Condition based management of gas turbine engine using neural networks

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CONDITION BASED MANAGEMENT OF GAS TURBINE ENGINE USING NEURAL NETWORKS

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2005

Condition Based Management of Gas Turbine Engine Using Neural Networks

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2005

ABSTRACT

Accurate prognostic models capable of predicting the performance degradation of the industrial gas turbine are critical for improving plant profitability, by reducing the cost of energy production and contributing to a cleaner environment. The main focus of this research work is to develop an accurate steady state prognostic model to predict the performance degradation of gas turbine compressor using Artificial Intelligence. The data for this research work have been taken from the gas turbine operating in a combined cycle power plant using natural gas.

As a part of this research, the following works have been done. Thermodynamic models are developed to find out gas turbine health indicating parameters like polytropic and isentropic efficiencies of compressor, gross thermal efficiency, heat rate, compressor pressure ratio and air flow rate. Various gas turbine operating parameters, design parameters and different thermodynamic tables are used in these models to determine the gas turbine health indicating parameters, since they are not measured directly.

Gas turbine performance depends not only on component degradation, but also on the ambient condition, load level, fuel type and specific installation hardware such as inlet and outlet ducting. In order to identify the real component's degradation, methodology to correct the data to the reference ambient condition has been incorporated into the developed models. The ISO standard recommends the user to use the correction factors given by the gas turbine supplier for the gas turbines used for the constant speed application, whereas it provides standard correction formula for the gas turbines used for variable speed application. This recommendation is mainly to avoid the dispute between the seller and buyer in meeting the guaranteed power output and heat rate. The thermodynamic models are developed based on both the supplier and the standard correction methodologies in order to find out their effects on the long term trending of the gas turbine health indicating parameters and also to make the developed model more generic, i.e. applicable to variable speed gas turbines also.

These corrected gas turbine health indicating parameters are then compared with the non degraded values. Non degraded gas turbine data are based on gas turbine performance acceptance tests performed immediately after commissioning, i.e. when the condition of the gas turbine is clean and good. But the performance acceptance tests have been conducted for 60%, 85%, 93% and 100% loads only. In order to determine the gas turbine health indicating parameters for the intermediate loads ranging from 60% to 100%, the curve fitting technique has been used to find out the best suitable curve and its equation for the performance tests readings.

ABSTRACT

The on-line, off-line washing and inlet guide vane cleaning activities would reduce the gas turbine's compressor degradation rates. The hybrid neural network model is developed using the Matlab tool-box to analyze the gas turbine compressor degradation. Various pre and post processing techniques and network layers have been used in the developed hybrid neural network model, and the best suitable technique has been selected. This hybrid neural network model is trained with gas turbine health indicating parameters trended for about 15000 Equivalent operating hours. The developed hybrid neural model learn the effects of on-line, off-line washing and inlet guide vane cleaning activities on the gas turbine's compressor degradation and predicts the gas turbine's compressor degradation rates. The verification of this model with the actual values has been done in order to find out their match with the real system. These predictions are compared with the expected and guaranteed values given by the gas turbine supplier. Maintenance decisions are suggested based on the deviation of the predicted gas turbine's compressor degradation with the expected values. The effect of cost has also been included in analyzing the performance of the gas turbine driving the generator.

The degradation rates vary greatly and are specific to each plant depending on the site location, surrounding environment, climatic conditions and plant layout. The adaptive nature of the neural network model allows the user to tune to the model specific to the particular gas turbine.

The study of different variants of the steady state model revealed that the hybrid neural network developed has the ability to replicate the complicated gas turbine's compressor degradation with great accuracy. It mainly depends on the extent and variety of training data available, type of pre-processing carried out, the choice of training method and the transfer function used. The evolution of the model shows it is a good tool to measure the condition of the gas turbine's compressor health for both constant speed and variable speed application.

The cost analysis of the model explains that even 1 MWhr of energy loss per hour due to the improper washing schedule leads to approximately half million dollar loss per annum. Normally the off-line washing plus compressor Inlet guide vane blade cleaning are done during the minor outages. (i.e. every 4000 equivalent operating hours). If one additional off-line washing plus compressor blade cleaning is performed in between this period, it results in good amount of energy saving of about 3960MWhr per 4000 equivalent operating hours. This energy saving is overridden by the power generation opportunity lost cost. It could be minimized by

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conducting the following changes. The power selling prices are very low during week ends and public holidays, if 2.5 days required for the manual washing is covered during in one of these days will leads to good amount of energy and cost savings. The gas turbine availability is around 92% per annum and planned outages are about 3%. The balance 5% is due to breakdown maintenance. The proper usage of this breakdown maintenance period (5%) could save around 8000MWhr of energy per annum.

The current research work is focused on the development of the hybrid neural network model to asses the gas turbine's compressor health and to suggest the appropriate washing schedule including the cost effects also. It is recommended that this could be extended to assess the degradation of the entire combined cycle power plant including other components such as turbine , combustor and heat recovery steam generator.

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LIST OF SYMBOLS

AMB	: Ambient condition
ANN	: Artificial neural network
CCPP	: Combined cycle power plant
Comp	: Compressor
C _p	: Specific heat capacity at constant pressure
CPH	: Condensate pre-heater
CWT	: Cooling water temperature
C/H	: Carbon Hydrogen ratio of fuel gas
C _v	: Specific heat capacity at constant volume
DC	: Direct Cooling
DCS	: Digital control system.
DP	: Differential pressure
Eff	: Efficiency
EH	: Engine Health indicating parameters.
EOH	: Equivalent operating hours
FD	: Forced draught fan
FG _{mf}	: Fuel gas mass flow rate
FP _{cor}	: Corrected fuel power input
Gen	: Generator
GT	: Gas turbine
H _{ca1}	: Enthalpy of the cooled air at the measured temperature t _{ca1} [kJ/kg]
H _{ca2}	: Enthalpy of the cooled air at the measured temperature t _{ca2} [kJ/kg]
H _{c1}	: Specific enthalpy of air at compressor intake at the measured temperature t _{c1} [kJ/kg]
H _{c2}	: Specific enthalpy of air at compressor intake at the measured temperature t _{c2} [kJ/kg]
H _{f,0}	: Specific enthalpy of the fuel at temperature t _f =15°C [kJ/kg]
H _f	: { Specific enthalpy of the fuel at the temperature t _f $\Delta H_f = c_{pf} \times \Delta t_f$ [kJ/kg] Approximately for standard natural gas fuel the specific heat is 2.2kJ/kg-K and for the standard fuel oil (CH1.684-disillate) the specific heat is 1.8 kJ/kg-K. }
H _u	: Low heat value of the fuel at 15°C, either measured or obtained from the fuel analysis [kJ/kg]
H _w	: Enthalpy of water/steam at the measured temperature t _w [kJ/kg]
HP	: High pressure
HR	: Uncorrected heat rate
HR _{cor}	: Corrected heat rate
HRSG	: Heat recovery steam generator
H _w	: Enthalpy of water/steam at the measured temperature t _w [kJ/kg]
I _{gross} '	: measured stator current
I _f	: calculated field current f (S) (from test certificate)
I _f '	: measured field current
I _{gross}	: calculated generator current [P _{gross} ' / (√3 * p.f. _N * U _N)]
IGV	: Inlet guide vane of compressor
IP	: Intermediate pressure
Isen	: Isentropic

LIST OF SYMBOLS

ISO	: International Standard's organization
LCV	: Lower calorific value
LP	: Low pressure
m_{ca}	: Cooling air flow [kg/s]
m_{En}	: Equivalent reduction of compressor inlet air mass flow considering mass flows and enthalpies of internal bleed; m_{En} enables simplified calculation of compressor output using only inlet and outlet terms [kg/s]
m_{Ex}	: Measured bleed air mass flow rate at compressor outlet for external consumers [kg/s]
m_f	: Measured mass flow of fuel entering the combustion chamber [kg/s]
m_m	: Measured rate of fuel consumption in [kg/s]
MSE	: Mean square error
m_{t1}	: Mass flow of flue gas at turbine inlet [kg/s]
m_{t2}	: Mass flow of flue gas at turbine outlet [kg/s]
m_w	: Measured water/steam injection flow rate for Nox control or power augmentation [kg/s]
N	: Speed in revolution per minute
n_0	: Reference speed
n_t	: Test speed
OEM	: Original equipment manufacturer
P	: Uncorrected Power output
PAC	: performance acceptance completion test
p_{amp}	: ambient pressure
P_b	: Booster power consumption
P_{bp}	: Booster power consumption [kW]
P_c	: Compressor power output
P_{cor}	: Corrected power output
P_{Cg}	: Coupling power at Generator
P_{cl}	: Mechanical losses (Coupling)
P_{gross}	: measured active power
$p.f.$	: measured active power factor
$p.f.$	: measured power factor
$p.f._N$	: power factor nominal (Design = 0.85)
P_{gt-ls}	: Generator losses [kW]
P_{gross}	: P_{gen} output for $p.f._N$ nominal
P_{gt}	: Output at generator terminals
$P_{L,C'}$	: actual Brush contact losses
$P_{L,C}$	: nominal Brush contact losses
$P_{L,Exc}$	: nominal field I^2R -losses
$P_{L,Exc'}$	: actual field I^2R -losses
$P_{L,FR}$	: nominal friction losses in bearing (Design = 540kW)
$P_{L,FR'}$	: actual friction losses in bearing (Design = 540kW)
$P_{L,SC}$	: actual short-circuit losses
$P_{L,SCN}$	: nominal short-circuit losses (Design = 1555kW)
$P_{LIR'}$	: actual core losses (Design = 588kW)
P_{LIR}	: nominal core losses (Design = 588kW)

LIST OF SYMBOLS

P_{ml}	: Mechanical losses (thrust and journal bearings)
PNN	: Probabilistic neural network
P_t	: test measured gross power output
P_o	: corrected net power output
Poly	: Polytropic
Pr	: the compressor pressure ratio
p_1	: Compressor inlet pressure
p_2	: Compressor outlet pressure
Q_c	: Compressor inlet
Q_{ca1}	: Cooling air cooler inlet
Q_{ca2}	: Cooling air cooler outlet
Q_{ex}	: External bleed
Q_f	: Fuel
Q_t	: Turbine outlet
Q_w	: Water / Steam injection
Q_{10}	: Net specific energy of the fuel at 15 °C [kJ/kg]
R	: Gas constant
$R_{L,20}$	: rotor winding (@20°C) Design –1.21
S_{gross}	: calculated apparent power ($\sqrt{3} * I_{gross} * U_N$)]
S'_{gross}	: measured apparent power
Si	: Silica
ST	: Steam turbine
STD	: Standard
T	: Reference absolute temperature
T_t	: Test absolute temperature
T_{amp}	: Ambient temperature (°C)
TIC	: Compressor inlet temperature (°C)
t_m	: mean temperature
t_1	: Compressor inlet temperature (°C)
t_2	: Compressor outlet temperature (°C)
T_{t1}	: temperature of flue gas at turbine inlet
T_{t2}	: temperature of flue gas at turbine outlet
U'_{gross}	: measured voltage
U_N	: voltage nominal (Design = 22000V)
vs	: vice versa
ΔP	: difference of total losses
η_b	: combustion chamber efficiency
η_g	: generator efficiency
$\eta_{(Cor)}$	: Corrected gross efficiency of CCPP.
η_t	: thermal efficiency of variable speed gas turbine
ΣP_L	: total losses referred to p.f. _N
$\Sigma P_L'$	: total losses of actual values.
$\emptyset$	: ambient relative humidity.
ΔT_{amp}	: difference between actual and reference ambient temperature
Δp_{amp}	: difference between actual and reference ambient pressure
$\Delta \emptyset$	: difference between actual and reference relative humidity

LIST OF SYMBOLS

ΔN	: difference between actual and reference speed
ΔCWT	: difference between actual and reference cooling water temperature
ΔP	: difference between actual and design power output percentages
θ	: ratio of the absolute test to reference ambient temperature.
δ	: ratio of the absolute test to reference ambient pressure.

CHAPTER – 1 INTRODUCTION

1.1 Background

The gas turbines used in power generating plants are highly complex, multi-component system and requires significant capital investment. As the power plant operators rely upon these units for revenue generation, it is highly desirable for the gas turbines to function at the highest possible performance and efficiency level for the duration of its operation life.

One of the key factors leading to performance losses during the plant operation is compressor fouling. This results from the adherence of the particles and small droplets to the blade surface, which in turn reduces the flow capacity and the pressure ratio of the unit. The above effects reduce the power output and efficiency of the gas turbine. Despite the use of advanced filtering methods and filter maintenance, the ingestion of substances that can cause fouling cannot be completely suppressed. The fouling rate depends largely on the site location, surrounding environment, layout of the air intake system, atmospheric parameters and plant maintenance. While the first four factors could not be controlled during operation, plant maintenance is critical for preventing extra costs resulting from degraded plant performance. The growing interest in life cycle costs of the heavy-duty gas turbines has prompted research on various prognostic and diagnostic technologies to investigate the trade-off between the performance improvements and associated maintenance costs.

Artificial Intelligence techniques have been effective in the areas of on-line sensor validation, monitoring, diagnostics and maintenance of power plant operations. Analyzing the system using Artificial Intelligence enables the power plant owners to operate the units at maximum profit.

The technology development in the gas turbine manufacturing has enhanced the combined cycle plants to operate at a maximum efficiency of about 59%. This high efficiency starts reducing after its commissioning due to various reasons. The losses can be estimated by using thermodynamic calculations. When analyzing the performance data over long periods of operation, mechanisms of degradation have to be taken into account. The main sources for degradation are corrosion and erosion effects in the compressor and turbine parts, turbine fouling, foreign object damages and thermal distortion. The total degradation of a gas turbine performance parameter is the sum of the four types of losses as shown in figure1.1.

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- Losses that can be recovered by an on-line washing (A),
- Losses that can be recovered by an off-line washing (B),
- Losses that can be recovered during major off-line inspection and maintenance (C),
- Losses that cannot be recovered at all (D).

The type C and type D losses are caused by degradation mechanism other than fouling and these losses cannot be recovered through online and offline washings. The type A, type B, type C are recoverable losses, whereas type D is non-recoverable losses. Type A and type B losses are the major losses, and compressor fouling is the main cause for these losses. It is difficult to differentiate the type A and type B losses. They can be kept at optimum level by proper scheduling of the offline and online washings.

Currently the online and offline washes are performed on a preventive schedule of 700 hours and 4000hrs respectively. The preventive schedule washing time depends mainly on the supplier and model of the engine. This maintenance task is performed without any engineering assessment of conditional need or optimal time to perform. In addition to the cost lost and maintenance time incurred, unnecessary washes generate an environmental impact with the used detergent and reduce the lifetime of the hot section components like combustion chamber internals, compressor and turbine blade coatings. The power plant owners operating the gas turbine will be benefited by having a module that assesses condition of the engine and predicts the time to do the washing.

1.2 Objective

The main objective of this project is to develop such a prognostic model to study the cumulative effect of type A and type B losses and to assess the effectiveness of online and offline washings at different time periods, thereby enabling the washing schedule to be optimized. The effect of compressor fouling can be estimated by analyzing the health indicating parameters like compressor efficiency, pressure ratio, discharge temperature, airflow rate, and gross power outputs. These parameters are not directly measured from the gas turbines, but can be estimated by using thermodynamic models. The thermodynamic models can accurately predict the behavior of the machine at that instant. Then these models can be analyzed by using neural network technique to find out the effect of compressor fouling alone (type A and type B losses).

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Figure 1.1

Classification of losses leading to overall gas turbine performance degradation

[Leusden, Sorgenfrey and Lutz (2003)]

1.3 Approach

In order to achieve the above objective, thermodynamic models have been developed to determine various performance characteristics of the gas turbine, which in-turn is used to train the neural networks. The figure 1.2 explains the thermodynamic model developed. The following activities have been performed in this research work to achieve the above objective.

Matlab programs have been prepared for estimating the corrected power output to the reference condition, overall gross thermal efficiency, gross heat rate, compressor air flow rate, compressor polytropic efficiency, compressor isentropic efficiency and compressor pressure ratio of gas turbine engine.

These engine health-indicating parameters calculated during the performance acceptance testing time (PAC) have been considered as the base reference value for this project. The

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calculations of the above engine health indicating parameters have been done before and after every on-line and off-line washing. The deviation between these values and their corresponding base reference values are found out and they have been plotted against the equivalent operating hours.

The effectiveness of the on-line and off-line washing from the above trends have been studied using neural networks. The neural network models are trained by using the above health indicating parameters with respect to the time period and the activities performed (like on-line washing, off-line washing & manual blade cleaning). After the completion of training, the neural network models predicts and forecast the machine behavior accurately and suggest best interval to perform any one of the above activities to operate the machine at maximum possible efficiency. The summary of the research work is shown in the figure 1.3

The effects of the manufacture's correction factors and standard correction factors on the engine health indicating parameters have been analyzed in order to generalize the developed engine degradation model. So that it can be applied to any gas turbine of constant speed type.

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2.1 Combined cycle concept

The data for this research work has been taken from the gas turbine in a combined cycle power plant. The following section explains the concepts and importance of the combined cycle power plant.

2.1.1 Combined cycle

A combined cycle is a thermodynamic system consisting of two or more power cycles. Each cycle uses different working fluids. Combining two independent power cycles together results in higher efficiency than operating them independently. Combined cycle process is shown in figure 2.1. The gas turbine's Brayton cycle and steam power system's Rankine cycle are two independent cycles that complement each other to form efficient combined cycles. The Brayton cycle has a high source temperature and rejects heat at a temperature such that it can be the energy source or supplement the energy source for the Rankine cycle in a combined cycle mode. [Siemens (2001)]

Figure 2.1

Combined cycle power plant [Siemens (2001)]

Compared to a normal fossil-fired steam power station, the CCPP gas turbine acts as a combination of both the furnace and the turbine. It delivers mechanical work to the generator and thermal energy via the hot exhaust gas to the boiler. The most commonly used working fluid for

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combined cycles are air and steam. Other working fluids like organic fluids, mercury vapor and others are used in limited scales only. The steam and air combined cycles have achieved widespread commercial applications due to the following reasons.

- The two cycles are thermodynamically complementary to each other. The heat rejected from the Brayton cycle (gas turbine) is at a temperature level that can be readily used by the Rankine cycle.(steam turbine)
- The two working fluids, water and air are available in abundance, inexpensive and not toxic.

The Sankey Diagram is shown in figure 2.2, which shows the various losses of CCPP.

Figure 2.2

Sankey diagram of a CCPP [Siemens (2001)]

2.1.2 System under Study

The gas turbine data used for this research work has been collected from the following type of CCPP – **Unfired, triple pressure, reheat, natural circulation and horizontal gas flow.**

Siemens V94.3A gas turbine engine general arrangement has been shown in figure 2.3.

The schematic diagram of this CCPP is shown in the figure 2.4.

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Figure 2.3

V94.3A Gas turbine engine general arrangement [Bernard Becker (2002)]

The rated capacity of V94.3A gas turbine engine is 268MW.

(V94 – represents engine belongs to 50Hz frequency category & the affix .3A represents engine is equipped with an annular type combustion chamber).

- Pressure ratio is 16.6
- Turbine inlet temperature according to ISO 2314 is 1230 °C
- Overall design thermal efficiency of the CCPP is 57% & NO_x Emission is 25ppm.
- Gas turbine thermal efficiency is 37.3%.
- Exhaust gas temperature and mass flow rate are 568 °C & 634 kg/s respectively.

Figure 2.4

Schematic Diagram of the single shaft CCPP.

[Wolfgang Menapace, Matthias Frankle and Bert Rukes(2003)]

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2.2 Classification of gas turbine degradation

The degradation of the gas turbine is mainly classified into following types

- Recoverable degradation.
- Non-recoverable degradation.
- Operational degradation.
- **Recoverable degradation**

Degradation that can be recovered through compressor water washing, filter changes, instrument calibration and auxiliary equipments.

- **Non- recoverable degradation**

Degradation that cannot be recovered through the above methods like compressor washing, etc is called non-recoverable degradation. But they may be partly recovered through casing cover lift and refurbishment like changing the seal ring clearances etc.

- **Operational Degradation**

The operational degradation is the sum of the recoverable and non-recoverable degradation.

2.3 Compressor fouling and cleaning

The main focus of this research work is to find the effect of compressor fouling in the performance of the gas turbine. The following section gives introduction about the fouling phenomenon of compressor, factors contributing the fouling and various cleaning methods available.

2.3.1 Compressor fouling phenomenon

One of the most common problems experienced in the gas turbine engine is the compressor fouling. Although this problem is not a typical destructive failure, it leads to large reduction in power output of the gas turbine engine. If left unchecked, it would also lead to premature hot section component erosion and premature failure of combustor liners etc.

Despite the use of an efficient inlet filter, normal operation of a gas turbine will result in the accumulation of deposits on the compressor airfoils and gas path passages. This fouling is caused by the airborne particles such as dirt, sand, industrial chemicals, oil, insects and salts. It

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alters the air profile and increases the surface roughness. Fouling results in degradation of inlet flow, compressor efficiency and a reduced compressor surge margin.

The degree of fouling is dependent on the site-specific factors like type and quantity of the airborne particles, airfoil coatings and ambient conditions. For example, evidence suggests that high humidity significantly increase the fouling rate. In general, the gas turbine power output without any compressor washing can be expected to degrade between 2% to 5% after 1000 operating hours. In the combined cycle plants, hot gas mass flow rate degradation outweighs the exhaust temperature increase and increases the degradation rate of the plant. [Jean-Pierre Stalder (1998)]

2.3.2 Factors causing fouling

The cause of fouling and fouling rates of axial gas turbine compressor is a combination of various factors that can be classified into following categories.

- Gas turbine design parameters.
- Site location and surrounding environment.
- Plant design and layout.
- Atmospheric parameters.
- Plant maintenance.

2.3.2.1 Gas turbine design parameters

Smaller engines are highly sensitivity to fouling, when compared to the larger engines. The degree of the particle deposition on blades increases with growing angle of attack. Further, the sensitivity to fouling also increases with increasing stage head. Multi-shaft engines are more sensitive to fouling than single shaft engines. Design parameters such as air inlet velocity at the inlet guide vanes (IGV), compressor pressure ratio, aerodynamic and geometrical characteristics will determine the inherent sensitivity to fouling for a specific compressor design.

2.3.2.2 Site location and surrounding environment

The geographical area, the climatic condition, the geological plant location and its surrounding environment are major factors influencing compressor fouling. These areas can be classified into desert, tropical, offshore, on-shore, rural, urban and industrial site locations. The

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expected air borne contaminants (dust, aerosols), their nature (salts, heavy metals etc.), concentration, particle sizes, weight distribution and climatic conditions are the important parameters influencing the rate and type of deposition.

2.3.2.3 Plant design and layout

Predominant wind directions can dramatically affect the compressor fouling type and rates. Orientation and elevation of air inlet / suction must be considered together with the location of air or water cooling towers in a combined cycle plant. The possibility of exhaust gas re-circulation into the air inlet, orientation of exhaust pipes from lube-oil tank vapour extractors, as well as with other local and specific sources of contaminants such as location of highways, industries, sea shores, etc. should be carefully considered.

Other plant design parameters that affect the rate of compressor fouling are the selection of air inlet filtration system (self cleaning, depth loading, cell- pocket and oil bath filter, etc.), the selection of filter media, the number of filtration stages, weather louvers, mist separators, coalescer, snow hoods, etc. Design parameters such as air velocity through the filters and their behavior under high humidity condition, pressure drops, etc play critical role in deciding the fouling nature of the engine. In case, if the conditioning systems are used, then appropriate mist eliminators should have been installed at the downstream of evaporative coolers. Inlet chilling in humid areas would result in continuous saturated conditions in the downstream. Thus, the presence of dust contamination in the air can combine with the moisture and additionally contribute to compressor fouling. [Jean-Pierre Stalder (1998)]

2.3.2.4 Plant maintenance

Quality of air filtration system maintenance, frequency of compressor blade washing, (the deposition leads to higher surface blade roughness which in turn leads to faster rate of degradation), can positively influence compressor fouling and its rate.

2.3.2.5 Atmospheric parameters

Ambient temperature, relative humidity (dry and wet bulb temperatures), wind forces, wind direction, precipitation, fog, smog, or mist condition and atmospheric suspended dust

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concentration related to air density are the parameters having very high impact on the rate of compressor fouling.

2.3.2.6 Fouling deposits

Most fouling deposits are mixtures of water wettable, water-soluble and water insoluble materials. Very often pH of 4 and lower can be measured in compressor blade deposits. This represents risk of pitting corrosion. These deposits become more difficult to remove if left untreated. The aging process bonds them more firmly to the airfoil surfaces and results in the reduction of cleaning efficiency. [Jean-Pierre Stalder (1998)]

Water-soluble compounds are hygroscopic in nature. These compounds also contain chlorides, which promotes the pitting corrosion of the compressor blades. Water insoluble compounds are mostly organic in nature, such as hydrocarbon residues or from silica (Si). These compounds are quite hard to remove.

2.3.3 Compressor cleaning process

In early days, the gas turbine cleaning has been done by crank soak washing and by injecting solid compounds such as nutshells or rice husks at full speed with the unit in operation. This method of on-line cleaning by soft erosion has mainly been replaced by wet cleaning due to the introduction of coated compressor blades. Further unburned solid cleaning compounds and ashes may also cause blockage of sophisticated turbine blade cooling systems. In the beginning of 80's, the combination of compressor on-line washings and off-line washings became popular in the industries. It is found that 5% airflow reduction due to fouled compressor blades leads to a reduction of power output by 13% and increases heat rate by 5.5%. [Jean-Pierre Stalder (1998)]

The gas turbine compressor washing has gained increasing attention by the owners due to large scale use of gas turbines in the combined cycle base load application and the increase of their nominal output. The typical effect of compressor on-line and off-line washing (crank washing) has been shown in the figure 2.5

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Figure 2.5

Typical effect of on line and off line compressor wet cleaning

[Roemer, M.J and Kacprzyński G.J (2001)]

Three different types of compressor cleaning methods are

- a. Dry-cleaning.
- b. Off-line washing.
- c. On-line washing.

2.3.3.1 Dry-cleaning

Dry cleaning employs the use of nutshells or rice as an abrasive media to scour the compressor surfaces. This method is rarely used today due to major drawbacks such as the erosion of airfoils, blade coatings and the plugging of turbine blade cooling holes.

2.3.3.2 Off-line washing

Off-line washing is established as the most effective cleaning method. Crank soaking with a cleaning fluid mixture allows the removal of deposits from all the compressor stages. The off-line washing procedure typically involves the injection of a cleaning solution for 15 minutes at crank speed, followed by a 20 minutes soaking and then thorough rinsing with de-mineralized water.

The off-line washing method reduces the centrifugal forces on the injected solution. It leads to better wetting and distribution of the cleaning solution over the blades and vane surfaces of all the stages. Conductivity and turbidity measurement of the rinsing water will help to assess the cleaning efficiency. The offline washing nozzles are designed to provide higher mass flow of bigger droplets. Normally they are known as jet nozzles.

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2.3.3.3 On-line washing

On-line washing is not a replacement to off-line washing. On-line washing can significantly decrease the fouling rate and maintain performance levels over an extended period of time. In addition to improving efficiency and heat rate, steady on-line washing can extend the period between the off-line washings. The on-line washing procedure typically includes the injection of a cleaning solution for 15 minutes followed by a de-mineral water rinse for at least 15 minutes. [Jean-Pierre Stalder (1998).]

The profiles of the first stage vane play critical roles in deciding the airflow rate through the gas turbine compressor. The effects of fouling on this first stage vanes are primarily responsible for a significant reduction of the air mass flow through the compressor, which in turn reduces the power output. The on-line washing is most effective in removing the deposits on the first two or three compressor stages. These stages tend to be most heavily fouled. The higher flow velocities in downstream stages minimize the adhering of deposits.

Droplets of cleaning solution may survive up to the 6th stage, after the 6th stage most of them get vaporized and the residue/ashes will be centrifuged along the compressor casing. Therefore, no cleaning solution will be required for removing deposits on downstream stages. A key element in effective on-line cleaning is the nozzle system. A sufficient number of properly oriented nozzles are required to create a spray pattern with uniform coverage. The droplets must be small enough in such way that it would not cause any blade erosion and light enough so as not to be dropped out of the air stream prematurely.

2.3.4 General compressor cleaning practices

The performance degradation of the compressor has high financial impact on the power plant operation. Therefore maintaining a clean compressor is a high priority task in all gas turbine power plants. The fouling effects vary from site to site depending on their specific site conditions. Every site has its own solution in terms of the type and frequency of washing. Experimentation with good performance monitoring technique is really the best way to optimize a wash program. [Jean-Pierre Stalder (1998).]

In general, base loaded units should be off-line washed whenever the plant comes down for maintenance. On-line cleaning with a detergent mixture should be employed 3-4 times per week followed by a de-mineral water rinsing. Depending on the resulting rate of fouling, an

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economic decision will need to be made whether additional shutdown for off-line crank washing is required or not. Moderate hour dispatch plants should generally be off-line washed monthly. Low hour peak plants should be off line washed quarterly. In addition to restoring the full performance capacity, the washing also removes any salt or other potentially corrosive deposits from the blade surface and saves the compressor blades.

2.4 Effects of various ambient factors on the combined cycle performance

The Combined cycle performance depends not only on component degradation but also on ambient condition, load level, fuel type and specific installation hardware such as inlet and outlet ducting. In order to identify the real components degradation the performance monitoring system must have a correction methodology. The methodology should correct the data to reference ambient condition and then it could be used for comparison with the baseline data. The overall gas turbine performance is normally referred to standard inlet conditions of gas turbine compressor inlet temperature, pressure and relative humidity of 1.01325bar, 15°C and 60%RH. The referred or corrected parameters take the values that the basic parameters would have at ISA sea level static conditions. This section explains the details about the effect of various ambient factors on the gas turbine engine performance and methods to correct the engine performance to the reference ambient conditions. [John W. Sawyer (1985)].

2.4.1 Effect of various ambient factors on the gas turbine performance

Typical forms of curves expressing the dependence of the gas turbine performance on the ambient conditions have been shown from Figure 2.6 to 2.11. Each gas turbine has its own curves based on their cycle parameters, component efficiency and mass flow rates. The curves shown in figure 2.6 to 2.11 are only sample of such curves. These curves are usually used to determine the values of correction factors for converting the actual performance of gas turbine from the actual condition to the reference condition. Since they represent the relatively small deviations around a certain operating condition their form is almost linear. The behavior of the gas turbine over its entire operating range includes non-linear parameter interrelations. So, one set of curves is valid only for operating conditions in the vicinity of one load setting. Normally the set of curves are available for each major load settings like 50%, 75% and 100%.

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2.4.1.1 Effect of Temperature

The fall of air temperature increases the density of the air, which leads to increase in the mass of air entering the compressor for a given engine speed. This causes the power output and mass flow rate to increase. The increase of compressor inlet temperature leads to a decrease of the power output of the gas turbine exhausts mass flow and heat consumption, whereas the heat rate of the gas turbine increases.

The figure 2.6 shows the effect of ambient temperature on power output, exhaust flow, heat consumption and heat rate. It has been observed from this figure that the variation of compressor inlet temperature from -18°C to 49°C varies the gas turbine power output from 120% to 80% of its design value, exhaust flow from 115% to 90% of its design value, heat consumption from 117% to 85% of design value and heat rate from 96% to 105% of its design value respectively.

2.4.1.1 Effect of Pressure

The fall of pressure reduces the air density and it leads to reduction in the mass of airflow into the engine for a given engine speed, which in-turn causes the power output to decrease. Typically, at any site the atmosphere pressure will fluctuate about $\pm 4\%$. The increase of ambient pressure tends to decrease the power output and exhaust mass flow. The figure 2.7 shows the

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effect of ambient pressure on the exhaust gas flow and power output. It has been observed from figure 2.7, the variation of ambient pressure (p_0/p_{0ref}) of about 90% to 110% from its rated ISO condition varies the power output from 90% to 110% and exhaust gas mass flow from 94% to 106% of its design values respectively. The heat rate and other cycle parameters are not affected by ambient pressure variation.

2.4.1.3 Effect of Humidity

The density variation of the air due to the humidity effect is less than the density variation due to the ambient temperatures. So the humidity of the air entering the engine has minor influence on the thermodynamic property of the cycle fluid. The major portion of this effect is due to the change in acoustic velocity of the fluid and the change in the ratio of their specific heats. The figure 2.8 shows the effect of humidity on power output and efficiency. The typical variation of about -10 to 40 $\{(h_{abs} - h_{abs-ref}) * 1000\}$ specific humidity varies the 99.5% to 101.2% of power output and 100.2% to 99% of the heat rate from its design values.

2.4.1.4 Effect of inlet and exhaust pressure losses

The increased inlet pressure loss will reduce the compressor suction pressure, which in-turn decreases the power output. The increase in the exhaust pressure loss will reduce the turbine expansion ratio, which in-turn also decreases the power output. In the figure 2.9 and figure 2.10

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the ratio of the variable measuring parameter values to the values at the reference condition are shown in abscissa and corresponding correction values in ordinate..

The increased inlet pressure loss decrease the power output (P_t/P_c), efficiency (η_t/η_{t0}) and exhaust gas flow (m_g/m_0), whereas it the exhaust gas enthalpy (h_g-h_0) increases. This effect of inlet pressure is shown in figure 2.9.

The increased exhaust pressure loss, decreases the power output (P_t/P_c) and efficiency (η_t/η_{t0}), whereas it increases the exhaust gas enthalpy (h_g-h_0). This effect of exhaust pressure loss is has been shown in the figure 2.10

2.4.1.5 Effect of fuels

In general the fuels with higher hydrogen content can produce more power output at a lower heat rate or higher efficiency. If the net specific energy of fuel gas deviates from the specified values, the gas turbine output and the gas turbine exhaust conditions will differ.

2.4.1.6 Effect of speed / frequency

Frequency deviation influences the performance of the gas turbine. The increase of frequency deviations (n/n_0) will lead to increase the exhaust gas mass flow (m_g/m_0) and this in turn increases the power output (P_t/P_c) and efficiency (η_t/η_{t0}) of the gas turbine. Negative frequency deviations will have vice versa effect. The figure 2.11 shows the effect of speed on gas turbine power output, efficiency and exhaust mass flow rate.

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Figure-2.11

Effect of Speed on the Power Output and Exhaust flow [John W. Sawyer (1985)]

The above parameters like ambient pressure, ambient temperature, ambient humidity, fuel and speed have effects on the exhaust gas flow and exhaust gas temperature which in turn would influence the performance of the bottoming cycle (steam turbine).

2.4.2 Ambient factor influencing the Steam turbine output

Some parameters do influence only the steam cycle output. Cooling water inlet temperature affects the performance of combined cycle dedicated for power generation application.

The steam turbine back-pressure and the steam turbine output depend strongly on the cooling water inlet temperature to the condenser. The increased cooling water inlet temperature to the condenser will increase the steam turbine back pressure and reduce the steam turbine output and vice versa.

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2.5 Correction of test results to reference conditions

The Gas turbine performance is highly influenced by the ambient parameters like intake air's (inlet air) temperature, pressure, humidity and also other factors like speed, calorific value of fuel etc. These parameters are variable with respect to time and other factors. (e.g. with lower ambient temperature and higher fuel calorific value, gas turbine can produce more power output and vice versa). It is wrong to do the direct comparison of the engine performance monitoring parameters under various conditions. It is also not always possible to run the engine at the specified reference or standard conditions. So, the results of the engine performance monitoring parameters have to be corrected to the reference conditions to facilitate their comparison at various conditions. The following paragraph gives the details about various techniques available for the correction of test result to the reference conditions. [Walsh (1998)]

2.5.1 Importance of parameter groups

Large number of variables is required to numerically describe the engine performance throughout the operational envelopes. The Bunkingham PI theorem reduces the large number of parameters to a small number of dimensionless parameter groups. In these groups, the parameters are multiplied together and each is raised to some exponent. The result greatly simplifies the understanding and graphical representation of engine performance. For instance, the steady state mass flow rate of a turbojet engine is a function of eight parameters as shown in the table 2.1

SN	Inlet mass flow is a function of	SN	Dimensionless group for inlet mass flow is a function of
1	Ambient temperature	1	Dimensionless group for engine speed
2	Ambient pressure		
3	Flight Mach number	2	Flight Mach number
4	Engine rotational speed	3	Dimensionless group for viscosity (has only a second-order effect, and is often ignored for initial calculations)
5	Engine diameter		
6	Gas constant of working fluid		
7	Gamma for working fluid		
8	Viscosity of working fluid		

Table 2.1

Conversion of normal parameters to Dimensionless groups

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The Buckingham PI theorem has been applied to the mass flow rate of a gas turbine engine. The parameter group for mass flow is then a function of only three parameter groups rather than of eight parameters.

2.5.2 Application of parameter groups

The parameter groups are widely used for the following applications. They are

- a. To study the component characteristics
- b. Engine steady state off-design performance analysis
- c. Comparison of sets of engine test data
- d. Scaling of engine and component designs
- e. Use of other working fluids
- f. Engine transient performance analysis.

2.5.3 Classification of parameter groups

The parameter groups are classified into four different types based on their applications and functions. [Walsh (1998)]. They are

- Dimensionless groups.
- Quasi-dimensionless groups.
- Referred or corrected groups.
- Scaling parameter groups.

Table 2.2 presents the parameter groups for overall engine performance and table 2.3 presents the corresponding groups for individual component's performance.

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	Performance parameter	Dimensionless Group	Quasi-dimensionless Group	Referred parameter	Scaling parameter
1	Temperature at station n (Tn)	$\frac{C_p \times (T_n/T_1 - 1)}{\gamma \times R}$	Tn/ T1 or TSn/T1	Tn/θ or TSn/θ	Tn/θ or TSn/θ
2	Pressure at station n (Pn)	$\frac{C_p \times (P_n/P_1^{(\gamma-1)/\gamma} - 1)}{\gamma \times R}$	Pn/ P1 or PSn/P1	Pn/δ or PSn/δ	Pn/δ or PSn/δ
3	Mass flow (W)	$\frac{W \times \sqrt{(T_1 \times R)}}{D_1^2 \times P_1 \times \sqrt{(\gamma)}}$	$\frac{W \times \sqrt{(T_1)}}{P_1}$	$\frac{W \times \sqrt{(\theta)}}{\delta}$	$\frac{W \times \sqrt{(\theta)}}{D_1^2 \times \delta}$
4	Rotational Speed (N)	$\frac{N \times D_1}{\sqrt{(\gamma \times R \times T)}}$	N / $\sqrt{(T_1)}$	N / $\sqrt{(\theta)}$	(D1 x N) / $\sqrt{(\theta)}$
5	Fuel Flow(WF)	$\frac{WF \times FHV \times \sqrt{R} \times \eta_{A31}}{C_p \times D_1^2 \times P_1 \times \sqrt{(T_1 \times \gamma)}}$	$\frac{WF \times FHV \times \eta_{A31}}{P_1 \times \sqrt{(T_1)}}$	$\frac{WF \times FHV \times \eta_{A31}}{\delta \times \sqrt{(\theta)}}$	$\frac{WF \times FHV \times \eta_{A31}}{D_1^2 \times \delta \times \sqrt{(\theta)}}$
6	Fuel air ratio (FAR)	$\frac{FAR \times FHV \times \eta_{A31}}{C_p \times T_1}$	$\frac{FAR \times FHV \times \eta_{A31}}{T_1}$	$\frac{FAR \times FHV \times \eta_{A31}}{\sqrt{(\theta)}}$	$\frac{FAR \times FHV \times \eta_{A31}}{\sqrt{(\theta)}}$
7	Shaft power (PW)	$\frac{P_W}{\gamma \times D_1^2 \times P_1 \times \sqrt{(\gamma \times R \times T_1)}}$	$\frac{P_W}{P_1 \times \sqrt{(T_1)}}$	$\frac{P_W}{\delta \times \sqrt{(\theta)}}$	$\frac{P_W}{D_1^2 \times \delta \times \sqrt{(\theta)}}$
8	Shaft power SFC (SFC)	$\frac{SFC \times FHV \times \gamma \times R \times \eta_{A31}}{C_p}$	SFC x FHV x η_{A31}	SFC x FHV x η_{A31}	SFC x FHV x η_{A31}
9	Shaft specific power (SPW)	$\frac{SPW}{\gamma \times R \times T_1}$	SPW / T1	SPW / θ	SPW / θ
10	Gross thrust (FG)	$\frac{F_G}{\gamma \times D_1^2 \times P_1}$	FG / P1	FG / δ	FG / (D1 ² x δ)
11	Momentum drag (FRAM)	$\frac{FRAM}{\gamma \times D_1^2 \times P_1}$	FRAM / P1	FRAM / δ	FRAM / (D1 ² x δ)
12	Gross thrust parameter (FG)	$\frac{FG / (A_9 \times PAMB) + 1}{\gamma \times D_1^2 \times P_1 / (PAMB)}$	$\frac{FG / (A_9 \times PAMB) + 1}{P_1 / (PAMB)}$	$\frac{FG / (A_9 \times PAMB) + 1}{P_1 / (PAMB)}$	$\frac{FG / (A_9 \times PAMB) + 1}{D_1^2 \times P_1 / (PAMB)}$
13	Thrust (SFC)	$\frac{SFC \times FHV \times \sqrt{(\gamma \times R)} \times \eta_{A31}}{C_p \times \sqrt{(T_1)}}$	$\frac{SFC \times FHV \times \eta_{A31}}{\sqrt{(T_1)}}$	$\frac{SFC \times FHV \times \eta_{A31}}{\sqrt{(\theta)}}$	$\frac{SFC \times FHV \times \eta_{A31}}{\sqrt{(\theta)}}$
14	Specific thrust (SFG)	$\frac{SFG}{\sqrt{(\gamma \times R \times T_1)}}$	SFG / $\sqrt{(T_1)}$	SFG / $\sqrt{(\theta)}$	SFG / $\sqrt{(\theta)}$
15	Gas velocity at station n (Vn)	$\frac{V_n}{\sqrt{(\gamma \times R \times T_1)}}$	Vn / $\sqrt{(T_1)}$	Vn / $\sqrt{(\theta)}$	Vn / $\sqrt{(\theta)}$
16	Density at station n (RHOn)	RHOn x R x T1 / P1	RHOn x T1 / P1	RHOn x θ / δ	RHOn x θ / δ

Table 2.2
Engine Parameter Groups [Walsh (1998)]

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SNo	Performance parameter	Dimensionless Group	Quasi-dimensionless Group	Referred parameter	Scaling parameter
17	Shaft Torque (TRQ)	$\frac{TRQ}{\gamma \times DI^2 \times P1}$	$TRQ / P1$	TRQ / δ	$TRQ / (DI^2 \times \delta)$
18	Shaft rate of acceleration (NU)	$\frac{NU \times J}{\gamma \times DI^2 \times P1}$	$NU / P1$	NU / δ	$NU \times J / (DI^2 \times \delta)$
19	Shaft time constant (TC)	$\frac{TC \times J \times \sqrt{(R \times T)}}{DI^4 \times P1 \times \sqrt{(\gamma)}}$	$\frac{TC \times \sqrt{(T1)}}{P1}$	$\frac{TC \times \sqrt{(\theta)}}{\delta}$	$\frac{TC \times J \times \sqrt{(\theta)}}{DI^4 \times \delta}$
20	Shaft gain (K)	$\frac{K \times J \times CP \times \sqrt{(T1)}}{DI \times FHV \times ETA^{34} \times \sqrt{(\gamma \times R)}}$	$K \times \sqrt{(T1)}$	$K \times \sqrt{(\theta)}$	$\frac{K \times j \times \sqrt{(\theta)}}{DI}$
21	Compressor efficiency (ETA2)	ETA2	ETA2	ETA2	ETA2
22	Turbine efficiency (ETA ⁴)	ETA ⁴	ETA ⁴	ETA ⁴	ETA ⁴
23	Work parameter ($\Delta H/T$)	$\Delta H/T$	$\Delta H/T$	$\Delta H/T$	$\Delta H/T$
24	Reynolds number (RE)	$\frac{P1 \times Vn \times DI}{R \times T1 \times VIS}$	$\frac{P1 \times Vn}{T1 \times VIS}$	$\frac{\delta \times Vn}{\theta \times VIS}$	$\frac{\delta \times Vn \times DI}{\theta \times VIS}$

Table 2.2 (Cont'd)

SNo	Performance parameter	Dimensionless groups	Quasi-dimensionless group	Referred parameter	Scaling parameter
1	Mass flow(W)	$\frac{W \times \sqrt{(T_{IN} \times R)}}{DI^2 \times P_{IN} \times \sqrt{(\gamma)}}$	$\frac{W \times \sqrt{(T_{IN})}}{P_{IN}}$	$\frac{W \times \sqrt{(\theta)}}{\delta}$	$\frac{W \times \sqrt{(\theta)}}{DI^2 \times \delta}$
2	Rotational Speed (N)	$\frac{N \times DI}{\sqrt{(\gamma \times R \times T_{IN})}}$	$\frac{N}{\sqrt{(T_{IN})}}$	$\frac{N}{\sqrt{(\theta)}}$	$\frac{DI \times N}{\sqrt{(\theta)}}$
3	Shaft power (PW)	$\frac{PW}{\gamma \times DI^2 \times P_{IN} \times \sqrt{(\gamma \times R \times T_{IN})}}$	$\frac{PW}{P_{IN} \times \sqrt{(T_{IN})}}$	$\frac{PW}{\delta \times \sqrt{(\theta)}}$	$\frac{PW}{DI^2 \times \delta \times \sqrt{(\theta)}}$
4	Shaft torque (TRQ)	$\frac{TRQ}{(\gamma \times DI^3 \times P_{IN})}$	$\frac{TRQ}{P_{IN}}$	$\frac{TRQ}{\delta}$	$\frac{TRQ}{DI^3 \times \delta}$
5	Compressor efficiency (ETA ²)	ETA ²	ETA ²	ETA ²	ETA ²

Table 2.3
Component parameter groups [Philip P. Walsh (1998)]

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SNo	Performance parameter	Dimensionless groups	Quasi-dimensionless group	Referred parameter	Scaling parameter
6	Turbine efficiency (ETA^4)	ETA^4	ETA^4	ETA^4	ETA^4
7	Work parameter ($\Delta H/T$)	$\Delta H/T$	$\Delta H/T$	$\Delta H/T$	$\Delta H/T$
8	Reynolds number (RE)	$\frac{P_{\text{IN}} \times V_n \times \text{DI}}{R \times T_{\text{IN}} \times \text{VIS}}$	$\frac{P_{\text{IN}} \times V_n}{T_{\text{IN}} \times \text{VIS}}$	$\frac{\delta \times V_n}{\theta \times \text{VIS}}$	$\frac{\delta \times V_n \times \text{DI}}{\theta \times \text{VIS}}$
9	Stage loading	$\Delta H/U^2$	$\Delta H/U^2$	$\Delta H/U^2$	$\Delta H/U^2$
10	Velocity ratio	V_A/U	V_A/U	V_A/U	V_A/U
11	Mach number	M	M	M	M

Table 2.3 (Cont'd)

2.5.3.1 Dimensionless groups

With fair precision the performance of a gas turbine engine can be determined using dimensionless groups. These dimensionless groups contain all variables affecting the engine or individual component's performance, including engine linear scale and fluid properties. It is also called non-dimensional groups or full dimensionless groups. The first column of the table 2.2 represents the dimensionless groups for main engine and component's performance parameters.

2.5.3.2 Quasi-dimensionless groups

The Quasi-dimensionless groups suit the most common situation of an engine or component design of fixed linear scale, using dry air as the working fluid. i.e. only operational condition and throttle setting are to be considered.

It is also called semi-dimensional groups. Second column of the table 2.2 represents the quasi-dimensionless groups for main engine and individual component's performance parameters.

2.5.3.3 Referred or corrected groups

The overall engine performance is frequently referred to standard inlet conditions of 1.01325bar and 288.15K. The referred or corrected parameters take the values that the basic

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parameters would have at ISA sea level static conditions. These parameter groups are directly proportional to the quasi-dimensionless groups and hence they are interchangeable in usage.

The difference is the substitution of theta (θ) and delta (δ) for engine or component inlet pressure and temperature, where as

Theta (θ) = inlet temperature / 288.15K

Delta (δ) = inlet pressure/1.01325 bar

The resulting groups are given in the third column of the table 2.2

2.5.3.4 Scaling parameter groups

They are mainly used in the concept design of new engines. The working fluid properties are omitted in these groups. They are used to quickly access the performance effects of linear scaling to an existing engine, or matching differentially scaled existing compressor and turbines. The fourth column of table 2.2 represents the scaling parameter groups for the main engine and component parameters.

2.5.4 First order effects

For a given operational condition, knowledge of the absolute values of inlet pressure and temperature allows easy calculation of the actual performance parameters. The off-design performance parameters to a level of first order accuracy are given in the table 2.2 and table 2.3. These tables show the interrelationship of the referred parameter groups. The value of these tables cannot be over emphasized. They enable 'on the spot' judgements during engine testing, or discussing in a meeting the impact of an extreme operating points. The parameter groups account for the first order approximation of gas turbine engine component characteristics, scaling, steady state and transient performance evaluation. [Walsh (1998)]

2.5.5 Second order effects

When a rigorous analysis must be pursued then all effects must be fully accounted and this invariably requires complex computer codes. There are various phenomena that have a second-order effect upon engine matching, and they will also affect the parameter group relationships. Although these effects may be ignored, if first-order accuracy is only required.

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[Walsh (1998)]. The following examples show the difference of the second order effect with the first order effect.

➤ Second order effect of Humidity and water or steam injection

The effect of water vapour on engine performance can be significant due to change of gas properties. To a first order accuracy level, this effect is small and may be neglected. But for a second order accuracy level this effect has significant influence over gas turbine performances and it has to be included.

➤ Second order effect of the Inlet and exit conditions

For a given engine design, non-standard inlet and exit conditions may cause the engine to deviate from its normal non-dimensional behavior. e.g.

- a. Different installation inlet and exhaust losses due to change of application filter blockage etc.
- b. Flow distortion at the first compressor inlet due to cross wind or aircraft pitch and yaw.

To a first order accuracy level, these effects are small and may be neglected. But for a second order accuracy level these effects have significant influence over gas turbine performances and they have to be included.

The application of parameter groups for analyzing the steady state performance yields the result to a first order accuracy level, whereas the correction factors specified by the equipment supplier incorporates the second order effects and they will provide more accurate results.

2.5.6 Correction of test results to the reference conditions for variable speed gas turbines

In case of variable speed characteristics, such as mechanical drive, the corrections shall be made as follows [ISO 2314:1989(E)]

2.5.6.1 Determination of output shaft test speed (n_t)

$$n_t = n_0 \sqrt{\theta}$$

where n_0 is the reference speed and θ is the ratio of the absolute test ambient temperature to the absolute reference ambient temperature.

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2.5.6.2 Determination of absolute test temperature (T_t)

$$T_t = T_0$$

where T is the absolute temperature for the reference conditions and θ is the ratio of the absolute test ambient temperature to the absolute reference ambient temperature.

2.5.6.3 Determination of corrected net shaft power output (P_c)

The net shaft power output P_t may be determined from the measured gross test shaft output. The corrected net shaft power output, P_c will then be given as follows

$$P_c = P_t / (\delta \sqrt{\theta})$$

where P_t is the test net shaft power outlet, δ is the ratio of the ambient absolute pressure to the reference ambient absolute pressure and θ is the ratio of the absolute test ambient temperature to the absolute reference ambient temperature.

2.5.6.4 Determination of the thermal efficiency (η_t)

The thermal efficiency of the variable speed gas turbine is calculated as follows

$$\eta_t = P_t / (m_m * (Q_{l0} + h_{f4} - h_0))$$

where m_m is the measured rate of fuel consumption in kilograms per second.

Q_{l0} is the net specific energy of the fuel at 15°C and constant pressure in kJ/kg.

h_{f4} is the specific enthalpy of the fuel at temperature T_{f4} entering the heat source (combustion chamber) in kJ/kg and h_0 is the specific enthalpy of the fuel at 15°C in kJ/kg.

2.5.7 Correction of test results to the reference conditions for constant speed gas turbines

Correction of test load and thermal efficiency for generator drive or other constant speed applications is less straightforward, since it is impossible to operate the engine at the same aerodynamic conditions. Therefore the gas turbine engine would be operating at off design point whenever the compressor inlet conditions are different from the reference conditions. Every effort shall be made to run the test at reference conditions. If this is not feasible, then the test will have to be based on proper correction curves. These corrections include the effect of parameters influencing load and efficiency including (but not limited to) compressor inlet temperature,

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compressor inlet and turbine exhaust pressures, speed and humidity. This correction curves should be supplied by the engine supplier since it is specific to that particular machine. The general shapes of the correction curves given by the ISO 2314 are shown in appendix A1. The effects of individual ambient parameters are given by the following figures in appendix A1.

Figure 2.12: Correction curve of CCPP output vs ambient temperature.

Figure 2.13: Correction curve of CCPP output vs ambient pressure.

Figure 2.14: Correction curve of CCPP output vs relative humidity.

Figure 2.15: Correction curve of CCPP output vs cooling water temperature deviation.

Figure 2.16: Correction curve of CCPP heat rate vs ambient temperature.

Figure 2.17: Correction curve of CCPP heat rate vs ambient pressure.

Figure 2.18: Correction curve of CCPP heat rate vs relative humidity.

Figure 2.19: Correction curve of CCPP heat rate vs cooling water temperature deviation.

Figure 2.20: Correction curve of CCPP-output vs gas turbine degradation over EOH

Figure 2.21: Correction curve of CCPP-heat rate vs gas turbine degradation over EOH

SN0.	Description	Power Output	Heat Rate	Efficiency	Exhaust temperature	Exhaust mass flow
1	Ambient pressure	❖	❖			❖
2	Ambient temperature	❖	❖	❖	❖	❖
3	Ambient humidity	❖	❖	❖	❖	❖
4	Speed	❖	❖	❖	❖	❖
5	Power	❖	❖	❖		❖
6	Inlet duct pressure drop	❖	❖	❖	❖	❖
7	Outlet duct pressure drop	❖	❖	❖	❖	
8	Heating value	❖	❖			❖
9	Power factor	❖	❖	❖		❖
10	Deterioration	❖	❖	❖		❖

Table 2.4

The effects of ambient parameters and other operating parameters on the Gas turbine health-indicating parameters. (GHI)

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The effect of ambient parameters and the operating parameters like speed and fuel flow etc on the equipment health indicating parameters like power output, heat rate, efficiency, exhaust temperature and exhaust gas flow rate are simplified and shown in table 2.4.

2.6 Introduction to the Gas turbine controllers for CCGP

The knowledge about the gas turbine controller plays vital role to understand the behavior of the gas turbine during various operating conditions. Figure 2.22 shows the concept of the GT controller for combined cycle plant. The GT controller controls the following operational states of the gas turbine engine. [Siemens (2001)]

- a) Start up.
- b) Synchronizing.
- c) Loading / unloading.
- d) Load limitation and Load rejection.
- e) Shutdown.

2.6.1 Various control devices to achieve GT controller Tasks

- a) Startup / Runup controller.
- b) Speed / Load controller
- c) Temperature controller.
- d) Load limit controller.
- e) Lift controllers of fuel oil valves.

Apart from the above controllers, the gas turbine has the following special controllers to protect the engine from abnormal operations.

- f) Compressor outlet pressure gradient limit controller.
- g) Compressor pressure ratio limit controller.
- h) Compressor discharge temperature limit controller.

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2.6.1.1 Startup/Runup controller

The runup function controller controls the speed of the gas turbine from turning gear speed to rated speed (50Hz). The gas turbine speed has been increased from turning gear speed to 60% rated speed using startup frequency convertor, which uses generator as motor and drives the gas turbine. At a speed of about 10% of rated speed, the fuel gas diffusion control valve opens to the minimum position and admits the fuel into the gas turbine. After reaching 15% of the rated speed, the ignition transformer will be switched on and ignites the gas turbine burner. If the flame monitoring system finds a successful flame-on signal in the combustion chamber within a certain time period (ie 5 seconds on fuel gas operation and 8 seconds on fuel oil operation) then it will allow the startup frequency convertor to increase the gas turbine speed to 60% of the rated speed, otherwise it trips the turbine system. At 60% of the rated speed the startup frequency converter is taken out of service and gas turbine drives by its own to reach the 100% rated speed. The gas turbine exhaust temperature mainly decides the slope of the speed gradient. The speed controller tries to maintain the slope in such a way that the gas turbine exhaust temperature will never exceed the design allowable limit.

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2.6.1.2 Speed Controller

The speed controller tries to maintain the gas turbine speed by about 1% greater than the grid speed and allows the auto or manual synchronizing device to do the synchronizing operation.

2.6.1.3 Load Controller

After synchronizing the machine with the grid, the load controller takes over the speed controller functions and controls the turbine load. The load controller pre-controls the fuel valve lift. The load controller thus controls operation over the entire load range from 0% to 100%. The other controllers like outlet temperature controller (OTC), inlet guide vane controller (IGV) and load set point determines the function of the load controller.

2.6.1.4 OTC Controller

The turbine inlet temperature cannot be measured directly due to its high range (i.e. 1250°C), so the turbine outlet temperature is measured by using twenty four thermocouples. Based on the actual ambient temperature, the average outlet temperature of these twenty four thermocouples is corrected. This corrected value is fed into the gas turbine controller, which determines the behavior of the OTC controller. The main function of the OTC controller is to control the gas flow rate and airflow rate to achieve the following criteria

- To maintain the temperature difference between average OTC temperature and main steam inlet temperature of the HP steam turbine less than 50°C in order to avoid thermal stress to the boiler HP superheater tubes. (for loads 0% to 25%).
- To maintain the average corrected OTC temperature less than 580°C. (for loads >90%).

2.6.1.5 IGV Controller

Once the HRSG outlet steam temperature optimized with the gas turbine exhaust temperature, (i.e. after reaching a load of about 25%) the gas turbine controller transfers the control from OTC to IGV controller. The main function of the IGV controller is to control the airflow rate of the gas turbine compressor and fuel gas flow rate based on the load set point. The inlet guide vane opening and fuel gas control valve opening are directly proportional to the load set point, with increase in load set point the openings will be increased and vice versa. OTC of

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the gas turbine also increases with the opening of IGV (i.e. with increase of load). After reaching an OTC of about 570°C the controller transfers the control from IGV controller to OTC controller. Further increase of gas turbine load is achieved by opening the gas control valve only and airflow rate cannot be increased further since it has been reached to its maximum value in the IGV controller itself.

2.7 Neural networks and artificial intelligence

2.7.1 Introduction to neural network concept

Neural network is a computer-based simulation of the living nervous system. It works quite differently from the conventional computing techniques. It has rigorous mathematical basis and needs statistically valid set of data for training the network. Although some amount of mathematics is involved, the main goal of neural network described here is to provide a hands-on guide without making too many assumptions about our skill level.

2.7.2 Working principle of neural networks

Simple neuron: A neuron is a nerve cell with all of its processes. It is one of the distinguishing features of animal. (Plants do not have the neurons). The type of neuron found in the retina is shown in figure 2.23. It is a bipolar neuron, which means it has two processes. The cell body contains the nucleus. Leading into the nucleus is one or more **dendrites**.

<p>3 Parts of a Typical Nerve Cell</p> <ul style="list-style-type: none"> Dendrites: Carry signals in Cell body: Contains nucleus Axon: Carries signals away	<p>Synapse: Point at which a nervous impulse passes from one neuron to another</p> <p>Sequence: Stimulate end of nerve fiber (> threshold?) Chemical & electrical changes start (the impulse) Nerve segment recovers to original state, ready for new impulse</p>
<p>Figure 2.23</p> <p>A simple neuron</p> <p>[Nelson and Illingworth (1991)]</p>	<p>Figure 2.24</p> <p>Nerve structure</p> <p>[Nelson and Illingworth (1991)]</p>

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Bundles of neurons, or nerve fibers, form the nerve structure is shown in the figure 2.24. In a simplified scenario, nerves conduct impulse from receptor organs (such as eyes or ears) to effector's organs (such as muscles or glands). The point between two neurons in a neural pathway, where the termination of the axon of one neuron comes into close proximity with the cell body or dendrites of another is called synapse. Through this synapse only the nervous passes impulse from one neuron to another. As a whole, the information transfer process is as follows

- Dendrites carry the signals in.
- Cell body contains nucleus.
- Axon carries signals away from the cell body.
- Signals come into synapses, are "weighed" and resulting quantities are summed
- If sum $\geq$ threshold for neuron. Then Neuron fires.
- Activity in nervous system can adjust signals.
- Threshold Functions integrate energy of incoming signals over space and time.
- Once the impulse is transmitted, the nerve segment recovers to its original state, ready for receiving a new impulse.

2.7.3 The Artificial Neuron

The artificial neuron is the basic element of the neural networks. Artificial neurons are much simpler than the biological neurons. This artificial neuron simulates six basic functions of natural neurons.

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They are

- behave
- react
- self-organize
- learn
- generalize
- forget Rather than executing the program.

Figure 2.25 shows the basics of artificial neuron. The various inputs to the network are represented by the vectors such as $X_{(1)}, X_{(2)}, X_{(3)} \dots X_{(n)}$. Each component of these inputs vectors are multiplied by a corresponding vector components of connection weights, these weights are represented by the vectors, such as $W_{(1)} W_{(2)} W_{(3)} \dots W_{(n)}$. In the simplest case, the scalar result obtained by the above multiplication are simply summed and passed through a transfer function to generate an output. All artificial neural networks are constructed from this basic building block with different structural arrangement depending on the need.

2.7.4.1 Neural Network Design

The neural network design is an iterative and complex process. It consists of the following steps.

- Arranging the neurons in various layers.
- Deciding the type of connections among neurons for different layers as well as among the neurons within a layer
- Deciding the way a neuron receives input and produces output.
- Determining the strength of connection within the network by allowing the network to learn the appropriate values of connection weights using the training data sets.

The neural networks are the simple clustering of the artificial neurons. This clustering occurs by creating layers, which are connected to each other. All the artificial neural networks have a similar structure of topology.

The neurons are grouped into layers. The input layer consists of neurons that receive input from the external environment. The output layer consists of neurons that communicate the output of the system to the user or external environment. Figure 2.26 shows simple neural network structure with one hidden layer, usually there will be larger number of hidden layer.

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When the input layer receives the input, its neurons produce outputs, which become input to the other layers of the system. The process continues until a certain condition is satisfied or until the output layer is invoked and fires their output to the external environment.

The network has to be trained with various training methods. The selection of the suitable training method plays critical role in achieving fast convergence and generalization of the network in such a way that the network developed will perform at its best. The selection of training methods could be done by using genetic algorithm and designing of experiments technique. If the hidden numbers of neurons are too many then it will lead to overfit. The overfit allows network to memorize the data and makes the network useless with new data sets. Overfit also avoids the generalization of the network.

2.7.4.2 Interlayer connections

The connections between layers are called inter-layer connections. The inter-layer connections are of different types. They are

- **Fully connected:** Each neuron on the first layer is connected to every neuron in the second layer.
- **Partially connected:** The neurons in the first layer need not to be connected to all neurons on the second layer.
- **Feed Forward:** The neurons in the first layer send their output to the neurons on the second layer, but they do not receive any input back from the neurons in the second layer.
- **Bi-directional:** The neurons in the first layer send their output to the neurons on the second layer and they receive the input back from the neuron in the second layer.

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Feed forward and bi-directional connections could be fully or partially connected.

- **Hierarchical:** The neurons of a lower layer communicate with neurons on the next level of layers.
- **Resonance:** The layers have bi-directional connections and they continue to send messages across the connections number of times, until a certain condition is achieved.

2.7.4.3 Intra-Layer connections

In more complex structures the neurons communicate among themselves within a layer, this is known as intra-layer connections. There are two types of intra-layer connections.

- **Recurrent:** The neurons within a layer are fully or partially connected to one another. The neurons also receives input from another layer, they communicate their outputs with one another before they are allowed to send their outputs to another layer.
- **On-centre/Off surround:** A neuron within a layer has excitatory connections to itself, with its immediate neighbors and has inhibitory connections to other neurons.

2.7.5.4 Learning

The brain basically learns from experience. Neural networks are sometimes called machine learning algorithms, because changing of its connection weights (training) causes the network to learn the solution to a problem. The strength of connection between the neurons is stored as a weight value for the specific connection. The system learns new knowledge by adjusting these connection weights. The learning ability of a neural network is determined by its architecture and by the algorithmic method chosen for training. The training method usually consists of one of three schemes.

- **Unsupervised learning:** The hidden neurons must find a way to organize themselves without the help from outside. In this approach, no sample outputs are provided to the network against which it can measure its predictive performance for a given vector of inputs.
- **Supervised learning:** This method works on reinforcement from outside. The connections among the neurons in the hidden layer are randomly arranged, then they reshuffled in such a way that the network will be at its best performance level. Both unsupervised learning and supervised learning suffer from relative slowness and

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inefficiency due to their dependence on the random shuffling to find the proper connections of weights.

- **Back propagation:** This method is proved highly successful in training the multilayered neural nets. The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connection between the layers and improves the performance of the network. It is a form of supervised learning.

2.7.4.5 Learning Laws

There are varieties of learning laws in common use. These laws are mathematical algorithms used to update the connection weights. The well-known Hebb's rule is main basis for most of these laws.

- **Hebb's Rule:** If a neuron receives an input from another neuron and if both are highly active (mathematically have the same sign), the weight between the neuron should be strengthened.
- **Hopfield Law:** This law is similar to Hebb's Rule with the exception that it specifies the magnitude of the strengthening or weakening. It states "if the desired output and the input are both active or both inactive, increment the connection weight by the learning rate otherwise decrement the weight by the learning rate respectively."
- **The Delta Rule:** This rule changes the connection weights in such a way that leads to minimizes the mean squared error of the network. The error is back propagated into previous layer. The process of back-propagating the network errors continues until the first layer is reached. It is also referred to as the Windrow-Hoff learning rule and the Least mean square learning rule.
- **Kohonen's Learning Law:** In the Kohonen's rule, the neurons compete for the opportunity to learn or to update their weights. The processing neuron with the largest output is declared the winner and has the capability of inhibiting its competitors as well as exciting its neighbors. Only the winner is permitted to output and the winner plus its neighbors are allowed to update their connection weights. This rule does not require desired output. Therefore it is widely used in the unsupervised methods of learning.

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2.7.4.6 Application of Neural Networks

Neural networks are used in the areas ranging from robotics, speech, signal processing, vision, and detection of heart malfunction etc. Basically most applications of neural networks fall into the following five categories.

They are

- **Prediction:** Uses input values to predict some output. e.g. pick the best stocks in the market, predict weather, identify the people with cancer risk.
- **Classification:** Use the input values to determine the classification. e.g. postal card segregation based on the address.
- **Data association:** It is similar to classification, but it also recognizes the data that contains errors. e.g. not only identify the character that is scanned but also identify the time when the scanner is not working properly.
- **Data conceptualization:** Analyze the inputs so that grouping relationships can be inferred. e.g. extract the names of a particular product from a database.
- **Data filtering:** Smooth an input signal. e.g. removing the noise out of the telephone signal.

2.7.5 Overview of Neural Network Structure

The connectivity of a neural network determines its structure. It is broadly classified as recurrent and non recurrent structures. Groups of neurons can be locally interconnected to form “cluster” that are only loosely or indirectly connected to other clusters. Alternatively, neurons can be organized into groups or layers that are connected (directionally) to other layers. Following are the different types of neural network structures. [Schalkoff (1997)]

- a. Feed Forward Neural Networks(FFNN)
- b. Recurrent Neural Networks(RNN)
- c. Competitive and Self-organizing Networks
- d. Radial Basis Function Neural Networks (RBFNN)
- e. Time Delay Neural Networks(TDNN) and
- f. Fuzzy Neural Networks.

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The feed forward neural network and radial basis function neural networks are mainly used in this research work. The reason for their selections and their basic characteristic are briefly discussed in the following paragraphs.

2.7.5.1 Overview of Feed Forward Neural Network Structure

The feed-forward network is composed of a hierarchy of processing units, organized in a series of two or more mutually exclusive sets of neurons or layers. General layout of the feed-forward neural network structure is shown in figure 2.27. The first layer receives the input applied to the network. The last layer is the point at which the overall mapping of the network input is available. Between these two extreme layers either zero or more internal layers are added for additional remapping or computing purposes.

Fig 2.27

General Layout of Feed-forward Network Structure [Schalkoff (1997)]

The links or weights connect each unit in one layer only to those in the next higher layer. There is an implied directionality in these connections. The figure 2.28 shows the typical Layered feed-forward network structure. The network shown consists of a layer of d inputs units (L_i), a layer of c output units (L_o) and a variable number (five shown in the figure 2.28) of internal or “hidden” layers (L_{hi}) of units. The role of the input layers is used to hold the input values and distribute these values to units in the next layer. The information flow in the network

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is restricted to flow layer by layer from the input to the output. Each layer based on its input computes an output vector and propagates this information to the succeeding layer. Thus, from an architectural view point, the feed-forward network allows parallelism (parallel processing) within each layer, but the flow of interlayer information is necessarily serial.

After selecting the appropriate network structure, reasonable training strategy has to be designed based on the specific application involved. Commonly, the FFNN networks are adjusted, or trained, so that a particular input leads to a specific target output. The network is adjusted based on a comparison of the output and the target until the network output matches the target. Typically many sets of input / target pairs are used to train the network. This process is known as supervised learning. These trained FFNN networks can thus learn by example, and be applied to real world problems of considerable complexity. Their most important advantage is in the ability to process data that are too complex for conventional technologies. The FFNN network derives its computing power from massively distributed structures and from its ability to learn from examples.

The FFNN networks learn more complex relationships among GT parameters from available experimental or simulated data. Neural computing is fault tolerant because the knowledge is not contained in one place, but it is distributed throughout the system. If some processing elements are destroyed the behavior of the network as a whole is only slightly altered. If more processing elements are destroyed the behavior of the network will degrade just a bit

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further, whereas traditional computing systems are rendered useless by even small amounts of damage to the memory.

The FFNN is considered as universal approximators due to its capability of approximating any finite function to any degree of accuracy. But still there are many practical unresolved issues, especially those related to the effects of training or learning. However it is concluded as follows [J.Scchalkoff (1997)].

- FF ANN networks with a single hidden layer are capable of approximating the class of “useful” functions.
- Lack of success in applications must be attributable due to
 - a. Faulty training.
 - b. Faulty architecture (eg. Incorrect numbers of hidden units)
 - c. Lack of a functional relationship between input and output.

The mapping power of the FF ANN is not inherent of the choice of specific activation function rather it is the multilayer feed-forward structure that leads to the general function approximation capability.

In general, the learning rule applied to the feed-forward neural network is mainly classified into two types

- a. Error adjusting and
- b. Gradient adjusting rule.

The error adjusting rule, adjust the connecting weights between nodes of adjacent layers according to errors between the current output and their expected output. In the gradient adjusting rule, the weights based on the gradient variation of the mean square errors between the current output and their expected output of all training samples.

The adjusting weights for the error-adjusting rule is given in equation no.1

$$W_{t+1} = W + \eta \cdot (Y_t - O_t) \cdot X_i \quad [1]$$

Where W is defined as weights, X_i is input vector; η is learning rate, Y_t and O_t are the expected output and current output respectively. Convergence speed of this rule is faster, but it valid only for the single layer neural network.

$$\delta E(W) / \delta W_{ji} = \sum_{p=1}^P \sum_{m=1}^M (Y_{pk} - O_{pk}) \cdot O_{pk} \cdot (1 - O_{pk}) \quad [2]$$

The gradient of the mean square error to weight for the gradient adjusting rule has been given in equation no.2; Where P is number of training samples. M is number of nodes in output

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layer. Y_{pk} is the expected output of sample p . O_{pk} is the current output of the sample p . E is the mean square error. W_{ji} is the weight connecting layer i and j .

It is obvious that the weights adjusting equation includes three factors, $(Y_{pk} - O_{pk})$, O_{pk} and $(1 - O_{pk})$. It can be concluded that when the gradient tends to zero; we can not simply infer that the iteration has completed and reached required accuracy of iteration. The cases may exist that O_{pk} or $(1 - O_{pk})$ tends to zero while $(Y_{pk} - O_{pk})$ is still very large. In this case, the training process has fallen into static area where convergence speed becomes very slow. Many improvements have been made in traditional BP algorithm to solve this problem, such as variable iteration step length, conjugate gradient and the least square algorithm. Although these improvements have some positive effects, the expediting convergence speed is at the cost of complexity of iteration and net structure.

The Feed-forward Back-Propagation Network (FFBPN) has been chosen for forecasting the various gas turbine healths indicating parameters (GHI) are due to the following reasons

- a. Its ability to approximate any finite function to high accuracy level.
- b. The BPN has got high ability to recognize the fault patterns despite the presence of noise. (Some fault data would not totally destroy the network performance).
- c. Its flexibility and straightforward structure makes it more suitable.
- d. Success achieved by many researchers like Lorenzo et al (2002) & Neophytos et al(2002) in the application of feed-forward neural networks for modeling the complex gas turbine health indicating parameters has also favored the use of this BPN for forecasting various health indicating parameters of this research work.

2.7.5.2 Overview of Radial Basis Function Neural Networks (RBFNNs)

In the nervous system of biological organisms there is evidence of neurons whose response characteristics are “local” or “tuned” to some region of input space. Best example is the orientation of sensitive cells of the visual cortex, whose response is sensitive to local regions of the retina.

The RBF network is a feed-forward structure with a modified hidden layer and training algorithm used for mapping. It consists of the input layer, a radial basis layer and the competitive layer. When an input is presented, the radial basis layer computes distances from the input vector to the training input vectors, and produces a vector whose elements indicate how close the

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input is to the training input. It then sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a compete transfer function in the competitive layer picks the maximum of these probabilities, and produces a '1' for the specified class and a '0' for the other classes. Figure 2.29 shows the RBFNN network architecture. [Schalkoff (1997)]

Normally the hidden layer of the RBFNN uses the Gaussian function to determine the “Center” of the unit’s receptive field. So the unit has maximum net activation, and correspondingly maximum output. { ie when $i=w$, $net(i)=0$ }. Thus, the unit sensitivity is seen to be local or distance dependent.

The designing of RBF Network structure consists of two processes as follows

- a. Determination of the RBF unit centers – this may be accomplished by either using C-means or similar algorithm and
- b. Using user selected results from a clustering procedure such as SOFM (Self organizing feature maps).

The RBF networks are often used for classification problems, although they are general mapping networks and posses “universal approximation” capabilities similar to FFNN. RBF networks have also been applied to speech processing, vision and image processing,

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controls and pattern recognition. The RBF networks are classified into two types based on its output layer. They are explained in the following paragraphs.

2.7.5.2.1 Generalized Regression Networks (GRNN)

It has radial basis layer and a linear output layer. It is often used for function approximation. The GRNN Neural network architecture is shown in figure 2.30

2.7.5.2.2 Probabilistic Neural Networks (PNN)

It has a radial basis layer and a competitive output layer. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. A compete transfer function on the output of the second layer picks the maximum of these probabilities and produces a 1 for that class and a 0 for the other classes. The architecture for this is shown in figure 2.31.

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Figure 2.31

PNN Architecture [Nelson and Illingworth (1991)]

The Probabilistic neural network (PNN) is a multi-layer feed forward network. The learning procedure of this network is supervised learning procedure. During learning procedure the PNN classifies the training patterns to classes (represented by the output nodes). When an unknown pattern is presented to the PNN, network estimates the probability that this pattern belongs to each class. The schematic presentation of the PNN has been shown in figure 2.32. The inputs are represented in equation 3 as follows

$$X_j = \{a_{1j}, a_{2j}, a_{3j} \dots a_{nj}\}, j=1 \dots m \quad [3]$$

The n nodes of the first layer represent the n -dimensional input. The m nodes of the second layer (hidden) represent the training patterns, while each one of the k nodes of the third (output) layer represents a class to which a pattern to be classified. Every node of the input layer

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of the PNN is linked to every node of the hidden layer. Each node of the hidden layer (representing a training pattern) is linked only to the node of the output layer that represents the class where the training pattern ‘belongs’. When a pattern $x \in \mathcal{R}^m$ is given as an input to the network, the output is the probability density functions: $P(S_i|x)$, $i=1, 2, \dots, k$. If we assume that the probability density functions, $P(x|S_i)$ are Gaussian, It is represent in equation 4 as follows

$$P(S_i|x) = [P(S_i) / P(x) \cdot (2\pi)^{m/2} \cdot \sigma_i^m \cdot |S_i|] \cdot \sum_{j=1}^{n_i} \exp [-(x-x_j^{(i)})^T (x-x_j^{(i)}) / 2\sigma_i^2] \quad [4].$$

Where, $x_j^{(i)}$ is the j -th pattern of the training set of patterns that belong to class i , $|S_i|=n_i$ is the number of the training patterns that to class i , σ_i is a smoothing parameter, $P(S_i)$ is the ‘a priori’ probability of class S_i , and $P(x)$ a normalization factor representing the ‘a priori’ probability of pattern x , which is constant assuming mutually exclusive classes, covering all possible situations. If we assume ‘a priori’ probability is equal for all classes.

Then $P(S_i) = 1/k$, $\{i = 1, 2, \dots, k\}$

Selection of the PNN network for the comparison of actual gas turbine health indicating parameter with the guaranteed and expected values provided by the manufacture is due to the following reason

- The PNN networks are more useful for classification problems.
- Their design is straight forward and guaranteed to converge to a Bayesian classifier provided it is given enough training data.
- These networks generalize well.
- Better suitability of probability density functions to analyze the degradation rate of the gas turbine. It is explained in the following paragraphs.

Probabilistic based techniques utilizes the known information on how the gas turbine health indicating parameters degrade over time to assess the current severity of the parameter distributions shifts and project their future state. This prognostic modeling approach concept has been shown in the figure 2.33. The parameter space is populated by two main components. These are the current condition and expected degradation path. Both are multi-variate Probability density function (PDFs) or 3-D statistical distributions. [Gregory et al (2001).]

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Figure 2.33

Prognostic Modeling Approach of gas turbine health indicating parameters degradation. [Gregory et al (2001).]

The figure 2.33 shows the top view of this distribution. The highest degree of overlap between the expected degradation path and the current condition is the most likely level of compressor fouling. In general, the probability that the current condition (C) may be attributed to a given fault (F) is determined by their joint probability density function. If C and F could be assumed to be normally distributed, the probability of association (P_a) has been shown in equation 5

$$P_a = 2\Phi \left(- \frac{(F-C)}{\sqrt{(\sigma_f^2 + \sigma_c^2)}} \right) = 2\Phi (-\beta) \quad [5]$$

Where,

F, C represents the mean of the distribution F and C respectively. The symbols σ_f , σ_c represents the standard deviation of the F and C distributions. The function Φ is the standard normal cumulative distribution. The notation β is defined as the fault index. Once the current severity level is known with a high degree of confidence, a fault weighted projection is performed using a modified double-exponential smoothing technique. This approach is a better than the simple multi-variate regression, since it weights the most recent performance degradation trends and evolve the current conditions towards the expected degradation path.

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2.7.7 Hybrid Neural System

Neural network has unique processing characteristic that enables it to perform the task, which would be difficult for a symbolic rule based system. However, neural network alone requires an interpretation either by a human or a rule based system. This motivates the integration of neural network and symbolic techniques within a hybrid system. This hybrid system increases the power of neural networks. [Kenneth et al (1999)]

The hybrid neural network system is classified into three different types. They are

- Unified hybrid systems
- Transformational hybrid systems
- Modular hybrid system.

2.7.7.1 Unified hybrid systems

It consists of systems that have all processing activities implemented by neural network elements. It has been shown in the figure 2.34.

2.7.7.2 Transformational hybrid systems

The most interesting feature of this system is the ability to insert, extract and refine symbolic knowledge within the framework of a neural network system. This transformational hybrid system has been classified into two types known as neural to symbolic transformational system and symbolic to neural transformational system. This system is shown in the figure 2.35.

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2.7.7.3 Modular Hybrid systems

They are comprised of several neural networks and rule-based modules. They have different degrees of coupling and integration. An important aspect is that they do not involve any changes regarding the conceptual operation of either the neural network or rule-based elements. The vast majority of hybrid systems fall into this category. It is shown in figure 2.36. The main reason is that they are powerful processors of information and are relatively easy to implement.

This research work needs different degrees of coupling and integration of several feed-forward back propagation neural networks (FFBNN) for forecasting the gas turbine health indicating parameters based on the compressor washing and Probabilistic neural networks(PNN) for comparing these parameters with the expected and guaranteed values given by the manufactures. The clustering of FFBNN and PNN networks along with rule based modules

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without any changes in the conceptual operation systems shows the requirement of the **modular hybrid system** for this research work.

2.8 Introduction to develop the neural network model using Matlab toolbox

2.8.1. Creation of Feed Forward network using Matlab toolbox

2.8.1.1 Network creation

The function `newff` creates a feedforward network. It requires four inputs and returns the network object. The first input is an R by 2 matrix of minimum and maximum values for each of the R elements of the input vector. The second input is an array containing the sizes of each layer. The third input is a cell array containing the names of the transfer functions to be used in each layer. The final input contains the name of the training function to be used.

For example, the following command creates a two-layer feedforward network. There is one input vector with two elements.

e.g. `net = newff([-1 2; 0 5],[3,1],{'tansig', 'purelin'}, 'traingd');`

The values for the first element of the input vector range between -1 and 2 , the values of the second element of the input vector range between 0 and 5 . There are three neurons in the first layer and one neuron in the second (output) layer. The transfer function in the first layer is tan-sigmoid and the output layer transfer function is pure linear. The training function used is `traingd`. The above command creates the network object, also initializes the weights and biases of the network.

2.8.1.2 Training the network

The network is ready for training after initializing the weights and biases. The training process requires a set of examples with network inputs `p` and target outputs `t`. During training the weights and biases of the network are iteratively adjusted to minimize the network performance. For the feed forward network the default performance function is mean square error. (MSE). The following code is used to train the network.

`[net, tr ]=train (net, p, t);`

The training record `tr` contains information about the progress of training.

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Different algorithms are available for training the feed forward network. They use the gradient of the performance function to determine the weights to minimize performance (MSE). In the basic back-propagation algorithm, the weights are moved in the direction of the negative gradient. There are various types of training algorithms are available. They are

Batch training (train), batch gradient descent (traingd), batch gradient descent with momentum algorithm (traingdm), variable learning rate algorithms (traingda, traingdx), resilient backpropagation algorithm (trainrp), conjugate gradient algorithms (traincgf, traingcp, traingcb, trainscg) and line search routine algorithms (srchgol, srchbre, srchhyb, srchcha, srchbac), Quasi-Newton algorithms (trainbfgf, trainoss) and Levenberg-Marquardt algorithm (trainlm).

2.8.1.3 Simulation of the network

The function sim simulates a network. sim command takes the network input p, and the network object net, and returns the network outputs a. The following command is used to simulate the network.

```
a = sim(net,p)
```

Where a is the output, net is network and p is the input.

2.8.1.4 Preprocessing and postprocessing techniques

Neural network training would be made more efficient if certain preprocessing steps have been performed on the network inputs and targets. This section describes various preprocessing routines.

2.8.1.4.1 Min and Max (premnmx, postmnmx, tramnmx)

The function premnmx are used to scale the inputs and targets so that they fall in the range of -1 to 1. The following codes illustrates the use of this function

```
[pn, minp, maxp, tn, mint, maxt] = premnmx(p,t);  
net = train(net, pn, tn);
```

The original network inputs and targets are given in the matrix p and t respectively. The normalized inputs and targets are pn and tn respectively. The values of pn and tn would be in the range of -1 to 1. The vectors minp and maxp contain the minimum and maximum values of the original inputs, and the vectors mint and maxt contains the minimum and maximum values of the

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original targets. The following codes will simulate the network that is trained by using previous codes, and normalize back the network output into the original units.

```
an = sim(net,pn);  
a = postmnmx(an, mint, maxt);
```

Whenever the trained network is used with new inputs they have to be preprocessed with the minimum and maximums computed for the training set. This is accomplished with the routine tramnmx. The following set of codes are used to simulate the new set of inputs to the network, which have been trained previously.

```
pnewn = tramnmx(pnew, minp, maxp);  
anewn = sim(net, pnewn);  
anew = postmnmx( anewn, mint, maxt);
```

2.8.1.4.2 Mean and Standard deviation (prestd, postd, trastd)

This method normalizes the inputs and targets so that they will have zero mean and unity standard deviation. The following code illustrates the use of prestd.

```
[pn,meanp,stdp,tn,meant,stdt]=prestd(p,t);  
net = train (net, pn, tn);
```

The original network inputs and targets are given in the matrices p and t. The pn and tn are the normalized inputs and targets respectively, they will have zero means and unity standard deviation. The vectors meanp and stdp contains the mean and standard deviations of the original inputs. The vectors meant and stdt contains the mean and the standard deviations of the original targets. The following codes are used to simulate the previously trained network and then convert the network output back into the original units.

```
an = sim(net,pn)  
a = poststd( an, meant, stdt);
```

Whenever the trained network is used with new inputs they have to be preprocessed with the means and standard deviations that were computed for the training set. This is accomplished with the routine trastd. The following set of codes are used to simulate the new set of inputs to the network which we have been trained previously.

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```
pnewn =trastd(pnew,meanp,stdp);  
anewn=sim(net,pnewn);  
anew =poststd(anew,meant,stdt);
```

2.8.2 Creation of Probabilistic Neural network model using Matlab toolbox

Probabilistic neural network (PNN) is used for the classification problems. Their design is straightforward and does not solely depend on training. This network generalizes well. The procedure for design a PNN in Matlab toolbox is briefly discussed as follows,

The inputs and targets have to be presented in the form of matrix.

e.g four input vectors and their corresponding targets are presented into the network as follows

```
P = [0 0; 1 1; 0 3; 1 4] ; Tc = [ 1 2 3 4];
```

The target matrix is to be provided with 1's at the right places. The function ind2vec is used to create a matrix with 0's except at the correct spots. The following code illustrates the creation of the required target matrix.

```
T = ind2vec(Tc)
```

The new matrix T is in the following format

```
T =  
(1,1) 1  
(2,2) 1  
(3,3) 1  
(4,4) 1
```

The function newpnn is used to create the PNN network.

```
net=newpnn(P,T);
```

sim function is used to simulate the developed network.

```
Y=sim(net,P);
```

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The following code has to be used to convert the output Y into a row Yc to make the classifications clear.

```
Yc =vec2ind(Y);
```

Final output is in the following format.

```
Yc = 1 2 3 4
```

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3.1 Gas turbine degradation models development

Thermodynamic degradation models for V94.3A gas turbine have been developed using matlab programming language and then these thermodynamic models are used to train the neural network model. These models need gas turbine operating parameters for more than 8000 EOH (>11 months) to learn the behavior of recoverable and non-recoverable losses of the gas turbine compressor. After training, the neural network model is used to segregate the recoverable & non-recoverable losses of the gas turbine compressor and suggest the suitable washing plan to minimize them after including the cost effects. These models serve as a good tool for the reducing the long term performance degradation of gas turbine due to its compressor fouling.

3.1.1 Measured parameters available on site

The measured parameters available on the site play a crucial role in selecting a method for calculating various gas turbine health indicating (GHI) parameters. [Bhargava Rakesh (1992)]. Figure 3.1 shows the measured parameters available under the site conditions. These parameters are continuously monitored by the operating systems available in the control room and they are available in both on-line and off-line formats.

3.2 Development of thermodynamic models to assess the gas turbine compressor performance

The following parameters play very crucial role in determining the gas turbine compressor performance.

- Compressor polytropic efficiency.
- Compressor isentropic efficiency.
- Pressure ratio.
- Power output of CCPP.
- Thermal Efficiency of CCPP.
- Heat rate of CCPP and
- Compressor air flow rate.

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These parameters cannot be measured directly. They have to be calculated using larger number of measured engine operating parameters, ambient conditions and fuel properties. Thermodynamic models have been prepared by using matlab to calculate all the above parameters. These parameters are called Gas turbine health indicating parameters. (i.e. GHI).

Figure 3.1

Measured parameters available on site

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3.2.1 Polytropic, Isentropic & Pressure ratio Calculation

The polytropic, isentropic and pressure ratio of the gas turbine compressor are determined by using compressor's inlet, outlet temperatures and pressures. These health-monitoring parameters give clear indication about the cleanliness of the compressor blades. Refer to appendix A2 for details about the procedure used for calculating these health-indicating parameters. [IGTI (1995)].

3.2.2 Generator efficiency & coupling gross power output calculation

The generator efficiency and coupling gross output are calculated using the measured gross power output, gross generator voltage, gross current, field current, power factor. See the appendix A3 for details about the calculation procedure used. The calculated efficiency, coupling gross power output and net power outputs have been corrected to the generator design power factor of 0.85. This correction helps to do the comparison of gross coupling power output and generator efficiency under various operating conditions.

3.2.3 Determination of mass flow rate, calorific value & carbon hydrogen ratio of fuel gas

The mass flow rate, calorific value and carbon hydrogen ratio of fuel gas are the critical parameters needed to determine the fuel gas power input to the gas turbine. The ISO 12213 standard has been used for determining fuel gas density. This calculation is very complicated, so the free software package using AGA8-92DC method has been used to determine the density of the fuel gas. The fuel gas composition (%mole), pressure and temperature of the fuel gas are given as inputs to this software AGA8-92DC and it gives the density of the fuel gas composition. The mass flow rate of the fuel gas is determined using the following formula

$$\text{Fuel gas mass flow rate} = \text{Fuel gas volumetric flow rate} \times \text{Density of fuel gas composition.}$$

The lower calorific value, higher calorific value and carbon hydrogen ratios of the fuel gas composition are determined as per the procedure given in the appendix A4.

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3.2.4 Corrected power output and heat rate calculation

The main objective of this research work is to trend the gas turbine compressor health indicating parameters on long term basis and suggest suitable actions to run the gas turbine in good healthy operating condition. Even though the power output is a measurable parameter it depends on various ambient conditions (like temperature, pressure and humidity etc) and standard engine conditions (like speed and power factor etc). These conditions are not constant, and are variable with respect to time and other factors. The direct comparison of actual power output and heat rate for long term trending will mislead and end up with wrong results, so the actual measured power output and heat rate are to be corrected to the specified design conditions.

Appendix A5 and A6 show the procedures to convert the actual measured power output and heat rate to the specified reference condition based on OEM corrections. The ratio of the corrected gross power output to the corrected fuel power input gives the gross efficiency of CCPP or it can be calculated as inverse to the gross heat rate. The procedures to convert the actual measured power output and heat rate to the specified reference condition based on STD corrections is represented in appendix A7.

3.2.5 Thermodynamic model

3.2.5.1 Thermodynamic model based on OEM corrections

Thermodynamic model has been developed for determining the gas turbine health indicating parameters (GHI). The matlab program has been written for the thermal model based on OEM corrections which includes logics from the following sub models.

- The compressor polytropic and isentropic efficiencies are determined using procedure given in appendix A2.
- The generator gross power output is corrected to the reference power factor of 0.85 by using procedure given in appendix A3.
- Calorific value and carbon hydrogen ratio of the fuel gas is calculated using procedure given in appendix A4.
- The power output and heat rate are corrected to the reference conditions using OEM correction that have been done by using the procedure given in the appendix A5 and A6.

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- The thermal model including all the above steps has been shown in the appendix A7.

SNo.		INPUTS	SNo.	OUTPUTS
1	General Thermal Properties	Compressor inlet temp	1	Corrected gross power output
2		Compressor outlet temp	2	Corrected heat rate
3		Compressor outlet press	3	Gross CCPP thermal efficiency
4		Ambient press	4	Compressor polytropic efficiency
5		Condensor water inlet temp	5	Compressor isentropic efficiency
6		Turbine speed	6	Compressor pressure ratio
7	Fuel Gas Properties	Nitrogen content	7	Lower calorific value of fuel gas
8		Co2 content	8	Fuel input power
9		Methane content	9	Carbon hydrogen ratio of fuel gas
10		Ethane content		
11		Propane content		
12		I-Butane content		
13		N-Butane content		
14		I-Pentane content		
15		N-Pentane content		
16		N-Hexane content		
17		N-Heptane content		
18		N-Octane content		
19		N-Nonane content		
20		Fuel mass flow rate		
22	Generator Details	Active power	10	Gross Power generator at coupling
23		Gen reactive power	11	Generator efficiency
24		Gross current	12	Gross power corrected to 0.85 pf
25		Power factor		
26		Gross voltage		
27		Field current		

Table 3.1

Inputs and Outputs for the thermodynamic model of the gas turbine engine

Appendix B1 contains details of the matlab program for the thermodynamic model based on OEM corrections. Table 3.1 represents the input and output parameters to the thermodynamic model. Table 3.2 in Appendix C1 represents the inputs and outputs for the above thermodynamic model based on OEM corrections at various EOH.

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3.2.5.2 Thermodynamic model based on STD corrections

The matlab program has been written for the thermal model based on OEM corrections which includes logics from the following sub models.

- The power output and heat rate are corrected to the reference conditions using STD corrections have been done by using the procedure given in appendix A8.
- The remaining procedures are similar to the thermodynamic model based on OEM corrections. Appendix A7 gives the details about the thermodynamic model.

The matlab programming has been written for the thermal model based on STD corrections. Refer to appendix B2 for the details about the program. Table 3.1 represents the input and output parameters to this thermodynamic model also. Table 3.3 in Appendix C2 represents the inputs and outputs for the above thermodynamic model based on STD corrections at various EOH.

3.2.6 Air flow rate Calculation

Most of the Industrial gas turbines used for power generation are of larger capacities, the air flow rate through the compressor and turbine inlet temperature of gas turbines are not measured directly due to very high amount of air flow (e.g., > 620kg/s) into the compressor, very high turbine inlet temperature (e.g., >1200°C) and their higher variation inside the combustion chamber. But these two parameters play critical role in determining the health condition of the individual components of gas turbine and the efficiency of the engine. Various methods available to determine the airflow rate are

- a. Using compressor characteristic curve.
- b. Stage stacking technique.
- c. Differential pressure method.
- d. Combustion analysis using exhaust dry oxygen.
- e. Mass and energy balance method.

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3.2.6.1 Model compressor characteristic curve given by OEM

The model characteristic given by the manufacture is a 3D graph, which inter-relates the airflow with respect to speed and pressure ratio of the compressor. It shows only the shape of the curve and it does not consist of any numerical value. This curve cannot be used for determining the accurate value of airflow, which is a must for this research work. Therefore this method is eliminated.

3.2.6.2 Stage stacking method

Complicate compressor blade and rotor internal dimensional details are required for using this method. Since it is very difficult to get all these details, application of this method is also eliminated.

3.2.6.3 Differential pressure method:

In the differential pressure method a plot of the ratio of scroll differential pressure to inlet static pressure ($\Delta P / PIC$) Vs referred speed (N_{Ref}) has to be created to find out how the compressor air flow is getting varied with respect to time period.

$$\frac{\Delta P}{PIC} = \frac{\text{Measured inlet scroll differential pressure, in. H}_2\text{O}}{\text{Compressor inlet absolute static pressure, in H}_2\text{O}}$$

Referred speed, $N_{Ref} = N / \text{SQRT} ((TIC)(R) / (540^\circ R) (53.532 \text{ lbf-ft /lbm} - ^\circ R))$

The compressor inlet temperature (TIC), gas constant(R) and Speed (N) are used to find out the referred speed (N_{Ref}).

➤ Concept of this method – In general the entrance to the compressor acts like a nozzle and ($\Delta P / PIC$) is therefore an indicator of airflow. A gradual decrease in ($\Delta P / PIC$) at a given referred speed is an indication of compressor fouling. Monitoring this information will allow a compressor-cleaning schedule to be developed. As a rule of thumb a decrease in airflow is proportional to the square root of the decrease in ($\Delta P / PIC$). Alternately a sudden drop in

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($\Delta P/PIC$) at a given referred speed is an indication of damaged components in a compressor flow path. [Siemens (2001)]

- Drawback of this method –This method can be used to access the variation of the air flow rate with respect to the operating period, which is good to access the condition of the compressor fouling and it is not able to find out the exact air flow rate value, which is needed to determine the efficiency of the individual components of gas turbine.

3.2.6.4 Combustion analysis on volume basis: [Corn forth (1992)]

In practice, combustion is hardly ever carried out in stoichiometric conditions. Some industrial burners may operate at air/fuel ratio which is extremely close to the stoichiometric value, but the majority of burners require a measure of air in excess of the stoichiometric quantity to ensure the complete combustion. Combustion is a chemical reaction in which the fuel and oxygen are combined to produce heat and combustion products. Atmospheric air contains 21% oxygen (by volume) and is the most convenient oxygen source. Stoichiometric combustion conditions are those where the relative fuel and air quantities are the theoretical minimum needs to produce complete combustion.

This analysis can be used to determine the stoichiometric air required for complete combustion of the fuel supplied and excess air supplied can be found out from the oxygen content in the exhaust gas (i.e., after combustion). This method has been clearly explained in appendix A9. A thermodynamic model has been prepared by using matlab program to determine the airflow rate using this method [Math Works Inc, (2000a)]. It has been illustrated in appendix B3. Input, design and output parameters of this model are given in the following table 3.4. The table 3.5 in the appendix C3 represents the inputs, design and outputs for the above thermodynamic model at various gas turbine loads. The percentage of error between the airflow rate value calculated by using the combustion analysis on volume basis and OEM's value is around 3.5% to 5.0%.

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Input parameters	Design parameters	Output parameters
composition of Methane	density of fuel	Percentage of excess air
composition of Ethane	density of air	Actual compressor air mass flow rate.
composition of Propane		
composition of Butane		
composition of Pentane		
composition of Hexane		
composition of Co2		
composition of N2		
Exhaust Oxygen content		
Volumetric fuel flow rate		
Ambient condition		

Table – 3.4

Input output parameters of combustion analysis on volume basis

3.2.6.5 Mass and energy balance method to find out the compressor inlet airflow

The mass and energy balance method is the best method recommended by International Standards [ISO 2314-1973] "Gas turbine acceptance tests" for calculating the air mass flow rate and turbine inlet temperature of the gas turbine by using relatively easily measurable parameters.

The concept of this method is the energy in and out from a control volume is equal.

$$\Sigma(\text{Energy In}) = \Sigma(\text{Energy Out}).$$

Input parameters required	Design parameters used	Output parameters
Fuel mass flow rate	Booster power consumption	Air flow rate
Calorific value of fuel	Specific enthalpy of fuel	Turbine inlet temperature
Fuel Temperature	Bleed air to comp air ratio	
Ambient condition details	Cooling air flow rate	
Gross power of Gasturbine	Generator loss	
Cooling air temperature	Mechanical loss	
Flue gas temperature	Burner efficiency	
Mass of steam / water injection	Generator efficiency	
Bleed air mass flow rate		

Table 3.6

Input and Output parameters of Mass and Energy Balance Method

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The data for this research work has been taken from single shaft gas turbine. The mass and energy balance method has been tuned to suit this single shaft machine. Appendix A10 explains this method. Matlab program has been written [Math Works Inc, (2000a)] for determining the air mass flow rate and turbine inlet temperature. It has been illustrated in appendix B4. Input, design and output parameters of this model are given in table 3.6. Table 3.7 in appendix C4 shows the comparison of the air inlet flow calculated using the Mass and energy balance method with OEM's values. These OEM's airflow rate calculation has been done before PAC test to set the gas turbine control functions.

The percentage of error between the airflow rate value calculated by using the mass & energy balance method and OEM's value is around 1.7%, which is quite low when compared to the error of about 3.5% to 5.0% obtained in the exhaust O₂ analysis method. This shows mass and energy balance method is the best method for calculating the inlet air mass flow rate of gas turbine by using relatively easily measurable parameters in the site. Table 3.8 in appendix C5 represents the inputs and outputs for the above thermodynamic model at various EOH.

3.3 Compressor washing details

The compressor on-line washing, off-line washing and manual IGV blade cleaning activities are noted for about 18000 EOH hours. Refer to table 3.9 in appendix A11 for details regarding the compressor washings.

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3.4 Development of hybrid neural network models to assess the gas turbine compressor performance

3.4.1 Task of the neural network models

The GHI parameter deviation determined by using the thermodynamic model has the typical profile as shown in the figure 3.5. The continuous line is the actual GHI parameter deviation determined using the thermodynamic model and the dotted lines are the prediction made about the GHI parameter deviation based on EOH and number of compressor washings to be performed.

Figure 3.5

Typical profile of the GHI parameter deviation with respect to EOH

The Points F1, F2 and F3 are the GHI parameter deviation obtained immediately after the gas turbine compressor off-line washing at various EOH's. The Profiles 1, 2 and 3 are the trending curves of the GHI parameter deviation with 4, 2 and 6 numbers of on-line washing per 1000 EOH respectively. The values S1, S2 and S3 are the mean slope of the profiles 1, 2 and 3

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respectively. These slope values (S1, S2 & S3) are inversely proportional to the number of on-line washings performed in that profile. The profile 4 (P4) and profile 5 (P5) are the trending curves to be predicted using the number of on-line washings performed. The points F4 and F5 are the GHI parameter deviation predicted after performing the off-line washing in the specified EOH's.

The general structure of the newly developed Hybrid neural network model to perform the task is shown in figure 3.6. The GHI parameter deviation profiles 1, 2, and 3 are represented as P1, P2 and P3 in the figure 3.6. The individual FFBN networks ANN(1), ANN(2),

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ANN(3)... ANN(n) are developed for all the individual profiles P1, P2, P3... Pn based on different on-line washing frequency per 1000EOH. The GHI parameter deviation obtained after the off-line washing F1, F2, F3 are used to develop the FFBPN network ANN(0).

Based on the no of on-line washing to be performed in the prediction profile, the suitable FFBPN network from ANN(1), ANN(2), ANN(3) ... ANN(N) is selected. This selected FFBPN network has been inputted with the range of EOH for which the prediction to be made. The output of this network gives the GHI parameter deviation corresponding to the new EOH inputted to the network. The time period where the new off-line washing line to performed has to be inputted to the ANN(0) network and this ANN(0) network gives the corresponding GHI parameter deviation after that particular of-fline washing. This prediction depends on the trending of the points F1, F2, F3 and their EOH's. The results of the predicted GHI parameter deviation obtained from selected ANN(n) and ANN(0) are merged together to obtained the profiles P4 and P5. The mean slope of the predicted profiles P4 and P5 have been computed and compared with the mean slope of the selected reference profile using PNN network. The output of the PNN gives the details about the deviation of the predicted GHI parameter deviation from the reference GHI parameter. [Leusden, Sorgenfrey and Lutz Dummel (2003),]

3.4.2 Gas turbine compressor performance modeling using hybrid neural networks

The Matlab neural network toolbox is equipped with a host of network structures and neural functions, which along with the user's manual provides a very broad perspective in the art of neural programming. The Hybrid neural network is used for the design and evaluation of the gas turbine compressor performance model. The general structure of the newly developed Hybrid neural network model to perform the task is shown in figure 3.6

The Inter-module communications of several FFBPN networks, PNN networks and the expert system makes the developed hybrid network model to replicate the complex gas turbine degradation profile. This inter-module communication by shared data structures enables faster runtime performance and allows more sophisticated messages to be passed. The use of feedback enables the dynamic nature of the system. All the above makes the developed hybrid neural network model more suitable to replicate the complex gas turbine degradation profile, its

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analysis and predictions. The hybrid neural network program has been structured to perform the following tasks.

- a. Recognize the training data presented,
- b. Perform the necessary pre-processing of data,
- c. Perform network training based on the variants of following - Training functions, training methods, number of iterations, mean squared error goal, number of hidden layers and neurons within such layers.
- d. Generate a mean square error versus number of iteration graph.
- e. Perform an internal simulation and generation of residual graph for verification.
- f. Allows the user to proceed with use of generated neural network model to simulate other engine operating scenarios.

3.4.2.1 Flow Diagram of the Hybrid Neural network model

The flow diagram shown in figure 3.7 explains details about the logic and steps involved in the new hybrid neural network model developed using the matlab toolbox.

The number of sets of reading for analyzing the on-line washing, off-line washing and number of GHI parameter deviation to be monitored are given as input to the program. Loop-A is created based on the number of on-line washing profiles to be analyzed. The individual profiles GHI parameter deviations and their corresponding EOH are inputted in matrix format inside this for loop. Similar approach has been followed and Loop-B is created to transfer input regarding the off-line washing profile to be analyzed. Then the details regarding the maximum EOH up to which prediction to be performed, frequency of the period of the prediction, number of off-line washings to be done and when these off-line washings to be done are inputted to the program (Loop-C1). Based on the maximum EOH upto which prediction to made and number of off-line washings to performed, the number of off-line washing profile set and their corresponding EOH are determined. (Loop C2).

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Figure 3.7 (Cont'd)

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After receiving all the above inputs, the EOH and GHI parameter deviations corresponding to off-line washing have been retrieved from Loop-B and used for analyzing the off-line washing effects. These inputs and targets are preprocessed in order to make the neural network training more efficient. A feed-forward backpropagation network ANN(0) is created by using the function “newff” in the following manner.

eg. { `net1=newff([uq2 uq4],[1,u1u],{'tansig','purelin'},'trainrp');` }

The values of the first element ranges from “uq2” (min value of the EOH) and “uq4” (max value of the EOH). The first layer (input) in the network has one neuron and the second layer (output) of the network consist of “u1u” (number of GHI parameter deviations to be monitored) neurons. The transfer function of the first layer is tan-sigmoid and the output layer is pure linear. The training function used is Resilient back-propagation “trainrp” It is a simple batch mode training algorithm with fast convergence and minimal storage requirements.

The ANN(0) network’s weights and biases are initialized and trained using the normalized inputs and targets. This ANN(0) network is simulated and its outputs are normalized using post-processing techniques. The residuals between the simulated outputs and corresponding targets have been plotted. The off-line washing EOH period in the prediction profile are retrieved from Loop-C1 and these inputs are normalized using the preprocessing techniques. The network ANN(0) is simulated using the new normalized inputs and its outputs are normalized using post-processing techniques. These outputs are stored in array format.

The EOH and GHI parameter deviations corresponding to the off-line washing have been retrieved from Loop-A and it is used for analyzing the on-line washing effects. A new “For Loop” (Loop-D) has been created with maximum iteration (n) equivalent to sum of actual (n1) and prediction (n2) on-line profile sets. The conditional command “IF” is used to check the number of iterations performed. If it is less than the actual on-line washing profile set, then the particular actual on-line washing profile (from Loop-A) is selected as reference profile, otherwise the particular prediction on-line washing profile (Loop-C2) is selected as reference profile. A new feed-forward network ANN(i) is created. (where i=1 ,2 ,3 n {actual + prediction profiles}). These feed-forward networks are also initialized, trained, simulated and normalized in the same way like ANN(0) (ie feed forward created for analyzing the off-line

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washing effects). The inputs for simulating the ANN(i) network is taken based on the iteration number. If the iteration number is less than the actual number of on-line profile set, then the inputs are retrieved from actual on-line profile(Loop-A), otherwise inputs are taken from the prediction on-line profile set.(Loop-C2). After simulation the outputs are normalized and stored in array format.

The slopes of the outputs (GHI Parameter deviation) have been determined by using the ratio of the deviation between the two successive outputs to their corresponding EOH deviations. These slope values have been fitted in a normal distribution and its mean value is calculated. If the current iteration is less than $n1$, then it transfers the control to the next step, otherwise it will opt the user to select on-line washing profile to kept as reference for the next iteration. After receiving the selection from the user, the program would check whether the current iteration is less n (actual + prediction profile). If the current iteration is less n then it transfers the control to the starting of the on-line washing effect analysis part of the program, otherwise it transfers the control to the next part of the program. This part of the program shows the usage of several feed-forward networks and the rule based modules without any changes regarding the conceptual operation of either the neural network or rule based modules. It falls into the classification of Modular hybrid neural system.

The predicted on-line washing inputs (EOH) and outputs (GHI parameter deviation) have been retrieved from the above part of the program and merged with the predicted offline washing inputs (EOH) and outputs (GHI parameter deviation). Sorting of the outputs in ascending order have been done based on the EOH. The actual and predicted profile outputs (GHI parameter deviation) have been plotted against their respective EOHs.

In this part, the EOH from which the comparison is to be made with the guaranteed degradation value has to be inputted to the program. A new “For Loop” (Loop-E) has been created with a maximum iteration value of 2. New feed-forward network, ANN (J) has been created. (J=1, represent the network corresponding to the guaranteed design GHI degradation value and J=2, represent the expected GHI degradation values.) . This network has been initialized, trained and simulated using the predicted EOH same like previous networks. The

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GHI outputs of this network is normalized and fitted into normal distribution. The mean value of this distribution is determined and stored.

A PNN network has been created to analysis the deviation between the predicted GHI parameters deviation with the guaranteed and expected GHI parameters deviation.

Cost of power generation, fuel cost, on-line & off-line washing cost and opportunity lost cost have to be inputted to the program. Refer to Table 4.18 and 4.19 in the appendix-D2 for the details regarding the above cost. The plot has been made between expected GHI parameter deviations with the predicted GHI parameter deviation. The algebraic sum of this curve area gives the cumulative energy lost or gained. Effects of the cost factors on the cumulative energy lost or gained have been done and result is displayed.

3.4.2.2 Matlab programming structure of the Hybrid Neural Network modeling

The detail logic of this hybrid neural network program has been explained in the figure 3.7. Kindly refer the appendix B4 for the hybrid matlab programming to assess the gas turbine engine health condition using **prestd** preprocessing technique. In this program the data are processed by prestd preprocessing and postprocessing techniques.

Preprocessing

```
[pn,meanp,stdp,tn,meant,stdt]=prestd(p,t);
```

Network creation

```
net = train (net, pn, tn);
```

```
an = sim(net,pn)
```

Post processing

```
a = poststd( an, meant, stdt);
```

```
pnewn =trastd(pnew,meanp,stdp);
```

Simulation with new inputs

```
anewn=sim(net,pnewn);
```

Post processing

```
anew =poststd(anew,meant,stdt);
```


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In the same way the matlab programming has been written for processing the data using **preminmax** technique also. The program structure is same like the above steps, only the codification of preprocessing, simulation and post processing steps would be as follows,

Preprocessing

```
[pn, minp, maxp,tn,mint, maxt] = preminmx(p,t);
```

Network creation

```
net = train(net, pn, tn);
```

```
an = sim(net,pn);
```

Post processing

```
a = postminmx(an, mint, maxt);
```

```
pnewn = tramnmx(pnew, minp, maxp);
```

Simulation with new inputs

```
anewn = sim(net, pnewn);
```

Post processing

```
anew = postminmx( anewn, mint, maxt);
```

The matlab program for directly using the raw data has also been written in the similar and it would not consist of any preprocessing and post processing steps.

Network creation

```
net = train(net, p, t);
```

Simulation

```
Anew=sim(net,pnew);
```

All the above three models are used for analyzing for gas turbine health assessment program.

CHAPTER 4 – RESULTS & DISCUSSIONS

4.1 Overview of thermodynamic model results

The outputs of the thermodynamic models have been analyzed in the following manner:-

- Analysis of the general curve profile of EHI Parameters.
- Curve fitting of the PAC test results.
- Analysis of the long term trending of EHI Parameters.
- Comparison of OEM and STD correction effects on EHI parameter trending.

4.1.1 Analysis of general curve profiles of EHI Parameters

The general profile of the CCPP gross efficiency has been studied under different circumstances. It has been plotted against CCPP corrected gross load based on OEM corrections, STD corrections, PAC test result and guaranteed curve. Figure 4.1 shows the profile of the CCPP gross thermal efficiency under the above four different circumstances.

In the figure 4.1 the gross thermal efficiency is plotted on the ordinate and CCPP gross load is plotted on the abscissa. The gross thermal efficiency increases with the increase of the CCPP gross load. The gradient of the gross thermal efficiency increase is higher from 220MW (60%) to 350MW (93%) of CCPP gross load when compared with CCPP gross load of above 350MW(>93%). This difference arises due to the change in the gas turbine controller from IGV mode to OTC mode. In the IGV mode the air flow rate is increased in proportion to the increase of the fuel flow rate and air/fuel ratio is maintained at optimum value. When the IGV reaches its maximum opening position the controller switches to OTC mode. In OTC control mode the fuel flow rate alone is increased until the turbine inlet temperature reaches 1250°C. This increased fuel flow reduces the gradient of gross thermal efficiency increase above 350MW (>93%) CCPP gross load. The figure 4.1 shows similar behavior of gross thermal efficiency when it is plotted against CCPP corrected gross load based on OEM corrections, STD corrections, PAC test result and guaranteed curve. The variation of gross thermal efficiency based on OEM corrections, STD corrections and PAC test result are within 0.5% and they are greater than 1.5% to 2.0% from the guaranteed curve. This analysis has been done as a part of verification of the developed thermodynamic models with actual system.

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Figure 4.2 and figure 4.3 shows the plot of gas turbine compressor polytropic efficiency and isentropic efficiency against the CCPP gross load respectively. These efficiencies increases with the respect to the load up to 350MW(93%) and above that it starts decreases due to switching of gas turbine controller from IGV mode to OTC mode at about 95% of CCPP gross load, where the gas turbine compressor reaches its design rated capacity.

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In figure 4.3 the gas turbine compressor pressure ratio has been plotted against CCPP gross load based on OEM and STD corrections. This pressure ratio increases with respect to the load. The gradient of increase compressor pressure ratio is higher up to 350MW (93%) of load, when compared with loads above 350MW (93%). The reason for the minimal increase of the pressure ratio (ie from 15.5 to 15.9) even after the IGV reaches its maximum position is due to higher pressure in the combustion chamber. This combustion chamber pressure increase is due to more fuel input after the GT controller switches from the IGV controller to OTC controller.

4.1.2 Curve fitting of the PAC test results

In order to find out the degradation level of the gas turbine engine, the actual value of the EHI parameters at different EOH have to be compared with the non-degraded values. The gas turbine PAC tests have been done immediately after commissioning, i.e. when the condition of the engine is clean and good. So these PAC test results are taken as the base reference values. The PAC tests have been conducted for 60%, 85%, 93% and 100% CCPP loads only. So the equation for the best fitted curve has been determined and it is used to find out the EHI parameters for all the intermediate CCPP loads ranging from 60% to 100%.

The general curve profiles are obtained by plotting the EHI parameters against the base parameter like CCPP gross load. The above curves have been fitted with various general curves like linear, quadratic, cubic etc. and the best suitable curve is selected based on the low norm of residuals. The equation for the best suitable curve is obtained by using matlab curve fitting tool box. This equation is used to generate the base reference value of the EHI parameter with respect to the specific base parameter.

The level of degradation of the engine is computed by finding the deviation between actual value of the EHI parameter at that particular EOH and the base reference value of the EHI parameter obtained by using the above equation. The PAC test results of compressor polytropic efficiency, compressor isentropic efficiency, CCPP gross thermal efficiency, compressor pressure ratio and compressor IGV position have been plotted against CCPP gross load based on OEM and STD corrections respectively. Figures 4.5 - 4.15 in Appendix D2 represent the above plots respectively.

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4.1.2.1 Curve fitting of Gas turbine compressor polytropic efficiency vs CCPP gross load based on OEM corrections:

GT compressor polytropic efficiency has been plotted against CCPP gross load and it is shown in the figure 4.5. This curve is represented with blue colour bold diamond marker in the figure 4.5. Various types of standard curves like linear, quadratic, cubic, power, exponential and Gaussian are fitted to this curve. The curves generated by quadratic and Gaussian equation shows closer match and lesser residuals (<0.1%) with the compressor polytropic efficiency curve plotted against CCPP gross load based on OEM corrections.

Figure 4.5
Curve fitting of GT Compressor Polytopic efficiency vs CCPP Load based on OEM corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Poly – Linear	0.87935	0.91756	0.87634	0.66308	
Poly – Quadratic	0.04193	0.99607	0.98821	0.20478	Good fit
Cubic	9.087×10^{-27}	1	-	-	-
Power	0.6032	0.94345	0.83034	0.77666	
Gaussian	0.04068	0.99619	0.98856	0.20169	
Exponential	0.08482	0.99205	-	-	

The best curve equation is poly quadratic : $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -0.000223$; $P_2 = 0.1591$; $P_3 = 64.09$;

Table 4.1
Equation selection for GT Compressor Polytopic efficiency vs CCPP Load based on OEM corrections

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The examine the goodness of fit has been done based on the Sum of squares due to error (SSE), R-square error, Adjusted R-square error and Root mean squared error (RMSE). Table 4.1 shows the selection of best suitable equation represent the non-degraded GT compressor polytropic efficiency from 60% to 100% CCPP gross loads. The curve generated by the quadratic equation has very low SSE, R-square and Adjusted R-square and RMSE errors of 0.04193, 0.99607, 0.98821 and 0.20478 respectively. It has been used to generate the non-degraded values of GT compressor polytropic efficiency for intermediate CCPP gross loads ranging from 60% to 100%. This non-degraded GT compressor polytropic efficiency represents the cleaner condition of gas turbine compressor and it has been compared with the current value to found out the degradation level of the gas turbine compressor.

4.1.2.2 Curve fitting of Gas turbine compressor isentropic efficiency vs CCPP gross load based on OEM corrections:

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Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Linear Polynomial	1.58905	0.90652	0.85978	0.89136	
Quad-Polynomial	0.0793	0.99534	0.98601	0.2816	Good fit
Cubic Polynomial	1.534×10^{-26}				
Power	1.13462	0.93325	0.79976	1.06518	
Rational	0.18032	0.98939	0.96818	0.4265	
Gaussian	0.07638	0.99551	0.98652	0.27637	
Exponential	1.76299	0.89629	0.8443	0.9388	
The best curve equation is Quadratic: $f(x) = P_1x^2 + P_2x + P_3$ $P_1 = -0.000294$; $P_2 = 0.2081$; $P_3 = 52.44$					
Table 4.2 Equation selection for GT Compressor Isentropic efficiency vs CCPP Load based on OEM corrections					

The figure 4.6 shows the plot of gas turbine compressor isentropic efficiency (PAC test value) against CCPP gross load based on OEM correction. The curves generated by using standard equations have also been plotted in the figure 4.6 to find out the best suitable curve to represent the above non degraded GT compressor isentropic efficiency from 60% to 100% CCPP gross load. This GT compressor isentropic efficiency increases gradually from 84.5% to 89.4%, after that it starts slowly decreasing. The peak efficiency reaches at about 93% of CCPP gross load. Table 4.2 shows the details about best fit equation to represent the non-degraded GT compressor isentropic efficiency. The curve generated by the quadratic equation also increases from 84.5% to 89.1%, after that it starts slowly decreasing. This shows the similar behaviour of this curve as like the non-degraded GT compressor isentropic efficiency curve with deviation less than 0.25%. So this quadratic equation has been chosen to represent the non-degraded GT compressor isentropic efficiency.

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4.1.2.3 Curve fitting of Gas turbine gross thermal efficiency vs CCPP gross load based on OEM corrections:

The CCPP gross thermal efficiency has been plotted against CCPP gross load based on OEM corrections in the figure 4.7. The other curves generated by the standard equation have also been plotted along with the above curve.

Figure 4.7
Curve fitting of CCPP Gross thermal efficiency vs CCPP gross load based on OEM corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Poly – Linear	0.27678	0.9792	0.96879	0.3720	
Poly – Quadratic	0.02172	0.99837	0.9951	0.14737	Good fit
Power	0.052297	0.9701	0.9612	0.3789	
Gaussian	0.02297	0.99827	0.99482	0.15157	
Exponential	0.36035	0.97292	0.95937	0.42447	

The best curve equation is Quadratic: $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -0.0001198$; $P_2 = 0.1026$; $P_3 = 37.64$;

Table 4.3
Equation selection for CCPP Gross thermal efficiency vs CCPP gross load based on OEM corrections

CHAPTER 4 – RESULTS & DISCUSSIONS

The CCPP gross thermal efficiency gradually increases from 54.5% to 59% for the corresponding increase in load from 220MW (60%) to 370MW (100%) respectively. The slope of the CCPP gross thermal efficiency curve decreases above 346MW (>93%) due to switch over of the GT controller from IGV mode to OTC mode. In the OTC mode, the fuel flow rate alone is increased in order to increase GT load to maximum. This is achieved by increasing turbine inlet temperature to rated design limit of 1230°C, whereas the airflow rate of the compressor is not increased as the IGV reaches its maximum opening position. Table 4.3 shows various standard equations examined to find out their fitness with the non degraded gross thermal efficiency curve. The quadratic curve increases from 54.5% to 59% for the corresponding increase of CCPP gross load from 60% to 100%. The slope of this curve decreases above 346MW (>93%). The curve generated by quadratic equation shows good match with the non degraded gross thermal efficiency curve. The residual generated by the quadratic curve is less than 0.1%. So it has been selected to represent the non degraded gross thermal efficiency curve.

4.1.2.4 Curve fitting of Gas turbine compressor pressure ratio vs CCPP gross load based on OEM corrections:

The figure 4.8 show the plot of GT compressor pressure ratio against CCPP gross load and along with the other curves generated by using standard equations. The GT compressor pressure ratio is increasing from 11.1 to 15.5 for the corresponding increase of CCPP gross load based on OEM correction from 220MW (60%) to 346MW (93%). This pressure ratio reaches 16.1 for 370MW (100%) load. The IGV opening of the GT compressor reaches its maximum opening position at about 95% of gross CCPP load. After this stage also, the GT compressor pressure ratio increase due to the increase of the back pressure in the combustion chamber. The increase of combustion chamber pressure occurs due to the addition of more fuel in the OTC controller mode operation of GT.

Table 4.4 shows results of various standard equations tried to fit with the GT compressor pressure ratio curve. Even though all of the standard curves generate lesser residuals with GT compressor pressure ratio curve, the curve generated by the linear equation has lesser RMSE of about 0.09289 and fits more closely with the GT compressor pressure ratio curve. The pressure ratio generated by this curve increase from 11.1 to 16.0 for the corresponding increase in the load

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from 60% to 100%, which is almost same like original non degraded GT compressor pressure ratio curve. It has been selected to represent non degraded GT compressor pressure ratio.

Figure 4.8
Curve fitting of GT Compressor pressure ratio vs CCPP gross load based on OEM corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Linear Poly	0.01726	0.9987	0.99806	0.09289	Good fit
Quad- Poly	0.01367	0.99897	0.99692	0.11693	
Cube	0.01467	0.99821	0.99001	0.1175	
Exponential	0.01370	0.99872	0.99710	0.11789	
Power	0.01406	0.99894	0.99683	0.11859	

The best curve equation is Linear Polynomial :
 $f(x) = P_1x + P_2$; $P_1 = 0.03238$; $P_2 = 3.977$;

Table 4.4
Equation selection for GT Compressor pressure ratio vs CCPP gross load based on OEM corrections

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4.1.2.5 Curve fitting of Gas turbine compressor pressure ratio vs CCPP gross load based on OEM corrections:

Figure 4.9
Curve fitting of GT compressor IGV position vs CCPP gross load based on OEM corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Linear Poly	80.38	0.98773	0.9816	6.339	
Quad- Poly	10.803	0.99835	0.99505	3.286	Good fit
Guassian	7.20108	0.9989	0.9967	2.6834	
Exponential	13.60989	0.9979	-	-	

The best curve equation is Quad Poly : $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -0.01996$; $P_2 = -0.4624$; $P_3 = 3.25$;

Table 4.5
Equation selection for GT compressor IGV position vs CCPP gross load based on OEM corrections

The figure 4.9 shows the plot of GT compressor IGV opening position against CCPP gross load based on OEM corrections. The IGV position increases from 0% to 60% for the corresponding increase of the CCPP gross load from 220MW (60%) to 320(85%) with a slope of around 2.4. The IGV opening increase to 95% for the load of about 347MW (93%) load. The slope of this part of the curve is around 4.4. The IGV reaches its maximum position of about 106% in between 93% to 100% and transfer the GT controller from IGV mode to OTC mode.

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The slope of IGV opening curve from 93% to 100% CCPP gross load is about 1.5. The fuel air ratio is controlled by the opening of the IGV and fuel gas premix control valve in order achieve the optimum thermal power out in the exhaust gas feeding the HRSG. This GT controller concept is used increases the part-load efficiency of the CCPP.

Table 4.5 shows the result of the various standard equations used to fit the non degraded GT compressor IGV position curve. The slopes of the curve by using the quadratic and Gaussian equations about 2,4 and 1.5 for the CCPP gross load ranges 60%-85%, 85%-93% and 93%-100% respectively. This replicates the similar behavior of this curves same like non degraded GT compressor IGV position curve. The RSME error of the quadratic curve is lesser than curve generated by Gaussian equation. So the quadratic equation has been chosen to represent the non degraded IGV position curve.

4.1.2.6 Curve fitting of Gas turbine compressor polytropic efficiency vs CCPP gross load based on STD corrections:

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Equation Type	SSE	R. Square	Adj. R. Square	RMSE	Remarks
Linear Poly	0.89654	0.91595	0.87392	0.66953	
Quadratic Poly	0.03924	0.99632	0.98896	0.1981	Good fit
Power	0.61639	0.94221	0.82663	0.78511	
Rational	0.0913	0.99144	0.97432	0.30215	
Guasian	0.03799	0.99644	0.98931	0.19492	
Exponential	1.03756	0.90273	0.85409	0.72026	
The best curve equation is Quadratic Polynomial : $f(x) = P_1x^2 + P_2x + P_3$ $P_1 = -0.000223$; $P_2 = 0.1591$; $P_3 = 64.09$;					
Table 4.6 Equation selection for GT compressor polytropic efficiency vs CCPP gross load based on STD corrections					

The gas turbine compressor polytropic efficiency has been plotted against the CCPP gross load based on STD corrections and it is shown in the figure 4.10. The GT compressor polytropic efficiency gradually increases and reaches its peak efficiency of about 92.5% at 346MW (93%) CCPP gross load based on STD corrections. After this load it starts decreasing and reaches about 92.1 at 370MW (100%) load. This phenomenon happens as the GT compressor IGV position reaches its maximum position at about 95% of CCPP gross load and reaches its rated capacity. Table 4.6 shows various standard equations used to examine the fitness of the curves generated by them with the GT compressor polytropic efficiency curve. The curve generated by the quadratic equation behaves in a similar manner to the GT compressor polytropic efficiency curve with its peak values reaching to about 92.4% at a CCPP gross load of about 93% and it starts decreasing for loads greater than 93%. So it has been chosen to represent the non-degraded GT compressor polytropic efficiency.

4.1.2.7 Curve fitting of Gas turbine compressor isentropic efficiency vs CCPP gross load based on STD corrections:

The figure 4.11 shows the plot of GT compressor isentropic efficiency against the CCPP gross load based on the STD corrections and curves generated by the standard equation like linear, quadratic, rational, exponential, power and Gaussian equations.

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Figure 4.11
Curve fitting of GT compressor isentropic efficiency vs CCPP gross load based on STD corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Linear Poly	1.61767	0.90484	0.85725	0.89935	
Quadratic Poly	0.07512	0.99558	0.98674	0.27407	Good fit
Power	1.15736	0.9319	0.79575	1.07581	
Rational	0.17732	0.98957	0.96871	0.42109	
Gaussian	0.07219	0.99575	0.98726	0.26868	
Exponential	1.79199	0.89458	0.84187	0.94657	

The best curve equation is quadratic polynomial: $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -0.0002991$; $P_2 = 0.211$; $P_3 = 52.07$;

Table 4.7
Equation selection for GT compressor isentropic efficiency vs CCPP gross load based on STD corrections

The GT compressor isentropic efficiency reaches its maximum of 89.5% at about 346MW (93%) of CCPP gross load based on STD correction and after that it starts decreasing. Table 4.7 shows the result of various equations applied to match the behavior of the GT compressor isentropic efficiency curve. This result shows that the curve generated by the quadratic polynomial has similar behaviour of GT compressor isentropic efficiency curve.

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Its value increases from 84.5% at load of 220MW(60%) and reaches peak value of about 89.4% at a load of 347MW(93%). Further increase of load above 93% leads to decrease the value and it reaches about 89% for 370MW (100%) CCPP gross load. This replicates the same behaviour of the isentropic efficiency curve. So the non degraded GT compressor isentropic efficiency curve is represented by this quadratic equation.

4.1.2.8 Curve fitting of Gas turbine gross thermal efficiency vs CCPP gross load based on STD corrections:

Figure 4.12
Curve fitting of Gross thermal efficiency vs CCPP Gross load based on STD corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Linear	0.3139	0.94679	0.96518	0.39617	
Quadratic Poly	0.00392	0.99971	0.99913	0.06262	Good fit
Power	0.1476	0.98909	0.96726	0.38419	
Rational	0.00972	0.99928	0.99784	0.09858	
Guasian	0.00338	0.99975	0.99925	0.05812	
Exponential	0.403	0.97014	0.95522	0.4493	

The best curve equation is Quadratic Polynomial : $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -0.0001341$; $P_2 = 0.1113$; $P_3 = 36.16$

Table 4.8
Equation selection for Gross thermal efficiency vs CCPP Gross load based on STD corrections

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The gas turbine gross thermal efficiency has been plotted against CCPP gross load based on STD corrections and shown in figure 4.12. This efficiency gradually increases from 54.5% at 60% CCPP gross load and reaches to 59% at 100% CCPP gross load, where the rate of increase of this efficiency decreases above 93% of CCPP gross load. This phenomenon occurs due to the change of GT controller mode from IGV to OTC. After it changes to OTC mode, more fuel is fired to increase the turbine inlet temperature to its rated design value of 1250°C. The standard equations are used to generate the curves and they have also been plotted in the figure 4.12

Table 4.8 show the result of standard equations used to match the behavior of the GT gross thermal efficiency curve. The curve generate by the quadratic equation starts increasing from 54.6% at 60%CCPP gross load and reaches to 58.9% at 100% CCPP gross load. The rate of increase of this efficiency decreases above 93% of CCPP gross load. So the non degraded gas turbine gross thermal efficiency is represented by the curves generated by the quadratic equation.

4.1.2.9 Curve fitting of Gas turbine compressor pressure ratio vs CCPP gross load based on STD corrections:

The figure 4.13 shows the plot of gas turbine compressor pressure ratio against the CCPP gross load based on STD corrections. The curves generated by the standard equations have also been plotted in the figure 4.13 to examine the best matched curve to replicate the behaviour of non degraded GT compressor pressure ratio. The GT compressor pressure ratio curve increase and reaches it maximum value of about 16.1 at 370MW (100%) CCPP gross load. The rate of increase of this pressure ratio decrease above 347MW (95%) CCPP gross load as GT compressor reaches its design rate of capacity. Still further increase of the GT compressor discharge pressure occurs due to the back pressure from the combustion chamber, which in turn increase because of more fuel addition in the OTC controller. The result of various standard equations used to fit this GT compressor pressure ratio curve has been shown in table 4.9. The curve generated by the quadratic equation reaches it maximum value of 16 at 370MW CCPP gross load and the rate of increase of this curve decrease above 95% of CCPP gross load. This confirms the behaviour of curve generated by the quadratic equation similar to the non degraded gas turbine compressor pressure ratio. So it has been chosen to represent the non degraded gas turbine compressor pressure ratio.

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Figure 4.13
Curve fitting of GT Compressor pressure ratio vs CCPP gross load based on STD corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Poly- Linear	0.01515	0.99886	0.99829	0.08705	
Poly -Quadratic	0.00971	0.99727	0.99781	0.04853	Good fit
Power	0.01008	0.99924	0.99886	0.071	
Rational	0.00984	0.99926	0.99778	0.09919	
Exponential	0.07201	0.99459	0.99188	0.18975	

The best curve equation is Polynomial Quadratic : $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = -1.777 \times 10^{-5}$; $P_2 = 0.043$; $P_3 = 2.477$

Table 4.9
Equation selection for GT Compressor pressure ratio vs CCPP gross load based on STD corrections

4.1.2.10 Curve fitting of Gas turbine compressor IGV opening vs CCPP gross load based on STD corrections:

The GT compressor inlet guide vane (IGV) has been used to control the GT compressor flow from 60% rated load to 95% rated load. This IGV opening along with the fuel gas premix valve opening controls the GT controller behaviour from 60% to 95% rated CCPP gross load in order to achieve high part-load efficiency of CCPP.

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Figure 4.14
Curve fitting of GT Compressor IGV position vs CCPP gross load based on STD corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Poly- Linear	72.41585	0.98895	0.98343	6.0173	
Poly- Quadratic	7.8107	0.99881	0.99642	2.79476	Good fit
Guasian	9.87568	0.99849	0.99548	3.14256	
Exponential	10.21845	0.99844			

The best curve equation is Polynomial Quadratic: $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = 0.001936$; $P_2 = -0.4205$; $P_3 = -2.987$;

Table 4.10
Equation selection for GT Compressor IGV position vs CCPP gross load based on STD corrections

The figure 4.14 shows the GT Compressor IGV position plot against the CCPP gross load based on STD corrections and curves generated by the standard equation to examine their fitness with GT Compressor IGV position curve. The IGV position increases with the increase of the CCPP gross load based on STD correction. The rate of IGV position increase from 220MW (60%) of CCPP gross load to 320MW (85%) of CCPP gross load is lesser when compared with

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the rate of IGV position increase from 320MW (85%) CCPP gross load to 347MW (93%). This phenomenon along with premix fuel control valve opening enables higher gas turbine exhaust gas power, which in turn enhances the CCPP to operate at high part-load efficiency. The curve fitting results of the various curves generated by using standard equations are shown in table 4.10. The rate of increase of the curve generated by using quadratic equation increase with respect to the CCPP gross load upto 93% of rated CCPP gross load. After that the rate of increase starts decreasing, which replicate the same behaviour of the non degraded GT compressor IGV opening position. So it has been selected to represent the non degraded GT compressor IGV opening position.

4.1.2.10 Curve fitting of Gas turbine compressor discharge temperature vs CCPP gross load based on STD corrections:

The gas turbine compressor discharge temperature (CDT) has been plotted against the CCPP gross load based on STD corrections and shown in the figure 4.15. The CDT temperature starts increasing from 380°C at 220MW (60%) CCPP gross load based on STD corrections and it reaches its peak value of 429°C at 370MW (100%) CCPP gross load. The gradient of the CDT temperature raise starts decreasing from 346MW(93%) CCPP gross load to 370MW(100%) when compared with the gradient from 60% to 93%. This change of gradient happened due to the shift of the gas turbine controller from IGV to OTC mode in between 93% to 100% of CCPP gross load. Table 4.10 shows the result of the various standard equation used to match the behavior of the gas turbine CDT curve. Result of errors generated by the various curve along with the CDT curve and figure 4.15 confirms that the profile of the curve generated by the quadratic equation is similar to the non degraded gas turbine CDT curve. So it has been selected to represent the non degraded gas turbine CDT profile.

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Figure 4.15
Curve fitting of GT Compressor discharge temperature vs CCPP gross load based on STD corrections

Equation Type	SSE	R.Square	Adj. R.Square	RMSE	Remarks
Poly-Linear	3.51442	0.99742	0.99612	1.3256	
Poly - Quadratic	0.07695	0.99994	0.99983	0.27739	Good fit
Power	12.60495	0.99073	0.9722	3.55035	
Exponential	4.08765	0.99699	0.99549	1.42962	

The best curve equation is Polynomial Quadratic: $f(x) = P_1x^2 + P_2x + P_3$
 $P_1 = 0.0004465$; $P_2 = 0.06603$; $P_3 = 343.2$

Table 4.11
Equation selection for GT Compressor discharge temperature vs CCPP gross load based on STD corrections

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4.1.3 Analysis of long term trending of GHI parameters

The degradation level of the gas turbine is determined by finding the deviation between actual values of the GHI parameter at that particular EOH to the non degraded base reference value of the GHI parameter. Table 4.12 represents the deviation of the GHI parameters from the non degraded base reference values calculated using the OEM and STD corrections.

The GHI parameters determined in the table 3.2 and the table 3.3 in the appendix C based on OEM and STD corrections using various gas turbine operating parameters along with their EOH have been transferred into table 4.12. They have been referred as actual GHI parameters. The non degraded GHI parameters are evaluated as a function of CCPP gross load by using the best curve representing the particular GHI parameter as discussed in section 4.1.2. These non degraded GHI parameters have been referred as projection GHI parameter. The deviation between the actual GHI parameters and Projection GHI parameters are computed and displayed for various EOHs.

The deviations of the GHI parameters like compressor polytropic efficiency, isentropic efficiency, IGV position and CCPP gross efficiencies based on OEM corrections have been plotted against the EOH. Figures 4.16 - 4.19 represent the above trending. In all the above figures, the GHI parameters are plotted in the ordinate and their corresponding EOH are plotted in the abscissa.

The figure 4.16 shows the plotting of the GT compressor polytropic efficiency deviation based on OEM corrections against the EOH. The trending of the GHI parameters starts after 4000 EOH, since the initial 4000 EOH are utilized for various commissioning activities of the gas turbine. The online washing and offline washing activities at various EOH are shown in the figure 4.16. The GT compressor polytropic efficiency deviation starts gradually increasing from 0.5% at 4800EOH to 2.4% at 8000EOH. The compressor online washings have been performed 4 times during this period. The on-line washing is performed every 720 EOH in this period and it is refer as Type-1 on-line washing pattern. The compressor on-line washing changes the slope of the GT compressor polytropic efficiency deviation. Minor inspections are done at every 4000 EOH for inspecting the combustion chamber components. During this period at 8000 EOH the compressor IGV blade manual cleaning and offline washings have been done.

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Sno	Date	Units	16/10/02	16/10/02	16/11/02	21/11/02	12/4/02	4/12/02	6/1/03	11/2/03	13/2/03	11/3/03
1	EOH	hrs	3665	3681	4441	4561	4860	4862	5652	6497	6498	7328
2	Actual	Gross Efficiency of CAPP	57.72	56.94	57.52	56.98	55.42	55.79	55.86	56.42	56.03	56.19
3		Polytropic Efficiency	90.81	91.02	90.87	91.64	91.50	90.01	89.99	89.68	88.91	89.66
4		Isentropic Efficiency	86.91	87.29	86.99	88.05	87.98	86.14	86.12	85.59	85.72	85.58
5		IGV Opening	107.91	74.95	107.91	107.39	66.77	20.71	21.08	36.13	46.45	32.86
6		Comp Dis Temp	427.86	417.27	427.70	423.45	410.79	390.76	393.52	398.16	396.26	398.68
7	Projection	Corrected Comp Dis Temp	433.56	420.64	433.68	432.45	415.20	393.19	394.28	404.55	411.01	403.97
8		Projected Gross efficiency	58.91	58.24	58.93	59.04	58.08	56.34	56.32	57.13	56.61	57.01
9		Projected Poly efficiency	92.45	92.28	92.45	92.39	92.19	90.69	90.68	91.44	91.82	91.34
10		Projected Isentropic efficiency	89.24	89.10	89.23	89.13	88.99	87.11	87.09	88.07	87.45	87.94
11		Projected IGV Opening	100.88	67.36	102.55	111.55	61.82	23.00	22.76	37.13	47.03	34.80
12	Deviation	Project Comp Discharge Temp	426.60	412.92	427.25	430.78	410.56	392.81	392.69	399.58	404.09	398.49
13		Deviation in CAPP Gross Efficiency	-1.19	-1.30	-1.41	-2.06	-2.66	-0.55	-0.46	-1.04	-1.53	-0.36
14		Deviation in polytropic eff	-1.64	-1.58	-0.75	-0.69	-0.68	-0.68	-1.51	-1.68	-1.27	-1.89
15		Deviation in Isentropic Eff	-2.33	-2.24	-1.09	-1.01	-0.97	-0.97	-2.13	-2.36	-2.15	-2.68
16		Deviation in Comp Dis Temp	6.97	6.42	1.67	4.64	0.39	1.60	3.88	5.48	6.62	9.27
17	Actual	Deviation in IGV Opening	-7.03	-5.36	4.16	-4.95	2.29	1.68	0.01	1.95	-0.69	-8.31
18		Gross Efficiency of CAPP	56.67	56.57	55.49	54.87	55.39	55.88	55.05	55.07	56.38	55.58
19		Polytropic Efficiency	90.81	90.87	91.64	91.50	90.01	89.99	90.23	89.66	90.72	90.13
20		Isentropic Efficiency	86.91	86.99	88.05	87.98	86.14	86.12	86.31	85.58	86.35	86.10
21		Comp pressure ratio	15.78	15.83	16.23	14.68	12.53	12.53	13.67	13.20	14.23	14.72
22	Projection	IGV Opening	107.91	107.91	107.39	66.77	20.71	21.08	44.94	32.86	53.87	49.25
23		Projected Gross efficiency of CAPP	58.99	59.01	59.06	58.13	56.44	56.52	57.38	56.96	57.80	57.81
24		Projected Comp Poly efficiency	92.47	92.47	92.46	92.11	90.61	90.69	91.52	91.13	91.87	91.88
25		Projected Comp Isen efficiency	89.28	89.27	89.26	88.87	86.97	87.08	88.13	87.64	88.57	88.59
26		Projected Comp Pressure ratio	15.52	15.57	15.67	14.24	12.57	12.64	13.42	13.02	13.86	13.87
27	Deviation	Projected IGV Opening	92.05	93.51	96.59	57.21	21.11	22.38	38.09	29.81	48.00	60.32
28		Deviation in CAPP Gross Efficiency	-2.31	-2.44	-3.57	-3.26	-1.05	-0.64	-2.33	-1.89	-1.79	-2.23
29		Deviation in Polyeff	-1.66	-1.60	-0.82	-0.61	-0.60	-0.70	-1.29	-1.47	-1.15	-1.76
30		Deviation in Iseneff	-2.37	-2.28	-1.21	-0.89	-0.83	-0.96	-1.82	-2.06	-1.64	-2.48
31		Deviation in Comp pressure ratio	0.26	0.26	0.56	0.44	-0.04	-0.11	0.26	0.18	0.37	0.36
32	Long term trending using STD corrections	Deviation in IGV Opening	15.86	14.40	10.79	9.56	-0.40	-1.31	6.85	3.05	5.87	14.18

Table 4.12

Deviation of actual values from the base reference values – Based on STD and OEM corrections

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Sno	Date	Units	11/3/03	27/3/03	13/4/03	13/05/03	24/06/03	24/06/03	25/7/03	30/7/03	18/8/03	18/8/03	15/9/03	15/9/03	26/09/03
1	EOH	hrs	7335	7732.5	8028	8767	8770	10009.6	10012.1	10518	11319	11321	11992	11995	12255.7
2	Gross Efficiency of CCPP	(%)	56.51	57.26	56.68	56.82	56.81	57.35	56.49	56.17	56.13	56.56	57.15	57.17	57.12
3	Polytropic Efficiency	(%)	90.01	90.70	90.54	90.72	90.28	90.82	90.13	90.26	89.87	91.88	90.75	90.74	90.64
4	Isentropic Efficiency	(%)	86.01	86.85	86.67	86.94	86.35	87.02	86.10	86.30	85.66	86.47	86.95	86.67	86.77
5	IGV Opening	(%)	39.78	77.08	56.46	53.87	49.25	71.42	62.49	58.25	80.95	61.75	57.01	86.27	72.76
6	Comp Dis Temp	Deg C	400.12	419.36	407.04	408.86	410.74	420.13	411.06	414.66	427.72	413.34	408.48	422.06	420.72
7	Corrected Comp Dis Temp	Deg C	406.60	421.96	413.65	413.44	413.30	421.58	416.52	416.25	430.52	418.89	414.44	425.54	422.40
8	Projected Gross efficiency	(%)	57.36	58.13	57.80	57.80	57.53	58.08	57.83	58.28	58.43	58.13	57.98	58.32	58.15
9	Projected Poly efficiency	(%)	91.65	92.22	92.00	92.00	91.79	92.19	92.02	91.96	92.31	92.38	92.12	92.32	92.23
10	Projected Isentropic efficiency	(%)	88.32	89.03	88.76	88.75	88.50	88.99	88.79	88.71	89.13	89.20	88.91	89.15	89.04
11	Projected IGV Opening	(%)	42.20	63.56	53.21	53.18	46.22	61.75	54.18	51.91	68.83	74.60	58.59	70.13	64.23
12	Project Comp Discharge Temp	(%)	401.91	411.31	406.83	406.82	403.72	410.53	407.25	406.26	413.54	411.24	409.18	414.09	411.59
13	Deviation in CCPP Gross Efficiency	(%)	-0.84	-0.87	-1.12	-0.98	-0.72	-0.73	-1.34	-1.58	-2.15	-1.87	-0.98	-1.83	-1.03
14	Deviation in polytropic eff	(%)	-1.70	-2.44	-1.47	-1.74	-1.59	-2.12	-2.05	-2.26	-1.31	-1.39	-1.20	-1.55	-1.54
15	Deviation in Isentropic Eff	(%)	-2.41	-3.46	-2.09	-2.48	-2.27	-3.03	-2.93	-3.22	-1.88	-1.97	-1.72	-2.21	-2.21
16	Deviation In Comp Dis Temp	(%)	9.99	16.98	6.18	11.46	10.80	14.84	15.85	15.59	10.07	7.39	8.58	9.22	11.15
17	Deviation in IGV Opening	(%)	-6.34	-21.48	1.64	-16.15	-8.53	-18.66	-19.12	-22.31	-5.91	-6.72	-9.47	-10.26	-13.22
18	Gross Efficiency of CCPP	(%)	56.08	55.80	56.08	56.75	57.13	55.86	56.50	56.39	57.71	56.40	57.17	56.29	56.94
19	Polytropic Efficiency	(%)	90.26	89.87	90.75	90.58	90.64	90.30	90.35	90.20	91.13	90.92	91.17	90.83	90.69
20	Isentropic Efficiency	(%)	86.30	85.66	86.94	86.67	86.77	86.21	86.29	86.06	87.39	87.15	87.48	86.99	87.11
21	Comp pressure ratio	(%)	14.11	15.00	14.58	14.99	14.71	15.44	15.40	15.58	15.48	14.83	15.08	15.11	15.02
22	IGV Opening	(%)	58.25	90.32	61.75	86.27	72.76	97.47	96.16	108.83	89.42	75.38	83.36	84.76	81.23
23	Projected Gross efficiency of CCPP	(%)	57.90	58.40	58.08	58.40	58.30	58.55	58.59	58.82	58.78	58.32	58.56	58.48	58.22
24	Projected Comp Poly efficiency	(%)	91.95	92.28	92.08	92.28	92.22	92.36	92.37	92.45	92.44	92.23	92.36	92.32	92.17
25	Projected Comp Isen efficiency	(%)	88.67	89.07	88.83	89.07	89.01	89.16	89.18	89.26	89.26	89.02	89.17	89.12	88.94
26	Projected Comp Pressure ratio	(%)	13.97	14.59	14.18	14.59	14.46	14.80	14.86	15.23	15.16	14.48	14.70	14.72	14.35
27	Projected IGV Opening	(%)	50.58	66.01	55.79	66.00	62.71	71.72	73.27	83.58	81.66	63.21	72.21	69.08	59.85
28	Deviation in CCPP Gross Efficiency	(%)	-1.82	-2.60	-2.01	-1.64	-1.18	-2.69	-2.10	-2.44	-1.08	-1.92	-1.40	-2.19	-2.13
29	Deviation in Polyeff	(%)	-1.69	-2.41	-1.33	-1.69	-1.58	-2.06	-2.02	-2.25	-1.31	-1.32	-1.19	-1.50	-1.48
30	Deviation in Iseneff	(%)	-2.37	-3.41	-1.90	-2.41	-2.23	-2.95	-2.89	-3.20	-1.87	-1.87	-1.69	-2.13	-2.11
31	Deviation in Comp pressure ratio	(%)	0.15	0.42	0.40	0.40	0.26	0.64	0.54	0.35	0.32	0.36	0.40	0.30	0.51
32	Deviation in IGV Opening	(%)	7.67	24.30	5.96	20.27	10.05	25.75	22.89	25.25	7.76	12.17	11.15	15.67	17.52

Table 4.12 (Cont'd)

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Sno	Date	Units	7/10/03	20/10/03	20/10/03	21/11/03	21/11/03	29/12/03	29/12/03	30/12/03	26/01/04	26/01/04	28/02/04	14/03/04	21/04/04	22/04/04	17/05/04	17/05/04
1	EOH	hrs	12469	12792	12794	13526	13530	14461.6	14464.6	14488	15112	15113	15997.5	16510	17561	17589.6	18184	18188
2	Gross Efficiency of CCPP	(%)	56.64	57.62	56.69	56.86	57.31	56.50	56.70	56.28	57.89	55.22	57.15	57.33	57.02	57.15	56.93	55.89
3	Polytropic Efficiency	(%)	90.12	91.46	90.30	90.35	90.12	90.01	90.20	89.92	91.13	90.52	90.92	91.17	90.83	90.90	90.83	89.25
4	Isentropic Efficiency	(%)	86.02	87.91	86.21	86.29	85.95	85.95	86.06	85.86	87.39	86.65	87.15	87.48	86.99	87.11	87.04	85.00
5	IGV Opening	(%)	83.53	79.88	97.47	96.16	108.16	57.11	108.83	50.84	89.42	54.98	75.38	83.36	84.76	81.23	73.49	31.80
6	Comp Dis Temp	Deg C	422.66	419.14	427.31	429.72	436.14	416.45	433.91	411.80	427.90	409.16	416.44	422.55	420.68	422.33	416.82	397.16
7	Corrected Comp Dis Temp	Deg C	426.59	420.26	432.54	432.81	438.50	418.37	436.44	413.92	429.70	414.39	420.85	424.24	425.13	424.61	420.43	405.02
8	Projected Gross efficiency	(%)	58.27	58.25	58.52	58.48	58.74	57.64	58.68	57.43	58.62	57.65	58.28	58.41	58.42	58.36	58.18	56.96
9	Projected Poly efficiency	(%)	92.30	92.29	92.41	92.40	92.46	91.88	92.46	91.71	92.44	91.89	92.30	92.37	92.37	92.34	92.25	91.29
10	Projected Isentropic efficiency	(%)	89.12	89.11	89.24	89.23	89.28	88.61	89.28	88.40	89.27	88.62	89.12	89.20	89.20	89.17	89.06	87.88
11	Projected IGV Opening	(%)	68.48	67.85	78.81	77.04	89.52	48.94	86.52	43.79	83.52	49.31	68.65	73.89	74.49	71.83	65.04	33.80
12	Project Comp Discharge Temp	(%)	413.39	413.13	417.70	416.97	422.06	404.94	420.85	402.63	419.63	405.11	413.47	415.66	415.91	414.80	411.94	338.02
13	Deviation in CCPP Gross Efficiency	(%)	-1.63	-0.64	-1.83	-1.63	-1.43	-1.14	-1.98	-1.15	-0.73	-2.43	-1.13	-1.08	-1.41	-1.21	-1.25	-1.06
14	Deviation in polytropic eff	(%)	-1.20	-1.39	-1.17	-1.57	-1.75	-1.91	-1.76	-1.73	-2.09	-2.22	-2.35	-1.11	-1.77	-1.69	-1.92	-1.86
15	Deviation in Isentropic Eff	(%)	-1.71	-1.97	-1.68	-2.24	-2.50	-2.73	-2.52	-2.49	-2.96	-3.15	-3.34	-1.58	-2.53	-2.41	-2.74	-2.65
16	Deviation in Comp Dis Temp	(%)	4.98	6.71	7.48	7.89	8.82	11.59	13.57	10.16	9.13	11.25	14.49	4.79	12.87	10.84	15.08	16.17
17	Deviation in IGV Opening	(%)	0.91	-4.27	-6.32	-7.53	-3.59	-13.22	-15.12	-8.14	-9.75	-11.29	-16.93	-0.89	-18.65	-11.15	-23.12	-26.55
18	Gross Efficiency of CCPP	(%)	56.04	55.83	56.54	54.66	54.46	54.23	55.47	54.14	53.69	54.13	54.80	56.05	56.86	56.73	56.84	57.55
19	Polytropic Efficiency	(%)	91.17	90.90	91.14	90.76	90.49	90.31	90.46	90.53	89.95	89.88	89.79	91.02	90.64	90.75	90.47	90.49
20	Isentropic Efficiency	(%)	87.49	87.13	87.45	86.90	86.55	86.28	86.50	86.58	85.85	85.73	85.59	87.34	86.71	86.85	86.47	86.52
21	Comp pressure ratio	(%)	15.02	14.79	14.89	15.02	14.80	14.85	14.90	14.96	14.31	14.44	14.61	14.39	15.33	15.42	15.27	15.17
22	IGV Opening	(%)	73.33	71.87	75.43	77.63	68.08	76.30	78.76	73.99	64.74	68.50	76.36	59.85	97.37	93.14	98.48	98.69
23	Projected Gross efficiency of CCPP	(%)	58.40	58.24	58.39	58.17	58.00	58.01	58.21	58.06	57.69	57.81	58.00	58.04	58.67	58.66	58.61	58.62
24	Projected Comp Poly efficiency	(%)	92.28	92.19	92.27	92.14	92.03	92.03	92.17	92.07	91.79	91.88	92.03	92.05	92.40	92.40	92.38	92.39
25	Projected Comp Isen efficiency	(%)	89.07	88.96	89.06	88.90	88.76	88.77	88.94	88.82	88.46	88.58	88.76	88.80	89.22	89.21	89.19	89.20
26	Projected Comp Pressure ratio	(%)	14.59	14.38	14.57	14.29	14.09	14.09	14.34	14.16	13.74	13.87	14.09	14.13	14.97	14.97	14.89	14.91
27	Projected IGV Opening	(%)	66.02	60.62	65.60	58.36	53.42	53.57	59.82	55.17	45.21	48.20	53.48	54.55	76.43	76.28	74.14	74.59
28	Deviation in CCPP Gross Efficiency	(%)	-2.36	-2.41	-1.85	-3.51	-3.54	-3.78	-2.75	-3.92	-4.00	-3.68	-3.20	-1.99	-1.81	-1.93	-1.77	-1.08
29	Deviation in Polyeff	(%)	-1.11	-1.28	-1.14	-1.38	-1.53	-1.72	-1.71	-1.54	-1.83	-2.00	-2.23	-1.03	-1.76	-1.66	-1.92	-1.89
30	Deviation in Iseneff	(%)	-1.58	-1.83	-1.61	-2.00	-2.21	-2.48	-2.44	-2.23	-2.62	-2.86	-3.17	-1.46	-2.50	-2.36	-2.72	-2.68
31	Deviation in Comp pressure ratio	(%)	0.44	0.42	0.32	0.74	0.72	0.76	0.55	0.80	0.57	0.58	0.53	0.25	0.36	0.45	0.38	0.26
32	Deviation in IGV Opening	(%)	7.31	11.25	9.83	19.28	14.66	22.73	18.95	18.82	19.52	20.31	22.88	5.30	20.93	16.86	24.34	24.10

Table 4.12(Cont'd)

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Figure 4.16
GT compressor polytropic efficiency deviation vs EOH based on OEM corrections

Figure 4.17
GT compressor isentropic efficiency deviation vs EOH based on OEM corrections

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After the IGV blade cleaning and compressor off-line washing activity the deviation of the GT compressor polytropic efficiency decreases and reaches only about 1.4% and not to its original value of 0%. This loss of 1.4% of GT compressor polytropic efficiency is due to non-recoverable losses. The loss of 1.0% which is recovered by this IGV blade manual cleaning and offline washing is considered as recoverable loss.

Three time compressor on-line washings have been done from 8000 EOH to 10518 EOH. The on-line washing is performed every 584 EOH in this period and it is refer as Type-2 on-line washing pattern. During this time period the GT compressor polytropic efficiency deviation increases from 1.4% to 2.2%. Compressor IGV bade cleaning and offline washing activities have been performed at 10626 EOH. The compressor polytropic efficiency deviation decreases to 1.4%. This confirms that loss of 1.4% of GT compressor polytropic efficiency deviation from its original value of 0% as non recoverable losses and recovered efficiency of about 0.8% deviation as recoverable losses.

The next compressor IGV blade cleaning and off-line washing activities have performed during the minor inspection at 12500EOH. Two compressor on-line washings have been performed between 11320 to 12260EOH with approximate time interval of 470 EOH. The GT compressor polytropic efficiency deviation decreases to 1.2% after the 12500EOH. This confirms the 1.2% is the non recoverable losses and 0.3% recovered by the manual blade cleaning and offline washing as recoverable loss.

The GT compressor Polytropic efficiency deviation decreases to 2.3% at 16000EOH. The compressor on-line washings have been done four times between 12500EOH and 16000EOH with approximate time interval of 875 EOH. The recoverable loss of 0.9% deviation has been occurred during the time period from 12500 EOH to 16000 EOH.

In order to have the easy reference of the number of on-line and time period between the equivalent operating hours, following methods of classifications are done.

The on-line washing is classified into following types based time interval between two successive on-line washings.

- Type-1 refers that one on-line washing is performed for every 720 EOH.
- Type-2 refers that one on-line washing is performed for every 584 EOH.
- Type-3 refers that one on-line washing is performed for every 470 EOH.

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The equivalent operating hours range is classified into four different types as follows

- Period-A refers the period between 4000 EOH and 8000 EOH.
- Period-B refers the period between 8000 EOH and 10600 EOH and
- Period-C refers the period between 10600 EOH and 12500 EOH.
- Period-D refer the period between 12500 EOH and 16000 EOH.

The above analysis confirms that after the IGV blade cleaning and off-line washing, the compressor polytropic efficiency reaches about 1.4% from its original non degraded value, which accounts this 1.4% as non recoverable losses. The compressor on-line washing of type-1, type-2 and type-3 accounts for 1.4%, 0.8%, 0.3% and 1.4% recoverable losses respectively for the period-A, period-B, period-C and period-D respectively. The slope of the GT compressor isentropic efficiency deviation curve in the period-A, period-B and period-C are about 4.479×10^{-2} , 3.649×10^{-2} and 2.063×10^{-2} respectively. This confirms that the increased number of compressor on-line reduces the slope of the GT compressor isentropic efficiency degradation profile.

The figure 4.17 shows the plotting of the GT compressor isentropic efficiency deviation based on OEM corrections against the EOH. The GT compressor isentropic efficiency deviation degradation curve has got similar shape like GT compressor polytropic efficiency deviation degradation profile. The compressor IGV blade manual cleaning and off-line washings at the 8000 EOH, 10626 EOH and 12500 EOH decreases the GT compressor isentropic efficiency deviation to 1.9%, 1.8% and 1.7% respectively from its original non degraded value of 0%. This confirms average of 1.8% of accounts for non recoverable GT isentropic efficiency losses. The compressor on-line washing of type-1, type-2 and type-3 accounts for 1.4%, 1.3%, 0.3% and 1.5% recoverable losses respectively for the period-A, period-B, period-C and period-D respectively. The slope of the GT compressor isentropic efficiency deviation curve in the period-A, period-B and period-C are about 6.407×10^{-2} , 5.232×10^{-2} and 2.947×10^{-2} respectively. This confirms that the increased number of compressor on-line reduces the slope of the GT compressor isentropic efficiency degradation profile.

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Figure 4.18

CCPP Gross thermal efficiency deviation vs EOH based on OEM corrections

Figure 4.19

GT compressor IGV position deviation vs EOH based on OEM corrections

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The CCPP gross thermal efficiency deviation from the non degraded value for various EOH has been plotted in the figure 4.18. The analysis shows that the compressor off-line and IGV blade manual cleaning activities reduces the CCPP gross thermal efficiency deviation to 0.5%, 0.7% and 0.8%. These are the non recoverable CCPP gross thermal efficiency at 8000 EOH, 10800 EOH and 12500 EOH respectively. The recoverable losses of about 1.5%, 1.0%, 0.4%, for the period-A, period-B, period-C are achieved with on-line washing of type-1, type-2 and type-3 respectively. The slope of the gross thermal efficiency deviation curve in the period-A, period-B and period-C are about 5.0×10^{-4} , 3.846×10^{-4} and 3.421×10^{-4} respectively. This shows that the increased number of on-line washing reduces the slope of the GHI parameter deviation profile.

The gas turbine under study is always used to run at below 90% of its rated capacity due to spinning reserve set by the power grid. The airflow rate of the gas turbine is controlled by the IGV position from the 60% rated load to around 95% rated load. (Refer the gas turbine controller of CCPP, figure 2.22). Under base load conditions the effect of fouling on the airflow rate and pressure ratio can be easily determined by comparing the actual output with the base reference value. But during part load operations the effect of fouling on the compressor airflow rate and pressure ratio is difficult to find out, since the IGV opens more and tries to compensate the degraded airflow rate and pressure ratio. So the effect of the airflow rate and pressure ratio can be determined by plotting the IGV position against the CCPP gross load. The fouling of the compressor will lead for more opening of the IGV.

The figure 4.19 shows the plot of GT compressor IGV position deviation from the non degraded IGV compressor position for various EOH. The IGV opening deviation gradually increases along with EOH during normal operation and reduces after the compressor IGV blade cleaning and off-line washings. The compressor IGV blade cleaning and off-line washing decreases the IGV opening position deviation from 2.5% to 0.5% of their non degraded value, whereas the compressor on-line washing decrease the slope of the increase of IGV opening deviation curve.

Figures 4.20 – 4.24 shows the plot of GT compressor polytropic efficiency deviation, isentropic efficiency deviation, CCPP gross efficiency deviation, compressor IGV position

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deviation and compressor discharge temperature deviation from their corresponding non degraded values based on STD corrections respectively for various EOH.

Figure 4.20
Compressor polytropic efficiency deviation vs EOH based on STD corrections

Figure 4.21
Compressor Isentropic efficiency deviation vs EOH based on STD corrections

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Figure 4.22
CCPP Gross thermal efficiency deviation vs EOH based on STD corrections

Figure 4.23
Compressor IGV position deviation vs EOH based on STD corrections

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Sno	Description	Equivalent operating hours(EOH)			Reference figure
		4800-8000 EOH	8000-10600 EOH	10600-12500 EOH	
1	Classification of period	Period - A	Period -B	Period-C	
2	Type of On-line washing	Type -1	Type-2	Type-3	
a. Analysis of GT compressor polytropic efficiency deviation profile with various EOH					
3	Non recoverable losses	1.5 %	1.4 %	1.3 %	Figure 4.20
4	Recoverable losses	1.25%	0.8%	0.3%	
5	Deviation of the curve	2.0	0.7	0.2	
6	Mean slope of the curve	6.25x 10 ⁻⁴	2.692 x 10 ⁻⁴	1.05 x 10 ⁻⁴	
b. Analysis of GT compressor isentropic efficiency deviation profile with various EOH					
7	Non recoverable losses	2.1 %	2.0 %	1.7 %	Figure 4.21
8	Recoverable losses	1.5%	1.1%	0.53%	
9	Deviation of the curve	2.5	1.1	0.3	
10	Mean slope of the curve	7.812x 10 ⁻⁴	4.231 x 10 ⁻⁴	1.578 x 10 ⁻⁴	
c. Analysis of CCPP gross thermal efficiency deviation profile with various EOH					
11	Non recoverable losses	1.2 %	0.75 %	1.1 %	Figure 4.22
12	Recoverable losses	1.2%	1.1%	0.53%	
13	Deviation of the curve	1.6%	1.0%	0.7%	
14	Mean slope of the curve	5.0x 10 ⁻⁴	3.846 x 10 ⁻⁴	3.6842 x 10 ⁻⁴	
d. Analysis of GT compressor IGV opening deviation profile with various EOH					
15	Non recoverable losses	0.6 %	1.0 %	0.7 %	Figure 4.23
16	Recoverable losses	2.0%	1.5%	1.0 %	
17	Deviation of the curve	2.5	2.0	0.7	
18	Mean slope of the curve	7.8125x 10 ⁻⁴	7.6923 x 10 ⁻⁴	3.6842 x 10 ⁻⁴	
e. Analysis of GT compressor CDT deviation profile with various EOH					
19	Non recoverable losses	0.6 %	0.75 %	0.45 %	Figure 4.24
20	Recoverable losses	1.2 %	0.8 %	0.65 %	
21	Deviation of the curve	1.5%	1.0%	0.50 %	
22	Mean slope of the curve	4.6875 x 10 ⁻⁴	3.571x 10 ⁻⁴	2.631 x 10 ⁻⁴	

Table 4.13

Consolidated results of analysis for the trending curves of the GHI parameters deviation based on STD corrections.

The plots of various GHI parameters deviation based on STD corrections shown in the figures 4.20 to 4.24 have been analyzed and the results are shown in the table 4.13. The non recoverable losses are losses of the GHI parameters obtained immediately after the completion of the IGV blade cleaning and off-line washing. The recoverable losses are the losses of the GHI parameters recovered by the IGV blade cleaning and off-line washing. The deviation of the curve

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is the difference of the GHI parameter from starting point to end point of the particular period. The mean slope of the curve is determined as the ratio of this deviation of the curve to the EOH range of that particular period.

The table 4.13 shows that the IGV blade manual cleaning and off-line washing performed at the end of the particular period reduces the recoverable losses of the gas turbine. This effect is observed in all the GHI parameter deviations plotted in figure 4.20 - 4.21.

The on-line washing frequencies are varied for the individual periods in order to study their effects on the GHI parameter deviations. Type-1, Type-2 and Type-3 on-line washing intervals are maintained in the period A, period B and period C respectively. The resulting slopes of the all GHI parameter deviation curves shown in table 4.13 are in decreasing trend from period A-C. This confirms that increased number of on-line washings reduces the slope of the GHI parameter degradation profiles.

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4.1.4 Comparison of OEM and STD corrections effects on GHI Parameter trending

The ISO 2314 standard recommends the gas turbine user to use the OEM corrections for the performance evaluation of the constant speed gas turbines and the same ISO 2314 standard specify the formula for determining the performance evaluation of the variable speed gas turbines. Comparison of the OEM and STD corrections analysis have been done in order to make the developed model more generic, applicable to any gas turbine and also to find out the deviation in the trending of the EHI parameters determined by using OEM and STD corrections.

Figure 4.25- 4.28 in shows the GT compressor polytropic efficiency deviation, isentropic efficiency deviation, CCPP gross efficiency deviation and IGV position deviation based on OEM and STD corrections plotted for various EOH.

The figure 4.25 and 4.26 shows the plot of GT compressor polytropic and isentropic efficiency deviation based on OEM and STD corrections for various EOH respectively.

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Figure 4.26
Comparison of compressor Isentropic efficiency deviation based on OEM and STD corrections

Figure 4.27
Comparison of CCPP Gross thermal efficiency deviation based on OEM and STD corrections

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The higher deviation of about 0.2% efficiency has been observed in the STD corrections from 5000EOH to 7000EOH and again from 13000EOH to 16000EOH. Their shapes are almost similar in the remaining EOH.

The comparison of CCPP gross thermal efficiency deviation based on the OEM and STD corrections for various EOH has been shown in figure 4.27. The deviation of about 0.3 % efficiency between OEM and STD has been observed corrections from 5000EOH to 7000EOH. From 13000EOH to 16000EOH the deviation of about 0.2% to 0.5% is observed. These deviations arise due to the first order and second order effects of various ambient factors on the gas turbine as discussed in the section 2.5.4 and 2.5.5. The STD corrections consider the effects of various ambient factors upto first order accuracy, whereas the OEM corrections consider the effects of various ambient factors upto second order accuracy. The gross thermal efficiency curve based on OEM and STD corrections has the same profile with minor deviations in its value. The GT compressor IGV position deviation based on OEM and STD corrections has plotted in the figure 4.28. The behavior of this curve is also same like the gross thermal efficiency deviation curve as discussed above.

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Even though the effects of the OEM and STD corrections are not identical to each other, the GHI parameters degradation curve has the same profile with minor deviations in its value.

All the above observation concludes that the developed thermodynamic degradation model could be treated as generic model and applicable to both constant speed and variable speed gas turbines. The accuracy level for the constant speed gas turbines other than V94.3A type would be up to only first order level, since the other types need their individual OEM corrections.

4.2 Gas turbine compressor performance assessment using hybrid neural network models

The industrial gas turbines are used to drive the electrical generators or the process compressors. In case of electrical generator application the cost lost or gained due to the compressor performance degradation could be easily analyzed, whereas for the process compressor application it is very difficult to assess. In order to facilitate the applicability of the developed neural network models for both applications, the analysis has been done in two major parts. The first part of the assessment is done based only on the thermal properties of the gas turbine and in the second part the effect of the cost has also been included along with the thermal properties.

4.2.1 Thermal assessment of Gas turbine engine using hybrid neural network models

Three different types of preprocessing techniques namely raw data, preminmax and prestd have been used for processing the data in the neural network models. The appendix B4 represents the programming of the neural network model using matlab programming tool. The inputs for different scenarios have been given to this model and their outputs are verified and analyzed.

The data from the long term trending of GHI parameters deviation from the table 4.12 have been converted into matrix format and given in Table 4.14.

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a) Equivalent operating hours reading set (A)
A1 = [4860 4862 5652 5654 6497 6498 6548 7328 7335 7733]; A2 = [8767 8770 10009 10012 10518]; A3 = [11319 11321 11992 11995 12256]; A4 = [8028]; A5 = [10626]; A6 = [12469];
b) Polytropic and Isentropic efficiencies deviation based on OEM corrections (B)
B1 = [-0.60 -0.70 -1.29 -1.47 -1.15 -1.44 -1.36 -1.76 -1.69 -2.41; ... -0.83 -0.96 -1.82 -2.06 -1.64 -2.03 -1.93 -2.48 -2.37 -3.41;]; B2 = [-1.68 -1.57 -2.05 -2.01 -2.25; -2.41 -2.23 -2.95 -2.89 -3.2;]; B3 = [-1.32 -1.18 -1.49 -1.42 -1.48; -1.87 -1.69 -2.13 -2.02 -2.11;]; B4 = [-1.33; -1.90;]; B5 = [-1.31; -1.87]; B6 = [-1.09; -1.58];
c) CCPP Gross efficiencies, Polytropic and Isentropic efficiencies, CDP deviation, IGV Position deviation based on OEM corrections (C)
C1 = [-0.37 -0.45 -0.48 -0.38 -0.61 -0.51 -0.66 -0.90 -1.45 -1.98; ... -0.60 -0.70 -1.29 -1.47 -1.15 -1.44 -1.36 -1.76 -1.69 -2.41; ... -0.83 -0.96 -1.82 -2.06 -1.64 -2.03 -1.93 -2.48 -2.37 -3.41; ... -0.13 -0.33 0.77 0.53 1.11 0.90 1.08 1.07 0.44 1.25; ... -0.04 -0.131 0.685 0.305 0.587 0.587 1.11 1.418 0.767 2.43;]; C2 = [-1.44 -1.31 -1.30 -1.34 -1.73; -1.68 -1.57 -2.05 -2.01 -2.25; -2.41 -2.23 -2.95 -2.89 -3.2; ... 1.21 0.77 1.91 1.62 1.04; 2.027 1.05 2.575 2.289 2.525;] C3 = [-0.83 -0.96 -1.12 -1.08 -1.13; -1.32 -1.18 -1.49 -1.42 -1.48; -1.87 -1.69 -2.13 -2.02 -2.11; ... 1.07 0.79 1.21 0.89 1.52; 1.217 1.115 1.567 1.168 1.752;] C4 = [-0.49; -1.33; -1.90; 1.20; 0.596;] C5 = [-0.61; -1.31; -1.87; 0.95; 0.776;] C6 = [-0.83; -1.11; -1.58; 1.31; 0.731;]
d) CCPP Gross efficiencies, Polytropic and Isentropic efficiencies, CDP deviation, IGV Position deviation based on STD corrections (D)
D1 = [-0.55 -0.46 -1.04 -0.83 -0.98 -0.72 -0.73 -1.34 -1.58 -2.15; -0.68 -0.68 -1.51 -1.68 -1.27 -1.51 ... -1.37 -1.89 -1.70 -2.44; -0.97 -0.97 -2.13 -2.36 -1.82 -2.15 -1.97 -2.68 -2.41 -3.46; 0.039 0.16 0.388 ... 0.548 0.662 0.958 1.105 0.927 0.999 1.697; -0.229 -0.168 -0.001 -0.195 0.069 0.304 0.967 0.831 0.634 2.148]; D2 = [-1.15 -1.03 -1.83 -1.63 -1.98; -1.74 -1.59 -2.12 -2.05 -2.26; -2.48 -2.27 -3.03 -2.93 -3.22; 1.146 ... 1.08 1.484 1.585 1.559; 1.615 0.853 1.866 1.912 2.232]; D3 = [-1.13 -1.08 -1.41 -1.21 -1.53; -1.39 -1.20 -1.55 -1.44 -1.54; -1.97 -1.72 -2.21 -2.06 -2.21; ... 0.739 0.858 0.922 0.981 1.15; 0.067 0.947 1.026 0.94 1.322]; D4 = [-0.98; -1.47; -2.09; 0.517; 0.164]; D5 = [-0.73; -1.31; -1.88; 1.007; 0.591]; D6 = [-1.24; -1.2; -1.71; 0.498; 0.091];
e) CCPP Gross efficiency deviation based on OEM corrections (E)
E1 = [-0.37 -0.45 -0.48 -0.38 -0.61 -0.51 -0.66 -0.90 -1.45 -1.98]; E2 = [-0.94 -0.92 -1.51 -1.44 -1.83]; E3 = [-0.83 -0.96 -1.12 -1.08 -1.23]; E4 = [-0.49]; E5 = [-0.61]; E6 = [-0.83];
Legend color used: CCPP Gross efficiency – black; comp poly efficiency – blue; comp isen efficiency-red; CDP- pink; CDT- pink; IGV Position-brown;
<p align="center">Table 4.14 Conversion of Inputs to Matrix</p>

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Sno.		Description of Inputs	Column Numbers									
			I	II	III	IV	V	VI	VII	VIII	IX	X
1	General	No. of on-line washing profiles used for training	3	3	3	3	3	3	3	3	3	3
2		Prediction required or not	1	1	1	1	1	1	1	1	1	1
3		No of off-line readings to be used for training	3	3	3	3	3	3	3	3	3	3
4		No of rows in the model output	2	2	2	2	6	6	1	1	1	1
	Training Details	Details regarding on-line washing										
5		a) First on-line washing profiles EOH	A1	A1	A1	A1	A1	A1	A1	A1	A1	A1
		b) First on-line washing profiles outputs	B1	B1	B1	B1	C1	D1	E1	E1	E1	E1
		c) No of on-line washings in first profile set	4	4	4	4	4	4	4	4	4	4
6		a) Second on-line washing profile EOH	A2	A2	A2	A2	A2	A2	A2	A2	A2	A2
		b) Second on-line washing profile output	B2	B2	B2	B2	C2	D2	E2	E2	E2	E2
		c) No. of on-line washings in the II profile set	3	3	3	3	3	3	3	3	3	3
7		a) Third on-line washing profile EOH	A3	A3	A3	A3	A3	A3	A3	A3	A3	A3
		b) Third on-line washing profile output	B3	B3	B3	B3	C3	D3	E3	E3	E3	E3
		c) No.of on-line washings in the III profile set	2	2	2	2	2	2	2	2	2	2
		Details regarding off-line washing										
8		a) First off-line washing EOH	A4	A4	A4	A4	A4	A4	A4	A4	A4	A4
		b) Outputs after first off-line washing	B4	B4	B4	B4	C4	D4	D4	D4	D4	D4
9		a) Second off-line washing EOH	A5	A5	A5	A5	A5	A5	A5	A5	A5	A5
		b) Outputs after first off-line washing	B5	B5	B5	B5	C5	D5	D5	D5	D5	D5
10		a) Third off-line washing EOH	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6
		b) Outputs after first off-line washing	B6	B6	B6	B6	C6	D6	D6	D6	D6	D6
11	Prediction Details	Enter EOH up to which prediction to be made	18200	30000	30000	16300	18200	18200	16300	16300	20500	20500
12		Enter no. of off-line washings in this period	1	4	5	0	1	1	0	1	1	3
13		Period at which I off-line washing to be performed	16300	16250	15250	NA	16300	16300	NA	14500	16300	14250
14		Period at which II off-line washing to be performed	NA	20250	18250	NA	NA	NA	NA	NA	NA	16250
15		Period at which III off-line washing to be performed	NA	24250	21250	NA	NA	NA	NA	NA	NA	18250
16		Period at which IV off-line washing to be performed	NA	28250	24250	NA	NA	NA	NA	NA	NA	NA
17		Preiod at which V off-line washing to be performed	NA	NA	27250	NA	NA	NA	NA	NA	NA	NA
18	Intermediate Inputs	Enter the reference profile to be selected based on the mean slope values.										
		a) For I on-line profile prediction set.	1/2/3	1/2/3	1	1	1	1	1/2/3	1	1	1
		b) For the II on-line profile prediction set.	1/2/3	1/2/3	2	NA	1	1	NA	1	1	1
		c) For the III on-line profile prediction set.	NA	1/2/3	3	NA	NA	NA	NA	NA	NA	1
		d) For the IV on-line profile prediction set.	NA	1/2/3	1	NA	NA	NA	NA	NA	NA	1
		e) For the V on-line profile prediction set	NA	NA	2	NA	NA	NA	NA	NA	NA	NA
		f) For the VI on-line profile prediction set	NA	NA	3	NA	NA	NA	NA	NA	NA	NA
19		Enter the starting period of analysis prediction profile and guaranteed / expected profileprofile	12250	12250	12250	12250	12250	12250	12250	12250	12250	
20		Enter '1' for cost analysis & '0' to skipping it	0	0	0	0	0	0	1	1	1	1

Table 4.15
Inputs to neural network models

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In the table 4.14, the value of the GHI parameters deviation and equivalent operating hours are represented by alphanumerical symbols.

- The alphabet “A” represent the matrix consist of equivalent operating hours values.
- The alphabet “B” represent the matrix consist of polytropic and isentropic efficiency deviation based on OEM corrections. In this matrix first row represent the polytropic efficiency deviations and second row represent isentropic efficiency deviations.
- The alphabet “C” represent the matrix consist of CCPP Gross, polytropic and isentropic efficiencies, CDP deviation, IGV position deviation based on OEM corrections. The rows of the matrix are arranged from one to five in the same sequence as mentioned as above.
- The alphabet “D” represent the matrix consist of CCPP Gross, polytropic and isentropic efficiencies, CDP deviation, IGV position deviation based on STD corrections. The rows of the matrix are arranged from one to five in the same sequence as mentioned as above.
- The alphabet “E” represent the matrix consist of CCPP gross efficiency deviation based on OEM corrections.

The numerical values are used to classify the time interval from where the above readings are taken. The numerical values 1, 2 and 3 represents the period-A (4800EOH to 8000EOH), period-B (8000EOH to 10600EOH) and period-C (10600EOH to 12500EOH) respectively. The numerical values 4, 5 and 6 represent the EOH when the first, second and third off-line compressor washings are performed.

eg. The alphanumerical symbol “E3” represent the matrix consist of CCPP gross efficiency deviation values from the period-C.

These alphanumerical symbols have been used to represent the input data to the various neural network models in Table 4.15.

4.2.1.1 Analysis of the on-line washing of type 1 with off-line washing at 16500 EOH

The main objective of this analysis is to verify the developed hybrid neural network model. The GHI parameters deviation and details about the compressor washings from 4800 EOH to 12600EOH are known and they are used for training the developed hybrid neural network model. Even though the GHI parameters deviation and details about the compressor washings from 12600EOH to 16800EOH are known, they have been hidden from the model. The model outputs are generated for 12600EOH to 16800EOH for the same condition as mentioned

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above. Then these outputs are compared with hidden real outputs of the gas turbine as a part verification of the developed hybrid model.

The compressor polytropic efficiency and isentropic efficiency deviations based on OEM corrections are analyzed by using this model. The data from the first column of the table 4.15 have been applied to the hybrid neural network model based on the Prestd technique as shown in appendix B4.

The analysis 1.1.1 explains the internal outputs of this model. The internal outputs are explained in steps.

➤ **Step 1**

In the first step, the individual networks are developed for off-line washing profile, first on-line washing profile, second on-line washing profile and third on-line washing profile respectively. The individual trained networks performance (MSE) and their residuals with the training values are shown in this step.

➤ **Step 2**

The mean slopes of the three on-line washing profiles are determined in the second step. These mean slopes indicate the rate of degradation of the EHI parameter and they are directly proportional to the engine degradation rate. The third on-line washing profile is having the lower mean slope value when compared with other two profiles.

➤ **Step 3**

The average time interval between the on-line washing profiles has been determined in this step. The third on-line washing profile has the lower most time interval between the on-line washings.

➤ **Step 4**

In this step the user is allowed to select the profile which is to be used as reference for the prediction part. The frequency of on-line washing interval maintained from 12500 to 18500 is almost equivalent to the type-1 washing interval. So the first on-line washing profile is selected as reference profile for the first and second prediction set. This selection has been done in order to verify the model prediction part with the actual machine behavior.

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Analysis 1.1.1 Analysis of gas turbine thermodynamic behavior using hybrid neural network model based on Prestd data processing technique

STEP-I. Network training performance and residuals between simulated outputs and targets

Network training for the Off-line washing set using Prestd technique

Network training for the first On-line washing profile using Prestd technique

Network training for the second On-line washing profile using Prestd technique

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Analysis 1.1.1 Cont'd

Network training for the **third On-line washing** profile set using Prestd Technique

STEP-II. Mean slope of the three Online washing profiles

$$\text{SLOPE} = 1.0\text{e-}03 * \{ -0.4479 \quad -0.3649 \quad -0.2063; \quad -0.6407 \quad -0.5232 \quad -0.2947 \}$$

STEP-III. Average time interval between the Online washing

First Online washing Profile	Second Online washing Profile	Third Online washing Profile
718.25hrs	583.67hrs	468.50hrs

STEP-IV. Prediction profile - Network training performance and residuals

First On-line washing profile is selected as reference profile

Network Training for **first prediction** set of Online washing using Prestd Technique

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Analysis 1.1.1 Cont'd

First On-line washing profile is selected as reference profile

Network training for **second prediction** set of On line washing using Prestd Technique

STEP-V. Comparison of actual profile and projection profile of the model

Figure 4.29

Neural network training and prediction based on Prestd technique for analysis 1.1.1

STEP-VI. Reference profile - Network training performance and residuals

Network training performance and residuals for guaranteed reference profile

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Analysis 1.1.1 Cont'd

Network training performance and residuals for the expected reference profile

Figure 4.30

Comparison of the reference profiles (Guaranteed and expected profile) with predicted profile upto 50000EOH for analysis 1.1.1

STEP-VII. Comparison of the reference profiles and the projected profile

Figure 4.31

Comparison of the reference profiles (Guaranteed and expected profile) with prediction profile upto 25000EOH for analysis 1.1.1

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Analysis 1.1.1 Cont'd**STEP-VIII.**

Analysis of the above profile using PNN Network gives following result

The Mean value of the Predicted profile is 0% deviation from the guaranteed profile.
The mean value of the Predicted profile is 50% greater than the expected profile.

STEP-IX Verification the neural network model based on Prestd Technique

Figure 4.32

Verification of the neural network model based on Prestd technique for analysis 1.1.1

➤ **Step 5**

The comparison between the prediction profile and the actual profile used for training the network has been done in order to verify the model. The resulting plot shown in figure 4.29 confirms good match between actual profile and prediction profile.

➤ **Step 6**

The new networks have been developed and trained for the guaranteed value and expected values of the polytropic and isentropic efficiency deviation parameters. These guaranteed and expected values have to be provided by the gas turbine supplier. Figure 4.30 shows the comparison of the reference profiles (Guaranteed and expected profile) with the predicted profile. These values are gradually in the decreasing trend

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from 0 to 25000 EOH. At 25000 EOH the major inspection of the gas turbine is to be done. During this inspection, some of the recoverable losses which could be retrieved only by casing cover lift are retrieved. Therefore there is a sharp raise at this point. After this point, it again starts to move in the gradual decrement path.

➤ Step 7

The above network represents the values for the inputs from 0 to 50000 EOH. From these network, the values for the operating range of the model ie 4800 EOH to 18200 EOH is simulated. Figure 4.31 shows the plot of the reference (guaranteed and expected values) against the polytropic and isentropic efficiency deviation for the operating range of the model. (ie from 4800 EOH to 18200 EOH).

➤ Step 8

The predicted polytropic and isentropic efficiencies have been compared with their respective guaranteed and expected values using PNN network. The result of the PNN analysis indicates that the predicted profile of the polytropic and isentropic efficiencies from 12250 EOH to 18200 EOH is almost equal to the guaranteed profile and 50% higher (adverse side) than the expected degradation profile. The above result indicates that the gas turbine is just operating at its guaranteed profile and well above (adverse side) the expected degradation profile.

➤ Step 9

The verification of the neural network model has been done at this step. The model is developed by using the actual polytropic and isentropic efficiencies degradation values from 4800 EOH to 12250 EOH hours. The verification of the network has been done from 12250 EOH to the 18200 EOH, in this part the actual values are fully hidden from the model training part. The inputs to the network are given in such a way that it will represent the actual inputs like average time interval between the on-line washing is about 720 EOH and one off-line washing is to be carried out at 16500 EOH. The outputs from the model and actual output from the gas turbine has been plotted in figure 4.32 as part of model verification. The figure 4.32 shows the model is good replica of the actual system.

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SNo	Pre and post data processing technique	Comparison with guaranteed value	Comparison with expected value	Reference
		On-line washing type		
		Type 1	Type 1	
1	Using prestd	+0% (equal)	-50% high	Analysis 1.1.1
2	Using preminmax	+5% less	-50% high	Appendix E2, Analysis 1.1.2
3	Using rawdata	-25%less	-50% high	Appendix E2, Analysis 1.1.3

Table 4.16

Consolidated output for the on-line washing of type 1 with Off-line washing at 16500 EOH

Different types of pre and post processing techniques are applied on the neural network model inputs and targets in order to make their training more efficient for getting the desired results. In order to select the particular pre and post processing techniques, the data from the first column of the table 4.15 have been analyzed using models based on preminmax and raw data processing technique and their results are explained in step by step manner. Refer the analysis 1.1.2 in the appendix E2 for the outputs based on preminmax technique and the analysis 1.1.3 in the appendix E2 for the outputs based on the raw data method. The consolidated outputs of the all three technique for these analyses are given in the table 4.16. The results of the prestd and preminmax technique are almost same and their verification part shows that they are good replica of the real system. Therefore, the remaining analyses are done by using only hybrid neural model based on Prestd technique.

The result from the table 4.16 concludes that the gas turbine is running at its guaranteed value and higher (adverse) than the expected degradation level with type-1 on-line washing and off-line washing interval of 4000 EOH. The performance of the gas turbine could be improved by changing the frequency of on-line and off-line washing.

4.2.1.2 Analysis - Online washing of different types with off-line washing interval of 4000 EOH

Currently the compressor off-line washing has been done for every 4000 EOH during the minor inspection and any one of the on-line washing types from type-1, type-2 and type-3 are followed. This analysis has been done in order to found out the effect of specific on-line washing type on the compressor polytropic and isentropic efficiency deviations up to 30000EOH

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Analysis 1.2**Analysis - Online washing of different types with Off-line washing interval of 4000 EOH**

				Performance of Network Training (MSE)		
				Different types of Online washing profile		
No.	Type of washing	Actual / Prediction Profile	No of Epochs	Type 1	Type 2	Type 3
I	Off-line	Actual	300	1.6049×10^{-5}	1.6051×10^{-5}	1.6051×10^{-5}
I	On-line	Actual	450	0.18305	0.180802	0.183148
II	On-line	Actual	450	0.0203714	0.0203709	0.0203709
III	On-line	Actual	450	0.138995	0.139005	0.138995
1	On-line	Prediction	450	0.18321	0.0204145	0.138995
2	On-line	Prediction	450	0.182648	0.0204276	0.138998
3	On-line	Prediction	450	0.183380	0.0204048	0.138996
4	On-line	Prediction	450	0.182988	0.0203715	0.138996
5	On-line	Prediction	450	0.181644	0.0203963	0.139007
PNN			450	0.0568930	0.0546135	0.0574245
PNN			450	0.0970264	0.116093	0.0974556
PNN Network Result		Comparison with Guaranteed value		15% Less	30% Less	45% Less
PNN Network Result		Comparison with Expected value		50% High	10% High	20% Less

Figure 4.33**Analysis – On-line washing of Type 1 with Off-line washing interval of 4000 EOH**

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Analysis 1.2 (Cont'd)

Figure 4.34

Analysis – On-line washing of **Type 2** with Off-line washing interval of 4000 EOH

Figure 4.35

Analysis – Online washing of **Type 3** with Off-line washing interval of 4000 EOH

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The data from the second column of the table 4.15 have been applied to the hybrid neural network model based on Prestd technique as inputs. The prediction of the compressor polytropic and isentropic efficiency are made up to 30000 EOH with offline washing interval of 4000 EOH. The analysis of this hybrid neural network model with prestd data processing technique has been shown in the analysis 1.2. Figure 4.33 - 4.35 shows the result of the model with on-line washing type-1, type-2 and type-3 respectively. These figures show the improvement of the gas turbine performance after changing the on-line washing from type 1 to type 3. The consolidated outputs of the neural network model for the above analysis has been given in the table 4.17

SNo	Pre and post data processing technique	Comparison with guaranteed value			Comparison with the expected value			Reference
		On-line washing type			On-line washing type			
		Type 1	Type 2	Type 3	Type 1	Type 2	Type 3	
1	Using prestd	+15% less	+30% less	+45% less	-50% high	-10% high	+20% less	Figure 4.33 Figure 4.34 Figure 4.35

Table 4.17

Consolidated output for the on-line washing of different types with off-line washing interval of 4000 EOH

In the table 4.17, the positive sign indicates the predicted degradation profile is lesser (better) than the guaranteed or the expected degradation profile, whereas negative sign indicates vice versa. The predicted profile of the compressor polytropic and isentropic efficiency deviations with the on-line washing of type 1, (ie on-line washing interval of about 720 EOH) when analyzed with PNN network indicates that the prediction profile is 15% lesser (better) than the guaranteed value and 50% higher (adverse) than the expected value. This analysis shows the gas turbine performance is below the expected level with this on-line and off-line washing schedule and types.

When the type of the on-line washing is changed to type 2, (ie on-line washing interval of about 584 EOH) the results of the above model indicates the predicted profile is about 30% lesser (better) than the guaranteed value and 10% higher (adverse) than the expected profile. The compressor polytropic and isentropic efficiency degradation profile with type 3 on-line washing (ie on-line washing interval of about 468 EOH) and off-line washing interval of 4000 EOH gives better result when compared to type 1 and type 2 on-line washings. The model indicates

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the predicted profile is about 45% lesser (better) than the guaranteed value and 20% lesser (better) than the expected value. The above results confirm that the gas turbine performance improves with type 3 washing and it runs at its maximum performance level.

Analysis 1.3

Analysis On-line washing Type 1,2,3,1,2 & 3 respectively with Off-line washing interval of 3000 EOH

No.	Type of washing	Actual/Prediction Profile	Chosen Profile	Performance of Network(MSE)	No. of Epochs
I	Off line	Actual	-	1.69042×10^{-5}	223
I	On line	Actual	-	0.181534	450
II	On line	Actual	-	0.0203862	450
III	On line	Actual	-	0.139004	450
1	On line	Prediction	1	0.180717	450
2	On line	Prediction	2	0.0203716	450
3	On line	Prediction	3	0.138995	450
4	On line	Prediction	1	0.183401	
5	On line	Prediction	2	0.020408	
4	On line	Prediction	3	0.138995	450
5	PNN 1			0.053809	100
6	PNN 2			0.0985538	100
PNN Analysis Result		Comparison with Guaranteed value		25% Less	
		Comparison with Expected value		10% Higher

Figure 4.36
Analysis – Online washing Type 1,2,3,1,2 & 3 respectively with Off-line washing interval of 3000 EOH

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4.2.1.3 Analysis of on-line washing type 1, 2, 3, 1, 2 & 3 respectively with off-line washing interval of 3000 EOH

Normally the off-line washing and IGV manual blade cleaning activities are performed during the minor inspection. These minor inspections are done for every 4000 EOH. This analysis has been done in order to determine the effect on polytropic and isentropic efficiency deviations, if these minor inspection intervals have been reduced to every 3000 EOH. The data from the third column of the table 4.15 have been applied to the neural network model as inputs. The prediction of the compressor polytropic and isentropic efficiencies are made up to 30000 EOH with off-line washing interval of 3000 EOH. The on-line washings are selected as type 1, 2, 3, 1, 2 & 3 respectively. The analysis of this neural network model with prestd data processing technique has been shown in the analysis 1.3. Figure 4.36 shows the comparison of the predicted profile with the reference profile. The PNN analysis of the predicted polytropic and efficiency profile with the reference profile shows it is 25% lesser (better) than the guaranteed value and higher (adverse) than 10% from the expected profile. This result predicts that the gas turbine degradation curve is in mid way between the guaranteed and expected gas turbine degradation lines with type-1, 2, 3, 1, 2 & 3 on-line washings respectively and off-line washing interval of 3000 EOH. Even though the performance of the gas turbine is fair it could further be improved by changing the frequency of on-line and off-line washing.

4.2.1.4 Analysis of on-line washing type 2 without any off-line washing from 12250 EOH to 17250 EOH

The situations like major overhauling of other units, problem with the other running units and combining the boiler annual statutory inspection along with the GT minor inspections, the minor inspections of this gas turbine is not exactly performed at 4000EOH. The main objective of this analysis is to found out the effect of the shifting of this minor inspection by 1000EOH on the gas turbine performance. The prediction of the compressor polytropic and isentropic efficiencies are made up to 17250 EOH without any off-line washing from 12250 EOH. The on-line washing frequency is selected as type 2. The data from the fourth column of the table 4.15 have been applied to the hybrid neural network model based on Prestd as inputs. The analysis of this neural network model with prestd data processing technique is shown in the analysis 1.4.

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Analysis 1.4**Analysis - Online washing Type 2 without any Off line washing between 12250 EOH to 17250 EOH**

No.	Type of washing	Actual/Prediction Profile	Chosen Profile	Performance of Network(MSE)	No. of Epochs
I	Off line	Actual	-	1.6094×10^{-5}	285
I	On line	Actual	-	0.18370	450
II	On line	Actual	-	0.0203708	450
III	On line	Actual	-	0.139005	450
1	On line	Prediction	2	0.0203709	450
5	PNN 1			0.0577939	100
6	PNN 2			0.9587330	100

PNN Analysis Result

Comparison with Guaranteed value

15% Less

Comparison with Expected value

35% High

Figure 4.37
Analysis - Online washing Type 2 without any Off line washing between 12250 EOH to 17250 EOH

The comparison of the predicted profile of the polytropic and isentropic efficiency with the reference value has been shown in Figure 4.37. The PNN analysis of the predicted profile with the reference profile shows that it is 15% lesser (better) than the guaranteed value and 35% higher (adverse) than the expected value.

This shows that the gas turbine run above (better) 15% from the guaranteed profile and 35% below (adverse) than the expected profile. This confirms the shifting of the minor

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inspection from 4000EOH to 5000EOH does not drastically affect the gas turbine degradation rate, but still it has minor impact when compared with the expected profile.

4.2.1.5 Verification of the neural network model with outputs obtained by using OEM corrections

In the cases discussed from the analysis 1.1 to 1.4 the developed hybrid neural network model has been tested with two GHI parameter deviations only. This analysis has been done in order to found out the validity of the developed hybrid neural network for five GHI parameters deviation. The data from the fifth column of the table 4.15 have been applied to the neural network model as inputs. These inputs consist of following GHI parameter deviation from 4800EOH to 12500EOH and the details about the on-line and off-line washings performed during this period.

- CCPP gross efficiency degradation.
- Compressor polytropic efficiency degradation.
- Compressor isentropic efficiency degradation.
- Compressor pressure ratio deviation and
- IGV Position deviation.

The predictions of the above outputs have been done by using neural network model from 12250 to 16500 EOH and they are directly plotted against the actual values of the gas turbine. These actual outputs of the gas turbine are hidden from the model and plotted only with result of this model. The analysis of this neural network model with prestd data processing technique has been shown in the analysis 1.5. The results of the above model has been plotted and shown in the figure 4.38.

It has been noticed that the actual values of the CCPP gross efficiency, polytropic and isentropic efficiency deviation are normally increasing in the negative side along the EOH, whereas the compressor pressure ratio and IGV opening deviation are increasing in the positive side along the EOH. The on-line and off-line washing tends to decrease their corresponding deviation. The similar characteristics are observed on the GHI parameters in the prediction part of the model. This confirms that developed hybrid model is capable of handling higher number of GHI parameters and good replica of the real system.

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Analysis 1.5**Analysis – Verification of Neural network model based on Prestd technique with 5 outputs obtained by using OEM corrections**

No.	Type of washing	Actual/Prediction Profile	Chosen Profile	Performance of Network(MSE)	No. of Epochs
I	Off line	Actual	-	1.6049×10^{-5}	454
I	On line	Actual	-	0.18305	450
II	On line	Actual	-	0.0203714	450
III	On line	Actual	-	0.138995	450
1	On line	Prediction	1	0.18321	450

Stop Training

Figure 4.38
Analysis – Verification of Neural network model based on Prestd technique with 5 outputs obtained by using OEM corrections

CHAPTER 4 – RESULTS & DISCUSSIONS

Analysis 1.6**Analysis – Verification of Neural network model based on Prestd technique with 5 outputs obtained by using STD corrections**

No.	Type of washing	Actual/Prediction Profile	Chosen Profile	Performance of Network(MSE)	No. of Epochs
I	Off line	Actual	-	1.6049×10^{-5}	326
I	On line	Actual	-	0.18235	450
II	On line	Actual	-	0.0192314	450
III	On line	Actual	-	0.148794	450
1	On line	Prediction	1	0.179322	450

Stop Training

Figure 4.39
Analysis – Verification of Neural network model based on Prestd technique with 5 outputs obtained by using STD corrections

CHAPTER 4 – RESULTS & DISCUSSIONS

4.2.1.6 Verification of the neural network model with outputs obtained by using the STD corrections.

The developed hybrid neural network model has applied to predict the behavior of the gas turbine degradation rate based on OEM corrections in the analysis 1.1 to 1.5. In order to verify the capability of this model to handling the GHI parameters deviation based on the STD correction this analysis has been done. The input data from the sixth column of the table 4.15 have been applied to the neural network model as inputs. These inputs consist of CCPP gross, polytropic, isentropic efficiency, CDT and IGV position deviation respectively from 4800 EOH to 12500 EOH and corresponding on-line and off-line washings performed. The prediction of the network has been done from 12250 EOH to 16500EOH with on-line washing of type-1 and without any off-line washing. The outputs of this analysis are shown in the analysis 1.6. The predicted outputs of the above analysis is plotted against the actual values of the GHI parameters deviation and shown in Figure 4.39.

The actual outputs of the GHI parameter deviation from 12250 to 16500EOH are hidden from the model training part and plotted only with result of the model. The figure 4.39 shows that predicted values of GHI parameter deviation behave in similar manner like the actual values hidden from the training of this model. This confirms the model is a good replica of the real system and has the capability of handing the GHI parameters based on STD corrections also.

4.2.2 Thermo-Economical assessment of gas turbine engine using the hybrid neural network models

The result of the thermal analyses show that the hybrid neural network model based on prestd and preminmax data processing techniques are the good replica of the real system. The neural network model based on prestd data processing technique is taken for cost analysis of the gas turbine engine degradation. The cost analysis of the system has been done using the CCPP gross efficiency degradation alone. The guaranteed degradation curve represents the minimum possible performance of the gas turbine and expected degradation curve represents the maximum possible performance of the gas turbine. Even though the comparison has been made between the guaranteed profile and predicted profile, the cost analysis has been done only based on the comparison between the predicted profile and expected profile.

CHAPTER 4 – RESULTS & DISCUSSIONS

The inputs to the hybrid neural model are given from the data in the seventh column of the table 4.15. The cumulative deviation of the CCPP gross efficiency degradation has been calculated for the given range of the EOH. Then the PNN network is used to compare the predicted degradation with the cumulative expected degradation given by the gas turbine supplier. Various scenarios are considered based on the site conditions and the cost analysis for those scenarios have been done and suggestions are made.

Following are various assumption made in the cost analysis

- The average power generation of the unit is considered as 310 MWhr even though in real applications it is fluctuating depending on the grid requirement and market bidding. This value of 310 MWhr is obtained by assuming that the unit will run at 340 MWhr during day time and 280 MWhr in night time.
- Cost of power generation and fuel cost are also assumed as S\$78.5 per MWhr and S\$58.9 per MWhr respectively. Refer the table 4.18 in the appendix D2 for the arrival of this value from the home electricity bill. In reality, the power generation cost is fluctuating with respect to the demand, market bidding and industrial usages. The fuel cost is on contract basis and the power plant owner has to pay the amount even though if they are not consuming due to some problem with their machines.
- Kindly refer the table 4.19 in the appendix D2 for the maintenance cost estimation of compressor off-line and on-line washing.

All the above assumptions are included in the cost analysis of the developed hybrid neural network model in order to find out the financial impact of the gas turbine degradation rate and their washings. This thermo-economical analysis is a good tool to asses the gas turbine health based on the thermodynamics and economical impacts.

CHAPTER 4 – RESULTS & DISCUSSIONS

Analysis 2.1**Cost Analysis: On-line washing of different types without any off-line washing from 12250 to 16500EOH**

				Performance of Network Training (MSE)		
				Different types of On-line washing profile		
No.	Type of washing	Actual / Prediction	No of Epoch	Type 1	Type 2	Type 3
I	Off-line	Actual	310	8.4x10 [^] (-6)	9.234x10 [^] (-6)	8.324x10 [^] (-6)
I	On-line	Actual	450	0.03224	0.03144	0.03156
II	On-line	Actual	450	0.28243	0.27341	0.29843
III	On-line	Actual	450	0.07873	0.07863	0.07883
1	On-line	Prediction	450	0.03075	0.282242	0.07932
PNN			450	0.0536804	0.0609077	0.0494964
PNN			450	0.0958049	0.0977097	0.0104509
PNN Network Result		Comparison with Guaranteed value		20% Less(+)	30% Less(+)	40%Less(+)
PNN Network Result		Comparison with Expected value		25% High(-)	20% High(-)	0%Similar
Cost Analysis	No of On-line washings			6	7	9
	Cost incurred for On-line washing			S\$6750	S\$7875	S\$10125
	Cumulative energy gained / lost			-5174.5MWhr	-3549.9MWhr	(+)2795.7MWhr
	Average Energy gained or lost /hr			-1.2175MW	-0.8352MW	(+)0.6578MW
	Cost of energy gained /lost			-S\$406,190	- S\$278,670	(+)S\$219,460
	Total cost gained / loss			-S\$412,940	-S\$286,550	(+)S\$209,340
	Remarks			Bad	Bad	Good

Table 4.20

Outputs of cost analysis for different types of online washing intervals from 12250 EOH to 16500 EOH

Figure 4.40

Cost Analysis of on-line washing of type 1 without any off-line washing from 12250 to 16500 EOH

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Analysis 2.1 (Cont'd)

Figure 4.41
Cost Analysis of on-line washing of type 2 without any off-line washing interval from 12250 to 16500 EOH

Figure 4.42
Cost Analysis of on-line washing of type 3 with off-line washing interval of 4000 EOH

CHAPTER 4 – RESULTS & DISCUSSIONS

4.2.2.1 Cost analysis of different types of on-line washing without any off-line washing from 12250 to 16250 EOH

Normally the minor inspection of the gas turbine is done for every 4000 EOH. (Approximately 5.5 months). So the cost analysis has been done for this scenario considering various types of on-line washing frequency.

- Type-1 refers that one on-line washing is performed for every 720 EOH.
- Type-2 refers that one on-line washing is performed for every 584 EOH.
- Type-3 refers that one on-line washing is performed for every 470 EOH

The data from the seventh column of the table 4.15 have been given as input to the hybrid neural network model based on prestd technique. These consists of CCPP gross efficiency deviation based on OEM corrections from 4800 EOH to 12500 EOH and various on-line & off-line washing performed during this period. The outputs of this model are shown in the analysis 2.1.

The intersection point of the predicted CCPP gross efficiency degradation profile with the expected efficiency degradation profile is the ideal period for doing the off-line washing. Figures 4.40 and 4.41 in the analysis 2.1 shows that if on-line washing frequency is followed as type 1 and type 2 intervals, the offline washing to be done at 14250 EOH without considering the power generation opportunity cost lost. If the lost of opportunity cost is considered the position would be shifted, this analysis has been done in the later scenarios.

Figure 4.42 in the analysis 2.1 shows that the type 3 online-washing interval maintains the degradation profile in-line with the expected degradation profile without any off-line washing. The table 4.20 in the analysis shows that the type 3 on-line washing interval gives better result when compared with the type 1 and type 2. This cost analysis also shows that the average energy lost per hour is of very small range from -1.2 MW to +0.65MW, but their cumulative cost effect for the overall period is very high.

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Analysis 2.2**Cost Analysis: On-line washing of type 1 with one off-line washing between 12250 and 16500 EOH**

No.	Type of washing	Actual / Prediction	No of Epochs	Performance of Network Training (MSE)
I	Off-line	Actual	4500	8.2153x10 ⁽⁻⁶⁾
I	On-line	Actual	450	0.0386842
II	On-line	Actual	450	0.291332
III	On-line	Actual	450	0.0803007
1	On-line	Prediction (type 1)	450	0.0394877
2	On-line	Prediction (type 1)	450	0.0394043
PNN			450	0.0564749
PNN			450	0.0106787
PNN Network Result		Comparison with Guaranteed value		50% Less (+)
PNN Network Result		Comparison with Expected value		20% Less (+)
Cost Analysis	No of On-line washings			7
	No of Offline washing			1
	Cost incurred for washings			S\$ 10625
	Opportunity lost cost			S\$ 364,560
	Cumulative energy gained / lost			+3965.8MWhr
	Average energy gained or lost /hr			+0.9333MW
	Cost of energy gained /lost			+S\$311,320
	Total cost gained / loss			(-)S\$63,868
	Remarks			Bad

Table 4.21

Outputs for the cost analysis of on-line washing type 1 with one off-line washing between 12250 EOH and 16500 EOH.

Figure 4.43

Cost Analysis: On-line washing of type 1 with one off-line washing between 12250 to 16500 EOH

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4.2.2.2 Cost analysis of on-line washing type 1 with one off-line washing between 12250 and 16500EOH

This analysis has been done in order to determine the economical impact of stopping the gas turbine for doing one off-line washing and compressor IGV blade cleaning activities in between the minor inspection interval of 4000 EOH. The data from the 8th column of the table 4.15 have been applied to the hybrid neural network model based on Prestd technique as inputs. The outputs of the model are shown in the analysis 2.2. Figure 4.43 in the analysis 2.2 shows the graphical output of this model.

Table 4.21 in the analysis 2.2 gives the statistical output data of this model. The thermal analysis using the model shows that the CCPP gross efficiency degradation is about 50% less (better) than the guaranteed value and 20% less (better) than the expected degradation value. But the cost analysis part of the model shows that there is net loss of around S\$ 63,868. The additional off-line washing improves the cumulative energy loss from -5174.5MWhr to +3965.8MWhr. But for doing this off-line washing plus compressor IGV blade cleaning job the gas turbine has to be stopped for 2.5days. This energy gained by additional off-line washing is over ridden by this opportunity lost cost and result in net loss. So it is not advisable to stop the gas turbine one time for doing an off-line washing plus compressor blade cleaning in between the minor outages. (ie for every 4000 EOH).

4.2.2.3 Cost analysis of on-line washing type 1 with one off-line washing between 12250 and 20500 EOH

This scenario represents the current practice of one offline washing plus manual cleaning of the IGV blade during every minor inspection period. The CCPP gross efficiency deviation based on OEM corrections and the washing details from the ninth column of the table 4.15 in have been given as inputs to the neural network model based on prestd technique. The outputs of the model are shown in the analysis 2.3.

The table 4.22 in the analysis 2.3 gives the statistical output data of the model. The thermal analysis using the model shows that the CCPP gross efficiency degradation is about 30% less (better) than the guaranteed value and 15% higher (adverse) than the expected degradation value.

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Analysis 2.3**Cost Analysis: On-line washing of type 1 with one off-line washing between 12500 EOH to 20500 EOH**

No.	Type of washing	Actual / Prediction	No of Epochs	Performance of Network Training (MSE)
I	Off-line	Actual	4500	5.0421x 10 [^] (-6)
I	On-line	Actual	450	0.0385619
II	On-line	Actual	450	0.293829
III	On-line	Actual	450	0.0802927
1	On-line	Prediction (type 1)	450	0.0386696
2	On-line	Prediction (type 1)	450	0.0374656
PNN			450	0.0517575
PNN			450	0.0514636
PNN Network Result		Comparison with Guaranteed value		30% Less (+)
PNN Network Result		Comparison with Expected value		15% High(-)
Cost Analysis	No of On-line washings			11
	No of Offline washing			1
	Cost incurred for washings			S\$ 17375
	Opportunity lost cost			S\$ 364560
	Cumulative energy gained / lost			-6690.4 MW ^{hr}
	Average energy lost or gained /hr			-1.574MW
	Cost of energy gained /lost			-S\$525,200
	Total cost gained / loss			-S\$542,570 (-S\$907,130)
	Remarks			Fair

Table 4.22

Outputs for cost Analysis of on-line washing of type 1 with one off-line washing from 12250 to 20500 EOH

Figure 4.44

Cost Analysis: On-line washing of type 1 with one off-line washing from 12250 to 20500 EOH

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Analysis 2.4 Cost Analysis: On-line washing of type 1 with off-line washing at 14250, 16250 and 18250 EOH respectively

No.	Type of washing	Actual / Prediction	No of Epochs	Performance of Network Training (MSE)
I	Off-line	Actual	50	9.042×10^{-6}
I	On-line	Actual	450	0.0386238
II	On-line	Actual	450	0.00294195
III	On-line	Actual	450	0.0802929
1	On-line	Prediction (type 1)	450	0.0386432
2	On-line	Prediction (type 1)	450	0.0386257
3	On-line	Prediction (type 1)	450	0.0386407
4	On-line	Prediction (type 1)	450	0.0385343
PNN			450	0.0525924
PNN			450	0.098670
PNN Network Result		Comparison with Guaranteed value		50% Less (+)
PNN Network Result		Comparison with Expected value		25% Less (+)

Cost Analysis Result	No of On-line washings		11
	No of Offline washing		3
	Cost incurred for washings		S\$ 27375
	Opportunity lost cost		(S\$1,081,315 for 3washes) (S\$ 360,438 for 1 wash)
	Cumulative energy gained / lost		+9,544.0MWhr
	Average energy gained or lost / hr		+2.24568MW
	Cost of energy gained /lost		+S\$749,200
	Total cost gained / loss		- S\$ 359,490
	Note	If one opportunity cost not considered (Minor Inspection).Net gain is +S\$948 If all the 3 opportunity cost not considered. Net gain is +S\$721,825	

Table 4.23
Outputs for the cost analysis of on-line washing type 1 with three off-line washing at 14250, 16250 and 18250 EOH respectively.

Figure 4.45
Cost Analysis: On-line washing of type 1 with off-line washing at 14250 EOH, 16250 EOH and 18250 EOH

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The graphical output of this model is shown Figure 4.44. The cost analysis part of the model shows that with opportunity lost consideration, there is net loss of around S\$ 907,130 per year. It is recommended by the gas turbine supplier that for every 4000 EOH, the gas turbine hot sections to be inspected compulsorily. Normally the offline washing and compressor blade cleaning activities are done during this period. So by deleting the opportunity lost cost, the net loss is around S\$542,570. (Approximately equal to 1.08% of the annual profit of gained by running this gas turbine). The net loss can be further minimized by using type 2 and type 3 on-line washing intervals.

4.2.2.4 Cost analysis of on-line washing type 1 with three off-line washing at 14250, 16250, 18250 EOH respectively

Normally two minor inspections are performed every year. In this scenario one additional off-line washing has been performed between this two minor inspection and their effects are analyzed in annual basis. The CCPP gross efficiency deviation based on OEM corrections and corresponding washing details from the tenth column of the table 4.15 have been given as input to the hybrid neural network model based on prestd technique. The outputs of the model are shown in Analysis 2.4.

Table 4.23 in the analysis 2.4 gives the statistical output data of the model. The graphical output of the thermal analysis using this model has been shown in Figure 4.45. It shows that the CCPP gross efficiency degradation is about 50% lesser (better) than the guaranteed value and 25% lesser (better) than the expected degradation value.

The cost analysis part of the model shows as follows,

- Net loss of around S\$ 359,490 per year. (All the three off-line washing plus compressor IGV blade cleaning opportunity cost lost are included).
- Net loss of around S\$949 per year. (The two off-line washing plus compressor IGV blade cleaning opportunity cost lost are included and remaining one off-line washing plus IGV blade cleaning opportunity is covered under the minor inspection).
- Net gain of around S\$ 721,825 per year. (All the three off-line washing plus compressor IGV blade cleaning opportunity cost lost are not included).

CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The evaluation of different variants of the steady state network model revealed that the hybrid neural network model has the ability to replicate the complicate gas turbine compressor degradation with great accuracy. The accuracy largely depends on the extended and variety of training data available, the type of pre-processing carried out, the choice of training method and the transfer function used.

The model possesses good flexibility in both training and prediction. This leads to the high adaptive nature of the model to the real system. The degradation rates vary and very specific to each plant depending on their site location, surrounding environment, climatic conditions and plant layout. The adaptive nature of the neural network model allows the user to tune the model specific to that engine. The decisions are taken based on the history of the engine and not from the standard recommendations. The training of the model is very easy, since it does not require any sophisticated geometrical details of the gas turbine internals. It is more user friendly and fast enough to be used.

The gas turbine GHI parameters degradation determination using OEM and STD corrections for the long term trending shows that degradation curve has the same profile with minor deviations in its value. This proves that the developed model is a good tool to asses the health of gas turbine compressor of both constant and variable speed types. The accuracy level for the constant speed gas turbines other than V94.3A type would be up to only first order level, since the other types need their individual OEM corrections.

The cost analysis of the model explains that even 1MWhr of energy loss per hour due to improper washing schedule leads to approximately half million dollar loss per annum.

All the above concludes that the developed hybrid neural network model is user friendly and very effective tool for analyzing the gas turbine compressor health monitoring.

5.2 Recommendations on scheduling of compressor washing:

The main findings and recommendations related to the hybrid neural network model developed for assessing the gas turbine compressor health are as follows:

Currently the on-line washings are done as preventive maintenance on monthly basis. (ie about every 720 EOH). Instead if the interval of on-line washing is decreased to 600 EOH the

CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS

energy lost could be reduced from 5175MWhr to 3550MWhr for a period of 4000 EOH. It could be reduced further by decreasing the on-line washing interval to 470EOH.

But frequent on-line washing using chemicals would have adverse effect on the blade coating and blade cooling holes blockage. To overcome the above problem, more frequent on-line washing could be done by using de-mineralized water. The profiles of the first stage vane play critical roles in deciding the airflow rate through the gas turbine compressor and it tends to be most heavily fouled. These deposits become more difficult to remove if left untreated and the aging process bonds them more firmly to the airfoil. The frequent on-line washing is most effective in removing the deposits on the first two or three compressor stages and significantly decreases the fouling rate and maintains good performance level. Its effects can be analyzed using the developed hybrid neural network model.

Normally the off-line washing plus compressor IGV blade cleaning are done during the minor outages. (ie every 4000 EOH) . If one additional off-line washing plus compressor blade cleaning is performed in between this period, it results in good amount of energy saving (3960MWhr per 4000EOH). But the lost of power generation opportunity cost overrides the energy saved.

- The power selling prices are very low during week ends and holidays. If the two and half days required for the washing is covered in one of these days it will leads to good amount of energy and cost saving.
- The gas turbine availability is around 92% (336days) per annum and planned minor inspection time is about 3% (11 days) per annum. The remaining (5%) 18 days are due to the unplanned breakdowns of the engine and auxiliary system. If 2.5 days from this unplanned breakdown slot is utilized for doing the compressor off-line washing it will lead to savings of about 8000MWhr per year.

The compressor off-line washing and IGV blade cleaning are combined during minor outage times. These two activities together take 2.5 days. The time duration of the compressor IGV blade cleaning and off-line washing are 2.25 days and two hours respectively. Even though the off-line washing needs only 2 hours, it requires gas turbine to be shutdown condition. The shutting down plus starting of the gas turbine and steam turbine takes roughly four hours. So far

CHAPTER 5 – CONCLUSION AND RECOMMENDATIONS

the effect of the off-line washing alone is not tested at the site. At least one trial attempt could be done and the effect of off-line washing alone can be analyzed using the hybrid neural model developed and based on the result, further decision could be made.

5.3 Challenges and Recommendations for Future Work

5.3.1 Extension to the present work

In this research work, main focus has been given to assess the effect of compressor fouling on the gas turbine performance by using the hybrid neural network model and recommendations are made to reduce the losses by proper planning of washing schedules. Further investigation should be devoted to the application of the developed hybrid neural network model in the following areas.

- Assessments of the recoverable and non-recoverable losses of the gas turbine based on the fouling of its combustor and turbine.
- The effects of fouling on the HRSG tube's internal surface, external surface, passing valves and steam traps could be assessed and recommendation regarding acid washing frequency of HRSG tubes internal surfaces, air jet cleaning of the HRSG tube's external surfaces, renewal of passing valves and steam traps could be made.
- Further works to be done in order to assess the fouling effects on the steam turbine performance and recommendations like silica washing of turbine could also be done.
- The hybrid neural network model could also used to investigate and study the following fouling inter effects in a CCPP and Cogeneration plant
 - a. The effects of the gas turbine fouling on the HRSG and the steam turbine performance.
 - b. The effects of the HRSG fouling on the gas turbine and steam turbine performance.

At least 3 years of operating data are required for training the developed model for all the above cases, but it is worth to proceed with the further research work in the above areas considering the 25 years of expected life from the CCPP.

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5.3.2 Improvements to the present work:

Neural network modeling is an empirical modeling. The result from this model depends on the data used for training it. So the training data should be representative of what an actual engine will produce. The present hybrid neural network model developed uses the base line reference data taken from the PAC test result. This PAC test is performed for 60%, 85%, 93% and 100% loads only, so the curve fitting technique has been used to derive the GHI values for the intermediate load values. If the data from the gas turbine simulator are used for generating this intermediate load values then the accuracy of this model would be further improved.

The thermo-economical analysis of the currently developed model has been done based on the average power generation of the unit, even though in real application it is fluctuating depending on the grid requirements and market bidding. Normally the market bidding is done every half an hour, it is very fluctuating due to the sudden raise in demand (other machines tripping), peak demand periods (Day times when the industries need more power) and off peak periods (like Sundays and public holidays). The SIMULINK software has got good compatibility with neural networks, so it could be used to generate output wave forms representing the fluctuating nature of cost and inputted to the developed hybrid neural network model. The outputs from this model would be useful the power plant operators in the real applications.

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Appendix A

APPENDIX – A1

Standard Correction Curves based on ISO 2314 (1989) for CCPP

<p>A line graph showing the relationship between CCPP output (k) and ambient temperature (°C). The x-axis ranges from -15 to 45 °C, and the y-axis ranges from 94 to 104 k. A blue line shows a linear increase in output with temperature. The formula $P_{cor} = k \cdot P_{meas}$ is noted.</p>	<p>A line graph showing the relationship between CCPP output (k) and ambient pressure (kPa). The x-axis ranges from 94 to 104 kPa, and the y-axis ranges from 94 to 104 k. A red line shows a linear increase in output with pressure. The formula $P_{cor} = k \cdot P_{meas}$ is noted.</p>
<p>Figure 2.12 CCPP Output vs Ambient temperature (DC) [ISO2314 (1989)]</p>	<p>Figure 2.13 CCPP Output vs Ambient pressure [ISO2314 (1989)]</p>
<p>A line graph showing the relationship between CCPP output (k) and relative humidity (%). The x-axis ranges from 30 to 90 %, and the y-axis ranges from 94 to 104 k. Two lines are shown: a green line for 37°C and a purple line for 5°C to 15°C. Both lines show a decrease in output with increasing humidity. The formula $P_{cor} = k \cdot P_{meas}$ is noted.</p>	<p>A line graph showing the relationship between CCPP output (k) and cooling water temperature deviation (°C). The x-axis ranges from -15 to 15 °C, and the y-axis ranges from 94 to 104 k. A red curve shows a decrease in output as the deviation increases. The formula $P_{cor} = k \cdot P_{meas}$ is noted.</p>
<p>Figure 2.14 CCPP Output vs Ambient relative humidity [ISO 2314(1989)]</p>	<p>Figure 2.15 CCPP Output vs Cooling water temp deviation [ISO 2314(1989)]</p>

APPENDIX – A1

Standard Correction Curves based on ISO 2314 (1989) for CCPP

<p>Figure 2.16 CCPP heat rate vs Ambient temperature [ISO2314 (1989)]</p>	<p>Figure 2.17 CCPP heat rate vs Ambient pressure [ISO2314 (1989)]</p>
<p>Figure 2.18 CCPP heat rate vs Ambient Relative humidity [ISO2314(1989)]</p>	<p>Figure 2.19 CCPP heat rate vs Cooling water temperature deviation [ISO2314 (1989)]</p>

APPENDIX – A1

Standard Correction Curves based on ISO 2314 (1989) for CCPP

<p>A graph showing the power correction factor P_{cor} as a function of operating hours. The y-axis is labeled k and the x-axis is labeled "Operating hours". The curve starts at a high value on the y-axis and decreases exponentially as operating hours increase. The equation $P_{cor} = k \cdot P_{meas}$ is written below the graph.</p>	<p>A graph showing the heat rate correction factor HR_{cor} as a function of operating hours. The y-axis is labeled k and the x-axis is labeled "Operating hours". The curve starts at a low value on the y-axis and increases exponentially as operating hours increase. The equation $HR_{cor} = k \cdot HR_{meas}$ is written below the graph.</p>
<p>Figure 2.20 CCPP Output vs Gas turbine degradation over operating hours [ISO2314 (1989)]</p>	<p>Figure 2.21 CCPP heat rate vs Gas turbine degradation over operating hours [ISO2314 (1989)]</p>

APPENDIX - A2

Calculation of polytropic, isentropic efficiencies and pressure ratio of gas turbine compressor

APPENDIX - A3

Calculation of Generator Gross Power output, Efficiency and Losses

Measured Parameters

U_{gross}' = measured voltage
 I_{gross}' = measured stator current
 I_f' = measured field current
 p.f. = measured power factor

Active Power

$$P_{gross}' = p.f.' * S_{gross}'$$

Actual Values

Rated Values

Apparent Power

$$S_{gross}' = \sqrt{3} \cdot U_{gross}' \cdot I_{gross}'$$

$$S_{gross} = \sqrt{3} \cdot I_{gross} \cdot U_N$$

Short - Circuit losses

$$P_{L,SC}' = P_{L,SCN} \cdot (I_{gross}' / I_N)^2$$

$$P_{L,SC} = P_{L,SCN} \cdot (I_{gross} / I_N)^2$$

Field I^2R losses

$$P_{L,Exc.}' = 1,21 \cdot R_{L,20} \cdot (I_f')^2$$

$$P_{L,Exc.} = 1,21 \cdot R_{L,20} \cdot (I_f)^2$$

Brush contact losses

$$P_{L,C}' = 2V \cdot I_f' \cdot 10^{-3}$$

$$P_{L,C} = 2V \cdot I_f \cdot 10^{-3}$$

Friction losses

$$P_{L,FR}' = 540 \text{ kW (design)}$$

$$P_{L,FR} = 540 \text{ kW (design)}$$

Core Losses

$$P_{L,IR}' = 588 \text{ kW (design)}$$

$$P_{L,IR} = 590 \text{ kW (design)}$$

Commutation of Losses

$$\Sigma P_L' = P_{L,FR}' + P_{L,IR}' + P_{L,SC}' + P_{L,Exc.}' + P_{L,RR}'$$

$$\Sigma P_L = P_{L,FR} + P_{L,IR} + P_{L,Exc} + P_{L,C} + P_{L,RR}$$

Difference of Total losses

$$\Delta P = \Sigma P_L - \Sigma P_L'$$

APPENDIX - A3

U_{gross}'	= measured voltage
I_{gross}'	= measured stator current
I_f'	= measured field current
P_{gross}'	= measured active power
S_{gross}'	= measured apparent power
p.f.'	= measured power factor
$P_{L,SC}$	= actual short-circuit losses
$P_{L,SCN}$	= nominal short-circuit losses (Design = 1555kW)
$P_{L,Exc}'$	= actual field I^2R -losses
$P_{L,C}'$	= actual Brush contact losses
$P_{L,FR}'$	= actual friction losses in bearing (Design = 540kW)
P_{LIR}'	= actual core losses (Design = 588kW)
$\sum P_L'$	= total losses of actual values
p.f. _N	= power factor nominal (Design = 0.85)
U_N	= voltage nominal (Design = 22000V)
I_{gross}	= calculated generator current $[P_{gross}' / (\sqrt{3} * p.f._N * U_N)]$
S_{gross}	= calculated apparent power $(\sqrt{3} * I_{gross} * U_N)$
I_f	= calculated field current f (S) (from test certificate)
$P_{L,SC}$	= nominal short-circuit losses
$P_{L,Exc}$	= nominal field I^2R -losses
$P_{L,C}$	= nominal Brush contact losses
$P_{L,FR}$	= nominal friction losses in bearing (Design = 540kW)
P_{LIR}	= nominal core losses (Design = 588kW)
$\sum P_L$	= total losses referred to p.f. _N
ΔP	= difference of total losses
$R_{L,20}$	= rotor winding (@20°C) Design -1.21
P_{gross}	= P_{gen} output for p.f. _N nominal
P_{Cg}	= Coupling power at Generator
η_g	= Generator Efficiency

APPENDIX - A4

Calculation of Calorific value and Carbon hydrogen ratio of the fuel gas.

APPENDIX - A5

Correction of Power output to reference conditions based on OEM corrections

APPENDIX - A5

Note: Since the real equations are proprietary properties of the manufacture, only the general structure of correction equations are given here.

APPENDIX - A6

Correction of Heat rate to reference conditions based on OEM corrections

APPENDIX - A6

1

Corrected Heat Rate Output

$$HR_{cor} = \left[\frac{\{ HR \}}{\{ P+c6 \}} * b7 \right] * b8$$

Note: Since the real equations are proprietary properties of the manufacture, only the general structure of correction equations are given here.

APPENDIX - A7

Correction of Power output to reference conditions based on STD corrections

APPENDIX – A8

Procedure for Calculating the Corrected CCPP gross efficiency

APPENDIX – A9

Air Flow Rate Calculation Using Combustion Analysis.

Combustion Analysis on Volume Basis:

Gas turbine airflow rate calculation using combustion analysis has been explained in the following paragraphs.

In practice, combustion is hardly ever carried out in stoichiometric conditions. Some industrial burners may operate at air/fuel ratio which is extremely close to the theoretical value, but majority of the burners require a measure of air in excess of the stoichiometric quantity to ensure complete combustion.

Combustion is a chemical reaction combining fuel and oxygen to produce heat and combustion products. Atmospheric air contains 21% Oxygen (By volume) and is the most convenient O₂ source. Stoichiometric combustion conditions are those where the relative fuel and air quantities are the theoretical minimum need to produce complete combustion.

The combustion reaction can be represented by way of a chemical equation for each constituent present in the fuel.

APPENDIX – A9

Calculation of Stoichiometric combustion products from One Volume (m³ or cf)

Constituent	Constituent (%Vol) m ³	Stoichiometric O ₂ /Air m ³			Combustion Product						
					CO ₂ m ³			H ₂ O m ³			N ₂ m ³
Methane	a%	a	2	2a	a	1	1a	a	2	2a	
Ethane	b%	b	3.5	3.5b	b	2	2b	b	3	3b	
Propane	c%	c	5	5c	c	3	3c	c	4	4c	
Butane	d%	d	6.5	6.5d	d	4	4d	d	5	5d	
Pentane	e%	e	8	8e	e	5	5e	e	6	6e	
Hexane	f%	f	9.5	9.5f	f	6	6f	f	7	7f	
CO ₂	z%						z				
N ₂	y%										y
		O ₂		sum1							
		N ₂ =O ₂ * 3.76									3.76O ₂
		Air=O ₂ * 4.76									
		Air =O ₂ * 4.76					sum2			sum3	sum4

Theoretical air requirement =sum1 *4.76 m³ of air / m³ of gas.

Wet Combustion Products = (sum2+sum3+sum4) m³ of air / m³ of gas.

Dry Combustion Products = (sum3+sum4) m³ of air / m³ of gas.

Note:- All Volumes at standard conditions 15°C, 101.324KPa & Dry.

Example: Analysis for methane is shown below

Applying the above table for the 100% Methane Gas Combustion.

Constituent	Constituent (%Vol) m ³	Stoichiometric O ₂ /Air m ³			Combustion Product						
					CO ₂ m ³			H ₂ O m ³			N ₂ m ³
Methane	100%	1	2	2	1	1	1	1	2	2	
		O ₂		2							
		N ₂ =2 * 3.76									7.52
		Air=2* 4.76									
		Air =9.52					1			2	7.52

APPENDIX – A9

Theoretical air requirement **Ao** = 9.52m³ of air / m³ of gas.

Wet Combustion Products **Vow** = 10.52m³ of flue gas / m³ of gas.

Dry Combustion Products **Vod** = 8.52m³ of flue gas / m³ of gas.

Therefore the Theoretical Air / Fuel Ratio for 100% Methane Gas is

$$\text{Air / Fuel Ratio} = 9.52.$$

1. Mass Flow rate of fuel is converted into volume flow rate

Fuel Flow (m³/sec) = Mass Flow (Kg/sec) / (Density of fuel @ 15°C, 101.325KPa, Dry)

2. Excess Air Calculation (λ):

Insufficient combustion air causes a reduction in fuel efficiency, produces highly toxic carbon monoxide gas and soot. To ensure there is enough oxygen to completely react with the fuel, extra combustion air is usually supplied. This extra air is called "Excess Air", and it is expressed as the percent air above the amount theoretically needed for complete combustion.

In real world combustion, the excess air required for gaseous fuels is typically about 15%. Significantly more may be needed for liquids and solid fuels.

A good estimate of excess air can be determined using the following formula. This calculation uses the oxygen concentration measured in the exhaust. If the CO concentration is very high it may be also be included in the excess air calculation.

$$\% \text{Excess Air} = \frac{V_o}{A_o} * \frac{\% O_2 \text{ Measured}}{(21 - \% O_2 \text{ Measured})} \times 100$$

$V_o/A_o=0.898$ (approximate) for Natural Gas

V_o – Stoichiometric dry combustion products vol/vol. fuel.

A_o – Stoichiometric air vol/vol fuel

O₂- Measured dry O₂ in combustion products (%volume)

APPENDIX – A9

The above formula is used to find out the excess air percentage by measuring the Dry O₂ percentage in the exhaust gas. Then the actual air supplied for combustion has been determined using the following procedure.

An expression of excess air is referred to as Lambda (λ). The relationship between % Excess air and Lambda is shown below.

$$\lambda = \frac{\% \text{ Excess Air}}{100} + 1$$

3. Actual Air flow Rate calculation (@ 15°C ,101.325KPa, Dry)

Air Flow Rate (m³/sec) $V_1 = \text{Fuel Flow (m}^3/\text{Sec)} * A/F * \lambda$

4. Converting this Volume Air Flow Rate (m³/sec) to the Volume at the given compressor air inlet condition.

$$P_1 V_1 / T_1 = P_2 V_2 / T_2$$

$$\text{Air inlet Flow rate} = V_2$$

5. Converting this Volume air flow to mass flow rate using the air density

(@ 015°C, 101.325KPa, Dry)

Mass flow Rate of air (kg/s) $Ma = V_2 * \rho_{\text{air}} (1.224 \text{ kg/m}^3)$

By using this method the air flow rate of the compressor has been determined at various known design conditions.

APPENDIX – A10

Mass and Energy Balance Method to find out the Compressor inlet Air flow rate

The mass and energy balance have been studied individually for the whole system, combustion chamber and compressor. The equation for compressor airflow rate and turbine inlet temperature has been found out by solving following three systems.

The concept of this method is energy in and energy out from a Control volume is equal.

➤ System Power Balance

$$\Sigma(\text{Energy In}) = \Sigma(\text{Energy Out})$$

$$E_{AIR IN} + E_{FUEL} + E_{INJ} = E_{EXH, M} + Q_{RAC} + Q_{ENCL} + (PWR_{GROSS, M} / \eta_{GEN}) + PWR_{MECH}.$$

Figure 3.2
System Power Balance Diagram

The mass and energy balance of the system is obtained as follows from the fig 3.2

$$Q_{c1} + Q_f + Q_w + Q_{ca2} + P_b = P_{gt} + Q_{ex} + Q_{ca1} + Q_{t2} + P_{ml} + P_{cl} + P_{gt-ls}$$

APPENDIX – A10

➤ Combustion Chamber Power Balance

Figure 3.3

Combustion Chamber Power Balance

The mass and energy balance equation of combustion chamber from the fig 3.3 is as follows

$$Q_{c2} + Q_f + Q_w + Q_{ca2} + P_b + \sum m_{c1} \cdot H_{c1} = Q_{ca1} + Q_{t1}$$

➤ Compressor Power Balance

Figure 3.4

Compressor Power Balance

APPENDIX – A10

The mass and energy balance equation for the compressor from the fig 3.4 is as follows

$$Q_{c1} + P_c = Q_{c2} + Q_{ex} + \Sigma m_{c1} \cdot H_{c1}$$

➤ Determination of Compressor inlet air mass flow rate using Mass and Energy Balance method

The mass flow m_{t1} at turbine inlet is

$$m_{t1} = m_{c1} + m_f + m_w - m_{ex} \quad [1]$$

and at turbine Outlet

$$m_{t2} = m_{t1} \quad [2]$$

The power balance equation of the system is obtained from the figure 3.2 as follows

$$m_{c1} \cdot H_{c1} + m_f \cdot [\eta_b \cdot (H_u + (H_f - H_{f,o})) + m_w \cdot H_w + m_{ca} \cdot H_{ca2} + P_b = \\ P_{gt} + m_{ex} \cdot H_{c2} + m_{ca} \cdot H_{ca1} + m_{t2} \cdot H_{t2} + P_{ml} + P_{cl} + (1/\eta_{gen} - 1) \cdot P_{gt} \quad [3]$$

By inserting the mass flow equation 1 & 2 in the Power balance equation 3, the calculation of the air mass flow at compressor inlet is obtained as follows

$$m_{c1} = \{ m_f \cdot [\eta_b \cdot (H_u + H_f - H_{f,o}) - H_{t2}] \cdot m_{ca} \cdot (H_{ca1} - H_{ca2}) - m_w \cdot (H_{t2} - H_w) + m_{ex} \cdot (H_{t2} - H_{c2}) - \\ (1/\eta_{gen} - 1) \cdot P_{gt} - P_{ml} - P_{cl} + P_b \} / (H_{t2} - H_{c1}) \quad [4]$$

The following Parameter's are required for the calculation of the air mass flow at compressor inlet

1) Measured data's required:

$H_u, m_f, m_{Ex}, m_w, P_b, P_{gt}, t_f, t_w, t_{ca2}, t_{c1}, t_{c2}, t_{t2}$

2) Design parameter's required.

$H_{f,o}, m_{En}/m_c, m_{ca}, P_{gl}, P_{ml}, \eta_b, \eta_{gen}$

APPENDIX – A11

Gas turbine compressor washing details

Date	Time	Type of washing	Profile number	Remarks
04/12/02	11.07 to 11.24	on-line washing	I Profile	
06/01/03	11.55 to 12.20	on-line washing		
11/02/03	08.55 to 09.30	on-line washing		
11/03/03	10.00 to 11.00	on-line washing		
08/04/03		Manual comp blade cleaning	II Profile	Minor inspection at 8000 EOH
10/04/03	10.30 to 02.00	off-line washing		
20/04/04	10.30 to 11.30	On-line washing		
13/05/03	10.30 to 11.00	On-line washing		
24/06/03	10.15 to 10.45	On-line washing		
26/07/03		Manual comp blade cleaning	III Profile	Generator rotor replacement outage
28/07/03	04.30 to 05.30	Off-line washing		
18/08/03	10.15 to 10.45	On-line washing		
15/9/03	11.00 to 11.30	On-line washing		
01/10/03	08.00 to 18.00	Man comp blade cleaning	IV Profile	Minor inspection at 12000 EOH
03/10/03	07.00 to 8.30	Off-line washing		
21/11/03	10.30 to 10.50	On-line washing		
29/12/03	10.30 to 11.00	On-line washing		
26/01/04	09.45 to 10.30	On-line washing		
01/03/04		Man Comp blade cleaning	V Profile	Minor inspection at 16000EOH
05/03/04	17.00 to 18.30	Off-line washing		
21/04/04	10.30 to 11.30	On-line washing		
17/05/05	10.00 to 10.30	On-line washing		

Table 3.8

Gas turbine compressor washing details.

Appendix B

APPENDIX - B1

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP gross thermal efficiency and its correction based on OEM

```

Disp ('Enter Inputs for determining the compressor performance'); pause;
t11=input('Temperature at compressor suction deg c'); pause
a21=input('Atmospheric pressure in barata')
%Conversion of degree C to degree Kelvin
t1=t11+273.13;
t21=input('Temperature at compressor discharge deg c'); pause
%Conversion of degree C to degree Kelvin
t2=t21+273.13;
tm=(t1+t2)/2;
p1=input('Pressure at the compressor suction at barata'); pause
p2=input('Pressure at the compressor discharge at barata'); pause
disp('Enter the inputs for correcting the Generator outputs')
g100=input('Measured active power in MW'); pause
g2=input('Gross voltage measured in Volts'); pause
g3=input('Gross current measured in Amps'); pause
g4=input('Field current measured in Amps '); pause
g6=input('Aux. power consumed in kW '); pause
disp('Entering the inputs for correcting the power output to standard reference condition'); pause
%b1=input('Gross power generated by CCPP in MW');
%a11=input('Ambient Temperature(Deg C)');
a11=t11;
%a21=input('Ambient Pressure (mbar)');
a31=input('Ambient Relative Humidity (%) '); pause
a4=input('Actual Speed in Hz '); pause; a41=a4*60;
a51=input('cooling water inlet temperature(deg C) '); pause
disp(' Kindly input the gas composition in the following format');
b3=input('Mass flow rate of fuel'); pause
m1=input('Percentage of Nitrogen N2 (%Mole)');
m2=input('Percentage of Carbon dioxide Co2(%Mole)');
m3=input('Percentage of Methane CH4 (%Mole)');
m4=input('Percentage of Ethane C2H6 (%Mole)');
m5=input('Percentage of Propane C3H8 (%Mole)');
m6=input('Percentage of I-Butane I-C4H10 (%Mole)');
m7=input('Percentage of N-Butane N-C4H10 (%Mole)');
m8=input('Percentage of N-Pentane I-C5H12(%Mole)');
ma8=input('Percentage of N-Pentane N-C5H12(%Mole)');
m9=input('Percentage of Hexane C6H14 (%Mole)');
m10=input('Percentage of Heptane C7H16 (%Mole)');
m11=input('Percentage of Octane C8H18 (%Mole)');
m12=input('Percentage of Nonane C9H20 (%Mole)');
disp('Details regrading the pressure and temperature of Natural Gas');
%m13=input('Pressure of the Natural Gas Mixture (barg)');
%m14=input('Temperature of the Natural Gas Mixture (Deg C)');
%m15=input('Compression factor of the Natural Gas Mixture');
m16=(m1*28.0135+m2*44.01+m3*16.043+m4*30.07+m5*44.097+m6*58.123+m7*58.123+m8*72.15 ...
+ma8*72.15+m9*86.177+m10*100.204+m11*114.231+m12*128.258)/100;
%higher Calorific values of Gas Compositon at STD
m17=(m1*0+m2*0+m3*891.56+m4*1562.14+m5*2219.17+m6*2879.76+m7*2879.76+m8*3538.6 ...
+ma8*3538.6+m9*4198.24+m10*4857.18+m11*5516.01+m12*6175.82)/100
%Lower Calorific values of gas composition at STD
m18=(m1*0+m2*0+m3*802.69+m4*1428.84+m5*2043.37+m6*2657.6+m7*2657.6+m8*3272
+ma8*3272+m9*3887.21+m10*4501.72+m11*5116.11+m12*5731.49)/100
disp('Higher Calorific value HCV in KJ/Kg');

```

APPENDIX - B1

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP gross thermal efficiency and its correction based on OEM

```

m28=m17*1000/m16;
disp('Lower Calorific Value LCV in KJ/Kg');
m29=m18*1000/m16;
%Calculation of Carbon Hydrogen Ratio
%Molar Mass of Different Compounds
%Carbon-12.011,Hydrogen-1.00794,Oxygen-15.9994,Nitrogen-14.00674 & S-32.066
m23=m1*14.00674; m24=m2*15.994;
m25=((m2+m3+2*m4+3*m5+4*m6+4*m7+5*m8+ma8*5+6*m9+7*m10+8*m11+9*m12)*12.011);
m26=((2*m3+3*m4+4*m5+5*m6+5*m7+6*m8+ma8*6+7*m9+8*m10+9*m11+10*m12)*2*1.00794);
disp('carbon to Hydrogen ratio');
m30=m25/m26;
%Transferring the input of LCV of gas into main program
a7=m29;
%Transferring the input of Carbon Hydrogen ratio into the program
a8=m30; R=0.287040;
%CP is the specific heat capacity at constant pressure
CP=0.103409*(10.^(1))*(tm.^(0))-0.2848870*(10.^(3))*(tm.^(1)) .
+0.7816818*(10.^(6))*(tm.^(2))-0.4970786*10.^(9)*tm.^(3)...
+0.1077024*(10.^(12))*(tm.^(4));
%CV is the specific heat capacity at constant volume
CV=CP-R;
%Y is the Gamma (specific heat capacity)
Y=CP/CV;
disp('Polytropic efficiency of compressor')
PolyEff=(R/CP)*log(p2/p1)/log(t2/t1)*100
disp('Isentropic efficiency of compressor')
Iseff=((p2/p1).^(R/CP)-1)/((t2/t1)-1)*100
disp('Pressure ratio of the compressor')
Pressureratio= p2/p1
disp('Calculation of Generator Efficiency');
%Calculation of apparent power
g8=sqrt(3)*g2*g3*10.^(-3);
g27=[366.621 365.358 344.467 344.367 314.592 314.518 221.225 221.047];
g28=[5.20 5.17 5.11 5.08 4.84 4.77 4.32 4.24]
g30=interp1(g27,g28,g100,'linear','extrap')
%Calculation of gross power generated
g1=(g100)*1000; g9=g1/g8;
%Calculation of short circuit losses
%Nominal short circuit losses is 1555kW from test certificate
%Nominal current from test certificate 11363A
%Psc=Pscn(Ig/In)^2 ; g10=1555*(g3/11363).^2
%Field I^2R losses calculation
%Plexc = 1.21*RI(If)^2
%RI=Rotor Winding (20deg C)losses from test certificate
g11=1.21*0.09583*(g4).^2*10.^(-3)
%Calculation of Brush contact losses
g12=2*g4*10.^(-3);
%Calculation of Efficiency of Generator
%Egen=P'gross/(P'gross + EPI)*100% Where EPI is total losses.
g13=g1/(540+590+g1+g10+g11+g12);
%calculation of generator current
%Igross,n=P'gross/(sqrt(3)*pfn*Un ; %pfn=0.85 & Un=22000V from test certificate
g14=g1*1000/(sqrt(3)*0.85*22000);

```

APPENDIX - B1

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP gross thermal efficiency and its correction based on OEM

```
%Calculation of apparent power nominal
g15=sqrt(3)*g14*22000*10.^(-3)
%Calculation of Field current Nominal
R=[0.000 108250 216500 324750 433000];
M= [1100 1516 2000 2570 3226 ];
g16=interp1(R,M,g15,'linear','extrap')
%Calculation of Short circuit losses Nominal
g17=1555*(g14/11363).^2;
%Calculation of Field I^2 R losses Nominal
g18=1.21*0.09583*(g16).^2/1000;
%Calculation of Brush contact losses
g19=2*(g16)*10.^(-3);
%Design friction losses & Core losses
g20=540; g21=590
%Calculation of total losses (Delta P)
g22=(540+565+g10+g11+g12)-(g20+g21+g17+g18+g19)
%Pgross output for pfn
g23=g1-(-g22)-g11
%Generator Efficiency in %
disp('Efficiency of Generator')
g24=100*(g23+g12)/((g20+g21+g17+g18+g19)+g23+g12)
%Calculation of coupling power at generator in kW
disp(' Power Generated at Coupling in kW');
g25=(g1+(540+590+g10+g11+g12)-g11)
%Net power output corrected for nominal power factor in kW
disp('Net Power Generator')
g26=(g100*1000)-(-g22)-g30*1000-g6
%Correction of power output to the standard reference condition
disp('Calculation of temperature correction');
%b1=input('Gross power generated by CCPP in MW');
b1=g25;
disp('Calculation of temperature correction');
b21=g25; a11=t11;
%Calculation of ambient relative humidity deviation from the rated RH of 85%
a3=(a31-85); a41;
%Calculation of actual speed deviation from rated speed of 3000rpm
a4=(a41-3000)*100/3000;
%Calculation temperature deviation from the rated temperature of 32 deg C
a1=a11-32;
%Calculation of pressure deviation from the rated pressure of 1013.25mbar
a21=a21*1000;
a2=a21-1013.25;
%Calculation of actual CWT deviation from rated CWT of 30 deg c
a5=a51-30;
%Percentage of load is required for calculating the CWT Cor.factor
a6=(g25/374225)*100
a62=(g100/370)*100
a61=(a6-a62)*100/a62;
%All Following correction factors below represents for power calculation
%Equation for temperature correction for Power
Y1=((a1.^2 *(1.1568e-005))+(a1*4.4113e-03)+(1.0e-0));
%Equation for pressure correction for Power
Y2=(a2*-9.6606e-04)+(1.0e-0);
```

APPENDIX - B1

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP gross thermal efficiency and its correction based on OEM

%Equation for Relative Humidity (Y3) and Speed (Y4) for power

if a11>37

$$Y3 = (-2.6166e-4 * a3 + 1.0e0);$$

$$Y4 = ((5.6152e-04 * a4.^2) - (1.2394e-02 * a4) + 1.0e-0);$$

elseif a11<=37 & a11>=27

$$Y3 = (-1.6089e-04 * a3 + 1.0e0);$$

$$Y4 = ((7.3045e-04 * (a4.^2)) - (1.0204e-02 * a4) + 1.0e0);$$

else

$$Y3 = (-1.1284e-04 * a3 + 1.0e0);$$

$$Y4 = ((1.0734e-03 * a4.^2) - (6.9596e-03 * a4) + 1.0e0);$$

end

%Equation for Cooling water temperature correction factor (based of CCPP load %) for Power

if a6>=97

$$Y5 = (-1.0467e-01 * a5.^3) + (2.7049e01 * a5.^2) + (4.9202e02 * a5);$$

elseif a6<97 & a6>=89

$$Y5 = (-9.6667e-02 * a5.^3) + (2.5152e01 * a5.^2) + (4.5752e02 * a5);$$

elseif a6<89 & a6>=72

$$Y5 = (-8.9333e-02 * a5.^3) + (2.2984e01 * a5.^2) + (4.1823e02 * a5);$$

elseif a6<72

$$Y5 = (-6.2667e-02 * a5.^3) + (1.6228e01 * a5.^2) + (2.9517e02 * a5);$$

end

%Equation for LCV correction factor base on C/H Ratio for power

if a8>3.15

$$Y6 = ((-2.3375e-11 * a7.^2) + (2.8980e-06 * a7) + (9.1631e-01));$$

elseif a8<=3.15 & a8>=3.06

$$Y6 = ((-2.0086e-11 * a7.^2) + (2.6261e-06 * a7) + (9.2001e-01));$$

elseif a8<3.06

$$Y6 = ((-1.9813e-11 * a7.^2) + (2.6011e-06 * a7) + (9.1927e-01));$$

end

% Correction for power calculation ends. Following equation represents correction factors for Heat Rate

if a6>=97

$$Z1 = (2.6001e-08 * a1.^4) + (5.6339e-07 * a1.^3) + (-1.6931e-05 * a1.^2) + (-8.7906e-05 * a1) + 1e0;$$

elseif a6<97 & a6>=89

$$Z1 = (-6.2413e-08 * a1.^4) + (6.6876e-07 * a1.^3) + (-4.9754e-06 * a1.^2) + (-1.8941e-04 * a1) + 1e0;$$

elseif a6<89 & a6>=72

$$Z1 = (-6.2096e-09 * a1.^4) + (9.0621e-08 * a1.^3) + (-7.4069e-06 * a1.^2) + (-2.1325e-04 * a1) + 1e0;$$

elseif a6<72

$$Z1 = (5.4337e-09 * a1.^4) + (2.5066e-07 * a1.^3) + (-7.6302e-06 * a1.^2) + (-2.8948e-04 * a1) + 1e0;$$

end

%Equation for pressure correction

$$Z2 = a2 * (-6.2158e-06) + (1.0e-0);$$

%Equation for Relative Humidity and Speed correction

if a11>37

$$Z3 = (-3.4566e-05 * a3 + 1.0e0);$$

$$Z4 = ((3.2575e-06 * a4.^3) + (-1.3891e-04 * a4.^2) - (1.3052e-03 * a4) + 1.0e-0);$$

elseif a11<=37 & a11>=27

$$Z3 = (-1.9218e-05 * a3 + 1.0e0);$$

$$Z4 = ((-4.244e-05 * a4.^3) + (-2.0532e-04 * a4.^2) + (1.1388e-03 * a4) + 1.0e0);$$

else

$$Z3 = (7.0601e-07 * a3 + 1.0e0);$$

$$Z4 = ((-5.9691e-06 * a4.^3) + (-2.4121e-04 * a4.^2) - (9.0995e-05 * a4) + 1.0e0);$$

end

%Equation for Partload power output of CCPP

APPENDIX - B1

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP gross thermal efficiency and its correction based on OEM

```

if a6>=88
    Z5=(-2.8459e-05*a61.^2)+(1.1881e-03 * a61)+1e0;
elseif a6<88 & a6>=73
    Z5=(-2.2705e-05*a61.^2)+(1.16910e-03*a61)+1e0;
elseif a6<=72
    Z5=(-2.1837e-06*a61.^4)+(1.6133e-05*a61.^3)+(-5.4043e-05*a61.^2)+(3.0804e-03*a61)+1e0;
end
%Equation for LCV Correction factor
if a8>3.15
    Z6=((3.9122e-12*a7.^2)+(-5.0669e-07*a7)+(1.0150e0));
elseif a8<=3.15 & a8>=3.06
    Z6=((3.9908e-12*a7.^2)+(-5.1650e-07*a7)+(1.0158e0));
elseif a8<3.06
    Z6=((3.7383e-12*a7.^2)+(-4.9584e-07*a7)+(1.0155e0));
end
%Following Display represent correction factor for power
disp('Correction of Measured POWER TO Rated Condition')
disp('Temperature correction factor-POWER is'); Y1
disp('Pressure correction factor-POWER is'); Y2
disp('Relative Humidity correction factor-POWER is') ; Y3
disp('Speed correction factor-POWER is'); Y4
disp('Cooling water temperature correction factor-POWER is'); Y5
disp('LCV of fuel gas correction factor-POWER is') ; Y6
disp('cummulative effect of correction factors apart from speed - POWER');Y7
disp('effect of correction incld speed/amb temp,press,RH,LCV- POWER');Y8
disp(' Effect of all correction factors including CWI temp on gross power generated(KW)');b2
%Following Display represent correction factor for Heat Rate
disp('Temperature correction factor-HEAT RATE is');Z1
disp('Pressure correction factor-HEAT RATE is');Z2
disp('Relative Humidity correction factor-HEAT RATE is');Z3
disp('Speed correction factor-HEAT RATE is');Z4
disp('Power Output correction factor-HEAT RATE is');Z5
disp('LCV of fuel gas correction factor-HEAT RATE');Z6
disp('Gross coupling power correction in MW hr')
Z10=((g25+Y5)*Y1*Y2*Y3*Y4*Y6)/1000
disp('Fuel Input power MW')
%Z9=(Mass Flow rate of fuel * LCV of Fuel)
Z9=b3*a7/1000
disp('Uncorrected Heat Rate')
%Z11 (Net Heat Rate) =(Fuel input power /Net power Cor NominalPF)x 3600
Z11=Z9*3600/g25
%Z12 Net Heat Rate corrected = (Z10*Z7*Z8*3600)/Z9
disp('Corrected Heat Rate')
Z13=(Z9/(g25+Y5/1000))*Z1*Z2*Z3*Z4*Z5*Z6*3600
% End of the program for Corrected power and Neat Heat Rate calculation
disp('Gross thermal efficiency of CCPP plant')
(Z10/Z9)*100

```

APPENDIX – B2

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP Gross thermal efficiency and its corrections based on STD

```

disp('Enter Inputs for determining the compressor performance'); pause;
t11=input('Temperature at compressor suction deg c'); pause
a21=input('Atmospheric pressure in barata')
%Conversion of degree C to degree Kelvin
t1=t11+273.13;
t21=input('Temperature at compressor discharge deg c'); pause
%Conversion of degree C to degree Kelvin
t2=t21+273.13;
tm=(t1+t2)/2;
p1=input('Pressure at the compressor suction at barata'); pause
p2=input('Pressure at the compressor discharge at barata'); pause
disp('Enter the inputs for correcting the Generator outputs')
g100=input('Measured active power in MW'); pause
g2=input('Gross voltage measured in Volts'); pause
g3=input('Gross current measured in Amps'); pause
g4=input('Field current measured in Amps '); pause
g6=input('Aux. power consumed in kW '); pause
disp('Entering the inputs for correcting the power output to standard reference condition'); pause
a11=t11;
%calculation temperature correction from the rated temperature of 32 deg C
a1=(273.13+a11)/(273.13+32);
%calculation of pressure deviation from the rated pressure of 1013.25mbar
a2=1013.25/a21;
a4=input('Actual Speed in Hz '); pause; a41=a4*60;
a51=input('cooling water inlet temperature(deg C) '); pause
disp(' Kindly input the gas composition in the following format');
b3=input('Mass flow rate of fuel'); pause
m1=input('Percentage of Nitrogen N2 (%Mole)');
m2=input('Percentage of Carbon dioxide Co2(%Mole)');
m3=input('Percentage of Methane CH4 (%Mole)');
m4=input('Percentage of Ethane C2H6 (%Mole)');
m5=input('Percentage of Propane C3H8 (%Mole)');
m6=input('Percentage of I-Butane I-C4H10 (%Mole)');
m7=input('Percentage of N-Butane N-C4H10 (%Mole)');
m8=input('Percentage of N-Pentane I-C5H12(%Mole)');
ma8=input('Percentage of N-Pentane N-C5H12(%Mole)');
m9=input('Percentage of Hexane C6H14 (%Mole)');
m10=input('Percentage of Heptane C7H16 (%Mole)');
m11=input('Percentage of Octane C8H18 (%Mole)');
m12=input('Percentage of Nonane C9H20 (%Mole)');
m16=(m1*28.0135+m2*44.01+m3*16.043+m4*30.07+m5*44.097+m6*58.123+m7*58.123+m8*72.15 ...
+ ma8*72.15 +m9*86.177+m10*100.204+m11*114.231+m12*128.258)/100;
%higher Calorific values of Gas Composition at STD
m17=(m1*0+m2*0+m3*891.56+m4*1562.14+m5*2219.17+m6*2879.76+m7*2879.76+m8*3538.6 ...
+ma8*3538.6 +m9*4198.24+m10*4857.18+m11*5516.01+m12*6175.82)/100
%Lower Calorific values of gas composition at STD
m18=(m1*0+m2*0+m3*802.69+m4*1428.84+m5*2043.37+m6*2657.6+m7*2657.6+m8*3272 ...
+ma8*3272 +m9*3887.21+m10*4501.72+m11*5116.11+m12*5731.49)/100
Disp('Higher Calorific value HCV in KJ/Kg');
m28=m17*1000/m16;
disp('Lower Calorific Value LCV in KJ/Kg');
m29=m18*1000/m16;
%Calculation of Carbon Hydrogen Ratio and Molar Mass of Different Compounds
%Carbon-12.011,Hydrogen-1.00794,Oxygen-15.9994,Nitrogen-14.00674 & S-32.066;
m23=m1*14.00674; m24=m2*15.994;

```

APPENDIX – B2

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency,

CCPP Gross thermal efficiency and its corrections based on STD

```

m25=((m2+m3+2*m4+3*m5+4*m6+4*m7+5*m8+ma8*5+6*m9+7*m10+8*m11+9*m12)*12.011);
m26=((2*m3+3*m4+4*m5+5*m6+5*m7+6*m8+ma8*6+7*m9+8*m10+9*m11+10*m12)*2*1.00794);
disp('carbon to Hydrogen ratio');
m30=m25/m26; %pause
%Transferring the input of LCV of gas into main program
a7=m29;
%Transferring the input of Carbon Hydrogen ratio into the program
a8=m30; R=0.287040;
%CP is the specific heat capacity at constant pressure
CP=0.103409*(10.^(1))*(tm.^(0))-0.2848870*(10.^(3))*(tm.^(1))...
+0.7816818*(10.^(6))*(tm.^(2))-0.4970786*10.^(9)*tm.^(3)...
+0.1077024*(10.^(12))*(tm.^(4));
%CV is the specific heat capacity at constant volume
CV=CP-R;
%Y is the Gamma (specific heat capacity)
Y=CP/CV;
disp('Polytropic efficiency of compressor')
PolyEff=(R/CP)*log(p2/p1)/log(t2/t1)*100
disp('Isentropic efficiency of compressor')
IseEff=((p2/p1).^(R/CP)-1)/((t2/t1)-1)*100
disp('Pressure ratio of the compressor')
Pressureratio= p2/p1
disp('Calculation of Generator Efficiency');
%Calculation of apparent power
g8=sqrt(3)*g2*g3*10.^(-3); g27=[366.621 365.358 344.467 344.367 314.592 314.518 221.225 221.047];
g28=[5.20 5.17 5.11 5.08 4.84 4.77 4.32 4.24]
g30=interp1(g27,g28,g100,'linear','extrap')
%Calculation of gross power generated
g1=(g100)*1000; g9=g1/g8;
%Calculation of short circuit losses
%Nominal short circuit losses is 1555kW from test certificate Nominal current from test certificate 11363A
%Psc=Pscn(Ig/In)^2
g10=1555*(g3/11363).^2
%Field I^2R losses calculation;
%Plexc = 1.21*RI(If)^2; RI=Rotor Winding (20deg C)losses from test certificate
g11=1.21*0.09583*(g4).^2*10.^(-3)
%Calculation of Brush contact losses
g12=2*g4*10.^(-3);
%Calculation of Efficiency of Generator Egen=P'gross/(P'gross + EPl)*100% Where EPl is total losses.
g13=g1/(540+590+g1+g10+g11+g12);
%calculation of generator current
%Igross,n=P'gross/(sqrt(3)*pfn*Un
%pfn=0.85 & Un=22000V from test certificate
g14=g1*1000/(sqrt(3)*0.85*22000);
%Calculation of apparent power nominal
g15=sqrt(3)*g14*22000*10.^(-3)
%Calculation of Field current Nominal
R=[0.000 108250 216500 324750 433000];
M= [1100 1516 2000 2570 3226 ]; g16=interp1(R,M,g15,'linear','extrap')
%Calculation of Short circuit losses Nominal
g17=1555*(g14/11363).^2;
%Calculation of Field I^2 R losses Nominal
g18=1.21*0.09583*(g16).^2/1000;
%Calculation of Brush contact losses
g19=2*(g16)*10.^(-3);

```


APPENDIX – B2

Determination of Polytropic efficiency, Isentropic efficiency, Generator efficiency, CCPP Gross thermal efficiency and its corrections based on STD

```
%Design friction losses & Core losses
g20=540; g21=590
%Calculation of total losses (Delta P)
g22=(540+565+g10+g11+g12)-(g20+g21+g17+g18+g19)
%Pgross output for pfn
g23=g1-(-g22)-g11
%Generator Efficiency in %
disp('Efficiency of Generator')
g24=100*(g23+g12)/((g20+g21+g17+g18+g19)+g23+g12)
%caculation of coupling power at generatorin kW
disp(' Power Generated at Coupling in kW');
g25=(g1+(540+590+g10+g11+g12)-g11)
%Net power output corrected for nominal power factor in kW
disp('Net Power Generator')
g26=(g100*1000)-(-g22)-g30*1000-g6
%Correction of power output to the standard reference condition
disp('caculation of temperature correction');
%b1=input('Gross power generated by CCPP in MW');
b1=g25;
disp('caculation of temperature correction');
b21=g25; a11=t11; a41;
%calculation of actual CWT deviation from rated CWT of 30 deg c
a5=a51-30;
%Percentage of load is required for calculating the CWT Cor.factor
a6=(g25/374225)*100;a62=(g100/370)*100;a61=(a6-a62)*100/a62;
%All Following correction factors below represents for power calculation
%calculation temperature correction from the rated temperature of 32 deg C
aa1=(273.13+a11)/(273.13+32);
%calculation of pressure deviation from the rated pressure of 1013.25mbar
aa2=(a21*1000)/1013.25;
%Equation for Cooling water temperature correction factor (based of CCPP load %)for Power
if a6>=97
    Y5=(-1.0467e-01*a5.^3)+(2.7049e01 * a5.^2)+(4.9202e02*a5);
elseif a6<97 & a6>=89
    Y5=(-9.6667e-02*a5.^3)+(2.5152e01 * a5.^2)+(4.5752e02*a5);
elseif a6<89 & a6>=72
    Y5=(-8.9333e-02*a5.^3)+(2.2984e01 * a5.^2)+(4.1823e02*a5);
elseif a6<72
    Y5=(-6.2667e-02*a5.^3)+(1.6228e01 * a5.^2)+(2.9517e02*a5);
end
disp ('Corrected Gross CCPP Power output in KW')
Pc = ((b1+Y5/1000)/(aa2*sqrt(aa1)))
% Correction for power calculation ends.
disp('Correction of Measured POWER TO Rated Condition')
disp('Temperature correction factor-POWER is'); sqrt(aa1)
disp('Pressure correction factor-POWER is');aa2
disp('Cooling water temperature correction factor-POWER is');Y5
%Z9=(Mass Flow rate of fuel * LCV of Fuel)
disp('Fuel Input power KW');Z9=b3*a7/(aa2*sqrt(aa1))
disp ('Corrected Gross CCPP efficiency');grossEff= (Pc*100)/Z9
disp ('Corrected Gross Heat rate');3600*100/grossEff
```

APPENDIX –B3

Matlab modeling - Air flow rate calculation using combustion analysis

```

disp('Air Density calculation using following parameters')
disp('Ambient Temperature, Pressure and Humidity values')
a1=input(' Ambient Temperature (Deg C) :');
a2=input(' Ambient Pressure (mm of Hg) :');
a3=input(' Humidity (%) :');
a4=input(' Exhaust Oxygen wet weight% :');
a5=input(' Exhaust Nitrogen wet weight% :');
a6=input(' Exhaust Arsenic wet weight% :');
a7=input(' Exhaust Carbondioxide weight% :');
a8=input(' Exhaust Water wet weight% :');
a9=input(' Mass flow rate of fuel (kg/s) :');
a10=input(' Density of fuel (kg/m3) :');
SVP = [ 4.58 4.92 5.29 5.68 6.10 6.54 7.01 7.51 8.04 ...
        8.61 9.21 9.85 10.52 11.24 11.99 12.79 13.64 14.54 ...
        15.49 16.49 17.55 18.66 19.84 21.09 22.40 23.78 25.24 ...
        26.77 28.38 30.08 31.86 33.74 35.70 37.78 39.95 42.23 ...
        44.62 47.13 49.76 52.51 55.40 58.42 61.58 64.89 68.35 ...
        71.97 75.75 79.70 83.83 88.14];
T= [ 0 1 2 3 4 5 6 7 8 ...
     9 10 11 12 13 14 15 16 17 ...
    18 19 20 21 22 23 24 25 26 ...
    27 28 29 30 31 32 33 34 35 ...
    36 37 38 39 40 41 42 43 44 ...
    45 46 47 48 49];
p=polyfit(T,SVP,5);
a=polyval(p,a1);
RHO=(1.2929 * (273.13/(273.13+a1))* ((a2-(a*a3))/760));
Density = RHO
p1=760-(a3*a);
R=p1/a2;
c2 =20.9*R;
%Molecular weight of Nitrogen;
b1=28.013;
%Molecular weight of Oxygen;
b2=31.998;
%Molecular weight of Arsenic;
b3=29.948;
%Molecular weight of water;
b4=18.015;
%Molecular weight of Carbon Di-oxide;
b5=44.010;
%Calculation of Wet Exhaust Gas on Volume basis;
SUM=((a4/b2)+(a5/b1)+(a6/b3)+(a7/b5)+(a8/b4));

```

APPENDIX –B3

OxygenwetVol=((a4/b2)/SUM) *100;
NitrogenwetVol=((a5/b1)/SUM)*100;
ArsenicwetVol=((a6/b3)/SUM)*100;
CarbondioxidewetVol=((a7/b5)/SUM)*100;
WaterwetVol=((a8/b4)/SUM)*100;
% Calculation of Dry Exhaust Gas on Volume basis;
SUM1=(OxygenwetVol+NitrogenwetVol+ArsenicwetVol+CarbondioxidewetVol);
OxygendryVol=100*(OxygenwetVol/SUM1)
NitrogendryVol=100*(NitrogenwetVol/SUM1);
ArsenicdryVol=100*(ArsenicwetVol/SUM1);
CarbondioxidedryWet=100*(CarbondioxidewetVol/SUM1);
EA=0.898*(OxygendryVol/(21-OxygendryVol))
Tair = (a9/a10)*(9.52);
Tact=Tair*(EA+1);
Tactvol=Tact*((760/273.13)*(273.13+a1)/p1);
Mact=(Tactvol*RHO)

APPENDIX – B4

Matlab Modeling – Indirect Air Flow Calculation Using Mass and Energy Balance Method

```

disp('Air Mass Flow Rate and Turbine Inlet Temp calculation - Indirect Method')
a1=input('Ambient Temperature(Deg C) :');
a2=input('Flue gas Outlet temperature(Deg C) :');
a5=input('Power Generated by the Machine (MW) :');
a6=input('Give input as For V64.3 as 0, V84.3 as 1 and V94.3 as 2 :');
TP1=input('Relative Humidity (%) eg 0.66 :');
a4=input('Compressor Outlet Temp (Deg C) :');
a9=input('Cooling air temperature (Deg C):') ;
mf=input('Mass flow rate of Natural Gas(kg/s):') ;
mw=input('Mass flow rate of Injected Water/steam (kg/s):');
Tw=input('Temperature of Injected Water/Steam (Deg C):');
a10=input('Natural Gas Inlet Temperature(Deg c):') ;
a11=input('Compressor Discharge Pressure (Bar):') ;
nb=input('Burner Efficiency (%):') ;
LCV=input('Calorific Value of Natural Gas LCV in (kJ/kg):');
MCA=input('Mass of the cooling air flow in the Gas Turbine(kg/s):');
GENEFF=input('Efficiency of the Generator (%):');
PLM=input('Design Mechanical Loss of Bearings (KW):') ;
PLG=input('Design Losses in the Gear Box(KW):') ;
BOS=input('Booster Power Consumption (KW):') ;
disp('IBR for V64.3 Type is 0.0148 & V84.3 machine is 0.01672 & V94.3 machie is 0.0245')
IBR=input('Comp Internal Bleed to Comp Suction air Ratio');
% Determination Natural Gas (Fuel) Enthalpy at the given temperature
%Specific heat capacity * (Temperature Difference between given temp and Stand Temp 15'C
%Specific Heat Capacity at Constant Pressure of Natural Gas 1.8KJ/Kg-k
Cp=1.8;Tref=15; Hg=Cp*(a10-Tref);
%Determination of Ratio of Generated Power to Design Power loss
switch a6
case 0
    a7=62; a8=188;
case 1
    a7=153; a8=425;
case 2
    a7=221; a8=612;
end
a3=(a5/a7)*100;
EDA=[ 0.00 1.00 2.00 3.00 4.01 5.01 6.01 7.01 8.01 9.02 10.02 11.02 12.02 13.03 14.03 15.03 16.03 17.04 ...
18.04 19.04 20.05 21.05 22.05 23.06 24.06 25.06 26.07 27.07 28.08 29.08 30.08 31.09 32.09 33.10 34.10...
35.11 36.11 37.12 38.12 39.13 40.13 41.14 42.14 43.15 44.15 45.16 46.16 47.17 48.18 49.18 50.19 55.22 ...
60.26 65.29 70.34 75.38 80.43 85.48 90.53 95.59 100.65 105.71 110.78 115.85 120.93 126.00 131.08 136.1 141.26...
146.35 151.45 156.55 161.65 166.76 171.87 176.99 182.11 187.24 192.50 197.50 202.64 207.78 212.93 218.08...
223.56 228.39 233.56 238.73 243.90 249.08 254.26 259.45 264.64 269.84 275.04 280.25 285.46 290.68 295.90...
301.13 306.36 311.59 316.84 322.08 327.33 332.59 337.85 343.12 348.39 353.67 358.95 364.24 369.54 374.83...
380.14 385.45 390.76 396.08 401.41 406.74 412.42 417.42 422.76 428.12 433.47 438.84 444.20 449.58 454.96...
460.34 465.73 471.13 476.53 481.94 487.35 492.77 498.19 503.62 509.05 514.49 519.94 525.39 530.85 536.31...
541.77 547.25 552.73 558.21 563.70 569.19 574.69 580.20 585.71 591.23 596.75 602.28 607.81 613.35 618.89
624.44...
630.00 635.56 641.12 652.27 657.85 663.44 669.03 674.63 680.23 685.84 691.46 697.08 702.70 708.33 713.96...
719.60 725.25 730.90 736.56 742.22 747.88 753.55 759.23 764.91 770.60 776.29 781.99 787.69 793.39 799.11...
804.82 810.54 816.27 822.00 827.74 833.22 839.22 844.97 850.73 856.49 862.25 868.02 873.80 879.58 885.36...
891.15 896.94 902.74 908.54 914.35 920.16 925.97 931.79 937.62 943.45 949.28 955.12 960.96 966.81 972.66...
978.51 984.37 990.10 996.10 1001.97 1007.85 1013.73 1019.61 1025.50 1031.39 1037.29 1043.19 1049.09...
1055.00 1060.91 1066.82 1072.74 1078.66 1084.59 1090.52 1096.45 1102.39 1108.33 1114.28 1120.23 1126.18...
1132.13 1138.09 1144.05 1150.02 1155.99 1161.96 1167.94 1173.91 1179.90 1185.88 1197.87 1203.86 1209.86...

```

APPENDIX – B4**Matlab Modeling – Indirect Air Flow Calculation Using Mass and Energy Balance Method**

1215.86 1221.86 1227.87 1233.88 1239.89 1245.91 1251.93 1257.95 1263.98 1270.01 1276.04 1282.07 1288.11...
1294.15 1300.19 1306.23 1312.28 1318.33 1324.38];

T=[0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33...
34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125...
130 135 140 145 150 155 160 165 170 175 180 185 190 195 200 205 210 215 220 225 230 235 240 245 250 255...
260 265 270 275 280 285 290 295 300 305 310 315 320 325 330 335 340 345 350 355 360 365 370 375 380 385...
390 395 400 405 410 415 420 425 430 435 440 445 450 455 460 465 470 475 480 485 490 495 500 505 510 515...
520 525 530 535 540 545 550 560 565 570 575 580 585 590 595 600 605 610 615 620 625 630 635 640 645 650...
655 660 665 670 675 680 685 690 695 700 705 710 715 720 725 730 735 740 745 750 755 760 765 770 775 780...
785 790 795 800 805 810 815 820 825 830 835 840 845 850 855 860 865 870 875 880 885 890 895 900 905 910...
915 920 925 930 935 940 945 950 955 960 965 970 975 980 990 995 1000 1005 1010 1015 1020 1025 1030...
1035 1040 1045 1050 1055 1060 1065 1070 1075 1080 1085 1090 1095 1100 1105 1110 1115 1120 1125 1130...
1135 1140 1145 1150 1155 1160 1165 1170 1175 1180 1185 1190 1195];

p=polyfit(T,EDA,7);

B=polyval(p,a1)

EWV = [0.00 1.86 3.72 5.58 7.44 9.30 11.16 13.02 14.88 16.74 18.60 20.47 22.33 24.19 26.05 27.92 29.78 31.64...
33.51 35.37 37.24 39.10 40.97 42.83 44.70 46.57 48.43 50.30 52.17 54.03 55.90 57.77 59.64 61.51 63.38 65.25...
67.12 68.99 70.86 72.73 74.60 76.47 78.34 80.21 82.09 83.96 85.83 87.71 89.58 91.45 93.33 102.71 112.09...
121.49 130.90 140.31 149.74 159.17 168.61 178.07 187.53 197.01 206.49 215.99 225.50 235.02 244.55 254.09...
263.64 273.20 282.78 292.37 301.96 311.58 321.20 330.84 340.49 350.15 359.82 369.51 379.21 388.92 398.65...
408.39 418.14 427.91 437.69 447.49 457.29 467.12 476.95 486.80 496.67 506.55 516.44 526.35 536.28 546.22...
556.17 566.14 576.12 586.12 596.14 606.17 616.21 626.27 636.35 646.44 656.55 666.67 676.81 686.97 697.14...
707.33 717.54 727.76 737.99 748.25 758.52 768.80 779.11 789.43 799.76 810.12 820.49 830.87 841.28 851.70...
862.14 872.59 883.06 893.55 904.06 914.58 925.13 935.69 946.26 956.85 967.47 978.09 988.74 999.40 1010.09...
1020.78 1031.50 1042.24 1052.99 1063.76 1074.55 1085.35 1096.17 1107.02 1117.87 1128.75 1139.65 1150.56...
1161.49 1172.44 1183.40 1194.39 1205.39 1216.41 1227.45 1238.51 1249.58 1260.68 1271.79 1282.91 1294.06...
1305.23 1316.41 1327.61 1338.83 1350.07 1361.32 1372.60 1383.89 1395.20 1406.52 1417.87 1429.23 1440.61...
1452.01 1463.43 1474.87 1486.32 1497.79 1509.28 1520.79 1532.31 1543.86 1555.42 1567.00 1578.59 1590.21...
1601.84 1613.84 1625.16 1636.85 1648.55 1660.27 1672.01 1683.77 1695.54 1707.33 1719.14 1730.97 1742.81...
1754.67 1766.55 1778.45 1790.36 1802.30 1814.24 1826.21 1838.19 1850.19 1862.21 1874.25 1886.30 1898.37...
1910.45 1922.56 1934.68 1946.81 1958.97 1971.14 1983.33 1995.53 2007.75 2019.99 2032.24 2044.51 2056.80...
2069.11 2081.43 2093.76 2106.12 2118.49 2130.87 2143.27 2155.69 2168.13 2180.58 2193.04 2205.52 2218.02...
2230.54 2243.07 2255.61 2268.17 2280.75 2293.34 2305.95 2318.58 2331.22 2343.87 2356.54 2369.23 2381.93...
2394.64 2407.38 2420.12 2432.88 2445.66 2458.08 2471.26 2484.08 2496.91 2509.76 2522.63 2535.51 2548.40...
2561.31 2574.31 2587.17 2600.12 2613.09 2626.07 2639.07];

T1=[0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34...
35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 55 60 65 70 75 80 85 90 95 100 105 110 115 120 125 130...
135 140 145 150 155 160 165 170 175 180 185 190 195 200 205 210 215 220 225 230 235 240 245 250 255...
260 265 270 275 280 285 290 295 300 305 310 315 320 325 330 335 340 345 350 355 360 365 370 375 380...
385 390 395 400 405 410 415 420 425 430 435 440 445 450 455 460 465 470 475 480 485 490 495 500 505 510...
515 520 525 530 535 540 545 550 555 560 565 570 575 580 585 590 595 600 605 610 615 620 625 630 635 640...
645 650 655 660 665 670 675 680 685 690 695 700 705 710 715 720 725 730 735 740 745 750 755 760 765 770...
775 780 785 790 795 800 805 810 815 820 825 830 835 840 845 850 855 860 865 870 875 880 885 890 895 900...
905 910 915 920 925 930 935 940 945 950 955 960 965 970 975 980 990 995 1000 1005 1010 1015 1020 1025...
1030 1035 1040 1045 1050 1055 1060 1065 1070 1075 1080 1085 1090 1095 1100 1105 1110 1115 1120 1125...
1130 1135 1140 1145 1150 1155 1160 1165 1170 1175 1180 1185 1190 1195 1200];

p1=polyfit(T1,EWV,7);

B1=polyval(p1,a1)

EMG = [520.95 527.07 533.20 539.34 545.48 551.63 557.79 563.95 570.12 576.31 582.49 588.69 594.89 601.10...
607.32 613.55 619.78 626.03 632.27 638.53 644.80 651.07 657.35 663.63 669.93 676.23 682.54 688.86 695.18...
701.51 707.85 714.20 720.55 726.92 733.28 739.66 746.05 752.44 758.84 765.24 771.65 778.08 784.50 790.94...
797.94 803.83 810.29 816.75 823.22 829.70 836.19 842.19 849.18 855.68 862.20 868.72 875.25 881.78 888.32...
894.87 901.43 907.99 914.56 921.14 927.72 934.31 940.91 947.51 954.12 960.74 967.36 973.99 980.63 987.27...
993.93 1000.58 1007.25 1013.92 1020.59 1027.28 1033.96 1040.66 1047.36 1054.07 1060.79 1067.51 1074.24...
1080.97 1087.71 1094.46 1101.21 1107.97 1114.73 1121.50 1128.28 1135.06 1141.85 1148.65 1155.45 1162.25...

APPENDIX – B4

Matlab Modeling – Indirect Air Flow Calculation Using Mass and Energy Balance Method

```

1169.07 1175.88 1182.71 1189.54 1196.37 1203.22 1210.06 1216.92 1223.77 1230.22 1237.51 1244.38 1251.26...
1258.15 1265.04 1271.94 1278.84 1285.75 1292.66 1299.58 1306.51 1313.43 1320.37 1327.31 1334.25 1341.20...
1348.16 1355.12 1362.08 1369.05 1376.03 1383.01 1389.99 1396.98 1403.98 1410.97 1417.98 1424.99 1432.00...
1439.02 1446.04 1453.07 1460.10 1467.14 1474.18 1481.22 1488.27 1495.33 1502.39 1509.45 ];
T2=[450 455 460 465 470 475 480 485 490 495 500 505 510 515 520 525 530 535 540 545 550 555 560 565 570...
575 580 585 590 595 600 605 610 615 620 625 630 635 640 645 650 655 660 665 670 675 680 685 690 695 700...
705 710 715 720 725 730 735 740 745 750 755 760 765 770 775 780 785 790 795 800 805 810 815 820 825 830...
835 840 845 850 855 860 865 870 875 880 885 890 895 900 905 910 915 920 925 930 935 940 945 950 955 960...
965 970 975 980 990 995 1000 1005 1010 1015 1020 1025 1030 1035 1040 1045 1050 1055 1060 1065 1070...
1075 1080 1085 1090 1095 1100 1105 1110 1115 1120 1125 1130 1135 1140 1145 1150 1155 1160 1165 1170...
1175 1180 1185 1190 1195 1200];
p3=polyfit(T2,EMG,5); B2=polyval(p3,a2)
PGR=[40 50 60 70 80 90 100 110];
MFR=[52 60 68 76 83 91 100 109];
p4=polyfit(PGR,MFR,4); B3=polyval(p4,a3)
PGR=[40 50 60 70 80 90 100 110];
MAR=[75 75 75 80 87 92 100 100];
p5=polyfit(PGR,MAR,4); B4=polyval(p5,a3)
TP=[ 100 90 80 70 60 50 40 30 20 10 0];
MFR50=[0.9225 0.928 0.937 0.945 0.9525 0.961 0.969 0.977 0.984 0.993 1];
p6=polyfit(TP,MFR50,2);
MFR45=[0.939 0.945 0.952 0.958 0.964 0.970 0.976 0.983 0.988 0.994 1];
p7=polyfit(TP,MFR45,2);
MFR40=[0.954 0.958 0.963 0.968 0.972 0.977 0.982 0.987 0.991 0.995 1];
p8=polyfit(TP,MFR40,2);
MFR35=[0.965 0.968 0.972 0.975 0.979 0.983 0.986 0.990 0.992 0.997 1];
p9=polyfit(TP,MFR35,2);
MFR30=[0.974 0.976 0.979 0.982 0.984 0.987 0.990 0.992 0.995 0.998 1];
p10=polyfit(TP,MFR30,2);
MFR25=[0.981 0.983 0.984 0.986 0.988 0.990 0.993 0.994 0.996 0.998 1];
p11=polyfit(TP,MFR25,2);
MFR20=[0.986 0.987 0.988 0.990 0.992 0.993 0.994 0.996 0.997 0.9985 1];
p12=polyfit(TP,MFR20,2);
MFR15=[0.989 0.991 0.992 0.993 0.994 0.995 0.996 0.997 0.998 0.999 1];
p13=polyfit(TP,MFR15,2);
MFR10=[0.992 0.993 0.994 0.995 0.9955 0.996 0.997 0.998 0.999 0.999 1];
p14=polyfit(TP,MFR10,2);
MFR05=[0.9945 0.995 0.996 0.996 0.997 0.997 0.998 0.998 0.999 0.999 1];
p15=polyfit(TP,MFR05,2);
MFR00=[0.9965 0.997 0.997 0.997 0.998 0.998 0.998 0.999 0.999 0.999 1];
p16=polyfit(TP,MFR00,2);
%Formula for determination of Enthalpy of Injected Steam/Water
%Hwater=H(Pt2*Twater)-h(Pt1)+H(ts(Pt2));
%X=H(Pt2*Twater)= 4.2*Twater
%X1=h(Pt2)=2750+2.45*Pt2
%Pt2 is Gas Turbine Outlet Pressure in bar ie ts(pt2)=(4064.5/(12108-logPt2))-236.25;
X=4.2*Tw; X1=2750+2.45*a11; X2=(4064.5/(12.108-log(a11)))-236.25; X3=polyval(p1,X2);
disp('Enthalpy of Water') ; X4=X-X1+X3; a1
if a1>45 & a1<51
    z1=polyval(p6,TP1); z2=polyval(p7,TP1); z3=(z1+z2)/2
end
if a1>40 & a1<46
    z1=polyval(p7,TP1); z2=polyval(p8,TP1); z3=(z1+z2)/2
end
if a1>35 & a1<41

```

APPENDIX – B4

Matlab Modeling – Indirect Air Flow Calculation Using Mass and Energy Balance Method

```

z1=polyval(p8,TP1); z2=polyval(p9,TP1); z3=(z1+z2)/2
end
if a1>30 & a1<36
    z1=polyval(p9,TP1); z2=polyval(p10,TP1); z3=(z1+z2)/2
end
if a1>25 & a1<31
    z1=polyval(p10,TP1); z2=polyval(p11,TP1); z3=(z1+z2)/2
end
if a1>20 & a1<26
    z1=polyval(p11,TP1); z2=polyval(p12,TP1); z3=(z1+z2)/2
end
if a1>15 & a1<21
    z1=polyval(p12,TP1); z2=polyval(p13,TP1); z3=(z1+z2)/2
end
if a1>10 & a1<16
    z1=polyval(p13,TP1); z2=polyval(p14,TP1); z3=(z1+z2)/2
end
if a1>5 & a1<11
    z1=polyval(p14,TP1); z2=polyval(p15,TP1); z3=(z1+z2)/2
end
if a1>0 & a1<6
    z1=polyval(p15,TP1) z2=polyval(p16,TP1) z3=(z1+z2)*0.5
end
%Determination of the quantities essential for the compressor mass flow;
%using ambient temperature (a1) and Relative Humidity (RH) by polyfitting(z3);
disp('The approximate compressor mass flow rate by OEMs curve'); z3
%Enthalpy of the Dry air (@compressor outlet);
B5=polyval(p,a4);
%Enthalpy of the water vapour (@compressor outlet);
B6=polyval(p1,a4);
%Enthalpy of the Compressor air outlet;
Hc2=(z3*B5+(1-z3)*B6)
%Determination of Ratio of Generated Power to Design Power loss
disp('Generated power to design power loss ratio'); a3
disp('compressor air Mass flow Ratio using power ratio') ; B3
disp('Corrected air flow ratio'); Y1=(B4*a8)/100
%Determination of Cooling air Enthalpy of the compressor and Enthalpy of Dry Cooling air
B7=polyval(p,a9);
%Enthalpy of Water vapour of cooling air
B8=polyval(p1,a9);
%Total Enthalpy of Cooling air
disp('Net Enthalpy of Cooling air'); Hca=(z3*B7+(1-z3)*B8)
disp('Enthalpy of compressor Inlet air'); Hc1=(z3*B+(1-z3)*B1)
disp('Enthalpy of Natural Gas'); B2
%Determination of Enthalpy of Air at Natural Gas Temperature
B9=polyval(p,a2); B10=polyval(p1,a2)
disp('Enthalpy of Flue Gas')
Ht2=((1+17.243)*B2 +(((Y1/mf)*z3)-17.243)*B9+((Y1/mf)*(1-z3)+(mw/mf)*B10)/((Y1/mf)+1+mw/mf)
disp('Mass flow rate of compressor inlet air (kg/s)');
Mair=(mf*((nb/100)*LCV+Hg-Ht2)-MCA*(Hc2-Hca)-mw*(Ht2-X4)-((100/GENEFF)*a5*1000) ...
-PLM-PLG+BOS)/(Ht2-Hc1)
disp('Turbine Inlet Enthalpy')
Ht1=((Mair-(IBR*Mair))*(Hc2-Hc1)+((100/GENEFF)*a5*1000)+PLM+PLG+BOS)/(Mair+mf) +Ht2
ph=polyfit(EMG,T2,5);
disp('Turbine inlet Temperature (deg C)'); TIT=polyval(ph,Ht1)

```


APPENDIX – B5

Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

disp ('The Gas Turbine Health Monitoring')
disp ('Select the no of set of readings to given for analysing the On-line washing '); pause
ux1 = input ('(a) The no of sets of reading for analyzing the On-line washing');
disp ('If you want to do the prediction on cycle period kindly enter "1" and if not enter "0" ')
vx1 = input ('Enter the required input for one prediction cycle')
    if vx1~=0 & vx1~=1
        disp ('The input entered for the prediction cycle is wrong')
    end
u2 = input ('(b) The no of sets of reading for analysing the Off-line washing');
u1u=input ('(c) The no of sets of output for the networks');
for k=1:ux1
    disp (' You are entering the readings for analysing the'); k
    disp (' the set of On-line washing')
    disp (' You are entering the readings for analysing the Ist set of reading for On-line washing')
    v(k).data = input ('Enter the corresponding EOH in matrix format');
    s(k).data = input ('Enter the corresponding deviation in the EHI parameters in matrix format');
    h=[v(k).data]; hh=[s(k).data]; c=size(h);cc=size(hh); vm=c(1,2);
    xm1(k).data=cc(1,1);xm2(k).data=cc(1,2);xyz=cc(1,2) ; xx(k).data=vm
    %Checking the no of columns in EOH matrix and Corresponding EHI Parameter are equal
    if (vm-xyz)~=0
        disp ('The no of inputs in EOH and deviation in EHI parameters are not equal')
        disp ('Re-check the inputs')
    end
end
for k1=1:u2
    disp (' You are entering the readings for analysing the'); k1
    disp (' the set of Off-line washing')
    disp (' You are entering the readings for analysing the Ist set of reading for Off-line washing')
    v1(k1).data = input ('Enter the corresponding EOH in matrix format');
    s1(k1).data = input ('Enter the corresponding deviation in the EHI parameters in matrix format');
    h1=[v1(k1).data];hh1=[s1(k1).data];u=size(h1);uu=size(hh1); um=u(1,2);
    ym1=u(1,1);ym2=uu(1,2)
    xx1(k1).data=um
    %Checking the no of columns in EOH matrix and Corresponding EHI Parameter are equal
    if (um-ym2)~=0
        disp ('The no of inputs in EOH and deviation in EHI parameters are not equal')
        disp ('Re-check the input')
    end
end
dz1=input ('Enter the Maximum EOH period upto which you want to do the prediction')
dy2=input ('Frequency period you want to do the prediction');
dz2=input ('Enter how many no of off line washing you want during this period')
    if dz2~=0
        %Transferring the control if prediction reading has at least one no. of Offline washing
        for i2i=1:dz2
            disp ('Enter the period when you want to do thoose Off line washing one by one')
            i2i
            dy1(i2i).data = input ('off line washing');
        end
        %Transfer last set of Online washing and the determination of range of the prediction period
        sa=[v(k).data];sa1=sa(1,vm); ddz2=k+dz2+1; ddz1=k+1;
        %Determination of Prediction reading set for Online washing & their elements
        for sa2=ddz1:ddz2
            if sa2 < ddz2

```


APPENDIX – B5

Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

    xa=sa1;xa1=dy2; xa2=dy1(sa2+1-ddz1).data;
    sb(sa2).data=[xa:xa1:xa2]; sa1=xa2;
    else
        sb(sa2).data=[sa1:xa1:dz1];
    end
end
else
    %Setting the prediction reading set range if there is no offline washing during this period
    sa=[v(k).data];sa1=sa(1,vm); sa2=k+1; sb(sa2).data=[sa1:dy2:dz1];
end
    yx1=ux1+dz2;
%Analysing the effects of Off-line washing
if u2 >= ux1
    fr1=ux1;
else
    fr1=ux1-1;
end
disp ('Analysing the effects of Off-line washing')
%Clubing the Offline washing EOH Periods into single matrix
for ri= 1:u2
    pt12(ri)=v1(ri).data
end
% Clubbing the Offline washing Targets into single matrix
for ai=1:u2
    tt121=s1(ai).data;
    for aj=1:u1u
        tt12(aj,ai)=tt121(aj,1)
    end
end
pt22=pt12; tt22=tt12; q1=pt22(1,1);
%Preprocessing the inputs using the Mean and Standard deviation methods
[ptn1,meanpt1,stdpt1,ttn1,meantt1,stdtt1]=prestd(pt22,tt22);
%Determination of maximum and minimum values of the inputs(EOH values)
uq1=size(ptn1);uq2=ptn1(1,1);uq3=uq1(1,2);uq4=ptn1(1,uq3)
%Creation of the feedforward network
net1=newff([uq2 uq4],[1,u1u],{'tansig','purelin'},'trainrp');
% net1=newff([uq2 uq4],[5,5,8,9,u1u],{'tansig','tansig','tansig','tansig','tansig'},'trainrp');
% {'tansig','tansig','tansig','tansig','tansig'},'traingdx');
% {'logsig','tansig','purelin','logsig','tansig','purelin','logsig','tansig','purelin'},'trainrp');
% {'purelin','purelin','purelin','purelin','purelin'},'trainrp');
% {'tansig','tansig','tansig','tansig','tansig','tansig','tansig','tansig','tansig'},'trainrp');
net1.trainParam.goal=1e-5; net1.trainParam.epochs=4500; net1.trainParam.show=100;
%Training of Network
net1=train(net1,ptn1,tt1);
disp ('The Network training has been completed. Hit any key to proceed with simulation with 1')
disp ('set of input from the training data');pause
Wn11=sim(net1,ptn1); W11=poststd(Wn11,meantt1,stdtt1);
%Starting of Simulation
Yn11=sim(net1,ptn1(:,1));
%Reverse normalisation process for the output Yn
Y11=poststd(Yn11,meantt1,stdtt1);
%Finding the residuals between the simulated output and the corresponding target values.
R11=Y11-tt22(:,1);
%Defining the variables which will be used for the plotting functions

```

APPENDIX – B5

Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

ww11=[1:1]
disp ('the simulation have been carried. Hit any key to churn out the deltas between the ')
disp (' simulated outputs and corresponding targets'); pause
plot(ww11,R11,'r*'), xlabel('Output parameter Designation')
ylabel('deltas'),title('Residual between simulated outputs and corresponding targets')
disp ('If you are satisfied with the performance of the network hit any key otherwise hit Esc');pause
disp ('Please enter the following input data for the desired engine simulation');
disp(' ')
% Transferring the Offline washing EOH value(Inputs)for which prediction to be made
if dz2~=0
jf=[dy1.data]
% Clubing of the Offline washing EOH (Inputs) values (actuals and predictions)
pnew11=[pt22 jf];
else
pnew11=[pt22];
end
%preprocessing the new inputs
pnewn11=trastd(pnew11,meantp1,stdpt1);
%Simulating the network
Ynewn11=sim(net1,pnewn11);
%Post Processing the Output
Ynew11=poststd(Ynewn11,meantt1,stdtt1)
disp ('The response of the engine to the given set of inputs are,');
%Offline washing EOH (Inputs) Matrix
pnew11
% Offline washing EHI Parameter Deviation (Targets)
Ynew11
subplot(2,2,1)
plot(pt22,tt22,'o',pnew11,Ynew11,'x');
%Analysing the Effects of On-line washing
disp ('Analysing the effects of On-line washing')
%Determination of total Online washing sets(actual+prediction)
u1=yx1+vx1; tj=1;fd=1;tj1=1;
for i=1:u1
txt=0
%Transferring the inputs(EOH) and targets(EHI Parameters deviation) of actual Online washing reading sets
if i <= ux1
pt=v(i).data; txt=s(i).data ; b=xx(i).data ; b1=pt(1,b)
xym2=[xm2(i).data]; xym1=[xm1(i).data]
else
% Transferring inputs (EOH) and targets (EHI Parameters deviation) for the prediction Online
% Washing set
pt=v(dx).data ; txt=s(dx).data ; b=xx(dx).data ; b1=pt(1,b)
xym2=[xm2(dx).data] ; xym1=[xm1(dx).data]
end
%Determination of Initial EOH matrix
p=pt(1,1); tx=0
%Creation of target matrix with initial target values in each rows
for xd1=1:xym2
for xd=1:xym1
tx(xd,xd1)=txt(xd,1);
end
end
end
tx; txt

```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```
%Normalising the Inputs and target by deducing their initial values
tt=txt-tx; pt=(pt-p);
%Preprocessing the inputs
ptn=0;meanpt=0;stdpt=0;ttn=0;meantt=0;stdtt=0;
[ptn,meanpt,stdpt,ttn,meantt,stdtt]=prestd(pt,tt);
    if i<ux1
        up1=size(ptn);up2=ptn(1,1);up3=up1(1,2);up4=ptn(1,up3);
    else
        up2=-1;up4=4
    end
%Creation of network
net=newff([up2 up4],[1,u1u],[ 'tansig','purelin'],'trainrp');
net.trainParam.goal=1e-5; net.trainParam.epochs=450; net.trainParam.show=5;
net=init(net);
%Training of Network
net=train(net,ptn,ttn);
disp ('The network training has been completed. Hit any key to proceed with simulation with ')
disp ('1 stset of input from the training data');pause
Wn=sim(net,ptn); W=poststd(Wn,meantt,stdtt);
%Starting of Simulation
Yn=sim(net,ptn(:,1));
%Reverse normalisation process for the output Yn
Y=poststd(Yn,meantt,stdtt);
%Finding the residuals between the simulated output and the corresponding target values.
R=Y-tt(:,1);
%Defining the variables which will be used for the plotting functions
ww=[1:1]
disp ('the simulation have been carried. Hit any key to churn out the deltas between the ')
disp ('simulated outputs and corresponding targets'); pause
plot(ww,R,'*'), xlabel('Output parameter Designation')
ylabel('deltas'),title('Residual between simulated outputs and corresponding targets')
disp ('If you are satisfied with the performance of the network hit any key otherwise hit Esc'); pause
disp ('Please enter the following input data for the desired engine simulation'); disp(' ')
%Transferring the actual inputs (EOH Matrix)
pnew=[pt];
%Preprocessing the inputs
pnewn=trastd(pnew,meanpt,stdpt)
%Simulating the network with new inputs
Ynewn=sim(net,pnewn);
%Normalising the outputs
Yxlnew=poststd(Ynewn,meantt,stdtt)
%Adding back the initial value deduced from the targets (for actual values)
    if i<= ux1
        Ynew=Yxlnew+tx; tt=txt+tx; pt=pt+p;
    else
        uxx1=ux1+1; lastloop=0; zq(tj).data=0; tz=0; tex1=0;
        if i>=uxx1
            % Storing the Last target values in temporary values
            zq(tj).data=s(dx).data; lastloop=zq(tj).data;
        end
        tk=tj-1; ent=size(lastloop);ent1=ent(1,2)
        % Creation of target values with initial target for equal no of Columns in the target matrix
        for ev1=1:ent1
            for ev2=1:xym1
```

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Gas turbine compressor health monitoring using Hybrid neural network model using

Prestd preprocessing technique

```

    tex1(ev2,ev1)=lastloop(ev2,ent1); tz(ev2,ev1)=txt(ev2,ent1);
end
end
tex1; tj=tj+1; Ynew=Yx1new+tex1;
%Adding back the initial value deduced from the targets and inputs (for prediction cycle)
tt=txt+tx; pt1=pnew+p; pt=pnew+pt1;
end
Ynew
pt
disp ('The response of the engine to the given set of inputs are,');
subplot(2,2,1)
plot(pt,tt,'o',pt,Ynew,'x');
%Creation of new inputs values for verifying the actual cycle (Online washing)
if i <= ux1
    ppnew1=(0:200:10000); aa=0;
    for a1=1:100
        pppnew1(a1)=ppnew1(1,a1);
        if pppnew1(a1)<=pt(1,b)
            aa=aa+1;
        end
    end
    aaa=ppnew1(1,aa); pnew1=(0:200:aaa);
else
    %Creation of new input values for prediction cycle (Online washing)
    pdnew=[sb(i).data]; pd=size(pdnew);pd1=pd(1,2); pnew1=(pdnew-pdnew(1,1));
end
%Preprocessing the new inputs
pnew1=trastd(pnew1,meanpt,stdpt); ds1=size(pnew1);ds2=ds1(1,2)
%Simulating the network
Ynewn1=sim(net,pnew1);
%Normalising the network
Yx2new1=poststd(Ynewn1,meantt,stdtt);
%Adding back the initial value deduced from the targets (for actual values)
if i<=ux1
    tx1=0
    for xd1=1:ds2
        for xd=1:xym1
            tx1(xd,xd1)=txt(xd,1);
        end
    end
    Ynew1=Yx2new1+tx1; pnew1=pnew1+p;
else
    %Adding back the initial value deduced from the targets (for prediction cycle)
    tx1=0; uxx2=ux1+1; lastnetworktarget=0; tx1=0; zq1(tj1).data=0;
    %Storing the last target values in temporary variables
    if i>=uxx2
        zq1(tj1).data=s(dx).data; lastnetworktarget=zq1(tj1).data;
    end
    tk1=tj1-1; lst=size(Yx2new1);lst1=lst(1,2); lnt=size(lastnetworktarget);lnt1=lnt(1,2);
    % Creation of target values with initial target for equal no of columns in the target matrix
    for xd1=1:lst1
        for xd=1:xym1
            tx1(xd,xd1)=lastnetworktarget(xd,lnt1);
        end
    end
end

```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

end
tj1=tj1+1;
if i<=ux1
    Ynew1=Yx2new1+tx1;
else
    if i>ux1
        Ynew121=0; Ynew111=0;
% Picking the values of last column of target value in the previous Cycles and determining the new target values
        if i<=u1
            for sq=1:u1u
                fi=i-1; Ynew111(sq,1)=Ynew11(sq,fi);
            end
            zw=Ynew111; hd=size(Yx2new1);hd1=hd(1,2);
            for re1=1:hd1
                for re=1:u1u
                    Ynew121(re,re1)=Ynew111(re,1);
                end
            end
            Ynew121; Ynew1=Yx2new1+Ynew121;
        end
    end
end
end
%Adding the initial value to the input matrix (EOH matrix)
pnew1=pnew1+pdnew(1,1);
end
tx1;pnew1=pnew1;Ynew1=Ynew1
subplot(2,2,2)
plot(pt,tt,'o',pnew1,Ynew1,'x');
if i<=ux1
    pt=[pt+p]; pnew1=pnew1;
else
    pnew1=pnew1;
end
%Storing the inputs and outputs in array format for easy transfer of the Outputs away from the loop
if i<=ux1
    r(i).data=Ynew; q(i).data=pt
end
rr(i).data=Ynew1; qq(i).data=pnew1;ug1=size(pnew1); ug=ug1(1,2)
%Determination of slope for analyzing the effect of Online washing
for kk=1:xym1
    for j=1:ug
        pnew2(j)=pnew1(1,j); Ynew2(kk,j)=Ynew1(kk,j);
    end
    gg=aa-1;
    %Calculation of the slope value
    for jj=1:gg
        slope(kk,jj)=(Ynew2(kk,jj+1)-Ynew2(kk,jj))/(pnew2(jj+1)-pnew2(jj));
    end
end
end
%Transferring the slope value to matrix format
XX =[slope];
%Fitting the slope value in a normal distribution and determining its slope value
[a,bbb,cgc,ddd]=normfit(XX');
disp ('Ist column refers the target of 1st Online washing cycle and II column refers to the target of 2 cycle...
```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

and so on');

```

    meanvalue(i).data=a;   bx=a;
    for jx=1:u1u
        ax(jx,i)=bx(1,jx)
    end
    ax
    u2x=ux1+1;   u3x=ux1+2
    %Setting the base profile for the prediction cycles based on the user option (Based on the slope value)
    if i >=ux1
        if i<u1
            disp('Kindly select the type of washing profile from the above loop')
            dx = input('Choose the best washing profile sets ');
            disp ('The minimum EOH period is 0');
            disp ('The maximum EOH Period is ')
            dz1
        end
    end
end

```

end

% Transferring the actual Inputs from the Online washing loop to outside

ii=0;

for n=1:ux1

ee=q(n).data; ee1=size(ee); eee1=ee1(1,2);

for n1=1:eee1

ii=ii+1; rrr(ii).data=ee(1,n1);

end

end

ant=ii

for m=1:ant

g1(m)=rrr(m).data;

end

g1

%Transferring the actual Outputs from the Online washing loop to Outside

k=0;jk=1;k1=1;k2k=1;jj1=1;c1c=0;

for n=1:ux1

ff=r(n).data; a1a=size(ff); a2a=a1a(1,1);a3a=a1a(1,2);b1b=a3a; a3a=a3a+c1c

for j1=1:a2a

for j1j=k2k:a3a

d1(j1,j1j).data=ff(j1,jj1);

if jj1~=b1b

jj1=jj1;

else

jj1=0;

end

jj1=jj1+1;

end

end

k2k=a3a+1; c1c=a3a;

end

d2=size(d1); dd1=d2(1,1); dd2=d2(1,2); atn1=dd2;

for i=1:dd1

for j=1:atn1

f(i,j)=d1(i,j).data;

end

end

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

f;
%Transferring the New inputs (for Prediction purpose) from the Online washing loop to outside
ix=0;
for n2=1:u1
    ee11=qq(n2).data; ee12=size(ee11); eee11=ee12(1,2);
    for n3=1:eee11
        ix=ix+1; rrr1(ix).data=ee11(1,n3);
    end
end
for mg=1:ix
    gh(mg)=rrr1(mg).data;
end
gh;
%Transferring the values of the Predicted Outputs from the Online washing loop to outside
ka=0;jka=1;k1a=1;k2a=1;jjb1=1;c1b=0;
for n2=1:u1
    ff11=rr(n2).data; a1b=size(ff11); a2b=a1b(1,1);a3b=a1b(1,2);b1a=a3b; a3b=a3b+c1b
    for j1a=1:a2b
        for j1b=k2a:a3b
            d3(j1a,j1b).data=ff11(j1a,jjb1);
            if jjb1~=b1a
                jjb1=jjb1;
            else
                jjb1=0
            end
            jjb1=jjb1+1;
        end
    end
    k2a=a3b+1; c1b=a3b;
end
d4=size(d3); dd11=d4(1,1); dd22=d4(1,2);
for ik=1:dd11
    for jk=1:dd22
        fl(ik,jk)=d3(ik,jk).data;
    end
end
fl;
disp('The actual values of the network'); g1,f
disp('The interpolated values of the network');gh,fl
%Clubbing the Online washing analysis and Offline washing analysis
zx=[ g1 pt22; f tt22]; [zx1,idx]=sort(zx(1,:));zx=zx(:,idx); zy=[ gh pnew11; fl Ynew11];
[zy1,idx]=sort(zy(1,:));zy=zy(:,idx)
%Plotting the EOH parameter and EHI Parameters Deviation of actual and Predicted cycles
plot(zx(1,:),zx(2:u2u,:),'o',zy(1,:),zy(2:u2u,:),'x')
disp('Analyzing the output using PNN Network')
xp=input('Enter the starting point of the prediction cycle(EOH)');
%Transferring the inputs & outputs of the base reference cycle and prediction cycle
Qnew1=[zy(1,:)]; Anew1=[zy(2:u2u,:)]; pyt12=[0:2000:50000];
for vr=1:2
    switch vr
        case 1
            tyt12=[1 0.993 0.988 0.985 0.982 0.980 0.978 0.976 0.975 0.973 0.972 0.971 0.970 0.975...
                0.973 0.972 0.971 0.970 0.969 0.9685 0.968 0.9675 0.967 0.9665 0.966 0.967];
        case 2

```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

tyt12=[1 0.995 0.992 0.990 0.988 0.987 0.986 0.985 0.984 0.9835 0.983 0.982 0.980 .985...
0.984 0.983 0.982 0.981 0.981 0.9800 0.979 0.9790 0.979 0.9785 0.978 0.978];
end
pyt22=pyt12; tyt22=[1-tyt12]*(-100);
switch ulu
case 1
tyt22
case 2
tyt22=[tyt22;tyt22];
case 3
tyt22=[tyt22;tyt22;tyt22];
case 4
tyt22=[tyt22;tyt22;tyt22; tyt22];
case 5
tyt22=[tyt22;tyt22;tyt22;tyt22; tyt22];
case 6
tyt22=[tyt22;tyt22;tyt22;tyt22; tyt22; tyt22];
end
q1=pyt22(1,1);
%Preprocessing the inputs using the Mean and Standard deviation methods
[pytn1,meanpyt1,stdpyt1,tytn1,meantyt1,stdtyt1]=prestd(pyt22,tyt22);
%Determination of maximum and minimum values of the inputs(EOH values)
uq1=size(pytn1);uq2=pytn1(1,1);uq3=uq1(1,2);uq4=pytn1(1,uq3)
%Creation of the feedforward network
net3=newff([uq2 uq4],[1,u1u],{'tansig','purelin'},'trainrp');
net1.trainParam.goal=1e-5; net1.trainParam.epochs=4500; net1.trainParam.show=100;
%Training of Network
net3=train(net3,pytn1,tytn1);
disp('The network training has been completed. Hit any key to proceed with simulation with 1st ...
set of input from thee training data'); pause
Wyn11=sim(net3,pytn1); W11=poststd(Wyn11,meantyt1,stdtyt1);
%Starting of Simulation
Yyn11=sim(net3,pytn1(:,1));
%Reverse normalisation process for the output Yn
Yy11=poststd(Yyn11,meantyt1,stdtyt1);
%Finding the residuals between the simulated output and the corresponding target values.
Ry11=Yy11-tyt22(:,1);
%Defining the variables which will be used for the plotting functions
wyw11=[1:1]
disp('the simulation have been carried. Hit any key to churn out the deltas between the simulated ouputs ...
and corresponding targets'); pause
plot(wyw11,Ry11,'r*'), xlabel('Output parameter Designation')
ylabel('deltas'),title('Residual between simulated outputs and corresponding targets')
disp('If you are ssatisfied with the performance of the network hit any key otherwise hit Esc'); pause
disp('Please enter the following input data for the desired engine simulation'); disp(' ')
pynew11=[Qnew1];
%preprocessing the new inputs
pynewn11=trastd(pynew11,meanpyt1,stdpyt1);
%simulating the network
Yynewn11=sim(net3,pynewn11);
%Post Processing the Output
Yynewn11=poststd(Yynewn11,meantyt1,stdtyt1)
disp('The response of the engine to the given set of inputs are,');
%Offline washing EOH (Inputs) Matrix

```


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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

pynew11; pynew11;
% Offline washing EHI Parameter Deviation (Targets)
Yynew11; Qnew2=pynew11;
Anew2=Yynew11; rql(vr).data=tyt22
rc1(vr).data=Qnew2; rc2(vr).data=Anew2;
Qnew11=size(Anew1); Qnew12=Qnew11(1,1); Qnew13=Qnew11(1,2); Qnew14=Qnew13-Qnew12;
Rnew11=size(Anew2); Rnew12=Rnew11(1,1); Rnew13=Rnew11(1,2); Rnew14=Rnew13-Rnew12; dc=Qnew1;
dw=size(dc); dw1=dw(1,1); dw2=dw(1,2); ky=0;
for p=1 :dw2
    xg=dc(1,p); xu=(xg-xp);
    if xu >1
        ky=ky;
    else
        ky=ky+1;
    end
end
ky; QQnew1=Qnew1(:, ky:dw2,:); AAnew1=Anew1(:, ky:dw2,:); AAnew2=Anew2(:, ky:dw2,:);
%Fitting the base reference cycle and prediction cycle outputs in a normal distribution
[Qa,Qbbb,Qcgc,Qddd]=normfit(AAnew2');
[Ra,Rbbb,Rcgc,Rddd]=normfit(AAnew1');
%Determination of the mean from the distribution
disp('Design degradation value'); Referencemean=Qa
disp('Prediction degradation value'); Comparisonmean=Ra
% Determination of the limit values of the reference cycle from -50% to +50% of its own value)
EMQ5=(50/100)*Qa; EMQ4=(60/100)*Qa; EMQ3=(70/100)*Qa; EMQ2=(80/100)*Qa; EMQ1=(90/100)*Qa;
EMQ51=(55/100)*Qa; EMQ41=(65/100)*Qa; EMQ31=(75/100)*Qa; EMQ21=(85/100)*Qa;
EMQ11=(95/100)*Qa; EPQ5=(150/100)*Qa; EPQ4=(140/100)*Qa; EPQ3=(130/100)*Qa; EPQ2=(120/100)*Qa;
EPQ1=(110/100)*Qa; EPQ51=(145/100)*Qa; EPQ41=(135/100)*Qa; EPQ31=(125/100)*Qa;
EPQ21=(115/100)*Qa; EPQ11=(105/100)*Qa;
EQ1=Qa;
EQ= ([EMQ5; EMQ51; EMQ4; EMQ41; EMQ3; EMQ31; EMQ2; EMQ21; EMQ1; EMQ11;...
    EPQ11; EPQ1; EPQ21; EPQ2; EPQ31; EPQ3; EPQ41; EPQ4; EPQ51; EPQ5]);
Ra1=Ra'
TCC3=[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 ];
TC3=ind2vec(TCC3); %convert the target from integer to vector
net4=newpnn(EQ,TC3); %calling PNN Network Function
Yr3=sim(net4,EQ); %simulate network
YCC3=vec2ind(Yr3) %converting output back into index
Yr4=sim(net4,Ra1) %using user's input
Yr5=vec2ind(Yr4)
switch vr
    case 1
        disp('The comparison has been made against Guaranteed value')
    case 2
        disp('The comparison has been made against Expected value')
end
%To display output in terms of Engine classification
%*****
disp(' ');
switch Yr5
    case 1
        disp('50% Less than Base reference value');
    case 2
        disp('45% Less than Base reference value');

```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

case 3
    disp ('40% Less than Base reference value');
case 4
    disp ('35% Less than Base reference value');
case 5
    disp ('30% Less than Base reference value');
case 6
    disp ('25% Less than the Base reference value');
case 7
    disp ('20% Less than Base reference value');
case 8
    disp ('15% Less than Base reference value');
case 9
    disp ('10% Less than Base reference value');
case 10
    disp ('5% Less than Base reference value');
case 11
    disp ('0% Similar like the Base reference value');
case 12
    disp (' 5% Greater than base reference value');
case 13
    disp (' 10% Greater than base reference value');
case 14
    disp (' 15% Greater than base reference value');
case 15
    disp (' 20% Greater than base reference value');
case 16
    disp (' 25% Greater than base reference value');
case 17
    disp (' 30% Greater than base reference value');
case 18
    disp (' 35% Greater than base reference value');
case 19
    disp (' 40% Greater than base reference value');
case 20
    disp (' 45% Greater than base reference value');
case 21
    disp (' 50% Greater than base reference value');
end
end
Qnew21=[rc1(1).data]; Anew21=[rc2(1).data]; Qnew22=[rc1(2).data]; Anew22=[rc2(2).data];
tytt1=[rq1(1).data];tytt2=[rq1(2).data];
Qsnew1=Qnew1(:, ky:dw2,:); Asnew1=Anew21(:, ky:dw2,:); Asnew2=Anew22(:, ky:dw2,:);
rc=[Anew21;Anew22]; rd=[Asnew1;Asnew2];
plot(QQnew1,rd,'o',Qnew1,Anew1,'x');
plot(pyt22,tytt1,'o',pyt22,tytt2,'x');
mc=[tytt1;tytt2];
plot(pyt22,mc,'o',Qnew1,Anew1,'x');
pause;
plot(Qnew2,rc,'o',Qnew1,Anew1,'x');
pause;
disp('If you want to do Cost Analysis of prediction cycle kindly enter"1" and if not enter "0" ')
jx1 = input('Enter option for the cost analysis of the prediction cycle')
if jx1~=0 & jx1~=1

```

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Gas turbine compressor health monitoring using Hybrid neural network model using Prestd preprocessing technique

```

disp('The input entered for the prediction cycle is wrong')
end
if jx1 > 0
mj=input('Kindly enter the average load per hour(MW hr)');
uj1 = input('Enter the cost($/MW hr) of the production for the power generation');
uj2 = input('Enter the cost($/MW hr of Energy production)of the Fuel- Natural gas');
uj3=input('Enter the cost($$) of the Online washing=Chemical cost+ Manpower cost');
uj4=input('Enter the cost($$)of the Offline washing + Manual Cleaning of IGV Blade -Chemical cost + Manpower cost');
disp('The Opportunity lost cost($$) due to Offline washing + Manual Cleaning of IGV Blade');
uy1=input('The no of days the power generation has been lost because of IGV Blade cleaning and Offline washing');
disp('Two days of power generation were lost because of Manual Cleaning of IGV Blade+Offline washing');
uj5=(uj1-uj2)*24*uy1*mj
disp('Net cost spend($$) by doing Offline + IGV Blade cleaning'); uj6=uj5+uj4
disp('Net cost ($$)spent for doing Online washing'); uj3
disp('No of Online washing performed in the prediction period'); rf7=round(rf6)
disp('No of Offline washing performed in the prediction period') ;dz2
disp('Total Cost($$) spent for Online washing');hf1=rf7*uj3
disp('Total Cost($$) spent for Offline washing'); hf2=dz2*(uj4+uj5)
disp('Total Cost($$) spent for both Online washing + Offline washing');hf=hf1+hf2
er1=Qnew1(:, ky:dw2,:); er2=Anew1(:, ky:dw2,:); er3=Anew22(:, ky:dw2,:); er4=-(er3-er2);
plot(Qsnew1,rd,'o',Qnew1,Anew1,'x');
%Conversion of % Deviation to actual value
er5=mj*dy2*er4/100; wr1=size(er5);wr2=wr1(1,2); qr1=[er1];qr2=[er2;er3;er4]; wr=0;
for as=1:wr2
wr = wr+er5(1,as); end
disp('Cummulative (MW hr) of energy wasted with reference to the reference washing... profile');wr
disp('Cummulative amount($$)of cost wasted(-) or cost gained(+) because of the energy lost');wq1=wr*uj1
disp('Net amount of money($$) profitted(+) or Lost(-)due to the washing profile selected in the... prediction part');
wq2=wq1-hf
disp(' The end of the program');
end

```

Appendix C

APPENDIX - C1

Table 3.2

Compressor Polytropic and Isentropic efficiencies, Pressure ratio and CcPP Gross efficiency determination based on OEM corrections

Sno.	Description	Units	PAC Test Results									
1	Date		1/10/2002	1/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	12/4/2002	4/12/2002
2	Time		15-16	16-17	9:00-11:00	13-15	17-19	10.3-11	11.3-12	10.3-11	11.3-12	10.3-11
3	EOH	hours	3128.00	3128.00	3152.00	3152.00	3152.00	4860.00	4860.00	4860.00	4860.00	5652.00
General Thermal Properties	Compressor Inlet Temperature	Deg C	32.63	31.94	31.64	32.10	31.37	30.12	31.41	30.12	31.41	27.03
	Compressor Outlet Temperature	Deg C	430.49	429.71	419.65	409.83	379.79	390.76	393.52	390.76	393.52	400.40
	Compressor Outlet Pressure	Deg C	16.08	16.12	15.57	14.47	11.34	12.69	12.69	12.69	12.69	13.88
	Compressor Inlet pressure	Deg C	1008.67	1008.27	1012.15	1009.91	1008.02	1012.87	1012.60	1012.87	1012.60	1014.99
7	Relative Humidity	%	58.17	61.26	59.47	59.51	49.32	58.52	51.22	58.52	51.22	77.84
9	Condensor water Inlet Temperature	Deg C	30.00	30.00	30.00	30.00	30.00	30.02	30.13	30.02	30.13	29.06
10	Turbine Speed	Hz	49.99	50.00	49.99	49.98	50.02	50.02	50.00	50.02	50.00	49.95
11	Nitrogen Content	%Mole	0.54	0.53	0.54	0.58	0.59	0.34	0.34	0.59	0.34	0.31
12	Co2 content	%Mole	1.26	1.26	1.26	1.25	1.24	1.23	1.18	1.24	1.23	1.27
13	Methane Content	%Mole	93.15	93.11	92.93	92.76	92.40	93.39	93.47	92.40	93.39	93.01
14	Ethane Content	%Mole	3.15	3.17	3.31	3.37	3.56	3.29	3.26	3.56	3.29	3.63
15	Propane Content	%Mole	1.14	1.15	1.20	1.26	1.34	0.97	0.98	1.34	0.97	0.98
16	i-Butane content	%Mole	0.35	0.35	0.34	0.35	0.39	0.34	0.34	0.39	0.34	0.36
18	i-Pentane content	%Mole	0.09	0.09	0.09	0.09	0.10	0.10	0.10	0.10	0.10	0.11
19	N-Pentane content	%Mole	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
20	N-Hexane content	%Mole	0.05	0.05	0.05	0.05	0.05	0.06	0.06	0.05	0.06	0.07
21	N-Heptane content	%Mole	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00
22	N-Octane content	%Mole	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.03	0.01
23	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	Gas outlet pressure	bar	26.33	26.22	26.32	26.40	26.67	26.27	26.28	26.67	26.27	26.20
25	Fuel Gas Temperature	Deg C	33.24	32.38	32.21	34.55	31.39	26.24	27.38	31.39	26.24	25.94
26	Active Power	MW	367.37	368.64	345.99	315.99	222.02	264.98	265.05	222.02	264.98	296.75
27	Gen Reactive Power	Mvar	-5.78	-6.44	-16.55	-29.04	-29.65	-7.69	-7.96	-29.65	-7.69	-2.52
28	Gross Current	kA	9.71	9.75	9.19	8.42	5.95	7.19	7.19	5.95	7.19	8.03
29	Power Factor		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
30	Gross Voltage	kV	21.91	21.91	21.91	21.91	21.85	21.40	21.40	21.85	21.40	21.52
31	Field Current	A	2098.00	2100.30	1976.65	1817.04	1442.14	1672.56	1674.64	1442.14	1672.56	1818.08
32	Density calculated	kg/m3	19.12	19.11	19.23	19.15	19.71	19.60	19.47	19.71	19.60	19.60
33	Carbon/Hydrogen ratio of fuel gas		3.13	3.13	3.14	3.14	3.15	3.13	3.13	3.15	3.13	3.14
34	Calorific LCV Calculated	kJ/kg	47662.07	47664.16	47648.93	47626.86	47619.54	47856.12	47916.58	47619.54	47856.12	47818.82
35	Fuel Mass flow rate calculated	kg/s	13.22	13.21	12.47	11.53	8.64	10.01	9.99	8.64	10.01	11.08
36	Corrected fuel power input	MW	630.42	631.02	593.18	549.39	413.07	479.44	478.11	413.07	479.44	531.36
37	Generator Efficiency (%)	%	98.95	98.95	98.97	98.99	98.98	99.00	99.00	98.98	99.00	98.99
38	Power Generated at Coupling	MW	370.42	370.92	348.14	317.98	223.57	266.74	266.80	223.57	266.74	298.66
39	Corrected Gross Power(Pc) =	MW	374.22	373.44	348.97	320.14	225.01	265.38	267.50	225.01	265.38	291.53
40	Corrected Heat Rate	kJ-hr/kg	6127.79	6113.83	6140.40	6218.25	6624.96	6454.82	6454.09	6624.96	6454.82	6359.28
41	Thermal Efficiency from Cor Power Rate	%	59.39	59.29	58.75	58.28	54.66	55.39	55.88	54.66	55.39	55.05
42	Polytropic efficiency	%	92.36	92.35	92.62	92.06	88.60	90.01	89.99	88.60	90.01	90.23
43	Isentropic efficiency	%	89.09	89.07	89.50	88.81	84.40	86.14	86.12	84.40	86.14	86.31
44	Pressure Ratio	%	15.94	15.99	15.38	14.33	11.25	12.53	12.53	11.25	12.53	13.67

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Table 3.2

Compressor Polytropic and Isentropic efficiencies, Pressure ratio and CcPP Gross efficiency determination based on OEM corrections

Sno.	Description	Units	6/1/2003	11/2/2003	11/2/2003	13/2/2003	11/3/2003	11/3/2003	27/3/03	13/4/03	13/05/03	13/05/03	24/06/03
1	Date		12.3-13	9.30-10.0	10.55 -	13.15 to	8.30-9.00	12 -12.30	11.30-	20.15 to	9 - 9.30	12.30 -13	9.0 -9.30
2	Time		5654.00	6497.00	6498.00	6548.00	7328.00	7335.00	7732.50	8028.00	8767.00	8770.00	10009.60
3	EOH	hours											
4	Compressor Inlet Temperature	Deg C	28.00	28.62	30.11	30.95	28.00	30.84	30.01	27.54	29.50	30.79	28.31
5	Compressor Outlet Temperature	Deg C	398.68	408.86	410.74	420.13	411.06	414.66	427.72	411.32	422.06	420.72	427.31
6	Compressor Outlet Pressure	Deg C	13.39	14.38	14.11	14.84	14.38	14.26	15.16	14.72	15.12	14.84	15.56
7	Compressor Inlet pressure	Deg C	1014.36	1010.36	1010.52	1007.50	1010.40	1010.10	1010.59	1009.53	1008.50	1008.24	1008.09
8	Relative Humidity	%	66.74	71.73	62.89	55.89	75.68	61.50	59.03	83.25	70.53	59.40	79.61
9	Condensor water Inlet Temperature	Deg C	29.05	27.84	28.32	28.63	29.48	29.89	29.56	30.45	30.34	30.51	30.43
10	Turbine Speed	Hz	50.04	49.97	50.02	49.98	49.97	49.99	50.00	50.01	49.98	50.00	50.01
11	Nitrogen Content	%Mole	0.31	0.53	0.53	0.53	0.58	0.55	0.43	0.52	0.48	0.47	0.51
12	Co2 content	%Mole	1.27	1.16	1.16	1.23	1.29	1.31	1.28	1.23	1.29	1.29	1.22
13	Methane Content	%Mole	93.05	92.52	92.55	92.48	90.82	91.05	91.37	91.47	91.62	91.62	91.89
14	Ethane Content	%Mole	3.59	3.74	3.72	3.73	4.66	4.53	4.53	4.35	4.27	4.27	4.08
15	Propane Content	%Mole	0.98	1.16	1.16	1.16	1.54	1.47	1.35	1.40	1.41	1.40	1.36
16	i-Butane content	%Mole	0.36	0.42	0.42	0.41	0.35	0.52	0.47	0.49	0.40	0.41	0.43
18	i-Pentane content	%Mole	0.11	0.11	0.10	0.10	0.31	0.13	0.13	0.12	0.12	0.12	0.12
19	N-Pentane content	%Mole	0.05	0.05	0.05	0.05	0.07	0.06	0.06	0.06	0.06	0.06	0.06
20	N-Hexane content	%Mole	0.07	0.05	0.05	0.05	0.06	0.06	0.07	0.06	0.06	0.06	0.06
21	N-Heptane content	%Mole	0.00	0.03	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03
22	N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
23	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	Gas outlet pressure	bar	26.22	26.12	26.14	25.98	26.12	26.13	26.01	26.01	25.96	25.98	26.11
25	Fuel Gas Temperature	Deg C	27.50	26.97	28.27	33.54	31.15	32.22	33.04	29.97	28.10	29.82	26.39
26	Active Power	MW	282.92	307.79	299.38	318.46	308.18	306.47	327.04	318.38	327.15	320.77	336.40
27	Gen Reactive Power	Mvar	-9.85	-6.54	-6.03	-1.07	-15.33	-17.08	0.09	-4.00	-4.98	-8.66	-7.17
28	Gross Current	kA	7.66	8.13	7.89	8.52	8.35	8.28	8.78	8.55	8.78	8.59	9.15
29	Power Factor		1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00	1.00	1.00	1.00
30	Gross Voltage	kV	21.52	21.98	21.98	21.78	21.48	21.26	21.49	21.70	21.68	21.68	21.27
31	Field Current	A	1736.12	1853.23	1820.09	1913.33	1828.02	1815.67	1951.85	1900.59	1938.50	1902.24	1975.95
32	Density calculated	kg/m3	19.48	19.56	19.46	18.97	19.76	19.58	19.34	19.56	19.73	19.48	19.78
33	Carbon/Hydrogen ratio of fuel gas		3.14	3.14	3.14	3.15	3.18	3.18	3.17	3.17	3.16	3.17	3.16
34	Calorific LCV Calculated	kJ/kg	47818.68	47756.02	47760.43	47686.80	47505.85	47516.02	47644.03	47648.69	47612.12	47612.72	47672.56
35	Fuel Mass flow rate calculated	kg/s	10.61	11.41	11.10	11.72	11.57	11.58	12.32	11.80	12.12	11.90	12.55
36	Corrected fuel power input	MW	508.39	546.81	530.86	560.35	552.23	550.26	587.56	565.77	579.54	567.86	601.81
37	Generator Efficiency (%)	%	98.99	98.99	98.99	98.98	98.99	98.99	98.98	98.99	98.98	98.98	98.97
38	Power Generated at Coupling	MW	284.76	309.72	301.27	320.46	310.15	308.43	329.10	320.39	329.21	322.79	338.54
39	Corrected Gross Power(Pc) =												
39	CCPP	MW	279.30	305.14	298.97	320.79	305.56	308.52	327.64	315.18	327.62	323.70	334.28
40	Corrected Heat Rate	kJ-hr/Kg	6394.90	6326.38	6335.77	6284.91	6357.12	6409.83	6414.98	6282.12	6297.42	6306.25	6343.91
41	Thermal Efficiency from Cor Power Rate	%	55.07	56.01	56.38	57.39	55.58	56.08	55.80	56.08	56.75	57.13	55.86
42	Polytropic efficiency	%	89.66	90.72	90.28	90.82	90.13	90.26	89.87	90.75	90.58	90.64	90.30
43	Isentropic efficiency	%	85.58	86.94	86.35	87.02	86.10	86.30	85.66	86.94	86.67	86.77	86.21
44	Pressure Ratio	%	13.20	14.23	13.96	14.72	14.23	14.11	15.00	14.58	14.99	14.71	15.44

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Table 3.2

Compressor Polytropic and Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination based on OEM corrections

Sno.	Description	Units	24/06/03	25/7/03	30/7/03	18/8/03	18/03	15/9/03	15/9/03	26/09/03
1	Date		11.30-12.00	11.00-12.00	12.00-13.00	9-9.30	11.30-12.00	10-10.30	13.0-13.30	10-10.30
2	Time		10012.11	10518.00	10626.00	11319.00	11321.00	11992.00	11995.00	12255.70
3	EOH	hours								
4	Compressor Inlet Temperature	Deg C	29.82	30.23	30.73	28.80	30.78	28.80	30.36	29.10
5	Compressor Outlet Temperature	Deg C	429.72	433.91	427.90	416.44	422.55	420.68	422.33	418.69
6	Compressor Outlet Pressure	Deg C	15.53	15.73	15.64	14.98	15.23	15.26	15.15	14.99
7	Compressor Inlet pressure	Deg C	1008.32	1009.86	1010.17	1009.87	1009.95	1009.97	1009.06	1008.98
8	Relative Humidity	%	68.75	64.59	60.14	75.25	61.22	73.25	59.75	65.69
9	Condensor water Inlet Temperature	Deg C	30.61	29.84	29.79	29.67	29.83	30.03	29.89	29.15
10	Turbine Speed	Hz	50.00	49.99	50.02	49.99	50.01	49.96	50.00	49.97
11	Nitrogen Content	%Mole	0.52	0.47	0.54	0.51	0.50	0.45	0.45	0.44
12	Co2 content	%Mole	1.31	1.39	1.25	1.23	1.23	1.18	1.20	1.24
13	Methane Content	%Mole	91.53	88.81	91.46	91.02	91.04	92.27	92.15	92.29
14	Ethane Content	%Mole	4.21	6.05	4.33	4.72	4.71	3.89	3.95	3.79
15	Propane Content	%Mole	1.45	1.91	1.41	1.46	1.44	1.26	1.28	1.34
16	i-Butane content	%Mole	0.45	0.56	0.44	0.46	0.46	0.39	0.47	0.43
18	i-Pentane content	%Mole	0.12	0.18	0.12	0.14	0.15	0.11	0.11	0.11
19	N-Pentane content	%Mole	0.06	0.09	0.06	0.07	0.07	0.06	0.06	0.05
20	N-Hexane content	%Mole	0.06	0.09	0.06	0.07	0.07	0.05	0.06	0.05
21	N-Heptane content	%Mole	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03
22	N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.08	0.01	0.01
23	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	Gas outlet pressure	bar	26.10	25.99	25.99	26.00	25.97	25.97	25.99	25.99
25	Fuel Gas Temperature	Deg C	27.63	30.84	31.68	29.48	31.21	29.83	31.15	29.54
26	Active Power	MW	335.39	346.51	343.38	325.99	332.02	332.74	330.27	324.94
27	Gen Reactive Power	Mvar	4.91	31.29	207.20	66.33	68.37	35.87	32.54	45.12
28	Gross Current	kA	8.95	9.34	10.50	8.85	9.03	8.93	8.85	8.73
29	Power Factor		1.00	0.99	0.86	0.98	0.98	0.99	0.99	0.98
30	Gross Voltage	kV	21.69	21.49	22.13	21.70	21.68	21.66	21.66	21.78
31	Field Current	A	2007.66	2138.54	2979.26	2197.73	2232.73	2105.33	2084.95	2108.63
32	Density calculated	kg/m3	19.78	20.19	19.38	19.70	19.54	19.35	19.27	19.36
33	Carbon/Hydrogen ratio of fuel gas		3.17	3.22	3.17	3.18	3.18	3.16	3.16	3.15
34	Calorific LCV Calculated	kJ/kg	47555.61	47400.66	47603.57	47639.27	47640.04	47755.56	47755.56	47720.57
35	Fuel Mass flow rate calculated	kg/s	12.51	13.00	12.57	12.07	12.30	12.32	12.20	11.97
36	Corrected fuel power input	MW	596.56	616.58	598.22	576.71	585.46	589.85	583.18	572.70
37	Generator Efficiency (%)	%	98.97	98.97	98.97	98.98	98.97	98.98	98.98	98.98
38	Power Generated at Coupling	MW	337.49	348.70	345.85	328.07	335.13	334.83	332.35	322.99
39	Corrected Gross Power(P _c) = [(P+P ₆ /1000)*(P1*P2*P3*P5)*P4]	MW	336.05	347.48	345.40	324.29	334.84	331.24	331.77	320.22
40	Corrected Heat Rate	kJ-hr/kg	6331.99	6350.63	6221.15	6294.04	6282.59	6308.57	6302.22	6349.71
41	Thermal Efficiency from Cor Power Rate	%	56.50	56.39	57.71	56.40	57.17	56.29	56.94	56.08
42	Polytropic efficiency	%	90.35	90.20	91.13	90.92	91.17	90.83	90.90	90.69
43	Isentropic efficiency	%	86.29	86.06	87.39	87.15	87.48	86.99	87.11	86.83
44	Pressure Ratio	%	15.40	15.58	15.48	14.83	15.08	15.11	15.02	14.85

APPENDIX - C1

Table 3.2

Compressor Polytropic and Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination based on OEM corrections

Sno.		Description	Units	7/10/2003	20/10/03	20/10/03	20/10/03	21/11/03	21/11/03	21/11/03	29/12/03	29/12/03	29/12/03	30/12/03	26/01/04
1		Date		8:40-9:10	9:3-10:0	11:3-12:0	11:3-12:0	8:00-8:30	8:00-8:30	13:13-30	8-8:30	11:00-11:30	11:00-11:30	8-8:30	10:30 - 11:30
2		Time		12:46:00	12:79:00	12:79:00	12:79:00	1:35:26:00	1:35:26:00	1:35:30:00	1:44:61:60	1:44:61:60	1:44:61:60	1:44:61:60	1:51:12:00
3		EOH	hours												
4	General Thermal Properties	Compressor Inlet Temperature	Deg C	27.37	27.96	29.88	29.88	25.62	25.62	25.56	26.06	29.34	29.34	25.55	25.46
5		Compressor Outlet Temperature	Deg C	414.41	414.18	418.22	418.22	413.13	413.13	411.66	414.47	421.20	421.20	413.51	407.80
6		Compressor Outlet Pressure	Deg C	15.19	14.98	15.07	15.07	15.20	15.20	14.97	15.05	15.10	15.10	15.16	14.45
7		Compressor Inlet pressure	Deg C	1011.26	1012.58	1012.95	1012.95	1011.62	1011.62	1011.40	1013.70	1013.60	1013.60	1013.53	1010.07
8	Fuel Gas Properties	Relative Humidity	%	78.94	77.25	64.98	64.98	85.88	85.88	81.93	79.52	61.17	61.17	83.12	84.91
9		Condensor water Inlet Temperature	Deg C	29.52	29.38	29.42	29.42	30.01	30.01	30.07	27.69	27.87	27.87	27.80	27.81
10		Turbine Speed	Hz	49.98	50.02	50.04	50.04	49.98	49.98	49.95	49.97	50.00	50.00	49.99	49.96
11		Nitrogen Content	%Mole	0.46	0.46	0.49	0.49	0.51	0.51	0.48	0.52	0.51	0.51	0.50	0.50
12	INPUTS	Co2 content	%Mole	1.20	1.20	1.20	1.20	0.87	0.87	0.86	1.17	1.17	1.17	1.13	1.15
13		Methane Content	%Mole	92.31	92.30	92.11	92.11	97.00	97.00	97.00	90.88	90.99	90.99	91.61	91.15
14		Ethane Content	%Mole	3.84	3.84	3.87	3.87	0.94	0.94	0.94	4.73	4.67	4.67	4.31	4.49
15		Propane Content	%Mole	1.27	1.31	1.41	1.41	0.43	0.43	0.44	1.55	1.53	1.53	1.40	1.60
16	Generator Details	i-Butane content	%Mole	0.42	0.39	0.39	0.39	0.18	0.18	0.18	0.48	0.47	0.47	0.44	0.46
17		i-Pentane content	%Mole	0.11	0.11	0.12	0.12	0.03	0.03	0.03	0.15	0.15	0.15	0.14	0.14
18		n-Pentane content	%Mole	0.06	0.06	0.06	0.06	0.01	0.01	0.01	0.08	0.08	0.08	0.07	0.07
19		n-Hexane content	%Mole	0.05	0.05	0.06	0.06	0.01	0.01	0.01	0.07	0.07	0.07	0.07	0.07
20	COMP	N-Heptane content	%Mole	0.03	0.03	0.03	0.03	0.01	0.01	0.01	0.03	0.03	0.03	0.03	0.03
21		N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
22		N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23		Gas outlet pressure	bar	25.98	26.01	25.98	25.98	26.15	26.15	26.18	26.18	26.16	26.16	26.17	26.14
24	Generator Details	Fuel Gas Temperature	Deg C	28.27	27.98	29.37	29.37	28.45	28.45	30.06	27.42	29.59	29.59	27.20	27.96
25		Active Power	MW	331.55	324.90	327.25	327.25	329.00	329.00	323.35	324.59	325.96	325.96	327.51	308.33
26		Gen Reactive Power	Mvar	18.59	36.55	35.84	35.84	23.16	23.16	18.83	47.55	50.20	50.20	50.80	45.67
27		Gross Current	kA	8.95	8.80	8.84	8.84	8.88	8.88	8.74	8.85	8.88	8.88	8.95	8.41
28	FUEL gas details	Power Factor		1.00	0.99	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99
29		Gross Voltage	kV	21.54	21.57	21.57	21.57	21.50	21.50	21.50	21.56	21.56	21.56	21.60	21.53
30		Field Current	A	2036.83	2070.22	2077.83	2077.83	2039.27	2039.27	2002.66	2111.44	2128.12	2128.12	2134.52	2038.60
31		Density calculated	kg/m3	19.42	19.49	19.41	19.41	18.25	18.25	18.16	20.08	19.85	19.85	19.87	19.93
32	FUEL gas details	Carbon/Hydrogen ratio of fuel gas		3.15	3.15	3.16	3.16	3.04	3.04	3.05	3.18	3.18	3.18	3.17	3.18
33		Calorific LCV Calculated	kJ/kg	47757.24	47759.00	47719.80	47719.80	48337.83	48337.83	48362.30	47691.74	47696.52	47696.52	47781.07	47727.87
34		Fuel Mass flow rate calculated	kg/s	12.24	12.05	12.13	12.13	12.05	12.05	11.85	12.08	12.10	12.10	12.15	11.76
35		Corrected fuel power input	MW	587.73	577.02	578.90	578.90	586.99	586.99	577.83	578.72	576.79	576.79	583.98	566.57
36	GEN	Generator Efficiency (%)	%	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.99
37		Power Generated at Coupling	MW	333.65	326.96	329.33	329.33	328.08	328.08	321.40	321.66	324.04	324.04	324.61	310.31
38		Corrected Gross Power(P _c) = [(P ₄ +P ₆ /1000)*(P ₁ *P ₂ *P ₃ *P ₅)*P ₄]	MW	327.65	321.16	327.15	327.15	318.38	318.38	312.18	312.36	320.17	320.17	314.40	301.41
39		Corrected Heat Rate	kJ-hr/Kg	6285.68	6316.70	6312.17	6312.17	6366.03	6366.03	6382.68	6419.04	6403.96	6403.96	6408.69	6485.61
40	CCPP	Thermal Efficiency from Cor Power Rate	%	56.04	55.83	56.54	56.54	54.66	54.66	54.46	54.23	55.47	55.47	54.14	53.69
41		Polytropic efficiency	%	91.17	90.90	91.14	91.14	90.76	90.76	90.49	90.31	90.46	90.46	90.53	89.95
42		Isentropic efficiency	%	87.49	87.13	87.45	87.45	86.90	86.90	86.55	86.28	86.50	86.50	86.58	85.85
43		Pressure Ratio	%	15.02	14.79	14.89	14.89	15.02	15.02	14.80	14.85	14.90	14.90	14.96	14.31
44															

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Table 3.2

Compressor Polytropic and Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination based on OEM corrections

Sno.	Description	Units	26/01/04	28/02/04	14/03/04	21/04/04	22/04/04	17/05/04	17/05/04
1	Date		12:00-12:30	10:00-10:30	10:00-10:30	10:00-10:30	15:30-16:30	10:00-10:30	14:00-14:30
2	Time		15:13:00	15:09:50	16:51:00	17:56:10	17:58:16	18:18:00	18:18:00
3	EOH	hours							
4	Compressor Inlet Temperature	Deg C	26.33	27.96	28.94	30.39	28.74	31.23	32.99
5	Compressor Outlet Temperature	Deg C	412.02	418.41	409.97	428.27	425.25	430.26	432.50
6	Compressor Outlet Pressure	Deg C	14.57	14.76	14.56	15.49	15.50	15.41	15.27
7	Compressor Inlet pressure	Deg C	1009.04	1010.20	1012.28	1010.43	1004.66	1009.30	1007.18
8	Relative Humidity	%	79.62	65.26	67.13	60.79	68.55	67.51	59.66
9	Condensor water Inlet Temperature	Deg C	27.86	28.41	28.83	30.43	30.70	31.23	31.26
10	Turbine Speed	Hz	50.08	50.00	49.97	50.00	49.98	50.02	49.99
11	Nitrogen Content	%Mole	0.50	0.49	0.75	0.51	0.49	0.52	0.52
12	Co2 content	%Mole	1.15	1.18	0.97	1.02	1.04	1.14	1.14
13	Methane Content	%Mole	91.14	90.75	89.95	92.37	92.30	92.39	92.29
14	Ethane Content	%Mole	4.49	4.85	5.05	3.84	3.93	3.72	3.78
15	Propane Content	%Mole	0.46	0.48	0.57	0.40	0.39	0.42	0.44
16	I-Butane content	%Mole	1.60	1.55	1.97	1.30	1.29	1.31	1.34
18	I-Pentane content	%Mole	0.14	0.15	0.15	0.12	0.12	0.11	0.11
19	N-Pentane content	%Mole	0.07	0.08	0.09	0.06	0.06	0.05	0.05
20	N-Hexane content	%Mole	0.07	0.08	0.06	0.06	0.06	0.05	0.05
21	N-Heptane content	%Mole	0.03	0.03	0.02	0.02	0.03	0.03	0.02
22	N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.01	0.01
23	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	Gas outlet pressure	bar	26.11	26.09	25.99	25.91	25.94	25.91	25.92
25	Fuel Gas Temperature	Deg C	28.72	29.51	29.92	30.15	29.20	30.67	31.93
26	Active Power	MW	311.21	315.16	315.19	338.05	338.73	334.36	330.98
27	Gen Reactive Power	Mvar	44.50	27.94	44.75	19.67	23.28	58.25	51.58
28	Gross Current	kA	8.48	8.49	8.42	8.87	8.89	9.06	8.94
29	Power Factor		0.99	1.00	0.99	1.00	1.00	0.99	0.99
30	Gross Voltage	kV	21.53	21.59	21.79	22.15	22.15	21.67	21.67
31	Field Current	A	2042.36	2002.68	2061.83	2062.61	2078.77	2188.99	2151.09
32	Density calculated	kg/m3	19.85	19.84	19.94	19.22	19.32	19.18	19.13
33	Carbon/Hydrogen ratio of fuel gas		3.19	3.20	3.22	3.16	3.16	3.16	3.76
34	Calorific LCV Calculated	kJ/kg	47691.25	47656.38	47663.86	47898.18	47888.02	47749.91	47750.46
35	Fuel Mass flow rate calculated	kg/s	11.83	11.96	11.74	12.47	12.49	12.42	12.28
36	Corrected fuel power input	MW	569.11	572.19	560.58	597.70	603.80	593.06	586.20
37	Generator Efficiency (%)	%	98.99	98.99	98.99	98.97	98.97	98.97	98.98
38	Power Generated at Coupling	MW	313.21	317.16	317.18	340.13	340.82	336.48	333.08
39	Corrected Gross Power(P _c) = [(P+P6/1000)*(P1*P2*P3*P5)*P4]	MW	305.40	312.26	313.62	339.62	339.45	337.04	337.55
40	Corrected Heat Rate	kJ-hr/kg	6460.70	6451.95	6335.75	6311.36	6307.56	6333.43	6336.43
41	Thermal Efficiency from Cor Power Rate	%	54.13	54.80	56.05	56.86	56.73	56.84	57.55
42	Polytropic efficiency	%	89.88	89.79	91.02	90.64	90.75	90.47	90.49
43	Isentropic efficiency	%	85.73	85.59	87.34	86.71	86.85	86.47	86.52
44	Pressure Ratio	%	14.44	14.61	14.39	15.33	15.42	15.27	15.17

Table 3.3
Compressor Polytropic, Isentropic efficiencies, Pressure ratio and CCPP Gross efficiency determination using STD Corrections

Sno.	Description	Units	PAC Test Results											
1	Date		1/10/2002	1/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	2/10/2002	12/4/2002	4/12/2002
2	Time		15-16	16-17	9:00-11:00	3152.00	3152.00	3152.00	3152.00	3152.00	3152.00	3152.00	10.3-11	11.3-12
3	EOH	hours	3128.00	3128.00	3128.00	3128.00	3128.00	3128.00	3128.00	3128.00	3128.00	3128.00	4860.00	4862.00
4	Compressor Inlet Temperature	Deg C	32.63	429.71	31.94	31.64	31.64	31.64	31.64	31.64	31.64	31.64	390.76	393.52
5	Compressor Outlet Temperature	Deg C	430.49	429.71	419.65	419.65	419.65	419.65	419.65	419.65	419.65	419.65	390.76	393.52
6	Compressor Outlet Pressure	Deg C	16.08	16.12	15.57	15.57	15.57	15.57	15.57	15.57	15.57	15.57	12.69	12.69
7	Ambient Pressure	Deg C	1009.77	1009.38	1013.22	1013.22	1013.22	1013.22	1013.22	1013.22	1013.22	1013.22	1013.62	1013.35
8	Condensor water Inlet Temperature	Deg C	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.00	30.02	30.13
9	Turbine Speed	Hz	49.99	50.00	49.99	49.99	49.99	49.99	49.99	49.99	49.99	49.99	50.02	50.00
10	Nitrogen Content	%Mole	0.54	0.53	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.54	0.34	0.34
11	Co2 content	%Mole	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.26	1.23	1.18
12	Methane Content	%Mole	93.15	93.11	92.93	92.93	92.93	92.93	92.93	92.93	92.93	92.93	93.39	93.47
13	Ethane Content	%Mole	3.15	3.17	3.31	3.31	3.31	3.31	3.31	3.31	3.31	3.31	3.29	3.26
14	Propane Content	%Mole	1.14	1.15	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	0.97	0.98
15	I-Butane content	%Mole	0.35	0.35	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34	0.34
16	N-Butane content	%Mole	0.19	0.20	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
17	I-Pentane content	%Mole	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.10	0.10
18	N-Pentane content	%Mole	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
19	N-Hexane content	%Mole	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.06	0.06
20	N-Heptane content	%Mole	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
21	N-Octane content	%Mole	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03
22	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	Gas outlet pressure	bar	26.33	26.22	26.32	26.32	26.32	26.32	26.32	26.32	26.32	26.32	26.27	26.28
24	Fuel Gas Temperature	Deg C	33.24	32.38	32.21	32.21	32.21	32.21	32.21	32.21	32.21	32.21	26.24	27.38
25	Active Power	MW	367.37	368.64	345.99	345.99	345.99	345.99	345.99	345.99	345.99	345.99	264.98	265.05
26	Gen Reactive Power	Mvar	-5.78	-6.44	-16.55	-16.55	-16.55	-16.55	-16.55	-16.55	-16.55	-16.55	-7.69	-7.96
27	Gross Current	kA	9.71	9.75	9.19	9.19	9.19	9.19	9.19	9.19	9.19	9.19	7.19	7.19
28	Power Factor		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
29	Gross Voltage	kV	21.91	21.91	21.91	21.91	21.91	21.91	21.91	21.91	21.91	21.91	21.40	21.40
30	Field Current	A	2098.00	2100.30	1976.65	1976.65	1976.65	1976.65	1976.65	1976.65	1976.65	1976.65	1672.56	1674.64
31	Density calculated	kg/m3	19.12	19.11	19.23	19.23	19.23	19.23	19.23	19.23	19.23	19.23	19.60	19.47
32	Carbon/Hydrogen ratio of fuel gas		3.13	3.13	3.14	3.14	3.14	3.14	3.14	3.14	3.14	3.14	3.13	3.13
33	Calorific LCV Calculated	kJ/kg	47662.07	47664.16	47648.93	47648.93	47648.93	47648.93	47648.93	47648.93	47648.93	47648.93	47856.12	47916.58
34	Fuel Mass flow rate calculated	kg/s	13.22	13.21	12.47	12.47	12.47	12.47	12.47	12.47	12.47	12.47	10.01	9.99
35	Corrected fuel power input	MW	630.42	631.02	593.18	593.18	593.18	593.18	593.18	593.18	593.18	593.18	479.44	478.11
36	Generator Efficiency (%)	%	98.95	98.95	98.97	98.97	98.97	98.97	98.97	98.97	98.97	98.97	99.00	99.00
37	Power Generated at Coupling	MW	370.42	370.92	348.14	348.14	348.14	348.14	348.14	348.14	348.14	348.14	266.74	266.80
38	Corrected Gross Power Output	MW	371.31	372.38	348.36	348.36	348.36	348.36	348.36	348.36	348.36	348.36	267.48	267.09
39	Corrected Heat Rate	kJ-Hr/Kg	6112.09	6100.43	6140.40	6140.40	6140.40	6140.40	6140.40	6140.40	6140.40	6140.40	6454.82	6454.09
40	Thermal Efficiency from Cor Power	%	58.90	59.01	58.73	58.73	58.73	58.73	58.73	58.73	58.73	58.73	55.79	55.86
41	Polytropic efficiency	%	92.36	92.35	92.62	92.62	92.62	92.62	92.62	92.62	92.62	92.62	90.01	89.99
42	Isentropic efficiency	%	89.09	89.07	89.50	89.50	89.50	89.50	89.50	89.50	89.50	89.50	86.14	86.14
43	Pressure Ratio	%	15.94	15.99	15.38	15.38	15.38	15.38	15.38	15.38	15.38	15.38	12.53	12.53

APPENDIX C2

Table 3.3
Compressor Polytropic, Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination using STD Corrections

Sno.	Description	Units	6/1/2003	11/2/2003	11/2/2003	13/2/03	11/3/2003	11/3/2003	27/3/03	13/4/03
1	Date									
2	Time		10.3-11	12.3-13	9.30-10.0	10.55 -	13.15 to	8.30-9.00	11.30-12.00	20.15 to 22.30
3	EOH	hours	5652.00	5654.00	6497.00	6498.00	6548.00	7328.00	7335.00	8028.00
4	Compressor Inlet Temperature	Deg C	27.03	28.00	28.62	30.11	30.95	28.00	30.84	30.01
5	Compressor Outlet Temperature	Deg C	400.40	398.68	408.86	410.74	420.13	411.06	414.66	427.72
6	Compressor Outlet Pressure	Deg C	13.88	13.39	14.38	14.11	14.84	14.38	14.26	15.16
7	Ambient Pressure	Deg C	1016.20	1015.46	1013.10	1013.21	1010.46	1013.32	1012.94	1013.84
8	Condensor water Inlet Temperature	Deg C	29.06	29.05	27.84	28.32	28.63	29.48	29.89	29.56
9	Turbine Speed	Hz	49.95	50.04	49.97	50.02	49.98	49.97	49.99	50.00
10	Nitrogen Content	%Mole	0.31	0.31	0.53	0.53	0.53	0.58	0.55	0.43
11	Co2 content	%Mole	1.27	1.27	1.16	1.16	1.23	1.29	1.31	1.28
12	Methane Content	%Mole	93.01	93.05	92.52	92.55	92.48	90.82	91.05	91.37
13	Ethane Content	%Mole	3.63	3.59	3.74	3.72	3.73	4.66	4.53	4.35
14	Propane Content	%Mole	0.98	0.98	1.16	1.16	1.16	1.54	1.47	1.35
15	I-Butane content	%Mole	0.36	0.36	0.42	0.42	0.41	0.35	0.52	0.47
16	N-Butane content	%Mole	0.19	0.19	0.22	0.22	0.23	0.29	0.28	0.26
17	I-Pentane content	%Mole	0.11	0.11	0.11	0.10	0.10	0.31	0.13	0.12
18	N-Pentane content	%Mole	0.05	0.05	0.05	0.05	0.05	0.07	0.06	0.06
19	N-Hexane content	%Mole	0.07	0.07	0.05	0.05	0.05	0.06	0.06	0.06
20	N-Heptane content	%Mole	0.00	0.00	0.03	0.03	0.03	0.03	0.03	0.03
21	N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
22	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	Gas outlet pressure	bar	26.20	26.22	26.12	26.14	25.98	26.12	26.13	26.01
24	Fuel Gas Temperature	Deg C	25.94	27.50	26.97	28.27	33.54	31.15	32.22	33.04
25	Active Power	MW	296.75	282.92	307.79	299.38	318.46	308.18	306.47	327.04
26	Gen Reactive Power	Mvar	-2.52	-9.85	-6.54	-6.03	-1.07	-15.33	-17.08	0.09
27	Gross Current	kA	8.03	7.66	8.13	7.89	8.52	8.35	8.28	8.78
28	Power Factor		1.00	1.00	1.00	1.00	1.00	0.99	0.99	1.00
29	Gross Voltage	kV	21.52	21.52	21.98	21.98	21.78	21.48	21.26	21.49
30	Field Current	A	1818.08	1736.12	1853.23	1820.09	1913.33	1828.02	1815.67	1951.85
31	Density calculated	kg/m3	19.60	19.48	19.56	19.46	18.97	19.76	19.58	19.34
32	Carbon/Hydrogen ratio of fuel gas		3.14	3.14	3.14	3.14	3.15	3.18	3.18	3.17
33	Calorific LCV Calculated	kJ/kg	47818.82	47818.68	47756.02	47760.43	47686.80	47505.85	47516.02	47644.03
34	Fuel Mass flow rate calculated	kg/s	11.08	10.61	11.41	11.10	11.72	11.57	11.58	12.32
35	Corrected fuel power input	MW	531.36	508.39	546.81	530.86	560.35	552.23	550.26	567.56
36	Generator Efficiency (%)	%	98.99	98.99	98.99	98.99	98.98	98.99	98.99	98.99
37	Power Generated at Coupling	MW	298.66	284.76	309.72	301.27	320.46	310.15	308.43	329.10
38	Corrected Gross Power Output	MW	299.87	285.64	310.70	301.58	321.37	311.97	309.07	329.81
39	Corrected Heat Rate	kJ-Hr/Kg	6359.28	6394.90	6326.38	6335.77	6284.91	6357.12	6409.83	6282.12
40	Thermal Efficiency from Cor Power	%	56.43	56.19	56.82	56.81	57.35	56.49	56.17	56.13
41	Polytropic efficiency	%	90.23	89.66	90.72	90.28	90.82	90.13	90.26	89.87
42	Isentropic efficiency	%	86.31	85.58	86.94	86.35	87.02	86.10	86.30	85.66
43	Pressure Ratio	%	13.67	13.20	14.23	13.96	14.72	14.23	14.11	15.00

APPENDIX C2

Table 3.3
Compressor Polytropic, Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination using STD Corrections

Sno.	Description	Units	13/05/03	13/05/03	24/06/03	24/06/03	25/7/03	30/7/03	18/8/03	18/8/03	15/9/03
1	Date		13/05/03	13/05/03	24/06/03	24/06/03	25/7/03	30/7/03	18/8/03	18/8/03	15/9/03
2	Time		9 - 9.30	12.30 - 13	9.0 - 9.30	11.30-12.00	11.00-12.00	12.00-13.00	9-9.30	11.30-12.00	10 -10.30
3	EOH	hours	8767.00	8770.00	10009.60	10012.11	10518.00	10626.00	11319.00	11321.00	11992.00
4	Compressor Inlet Temperature	Deg C	29.50	30.79	28.31	29.82	30.23	30.73	28.80	30.78	28.80
5	Compressor Outlet Temperature	Deg C	422.06	420.72	427.31	429.72	433.91	427.90	416.44	422.55	420.68
6	Compressor Outlet Pressure	Deg C	15.12	14.84	15.56	15.53	15.73	15.64	14.98	15.23	15.26
7	Ambient Pressure	Deg C	1011.42	1011.05	1011.65	1011.90	1013.60	1013.90	1013.47	1013.73	1014.09
8	Condensor water Inlet Temperature	Deg C	30.34	30.51	30.43	30.61	29.84	29.79	29.67	29.83	30.03
9	Turbine Speed	Hz	49.98	50.00	50.01	50.00	49.99	50.02	49.99	50.01	49.96
10	Nitrogen Content	%Mole	0.48	0.47	0.51	0.52	0.47	0.54	0.51	0.50	0.45
11	Co2 content	%Mole	1.29	1.29	1.22	1.31	1.39	1.25	1.23	1.23	1.18
12	Methane Content	%Mole	91.62	91.62	91.89	91.53	88.81	91.46	91.02	91.04	92.27
13	Ethane Content	%Mole	4.27	4.27	4.08	4.21	6.05	4.33	4.72	4.71	3.89
14	Propane Content	%Mole	1.41	1.40	1.36	1.45	1.91	1.41	1.46	1.44	1.26
15	I-Butane content	%Mole	0.40	0.41	0.43	0.45	0.56	0.44	0.46	0.46	0.39
16	N-Butane content	%Mole	0.24	0.25	0.24	0.26	0.40	0.29	0.30	0.30	0.24
17	I-Pentane content	%Mole	0.12	0.12	0.12	0.12	0.18	0.12	0.14	0.15	0.11
18	N-Pentane content	%Mole	0.06	0.06	0.06	0.06	0.09	0.06	0.07	0.07	0.06
19	N-Hexane content	%Mole	0.06	0.06	0.06	0.06	0.09	0.06	0.07	0.07	0.05
20	N-Heptane content	%Mole	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03
21	N-Octane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.08
22	N-Nonane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	Gas outlet pressure	bar	25.96	25.98	26.11	26.10	25.99	25.99	26.00	25.97	25.97
24	Fuel Gas Temperature	Deg C	28.10	29.82	26.39	27.63	30.84	31.68	29.48	31.21	29.83
25	Active Power	MW	327.15	320.77	336.40	335.39	346.51	343.38	325.99	333.02	332.74
26	Gen Reactive Power	Mvar	-4.98	-8.66	-7.17	4.91	31.29	207.20	66.33	68.37	35.87
27	Gross Current	kA	8.78	8.59	9.15	8.95	9.34	10.50	8.85	9.03	8.93
28	Power Factor		1.00	1.00	1.00	1.00	0.99	0.86	0.98	0.98	0.99
29	Gross Voltage	kV	21.68	21.68	21.27	21.69	21.49	22.13	21.70	21.68	21.66
30	Field Current	A	1938.50	1902.24	1975.95	2007.66	2138.54	2979.26	2197.73	2232.73	2105.33
31	Density calculated	kg/m3	19.73	19.48	19.78	19.78	20.19	19.38	19.70	19.54	19.35
32	Carbon/Hydrogen ratio of fuel gas	kJ/kg	3.16	3.17	3.16	3.17	3.22	3.17	3.18	3.18	3.16
33	Calorific LCV Calculated	kg/s	47612.12	47612.72	47672.56	47555.61	47400.66	47603.57	47639.27	47640.04	47776.61
34	Fuel Mass flow rate calculated	MW	12.12	11.90	12.55	12.51	13.00	12.57	12.07	12.30	12.32
35	Corrected fuel power input	%	579.54	567.86	601.81	596.56	616.58	598.22	576.71	585.46	589.85
36	Generator Efficiency (%)		98.98	98.98	98.97	98.97	98.97	98.97	98.98	98.97	98.98
37	Power Generated at Coupling	MW	329.21	322.79	338.54	337.49	348.70	345.85	328.07	335.13	334.83
38	Corrected Gross Power Output	MW	331.31	324.36	341.17	339.19	349.59	346.34	329.60	335.64	336.32
39	Corrected Heat Rate	kJ-hr/Kg	6297.42	6306.25	6343.91	6331.99	6350.63	6221.15	6294.04	6282.59	6308.57
40	Thermal Efficiency from Cor Power	%	57.17	57.12	56.69	56.86	56.70	57.89	57.15	57.33	57.02
41	Polytropic efficiency	%	90.58	90.64	90.30	90.35	90.20	91.13	90.92	91.17	90.83
42	Isentropic efficiency	%	86.67	86.77	86.21	86.29	86.06	87.39	87.15	87.48	86.99
43	Pressure Ratio	%	14.99	14.71	15.44	15.40	15.58	15.48	14.83	15.08	15.11

APPENDIX C2

Table 3.3
Compressor Polytropic, Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination using STD Corrections

Sno.	Description	Units	15/9/03	26/09/03	7/10/2003	20/10/03	20/10/03	21/11/03	21/11/03	21/11/03	29/12/03	29/12/03
1	Date		13.0-13.30	10-10.3	8.40-9.10	9.3-10.0	11.3-12.0	8:00-8:30	13-13:30	13-13:30	8-8:30	11:00-11:30
2	Time		11995.00	12255.70	12469.00	12792.00	12794.00	13526.00	13530.00	13530.00	14461.60	14464.60
3	EOH	hours	30.36	29.10	27.37	27.96	29.88	25.62	25.56	25.56	26.06	29.34
4	Compressor Inlet Temperature	Deg C	422.33	418.69	414.41	414.18	418.22	413.13	411.66	411.66	414.47	421.20
5	Compressor Outlet Temperature	Deg C	15.15	14.99	15.19	14.98	15.07	15.20	14.97	14.97	15.05	15.10
6	Compressor Outlet Pressure	Deg C	1013.13	1013.03	1013.72	1014.88	1014.27	1014.14	1013.87	1013.87	1016.41	1016.46
7	Ambient Pressure	Deg C	29.89	29.15	29.52	29.38	29.42	30.01	30.07	30.07	27.69	27.87
8	Condensor water Inlet Temperature	Hz	50.00	49.97	49.98	50.02	50.04	49.98	49.95	49.95	49.97	50.00
9	Turbine Speed	%Mole	0.45	0.44	0.46	0.46	0.49	0.51	0.48	0.48	0.52	0.51
10	Nitrogen Content	%Mole	1.20	1.24	1.20	1.20	1.20	0.87	0.86	0.86	1.17	1.17
11	Co2 content	%Mole	92.15	92.29	92.31	92.30	92.11	97.00	97.00	97.00	90.88	90.99
12	Methane Content	%Mole	3.95	3.79	3.84	3.84	3.87	0.94	0.94	0.94	4.73	4.67
13	Ethane Content	%Mole	1.28	1.34	1.27	1.31	1.41	0.43	0.44	0.44	1.55	1.53
14	Propane Content	%Mole	0.47	0.43	0.42	0.39	0.39	0.18	0.18	0.18	0.48	0.47
15	I-Butane content	%Mole	0.24	0.23	0.24	0.25	0.26	0.04	0.04	0.04	0.35	0.34
16	N-Butane content	%Mole	0.11	0.11	0.11	0.11	0.12	0.03	0.03	0.03	0.15	0.15
17	I-Pentane content	%Mole	0.06	0.05	0.06	0.06	0.06	0.01	0.01	0.01	0.08	0.08
18	N-Pentane content	%Mole	0.06	0.05	0.05	0.05	0.06	0.01	0.01	0.01	0.07	0.07
19	N-Hexane content	%Mole	0.03	0.03	0.03	0.03	0.03	0.01	0.01	0.01	0.03	0.03
20	N-Heptane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01
21	N-Octane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	N-Nonane content	%Mole	25.99	25.99	25.98	26.01	25.98	26.15	26.18	26.18	26.18	26.16
23	Gas outlet pressure	bar	31.15	29.54	28.27	27.98	29.37	28.45	30.06	30.06	27.42	29.59
24	Fuel Gas Temperature	Deg C	330.27	324.94	331.55	324.90	327.25	329.00	323.35	323.35	324.59	325.96
25	Active Power	MW	32.54	45.12	18.59	36.55	35.84	23.16	18.83	18.83	47.55	50.20
26	Gen Reactive Power	Mvar	8.85	8.73	8.95	8.80	8.84	8.88	8.74	8.74	8.85	8.88
27	Gross Current	kA	0.99	0.98	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.99
28	Power Factor		21.66	21.78	21.54	21.57	21.57	21.50	21.50	21.50	21.56	21.56
29	Gross Voltage	kV	2084.95	2108.63	2036.83	2070.22	2077.83	2039.27	2002.66	2002.66	2111.44	2128.12
30	Field Current	A	19.27	19.36	19.42	19.49	19.41	18.25	18.16	18.16	20.08	19.85
31	Density calculated	kg/m3	3.16	3.15	3.15	3.15	3.16	3.04	3.05	3.05	3.18	3.18
32	Carbon/Hydrogen ratio of fuel gas	kJ/kg	47755.56	47720.57	47757.24	47759.00	47719.80	48337.83	48362.30	48362.30	47691.74	47696.52
33	Calorific LCV Calculated	kg/s	12.20	11.97	12.24	12.05	12.13	12.05	11.85	11.85	12.08	12.10
34	Fuel Mass flow rate calculated	MW	583.18	572.70	587.73	577.02	578.90	586.99	577.83	577.83	578.72	576.79
35	Corrected fuel power input	%	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98
36	Generator Efficiency (%)		332.35	322.99	333.65	326.96	329.33	328.08	321.40	321.40	321.66	324.04
37	Power Generated at Coupling	MW	333.28	324.27	336.04	328.37	330.13	331.28	324.68	324.68	322.98	323.65
38	Corrected Gross Power Output	kJ-hr/Kg	6302.22	6349.71	6285.68	6316.70	6312.17	6366.03	6382.68	6382.68	6419.04	6403.96
39	Corrected Heat Rate	%	57.15	56.62	57.18	56.91	57.03	56.44	56.19	56.19	55.81	56.11
40	Thermal Efficiency from Cor Power	%	90.90	90.69	91.17	90.90	91.14	90.76	90.49	90.49	90.31	90.46
41	Polytropic efficiency	%	87.11	86.83	87.49	87.13	87.45	86.90	86.55	86.55	86.28	86.50
42	Isentropic efficiency	%	15.02	14.85	15.02	14.79	14.89	15.02	14.80	14.80	14.85	14.90
43	Pressure Ratio											

APPENDIX C-2

Table 3.3
Compressor Polytropic, Isentropic efficiencies, Pressure ratio and C_{CPP} Gross efficiency determination using STD Corrections

Sno.	Description	Units	30/12/03	26/01/04	26/01/04	28/02/04	14/03/04	21/04/04	22/04/04	17/05/04	17/05/04
1	Date		8-8:30	10:30 -	12:00-12:30	10:00-10:30	10:00-10:30	10:00-10:30	15:30-16:30	10:00-10:30	14:00-14:30
2	Time		14488.00	15112.00	15113.00	15997.50	16510.00	17561.00	17589.64	18184.00	18188.00
3	EOH	hours	25.55	25.46	26.33	27.96	28.94	30.39	28.74	31.23	32.99
4	Compressor Inlet Temperature	Deg C	413.51	407.80	412.02	418.41	409.97	428.27	425.25	430.26	432.50
5	Compressor Outlet Temperature	Deg C	15.16	14.45	14.57	14.76	14.56	15.49	15.50	15.41	15.27
6	Compressor Outlet Pressure	Deg C	1016.30	1012.89	1011.90	1013.68	1014.42	1013.21	1007.44	1012.32	1010.23
7	Ambient Pressure	Deg C	27.80	27.81	27.86	28.41	28.83	30.43	30.70	31.23	31.26
8	Condensor water Inlet Temperature	Hz	49.99	49.96	50.08	50.00	49.97	50.00	49.98	50.02	49.99
9	Turbine Speed	Hz	0.50	0.50	0.50	0.49	0.75	0.51	0.49	0.52	0.52
10	Nitrogen Content	%Mole	1.13	1.15	1.15	1.18	0.97	1.02	1.04	1.14	1.14
11	Co2 content	%Mole	91.61	91.15	91.14	90.75	89.95	92.37	92.30	92.39	92.29
12	Methane Content	%Mole	4.31	4.49	4.49	4.85	5.05	3.84	3.93	3.72	3.78
13	Ethane Content	%Mole	1.40	1.60	0.46	0.48	0.57	0.40	0.39	0.42	0.44
14	Propane Content	%Mole	0.44	0.46	1.60	1.55	1.97	1.30	1.29	1.31	1.34
15	I-Butane content	%Mole	0.31	0.33	0.33	0.35	0.43	0.29	0.29	0.25	0.25
16	N-Butane content	%Mole	0.14	0.14	0.14	0.15	0.15	0.12	0.12	0.11	0.11
17	I-Pentane content	%Mole	0.07	0.07	0.07	0.08	0.09	0.06	0.06	0.05	0.05
18	N-Pentane content	%Mole	0.07	0.07	0.07	0.08	0.06	0.06	0.06	0.05	0.05
19	N-Hexane content	%Mole	0.03	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.02
20	N-Heptane content	%Mole	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
21	N-Octane content	%Mole	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	N-Nonane content	%Mole	26.17	26.14	26.11	26.09	25.99	25.91	25.94	25.91	25.92
23	Gas outlet pressure	bar	27.20	27.96	28.72	29.51	29.92	30.15	29.20	30.67	31.93
24	Fuel Gas Temperature	Deg C	327.51	308.33	311.21	315.16	315.19	338.05	338.73	334.36	330.98
25	Active Power	MW	50.80	45.67	44.50	27.94	44.75	19.67	23.28	58.25	51.58
26	Gen Reactive Power	Mvar	8.95	8.41	8.48	8.49	8.42	8.87	8.89	9.06	8.94
27	Gross Current	kA	0.99	0.99	0.99	1.00	0.99	1.00	1.00	0.99	0.99
28	Power Factor		21.60	21.53	21.53	21.59	21.79	22.15	22.15	21.67	21.67
29	Gross Voltage	kV	2134.52	2038.60	2042.36	2002.68	2061.83	2062.61	2078.77	2188.99	2151.09
30	Field Current	A	19.87	19.93	19.85	19.84	19.94	19.22	19.32	19.18	19.13
31	Density calculated	kg/m3	3.17	3.18	3.19	3.20	3.22	3.16	3.16	3.16	3.76
32	Carbon/Hydrogen ratio of fuel gas	kJ/kg	47781.07	47727.87	47691.25	47656.38	47663.86	47898.18	47888.02	47749.91	47750.46
33	Calorific LCV Calculated	kg/s	12.15	11.76	11.83	11.96	11.74	12.47	12.49	12.42	12.28
34	Fuel Mass flow rate calculated	MW	583.98	566.57	569.11	572.19	560.58	597.70	603.80	593.06	586.20
35	Corrected fuel power input	%	98.98	98.99	98.99	98.99	98.99	98.97	98.97	98.97	98.98
36	Generator Efficiency (%)		324.61	310.31	313.21	317.16	317.18	340.13	340.82	336.48	333.08
37	Power Generated at Coupling	MW	326.30	312.99	315.79	318.54	317.96	341.07	344.68	337.31	333.63
38	Corrected Gross Power Output		6408.69	6485.61	6460.70	6451.95	6335.75	6311.36	6307.56	6333.43	6336.43
39	Corrected Heat Rate	kJ-hr/Kg	55.87	55.24	55.49	55.67	56.72	57.06	57.09	56.88	56.92
40	Thermal Efficiency from Cor Power	%	90.53	89.95	89.88	89.79	91.02	90.64	90.75	90.47	90.49
41	Polytropic efficiency	%	86.58	85.85	85.73	85.59	87.34	86.71	86.85	86.47	86.52
42	Isentropic efficiency	%	14.96	14.31	14.44	14.61	14.39	15.33	15.42	15.27	15.17
43	Pressure Ratio										

APPENDIX – C3

Gas turbine compressor inlet air flow rate using combustion analysis

Load(MW)	236.08	262.07	276.3	223.75	125.53	128.55	188.865	141.64	94.432
Fuel Mass flow rate(kg/s)	12.703	13.68	14.263	12.27	8.223	8.313	10.74	8.843	6.711
Density at 0°C	0.717	0.717	0.717	0.717	0.717	0.717	0.717	0.717	0.717
Exhaust Gas Comp(wt%)									
Oxygen	13.823	14.192	14.128	13.473	14.257	14.648	14.105	14.513	16.156
Nitrogen	72.221	73.503	73.631	71.225	71.36	72.385	72.27	72.342	72.629
Arsenic	1.208	1.229	1.231	1.192	1.194	1.211	1.209	1.21	1.215
Carbon-dioxide	5.758	5.773	5.846	5.785	5.275	5.219	5.572	5.307	4.238
Water	6.992	5.303	5.166	8.325	7.914	6.557	6.843	6.628	5.762
Sulphur-Di-oxide	0	0	0	0	0	0	0	0	0
Ambient Conditions									
Temperature(°C)	32	15	5	40	40	32	32	32	32
RH(%)	0.8	0.6	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Press. (Bar)	1.013	1.013	1.013	1.013	1.013	1.013	1.013	1.013	1.013
Calculated air flow (By OEM) (kg/s)	597.821	641.91	660.77	574.302	423.276	432.667	522.607	452.45	432.74
Calculated air flow(kg/s) (Using Exhaust analysis& Matlab)	574.5	629.8	649.86	546.3	402	416	503.6	435.6	414.8
Percentage of Error	3.90	1.89	1.65	4.88	5.03	3.85	3.64	3.73	4.15

Table 3.5

Gas turbine compressor inlet air flow rate using combustion analysis

APPENDIX – C4

**Comparison of Indirect air flow calculation using
Mass and Energy balance method with OEM values**

Sno		Description	UNITS	By Manufacture		By using Matlab	
1	INPUTS	Ambient Temperature	Deg C	31.59	32	31.59	32
2		Flue Gas temperature	Deg C	599	601	599	601
3		Power Generated	MW	236.2	236.8	236.2	236.8
4		Type of Machine (V64.3 /v84.3/v94.3)	0,1,2	2	2	2	2
5		Relative Humidity	(%)	60.27	84.8	60.27	84.8
6		Compressor Outlet Temperature	Deg C	433.1	431.9	433.1	431.9
7		Cooling Air Temperature	Deg C	160	156	160	156
8		Mass flow rate of fuel	kg/s	13.251	13.758	13.251	13.758
9		Mass flow rate of Injection water	kg/s	0	0	0	0
10		Temperature of Injection Water	Deg C	0	0	0	0
11		Temperature of fuel gas	Deg C	30	28	30	28
12		Compressor Outlet Pressure	abs bar	15.93	15.9	15.93	15.9
13		Burner Efficiency	(%)	99.8	99.8	99.8	99.8
14		Calorific value of Fuel (LHV)		47209	45777	47209	45777
15		Mass of Cooling air flow	kg/s	35	35	35	35
16		Generator Efficiency	(%)	98.4	98.4	98.4	98.4
17		Bearing loss	KW	772	771	772	771
18		Gearbox loss	KW	0	0	0	0
19		Booster power consumption	KW	505	500	505	500
20		Compressor inlet air to bleed air ratio		0.016	0.016	0.016	0.016
21	OUTPUTS	Compressor Inlet air mass flow rate	kg/s	598.18	595.43	588	586
22		Percentage of Error in compressor air mass flow rate	(%)			1.70	1.58

TABLE – 3.7

**Comparison of Indirect air flow calculation using Mass and Energy balance method with
OEM values**

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Table 3.8
Indirect air flow rate calculation using Mass and Energy balance method for various EOH

Sno.	Description	Units	PAC Test result											
	Date		1/10/02	1/10/02	2/10/02	2/10/02	2/10/02	2/10/02	2/10/02	12/4/02	4/12/02	6/1/03		
1	Date													
2	Time		15-16	16-17	9:00-11:00	13-15	17-19	10.3-11	11.3-12	10.3-11	11.3-12	10.3-11	12.3-13	
3	EOH		3128.00	3128.00	3152.00	3152.00	3152.00	4860.00	4862.00	4860.00	4862.00	5652.00	5654.00	
4	Relative Humidity	(%)	58.17	61.26	59.47	59.51	49.32	58.52	51.22	58.52	51.22	77.84	66.74	
5	Ambient Pressure	mbara	1009.77	1009.38	1013.22	1010.89	1008.78	1013.62	1013.35	1013.62	1013.35	1016.20	1015.46	
6	Ambient Temperature	Deg C	35.43	34.94	31.59	34.47	32.56	32.32	34.64	32.32	34.64	28.51	30.34	
7	Compressor Inlet Temperature	Deg C	32.63	31.94	31.64	32.10	31.37	30.12	31.41	30.12	31.41	27.03	28.00	
8	Compressor Outlet Temperature	Deg C	430.49	429.71	419.65	409.83	379.79	390.76	393.52	390.76	393.52	400.40	398.68	
9	Compressor Outlet Pressure	mbara	16.08	16.12	15.57	14.47	11.34	12.69	12.69	12.69	12.69	13.88	13.39	
10	Sealing air temperature	Deg C	146.40	146.25	141.25	136.70	121.60	125.78	127.24	125.78	127.24	129.56	128.41	
11	GT Exhaust Gas Temperature	Deg C	601.67	600.87	589.94	588.72	589.93	590.99	591.92	590.99	591.92	584.83	586.78	
12	Turbine Speed	Hz	49.99	50.00	49.99	49.98	50.02	50.02	50.00	50.02	50.00	49.95	50.04	
13	Gas Turbine Load	MW	238.62	238.62	222.95	199.79	128.82	162.27	161.74	162.27	161.74	188.05	177.85	
14	Actual IGV Position	(%)	107.81	107.81	87.65	58.27	0.42	20.71	21.08	20.71	21.08	44.94	32.86	
15	Gas outlet pressure	bara	26.33	26.22	26.32	26.40	26.67	26.27	26.28	26.27	26.28	26.20	26.22	
16	Fuel Gas Temperature	Deg C	33.24	32.38	32.21	34.55	31.39	26.24	27.38	26.24	27.38	25.94	27.50	
17	Carbon/Hydrogen ratio of fuel gas calculated		3.13	3.13	3.14	3.14	3.15	3.13	3.13	3.13	3.13	3.14	3.14	
18	Calorific LCV Calculated	kJ/kg	47662.07	47664.16	47648.93	47626.86	47619.54	47856.12	47916.58	47856.12	47916.58	47818.82	47818.68	
19	Fuel Mass flow rate calculated	kg/s	13.22	13.21	12.47	11.53	8.64	10.01	9.99	10.01	9.99	11.08	10.61	
20	Generator Efficiency (%)	(%)	98.95	98.95	98.97	98.99	98.98	99.00	99.00	99.00	99.00	98.99	98.99	
21	Air mass Flow rate (kg/s) - Uncorrected	kg/s	600.09	608.29	588.56	554.65	445.17	497.16	494.66	497.16	494.66	534.40	515.90	
22	Air mass Flow rate (kg/s) - Corrected	kg/s	602.01	608.35	583.67	554.54	450.07	497.16	494.66	497.16	494.66	534.40	515.90	

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Table 3.8
Indirect air flow rate calculation using Mass and Energy balance method for various EOH

Sno.	Description	Units	11/2/03	11/2/03	13/2/03	11/3/03	11/3/03	27/3/03	13/4/03	13/05/03	13/05/03
1	Date		9.30-10.0	10.55 - 11.15	13.15 to 14.45	8.30-9.00	12 -12.30	11.30-12.00	20.15 to 22.30	9 - 9.30	12.30 -13
2	Time		6497.00	6498.00	6548.00	7328.00	7335.00	7732.50	8028.00	8767.00	8770.00
3	EOH		71.73	62.89	55.89	75.68	61.50	59.03	83.25	70.53	59.40
4	Relative Humidity	(%)	1013.10	1013.21	1010.46	1013.32	1012.94	1013.84	1011.99	1011.42	1011.05
5	Ambient Pressure	mbara	30.10	32.03	32.90	29.74	32.69	33.10	27.92	31.31	32.82
6	Ambient Temperature	Deg C	28.62	30.11	30.95	28.00	30.84	30.01	27.54	29.50	30.79
7	Compressor Inlet Temperature	Deg C	408.86	410.74	420.13	411.06	414.66	427.72	411.32	422.06	420.72
8	Compressor Outlet Temperature	Deg C	14.38	14.11	14.84	14.38	14.26	15.16	14.72	15.12	14.84
9	Compressor Outlet Pressure	mbara	133.62	134.41	136.59	133.96	135.71	141.38	132.85	139.08	137.95
10	Sealing air temperature	Deg C	585.82	585.13	589.10	586.18	587.75	588.82	587.01	588.54	589.89
11	GT Exhaust Gas Temperature	Deg C	49.97	50.02	49.98	49.97	49.99	50.00	50.01	49.98	50.00
12	Turbine Speed	Hz	198.85	193.17	208.56	198.57	195.92	214.78	205.92	214.59	208.30
13	Gas Turbine Load	MW	53.87	49.25	71.42	62.49	58.25	90.32	61.75	86.27	72.76
14	Actual IGV Position	(%)	26.12	26.14	25.98	26.12	26.13	26.01	26.01	25.96	25.98
15	Gas outlet pressure	bara	26.97	28.27	33.54	31.15	32.22	33.04	29.97	28.10	29.82
16	Fuel Gas Temperature	Deg C									
17	Carbon/Hydrogen ratio of fuel gas calculated		3.14	3.14	3.15	3.18	3.18	3.17	3.17	3.16	3.17
18	Calorific LCV Calculated	kJ/kg	47756.02	47760.43	47686.80	47505.85	47516.02	47644.03	47648.69	47612.12	47612.72
19	Fuel Mass flow rate calculated	kg/s	11.41	11.10	11.72	11.57	11.58	12.32	11.80	12.12	11.90
20	Generator Efficiency (%)	(%)	98.99	98.99	98.98	98.99	98.99	98.98	98.99	98.98	98.98
INPUTS											
21	Air mass Flow rate (kg/s) - Uncorrected	kg/s	541.91	531.24	546.56	547.86	547.80	570.50	556.96	573.11	559.83
22	Air mass Flow rate (kg/s) - Corrected	kg/s									

Table 3.8
Indirect air flow rate calculation using Mass and Energy balance method for various EOH

Sno.	Description	Units	24/06/03	24/06/03	25/7/03	30/7/03	18/8/03	15/9/03	15/9/03	26/09/03
1	Date		9.0 -9.30	11.30-12.00	11.00-12.00	12.00-13.00	9-9.30	10 -10.30	13.0-13.30	10-10.3
2	Time		10009.60	10012.11	10518.00	10626.00	11319.00	11992.00	11995.00	12255.70
3	EOH		79.61	68.75	64.59	60.14	75.25	73.25	59.75	65.69
4	Relative Humidity	(%)	1011.65	1011.90	1013.60	1013.90	1013.47	1013.73	1013.13	1013.03
5	Ambient Pressure	mbara	29.13	31.79	32.30	32.69	29.90	30.81	32.48	30.96
6	Ambient Temperature	Deg C	28.31	29.82	30.23	30.73	28.80	28.80	30.36	29.10
7	Compressor Inlet Temperature	Deg C	427.31	429.72	433.91	427.90	416.44	422.55	422.33	418.69
8	Compressor Outlet Temperature	Deg C	15.56	15.53	15.73	15.64	14.98	15.23	15.15	14.99
9	Compressor Outlet Pressure	mbara	137.73	142.26	141.59	139.33	136.56	139.35	139.29	136.23
10	Sealing air temperature	Deg C	589.58	590.02	595.85	588.91	588.07	589.59	589.49	587.94
11	GT Exhaust Gas Temperature	Deg C	50.01	50.00	49.99	50.02	49.99	50.01	49.96	49.97
12	Turbine Speed	Hz	224.61	223.35	233.13	225.73	212.06	216.91	217.85	211.99
13	Gas Turbine Load	MW	97.47	96.16	108.83	89.42	75.38	83.36	84.76	81.23
14	Actual IGV Position	(%)	26.11	26.10	25.99	25.99	26.00	25.97	25.97	25.99
15	Gas outlet pressure	bara	26.39	27.63	30.84	31.68	29.48	31.21	29.83	31.15
16	Fuel Gas Temperature	Deg C	3.16	3.17	3.22	3.17	3.18	3.16	3.16	3.15
17	Carbon/Hydrogen ratio of fuel gas calculated		47672.56	47555.61	47400.66	47603.57	47639.27	47776.61	47755.56	47720.57
18	Calorific LCV Calculated	kJ/kg	12.55	12.51	13.00	12.57	12.07	12.30	12.32	11.97
19	Fuel Mass flow rate calculated	kg/s	98.97	98.97	98.97	98.97	98.98	98.97	98.98	98.98
20	Generator Efficiency (%)	(%)								
21	Air mass Flow rate (kg/s) - Uncorrected	kg/s	576.07	576.45	587.28	588.69	565.54	577.55	573.88	579.83
	Air mass Flow rate (kg/s) - Corrected	kg/s	0.00	0.00	585.11	588.16	0.00	0.00	0.00	0.00
22										

Table 3.8
Indirect air flow rate calculation using Mass and Energy balance method for various EOH

Sno.	Description	Units	7/10/03	20/10/03	20/10/03	20/10/03	21/11/03	21/11/03	21/11/03	29/12/03	29/12/03	29/12/03	30/12/03
1	Date	Units											
2	Time		8.40-9.10	9.3-10.0	11.3-12.0	8.00-8.30	13-13.30	8-8.30	10.0-10.3	11.00-11.30	8-8.30		
3	EOH		12469.00	12792.00	12794.00	13526.00	13530.00	14461.60	14463.60	14464.60	14488.00		
4	Relative Humidity	(%)	78.94	77.25	64.98	85.88	81.93	79.52	66.82	61.17	83.12		
5	Ambient Pressure	mbara	1013.72	1014.88	1014.27	1014.14	1013.87	1016.41	1016.99	1016.46	1016.30		
6	Ambient Temperature	Deg C	28.71	28.42	31.14	26.63	26.62	27.10	29.75	31.10	26.77		
7	Compressor Inlet Temperature	Deg C	27.37	27.96	29.88	25.62	25.56	26.06	28.14	29.34	25.55		
8	Compressor Outlet Temperature	Deg C	414.41	414.18	418.22	413.13	411.66	414.47	421.96	421.20	413.51		
9	Compressor Outlet Pressure	mbara	15.19	14.98	15.07	15.20	14.97	15.05	15.17	15.10	15.16		
10	Sealing air temperature	Deg C	137.24	135.74	137.67	135.30	134.26	135.17	138.46	139.11	135.71		
11	GT Exhaust Gas Temperature	Deg C	586.48	585.70	587.49	584.02	583.54	584.72	586.54	587.17	583.88		
12	Turbine Speed	Hz	49.98	50.02	50.04	49.98	49.95	49.97	49.96	50.00	49.99		
13	Gas Turbine Load	MW	216.51	211.61	213.41	216.78	211.76	213.26	215.52	213.79	215.43		
14	Actual IGV Position	(%)	73.33	71.87	75.43	77.63	68.08	76.30	84.16	78.76	73.99		
15	Gas outlet pressure	bara	25.98	26.01	25.98	26.15	26.18	26.18	26.15	26.16	26.17		
16	Fuel Gas Temperature	Deg C	28.27	27.98	29.37	28.45	30.06	27.42	29.18	29.59	27.20		
17	Carbon/Hydrogen ratio of fuel gas calculated		3.15	3.15	3.16	3.04	3.05	3.18	3.17	3.18	3.17		
18	Calorific LCV Calculated	kJ/kg	47757.24	47759.00	47719.80	48337.83	48362.30	47691.74	47758.50	47696.52	47781.07		
19	Fuel Mass flow rate calculated	kg/s	12.24	12.05	12.13	12.05	11.85	12.08	12.06	12.10	12.15		
20	Generator Efficiency (%)	(%)	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98	98.98		
21	Air mass Flow rate (kg/s) - Uncorrected	kg/s	586.00	580.17	584.30	572.67	566.63	565.34	576.46	581.83	571.35		
22	Air mass Flow rate (kg/s) - Corrected	kg/s	0.00	0.00	0.00	0.00	0.00	0.00	12.06	12.10	563.58		

Table 3.8
Indirect air flow rate calculation using Mass and Energy balance method for various EOH

Sno.	Description	Units	26/01/04	26/01/04	28/02/04	14/03/04	21/04/04	22/04/04	17/05/04	17/05/04
1	Date		10.30 - 11.30	12.00-12.30	10.00-10.30	10.00-10.30	10.00-10.30	15.30-16.30	10.00-10.30	14.00-14.30
2	Time		15112.00	15113.00	15997.50	16510.00	17561.00	17589.64	18184.00	18188.00
3	EOH									
4	Relative Humidity	(%)	84.91	79.62	65.26	67.13	60.79	68.55	67.51	59.66
5	Ambient Pressure	mbara	1012.89	1011.90	1013.68	1014.42	1013.21	1007.44	1012.32	1010.23
6	Ambient Temperature	Deg C	26.71	28.09	29.91	30.57	32.26	30.43	33.21	34.74
7	Compressor Inlet Temperature	Deg C	25.46	26.33	27.96	28.94	30.39	28.74	31.23	32.99
8	Compressor Outlet Temperature	Deg C	407.80	412.02	418.41	409.97	428.27	425.25	430.26	432.50
9	Compressor Outlet Pressure	mbara	14.45	14.57	14.76	14.56	15.49	15.50	15.41	15.27
10	Sealing air temperature	Deg C	132.52	135.39	136.41	132.92	141.85	140.74	141.83	142.36
11	GT Exhaust Gas Temperature	Deg C	581.83	583.31	585.13	588.66	592.57	590.93	593.29	594.44
12	Turbine Speed	Hz	49.96	50.08	50.00	49.97	50.00	49.98	50.02	49.99
13	Gas Turbine Load	MW	200.86	203.43	207.28	202.64	222.90	223.17	221.11	218.45
14	Actual IGV Position	(%)	64.74	68.50	76.36	59.85	97.37	93.14	98.48	98.69
15	Gas outlet pressure	bara	26.14	26.11	26.09	25.99	25.91	25.94	25.91	25.92
16	Fuel Gas Temperature	Deg C	27.96	28.72	29.51	29.92	30.15	29.20	30.67	31.93
17	Carbon/Hydrogen ratio of fuel gas calculated		3.18	3.19	3.20	3.22	3.16	3.16	3.16	3.76
18	Calorific LCV Calculated	kJ/kg	47727.87	47691.25	47656.38	47663.86	47898.18	47888.02	47749.91	47750.46
19	Fuel Mass flow rate calculated	kg/s	11.76	11.83	11.96	11.74	12.47	12.49	12.42	12.28
20	Generator Efficiency (%)	(%)	98.99	98.99	98.99	98.99	98.97	98.97	98.97	98.98
21	Air mass Flow rate (kg/s) - Uncorrected	kg/s	551.84	549.69	553.89	556.59	581.22	581.51	574.18	569.67
22	Air mass Flow rate (kg/s) - Corrected	kg/s	546.08	545.28	549.98	553.15	579.72	581.72	573.98	572.30

Table 4.3
Deviation of actual values from the base reference values - Based on STD and OEM corrections

Sno		Date	Units	16/10/02	16/10/02	16/11/02	21/11/02	12/4/02	4/12/02	6/1/03	6/1/03	11/2/03	11/2/03	12/2/03	11/3/03
1	EOH		nrs	3665	3681	4441	4561	4860	4862	5652	5654	6497	6498	6546	7328
2	Actual	Gross Efficiency of CCPP	(%)	57.72	56.94	57.52	56.98	55.42	55.79	55.86	56.43	56.42	56.03	56.25	56.19
3		Polytropic Efficiency	(%)	90.81	91.02	90.87	91.64	91.50	90.01	89.99	90.23	89.68	89.82	88.91	89.66
4		Isentropic Efficiency	(%)	86.91	87.29	86.99	88.05	86.14	86.14	86.12	86.31	85.59	85.72	84.59	85.58
5		IGV Opening	(%)	107.91	107.91	107.91	107.91	66.77	20.71	21.08	44.94	36.13	46.45	23.89	32.86
6		Comp Dis Temp	Deg C	427.86	417.27	427.70	423.45	410.79	390.76	393.52	400.40	398.16	404.36	396.26	398.68
7		Corrected Comp Dis Temp	Deg C	433.56	420.64	433.68	432.45	415.20	393.19	394.28	407.04	404.55	411.01	401.57	403.97
8		Gross Efficiency	(%)	58.91	58.24	58.93	59.04	58.06	56.34	56.32	57.48	57.13	57.56	56.61	57.01
9		Projected Poly efficiency	(%)	92.45	92.28	92.45	92.39	92.19	90.69	90.68	91.75	91.44	91.82	90.96	91.34
10		Projected Isentropic efficiency	(%)	89.24	89.10	89.23	89.13	88.99	87.11	87.09	88.45	88.07	88.53	87.45	87.94
11		Projected IGV Opening	(%)	100.88	67.36	102.55	111.55	61.82	23.00	22.76	44.94	37.13	47.03	27.44	34.80
12	Deviation	Project Comp Discharge Temp	(%)	426.60	412.92	427.25	430.78	410.56	392.81	392.69	403.15	399.58	404.09	394.98	398.49
13		Deviation in CCPP Gross Efficiency	(%)	-1.19	-1.30	-1.41	-2.06	-2.66	-0.55	-0.46	-1.04	-0.71	-1.53	-0.36	-0.83
14		Deviation in polytropic eff	(%)	-1.64	-1.58	-0.75	-0.69	-0.68	-0.68	-1.51	-1.68	-1.27	-1.51	-1.37	-1.89
15		Deviation in Isentropic Eff	(%)	-2.33	-2.24	-1.09	-1.01	-0.97	-0.97	-2.13	-2.36	-1.82	-2.15	-1.97	-2.68
16		Deviation in Comp Dis Temp	(%)	6.97	6.42	1.67	4.64	0.39	1.60	3.88	5.48	6.62	9.58	11.05	9.27
17		Deviation in IGV Opening	(%)	-7.03	-5.36	4.16	-4.95	2.29	1.68	0.01	1.95	-0.69	-3.04	-9.67	-8.31
18		Gross Efficiency of CCPP	(%)	56.67	56.57	55.49	54.87	55.39	55.88	55.05	55.07	56.01	56.38	57.39	55.58
19		Polytropic Efficiency	(%)	90.81	90.87	91.64	91.50	90.01	89.99	90.23	89.66	90.72	90.28	90.82	90.13
20		Isentropic Efficiency	(%)	86.91	86.99	88.05	87.98	86.14	86.12	86.31	85.58	86.94	86.35	87.02	86.10
21		Comp pressure ratio	(%)	15.78	15.83	16.23	14.68	12.53	12.53	13.67	13.20	14.23	13.96	14.72	14.23
22	Actual	IGV Opening	(%)	107.91	107.91	107.39	66.77	20.71	21.08	44.94	32.86	53.87	49.25	71.42	62.49
23		Projected Gross efficiency of CCPP	(%)	58.99	59.01	59.06	58.13	56.44	56.52	57.38	56.96	57.80	57.62	58.23	57.81
24		Projected Comp Poly efficiency	(%)	92.47	92.47	92.46	92.11	90.61	90.69	91.52	91.13	91.87	91.72	92.18	91.88
25		Projected Comp Isen efficiency	(%)	89.28	89.27	89.26	88.87	86.97	87.08	88.13	87.64	88.57	88.39	88.95	88.59
26		Projected Comp Pressure ratio	(%)	15.52	15.57	15.67	14.24	12.57	12.64	13.42	13.02	13.86	13.66	14.36	13.87
27		Projected IGV Opening	(%)	92.05	93.51	96.59	57.21	21.11	22.38	38.09	29.81	48.00	43.42	60.32	48.32
28		Deviation in CCPP Gross Efficiency	(%)	-2.31	-2.44	-3.57	-3.26	-1.05	-0.64	-2.33	-1.89	-1.79	-1.23	-0.84	-2.23
29		Deviation in Polyeff	(%)	-1.66	-1.60	-0.82	-0.61	-0.60	-0.70	-1.29	-1.47	-1.15	-1.44	-1.36	-1.76
30		Deviation in Iseneff	(%)	-2.37	-2.28	-1.21	-0.89	-0.83	-0.96	-1.82	-2.06	-1.64	-2.03	-1.93	-2.48
31	Long term trending using OEM corrections	Deviation in Comp pressure ratio	(%)	0.26	0.26	0.56	0.44	-0.04	-0.11	0.26	0.18	0.37	0.30	0.36	0.36
32		Deviation in IGV Opening	(%)	15.86	14.40	10.79	9.56	-0.40	-1.31	6.85	3.05	5.87	5.84	11.10	14.18

Table 4.3
Deviation of actual values from the base reference values - Based on STD and OEM corrections

Sno		Date	Units	11/3/03	27/3/03	13/4/03	13/05/03	13/05/03	24/06/03	24/06/03	25/7/03	30/7/03	18/8/03	18/8/03	15/9/03	15/9/03	25/09/03
1	Long term trending using STD corrections	EOH	hrs	7335	7732.5	8028	8767	8770	10009.6	10012.11	10516	10626	11319	11321	11992	11995	12255.7
2		Gross Efficiency of CCPP	(%)	56.51	57.26	56.68	56.82	56.81	57.35	56.49	56.17	56.13	56.13	56.15	56.15	57.17	57.12
3		Polytropic Efficiency	(%)	90.01	90.70	90.54	90.72	90.28	90.82	90.13	90.26	89.87	91.88	90.75	90.74	90.58	90.64
4		Isentropic Efficiency	(%)	86.01	86.85	86.67	86.94	86.35	87.02	86.10	86.30	85.66	88.47	86.94	86.95	86.67	86.77
5		IGV Opening	(%)	39.78	77.08	56.46	53.87	49.25	71.42	62.49	58.25	90.32	80.95	61.75	57.01	86.27	72.76
6		Comp Dis Temp	Deg C	400.12	419.36	407.04	408.86	410.74	420.13	411.06	414.56	427.72	413.34	411.32	408.48	422.06	420.72
7		Corrected Comp Dis Temp	Deg C	406.60	421.96	413.65	413.44	413.30	421.58	416.52	416.25	430.52	418.89	417.42	414.44	425.54	422.40
8		Projected Gross efficiency	(%)	57.36	58.13	57.80	57.80	57.53	58.06	57.63	57.75	58.28	58.43	58.13	57.98	58.32	58.15
9	Long term trending using OEM corrections	Projected Poly efficiency	(%)	91.65	92.22	92.00	92.00	91.79	92.19	92.02	91.96	92.31	92.38	92.22	92.12	92.32	92.23
10		Projected Isentropic efficiency	(%)	88.32	89.03	88.76	88.75	88.50	88.99	88.79	88.71	89.13	89.20	89.02	88.91	89.15	89.04
11		Projected IGV Opening	(%)	42.20	63.56	53.21	53.18	46.22	61.75	54.18	51.91	68.83	74.60	63.39	58.59	70.13	64.23
12		Project Comp Discharge Temp	(%)	401.91	411.31	406.83	406.82	403.72	410.53	407.25	406.26	413.54	415.96	411.24	409.18	414.09	411.59
13	Long term trending using OEM corrections	Deviation in CCPP Gross Efficiency	(%)	-0.84	-0.87	-1.12	-0.98	-0.72	-0.73	-1.34	-1.58	-2.15	-1.87	-0.98	-1.83	-1.15	-1.03
14		Deviation in polytropic eff	(%)	-1.70	-2.44	-1.47	-1.74	-1.59	-2.12	-2.05	-2.26	-1.31	-1.39	-1.20	-1.55	-1.44	-1.54
15		Deviation in Isentropic Eff	(%)	-2.41	-3.46	-2.09	-2.48	-2.27	-3.03	-2.93	-3.22	-1.88	-1.97	-1.72	-2.21	-2.06	-2.21
16		Deviation in Comp Dis Temp	(%)	9.99	16.98	6.18	11.46	10.80	14.84	15.85	15.59	10.07	7.39	8.58	9.22	9.81	11.15
17	Long term trending using OEM corrections	Deviation in IGV Opening	(%)	-6.34	-21.48	1.64	-16.15	-8.53	-18.66	-19.12	-22.31	-5.91	-6.72	-9.47	-10.26	-9.40	-13.22
18		Gross Efficiency of CCPP	(%)	56.08	55.80	56.08	56.75	57.13	55.86	56.50	56.39	57.71	56.40	57.17	56.29	56.94	56.08
19		Polytropic Efficiency	(%)	90.26	89.87	90.75	90.58	90.30	90.35	90.20	91.13	90.92	91.17	90.83	90.90	90.69	90.69
20		Isentropic Efficiency	(%)	86.30	85.66	86.94	86.67	86.77	86.21	86.29	86.06	87.39	87.15	87.48	86.99	87.11	86.83
21		Comp pressure ratio	(%)	14.11	15.00	14.58	14.99	14.71	15.44	15.40	15.58	15.48	14.83	15.08	15.11	15.02	14.85
22		IGV Opening	(%)	58.25	90.32	61.75	86.27	72.76	97.47	96.16	108.83	89.42	75.38	83.36	84.76	81.23	77.37
23		Projected Gross efficiency of CCPP	(%)	57.90	58.40	58.08	58.40	58.30	58.55	58.59	58.82	58.78	58.32	58.36	58.48	58.50	58.22
24		Projected Comp Poly efficiency	(%)	91.95	92.28	92.08	92.28	92.22	92.36	92.37	92.45	92.44	92.23	92.36	92.32	92.33	92.17
25	Long term trending using OEM corrections	Projected Comp Isen efficiency	(%)	88.67	89.07	88.83	89.07	89.01	89.16	89.18	89.26	89.26	89.02	89.17	89.12	89.13	88.94
26		Projected Comp Pressure ratio	(%)	13.97	14.59	14.18	14.59	14.46	14.80	14.86	15.23	15.16	14.48	14.82	14.70	14.72	14.35
27		Projected IGV Opening	(%)	50.58	86.01	55.79	86.00	62.71	73.27	73.27	83.58	81.66	63.21	72.21	69.08	69.54	59.85
28		Deviation in CCPP Gross Efficiency	(%)	-1.82	-2.60	-2.01	-1.82	-1.18	-2.69	-2.10	-2.44	-1.08	-1.92	-1.40	-2.19	-1.56	-2.13
29	Long term trending using OEM corrections	Deviation in Polyeff	(%)	-1.69	-2.41	-1.33	-1.69	-1.58	-2.06	-2.02	-2.25	-1.31	-1.32	-1.19	-1.50	-1.42	-1.48
30		Deviation in IsenEff	(%)	-2.37	-3.41	-1.90	-2.41	-2.23	-2.95	-2.89	-3.20	-1.87	-1.87	-1.69	-2.13	-2.02	-2.11
31		Deviation in Comp pressure ratio	(%)	0.15	0.42	0.40	0.40	0.26	0.64	0.54	0.35	0.32	0.36	0.26	0.40	0.30	0.51
32		Deviation in IGV Opening	(%)	7.67	24.30	5.96	20.27	10.05	25.75	22.89	25.25	7.76	12.17	11.15	15.67	11.68	17.52

Table 4.3
Deviation of actual values from the base reference values - Based on STD and OEM corrections

Sno		Date	Units	7/10/03	20/10/03	20/10/03	21/11/03	21/11/03	29/12/03	29/12/03	30/12/03	26/01/04	26/01/04	28/02/04	14/03/04	21/04/04	22/04/04	17/05/04	17/05/04
1	Long term trending using STD corrections	EOH	hrs	12469	12792	12794	13526	13530	14461.6	14464.6	14468	15112	15113	15997.5	16510	17561	17589.64	18184	18186
2		Gross Efficiency of CGPP	(%)	56.64	57.62	56.69	57.31	56.50	56.70	56.28	57.89	55.22	57.15	57.33	57.15	57.02	57.02	56.93	55.89
3		Polytropic Efficiency	(%)	90.12	91.46	90.30	90.35	90.12	90.01	90.20	89.92	91.13	90.52	90.92	91.17	90.83	90.90	90.83	89.25
4		Isentropic Efficiency	(%)	86.02	87.91	86.21	86.29	85.95	85.95	85.95	85.86	87.39	86.65	87.15	87.48	86.99	87.11	87.04	85.00
5		IGV Opening	(%)	83.53	79.88	97.47	96.16	108.16	57.11	108.83	50.84	89.42	54.98	75.38	83.36	84.76	81.23	73.49	31.80
6		Comp Dis Temp	Deg C	422.66	419.14	427.31	429.72	436.14	416.45	433.91	411.80	427.90	409.16	416.44	422.55	420.68	422.33	416.82	397.16
7		Corrected Comp Dis Temp	Deg C	426.59	420.26	432.54	432.81	438.50	418.37	436.44	413.92	429.70	414.39	420.85	424.24	424.61	424.61	420.43	405.02
8		Projected Gross efficiency	(%)	58.27	58.25	58.52	58.48	58.74	57.64	58.68	57.43	58.62	57.65	58.28	58.41	58.42	58.36	58.18	56.96
9		Projected Poly efficiency	(%)	92.30	92.29	92.41	92.40	92.46	91.88	92.46	91.71	92.44	91.89	92.30	92.37	92.37	92.34	92.25	91.29
10		Projected Isentropic efficiency	(%)	89.12	89.11	89.24	89.23	89.28	88.61	89.28	88.40	89.27	88.62	89.12	89.20	89.20	89.17	89.06	87.88
11		Projected IGV Opening	(%)	68.48	67.85	78.81	77.04	89.52	48.94	86.52	43.79	83.52	49.31	68.65	73.89	74.49	71.83	65.04	33.80
12		Project Comp Discharge Temp	(%)	413.39	413.13	417.70	416.97	422.06	404.94	420.85	402.63	419.63	405.11	413.47	415.66	415.91	414.80	411.94	398.02
13		Deviation in CGPP Gross Efficiency	(%)	-1.63	-0.64	-1.83	-1.63	-1.43	-1.14	-1.98	-1.15	-0.73	-2.43	-1.13	-1.08	-1.41	-1.21	-1.25	-1.06
14		Deviation in polytropic eff	(%)	-1.20	-1.39	-1.17	-1.57	-1.75	-1.91	-1.76	-1.73	-2.09	-2.22	-2.35	-1.11	-1.77	-1.69	-1.92	-1.86
15		Deviation In Isentropic Eff	(%)	-1.71	-1.97	-1.68	-2.24	-2.50	-2.73	-2.52	-2.49	-2.96	-3.15	-3.34	-1.58	-2.53	-2.41	-2.74	-2.65
16		Deviation In Comp Dis Temp	(%)	4.98	6.71	7.48	7.89	8.82	11.59	13.57	10.16	9.13	11.25	14.49	4.79	12.87	10.84	15.08	16.17
17		Deviation in IGV Opening	(%)	0.91	-4.27	-6.32	-7.53	-3.59	-13.22	-15.12	-8.14	-9.75	-11.29	-16.93	-0.89	-18.65	-11.15	-23.12	-26.55
18	Long term trending using OEM corrections	Gross Efficiency of CGPP	(%)	56.04	55.83	56.54	54.66	54.46	54.23	55.47	54.14	53.69	54.13	54.80	56.05	56.86	56.73	56.84	57.55
19		Polytropic Efficiency	(%)	91.17	90.90	91.14	90.76	90.49	90.31	90.46	90.53	89.95	89.88	89.79	91.02	90.64	90.75	90.47	90.49
20		Isentropic Efficiency	(%)	87.49	87.13	87.45	86.50	86.55	86.28	86.50	86.58	85.85	85.73	85.59	87.34	86.71	86.85	86.47	86.52
21		Comp pressure ratio	(%)	15.02	14.79	14.89	15.02	14.80	14.85	14.90	14.96	14.31	14.44	14.61	14.39	15.33	15.42	15.27	15.17
22		IGV Opening	(%)	73.33	71.87	75.43	77.63	68.08	76.30	78.76	73.99	64.74	68.50	76.36	59.85	97.37	93.14	98.48	98.69
23		Projected Gross efficiency of CGPP	(%)	58.40	58.24	58.39	58.17	58.00	58.01	58.21	58.06	57.69	57.81	58.00	58.04	58.67	58.66	58.61	58.62
24		Projected Comp Poly efficiency	(%)	92.28	92.19	92.27	92.14	92.03	92.03	92.17	92.07	91.79	91.88	92.03	92.05	92.40	92.40	92.38	92.39
25		Projected Comp Isen efficiency	(%)	89.07	88.96	89.06	88.90	88.76	88.77	88.94	88.82	88.46	88.58	88.76	88.80	89.22	89.21	89.19	89.20
26		Projected Comp Pressure ratio	(%)	14.59	14.38	14.57	14.29	14.09	14.09	14.34	14.16	13.74	13.87	14.09	14.13	14.97	14.97	14.89	14.91
27		Projected IGV Opening	(%)	66.02	60.82	65.60	58.36	53.42	53.57	59.82	55.17	45.21	48.20	53.48	54.55	76.43	76.28	74.14	74.59
28		Deviation In CGPP Gross Efficiency	(%)	-2.36	-2.41	-1.85	-3.51	-3.54	-3.78	-2.75	-3.92	-4.00	-3.68	-3.20	-1.99	-1.81	-1.93	-1.77	-1.08
29		Deviation in Polyeff	(%)	-1.11	-1.28	-1.14	-1.38	-1.53	-1.72	-1.71	-1.54	-1.83	-2.00	-2.23	-1.03	-1.76	-1.66	-1.92	-1.89
30		Deviation in Isen eff	(%)	-1.58	-1.83	-1.61	-2.00	-2.21	-2.48	-2.44	-2.23	-2.62	-2.86	-3.17	-1.46	-2.50	-2.36	-2.72	-2.68
31		Deviation in Comp pressure ratio	(%)	0.44	0.42	0.32	0.74	0.72	0.76	0.55	0.80	0.57	0.58	0.53	0.25	0.36	0.45	0.38	0.26
32		Deviation in IGV Opening	(%)	7.31	11.25	9.83	19.28	14.66	22.73	18.95	18.82	19.52	20.31	22.88	5.30	20.93	16.86	24.34	24.10

Appendix D

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

Analysis 1.1.2 Analysis of gas turbine thermodynamic behavior using hybrid neural network model based on Preminmax data processing technique

STEP-I. Network training performance and residuals between simulated outputs and targets

Network training for the Off-line washing set using Preminmax technique

Network training for the first On-line washing profile using Preminmax technique

Network training for the second On-line washing profile using Preminmax Technique

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

Network training for the third On-line washing profile set using Preminmax Technique

STEP-II. Mean slope of the three On-line washing profiles

$$\text{SLOPE} = 1.0\text{e-}03 * \{ -0.4479 \ -0.3649 \ -0.2063; \ -0.6407 \ -0.5232 \ -0.2947 \}$$

STEP-III. Average time interval between the On-line washing

First Online washing Profile	Second Online washing Profile	Third Online washing Profile
718.25hrs	583.67hrs	468.50hrs

STEP-IV. Prediction profile - Network training performance and residuals

First Online washing profile is selected as reference profile

Network Training for first prediction set of Online washing using Preminmax Technique

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

First Online washing profile is selected as reference profile

Network training for second prediction set of On-line washing using Preminmax Technique

STEP-V. Comparison of actual profile and projection profile of the model

Neural Network Training and Prediction based on Preminmax technique

STEP-VI. Reference profile - Network training performance and residuals

Network training performance and residuals for guaranteed reference profile

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Thermal assessment of gas turbine engine using hybrid neural network models

Network training performance and residuals for the expected reference profile

Comparison of the reference (Guaranteed and Expected) profile with predicted profile

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

STEP-VII. Comparison of the reference profile and the projected profile

STEP-VIII. Analysis of the above profile using PNN Network gives following result

- The Mean value of the Predicted profile is 5% less than the guaranteed profile.
- The mean value of the Predicted profile is 50% greater than the expected profile.

STEP-IX Verification the Neural network model based on Preminmax Technique

Verification of the neural network model based on Preminmax technique

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

Analysis 1.1.3 Analysis of gas turbine thermodynamic behavior using hybrid neural network model based on raw data

STEP-I. Network training performance and residuals between simulated outputs and targets

Network training for the Off-line washing set using Raw data technique

Network training for the first On-line washing profile using Raw data technique

Network training for the second On-line washing profile using Raw data Technique

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

Network training for the third On-line washing profile set using Raw data Technique

STEP-II. Mean slope of the three On-line washing profiles

$$\text{SLOPE} = 1.0\text{e-}03 * \{ -0.4479 \ -0.3649 \ -0.2063; \ -0.6407 \ -0.5232 \ -0.2947 \}$$

STEP-III. Average time interval between the On-line washing

First Online washing Profile	Second Online washing Profile	Third Online washing Profile
718.25hrs	583.67hrs	468.50hrs

STEP-IV. Prediction profile - Network training performance and residuals

First Online washing profile is selected as reference profile

Network Training for first prediction set of On-line washing using Raw data Technique

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

First Online washing profile is selected as reference profile

Network training for second prediction set of On-line washing using Raw data Technique

STEP-V. Comparison of actual profile and projection profile of the model

Neural Network Training and Prediction based on Raw data technique

STEP-VI. Reference profile - Network training performance and residuals

Network training performance and residuals for guaranteed reference profile

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

Network training performance and residuals for the expected reference profile

Comparison of the reference (guaranteed and expected) profile and predicted profile

APPENDIX – D1

Thermal assessment of gas turbine engine using hybrid neural network models

STEP-VII. Comparison of the reference profile and the projected profile

STEP-VIII. Analysis of the above profile using PNN Network gives following result

- The Mean value of the Predicted profile is 25% higher than the guaranteed profile.
- The mean value of the Predicted profile is 50% greater than the expected profile.

STEP-IX Verification the Neural network model based on Raw data Technique

Verification of the neural network model based on Raw data technique

APPENDIX – D2

Cost estimation - Power generation cost and maintenance work cost

a) Electricity Production Cost Estimation					
Sno	Description	Variable	Formula	Percentage	Cost (\$ / MWhr)
1	Cost of electricity from home application bill is 16.35 cents per unit	C1			163.5
2	Cost of electricity	C2	$1000 \times C1$		163.5
3	Estimated cost of power transmission and distribution	C3	$C3 \times 0.35$	25%	40.875
4	Estimated profit for power transmission and distribution	C4	$C4 \times 0.15$	15%	24.525
5	Estimated selling cost by power generating companies	C5	$C2 - (C3 + C4)$		98.1
6	Estimated fuel cost	C6		60%	58.9
7	Estimated maintenance cost	C7		10%	9.8
8	Estimated staff salary and other expenses	C8		5%	4.9
9	Estimated over head expenses	C9		5%	4.9
10	Estimated profit	C10		20%	19.6
11	Estimated cost of production	C11	$(C6 + C7 + C8 + C9)$		78.5
Opportunity lost cost estimation / day					
12	Average energy generation / day Day time + Night time = {12hrs x 330 + 12hrs x 290} / 24hr }	C12		310MW	
13	Average cost of production / day	C13	$C12 \times C11 \times 24 \text{ hr}$		584,040
14	Average fuel cost / day	C14	$C6 \times C12 \times 24 \text{ hr}$		438,216
15	Average loss per /day	C15	$C13 - C14$		145,824

Table 4.18
Power generation and fuel cost estimation

APPENDIX – D2

Cost estimation - Power generation cost and maintenance work cost

Maintenance cost estimation			
Sno.	Description	Units	Estimated Cost (S\$)
1	Online washing cost estimation		
	Cost of washing solution	100 litres x S\$ 5	500
	Cost of demineralized water	1000 litres x S\$0.5	500
	Cost of technician man hour utilized	1 no. x 3 hr x 20	60
	Cost of helper man-hour utilized	1 no x 3 hr x 10	30
	Cost of energy consumption by washing pump	½ hr x 30kW x 16.35	25
	Total cost for one Online washing		1125
2	Offline washing cost estimation		
	Cost of washing solution	200 litres x S\$ 5	1000
	Cost of demineralized water	2000 litres x S\$0.5	1000
	Cost of technician man hour utilized	1 no. x 24 hr x S\$20	480
	Cost of helper man-hour utilized	4 no x 24 hr x S\$10	960
	Scaffolding provision for IGV blade cleaning	1 x S\$1535	1535
	Cost of energy consumption by washing pump	½ hr x 30kW x 16.35	25
	Total cost for one Off line washing		5000

Table 4.19

Washing maintenance cost estimation