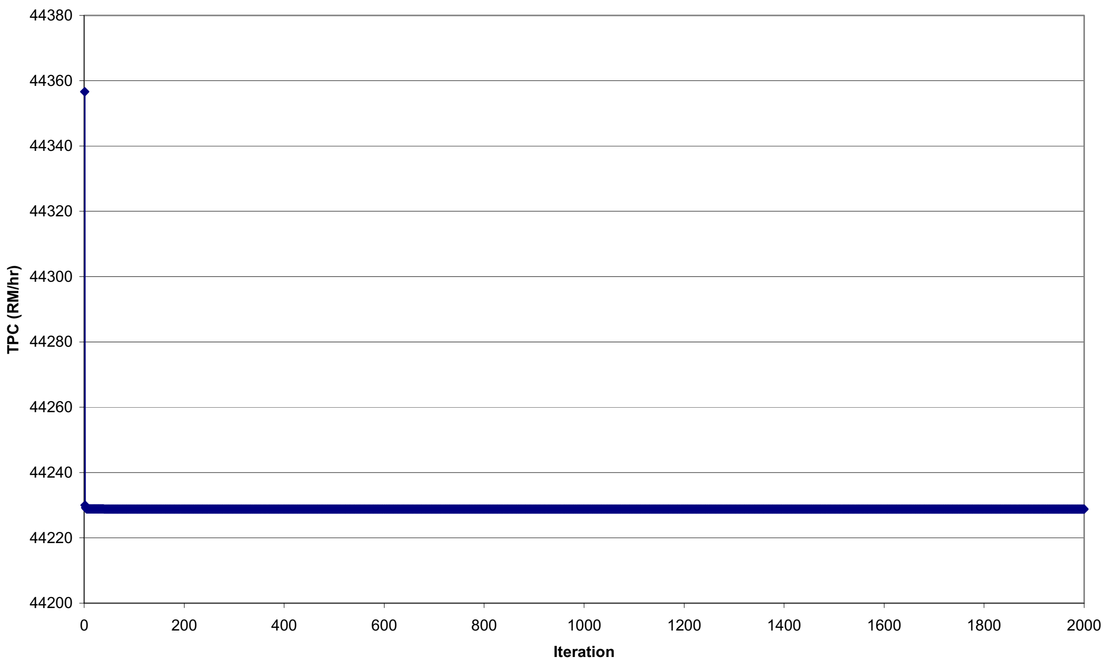

Figure 8.3: Test 2 EPL-PSO performance with increase number of generations

8.4 Test Three

After the EPL-PSO was tested with actual plant data in Test Two, the standard model from Test One was used again in Test Three in order to test the EOH constraints algorithm. In this test, the test condition in Test Two was intentionally modified to create a common and easy visualized condition, where the correct results could be predicted. Two sets of EOH parameters were created in this simulation. The test results were then compared against predicted results.

8.4.1 Test Three: Test Conditions

Slight modification was made to test condition in Test Two to create a test condition for this simulation. The modifications were the load demand data, where the demand was reduced such that only three gas turbines would be selected to produce power at each interval. Its system operator data and the load demand were tabulated in Table 8.9 and Table 8.12 respectively.

Two sets of EOH parameters of the system were created in this simulation and are tabulated in Table 8.13. The first set of EOH parameters were created such that Unit 1 and Unit 2 were not within the allowable EOH difference, which was less than 500 hours. Indirectly these settings would force the optimizer to select only one and the cheapest gas turbine to operate among these two units. The same purpose was created again in the second set of EOH parameters, where this time Unit 2 and Unit 3 were chosen.

The test was performed with 1000 iterations for the solution to convergence. Adaptation of Particle Swarm parameters are tabulated in Table 8.2.

Table 8.12: Load demand data for Test Three

t	Power Demand (MW)
1	0
2	250
3	300
4	280
5	280
6	300
7	300
8	220
9	220
10	270

Table 8.13: EOH constraints parameters

Unit	Current EOH	Next EOH for Maintenance	Allowable EOH Diff.
SET 1			
1	3000	10000	500
2	3400	10000	500
3	5000	10000	500
4	7000	10000	500
SET 2			
1	3000	10000	500
2	3600	10000	500
3	3700	10000	500
4	7000	10000	500

8.4.2 Test Three: Simulation Results and Discussions

The simulation results of Test Three are tabulated in Table 8.14 through Table 8.16. The simulation of this test condition without EOH constraint was carried as a benchmark for comparisons. As shown in Table 8.14, Unit 4 was prioritized as the most expensive unit to operate. The total production cost of $31,614 was obtained for 1000 generations run.

When EOH constraint was incorporated to the simulation, the results for Set 1 EOH constraint indicated that the optimizer had given an accurate unit commitment by not committing Unit 1 and Unit 2 at the same time. The optimizer again shown its accuracy when tested with Set 2 EOH constraint, where Unit 2 and Unit 3 were not committed at the same time. However, due to EOH constraints, the TPC obtained from Set 1 and Set 2 were slightly higher as compared to the simulation results without EOH constraint as shown in Table 8.14.

The results as shown in Table 8.14 through Table 8.16 also showed that other constraints as defined, namely reserve constraints, power demand, minimum up / down time and generator power limits were satisfied.

In conclusion, the proposed EOH constraint algorithm had incorporated well in the EPL-PSO method and gave the correct results as predicted.

Table 8.14: Simulation results (without EOH constraints)

t	Unit 1 (MW)	Unit 2 (MW)	Unit 3 (MW)	Unit 4 (MW)	Total Power Generated (MW)	Fitness	Error
1	0	0	0	0	0	0	0
2	60.00	60.01	129.99	0	250.00	30,165.41	0
3	86.57	83.43	130.00	0	300.00	189.98	0
4	73.20	76.80	130.00	0	280.00	179.85	0
5	73.14	76.86	130.00	0	280.00	179.85	0
6	86.54	83.46	130.00	0	300.00	189.98	0
7	86.57	83.43	130.00	0	300.00	189.98	0
8	75.70	77.54	66.76	0	220.00	172.22	0
9	75.84	77.60	66.55	0	220.00	172.22	0
10	65.96	74.04	130.00	0	270.00	174.89	0
					TPC	31,614.37	

Table 8.15: Set 1 simulation results (with EOH constraints)

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Generated	Fitness	Err
1	0	0	0	0	0	0	0
2	0	60.00	130.00	60.00	250.00	30166.23	0
3	0	87.03	130.00	82.97	300.00	190.93	0
4	0	78.22	130.00	71.78	280.00	180.73	0
5	0	78.23	130.00	71.77	280.00	180.73	0
6	0	87.03	130.00	82.97	300.00	190.93	0
7	0	87.02	130.00	82.98	300.00	190.93	0
8	0	79.09	66.41	74.49	220.00	173.10	0
9	0	79.03	66.29	74.68	220.00	173.10	0
10	0	74.68	130.00	65.32	270.00	175.74	0
					TPC	31622.41	

Table 8.16: Set 2 simulation results (with EOH constraints)

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Generated	Fitness	Err
1	0	0	0	0	0	0	0
2	60.00	0	130.00	60.00	250.00	30166.00	0
3	88.91	0	130.00	81.09	300.00	191.04	0
4	77.50	0	130.00	72.50	280.00	180.85	0
5	77.47	0	130.00	72.53	280.00	180.85	0
6	88.89	0	130.00	81.11	300.00	191.04	0
7	88.88	0	130.00	81.12	300.00	191.04	0
8	79.97	0	66.86	73.17	220.00	173.23	0
9	79.93	0	66.69	73.38	220.00	173.23	0
10	71.79	0	130.00	68.21	270.00	175.85	0
					TPC	31623.13	

8.5 Test Four

Upon concluding the above tests, the proposed EPL-PSO method was proven to be a competitive method in this optimization problem. In Test Four, the complete developed model and objective functions as documented in Chapter 4 was tested. This included the emissions model and emissions constraints. The real time data obtained from the DCS and PMS9000 system as mentioned in Section 6.3 was used. Because of unavailable emission data from this plant, data from similar type of gas turbine were taken from other plant instead. Finally the test results were then compared against current plant operations.

Besides, further test were carried out with different generations to study the behavior of EPL-PSO algorithm in solving this complete Environmental Unit Commitment optimization problem.

8.5.1 Test Four: Test Conditions

Test conditions for this simulation were mainly based on Test Two. Its system operator data and the load demand were as tabulated in Table 8.9 and Table 8.10 respectively. The changes to Table 8.9 were:

a. With reference to the simulation results from Test Two, GT4 and GT5 were found operating at maximum design power output (130 MW), whereas the actual plant data showed that GT4 and GT5 only operated at around 120 MW. One of possible reasons was the gas turbine might not able to operate at full load as designed, due to actual operating conditions, which was not taking consideration into the model at this moment, such as ambient condition and etc. Therefore, individual gas turbine maximum power output, Pmax was reduced to 125 MW in this simulation to reflect as close as possible to the actual conditions.

b. The startup and shut down cost was determined from Equation 4.7, instead of assuming constant as implemented in Test Two. However, the actual gas turbine startup and shut down cost coefficient could not be obtained from the plant in this research. The coefficients therefore were assumed and are tabulated in Table 8.17.

The real time data obtained from the DCS and PMS9000 system as mentioned in Section 6.3 was used. However, no emission instrumentations for NOx, CO and SO2 were present at Connaught Bridge Power Station. (CBPS) Therefore, emission data for this simulation was obtained from other power station that had similar type of gas turbine. These data were acquired from the two gas turbines (GT1 and GT2) manufactured by ABB (same model with CBPS) and GE of a combined cycle plant at Gelugor Power Station (GPS), via the similar system architecture as elaborated in Section 6.3. The emission data of GT1 and GT2 are illustrated in Figure 8.4 and Figure 8.5 respectively. In this simulation, the plant's GT3 and GT5 emission model were modeled with GT1 data, while GT4 and GT6 with GT2 data. With this data, the emission model of the gas turbines were generated with the developed modeling tools (Section 4.5) and the polynomial model coefficient are tabulated in Table 8.17.

The results reported here represented the average of the entire population across 20 runs in order to address the stochastic nature of PSO. Total of five test run were performed to investigate the characteristics of the EPL-PSO method for this optimization problem, each with 50, 100, 250, 500 and 1000 generations.

Adaptation of Particle Swarm parameters are shown in Table 8.2 and Table 8.18, as determined in Section 7.3.2.6. The multiobjective weight W of 50% was taken in this simulation, which represented the relative weight assigned to the total production cost and consequently (1-W) was the relative weight assigned to the emission (please refer to Chapter 4). While each individual emissions penalty factor W_n, or commonly terms as weightage, were considered equally important in this simulation, and therefore value of 1/3 was taken.

Two sets of emission parameters of the system were created in this simulation and are tabulated in Table 8.19. The first set (SET 1) of emission parameters were created with very high allowable emission limits, such that the final multi-objective optimum results with consideration of emissions could be studied against the actual plant operation data.

Table 8.17: Gas turbine generator startup and shutdown cost coefficient and emissions model coefficient

GT	EU	GT 3	GT 4	GT 5	GT6
Pmin	MW	60	60	60	60
Pmax	MW	125	125	125	125
Cold Start, C_c	GJ	85	101	114	94
Fixed Cost, C_F	$	20.59	20.59	22.57	10.65
Thermal Time, α	hour	0.2	0.2	0.2	0.18
<u>Nox</u>					
B1	ppm	66.2738	71.99455	66.2738	71.99455
B2	ppm/MW	-1.35705	-1.532344	-1.35705	-1.532344
B3	ppm/MW^2	1.823837E-02	2.013583E-02	1.823837E-02	2.013583E-02
<u>CO</u>					
C1	ppm	-86.20895	10.5093	-86.20895	10.5093
C2	ppm/MW	3.423565	0.2042628	3.423565	0.2042628
C3	ppm/MW^2	-4.327569E-02	1.085087E-03	-4.327569E-02	1.085087E-03
C4	ppm/MW^3	1.773579E-04	0	1.773579E-04	0
<u>SO2</u>					
D1	ppm	-9.709012	1.952993	-9.709012	1.952993
D2	ppm/MW	0.1511922	-1.044413E-02	0.1511922	-1.044413E-02
D3	ppm/MW^2	9.922996E-04	8.388499E-05	9.922996E-04	8.388499E-05
D4	ppm/MW^3	-6.638899E-06	0	-6.638899E-06	0
D5	ppm/MW^4	-7.44982E-08	0	-7.44982E-08	0
D6	ppm/MW^5	-2.543984E-09	0	-2.543984E-09	0
D7	ppm/MW^6	2.420945E-11	0	2.420945E-11	0

Table 8.18: Test Four EPL-PSO parameters

Population size	20
Maximum iteration	2000
PSO Inertia weight, *w*	0.5
Multi-objective weight, *W*	0.5
Penalty factor for NOx Parameter, *w1*	0.33
Penalty factor for CO Parameter, *w2*	0.33
Penalty factor for SO2 Parameter, *w3*	0.33

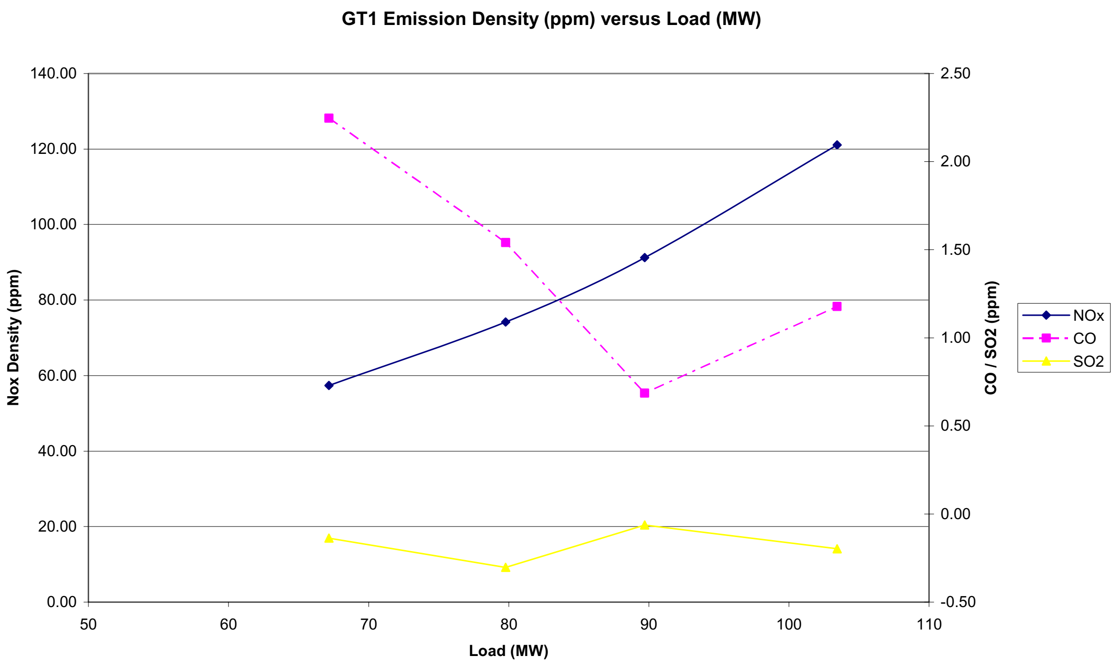

Figure 8.4: GT1 emissions data

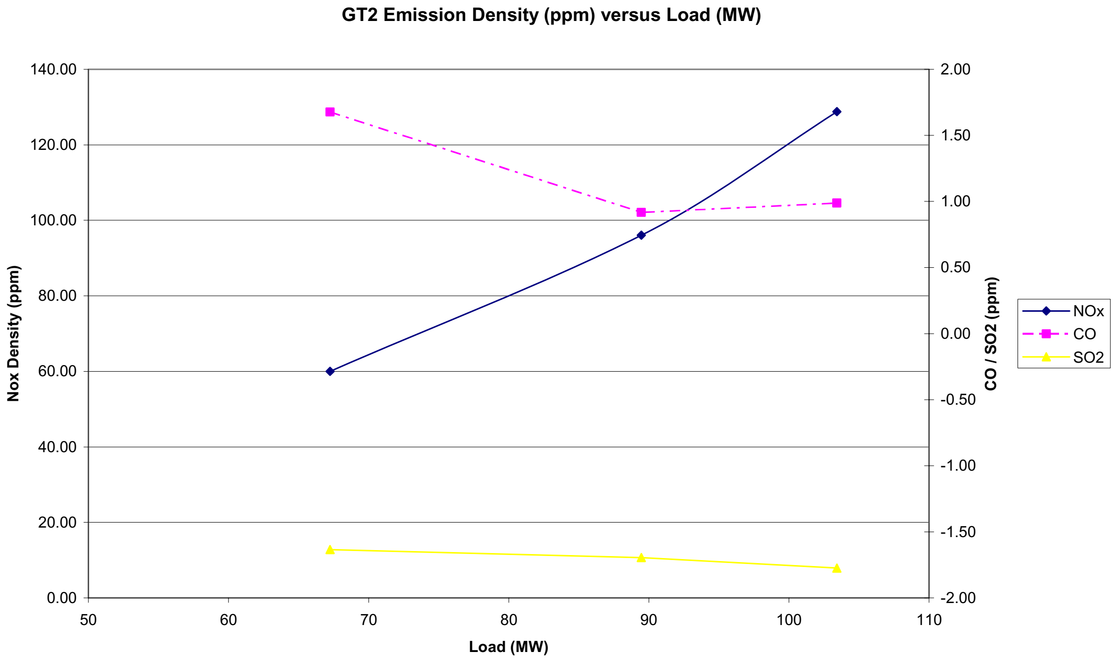

Figure 8.5: GT2 emissions data

Table 8.19: Emissions constraints parameters

GT	Allowable NOx Limits (ppm)	Allowable CO Limits (ppm)	Allowable SO2 Limits (ppm)
SET 1			
3	300	50	10
4	300	50	10
5	300	50	10
6	300	50	10
SET 2			
3	180	50	10
4	180	50	10
5	180	50	10
6	180	50	10

The first set (SET 1) of data also was used to simulate with different generations to study the behavior of EPL-PSO algorithm in solving this complete optimization problem.

In SET 2, the allowable emission limit of NOx was reduced slightly lower to the emission results from SET 1. These settings would indirectly force the optimizer to commit and operate higher load on alternative gas turbines. The results would then be studied and discussed in details in following section.

8.5.2 Test Four: Simulation Results and Discussions

8.5.2.1 SET 1

The simulation results of Test Four – SET 1 are tabulated in Table 8.20. The simulation of this test condition which was set with very high allowable emission limits was carried out to provide better study and comparison against actual plant condition. The actual TPC was recalculated with the non-constant startup cost formulation based on the collected actual plant operating data. TPC value of $12,411 was obtained. With the emission model generated above, the emission of NOx, CO and SO2 were estimated with reference to the actual plant operating data. The calculated and simulated results are tabulated in Table 8.20 for comparisons.

As shown in the table, GT5 was still prioritized as the cheapest unit to operate as shown in the previous test. The average total production cost (TPC) of $12,326 was obtained for 20 run with 1000 generations. This indicated cost savings of $85, which is equivalent to 0.685% as compared to the actual plant data. The simulation results again had shown that the proposed EPL-PSO method provided better optimized solution where the total emission of NOx and CO was lower than the actual plant data. Although emission SO2 showed higher than the actual plant data, but as an overall, the total emission was still much lower.

Table 8.20: Test Four - simulation results comparison with actual plant operation data (SET 1)

	Actual (MW)					EPL-PSO (MW)				
T	GT3	GT4	GT5	GT6	Total	GT3	GT4	GT5	GT6	Total
1	0	0	0	0	0	0	0	0	0	0
2	0	112.52	61.08	86.90	259.83	91.74	77.94	90.81	0	260.50
3	113.88	113.29	113.83	108.68	449.68	110.11	108.50	125.00	106.07	449.68
4	121.25	119.15	122.03	118.25	480.68	116.31	119.68	125.00	119.68	480.68
5	121.12	116.50	117.69	116.51	471.81	113.81	118.91	125.00	114.09	471.81
6	120.52	67.50	67.54	114.18	369.74	98.76	86.60	98.06	86.31	369.74
7	96.71	68.05	66.59	95.17	326.51	89.58	75.51	86.59	74.83	326.51
8	120.00	98.30	118.86	112.14	449.30	110.06	108.29	125.00	105.95	449.30
9	120.68	117.39	117.51	115.01	470.59	113.61	118.28	125.00	113.70	470.59
10	111.09	118.58	116.66	105.56	451.90	110.52	109.50	125.00	106.89	451.90
11	97.58	117.01	115.44	93.42	423.45	104.99	97.14	125.00	96.33	423.45
12	78.33	116.68	115.57	72.61	383.19	101.46	90.96	100.28	90.49	383.19
13	98.49	113.34	112.63	99.49	423.95	105.07	97.40	125.00	96.48	423.95
14	100.27	113.31	113.73	95.47	422.77	104.83	96.88	125.00	96.06	422.77
15	89.86	112.20	111.77	83.60	397.43	98.93	86.91	125.00	86.58	397.43
16	80.86	92.54	91.95	80.73	346.09	93.60	79.88	93.23	79.39	346.09
17	101.08	92.95	93.97	91.70	379.71	100.80	89.82	99.72	89.37	379.71
			Total Cost ($)		**12,411**					**12,326**
			Savings ($)							**+85**
										0.685%
			Total NOx (ppm)		**8,179.21**					**8,059.46**
			Total CO(ppm)		**1,504.74**					**1,425.85**
			Total SO2 (ppm)		**120.56**					**148.65**
			Total Emission (ppm)		**9,804.51**					**9,633.96**

Besides, the simulation results again showed that all constraints as defined, namely reserve constraints, power demand, minimum up / down time, generator power limits and emission (NOx, CO, SO2) allowable limits were satisfied.

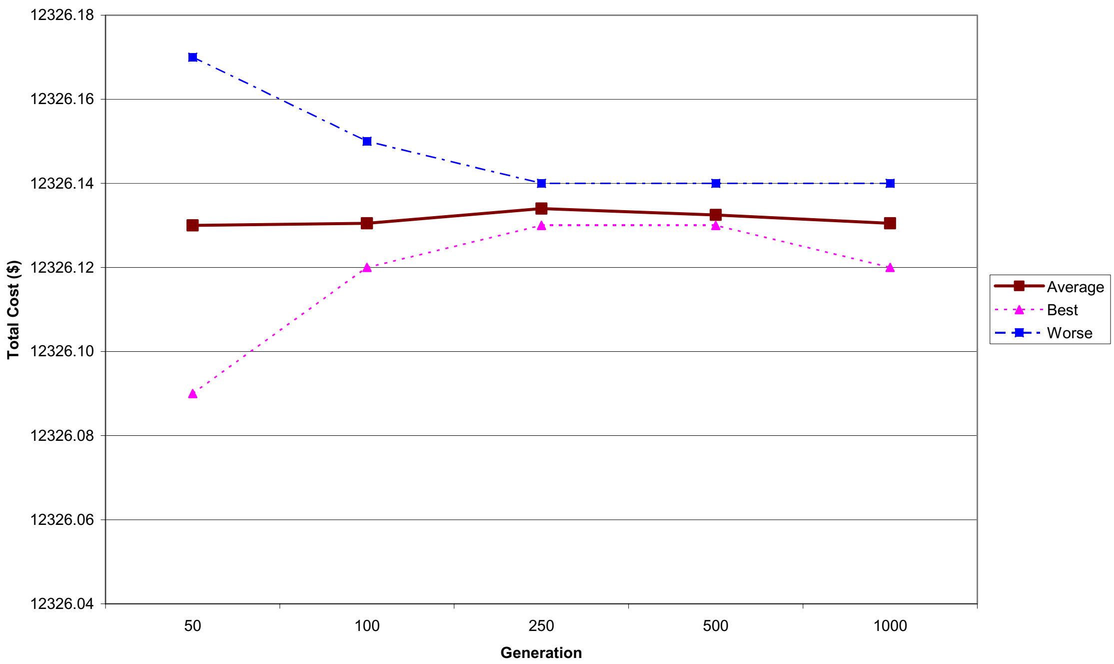

Figure 8.6: EPL-PSO average results from 20 runs in Test Four with increase number of generations

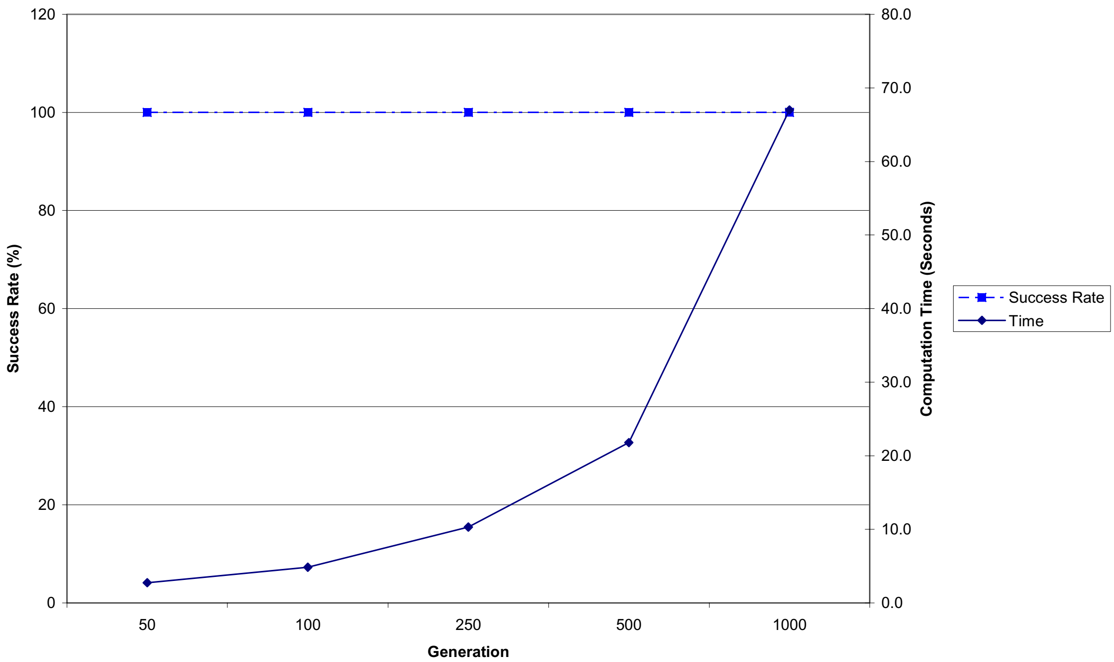

Figure 8.7: EPL-PSO performance in Test Four with increase number of generations

When further test were performed with different generations, it appears that the EPL-PSO algorithm could achieve optimum results with just few iterations and performs consistent results with only maximum \$0.08 difference between the best and worst value. As illustrated in Figure 8.6 and Figure 8.7, it showed that EPL-PSO algorithm had good success rate (100%) in all simulations and the total production cost obtained did not appear to be dependent on the number of generation. Figure 8.7 also indicated that the execution time increases in a quadratic manner with the increase of generations.

8.5.2.2 SET 2

In SET 2, when the allowable emission limit of NOx was reduced slightly lower to the emission results from SET 1, the optimizer appeared had generated an optimum results among the several objective functions (multi-objective), which were minimum TPC and total emissions (NOx, CO and SO2) and trying to prevent any of the gas turbine releasing NOx more than the allowable limits. The simulation results of Test Four – SET 2 are tabulated in Table 8.21.

Based on the emission model, GT3 and GT5 would generate higher NOx emission content as compared to GT4 and GT6. As predicted, the settings in SET 2 would indirectly force the optimizer to commit and operate higher load on alternative gas turbines, where in this case, GT3 and GT5 should operate with lower load as compare to the SET 1 results. As shown in the table, although GT5 was prioritized as the cheapest unit to operate (as demonstrated in the previous test), GT5 was forced to operate at lower load in order to satisfy emission (NOx) constraint.

As tabulated in the table, the simulation results again had shown that the proposed EPL-PSO method provided better optimized solution. The average total production cost of \$12,412 was obtained for 20 run with 1000 generations. Although the TPC obtained was very close to the actual plant data (with only 0.008% higher operating cost), but the total emission released (ppm) of NOx, CO and SO2 was lower than the actual plant data. The simulation results again showed that the constraints as defined, namely reserve constraints, power demand, minimum up / down time, generator power limits and emission (NOx, CO, SO2) allowable limits were satisfied.

Table 8.21: Test Four - simulation results comparison with actual plant operation data (SET 2)

	Actual (MW)					EPL-PSO (MW)				
T	GT3	GT4	GT5	GT6	Total	GT3	GT4	GT5	GT6	Total
1	0	0	0	0	0	0	0	0	0	0
2	0	112.52	61.08	86.90	259.83	91.81	77.77	90.92	0	260.50
3	113.88	113.29	113.83	108.68	449.68	111.21	112.09	118.13	108.24	449.68
4	121.25	119.15	122.03	118.25	480.68	125.00	119.62	118.14	117.92	480.68
5	121.12	116.50	117.69	116.51	471.81	116.15	119.32	118.12	118.22	471.81
6	120.52	67.50	67.54	114.18	369.74	98.75	86.61	98.10	86.28	369.74
7	96.71	68.05	66.59	95.17	326.51	89.53	75.53	86.59	74.86	326.51
8	120.00	98.30	118.86	112.14	449.30	110.93	112.03	118.13	108.20	449.30
9	120.68	117.39	117.51	115.01	470.59	115.52	119.14	118.14	117.79	470.59
10	111.09	118.58	116.66	105.56	451.90	111.78	112.94	118.13	109.05	451.90
11	97.58	117.01	115.44	93.42	423.45	108.68	105.03	106.48	103.26	423.45
12	78.33	116.68	115.57	72.61	383.19	101.50	90.89	100.32	90.48	383.19
13	98.49	113.34	112.63	99.49	423.95	108.78	105.30	106.52	103.35	423.95
14	100.27	113.31	113.73	95.47	422.77	108.55	104.83	106.38	103.01	422.77
15	89.86	112.20	111.77	83.60	397.43	104.23	95.67	102.51	95.02	397.43
16	80.86	92.54	91.95	80.73	346.09	93.60	79.83	93.27	79.40	346.09
17	101.08	92.95	93.97	91.70	379.71	100.84	89.75	99.75	89.36	379.71
	Total Cost ($)				**12,411**					**12,412**
	Savings ($)									**-1**
										-0.008%
	Total NOx (ppm)				**8,179.21**					**8,020.88**
	Total CO(ppm)				**1,504.74**					**1,402.63**
	Total SO2 (ppm)				**120.56**					**100.53**
	Total Emission (ppm)				**9,804.51**					**9,524.04**

8.6 Conclusion Remarks

The simulation above had been conducted successfully and had achieved the objectives. The first simulation provided good comparison of the optimization algorithm (EPL-PSO) in terms of its accuracy, reliability and performance against benchmark simulation data, with particular reference to Cheng, Liu, and Liu (2000) and Kazarlis, Bakirtzis, and Petridis (1996). The subsequent test was then simulated against real-time data of current plant operations gathered from the DCS and PMS9000 system.

The results from these two tests showed that the EPL-PSO algorithm as reported in Tiew-On Ting and Loo C.K. (2003) provides better optimum, consistent and reliable results, while satisfying all the constraints with the best computation time. The simulation results obtained in the study with plant operation data was however still subject to other unavailable or uninformed information of actual plant conditions and constraints, such as maintenance, resources, other plant conditions, etc, which lead to plant different operational method and decision.

In conclusion, the proposed EOH constraint algorithm had incorporated well in the EPL-PSO method and gave the correct results as logically predicted, in both of the simulations. Besides achieving better optimum results, which is minimum total production cost and emission cost , the simulation results also showed that all constraints as defined, namely reserve constraints, power demand, minimum up / down time, generator power limits and emission (NOx, CO, SO2) allowable limits were satisfied,

CHAPTER 9

CONCLUSIONS AND RECOMMENDATIONS

9.1 Conclusions

This work demonstrated a method for simulating and optimizing the load dispatch of the open cycle gas turbine plant with incorporating operational, maintenance and environmental parameters. Based on the model and knowledge found in the literature, the performance and emission model of gas turbine was established and implemented into Extended Priority List – Particle Swarm Optimization (EP-PSO) algorithm. All these formulations were then coded using Visual Basic.

Gas turbine performance calculations were based on ASME standard (PTC 22 -1985) and other industrial accepted tests methodology. This formulation was compared to the installed performance monitoring system (PMS9000) and plant performance test report. The performance model was validated successfully with both the test. The validation results had shown the capability of model and the developed software to predict accurately the behavior of the input-output of the machines. . The error of ± 4.5% and ± 0.25% were obtained when compared against real-time and performance test report respectively.

In this work, an advance and recent artificial intelligence technique, namely particle swarm optimization (PSO) was used and enhanced by incorporating with Extended Priority List method, in according to report [66]. All the simulations had been conducted and tested the optimization model as well as the optimization algorithm (EPL-PSO) successfully. The test results indicated that the developed optimization problem formulation and the improved EPL-PSO provided a better optimized solution, either the EPL-PSO algorithm against other method in the benchmark problem or the achievement of optimum multi-objective solution of cost and emission as compared to the actual plant data, without violating the consideration of EOH and emissions constraints. A cost savings of 0.685% and 0.1157% were obtained when simulation were conducted based on actual plant condition and against benchmark problem respectively.

Further simulation test on the behavior of the proposed method, EPL-PSO algorithm against benchmark problem were also successfully conducted. The simulation results also indicated good reliabilities and consistencies of the method, which gave 100% success rates in all the simulations and less than 0.02% difference between the best and the worst case. The proposed method also shows good performance with the best computation time of only 31.5 seconds for 500 generations as compared to other artificial intelligence methods such as EP and GA, which required more than 2 times computational time than EPL-PSO algorithm. It appeared that the EPL-PSO algorithm provided better global optimum results, better success rates and computation speed.

The implementation of environmental and maintenance parameters into the optimization problem had been successfully demonstrated. When EOH constraint was incorporated to the simulation, the results for Test Three - Set 1's EOH constraint indicated that the optimizer provided an accurate unit commitment by not committing Unit 1 and Unit 2 at the same time. The optimizer again had shown its accuracy when tested in Set 2 EOH constraint, where Unit 2 and Unit 3 were not committed at the same time. In Test Four - SET 2, when the allowable emission limit of NOx was reduced lower, the optimizer seemed had generated an optimum results among the several objective functions (multi-objective), which were minimum TPC and total emissions (NOx, CO and SO2) and trying to prevent any of the gas turbine releasing NOx more than the allowable limits. As predicted, the settings in SET 2 could indirectly force the optimizer to commit and operate higher load on alternative gas turbines.

In conclusion, the multi-objectives total production cost (TPC) objective functions, the proposed EOH constraint, emissions model and constraints algorithm incorporated well in the EPL-PSO method and gave the correct results as required, without violating any of the constraints as defined in Chapter 6.

9.2 Contributions of Research Work

This research work has contributed to the development of improved optimization model for power load dispatch problem and optimization procedure based on the recent Particle Swarm Optimization (PSO) method. The various test cases that had been taken for validation could be used as benchmark for future similar research work, such as the development of other new optimization algorithm for similar load dispatch problem or other similar optimization model that can be solved using the improved PSO optimization method.

Furthermore, the developed load dispatch optimization software documented herein has significant potential to be used for actual plant application. Independent power producer (IPP), power plant with power deregulation system in the country such as America and Singapore, and national load dispatching operation, which supply electricity power based on the demand from the customers, could utilize this software or solution to determine their generator commitment and load dispatch scheduling with reference to the forecast power purchase demand.

Similar application could be potentially implemented for even individual heavy industries plant such as paper mill and petro-chemical plant, who has own power generator such as open cycle gas turbine plant or combined cycle plant. The solution would provide the cheapest operating solution by committing and load dispatching the right machines, whether the generated electricity power is for the plant usage or purchased by the national grid system.

9.3 Recommendations for Future Works

Performance model of generator were found to be machine specific to gas turbine only. It is recommended that similar method of input-output model as documented to be expanded to cater for different models of generator such as steam turbine, diesel engine and combined cycle. Methods for quantifying aerothermal performance of these machines are given in ASME PTC standard. With this model development, the usage of this software therefore can be further expanded for top management level of national load dispatching operation such as National Load Dispatch Center.

In order to further improve model accuracy against actual dependent actual operating conditions parameters, such as ambient conditions, fuel gas conditions, compressor inlet guide vane and fuel gas ratio settings, model of Pmin / Pmax and machined input-output with reference to these parameters are recommend to be developed and incorporated to this gas turbine performance model.

With the design of the developed optimization model, other parameters can be incorporated easily into it. It is recommend incorporating electrical constraints such as power transmission lost which dependent on the location of the generators to reflect as close as possible to the actual conditions for accurate decision making. Other parameters can be included are fuel supply and human resource constraints.

Besides, recent research work on Hybrid Particle Swarm Optimization (HPSO) can be further developed and incorporated into this research work to further improve on the current EPL-PSO optimization method. With the advantages of HPSO, which taking the unit commitment into PSO, may provide more global optimum results and worth for further research and development.

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APPENDIX – A

Current Gas Turbine Maintenance Guidelines
Based on Equivalent Operating Hours (EOH)

Appendix A: Current Gas Turbine Maintenance Guidelines Based on Equivalent Operating Hours (EOH) Source: GE

Maintenance costs and availability are two of the most important concerns to a power station. Therefore, the emphasis is always on the type of inspection and the operating factors that influence maintenance schedules. Normally, the plant operators follow closely the maintenance program that has been outlined by the OEM. There are many factors that can influence components life and these must be understood and accounted for in the maintenance planning.

Start up and shut down cycles introduce large temperature changes. Because inertia, parts exposed to hot gases during transient operation are subject to steep thermal gradients. Depending on the part shape and the gradient direction, mechanical stresses may exceed the limits of material characteristics. The effect of thermal cycles is greater on the hot gas path components for this type of operation. Rapid startup and shut down cause high stresses on the hot gas path components. The worst effects were caused by machine trip, especially from full load. A full load trip is not catastrophic in itself, but the resultant life reduction is equivalent to that of about 10 normal shutdowns.

Gas turbine wears out in different ways for different service duties. Thermal mechanical fatigue is the dominant liuiter of life for peaking machines, while creep, oxidation and corrosion are the dominant liuiters of life for continuos duty machine. Interactions of these mechanisms are considered in the General Electric (GE) design criteria, but to a great extent are second order effects. For that reason, GE bases gas turbine maintenance requirements on independent counts of starts and hours. Whichever criteria limit is first reached determines the maintenance interval.

While GE does not ascribe to the equivalency of starts to hours, there are some factors need to be considered such as fuel type and quality, firing temperature settings, etc. These influence in a unit's operation, the hot gas path maintenance 'rectangle' that describes the specific maintenance criteria for this operation is reduced from the ideal case.

As an alternative to GE approach, this is sometimes employed by other manufacturers, converts each start cycle to an equivalent number of operating hours (EOH) with inspection intervals based on the equivalent hours count. Fast rate changes in the turbine inlet temperature and operating periods at gas temperature above the base load level impose additional stresses on the components in the hot gas path. Their influence on the life of these components is considered by determining the EOH at base load. For this purpose, different operating events and operating periods in different temperature ranges are weighted with different factors and then added. The interval between two inspections is the determined by EOH which are calculated according to the following formula:

$$T_{ae} = a_1 n_1 + a_2 n_2 + \Sigma a_3 n_3 + b_1 t_1 + b_2 t_2$$

Where,

n_1	= number of starts
n_2	= number of fast rate loading procedure
n_3	= number of other fast rate temperature changes
t_1	= operating hours up to base load
t_2	= operating hours for base load to peak load
a_1, a_2, a_3, b_1, b_2	= weighting factors

It is recommended to have 4,000 hour (not longer than 2 years) interval for maintenance inspections and 20,000 hour (not longer than 8 years) interval for major inspection.

APPENDIX – B

Gas Turbine Performance Correction Curves
(Chart and Software Coding)

Appendix B: Gas Turbine Performance Correction Curve For ABB Gas Turbine 13E

Two important gas turbine key performances indicators that were corrected were generator power output and heat rate. The heat rate and power output will be adjusted to correspond to the selected exhaust temperature, turbine speed, and compressor inlet temperature using the correction factors supplied by the manufacturer.

These correction factors are usually given in graph format as shown in following pages of this appendix. The formulation of these correction factors are illustrated as below:

a. Correction factors for power output

i. Compressor Inlet Temperature Correction Factor

TCPCompInR = 1.10014 - 6.344012*10^-3* TBAmb- 2.10927*10^-5* TBAmb^2 + 4.114544*10^-8* TBAmb ^3 + 3.992891*10^-9* TBAmb^4

TCPCompInT = 1.10014 - 6.344012*10^-3*TIAmb - 2.10927*10^-5* TIAmb^2 + 4.114544*10^-8* TIAmb^3 + 3.992891*10^-9* TIAmb^4

TCPCompIn = TCPCompInR/ TCPCompInT

ii. Ambient Pressure Correction Factor

OCPBaroT= PBAmb/ PIAmb

iii. Ambient Humidity Correction Factor

At rated condition,

gt3_Hambrel = 1

IF (gt3_Hambrel >= 0.6) AND (gt3_Hambrel <=0.7) THEN

gt3_Xo1 = -7.355633*10^-3 + 1.74687*10^-3*TIAmb - 7.890294*10^-5* TIAmb^2 + 1.847888*10^-6* TIAmb^3 - 1.022464*10^-8* TIAmb^4

gt3_Xo2 = 1.383536*10^-2 - 1.77747*10^-3*TIAmb+ 1.252156*10^-4* TIAmb^2 - 2.871697*10^-6* TIAmb^3 + 2.879362*10^-8* TIAmb^4

gt3_Xo12 = (gt3_Hambrel - 0.6)/(0.7-0.6)*(gt3_Xo2 - gt3_Xo1) + gt3_Xo1

ELSE gt3_Xo12 = 0

IF (gt3_Hambrel >=0.7) AND (gt3_Hambrel <=0.8) THEN

gt3_Xo2 = 1.383536*10^-2 - 1.77747*10^-3*TIAmb+ 1.252156*10^-4* TIAmb^2 - 2.871697*10^-6* TIAmb^3 + 2.879362*10^-8* TIAmb^4

gt3_Xo3 = 1.095735*10^-2 - 8.503463*10^-4*TIAmb+ 4.910065*10^-5* TIAmb^2 - 4.0506*10^-7* TIAmb^3 + 4.070496*10^-9* TIAmb^4

gt3_Xo23 = (gt3_Hambrel - 0.7)/(0.8-0.7)*(gt3_Xo5 - gt3_Xo2) + gt3_Xo2

ELSE gt3_Xo23 = 0

IF (gt3_Hambrel >=0.8) AND (gt3_Hambrel <=0.9) THEN

gt3_Xo3 = 1.095735*10^-2 - 8.503463*10^-4*TIAmb+ 4.910065*10^-5* TIAmb^2 - 4.0506*10^-7* TIAmb^3 + 4.070496*10^-9* TIAmb^4

gt3_Xo4= 1.800569*10^-2 - 2.358028*10^-3*TIAmb+ 1.538443*10^-4* TIAmb^2 - 3.114443*10^-6* TIAmb^3 + 2.873133*10^-8* TIAmb^4

gt3_Xo34 = (gt3_Hambrel - 0.8)/(0.9-0.8)*(gt3_Xo4 - gt3_Xo3) + gt3_Xo3

ELSE gt3_Xo34 = 0

IF (gt3_Hambrel >=0.9) AND (gt3_Hambrel <=1.0) THEN

```
          gt3_Xo4=  1.800569*10^-2 - 2.358028*10^-3*TIAmb+
          1.538443*10^-4* TIAmb^2 - 3.114443*10^-6* TIAmb^3 +
          2.873133*10^-8* TIAmb^4

          gt3_Xo5 =  -2.916796*10^-3 + 1.492734*10^-3*TIAmb -
          5.363904*10^-5* TIAmb^2 + 1.393923*10^-6* TIAmb^3 -
          3.977936*10^-9* TIAmb^4

          gt3_Xo45 = (gt3_Hambrel - 0.9)/(1.0-0.9)*( gt3_Xo5 -
          gt3_Xo4) + gt3_Xo4

          ELSE gt3_Xo45 =0

IF gt3_Xo12 <> 0  THEN
          gt3_Xoo = gt3_Xo12
ELSE IF gt3_Xo23 <> 0  THEN
          gt3_Xoo = gt3_Xo23
ELSE IF gt3_Xo34 <> 0  THEN
          gt3_Xoo = gt3_Xo34
ELSE gt3_Xoo = Xo45


HCPAmbR= 0.996879 + 0.5831575* gt3_Xoo - 4.742494* gt3_Xoo^2
+ 37.67406* gt3_Xoo^3 - 133.8088* gt3_Xoo^4
```

At test condition,

```
gt3_Hambrelt = HIAmb/ HBAmb

IF (gt3_Hambrelt >= 0.6) AND (gt3_Hambrelt <=0.7)  THEN

          gt3_Xo1t = -7.355633*10^-3 + 1.74687*10^-3*TIAmb -
          7.890294*10^-5* TIAmb^2 + 1.847888*10^-6* TIAmb^3 -
          1.022464*10^-8* TIAmb^4

          gt3_Xo2 = 1.383536*10^-2 - 1.77747*10^-3*TIAmb+
          1.252156*10^-4* TIAmb^2 - 2.871697*10^-6* TIAmb^3 +
          2.879362*10^-8* TIAmb^4

          gt3_Xo12t = (gt3_Hambrelt - 0.6)/(0.7-0.6)*( gt3_Xo2t -
          gt3_Xo1t) + gt3_Xo1t

          ELSE gt3_Xo12t = 0

IF (gt3_Hambrelt >=0.7) AND (gt3_Hambrelt <=0.8)  THEN
```

```
        gt3_Xo2t = 1.383536*10^-2 - 1.77747*10^-3*TIAmb+
        1.252156*10^-4* TIAmb^2 - 2.871697*10^-6* TIAmb^3 +
        2.879362*10^-8* TIAmb^4

        gt3_Xo3t =  1.095735*10^-2 - 8.503463*10^-4*TIAmb+
        4.910065*10^-5* TIAmb^2 - 4.0506*10^-7* TIAmb^3 +
        4.070496*10^-9* TIAmb^4

        gt3_Xo23t = (gt3_Hambrelt - 0.7)/(0.8-0.7)*( gt3_Xo3t -
        gt3_Xo2t) + gt3_Xo2t

        ELSE gt3_Xo23t = 0

  IF (gt3_Hambrelt >=0.8) AND (gt3_Hambrelt <=0.9)  THEN

        gt3_Xo3t =  1.095735*10^-2 - 8.503463*10^-4*TIAmb+
        4.910065*10^-5* TIAmb^2 - 4.0506*10^-7* TIAmb^3 +
        4.070496*10^-9* TIAmb^4

         gt3_Xo4t =  1.800569*10^-2 - 2.358028*10^-3*TIAmb+
        1.538443*10^-4* TIAmb^2 - 3.114443*10^-6* TIAmb^3 +
        2.873133*10^-8* TIAmb^4

        gt3_Xo34t = (gt3_Hambrelt - 0.8)/(0.9-0.8)*( gt3_Xo4t -
        gt3_Xo3t) + gt3_Xo3t

        ELSE gt3_Xo34t = 0

   IF (gt3_Hambrelt >=0.9) AND (gt3_Hambrelt <=1.0)  THEN

        gt3_Xo4t =  1.800569*10^-2 - 2.358028*10^-3*TIAmb+
        1.538443*10^-4* TIAmb^2 - 3.114443*10^-6* TIAmb^3 +
        2.873133*10^-8* TIAmb^4

        gt3_Xo5t =  -2.916796*10^-3 + 1.492734*10^-3*TIAmb -
        5.363904*10^-5* TIAmb^2 + 1.393923*10^-6* TIAmb^3 -
        3.977936*10^-9* TIAmb^4

        gt3_Xo45t = (gt3_Hambrelt - 0.9)/(1.0-0.9)*( gt3_Xo5t -
        gt3_Xo4t) + gt3_Xo4t

        ELSE gt3_Xo45t =0

IF gt3_Xo12t <> 0  THEN
        gt3_Xoot = gt3_Xo12t
ELSE IF gt3_Xo23t <> 0  THEN
        gt3_Xoot = gt3_Xo23
ELSE IF gt3_Xo34t <> 0  THEN
        gt3_Xoot = gt3_Xo34t
ELSE gt3_Xoot = gt3_Xo45t
```

ENDIF

HCPAmbT = 0.996879 + 0.5831575* gt3_Xoot - 4.742494* gt3_Xoot^2 + 37.67406* gt3_Xoot^3 - 133.8088* gt3_Xoot^4

HCPAmb = HCPAmbR/ HCPAmbT

iv. Power correction factor

At rated condition,

IF (WBFactor >= 0.7) AND (WBFactor <=0.85) THEN

gt3_c-cgen07a = 1.000305 + 8.888523*10^-6* WBGenOut - 6.964832*10^-8* WBGenOut^2 + 7.225595*10^-10* WBGenOut^3 - 1.812956*10^-12* WBGenOut^4

gt3_c-cgen085b = 0.9995314 + 7.227678*10^-6* WBGenOut - 1.159226*10^-7* WBGenOut^2 + 5.61783*10^-10* WBGenOut^3 - 1.052701*10^-12* WBGenOut^4

gt3_c-cgenaa = (WBFactor - 0.7)/(0.85-0.7)*(gt3_c-cgen085b - gt3_c-cgen07a) + gt3_c-cgen07a

ELSE gt3_c-cgenaa = 0

IF (WBFactor >= 0.85) AND (WBFactor <=0.9) THEN

gt3_c-cgen085b = 0.9995314 + 7.227678*10^-6* WBGenOut - 1.159226*10^-7* WBGenOut^2 + 5.61783*10^-10* WBGenOut^3 - 1.052701*10^-12* WBGenOut^4

gt3_c-cgen09c = 1.000144 - 2.281484*10^-5* WBGenOut + 2.36209*10^-7* WBGenOut^2 - 1.313404*10^-9* WBGenOut^3 + 2.395435*10^-12* WBGenOut^4

gt3_c-cgenbb = (WBFactor - 0.85)/(0.9-0.85)*(gt3_c-cgen09c - gt3_c-cgen085b) + gt3_c-cgen085b

ELSE gt3_c-cgenbb = 0

IF (WBFactor >= 0.9) AND (WBFactor <=1.0) THEN

gt3_c-cgen09c = 1.000144 - 2.281484*10^-5* WBGenOut + 2.36209*10^-7* WBGenOut^2 - 1.313404*10^-9* WBGenOut^3 + 2.395435*10^-12* WBGenOut^4

```
        gt3_c-cgen10d = 0.999474 - 2.509323*10^-5* WBGenOut +
        2.980888*10^-7* WBGenOut^2 - 2.128915*10^-9*
        WBGenOut^3 + 4.913864*10^-12* WBGenOut^4

        gt3_c-cgencc = (WBFactor - 0.9)/(1.0-0.9)*( gt3_c-cgen10d -
        gt3_c-cgen09c) + gt3_c-cgen09c

        ELSE gt3_c-cgencc = 0

IF gt3_c-cgenaa <> 0  THEN
        DCEPowerR = gt3_c-cgenaa
ELSE IF gt3_c-cgenbb <> 0  THEN
        DCEPowerR = gt3_c-cgenbb
ELSE DCEPowerR = gt3_c-cgencc
ENDIF
```

At test condition,

```
IF (PowerFactor >= 0.7) AND (PowerFactor <=0.85)  THEN

        gt3_c-cgen07 = 1.000305 + 8.888523*10^-6* Pact -
        6.964832*10^-8* Pact^2 + 7.225595*10^-10* Pact^3 -
        1.812956*10^-12* Pact^4

        gt3_c-cgen085 = 0.9995314 + 7.227678*10^-6* Pact -
        1.159226*10^-7* Pact^2 + 5.61783*10^-10* Pact^3 -
        1.052701*10^-12* Pact^4

        gt3_c-cgena = (PowerFactor - 0.7)/(0.85-0.7)*( gt3_c-cgen085
        - gt3_c-cgen07) + gt3_c-cgen07

        ELSE gt3_c-cgena = 0

IF (PowerFactor >= 0.85) AND (PowerFactor <=0.9)  THEN

        gt3_c-cgen085 = 0.9995314 + 7.227678*10^-6* Pact -
        1.159226*10^-7* Pact^2 + 5.61783*10^-10* Pact^3 -
        1.052701*10^-12* Pact^4

         gt3_c-cgen09 = 1.000144 - 2.281484*10^-5* Pact +
        2.36209*10^-7* Pact^2 - 1.313404*10^-9* Pact^3 +
        2.395435*10^-12* Pact^4
        gt3_c-cgenb = (PowerFactor - 0.85)/(0.9-0.85)*( gt3_c-cgen09
        - gt3_c-cgen085) + gt3_c-cgen085

        ELSE gt3_c-cgenb = 0
```

```
IF (PowerFactor >= 0.9) AND (PowerFactor <=1.0)  THEN

        gt3_c-cgen09 = 1.000144 - 2.281484*10^-5* Pact +
        2.36209*10^-7* Pact^2 - 1.313404*10^-9* Pact^3 +
        2.395435*10^-12* Pact^4

        gt3_c-cgen10 = 0.999474 - 2.509323*10^-5* Pact +
        2.980888*10^-7* Pact^2 - 2.128915*10^-9* Pact^3 +
        4.913864*10^-12* Pact^4

        gt3_c-cgenc = (PowerFactor - 0.9)/(1.0-0.9)*( gt3_c-cgen10 -
        gt3_c-cgen09) + gt3_c-cgen09

        ELSE gt3_c-cgenc = 0

IF gt3_c-cgena <> 0  THEN
        DCEPowerT = gt3_c-cgena
ELSE IF gt3_c-cgenb <> 0  THEN
        DCEPowerT = gt3_c-cgenb
ELSE DCEPowerT = gt3_c-cgenc
ENDIF

DCEPower = DCEPowerT/ DCEPowerR
```

v. Speed correction factor

```
gt3_Nrel = 1

SCPSpeedR = -1.350526 + 2.027797* gt3_Nrel + 0.967181*
gt3_Nrel^2 + 0.6600308* gt3_Nrel^3 - 1.302787* gt3_Nrel^4

SCPSpeedT = -1.350526 + 2.027797* gt3_Nrelt + 0.967181*
gt3_Nrelt^2 + 0.6600308* gt3_Nrelt^3 - 1.302787* gt3_Nrelt^4

SCPSpeed = SCPSpeedR/ SCPSpeedT
```

b. Corrected generator net power output (MW)

```
PsCr = (WIActivePwr* OCPBaroT * TCPCompIn *  DCEPower* SCPSpeed*
HCPAmb) - (WIAuxil/1000);
```

c. Correction factors for thermal efficiency

i. Compressor Inlet Temperature Factor

$TCECompInR = 1.028863 - 1.732264*10^{-3}* RTAmb - 1.930892*10^{-5}* RTAmb^2 + 1.125815*10^{-7} * RTAmb^3 + 3.722623*10^{-10} * RTAmb^4$

$TCECompInT = 1.028863 - 1.732264*10^{-3}*TIAmb - 1.930892*10^{-5}* TIAmb^2 + 1.125815*10^{-7}* TIAmb^3 + 3.722623*10^{-10}* TIAmb^4$

$TCECompIn = TCECompInR/ TCECompInT$

ii. Ambient Humidity Factor

At rated condition,

$HCEAmbR = 1.00095 - 0.2328285* gt3\_Xoo + 2.733344* gt3\_Xoo^2 - 46.19359* gt3\_Xoo^3 + 219.1551* gt3\_Xoo^4$

At test condition,

$HCEAmbT = 1.00095 - 0.2328285* gt3\_Xoot + 2.733344* gt3\_Xoot^2 - 46.19359* gt3\_Xoot^3 + 219.1551* gt3\_Xoot^4$

$HCEAmb = HCEAmbR/ HCEAmbT$

iii. Power Correction Factor

The correction factor used is from the same correction curve that is used for corrected power computation.

$DCEPower = DCEPowerT/ DCEPowerR$

iv. Speed Correction Factor

$gt3\_Nrel = 1$

$SCESpeedR = 1.89638*10^{-6} + 0.6871407* gt3\_Nrel + 1.19096* gt3\_Nrel^3 - 0.5641574* gt3\_Nrel^3 - 0.3136273* gt3\_Nrel^4$

$gt3\_Nrelt = SBTurbine/ SIShaft$

SCESpeedT = 1.89638*10^-6 + 0.6871407* gt3_Nrelt + 1.19096* gt3_Nrelt^2 - 0.5641574* gt3_Nrelt^3 - 0.3136273* gt3_Nrelt^4

SCESpeed = SCESpeedR/ SCESpeedT

d. Corrected thermal efficiency, EffCr (%)

EffCr = (Eff * TCECompIn* DCEPower* SCESpeed* HCEAmb) * (1 - (WIAuxil / (1000000/ Ps)))

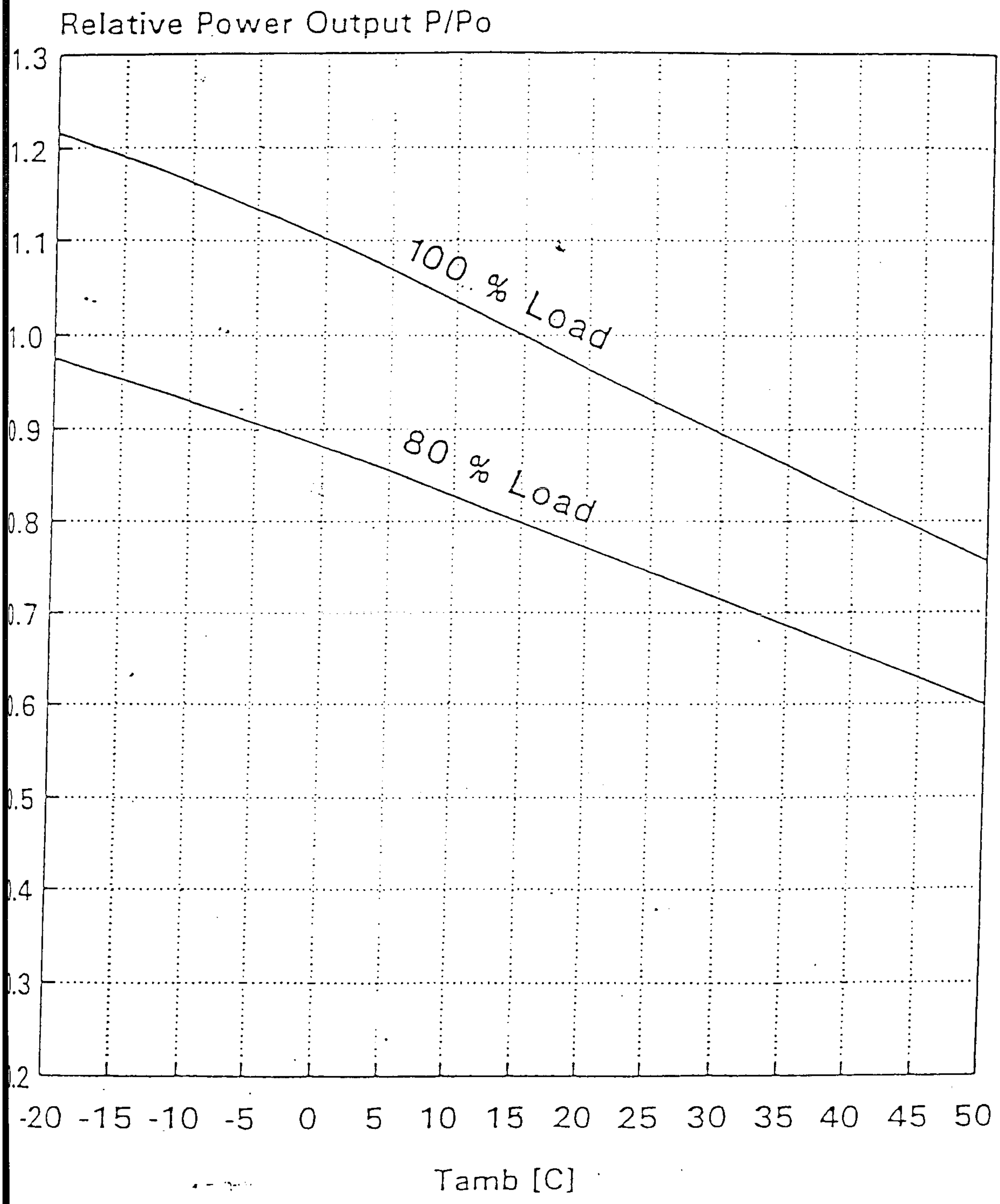
e. Corrected generator net heat rate, HRCr (kJ/kwh)

HRCr = 3600/ Effcr*100

ABB GT 13E : CONNAUGHT BRIDGE
CORRECTION CURVE FOR POWER OUTPUT
SIMPLE CYCLE

Document no.:

ANNEX 9.1 HPGTX 434 006



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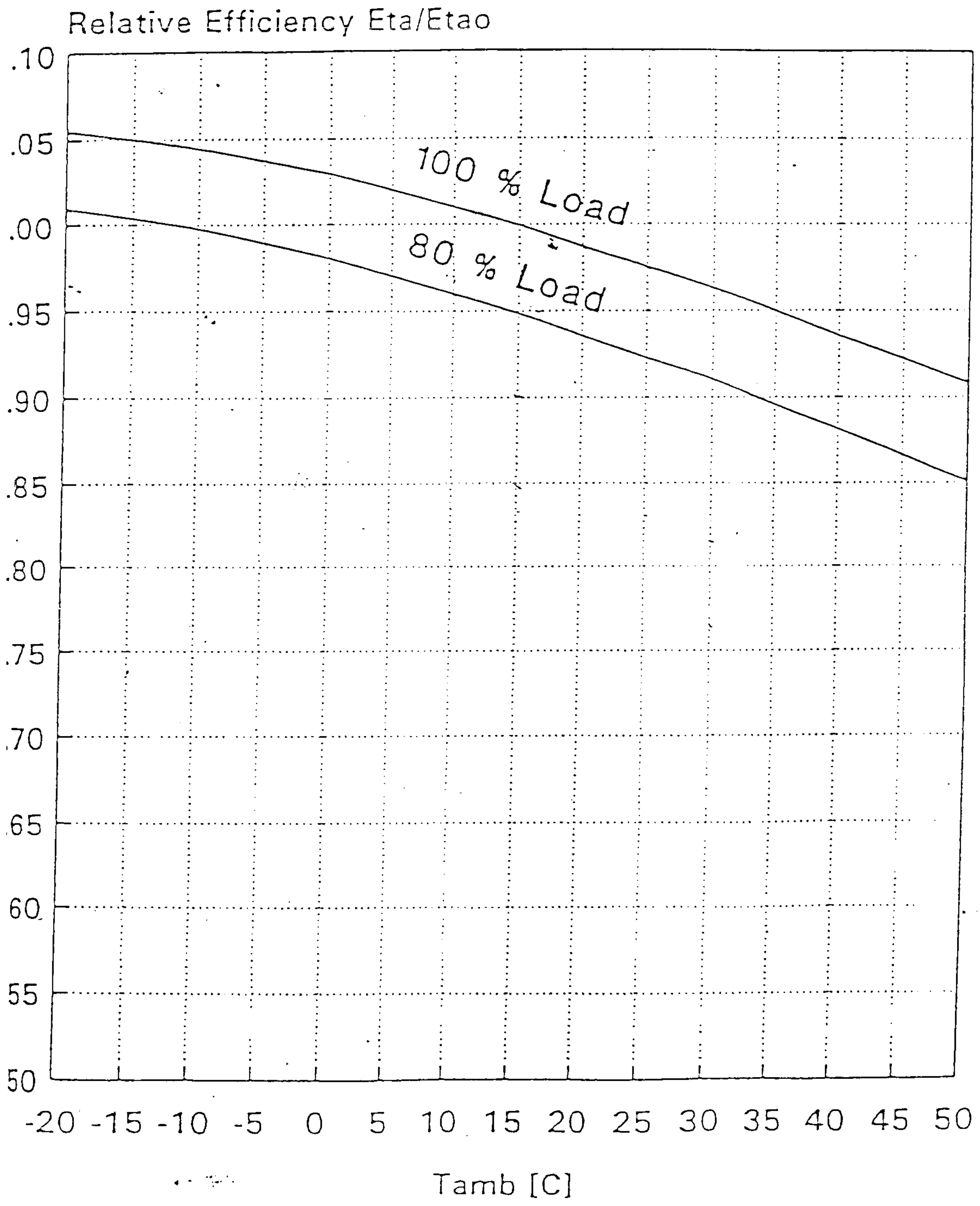
		Der. from:	GMD 1072628	HTCT 71 441				
..-04-07 ROTH		Replaces:						

10.90

ABB GT 13E : CONNAUGHT BRIDGE
CORR. CURVE FOR THERMAL EFFICIENCY
SIMPLE CYCLE

Document no.:

ANNEX 9.2 HPGTX 434 006



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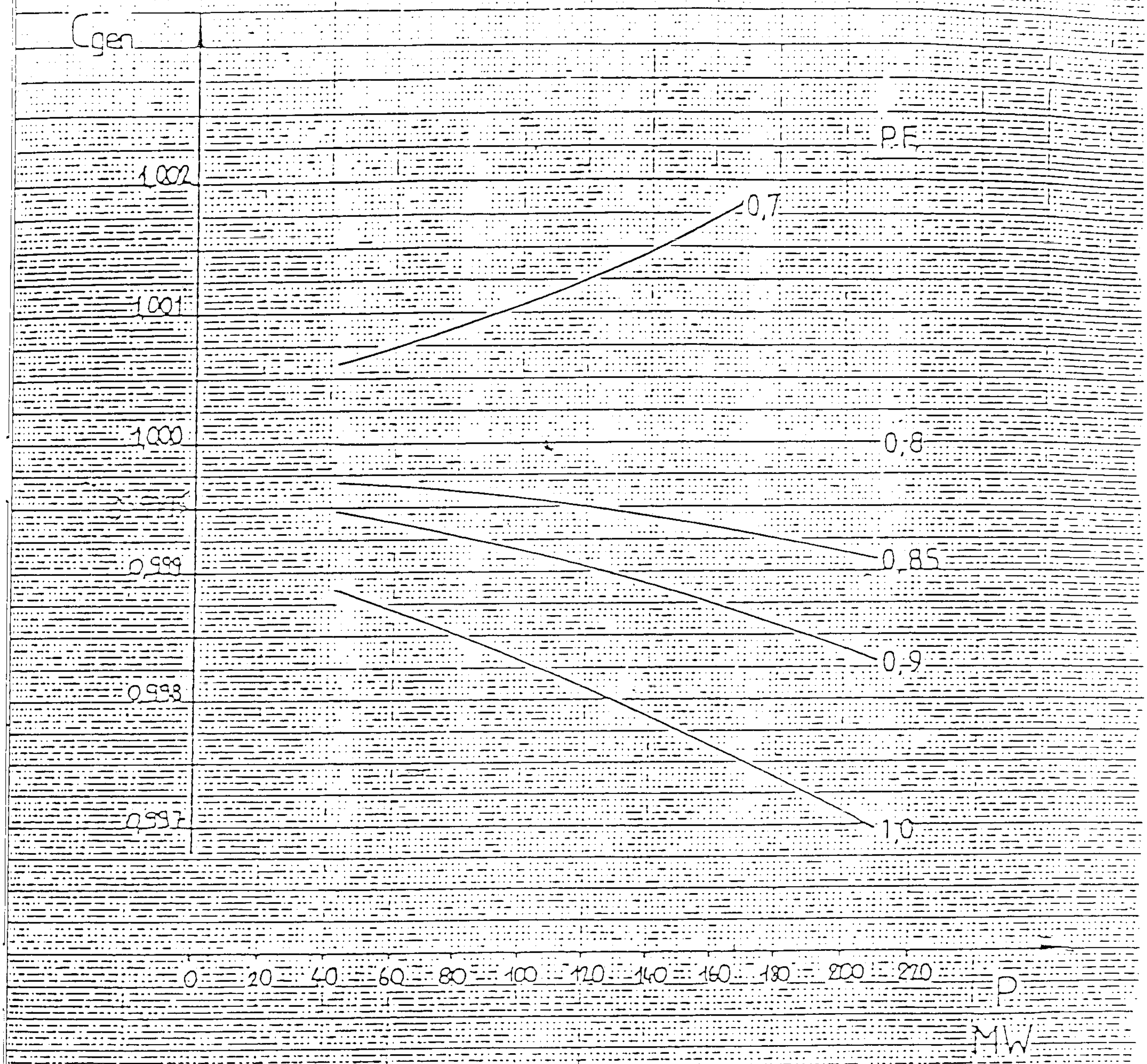


P = active output power of generator

Cgen = correction factor for power factor

Änd.:

POWER PLANT : VORRAT GT13E MC

GENERATOR TYPE : WY21L-097LLT

S [kVA]	cos phi	U [V]	f [Hz]
218000.	.800	15750.	50.

Altitude : 0 m

WBZ-Best.:	PZ NR 4495	
Fach:		
Entstand aus:		
Ersatz für:		
Ersetzt durch:		
Gezeichnet	15.12.89	PFEFFERL
Geprüft	15.12.89	
Gesehen	23.1.90	

GEN. CORRECTION FACTOR

HTCM 647772-9

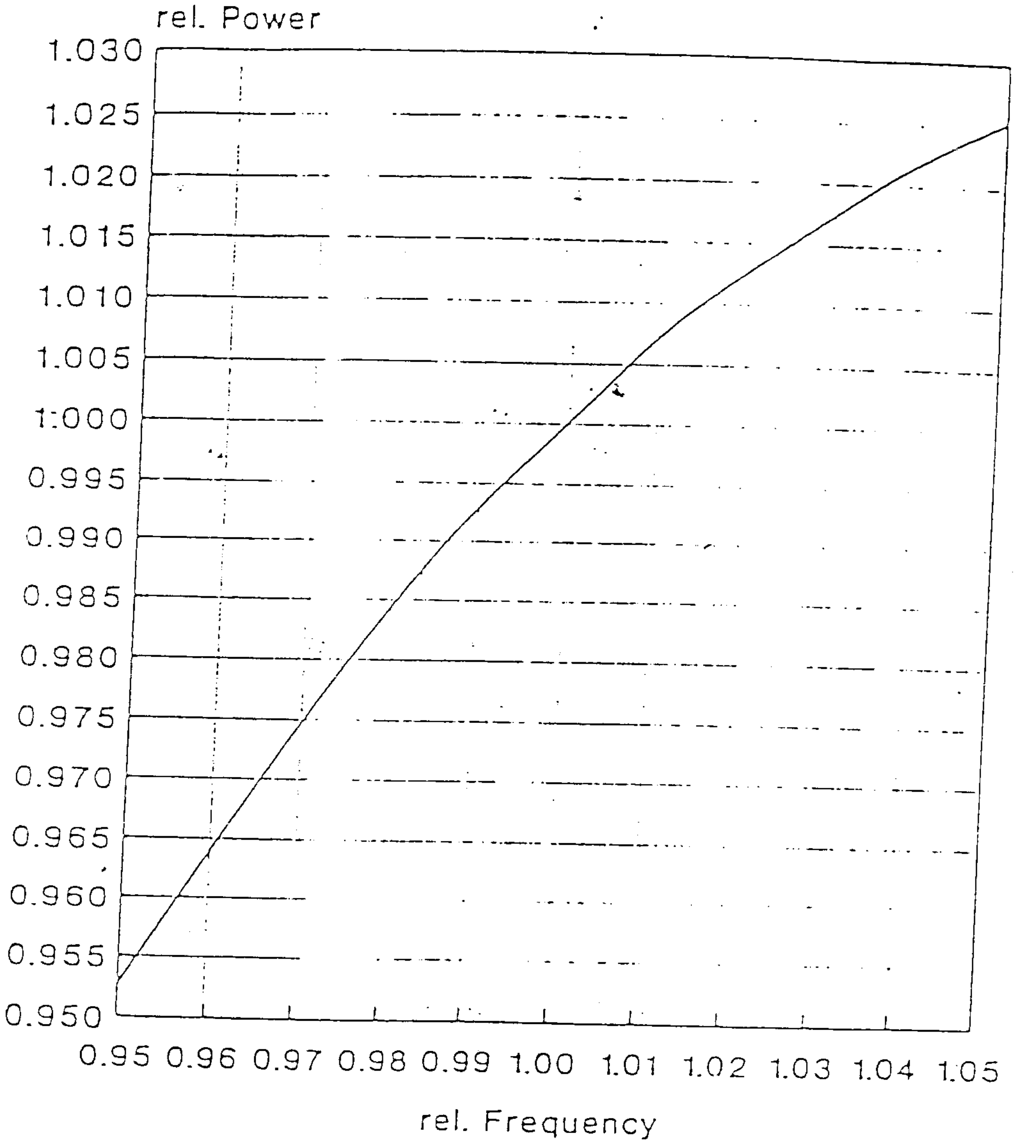
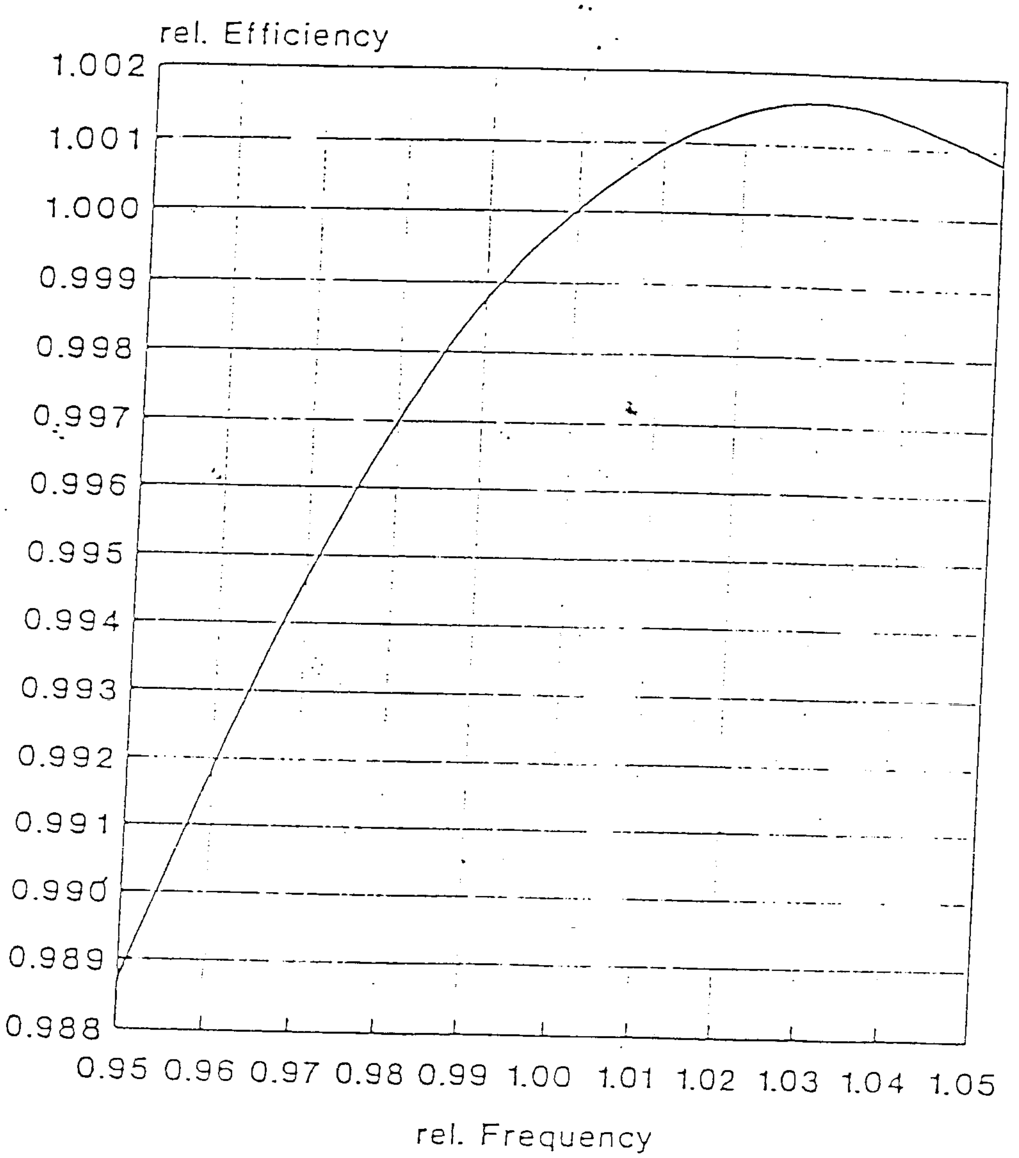
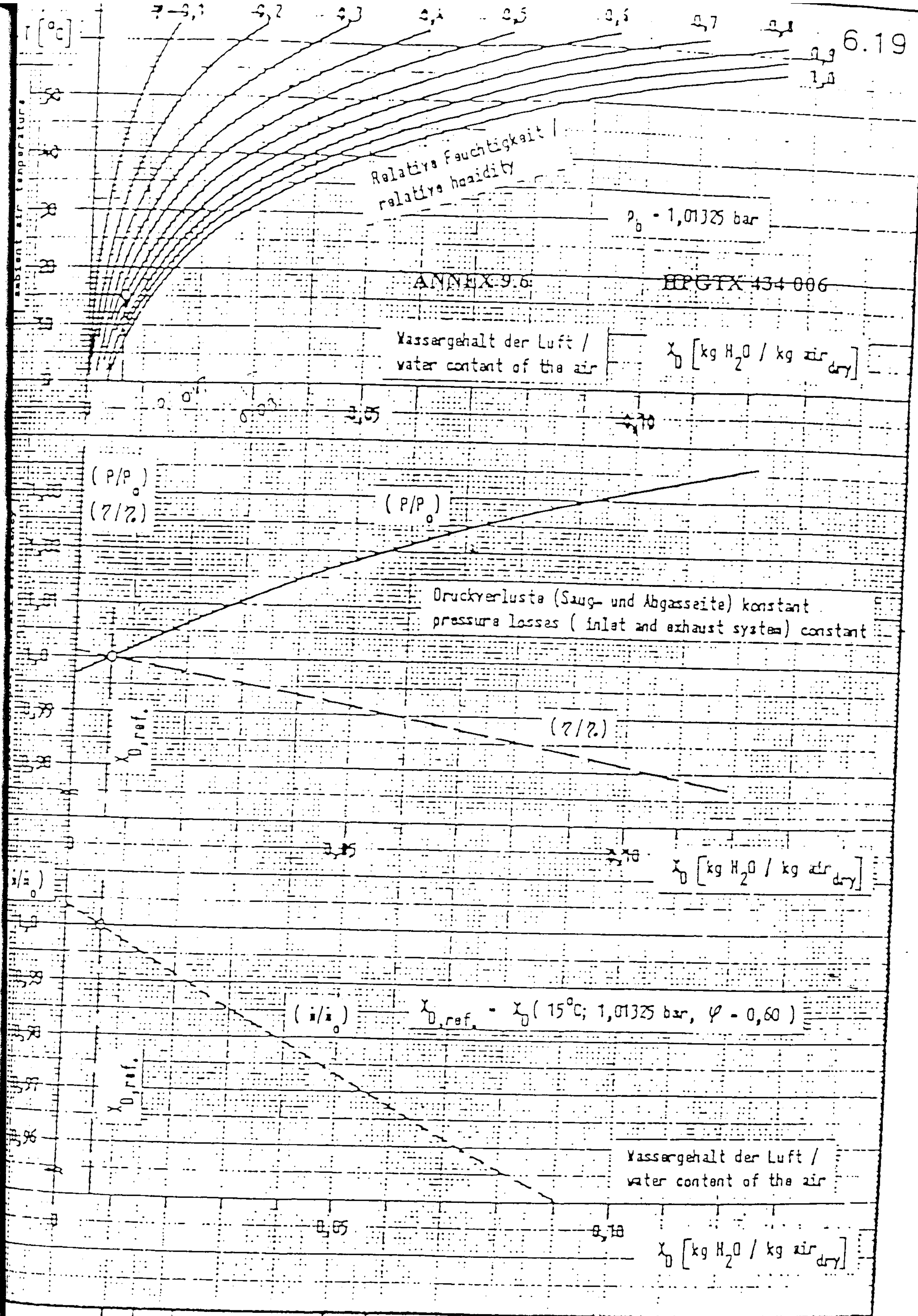


ABB BROWN BOVERI ...aftwerke AG Dept. : KW/GR	GT13E Influence of Speed on Power ISO, Base Load	ausgest.: 11.06.92 Sv geprüft: geprüft: 11.06.92 Fu freigeg.: " Fu entst. aus: Ersatz für: GMD 1072679 GMD 1 072 698



ROWN BOVERI ftwerke AG pt.: KW/GR	GT13E Influence of Speed on Efficiency ISO, Base Load	ausgest.: 11.06.92 Sy geprüft: geprüft: 11.06.92 E. freigeg.: " E. entst. aus: Ersatz für: GMD 1072680 GMD 1 072 699



Änd.	Ausgest.	30.8.78	Maßstab	Entstand aus: GMO 1 072 230
	Gepr.			Ersatz für:
				Ersetzt durch:

Titel GT 13 E

Einfluß der Luftfeuchtigkeit /

Influence of humidity

Format	Sprache	Blatt-Nr.	Anz. Blatt
A 4	D/E	1	1

GMO 1 072 368

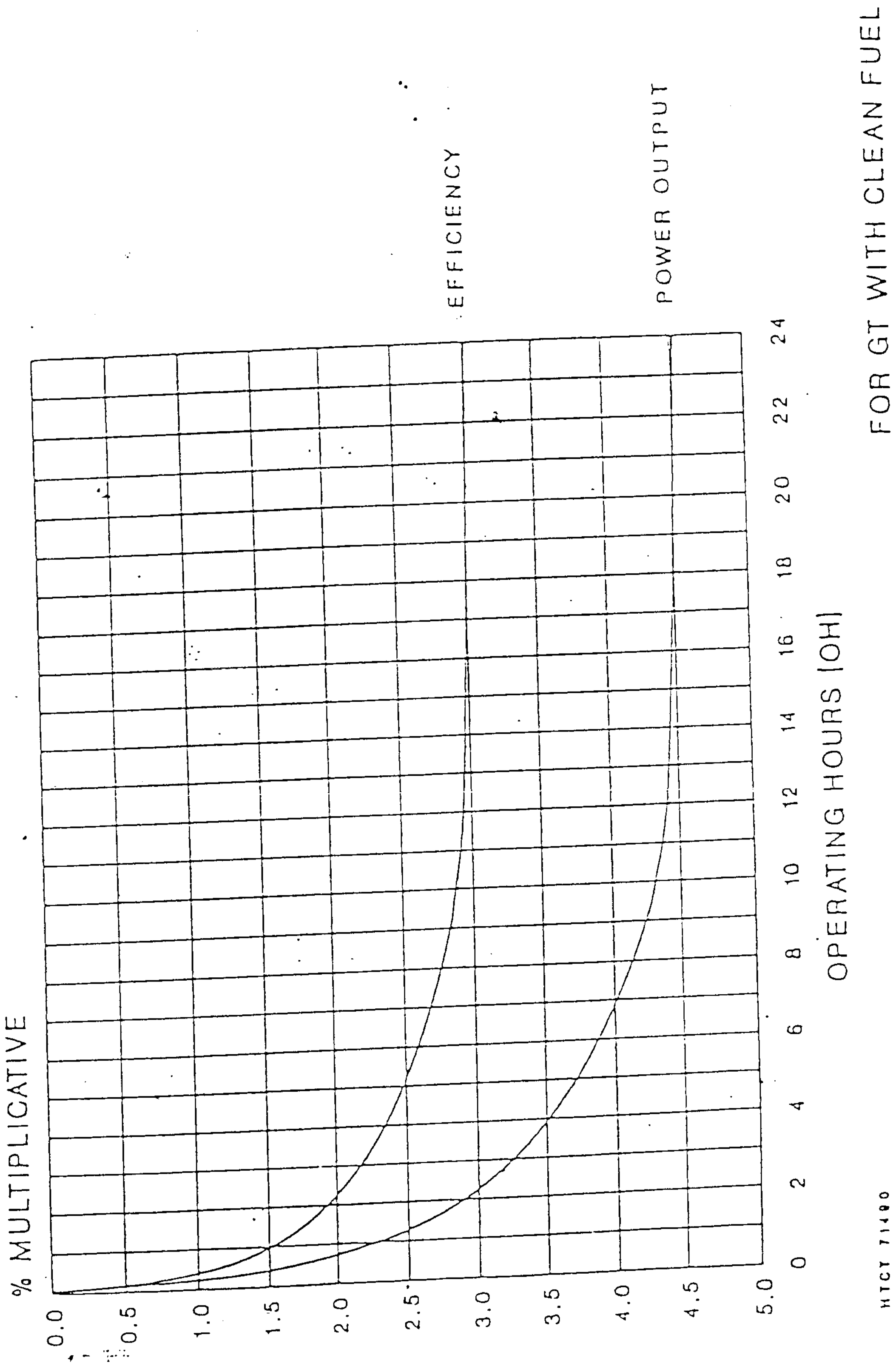
BOVERI

EXPECTED NON RECOVERABLE DETERIORATION
OF POWER OUTPUT AND EFFICIENCY

Document no.:

ANNEX 9.9

HPGTX 434 006



HTCT 71490
KWQT-2/NK

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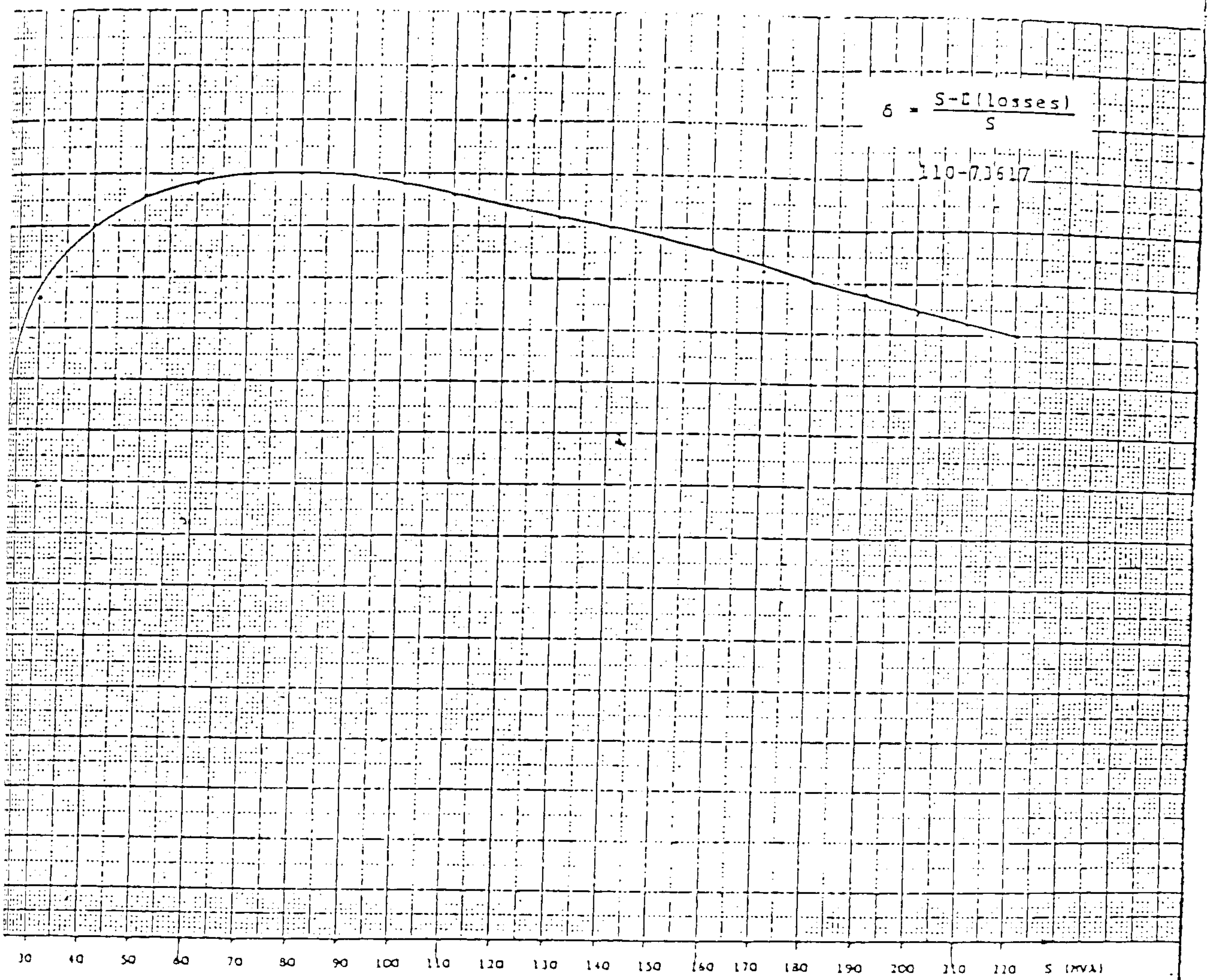
ANNEX 9.10 HPGTX 434 006



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	PRODUCT TRANSFORMER 180 MVA	INTERNAL STANDARD	
	DRAWING TITLE Efficiency diagram for transformer No. 04 BAT 01	REPL. FOR	
		REPL. OF -	
		DRAWING NO. T1-409591	REV. 0

APPENDIX C

Least Square Method

Appendix C: Polynomial Least Square Regression Techniques

Least square regression is one of the mathematical procedure for finding the best fitting curve to a given set of points by minimizing the sum of the squares of the offsets ("the residuals") of the points from the curve. The sum of the squares of the offsets is used instead of the offset absolute values because this allows the residuals to be treated as a continuous differentiable quantity.

Generalizing from a straight line (i.e., first degree polynomial) to a *k*th degree polynomial can be represented as

$$y = a_0 + a_1 x + \ldots + a_k x^k, \qquad \text{Eq (C.1)}$$

and the residual is given by

$$R^2 \equiv \sum_{i=1}^{n} [y_i - (a_0 + a_1 x_i + \ldots + a_k {x_i}^k)]^2. \qquad \text{Eq (C.2)}$$

The partial derivatives (again dropping superscripts) are

$$\frac{\partial(R^2)}{\partial a_0} = -2 \sum [y - (a_0 + a_1 x + \ldots + a_k x^k)] = 0 \qquad \text{Eq (C.3)}$$

$$\frac{\partial(R^2)}{\partial a_1} = -2 \sum [y - (a_0 + a_1 x + \ldots + a_k x^k)] x = 0 \qquad \text{Eq (C.4)}$$

$$\frac{\partial(R^2)}{\partial a_k} = -2 \sum [y - (a_0 + a_1 x + \ldots + a_k x^k)] x^k = 0. \qquad \text{Eq (C.5)}$$

These lead to the equations

$$a_0 n + a_1 \sum x + \ldots + a_k \sum x^k = \sum y \qquad \text{Eq (C.6)}$$

$$a_0 \sum x + a_1 \sum x^2 + \ldots + a_k \sum x^{k+1} = \sum xy \qquad \text{Eq (C.7)}$$

$$a_0 \sum x^k + a_1 \sum x^{k+1} + \ldots + a_k \sum x^{2k} = \sum x^k y \qquad \text{Eq (C.8)}$$

or, in matrix form

$$\begin{bmatrix} n & \sum x & \cdots & \sum x^k \\ \sum x & \sum x^2 & \cdots & \sum x^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum x^k & \sum x^{k+1} & \cdots & \sum x^{2k} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} \sum y \\ \sum xy \\ \vdots \\ \sum x^k y \end{bmatrix}.$$

Eq (C.9)

This is a Vandermonde matrix. We can also obtain the matrix for a least squares fit by writing

$$\begin{bmatrix} 1 & x_1 & \cdots & {x_1}^k \\ 1 & x_2 & \cdots & {x_2}^k \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \cdots & {x_n}^k \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_k \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}.$$

Eq (C.10)

Premultiplying both sides by the transpose of the first matrix then gives

$$\begin{bmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \\ \vdots & \vdots & \ddots & \vdots \\ {x_1}^k & {x_2}^k & \cdots & {x_n}^k \end{bmatrix} \begin{bmatrix} 1 & x_1 & \cdots & {x_1}^k \\ 1 & x_2 & \cdots & {x_2}^k \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & \cdots & {x_n}^k \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_k \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \\ \vdots & \vdots & \ddots & \vdots \\ {x_1}^k & {x_2}^k & \cdots & {x_n}^k \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix},$$

Eq (C.11)

so,

$$\begin{bmatrix} n & \sum x & \cdots & \sum x^n \\ \sum x & \sum x^2 & \cdots & \sum x^{n+1} \\ \vdots & \vdots & \ddots & \vdots \\ \sum x^n & \sum x^{n+1} & \cdots & \sum x^{2n} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} \sum y \\ \sum xy \\ \vdots \\ \sum x^k y \end{bmatrix}.$$

Eq (C.12)

As before, given *m* points (x_i, y_i) and fitting with polynomial coefficient a_0, ..., a_n gives

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} 1 & x_1 & {x_1}^2 & \cdots & {x_1}^n \\ 1 & x_2 & {x_2}^2 & \cdots & {x_2}^n \\ \vdots & \vdots & \ddots & \vdots & \\ 1 & x_m & {x_m}^2 & \cdots & {x_m}^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix},$$ Eq (C.13)

In matrix notation, the equation for a polynomial fit is given by

$$\mathbf{y} = \mathsf{X}\mathbf{a}.$$ Eq (C.14)

This can be solved by premultiplying by the matrix transpose X^{T},

$$\mathsf{X}^{\mathrm{T}}\mathbf{y} = \mathsf{X}^{\mathrm{T}}\mathsf{X}\mathbf{a}.$$ Eq (C.15)

This matrix equation can be solved numerically, or can be inverted directly if it is well formed, to yield the solution vector

$$\mathbf{a} = (\mathsf{X}^{\mathrm{T}}\mathsf{X})^{-1}\mathsf{X}^{\mathrm{T}}\mathbf{y}.$$ Eq (C.16)

APPENDIX – D

Gauss Elimination Method

Appendix D: Gauss Elimination method

$$\mathsf{A}\mathbf{x} = \mathbf{b}.$$

To perform Gaussian elimination starting with the system of equations

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix},$$

compose the "augmented matrix equation"

$$\left[\begin{array}{cccc|c} a_{11} & a_{12} & \cdots & a_{1k} & b_1 \\ a_{21} & a_{22} & \cdots & a_{2k} & b_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} & b_k \end{array}\right] \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix}.$$

Here, the column vector in the variables **x** is carried along for labeling the matrix rows. Now, perform elementary row and column operations to put the augmented matrix into the upper triangular form

$$\left[\begin{array}{cccc|c} a'_{11} & a'_{12} & \cdots & a'_{1k} & b'_1 \\ 0 & a'_{22} & \cdots & a'_{2k} & b'_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & a'_{kk} & b'_k \end{array}\right].$$

Solve the equation of the *k*th row for x_k, then substitute back into the equation of the $(k-1)$ st row to obtain a solution for x_{k-1}, etc., according to the formula

$$x_i = \frac{1}{a'_{ii}} \left(b'_i - \sum_{j=i+1}^{k} a'_{ij} x_j \right).$$

APPENDIX – E

Gas Turbine Input Output Model Validation Data
(Against Plant Actual Data)

Appendix E: Gas Turbine Input-Output Model Validation Data (Against Plant Actual Data)

Unit 3 Real-Time Data From 08:00 to 09:00 3rd Jan2003

Load	Actual HR	Actual Heat Consumption	Model Heat Consumption	Error	%Error
60.36751	14089.85	850.5691608	844.8815665	5.687594305	0.668680992
62.4306	13797.35	861.3768389	861.469388	-0.092549108	-0.010744323
62.87984	13690.94	860.8841166	865.0904065	-4.206289851	-0.488601168
64.31437	13718.92	882.3236969	876.6747345	5.648962339	0.640236951
66.64738	13402.44	893.2375116	895.5847152	-2.347203627	-0.262774861
67.72329	13345.03	903.7693367	904.3346536	-0.56531684	-0.062551009
69.06722	13263.85	916.097246	915.2902312	0.807014805	0.088092701
70.50176	13157.5	927.6269072	927.0162466	0.610660599	0.06583041
71.84947	13058.77	938.2657034	938.0624191	0.203284251	0.021665958
73.64264	12887.28	949.0533216	952.8046215	-3.751299876	-0.395267557
74.54111	12872.93	959.5624912	960.2105108	-0.648019685	-0.067532828
76.51171	12717.12	973.0085975	976.4988301	-3.490232658	-0.358705223
77.67821	12662.74	983.6189769	986.1699191	-2.550942227	-0.259342518
78.93532	12606.59	995.1052158	996.616531	-1.511315256	-0.151874921
80.72849	12492.8	1008.52488	1011.561444	-3.036564462	-0.301089693
81.44464	12521.97	1019.847339	1017.544427	2.302912016	0.225809484
82.79347	12447.22	1030.548536	1028.83527	1.713265354	0.166247905
84.12453	12407.09	1043.740615	1040.005818	3.734796587	0.35782804
85.92196	12274.16	1054.619885	1055.135102	-0.515217332	-0.048853368
86.28092	12363.45	1066.72984	1058.162706	8.567134636	0.803121307
88.61227	12182.63	1079.530499	1077.876221	1.654277562	0.153240466
89.60224	12166.61	1090.155509	1086.273474	3.882034872	0.356099184
91.84794	11999.26	1102.107313	1105.380207	-3.272894943	-0.296966993
92.20564	12065.67	1112.522824	1108.430998	4.091826363	0.367797071
94.80905	11870.9	1125.468752	1130.696737	-5.227985619	-0.464516284
95.70834	11888.35	1137.814244	1138.413068	-0.598823892	-0.052629319
97.50314	11781.88	1148.770295	1153.851866	-5.081570475	-0.442348701
96.63271	11916.04	1151.479238	1146.358043	5.121194355	0.44474917
96.99145	11908.48	1155.020742	1149.445091	5.575651107	0.482731686
96.63271	11951.33	1154.889406	1146.358043	8.531362691	0.738716854
96.72334	11940.47	1154.92214	1147.137743	7.784396103	0.674019125
97.35151	11865.79	1155.152574	1152.545563	2.607010937	0.22568542
96.03443	11974.78	1149.991172	1141.21426	8.776911187	0.763215528
95.67625	11982.28	1146.419617	1138.137498	8.282118372	0.722433414
93.16901	12175.53	1134.382076	1116.657645	17.72443176	1.562474596
92.54314	12144	1123.843892	1111.311376	12.53251593	1.115147399
90.57128	12268.2	1111.146577	1094.508335	16.63824211	1.497393994
89.58347	12256.39	1097.969946	1086.114116	11.8558303	1.079795521
88.06027	12336.2	1086.329103	1073.200764	13.1283384	1.208504712
86.0017	12463.95	1071.920889	1055.807481	16.11340724	1.503227282
85.37583	12422.44	1060.576126	1050.532779	10.04334692	0.946970866
83.76215	12512.32	1048.058825	1036.961846	11.09697908	1.058812618

82.41841	12576.28	1036.517001	1025.692789	10.82421257	1.044287026
81.52595	12573.92	1025.100773	1018.224238	6.876535406	0.670815552
81.61699	12497.75	1020.028737	1018.985524	1.043212777	0.102272881
81.97631	12423.54	1018.435966	1021.991487	-3.555520617	-0.349115775
82.4391	12326.13	1016.155064	1025.866084	-9.711020026	-0.955663203
81.9908	12412.57	1017.716544	1022.112749	-4.396204783	-0.431967507
82.61992	12320.6	1017.926986	1027.380884	-9.453897175	-0.928740205
81.84765	12447.12	1018.767521	1020.914919	-2.147398127	-0.210783921
82.11553	12428.47	1020.570401	1023.156713	-2.586312077	-0.253418292
81.7571	12460.53	1018.736797	1020.157397	-1.420599818	-0.139447188
81.7571	12481.48	1020.449609	1020.157397	0.292211427	0.028635557
84.89676	12132.82	1030.037108	1046.499498	-16.46239079	-1.598232789
84.80504	12246.26	1038.544569	1045.727727	-7.183158164	-0.691656225
86.51158	12110.1	1047.663885	1060.109264	-12.44537898	-1.187917151
87.90976	12054.03	1059.666884	1071.926783	-12.25989916	-1.156957846
89.25754	11982.83	1069.557928	1083.347841	-13.78991261	-1.28930956
90.69216	11921.32	1081.170261	1095.536619	-14.3663584	-1.328778539
92.12677	11890.01	1095.388217	1107.758148	-12.36993102	-1.129273698
93.11085	11878.52	1106.019094	1116.16057	-10.14147645	-0.916935025
94.37551	11851.86	1118.525332	1126.98137	-8.456037873	-0.755998781
96.79332	11706.58	1133.118744	1147.739879	-14.62113494	-1.29034446
97.06357	11763.28	1141.785952	1150.06595	-8.27999832	-0.725179558
97.50999	11799.34	1150.553525	1153.910887	-3.357362043	-0.291804072
99.57324	11674.31	1162.448871	1171.722604	-9.273732514	-0.797775519
100.558	11683.03	1174.822131	1180.247827	-5.425696351	-0.461831303
101.1847	11706.18	1184.486311	1185.681324	-1.195012571	-0.100888677
101.902	11710.69	1193.342732	1191.908014	1.434718158	0.120226832
104.1486	11574.15	1205.431519	1211.463266	-6.031747332	-0.500380755
104.5923	11616.53	1214.999591	1215.33492	-0.335328974	-0.027599102
104.6829	11656.62	1220.248786	1216.125867	4.122919173	0.337875294
104.6829	11656.62	1220.248786	1216.125867	4.122919173	0.337875294
106.0269	11545.63	1224.147357	1227.874499	-3.727141949	-0.304468406
107.2855	11511.31	1234.996649	1238.902734	-3.906084821	-0.31628303
108.1787	11499.01	1243.947953	1246.744554	-2.796601179	-0.224816575
110.0625	11371.7	1251.597731	1263.325045	-11.72731366	-0.936987449
109.2546	11500.04	1256.43227	1256.207283	0.224987268	0.017906836
110.961	11438.03	1269.175247	1271.253241	-2.077994521	-0.163727943
112.5767	11371.78	1280.197466	1285.542281	-5.344815	-0.417499264
110.961	11531.56	1279.553429	1271.253241	8.300187809	0.648678486
111.6783	11475.24	1281.535295	1277.591808	3.943487181	0.307715846
111.7689	11466.26	1281.571267	1278.392997	3.178270075	0.247997919
111.229	11519.97	1281.354743	1273.620517	7.734226004	0.603597563
110.961	11531.56	1279.553429	1271.253241	8.300187809	0.648678486
111.4102	11486.67	1279.732202	1275.221727	4.510474545	0.352454563
111.7689	11451.09	1279.875733	1278.392997	1.482735862	0.115849986
111.497	11478.04	1279.767026	1275.988939	3.778087115	0.295216789
111.6798	11444.1	1278.074799	1277.605072	0.469727414	0.036752733
112.2196	11390.96	1278.288975	1282.38055	-4.0915749	-0.320082155
111.8419	11432.22	1278.601206	1279.038642	-0.437436227	-0.034212092
112.7372	11406.02	1285.882758	1286.963996	-1.081237613	-0.084085241

113.6363	11349.43	1289.707232	1294.935857	-5.228624309	-0.405411723
113.7269	11400.99	1296.59925	1295.739876	0.859373767	0.066279058
114.6222	11345.31	1300.424392	1303.692153	-3.267761548	-0.25128424
116.3297	11258.91	1309.745623	1318.894045	-9.14842259	-0.698488503
115.0596	11430.9	1315.234782	1307.581899	7.652882566	0.581864369
115.7783	11377.74	1317.295395	1313.97984	3.315555311	0.25169414
115.7783	11377.74	1317.295395	1313.97984	3.315555311	0.25169414
115.6877	11386.33	1317.258329	1313.172855	4.085473777	0.310149777
117.1219	11266.4	1319.542174	1325.962807	-6.420632946	-0.486580351
115.7783	11407.04	1320.687699	1313.97984	6.707859501	0.507906563
115.6877	11400.99	1318.954311	1313.172855	5.781455459	0.438336295
117.6616	11246.05	1323.228237	1330.784258	-7.556021154	-0.571029316
115.3291	11435.16	1318.806711	1309.98005	8.82666129	0.669291505
116.6614	11298.83	1318.137326	1321.85257	-3.715243493	-0.281855571
116.752	11290.37	1318.173278	1322.660961	-4.487683181	-0.340447137
115.8644	11366.46	1316.968068	1314.746863	2.221204572	0.168660473
117.4541	11243.84	1320.635108	1328.929991	-8.294883303	-0.628098046
116.4678	11335.59	1320.231229	1320.125584	0.105644795	0.008001992
116.018	11377.94	1320.045843	1316.115506	3.930336837	0.29774245
116.2864	11367.24	1321.855418	1318.50797	3.347447521	0.253238552
116.9137	11323.57	1323.880466	1324.104079	-0.22361287	-0.016890715
117.1858	11268.64	1320.524593	1326.53342	-6.008826746	-0.455033308
115.659	11411.99	1319.899351	1312.917249	6.982102854	0.528987521
117.0044	11299.99	1322.14855	1324.913728	-2.765178005	-0.209142763
117.0044	11299.99	1322.14855	1324.913728	-2.765178005	-0.209142763
116.8268	11316.55	1322.076324	1323.328474	-1.252150522	-0.09471091

Unit 4 Real-Time Data From 08:00 to 09:00 3rd Jan2003

Load	Actual	Actual Heat Consumption	Model Heat Consumption	Error	%Error
51.61478	15138.11	781.3502173	787.1021755	-5.751958264	-0.736156225
53.00898	14951.64	792.5711857	796.4164803	-3.845294598	-0.485167095
54.57968	14743.67	804.7047906	807.1108706	-2.406080014	-0.299001577
54.66665	14842.86	811.4094326	807.7090943	3.700338348	0.45603837
55.62559	14681.79	816.683231	814.3465379	2.336693073	0.286119879
54.92832	14864.21	816.4660834	809.5127771	6.953306356	0.85163444
55.10263	14788.49	814.8846927	810.7174293	4.167263447	0.511393021
55.93958	14566.49	814.8433327	816.5361696	-1.692836886	-0.207749983
56.63642	14537.91	823.3751767	821.423901	1.95127568	0.236985002
58.03194	14281.55	828.7860527	831.3270965	-2.541043785	-0.30659828
59.51181	14116.41	840.0931098	841.9911177	-1.898007934	-0.225928282
61.86641	13779.7	852.5005699	859.2869114	-6.786341479	-0.796051254
63.69737	13602.27	866.428825	873.0005082	-6.571683192	-0.758479289
64.50688	13645.21	880.209924	879.133725	1.076199094	0.122266185
66.24741	13458.54	891.5934174	892.4598526	-0.866435205	-0.097178286
66.38265	13590.51	902.1740687	893.5030198	8.671048844	0.96112814
68.12123	13411.44	913.6037889	907.0086793	6.595109556	0.721878525
70.73314	13057.72	923.6135368	927.61355	-4.000013197	-0.433082998
71.51682	13093.83	936.4290832	933.8650447	2.564038477	0.273810214
71.86377	13171.77	946.5730498	936.6424074	9.930642341	1.049115263
74.64785	12849.74	959.2054641	959.1334744	0.071989695	0.007505138
75.51942	12838.24	969.5364386	966.2448076	3.291631025	0.339505654
76.99787	12728.61	980.0758581	978.3785939	1.697264161	0.173176816
78.47834	12622.9	990.624238	990.6125824	0.011655605	0.001176592
79.69413	12561.66	1001.090565	1000.717357	0.373208014	0.037280145
82.48094	12260.73	1011.276535	1024.05616	-12.77962403	-1.263712108
82.47986	12382.94	1021.343158	1024.047071	-2.703913546	-0.264740947
84.91508	12156.3	1032.253187	1044.615505	-12.36231801	-1.197605216
85.00297	12292.15	1044.869258	1045.360487	-0.491229546	-0.047013494
86.22353	12240.39	1055.409634	1055.723353	-0.313718386	-0.029724798
87.87396	12151.06	1067.76176	1069.781753	-2.019992725	-0.189180096
90.04918	12006.09	1081.13856	1088.376741	-7.238181548	-0.669496198
90.92073	12005.47	1091.546096	1095.844247	-4.298150878	-0.393767235
91.6177	12008.66	1100.205809	1101.821572	-1.615762281	-0.146860003
92.04943	12072.67	1111.282392	1105.52634	5.756052031	0.517964837
93.6182	11948.75	1118.620467	1118.999524	-0.379057129	-0.033886125
93.09595	12022.99	1119.291676	1114.512561	4.779115065	0.426976736
92.2256	12150.92	1120.625888	1107.038526	13.58736146	1.212479705
93.96507	11932.81	1121.267327	1121.980429	-0.713101916	-0.06359785
92.92139	12062.69	1120.881922	1113.01315	7.868771512	0.702016096
94.2275	11918.54	1123.054228	1124.236009	-1.18178126	-0.105229225
95.70819	11810.52	1130.363492	1136.966022	-6.602529886	-0.584106788
97.09976	11732.96	1139.2676	1148.931082	-9.663482196	-0.84821882
97.96801	11727.63	1148.932573	1156.39466	-7.462086684	-0.649479948
97.27061	11903.98	1157.907396	1150.399903	7.507492699	0.648367281
97.96639	11856.67	1161.555157	1156.380736	5.174420843	0.445473537

97.70639	11904.17	1163.113477	1154.146	8.967476828	0.770988988
98.81172	11779.51	1163.953644	1163.644425	0.309218492	0.026566221
98.89966	11769.38	1163.98768	1164.399858	-0.412177111	-0.035410779
100.1199	11706.52	1172.055612	1174.876823	-2.821211529	-0.240706286
101.9483	11569.9	1179.531636	1190.551154	-11.01951741	-0.93422822
102.0326	11643.38	1188.004334	1191.272961	-3.268626367	-0.275135896
102.0326	11676.61	1191.394877	1191.272961	0.121916931	0.010233125
102.4687	11694.74	1198.344805	1195.0056	3.339204568	0.278651399
103.1649	11650.65	1201.938142	1200.959267	0.978875674	0.081441435
103.6889	11610.43	1203.872715	1205.435761	-1.5630455	-0.129834781
102.9926	11686.28	1203.600362	1199.48644	4.113921219	0.341801261
103.8611	11607.82	1205.600954	1206.905939	-1.30498513	-0.108243538
103.2528	11657.81	1203.701524	1201.710474	1.991050066	0.165410613
102.9926	11686.28	1203.600362	1199.48644	4.113921219	0.341801261
103.7768	11584.24	1202.175358	1206.186276	-4.010917925	-0.333638342
102.6385	11683.98	1199.226181	1196.45828	2.767900843	0.230807239
103.1633	11626.5	1199.428107	1200.945592	-1.517484162	-0.126517309
105.2488	11451.84	1205.292418	1218.73558	-13.44316221	-1.11534446
105.6712	11499.77	1215.194496	1222.329517	-7.135020933	-0.587150531
107.2369	11432.63	1225.9998	1235.619582	-9.619781897	-0.784647917
107.3184	11479.47	1231.958353	1236.309924	-4.351570369	-0.353223821
107.3184	11510.46	1235.28415	1236.309924	-1.025773153	-0.083039449
105.5832	11733.47	1238.85731	1221.581061	17.27624851	1.394530942
109.4148	11367.63	1243.786963	1254.012287	-10.22532404	-0.822112174
108.0144	11517.76	1244.083936	1242.199082	1.884854124	0.151505382
106.8824	11651.05	1245.292187	1232.615074	12.6771128	1.018003079
107.6664	11569.14	1245.607655	1239.255924	6.3517305	0.509930272
108.0144	11533.16	1245.747358	1242.199082	3.548275884	0.284831099
108.1866	11515.44	1245.816301	1243.654359	2.161941824	0.173536164
107.9265	11526.82	1244.049339	1241.455954	2.593384958	0.208463192
108.3624	11482.06	1244.223579	1245.139311	-0.91573201	-0.07359867
108.7984	11484.17	1249.459321	1248.818783	0.640537979	0.051265213
111.5839	11268.43	1257.375366	1272.203431	-14.82806462	-1.179287031
110.7985	11444.36	1268.017921	1265.632641	2.38528026	0.188110926
112.2785	11359.44	1275.420884	1277.998486	-2.577602184	-0.202098164
112.0184	11399.73	1276.979515	1275.830284	1.149231306	0.089996064
111.8426	11432.52	1278.642761	1274.363572	4.279189526	0.334666543
112.6413	11392.55	1283.271642	1281.019091	2.252551571	0.175531937
113.7706	11313.47	1287.14027	1290.392788	-3.252517652	-0.252693333
113.338	11355.09	1286.96319	1286.807244	0.155946842	0.012117428
112.6413	11422.76	1286.674536	1281.019091	5.655445244	0.439539688
111.4353	11534.81	1285.385013	1270.961672	14.42334072	1.122102761
112.5693	11422.76	1285.852097	1280.41998	5.432117501	0.422452747
113.5286	11329.71	1286.246115	1288.387819	-2.14170421	-0.166508119
113.006	11380.21	1286.032011	1284.051072	1.980938913	0.154034961
111.2628	11506.48	1280.243183	1269.519336	10.72384699	0.837641406
111.4353	11458.75	1276.909244	1270.961672	5.947571798	0.465778741
110.3013	11526.39	1271.375801	1261.463425	9.91237598	0.779657436
112.4812	11280.63	1268.858799	1279.686666	-10.82786673	-0.853354742
111.2628	11414.69	1270.030371	1269.519336	0.51103458	0.040237981

110.8261	11380.31	1261.235374	1265.863865	-4.628490494	-0.366980707
111.7839	11363.38	1270.242934	1273.873614	-3.630680036	-0.285825643
112.4812	11325.73	1273.931701	1279.686666	-5.754964606	-0.451748285
111.7687	11402.51	1274.443719	1273.746724	0.696995304	0.05469016
111.2444	11454.32	1274.228956	1269.365433	4.863523161	0.381683617
112.205	11374.61	1276.288115	1277.386011	-1.097895733	-0.086022562
112.1326	11359.68	1273.790454	1276.782529	-2.992075861	-0.234895453
111.5927	11419.84	1274.370779	1272.276945	2.093833733	0.164303338
112.205	11359.75	1274.620749	1277.386011	-2.765262033	-0.216947828
112.117	11383.21	1276.251356	1276.652475	-0.401119659	-0.031429519
113.338	11279.7	1278.418639	1286.807244	-8.388604978	-0.656170422
112.3774	11372.62	1278.025467	1278.82234	-0.796873685	-0.062351941
111.7687	11417.41	1276.109073	1273.746724	2.362348934	0.18512124
112.6413	11346.93	1278.132946	1281.019091	-2.886144535	-0.225809415
112.205	11374.61	1276.288115	1277.386011	-1.097895733	-0.086022562
112.205	11374.61	1276.288115	1277.386011	-1.097895733	-0.086022562
111.5927	11449.71	1277.704053	1272.276945	5.427107682	0.424754674
112.117	11398.08	1277.918535	1276.652475	1.266060131	0.099072053
112.6413	11346.93	1278.132946	1281.019091	-2.886144535	-0.225809415
113.25	11273.43	1276.715948	1286.077064	-9.361116153	-0.733218393
111.6807	11426.09	1276.073729	1273.011957	3.061772512	0.23993696
111.5942	11434.63	1276.038387	1272.289476	3.748911066	0.293792969

Unit 5 Real-Time Data From 08:00 to 09:00 3rd Jan2003

Load	Actual	Actual Heat Consumption	Model	Error	%Error
50.71194	14808.82	750.9839913	777.3658678	-26.38187646	-3.512974546
52.38313	14601.76	764.8858923	790.2991662	-25.41327388	-3.322492169
54.14061	14323.17	775.4651609	803.5282952	-28.06313426	-3.618877503
55.89993	14061.75	786.0508407	816.5444764	-30.49363573	-3.879346494
56.33837	14118.53	795.414967	819.7680745	-24.35310749	-3.06168585
57.30516	14090.38	807.4514804	826.8621137	-19.41063338	-2.403938051
56.42717	14363.77	810.5068916	820.4203562	-9.913464559	-1.223119095
57.30516	14177.84	812.4633897	826.8621137	-14.39872409	-1.772230512
56.25143	14437.56	812.1333957	819.129272	-6.995876307	-0.861419607
56.95367	14263.41	812.3535462	824.2845666	-11.93102036	-1.468698009
56.69172	14298.21	810.5901178	822.3626153	-11.77249748	-1.452336665
56.51412	14342.16	810.5345513	821.0588776	-10.52432626	-1.298442644
56.77867	14247.77	808.9694311	823.0006944	-14.03126336	-1.734461504
56.95442	14204.77	809.0244366	824.2900679	-15.26563136	-1.886918451
57.57046	14084.72	810.8638094	828.8069648	-17.94315544	-2.212844528
59.82358	13730.62	821.414844	845.3402342	-23.92539018	-2.912704872
61.08461	13608.38	831.262585	854.639053	-23.37646801	-2.812164102
62.02257	13552.68	840.572044	861.5908002	-21.01875626	-2.500530015
62.90025	13475.19	847.5928198	868.1284494	-20.53562963	-2.422817791
63.87135	13459.46	859.6738805	875.4029413	-15.72906085	-1.829654385
65.36665	13287.4	868.5528252	886.6955332	-18.14270798	-2.088843355
67.12485	13223.46	887.622769	900.1230866	-12.50031764	-1.408291684
68.44321	13123.09	898.1864047	910.2994263	-12.11302163	-1.348608882
69.58752	13094.09	911.1852498	919.2062835	-8.021033732	-0.880285731
71.69838	12847.72	921.1607107	935.8098051	-14.64909445	-1.590286502
73.9023	12691.27	937.9140429	953.3689531	-15.45491019	-1.647796011
73.9023	12874.13	951.4278175	953.3689531	-1.941135608	-0.204023424
75.22067	12766.5	960.3046836	963.9725342	-3.66785063	-0.381946552
76.80467	12642.11	970.9730867	976.8029134	-5.829826785	-0.600410749
79.12978	12457.57	985.7647734	995.7996004	-10.03482695	-1.017973782
80.88774	12361.63	999.9043134	1010.280971	-10.3766573	-1.03776503
81.15421	12489.04	1013.538175	1012.484487	1.053688061	0.103961359
82.29781	12474.43	1026.61827	1021.965813	4.652457225	0.453182781
84.67014	12274.82	1039.310728	1041.759301	-2.44857334	-0.235595888
85.55097	12310.62	1053.185482	1049.151259	4.034223692	0.383049687
86.25415	12341.1	1064.471091	1055.069143	9.401948062	0.883250672
89.06689	12096.1	1077.362008	1078.893112	-1.531104247	-0.142116042
89.06689	12210.35	1087.5379	1078.893112	8.644787936	0.794895326
91.26526	12064.43	1101.063341	1097.688554	3.374786414	0.306502477
92.32004	12059.61	1113.343678	1106.762554	6.581124043	0.591113434
93.20087	12058.49	1123.861759	1114.367881	9.493877543	0.844754924
96.01366	11831.5	1135.985618	1138.816881	-2.83126262	-0.24923402
94.87111	12094.4	1147.409153	1128.856982	18.5521711	1.616874945
95.39987	12065.22	1151.02042	1133.461655	17.55876483	1.525495511
94.4348	12184.59	1150.64932	1125.063693	25.58562649	2.223581595

95.31112	12076.1	1150.986616	1132.688209	18.2984071	1.5898019
95.31112	12076.1	1150.986616	1132.688209	18.2984071	1.5898019
94.87111	12130.32	1150.816923	1128.856982	21.95994137	1.908204592
95.48861	12036.88	1149.38494	1134.23524	15.14969984	1.318070154
95.45975	12044.77	1149.790733	1133.98363	15.80710296	1.374780863
96.15524	11889.04	1143.193495	1140.053623	3.139871267	0.274657902
95.627	11970.5	1144.703004	1135.442095	9.260908225	0.809022794
95.71628	11959.69	1144.737037	1136.220965	8.516071306	0.743932539
95.9804	11927.83	1144.837895	1138.526424	6.31147059	0.55129819
95.18432	12024.41	1144.535289	1131.58356	12.95172974	1.131614714
95.44844	11974.27	1142.925392	1133.885033	9.040359021	0.790984179
96.59792	11906.76	1150.16825	1143.923983	6.244266988	0.542900309
98.98615	11740.89	1162.185499	1164.880531	-2.695032767	-0.231893512
100.6631	11687	1176.44965	1179.644593	-3.194942822	-0.271574973
101.2211	11738.67	1188.20109	1184.559196	3.641893576	0.306504817
102.5457	11716.95	1201.52284	1196.214773	5.308066491	0.441778243
105.1987	11553.23	1215.384777	1219.407692	-4.022915243	-0.330999311
104.4025	11736.89	1225.360658	1212.480568	12.88009022	1.051126469
105.0239	11702.5	1229.04219	1217.890148	11.15204126	0.907376602
104.5811	11750.34	1228.863483	1214.037579	14.82590347	1.206472784
105.1987	11683.71	1229.111103	1219.407692	9.703411133	0.789465745
105.288	11690.11	1230.828302	1220.182183	10.64611908	0.864955662
106.7899	11595.67	1238.30044	1233.11412	5.186320159	0.418825674
108.0252	11578.65	1250.785982	1243.579301	7.206681247	0.576172211
109.3332	11527.42	1260.329716	1254.429845	5.899871435	0.468121267
110.6624	11525.17	1275.402973	1265.13919	10.26378249	0.804748202
112.2428	11452.65	1285.477503	1277.332011	8.145492297	0.633654986
113.049	11533.55	1303.856294	1283.272911	20.58338256	1.578654232
113.8349	11539.46	1313.593275	1288.849767	24.74350848	1.883650666
114.2776	11541.27	1318.908637	1291.887899	27.02073747	2.048719428
112.9603	11610.66	1311.543637	1282.629696	28.91394063	2.204573284
113.8465	11568.65	1317.050312	1288.930362	28.11994991	2.135070289
110.6638	11811.69	1307.1265	1265.150271	41.97622854	3.211336358
113.9366	11522.22	1312.802571	1289.554588	23.24798299	1.770866656
117.8259	11185.18	1317.9039	1312.838618	5.065282297	0.384343828
111.454	11377.61	1268.080145	1271.329145	-3.248999925	-0.256214084
113.7579	11321.02	1287.855461	1288.313465	-0.45800382	-0.035563294
113.4935	11467.74	1301.51395	1286.454853	15.05909643	1.157044566
115.0871	11396.63	1311.605096	1297.23046	14.37463648	1.095957657
113.7579	11569.91	1316.168665	1288.313465	27.85519991	2.116385282
120.9228	10916.6	1320.065838	1324.339543	-4.273704518	-0.323749346
108.6972	10918.21	1186.778856	1249.187696	-62.40883998	-5.258674745
112.9467	11038.89	1246.806197	1282.530839	-35.72464135	-2.86529225
107.5424	11652.85	1253.175456	1239.511084	13.66437155	1.090379762
110.2903	11675.66	1287.712044	1262.178287	25.5337575	1.982877897
113.3006	11581.23	1312.160308	1285.082607	27.07770085	2.063597008
116.2927	11308.64	1315.112279	1304.613805	10.49847369	0.798294857
114.4518	11581.41	1325.513221	1293.061517	32.4517038	2.448236901
112.8573	11678.59	1318.014135	1281.879447	36.13468804	2.741600949
110.7322	11677.66	1293.092983	1265.691112	27.40187032	2.119095122

115.3348	11347.27	1308.735116	1298.806186	9.928929803	0.758666111
113.1218	11644.21	1317.213995	1283.798813	33.41518222	2.53680741
111.7046	11733.08	1310.639008	1273.255174	37.38383446	2.852336473
114.3609	11440.3	1308.323004	1292.450688	15.87231676	1.213180286
114.273	11493.68	1313.417295	1291.856737	21.56055759	1.641561877
114.273	11523.82	1316.861483	1291.856737	25.00474581	1.898813667
114.0085	11579.78	1320.193348	1290.05044	30.1429082	2.283219215
114.7163	11540.99	1323.939671	1294.818861	29.12081032	2.199557197
114.6269	11534.94	1322.214414	1294.228266	27.98614809	2.116611935
114.1836	11578.07	1322.025714	1291.249386	30.77632814	2.327967439
112.8558	11640.77	1313.728411	1281.868495	31.85991597	2.425152391
107.1892	12249.31	1312.993739	1236.516527	76.47721232	5.824644096
113.7395	11447.97	1302.086384	1288.184973	13.90141034	1.067625813
112.1487	11619.41	1303.101726	1276.625302	26.47642429	2.031800262
114.4511	11424.25	1307.517979	1293.056827	14.46115251	1.10600028
114.1828	11510.43	1314.293127	1291.243936	23.04919075	1.753732884
114.805	11479.75	1317.932699	1295.401362	22.53133662	1.709596905
112.8565	11670.58	1317.100812	1281.873606	35.22720567	2.674602077

Unit 6 Real-Time Data From 08:00 to 09:00 3rd Jan2003

Load	Actual	Actual Heat Consumption	Model	Error	%Error
55.83154	14672.19	819.1709629	814.6300565	4.540906346	0.554329505
58.27026	14285.93	832.4448554	833.2939803	-0.849124847	-0.102003735
59.14185	14291.81	845.2440832	839.9949286	5.249154683	0.621022352
58.96676	14417.67	850.1632866	838.6475133	11.51577331	1.354536651
57.66209	14794.16	853.0621854	828.6277765	24.43440888	2.864317432
58.75603	14491.26	851.4489073	837.0266887	14.42221864	1.693844283
60.49509	14194.79	858.7150986	850.4307479	8.284350714	0.964737982
60.58252	14284.55	865.3940361	851.106317	14.28771909	1.651007344
63.97124	13715.36	877.3885862	877.4154944	-0.026908186	-0.003066849
63.88707	13889.57	887.3639309	876.7590766	10.60485423	1.195096382
66.23239	13611.47	901.5201895	895.1056674	6.414522101	0.711522845
67.36318	13562.28	913.5983089	903.9930182	9.605290645	1.051369136
69.18836	13394.55	926.7469474	918.3949536	8.351993834	0.901216223
70.05931	13387.19	937.8972942	925.2921979	12.60509634	1.34397406
72.60323	13094.25	950.6848444	945.5299734	5.154871064	0.542227121
72.3172	13246.26	957.9324337	943.2476713	14.68476238	1.532964316
73.44893	13184.29	968.3719933	952.2881434	16.08384989	1.660916466
74.06006	13191.81	976.9862401	957.1812342	19.80500586	2.027152999
76.14499	12939.04	985.2430714	973.933968	11.30910339	1.147849066
76.92811	12942.1	995.6112924	980.2502219	15.36107048	1.54287829
77.10111	12957.03	999.0013953	981.6473035	17.35409184	1.737143904
78.842	12785.62	1008.043852	995.7413149	12.30253716	1.220436703
80.05799	12701.63	1016.866968	1005.623849	11.24311851	1.105662674
81.08903	12698.99	1029.748781	1014.027779	15.72100182	1.526683217
82.00835	12667.72	1038.858815	1021.540059	17.31875648	1.667094337
83.14193	12631.73	1050.226411	1030.8278	19.39861187	1.847088557
85.92627	12361.64	1062.189616	1053.756103	8.43351325	0.793974364
87.14673	12309.69	1072.749231	1063.857983	8.891248222	0.828828208
88.16208	12329.69	1087.011116	1072.286164	14.72495259	1.354627599
89.90406	12210.7	1097.791505	1086.796749	10.99475621	1.001534094
90.74562	12235.6	1110.327108	1093.829896	16.49721193	1.485797456
93.00976	12074.31	1123.028675	1112.826332	10.20234311	0.908466839
92.65891	12254.82	1135.518263	1109.875551	25.64271195	2.258238619
93.85254	12198.37	1144.848008	1119.925073	24.92293531	2.176964552
93.67614	12256.81	1148.17065	1118.438011	29.73263843	2.589566146
94.02528	12230.45	1149.971486	1121.381919	28.58956666	2.486110917
93.55895	12293.91	1150.205311	1117.450457	32.75485421	2.847739781
93.12501	12349.34	1150.032411	1113.796196	36.23621456	3.150886376
93.64721	12228.72	1145.18551	1118.194192	26.99131748	2.356938439
92.1292	12400.19	1142.419585	1105.425426	36.9941585	3.238228668
93.35198	12206.58	1139.508412	1115.707041	23.80137126	2.088740285
92.91738	12261.82	1139.336188	1112.049129	27.28705951	2.394996296
93.61759	12182.87	1140.530929	1117.944577	22.58635186	1.980336639
93.70591	12171.76	1140.565847	1118.688928	21.87691943	1.918075969
93.35633	12215.85	1140.426924	1115.743674	24.68325007	2.164386824
94.49338	12073.63	1140.878108	1125.332932	15.5451759	1.36256238
92.56749	12306.67	1139.197552	1109.107103	30.0904495	2.64137238
92.74059	12247.82	1135.870053	1110.562278	25.30777457	2.228051924

92.47909	12244.99	1132.405532	1108.364207	24.04132505	2.123031402
94.43419	12040.63	1137.047141	1124.833081	12.21406058	1.074191222
94.43419	12040.63	1137.047141	1124.833081	12.21406058	1.074191222
93.20959	12193.63	1136.563253	1114.508142	22.05511088	1.940508883
95.27883	12026.29	1145.85084	1131.972964	13.87787615	1.211141595
95.54304	12065.11	1152.737287	1134.209476	18.52781179	1.607288321
97.4586	11870.65	1156.89693	1150.468678	6.428251912	0.555646034
97.4586	11905.46	1160.289464	1150.468678	9.820785778	0.846408253
97.37055	11985.38	1167.023043	1149.71961	17.30343206	1.482698407
98.59144	11893.22	1172.569686	1160.12072	12.44896557	1.061682365
99.37604	11887.53	1181.335657	1166.8216	14.51405675	1.228614126
99.72304	11864.26	1183.140075	1169.78931	13.35076499	1.128417951
99.66069	11901.18	1186.079811	1169.255875	16.82393578	1.418448879
100.7049	11849.41	1193.293649	1178.20045	15.09319949	1.264835315
100.5304	11936.77	1200.008263	1176.704098	23.30416453	1.942000339
101.5808	11876.01	1206.374597	1185.721096	20.65350049	1.712030454
101.9292	11870.17	1209.916932	1188.717039	21.19989311	1.752177571
103.2348	11791.16	1217.258044	1199.966933	17.29111133	1.42049678
103.4144	11811.94	1221.524688	1201.517305	20.00738285	1.637902455
103.0624	11859.3	1222.24792	1198.479356	23.76856425	1.944659823
102.8864	11878.88	1222.175199	1196.961365	25.21383444	2.063029463
102.9744	11852.24	1220.477303	1197.720278	22.75702416	1.864600359
102.9744	11852.24	1220.477303	1197.720278	22.75702416	1.864600359
102.626	11891.05	1220.330897	1194.71663	25.61426726	2.098960808
102.7984	11871.82	1220.404101	1196.202615	24.20148613	1.983071518
104.8044	11701.62	1226.381263	1213.539371	12.84189227	1.047137024
104.1076	11809.77	1229.486811	1207.507659	21.97915203	1.787668792
103.8472	11838.32	1229.376385	1205.256195	24.12018944	1.961985746
104.1076	11825.77	1231.152533	1207.507659	23.64487363	1.920547861
104.6938	11766.15	1231.842955	1212.581298	19.26165705	1.563645509
103.5636	11889.94	1231.36499	1202.805772	28.55921779	2.319313771
103.1269	11922.35	1229.514996	1199.03583	30.47916671	2.478958517
104.4333	11778.49	1230.06658	1210.325738	19.74084158	1.604859599
103.5636	11873.86	1229.699687	1202.805772	26.8939151	2.18703114
104.326	11794.4	1230.462574	1209.39709	21.06548417	1.711997147
103.9772	11832.56	1230.316458	1206.380019	23.93643898	1.945551393
103.5403	11880.71	1230.132278	1202.604526	27.52775132	2.237787905
103.9772	11832.56	1230.316458	1206.380019	23.93643898	1.945551393
104.5648	11772.72	1231.012112	1211.464162	19.54795053	1.587957611
104.043	11829.64	1230.791235	1206.948982	23.84225203	1.937148345
105.4393	11726.69	1236.453985	1219.044203	17.40978177	1.40804122
105.002	11789.63	1237.934729	1215.251726	22.68300308	1.832326256
104.478	11863.26	1239.449678	1210.712675	28.73700375	2.318529284
106.2255	11690.78	1241.858951	1225.872687	15.98626381	1.287284985
107.0118	11671.67	1249.006416	1232.715122	16.29129382	1.304340283
106.5746	11733.46	1250.488806	1228.908964	21.57984252	1.72571257
107.0132	11766.38	1259.157976	1232.727316	26.43065976	2.099074164
108.3877	11674.3	1265.350526	1244.719772	20.63075441	1.630437889
108.3877	11705.76	1268.760403	1244.719772	24.04063145	1.894812558
110.4717	11561.63	1277.232921	1262.978844	14.25407691	1.116012332
110.1227	11643.01	1282.159697	1259.914656	22.2450413	1.734966506
111.8675	11529.21	1289.7439	1275.259607	14.48429227	1.123036308

110.9088	11670.88	1294.403296	1266.820177	27.58311842	2.130952425
110.5715	11713.6	1295.190322	1263.855553	31.3347697	2.419317776
110.3797	11721.63	1293.830003	1262.170842	31.65916066	2.446933568
112.4766	11557.16	1299.910062	1280.631615	19.27844776	1.483060122
110.7291	11732.57	1299.136917	1265.240444	33.89647298	2.609153242
112.6374	11578.09	1304.125955	1282.051113	22.07484125	1.692692426
111.7649	11665.03	1303.740911	1274.355491	29.38542055	2.253930999
112.0258	11638.89	1303.855963	1276.654992	27.2009712	2.086194485
112.4632	11610.21	1305.721369	1280.513348	25.20802143	1.930581978
113.3343	11554.51	1309.522303	1288.209481	21.31282162	1.627526433
112.3587	11685.53	1312.97096	1279.591173	33.37978636	2.54230957
112.8831	11648.75	1314.947011	1284.221143	30.72586836	2.336662093
114.1042	11543.54	1317.166397	1295.024884	22.14151301	1.680995891
112.5352	11713.1	1318.136051	1281.148856	36.98719495	2.806022559
113.4069	11626.51	1318.526457	1288.851624	29.67483289	2.250605798
113.7548	11592.33	1318.683181	1291.930328	26.75285268	2.028755131
112.0093	11781.54	1319.642048	1276.509523	43.13252531	3.268501892
114.7198	11498.56	1319.112503	1300.483398	18.6291059	1.412245419

APPENDIX – F

Gas Turbine Input Output Model Validation Data
(Against Performance Test Report)

Appendix F: Gas Turbine Input Output Model Validation Data (Against Performance Test Report)

Unit 3: (reference: [14])

Load	Actual	Heat Consumption	Model	Error	%Error
126.14	12401.04	1564.267186	1565.223939	-0.956753333	-0.061163038
101.67	14262.25	1450.042958	1447.251706	2.791251082	0.192494372
76.41	17220.37	1315.808472	1318.541389	-2.732916993	-0.207698693
50.89	23231.6	1182.256124	1181.357705	0.898419244	0.07599193

Unit 4: (reference: [15])

Load	Actual	Heat Consumption	Model	Error	%Error
129.97	12026.98	1563.146591	1563.969275	-0.822684402	-0.052630022
102.77	12684.31	1303.566539	1300.859661	2.706877794	0.207651678
78.66	13769	1083.06954	1085.850655	-2.781115062	-0.25678084
52.96	16548.4	876.403264	875.5063423	0.89692167	0.102341206

APPENDIX – G

Simulation Results

APPENDIX – G-1

Simulation Results- Test One

Appendix G-1: Simulation Results – Test 1

With 25 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:24	565321.9	0	0	0	0	2
2	4/12/2004 16:24	565341.3	0	0	0	0	2
3	4/12/2004 16:24	565431.9	0	0	0	0	1
4	4/12/2004 16:24	565347	0	0	0	0	2
5	4/12/2004 16:24	565362.3	0	0	0	0	2
6	4/12/2004 16:24	565377.4	0	0	0	0	2
7	4/12/2004 16:24	565404.8	0	0	0	0	2
8	4/12/2004 16:24	565375.8	0	0	0	0	1
9	4/12/2004 16:24	565405	0	0	0	0	2
10	4/12/2004 16:24	565401.7	0	0	0	0	2
11	4/12/2004 16:24	565399	0	0	0	0	2
12	4/12/2004 16:24	565354.9	0	0	0	0	2
13	4/12/2004 16:24	565430.9	0	0	0	0	1
14	4/12/2004 16:24	565425.9	0	0	0	0	2
15	4/12/2004 16:24	565348.3	0	0	0	0	2
16	4/12/2004 16:24	565408.6	0	0	0	0	2
17	4/12/2004 16:24	565412.9	0	0	0	0	1
18	4/12/2004 16:24	565354.9	0	0	0	0	2
19	4/12/2004 16:24	565379.9	0	0	0	0	2
20	4/12/2004 16:24	565361.4	0	0	0	0	
	Success		100	%			1.789474
	Best TPC	565321.9					
	Worse TPC	565431.9					
	Average TPC	565382.3					

With 50 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:21	565309.6	0	0	0	0	3
2	4/12/2004 16:21	565276.7	0	0	0	0	3
3	4/12/2004 16:21	565270.4	0	0	0	0	4
4	4/12/2004 16:21	565320.9	0	0	0	0	3
5	4/12/2004 16:21	565329.1	0	0	0	0	3
6	4/12/2004 16:21	565333	0	0	0	0	4
7	4/12/2004 16:21	565321	0	0	0	0	3
8	4/12/2004 16:21	565287.4	0	0	0	0	4
9	4/12/2004 16:21	565291.8	0	0	0	0	3
10	4/12/2004 16:22	565362.8	0	0	0	0	3
11	4/12/2004 16:22	565269.4	0	0	0	0	4
12	4/12/2004 16:22	565318.4	0	0	0	0	3
13	4/12/2004 16:22	565317.1	0	0	0	0	4
14	4/12/2004 16:22	565295.3	0	0	0	0	3
15	4/12/2004 16:22	565285.4	0	0	0	0	3
16	4/12/2004 16:22	565355.9	0	0	0	0	4
17	4/12/2004 16:22	565353.8	0	0	0	0	3
18	4/12/2004 16:22	565307.9	0	0	0	0	3
19	4/12/2004 16:22	565298.4	0	0	0	0	4
20	4/12/2004 16:22	565328.3	0	0	0	0	
	Success		100	%			3.368421
	Best TPC	565269.4					
	Worse TPC	565362.8					
	Average TPC	565311.6					

With 100 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:16	565262.1	0	0	0	0	7
2	4/12/2004 16:16	565213	0	0	0	0	6
3	4/12/2004 16:16	565258.5	0	0	0	0	6
4	4/12/2004 16:17	565238.3	0	0	0	0	7
5	4/12/2004 16:17	565254.2	0	0	0	0	6
6	4/12/2004 16:17	565279.3	0	0	0	0	7
7	4/12/2004 16:17	565238.9	0	0	0	0	6
8	4/12/2004 16:17	565230.8	0	0	0	0	7
9	4/12/2004 16:17	565243.5	0	0	0	0	6
10	4/12/2004 16:17	565219.6	0	0	0	0	6
11	4/12/2004 16:17	565258.8	0	0	0	0	7
12	4/12/2004 16:17	565259.8	0	0	0	0	6
13	4/12/2004 16:18	565231.7	0	0	0	0	7
14	4/12/2004 16:18	565227.5	0	0	0	0	6
15	4/12/2004 16:18	565241.8	0	0	0	0	6
16	4/12/2004 16:18	565240.8	0	0	0	0	7
17	4/12/2004 16:18	565246.1	0	0	0	0	6
18	4/12/2004 16:18	565270.9	0	0	0	0	7
19	4/12/2004 16:18	565217.6	0	0	0	0	6
20	4/12/2004 16:18	565226.6	0	0	0	0	
	Success		100	%			6.421053
	Best TPC	565213					
	Worse TPC	565279.3					
	Average TPC	565243					

With 250 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:30	565189.6	0	0	0	0	16
2	4/12/2004 16:30	565190.3	0	0	0	0	16
3	4/12/2004 16:31	565186	0	0	0	0	17
4	4/12/2004 16:31	565200.1	0	0	0	0	16
5	4/12/2004 16:31	565215.5	0	0	0	0	16
6	4/12/2004 16:31	565193.4	0	0	0	0	16
7	4/12/2004 16:32	565188.4	0	0	0	0	16
8	4/12/2004 16:32	565199.8	0	0	0	0	15
9	4/12/2004 16:32	565219.9	0	0	0	0	16
10	4/12/2004 16:32	565204.9	0	0	0	0	16
11	4/12/2004 16:33	565181.3	0	0	0	0	16
12	4/12/2004 16:33	565185.6	0	0	0	0	15
13	4/12/2004 16:33	565210	0	0	0	0	16
14	4/12/2004 16:33	565187.8	0	0	0	0	16
15	4/12/2004 16:34	565208.7	0	0	0	0	15
16	4/12/2004 16:34	565198.5	0	0	0	0	16
17	4/12/2004 16:34	565191.6	0	0	0	0	16
18	4/12/2004 16:34	565214.4	0	0	0	0	16
19	4/12/2004 16:35	565205.6	0	0	0	0	15
20	4/12/2004 16:35	565200.5	0	0	0	0	
	Success		100	%			15.84211
	Best TPC	565181.3					
	Worse TPC	565219.9					
	Average TPC	565198.6					

With 500 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:40	565175.3	0	0	0	0	34
2	4/12/2004 16:40	565189.6	0	0	0	0	34
3	4/12/2004 16:41	565184.3	0	0	0	0	32
4	4/12/2004 16:42	565175.9	0	0	0	0	32
5	4/12/2004 16:42	565189.2	0	0	0	0	31
6	4/12/2004 16:43	565173.6	0	0	0	0	31
7	4/12/2004 16:43	565186.9	0	0	0	0	31
8	4/12/2004 16:44	565170.8	0	0	0	0	31
9	4/12/2004 16:44	565192.6	0	0	0	0	32
10	4/12/2004 16:45	565184.4	0	0	0	0	31
11	4/12/2004 16:45	565169.7	0	0	0	0	31
12	4/12/2004 16:46	565181.4	0	0	0	0	31
13	4/12/2004 16:46	565175.4	0	0	0	0	31
14	4/12/2004 16:47	565173.3	0	0	0	0	31
15	4/12/2004 16:47	565176.8	0	0	0	0	31
16	4/12/2004 16:48	565191.1	0	0	0	0	31
17	4/12/2004 16:48	565187.5	0	0	0	0	32
18	4/12/2004 16:49	565172.1	0	0	0	0	31
19	4/12/2004 16:49	565194.9	0	0	0	0	31
20	4/12/2004 16:50	565182.1	0	0	0	0	
	Success		100	%			31.52632
	Best TPC	565169.7					
	Worse TPC	565194.9					
	Average TPC	565181.3					

With 750 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 16:54	565176.4	0	0	0	0	47
2	4/12/2004 16:55	565166.5	0	0	0	0	47
3	4/12/2004 16:55	565174.1	0	0	0	0	50
4	4/12/2004 16:56	565178.1	0	0	0	0	48
5	4/12/2004 16:57	565180.1	0	0	0	0	48
6	4/12/2004 16:58	565173.6	0	0	0	0	47
7	4/12/2004 16:59	565171.9	0	0	0	0	47
8	4/12/2004 16:59	565166.7	0	0	0	0	47
9	4/12/2004 17:00	565183.3	0	0	0	0	47
10	4/12/2004 17:01	565176.4	0	0	0	0	47
11	4/12/2004 17:02	565164.7	0	0	0	0	47
12	4/12/2004 17:02	565175.8	0	0	0	0	47
13	4/12/2004 17:03	565165.3	0	0	0	0	47
14	4/12/2004 17:04	565164.3	0	0	0	0	47
15	4/12/2004 17:05	565172.4	0	0	0	0	47
16	4/12/2004 17:06	565178.3	0	0	0	0	47
17	4/12/2004 17:06	565178.8	0	0	0	0	47
18	4/12/2004 17:07	565171.8	0	0	0	0	47
19	4/12/2004 17:08	565164.9	0	0	0	0	48
20	4/12/2004 17:09	565175.6	0	0	0	0	
	Success		100	%			47.31579
	Best TPC	565164.3					
	Worse TPC	565183.3					
	Average TPC	565173					

With 1000 iterations

RUN	TIME	TPC	Error	sNOx	sCO	sSO2	Time, sec
1	4/12/2004 17:12	565174.1	0	0	0	0	63
2	4/12/2004 17:13	565169.2	0	0	0	0	64
3	4/12/2004 17:14	565173.3	0	0	0	0	68
4	4/12/2004 17:15	565168	0	0	0	0	66
5	4/12/2004 17:16	565166.1	0	0	0	0	65
6	4/12/2004 17:17	565169.1	0	0	0	0	62
7	4/12/2004 17:18	565177.5	0	0	0	0	66
8	4/12/2004 17:19	565174.4	0	0	0	0	101
9	4/12/2004 17:21	565170.7	0	0	0	0	171
10	4/12/2004 17:24	565168.7	0	0	0	0	101
11	4/12/2004 17:25	565172.3	0	0	0	0	81
12	4/12/2004 17:27	565170.1	0	0	0	0	63
13	4/12/2004 17:28	565168	0	0	0	0	88
14	4/12/2004 17:29	565170	0	0	0	0	64
15	4/12/2004 17:30	565162.6	0	0	0	0	81
16	4/12/2004 17:32	565179.1	0	0	0	0	74
17	4/12/2004 17:33	565162.7	0	0	0	0	65
18	4/12/2004 17:34	565173.6	0	0	0	0	62
19	4/12/2004 17:35	565167	0	0	0	0	62
20	4/12/2004 17:36	565168.9	0	0	0	0	
	Success		100	%			77.21053
	Best TPC	565162.6					
	Worse TPC	565179.1					
	Average TPC	565170.3					

APPENDIX – G-2

Simulation Results - Test Two

Appendix G-2: Simulation Results – Test 2

Final results of each run (with 2000 iterations)

RUN	TIME	TPC	Error	sNOx	sCO	sSO2
1	4/13/2004 15:03	44228.82	0	0	0	0
2	4/13/2004 15:04	44228.82	0	0	0	0
3	4/13/2004 15:05	44228.82	0	0	0	0
4	4/13/2004 15:06	44228.82	0	0	0	0
5	4/13/2004 15:07	44228.82	0	0	0	0

Final results of each interval for each run (with 2000 iterations)

RUN **1**

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60	70.5	130	0	260.5	260.5	30170.25	0	0	0	0
3	99.67047	130	130	90.00953	449.68	449.68	10287.38	0	0	0	0
4	117.8457	130	130	102.8343	480.68	480.68	303.9402	0	0	0	0
5	112.7151	130	130	99.09493	471.81	471.81	299.1487	0	0	0	0
6	82.44532	81.12238	130	76.17223	369.74	369.7399	246.6831	0	0	0	0
7	62.43587	72.771	130	61.30309	326.51	326.5099	225.1186	0	0	0	0
8	99.84558	130	130	89.45439	449.3	449.3	287.1844	0	0	0	0
9	112.0085	130	130	98.5815	470.59	470.59	298.4931	0	0	0	0
10	101.459	130	130	90.44095	451.9	451.9	288.552	0	0	0	0
11	85.20471	130	130	78.24529	423.45	423.45	273.7904	0	0	0	0
12	88.07154	84.51526	130	80.60313	383.19	383.1899	253.5581	0	0	0	0
13	85.48428	130	130	78.46569	423.95	423.95	274.0459	0	0	0	0
14	84.72696	130	130	78.04298	422.77	422.77	273.443	0	0	0	0
15	70.36346	130	130	67.06648	397.43	397.4299	260.6814	0	0	0	0
16	71.67416	76.19434	130	68.22146	346.09	346.09	234.7819	0	0	0	0
17	86.66725	83.55869	130	79.484	379.71	379.71	251.7722	0	0	0	0

Appendix G-2

RUN **2**

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60	70.5	130	0	260.5	260.5	30170.25	0	0	0	0
3	100.0288	130	130	89.6512	449.68	449.68	10287.38	0	0	0	0
4	117.8748	130	130	102.8051	480.68	480.68	303.9402	0	0	0	0
5	112.7475	130	130	99.06249	471.81	471.81	299.1487	0	0	0	0
6	82.42783	81.03009	130	76.28201	369.74	369.7399	246.6831	0	0	0	0
7	62.49298	72.76794	130	61.24904	326.51	326.5099	225.1186	0	0	0	0
8	99.91333	130	130	89.38664	449.3	449.3	287.1844	0	0	0	0
9	112.0501	130	130	98.53982	470.59	470.59	298.4931	0	0	0	0
10	101.4913	130	130	90.40862	451.9	451.9	288.552	0	0	0	0
11	85.20801	130	130	78.24197	423.45	423.45	273.7904	0	0	0	0
12	88.08327	84.49985	130	80.60686	383.19	383.19	253.5581	0	0	0	0
13	85.41229	130	130	78.5377	423.95	423.95	274.0459	0	0	0	0
14	84.69513	130	130	78.0748	422.77	422.7699	273.443	0	0	0	0
15	70.8549	130	130	66.57344	397.43	397.4283	260.681	0	0	0	0
16	71.65942	76.18948	130	68.24104	346.09	346.09	234.7819	0	0	0	0
17	86.75591	83.58768	130	79.36636	379.71	379.71	251.7722	0	0	0	0

RUN 3

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60	70.5	130	0	260.5	260.5	30170.25	0	0	0	0
3	100.1115	130	130	89.56849	449.68	449.68	10287.38	0	0	0	0
4	117.8861	130	130	102.7939	480.68	480.6799	303.9402	0	0	0	0
5	112.6653	130	130	99.14465	471.81	471.81	299.1487	0	0	0	0
6	82.37156	81.04492	130	76.32346	369.74	369.7399	246.6831	0	0	0	0
7	62.46159	72.81451	130	61.23385	326.51	326.51	225.1186	0	0	0	0
8	99.91833	130	130	89.38162	449.3	449.3	287.1844	0	0	0	0
9	111.9603	130	130	98.62963	470.59	470.59	298.4931	0	0	0	0
10	101.419	130	130	90.48092	451.9	451.9	288.552	0	0	0	0
11	85.18701	130	130	78.26298	423.45	423.45	273.7904	0	0	0	0
12	88.1309	84.53107	130	80.52798	383.19	383.1899	253.5581	0	0	0	0
13	85.34796	130	130	78.60201	423.95	423.95	274.0459	0	0	0	0
14	84.75146	130	130	78.01848	422.77	422.77	273.443	0	0	0	0
15	70.3316	130	130	67.09835	397.43	397.43	260.6814	0	0	0	0
16	71.7447	76.14224	130	68.20302	346.09	346.09	234.7819	0	0	0	0
17	86.69592	83.53848	130	79.47555	379.71	379.71	251.7722	0	0	0	0

RUN 4

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60	70.5	130	0	260.5	260.5	30170.25	0	0	0	0
3	99.72275	130	130	89.95723	449.68	449.68	10287.38	0	0	0	0
4	117.8178	130	130	102.8621	480.68	480.68	303.9402	0	0	0	0
5	112.8064	130	130	99.00352	471.81	471.8099	299.1487	0	0	0	0
6	82.45741	81.06451	130	76.21802	369.74	369.7399	246.6831	0	0	0	0
7	62.39801	72.8107	130	61.30127	326.51	326.51	225.1186	0	0	0	0
8	99.82144	130	130	89.47852	449.3	449.3	287.1844	0	0	0	0
9	111.9964	130	130	98.59359	470.59	470.59	298.4931	0	0	0	0
10	101.3897	130	130	90.51022	451.9	451.9	288.552	0	0	0	0
11	85.18033	130	130	78.26968	423.45	423.45	273.7904	0	0	0	0
12	88.14271	84.52292	130	80.52434	383.19	383.1899	253.5581	0	0	0	0
13	85.3667	130	130	78.58325	423.95	423.95	274.0459	0	0	0	0
14	84.71027	130	130	78.05968	422.77	422.77	273.443	0	0	0	0
15	70.375	130	130	67.05495	397.43	397.43	260.6814	0	0	0	0
16	71.81449	76.12717	130	68.14828	346.09	346.0899	234.7819	0	0	0	0
17	86.66966	83.56107	130	79.47923	379.71	379.71	251.7722	0	0	0	0

RUN **5**

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60	70.49997	130	0	260.5	260.5	30170.25	0	0	0	0
3	100.5816	130	130	89.09842	449.68	449.68	10287.38	0	0	0	0
4	117.7404	130	130	102.9395	480.68	480.68	303.9402	0	0	0	0
5	112.817	130	130	98.993	471.81	471.8099	299.1487	0	0	0	0
6	82.45131	81.05255	130	76.23608	369.74	369.7399	246.6831	0	0	0	0
7	62.29963	72.79486	130	61.41548	326.51	326.5099	225.1186	0	0	0	0
8	99.99402	130	130	89.30594	449.3	449.3	287.1844	0	0	0	0
9	111.9669	130	130	98.62309	470.59	470.59	298.4931	0	0	0	0
10	101.4082	130	130	90.49173	451.9	451.9	288.552	0	0	0	0
11	85.18033	130	130	78.26968	423.45	423.45	273.7904	0	0	0	0
12	88.13268	84.44131	130	80.61597	383.19	383.1899	253.5581	0	0	0	0
13	85.4133	130	130	78.53667	423.95	423.95	274.0459	0	0	0	0
14	84.73651	130	130	78.03344	422.77	422.77	273.443	0	0	0	0
15	70.35715	130	130	67.07281	397.43	397.43	260.6814	0	0	0	0
16	71.70401	76.19644	130	68.1895	346.09	346.09	234.7819	0	0	0	0
17	86.6848	83.57382	130	79.45132	379.71	379.7099	251.7722	0	0	0	0

APPENDIX – G-3

Simulation Results - Test Three (SET 1)

Appendix G-3: Simulation Results – Test 3 SET 1

With 1000 iterations

RUN **1**

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	0	60.00238	129.9976	60	250	250	30166.23	0	0	0	0
3	0	87.03253	130	82.96743	300	300	190.9296	0	0	0	0
4	0	78.22388	130	71.77608	280	279.9999	180.7262	0	0	0	0
5	0	78.23325	130	71.76671	280	279.9999	180.7262	0	0	0	0
6	0	87.03247	130	82.96748	300	299.9999	190.9296	0	0	0	0
7	0	87.02191	130	82.97805	300	300	190.9296	0	0	0	0
8	0	79.09468	66.41467	74.49066	220	220	173.1007	0	0	0	0
9	0	79.03279	66.29187	74.67532	220	220	173.1016	0	0	0	0
10	0	74.68182	130	65.31815	270	270	175.7414	0	0	0	0

APPENDIX – G-4

Simulation Results - Test Three (SET 2)

Appendix G-4: Simulation Results – Test 3 SET 2

With 1000 iterations

RUN 1

t	Unit 1	Unit 2	Unit 3	Unit 4	Power Demand	Power Generated	Fitness	Err	NOx	CO	SO2
1	0	0	0	0	0	0	0	0	0	0	0
2	60.00154	0	129.9985	60	250	250	30166	0	0	0	0
3	88.9126	0	130	81.08738	300	300	191.0365	0	0	0	0
4	77.50366	0	130	72.49631	280	280	180.8547	0	0	0	0
5	77.46527	0	130	72.5347	280	280	180.8547	0	0	0	0
6	88.88727	0	130	81.11269	300	300	191.0365	0	0	0	0
7	88.87708	0	130	81.12289	300	300	191.0365	0	0	0	0
8	79.97213	0	66.8573	73.17053	220	220	173.2309	0	0	0	0
9	79.93417	0	66.68637	73.37945	220	220	173.2305	0	0	0	0
10	71.79388	0	130	68.20605	270	269.9999	175.8468	0	0	0	0

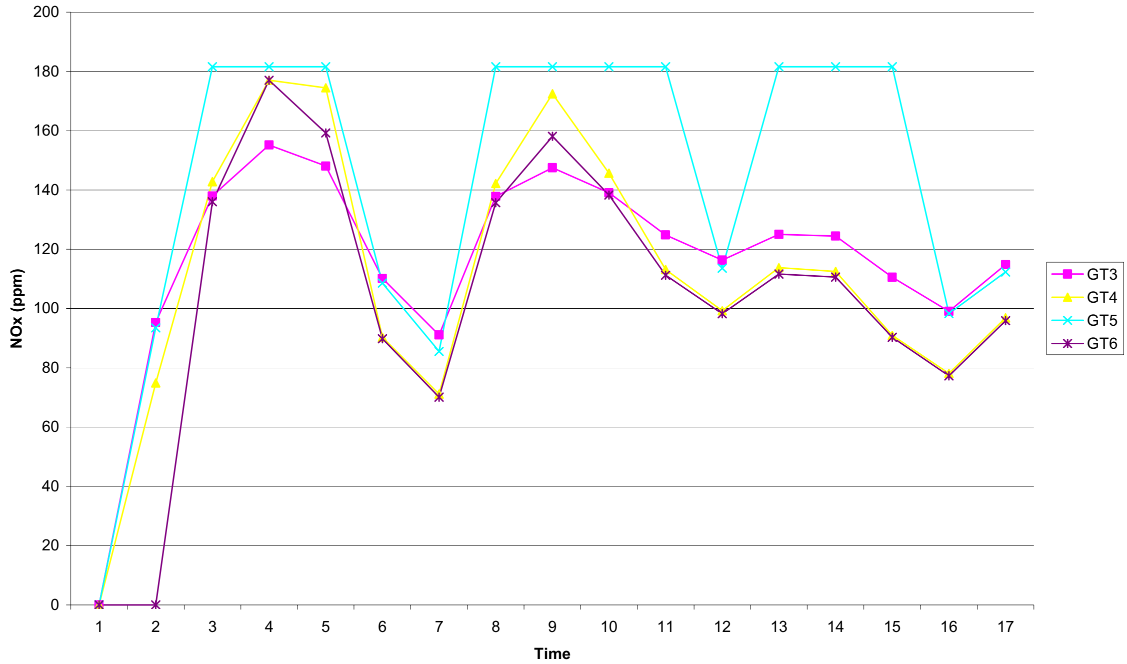
APPENDIX – G-5

Simulation Results - Test Four (SET 1)

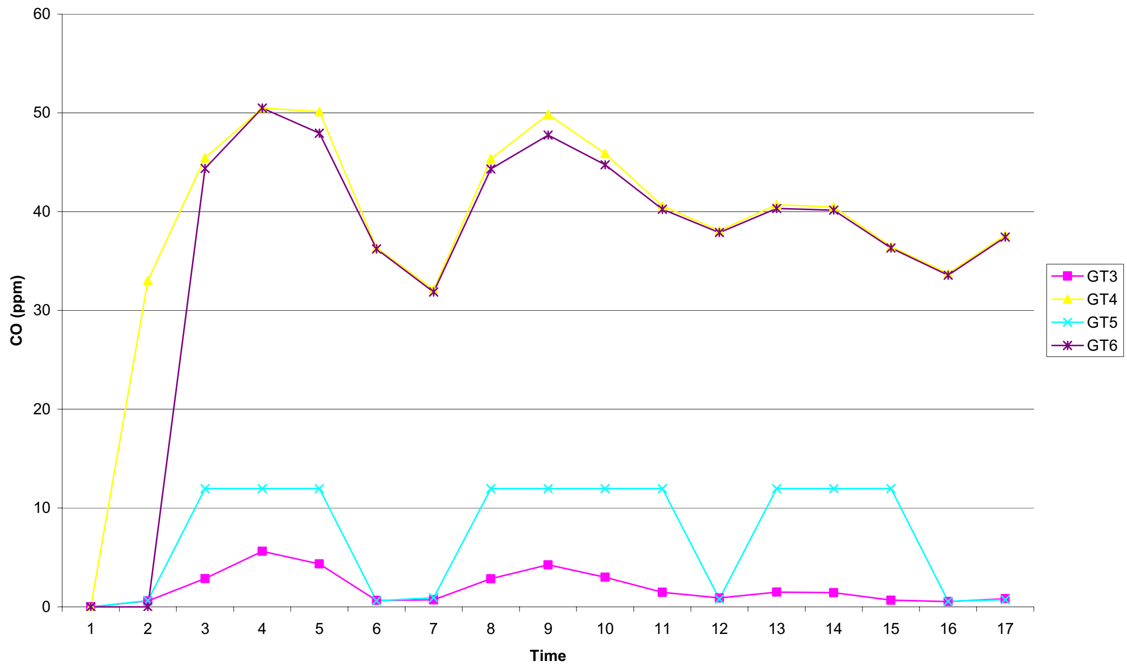
Appendix G-5: Simulation Results – Test 4 SET 1

Final results of each run (with 1000 iterations)

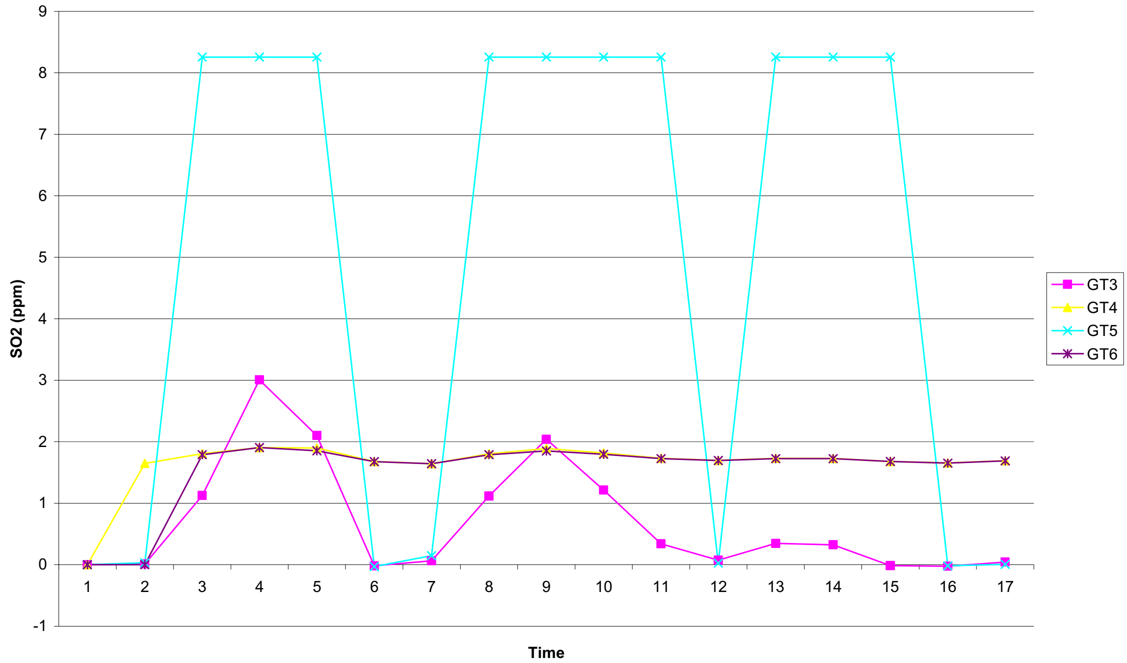
RUN	TIME	TPC	Error	sNOx	sCO	sSO2
1	4/18/2004 12:30	12326.13	0	8059.519	1425.755	148.6741
2	4/18/2004 12:31	12326.13	0	8059.517	1425.762	148.6643
3	4/18/2004 12:32	12326.13	0	8059.461	1425.853	148.6448
4	4/18/2004 12:34	12326.13	0	8059.524	1425.755	148.6555
5	4/18/2004 12:34	12326.13	0	8059.468	1425.817	148.6623
6	4/18/2004 12:35	12326.13	0	8059.431	1425.855	148.6663
7	4/18/2004 12:36	12326.13	0	8059.538	1425.729	148.6674
8	4/18/2004 12:37	12326.13	0	8059.492	1425.759	148.6897
9	4/18/2004 12:38	12326.13	0	8059.507	1425.772	148.6697
10	4/18/2004 12:38	12326.13	0	8059.515	1425.779	148.6471
11	4/18/2004 12:39	12326.13	0	8059.503	1425.794	148.6481
12	4/18/2004 12:40	12326.13	0	8059.515	1425.749	148.6756
13	4/18/2004 12:41	12326.13	0	8059.547	1425.747	148.6535
14	4/18/2004 12:42	12326.12	0	8059.46	1425.85	148.6492
15	4/18/2004 12:42	12326.14	0	8059.482	1425.774	148.6777
16	4/18/2004 12:43	12326.13	0	8059.458	1425.838	148.6567
17	4/18/2004 12:44	12326.14	0	8059.521	1425.732	148.6646
18	4/18/2004 12:44	12326.13	0	8059.516	1425.746	148.6676
19	4/18/2004 12:45	12326.13	0	8059.486	1425.776	148.6786
20	4/18/2004 12:46	12326.13	0	8059.498	1425.792	148.6608
	Best	12326.12				
	Worst	12326.14				
	Average	12326.13				



GT NOx emission (ppm) versus each interval



GT CO emission (ppm) versus each interval



GT SO2 emission (ppm) versus each interval

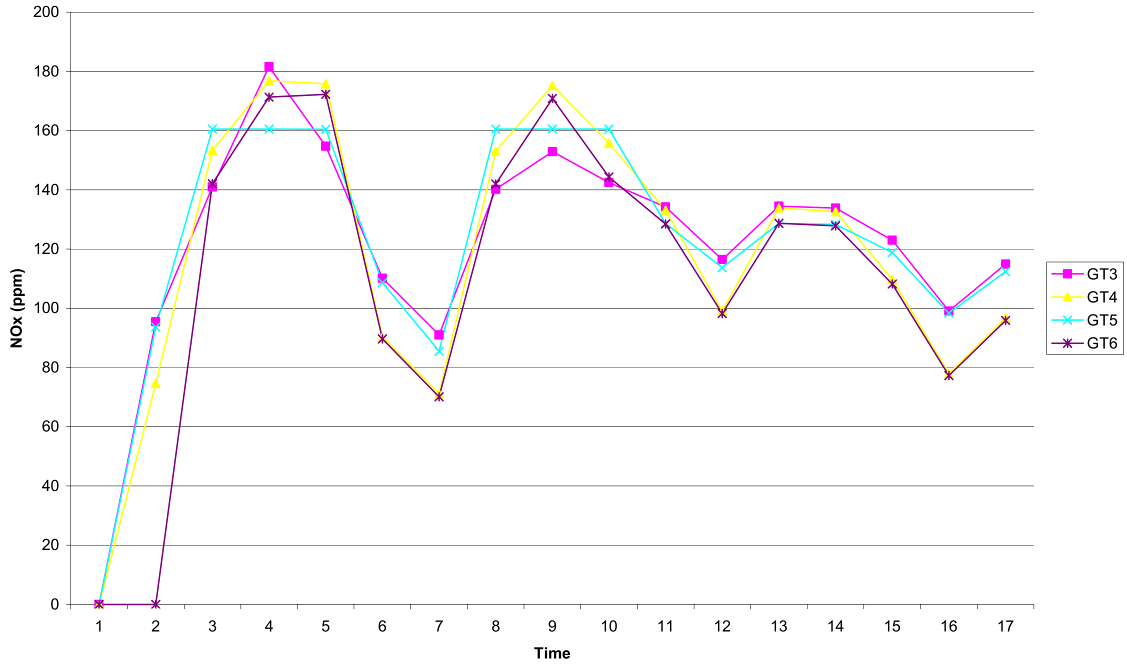
APPENDIX G-6

Simulation Results - Test Four (SET 2)

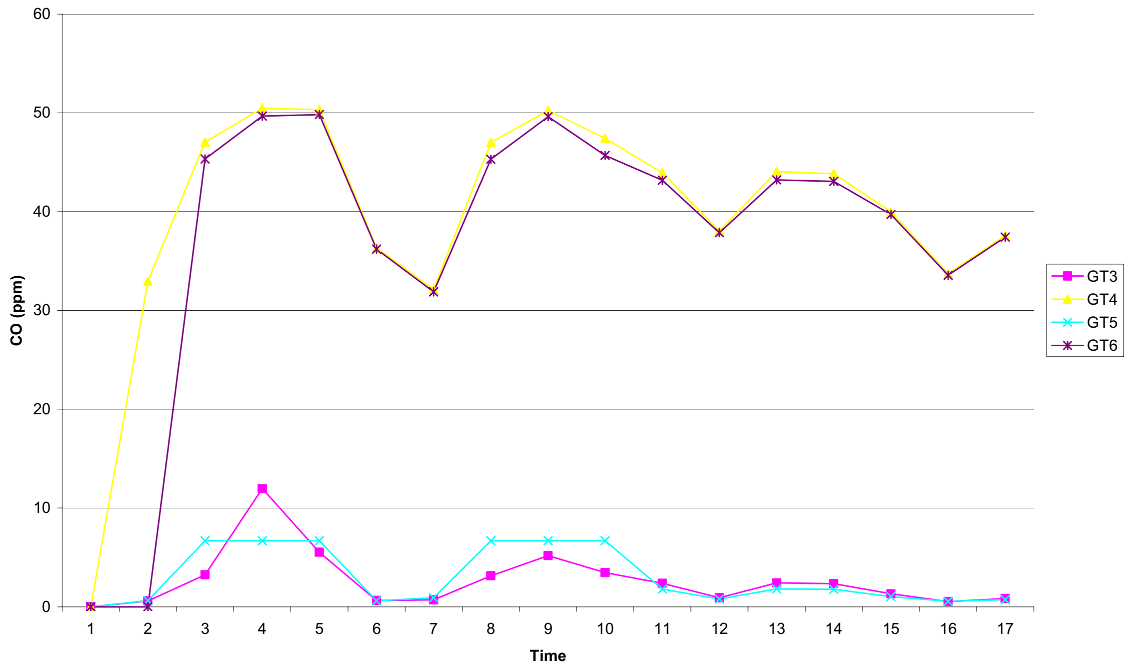
Appendix G-6: Simulation Results – Test 4 SET 2

Final results of each run (with 1000 iterations)

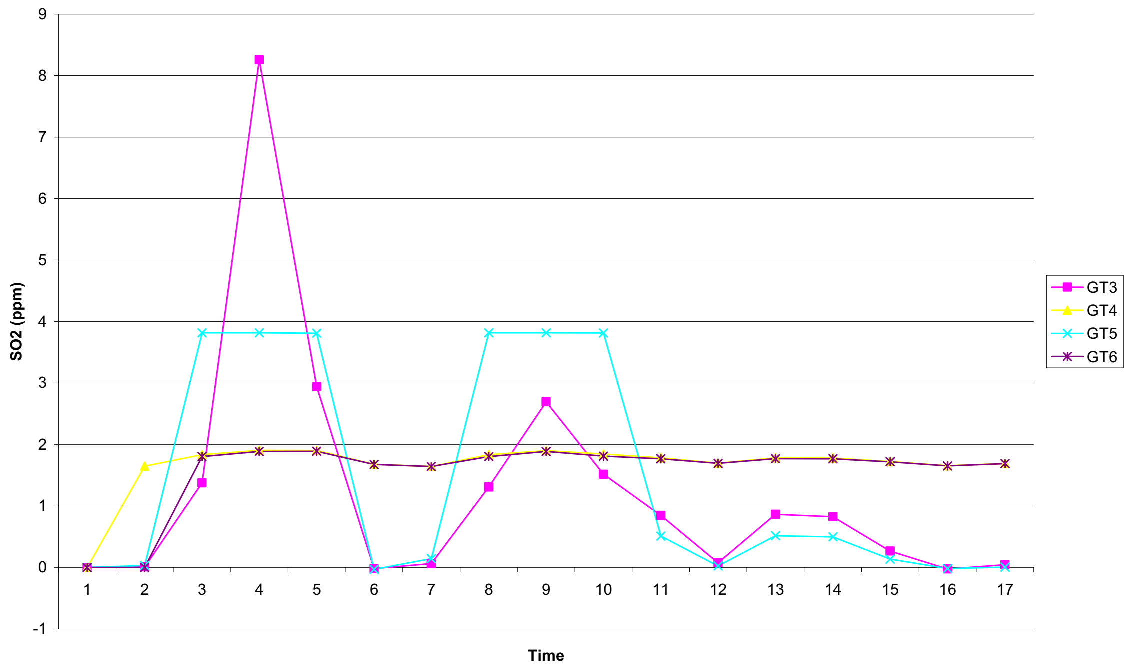
RUN	TIME	TPC	Error	sNOx	sPart	sSO2
1	4/18/2004 15:51	12412.17	0	8021.541	1402.039	99.01551
2	4/18/2004 15:52	12412.16	0	8021.403	1402.549	99.84451
3	4/18/2004 15:53	12412.31	0	8021.031	1402.213	99.33286
4	4/18/2004 15:53	12412.24	0	8021.124	1402.519	99.90869
5	4/18/2004 15:54	12412.37	0	8021.013	1402.197	99.53197
6	4/18/2004 15:55	12412.11	0	8021.514	1402.474	99.71194
7	4/18/2004 15:56	12412.19	0	8021.431	1402.167	99.12357
8	4/18/2004 15:56	12412.16	0	8021.181	1402.059	99.23388
9	4/18/2004 15:57	12412.33	0	8020.857	1402.129	99.37423
10	4/18/2004 15:58	12412.17	0	8021.025	1402.174	99.48637
11	4/18/2004 15:59	12412.26	0	8020.768	1402.595	100.3505
12	4/18/2004 15:59	12412.2	0	8020.68	1402.809	100.5441
13	4/18/2004 16:00	12412.32	0	8021.149	1402.328	99.59727
14	4/18/2004 16:01	12412.04	0	8020.884	1402.633	100.5256
15	4/18/2004 16:02	12412.18	0	8020.704	1401.877	99.43569
16	4/18/2004 16:03	12412.11	0	8020.709	1402.582	100.6169
17	4/18/2004 16:04	12412.23	0	8020.028	1404.355	104.4598
18	4/18/2004 16:05	12412.27	0	8019.979	1404.911	105.4774
19	4/18/2004 16:06	12412.34	0	8021.344	1402.04	98.97891
20	4/18/2004 16:07	12412.13	0	8021.346	1401.955	98.93114
	Best	12412.04				
	Worst	12412.37				
	Average	12412.21				



GT NOx emission (ppm) versus each interval



GT CO emission (ppm) versus each interval



GT SO2 emission (ppm) versus each interval