Declaration

This is to certify that

(i) The thesis comprises my original work towards the degree of Master of Technology in Instrumentation and Control Engineering at Nirma University and has not been submitted elsewhere for a degree.

(ii) Due acknowledgement has been made in the text to all other material used.

Zeel Christian
13MICC03

Undertaking for Originality of the Work

I, Zeel Christian, Roll.No.13MICC03, give undertaking that the Major Project entitled "Part Load Stability Analysis of a Gas Turbine" submitted by me, towards the partial fulfilment of the requirements for the degree of Master of Technology in Instrumentation and Control Engineering (Control and Automation) of Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere; it will result in severe disciplinary action.

____

Signature of Student

Date: __________________

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Signature of Guide

Certificate

This is to certify that the Major Project entitled **"Part Load Stability Analysis of a Gas Turbine"** submitted by **Ms. Zeel Christian (13MICC03)**, towards the partial fulfillment of the requirements for the degree of Master of Technology in Instrumentation and Control Engineering (Control and Automation) of Nirma University, Ahmedabad is the record of work carried out by him under my supervision and guidance. In my opinion the submitted work has reached a level required for being accepted for examination. The results embodied in this major project to the best of my knowledge haven't been submitted to any other university or institution for award of any degree or diploma.

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Acknowledgement

I owe a debt of gratitude to **Mr. Vikas Handa** (Engineering Manager), **Dr. Prabhanjana Kalya** (Engineering Technical Leader) and **Mr. Akilez Krishnamurthy** (Engineer/Technologist) for the vision and foresight which inspire me to conceive this project.

It is also my duty to record my thankfulness to **Dr. Jayesh Barve, Dr. Dipak Adhyaru** and **Mr. J. B. Patel** from whom I have been inspiring and helping me to grab this wonderful opportunity.

I extend my gratitude **Institute of Technology, Nirma University, Ahmedabad** for giving me this opportunity.

Finally, I take this opportunity to acknowledge the service of the total team of **GE-HTC (Power and Water- NPI Controls)** and everyone who collaborated directly and indirectly to complete this report.

- Zeel Christian
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Abstract

Majority of the Gas Turbines are designed to operate at their rated power output conditions, typically referred as base load conditions. The performance of a gas turbine at part load may vary from its base load performance. The purpose of this study is to analyze stability of Gas Turbines under part load conditions. This study involves a stability analysis of control strategies during part load operation and proposes control actions that can enhance performance.

As a part of this study, analysis of field data will be done first to observe the performance/stability of controls strategies. A simulation will be setup to replicate the site behaviour and will be used to perform root cause analysis. Once the cause, if any, is understood, feasible solutions will be explored and implemented in simulation environment. The complete process will also be documented in detail.

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Chapter 1

Introduction

1.1 Gas Turbine

Gas turbine works on Brayton cycle. Gas turbines are thermodynamic systems that convert chemical energy of fuel into mechanical energy. Air from the atmosphere enters the compressor where it is compressed. The compressed air is then combined and burned with fuel in the combustion chamber. The combustor increases both the temperature and the specific volume of the air. The hot air is then fed into the turbine where it is expanded. The expansion of the air creates a positive shaft work transfer. The expanded air is then exhausted to the atmosphere.

1.1.1 The Brayton cycle

The Brayton cycle consists of two adiabatic work transfers and two constant pressure heat transfer processes.

From State 1 to 2: The gas undergoes an isentropic, adiabatic compression. This process increases the temperature, pressure, and density of the gas.

From State 2 to 3: Heat is added at constant pressure. For a gas-turbine, heat is added through a combustion process.

From State 3 to 4: When gas passes through turbine an adiabatic isentropic expansion takes place which decreases the temperature and pressure of the gas.

For the closed Brayton cycle, heat is removed from the gas between State 4 and State 1 via a heat exchanger.

3 major components of gas turbine

- Compressor

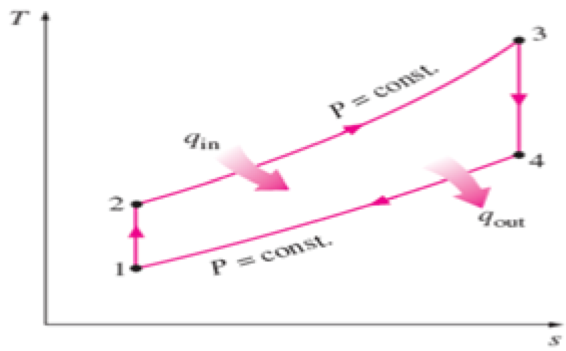


Figure 1.1: T-s diagram for Brayton Cycle*

Source: *http://www.yildiz.edu.tr/ dagdas/Brayton%20cycle.pdf*

- Combustor
- Turbine

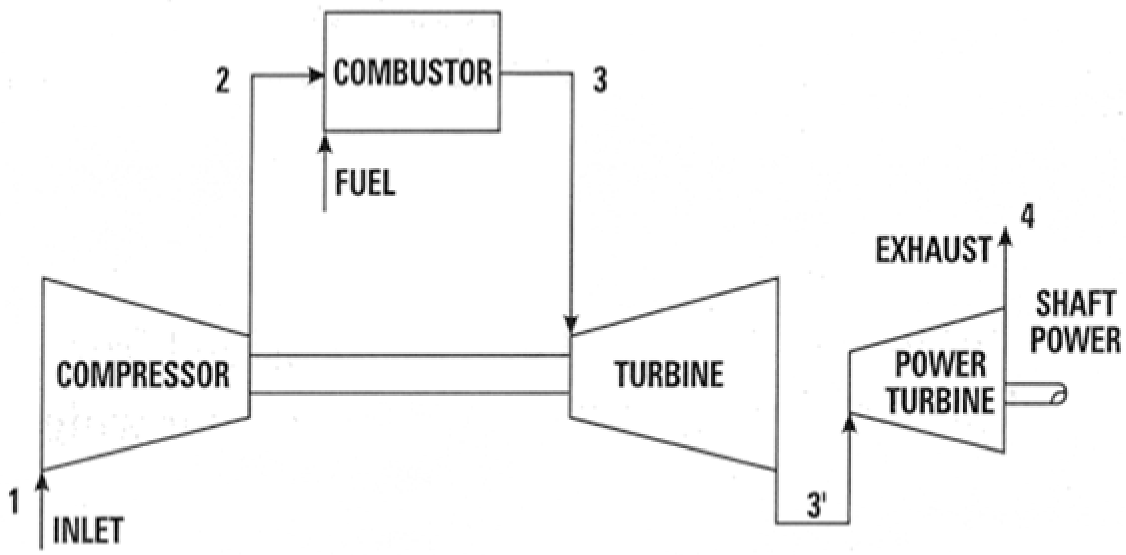


Figure 1.2: Gas Turbine Block Diagram*

Source: *http://www.allstar.fiu.edu/aero/turbine3.html*

1.1.2 Compressor

3 main parts of the compressor

- IGV (Inlet Guide Vanes)

- Axial flow compressor
- Exit guide vanes

IGV (Inlet Guide Vanes)

IGVs are arranged at compressor inlet. Main Purpose of IGV is to control and direct the inflow of air to the compressor. The angle of the inlet guide vane could be change so as to have the smooth aerodynamics of the air flowing to the compressor.

Axial flow compressor

Rotation of the blades of the compressors provides pressure rise at each stage of the compressors. There are total of 14 -17 stage compressor used in the gas turbine. There are two types of blades: Rotating blades which are attached to the shaft and static blades which are connected to the casing of the compressor. The rotating blades increase the velocity of the incoming air and the static blades direct the flow for next rotating stage.

Exit guide vanes

The two rows of the exit guide vanes obtain the maximum pressure increase before the air goes to the combustion system.

1.1.3 Combustor

Combustion chamber is a component of gas turbine in which the fuel is combined with air from the compressor and burned. The combustion chamber functions like a heat exchanger and can be modeled as a constant pressure device. Combustion process raises the temperature of air in the system by converting the chemical potential energy of the reactants to thermal energy. There is no work transfer involved in the reaction. Following are some components that are involved in combustion process.

Combustion casing

Allow compressor discharge air to be directed through the flow sleeves into combustion liners.

Spark plug

Initiate the combustion process.

A combustion liner

Combustion liner contains the combustion process and energy released from combustion is added to the air flow.

Can cover

Can cover contain passage for fuel flow to fuel nozzles mounted on it.

Flame detector

Flame detector indicates whether the flame exist in the can.

Crossfire tubes

They are located in aft combustor cans. They provide sealed pathway for flame to travel from one combustor chamber to another.

Flow sleeves

Give pathway to compressor discharge air and gases from the combustion chamber to the transition piece.

Transition Piece

Direct hot combustion gases from liner assembly to the 1st stage nozzle of turbine section.

1.1.4 Turbine

High temperature and pressure gas enters into turbine from combustion chamber, where it expands down to exhaust pressure and produces a shaft work output. Each stage of the turbine consists of a row of stationary blades followed by a row of rotating blades. This is the reverse of the order in the compressor. In the compressor energy is added to the gas by the rotor blades, and then converted to static pressure by the stator vanes. In the turbine, the stator blades increase gas velocity, and then the rotor blades extract energy. The stator blades and rotor blades are air-foils that provide for a smooth flow of the gases. As the air-stream enters the turbine section from the combustion section, it is accelerated through the first stage stator blades. The stator blades (also called nozzles) form convergent ducts that convert the gaseous heat and pressure energy into higher velocity gas flow. In addition to accelerating the gas, the nozzles "turn" the flow to direct it into the rotor blades at the optimum angle.

1.2 Basic operations of gas turbine

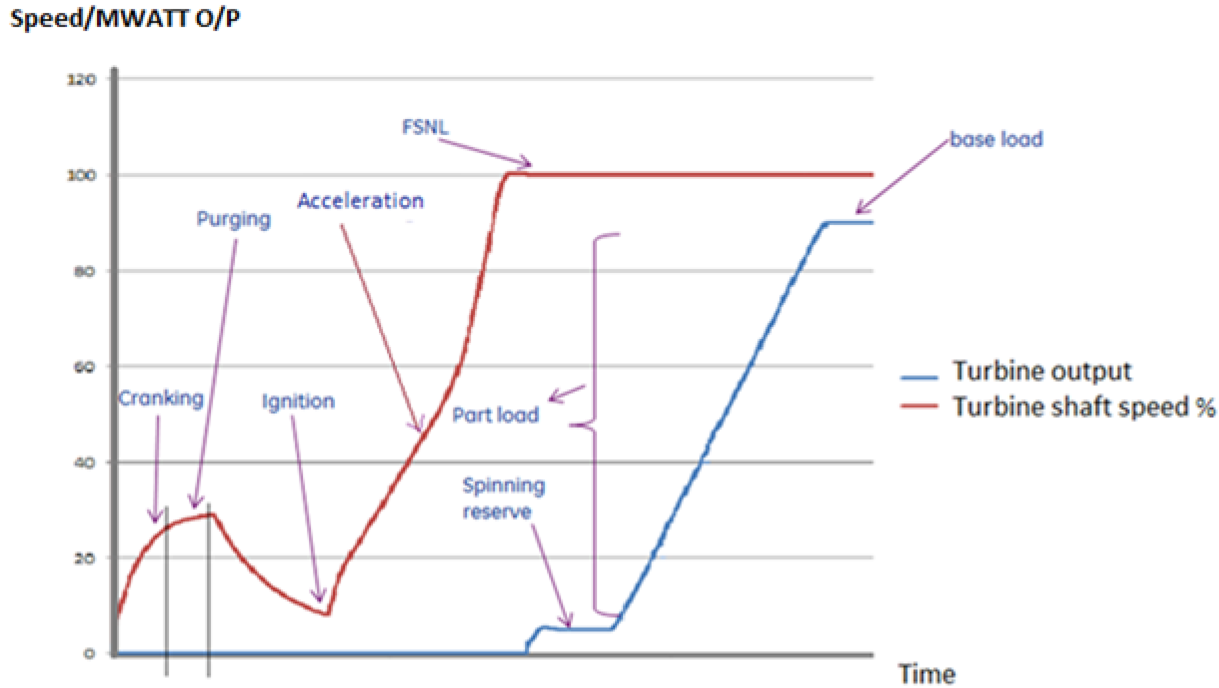


Figure 1.3: Gas Turbine Operation

Cranking: After all the start checks have been completed successfully, cranking device is started to take the turbine shaft speed up to 25% to 30% of the final speed. Cranking motor is required to speed up unfired turbine.

Purging: Even though, the ignition speed of the turbine is only 10% to 15%, the extra power that has been produced is used for purging. Before igniting the turbine purge sequence has been done for cleaning the turbine. Purging removes combustible or heat recovery elements from the turbine to ensure safe ignition.

Ignition: After completion of purging sequence, turbine is allowed to slow down speed up to 10% to 15%. Ignition sequence includes turning on the power to spark plugs for initiating the ignition. Necessary fuel is injected in to the combustor. Flame is detected by flame detectors, which are arranged at the opposite side of the spark plug. Fuel is reduced to the warm up level. After completion of warm up, fuel is allowed to increase and turbine starts accelerating.

Acceleration: After completion of cranking, purging and ignition sequences, turbine starts accelerating. When speed reaches up to 50% to 80% of the speed, turbine can be self-sustained and no cranking devices are needed. IGVs also start opening, which were closed to avoid compressor surge. Between the speed of 80% to 90%, IGVs settle down on predefined angle.

FSNL and Synchronization When turbine shaft speed reaches its 100% speed, that condition is called FSNL (Full Speed No Load). Now turbine is in the condition in which it can be synchronized with the grid. Synchronization is initiated by closing the breaker. Breaker connects the generator to the grid.

Spinning reserve After synchronization with the grid, turbine will be at spinning reserve load, which is predefined load and can be different for different gas turbines. Spinning reserve is the stage of turbine at which it has capability to produce more output but has not been commanded to produce more than the spinning reserve load.

Part load and Base load When turbine reaches spinning reserve load, it waits for the command to reach preselected intermediate load or the base load. Base load is the maximum load that can be produced, which is limited by the combustor temperature and/or exhaust temperature of turbine. Because IGVs are at its maximum position so we cant further increase airflow and combustor temperature becomes so high so that we cant further increase fuel flow. Any intermediate load between spinning reserve load to base load can be defined as part load.

1.3 Gas turbine controls

1.3.1 Gas turbine effectors

IGV (Inlet guide vanes)

IGV (Inlet Guide Vanes) are actuators to control the inlet air flow to the turbine. By actuating the angle of IGVs we can regulate the air inflow. Turbine exhaust temperature is a primary controlled variable in temperature control. Exhaust temperature is measured by an array of thermocouple.

Exhaust temperature is compared with the reference exhaust temperature value for IGV control. Error signal is generated through that is fed to the controller. Depending on the error controller gives reference command to the IGV to regulate its angular position. IGV changes its angle that again is compared with the reference angle from controller 1. Error in the IGV angle is corrected by inner control loop, if any. Outer loop takes care of the exhaust temperature and inner loop controls IGV angle.

FSR (Fuel Stroke Reference)

FSR controls the inflow of fuel into combustor. FSR control is a simple min select block as shown in figure which controls the fuel flow accordingly in different modes of operation.

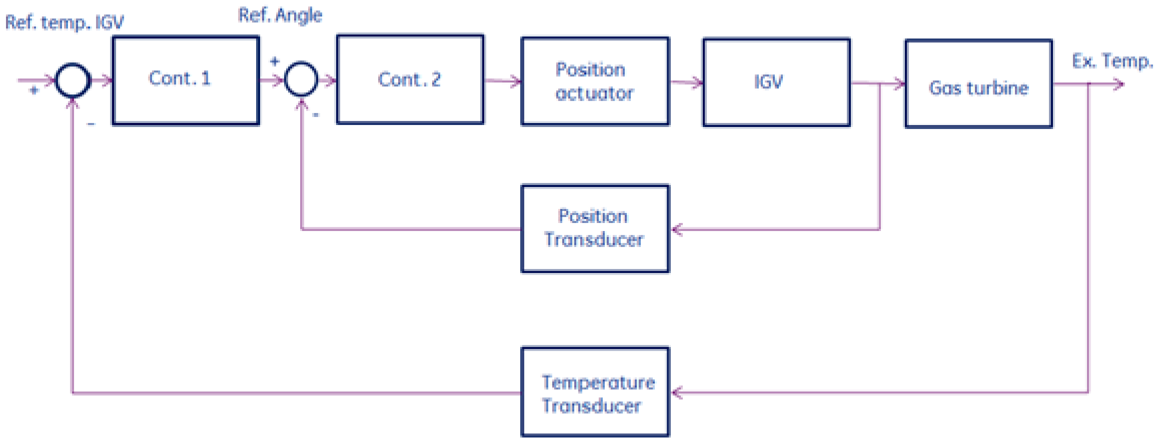


Figure 1.4: IGV Control

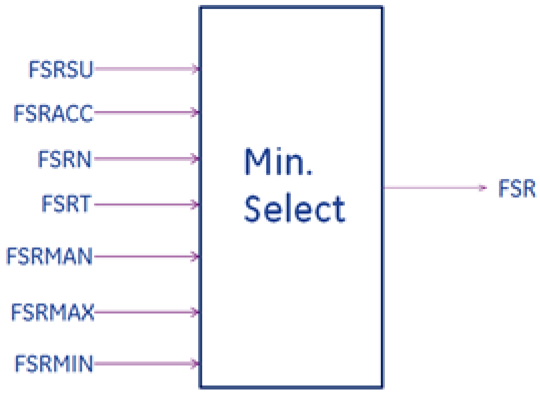


Figure 1.5: FSR Control

Main controlling FSRs throughout the operations are FSRSU (Startup FSR), FSRACC (Acceleration FSR), FSRN (Speed/load Control FSR) and FSRT (Temperature Control FSR). FSRMIN and FSRMAX determine upper and lower limits for FSR.

IBH (Inlet Bleed Heat)

Anti-icing of inlet components is occasionally required for gas turbine in a cold and humid ambient environment. One method utilized to combat the formation of ice is to bleed hot gas turbine compressor discharge air and re-circulate this air to the inlet to warm the inlet air flow. This control is designed to prevent the formation of ice from humid air and only limited effectiveness at melting ice and snow already present on compressor inlet components.

1.3.2 Gas turbine control

Start up control

From cranking to FSNL turbine is in startup control mode. The main two active effectors in startup control mode are FSRSU (Fuel Stroke Reference Startup) and FSRACC (Fuel Stroke Reference Acceleration). The purpose of startup FSRSU is to transition the turbine from ignition through warm up. The FSRSU control algorithm is enabled when master protective logic becomes true. The algorithm holds FSRSU at 0% until the ignition permissive is energized & firing logic becomes true. After these all permissive are completed successfully, FSRSU steps to the firing fuel command. Fuel flow is maintained at firing level until the ignition is confirmed by flame detectors.

Once the warm up sequence has been completed successfully start up acceleration command logic becomes TRUE. The FSRACC is used to prevent over firing during start up and preventing the machine from operating on temperature control during start up. As the machine continues to accelerate the starting means contribution will reduce. As the turbine approaches to FSNL the control will switch to speed control (FSRN), and FSRACC hovers slightly higher.

IGV remains at its predetermined angle to allow the minimum amount of air flow during start up to prevent the turbine from surge.

Part load control

After reaching at FSNL, turbine is synchronized with the grid by closing the breaker. After synchronization has been done, turbine will be at predetermined spinning reserve load. As load increases turbine exhaust temperature will go up. When it starts approaching the reference exhaust temperature limit IGVs start opening, to allow more air to the turbine.

To generate more power output, it is needed to supply more fuel. Now at this part load region of operation FSRN is the controlling effector, which is also known as Speed/load control or Droop control. The purpose of FSRN is to maintain electrical grid frequency constant. Generally, a drop in an electrical grid frequency indicates that the power generation capability of the grid is less than demanded load and vise verse. If electrical grid frequency goes below rated frequency turbine will be commanded to generate more power output by increasing its speed. For increasing the speed FSRN is the effector. The droop response of a turbine generator governor is typically referred to in terms of percentage frequency variation required to cause a 100% turbine load output change. The standard droop response configuration for GE gas turbine generator application is 4% droop response.

Base load control

As load increases, turbine exhaust temperature also goes up. When exhaust temperature starts increasing IGVs also start increasing angle accordingly. When it touches the reference exhaust temperature limit IGVs are at its maximum angle. At the base load condition FSRT (Fuel Stroke Reference Temperature) is the controlling effector, and IGVs are fully open so to control temperature at base load we need to modify fuel flow by FSRT. When exhaust temperature starts increasing IGVs also start increasing its angle accordingly.

1.4 DRY LOW NO_X (DLN1) Combustion System

1.4.1 Introduction

The regulatory requirements for low emissions from gas turbine power plants have increased during the past 10 years. Environmental agencies throughout the world are now demanding lower rates of emissions of NO_X and other pollutants from both new and existing gas turbines. Traditional methods of reducing NO_X emissions from combustion turbines (water and steam injection) are limited in their ability to reach the utmost low levels required in many regions.

Since the commercial introduction of GEs DLN combustion systems for natural-gas-fired heavy-duty gas turbines in 1991, systems have been installed in more than 222 machines, from the most modern FA+e technology to field retrofits of older machines.

1.4.2 DLN1 Combustor

The GE DLN1 combustor is a two-stage premixed combustor which can operate on gas as well as liquid fuel. As shown in figure 1.6 the combustion system includes four major components: fuel injection system, liner, venturi and cap/centerbody assembly.

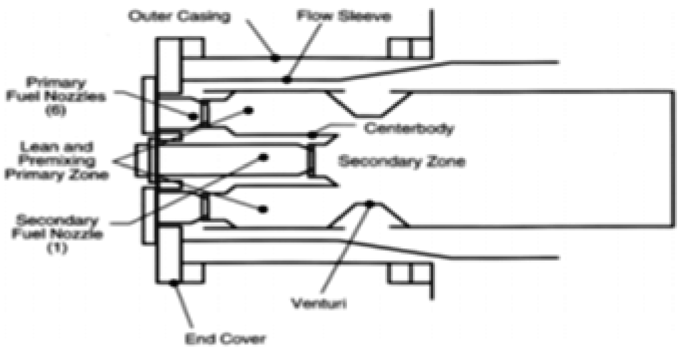


Figure 1.6: Dry Low NO_X Combustor*

Source: *Davis & Black, p. 3, Figure 5*

The GE DLN-1 combustion system operates in different combustion modes, illustrated in Figure: 1.7 during premixed natural gas or oil fuel operation.

The components form two zones in the combustor. In premixed mode, the primary zone thoroughly mixes the fuel and delivers a uniform, lean, unburned fuel-air mixture to the secondary zone.

1.4.3 Operating Modes of DLN

Primary: A mode where all the fuel is entering the primary nozzles with combustion occurring in the primary combustion zone. This is achieved by setting the fuel splitter valve (GSV) to 100% position. This mode of operation is used to ignite, accelerate and operate the machine over low- to mid-loads, up to a pre-selected combustion reference temperature. Primary operation occurs from ignition to full speed and then no load to 35% approx. load.

Lean-Lean: In this mode, fuel is passing into both the primary and secondary combustion zones, with combustion occurring in both zones. The primary split can vary from 50-70%. To do so, the fuel splitter valve is moved to an intermediate position. This mode of operation is used for intermediate loads between two pre-selected combustion reference temperatures. In this mode of operation load varies from 35 to 70%.

Secondary transfer: In this mode of operation GSV moves to full secondary, supplying fuel to the secondary nozzle only, so no more fuel is flowing through the primary nozzle. Flame is in the secondary zone only. Transfer valve begins to open, thus passing all fuel into the secondary combustion zone only. Primary zone flames out due to lack of the fuel and all combustion occurs in the secondary zone only. This mode is necessary to extinguish the flame in the primary zone, before fuel is reintroduced into what becomes the primary premixing zone.

Premix transfer In this mode of operation, GSV ramps from 0% to typically 80% primary split. Flame is in the secondary stage only. This is a transition mode between secondary transfer and premix steady state and is characterized by the transfer valve beginning to close following the primary valve opening. Fuel is being admitted into the primary and secondary combustion zones through the primary, secondary and transfer fuel passages, with combustion occurring only in the secondary zone.

Premix steady state This is the optimal mode of operation for a DLN1 turbine with the lowest NO_X and CO obtainable. In this mode fuel is entering both the primary and secondary zones through the primary and secondary fuel nozzles, with combustion occurring only in the secondary zone. The transfer valve is fully closed and no fuel is entering through the transfer fuel passage. Approximately 80% of the fuel is "premixing in the primary zone before combustion occurs in the secondary combustion zone downstream of the venturi.

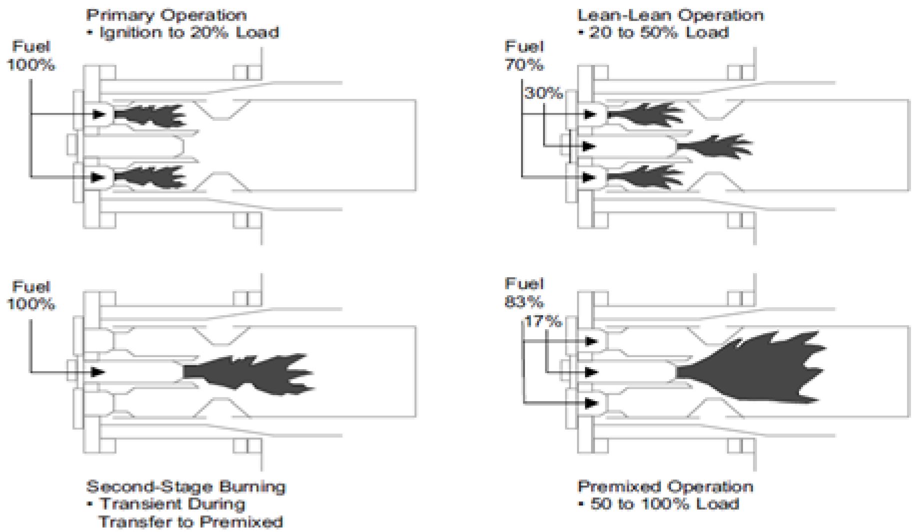


Figure 1.7: Fuel-staged Dry Low NO_X Operating Modes*

Source: *Davis & Black, p. 4, Figure 6*

1.4.4 Emission Performance

The emissions performance of the DLN1 combustor varies as the mode of combustor operation varies with load. The NO_X and CO emissions created by a DLN1 system operating on natural gas vary as the load increases.

NO_X and CO emissions from the DLN1 combustor at less than 35% gas turbine load are similar to those from the non DLN system. This is expected as both systems are diffusion flame combustors in this range.

Between 35 and 70% load, the DLN1 system is in the lean-lean mode. There is a flow split between the primary nozzles and secondary nozzles. This produces the lower NO_X emissions. But note that as fuel flow increases with load, the NO_X emissions increase.

From 70% to 100% load, the DLN1 system is operating as a premixed combustor. Significant reduction in NO_X emissions are observed while CO emissions are comparable to those from the non DLN system.

Chapter 2

Literature Survey

This chapter gives a review of literature related to this project work. It gives outline of gas turbine basics and different controls of gas turbine.

2.1 Gas turbines

Rowen [1983] represents simplified mathematical model for gas turbine to study its dynamics power system studies and thermodynamic properties. For both liquid as well as gas fuel system the entire range from 18 MW to 106 MW is covered. The purpose of this paper is limited to single shaft single simple cycle gas turbines only. Gas turbine acceleration, Speed, temperature controls are also discussed.

Speed control is designed for droop as well as isochronous control and operates on speed error. Speed controller is straight proportional controller. Isochronous controller is PI controller. Under part load condition speed governor is primary means for turbine controls. Combustor inside temperature is one of the limiting factors for megawatt output. Exhaust temperature is measured with the help of array of thermocouple. As the load increases exhaust temperature also starts increasing. At the full load it reaches its maximum temperature. The acceleration control acts during startup of the gas turbine. The purpose of the acceleration control is to control turbine acceleration rate and preventing it to over fire during start up.

In the previous Rowens simplified model [1983] prior work is concentrated on generator drive applications where operation was limited to a narrow range of turbine speed. Earlier model assumes both IGV angle and ambient temperature at constant. Rowens [1992] paper explores these limitations in the context of more general case of variable speed mechanical drive application. Some specific features are also added in this model. Only isochronous governor control is modeled. Only gas fuel control system is modeled. The control system discussed here are speed control, acceleration control, temperature control, IGV control and upper and lower limit fuel control. This paper discusses many of the features and characteristics that affect the application of heavy duty single shaft GT to variable mechanical drive applications. It also offers high flexibility and fairly accurate, yet still simple mathematical representation of GT and its fuel control system. This paper offers features such as modulating IGC, calculation of exhaust flow and accommodation of variable ambient temperature that were not included in Rowens [1983] paper.

Soon Kiat Yee [2008] discusses a comparative analysis and an overview of various models of gas turbines in this paper. This paper explains a short overview of gas turbine and brief direct comparison of two most widely used models of the gas turbine (IEEE and Rowen) suitable for small and large disturbance stability studies is also presented. The main differences between the two models are highlighted and the possible simplification of the Rowen model is explained. The IEEE model is split into two parts: one pertaining to the controls of the gas turbine (the temperature control loop, the air flow control loop and the fuel flow control loop) and the other representing the thermodynamic characteristics of the turbine. Comparison of the IEEE model to that presented in Rowens first paper explores that the main difference is the control action necessary to maintain a high firing temperature. This action of the IGVs is included in the later Rowens model. The IEEE model assumed a fixed compressor ratio, which is only valid for a relatively constant rotor speed. Their different degree of complexity makes various models suitable for different types of studies. The actual turbine control representation, however, must be carefully verified to ensure that the selected model is adequate for the intended study. The main aim of this particular study is to understand and critically assess suitable models for system stability studies, especially those for transient and small disturbance stability studies. The IEEE and the Rowens model have been chosen as they are some of the most simplified ones.

2.2 Gas turbine controls

Salah I. Al-Majed and Saudi Aramco [2010] discusses about the gas turbine and generator controls with the objective to enhance intuitive user understanding. The paper also focuses on control issues like droop and isochronous modes of governor control and excitation system voltage control. The droop control settings will specify how much fuel is admitted when frequency drops and how much fuel should be reduced when frequency rises. When the frequency drops, the governor will increase fuel in order to meet the new power demand by the droop line without bringing the frequency back to the rated value. Governor Isochronous Control behaves slightly different than droop control. An isochronous governor delivers power exactly to maintain the frequency. Usually, isochronous is utilized when a generation or a cogeneration plant is isolated from the grid. This way, the frequency will be maintained by the isochronous governor while other generators will be in droop control.

An excitation system will contain three limiters: Overexcitaion (OEL), Underecitation (UEL) and Overflox (OFL). The OEL will prevent overheating of the rotor DC windings, while the UEL will prevent the torque angle from becoming too big which will break the flux linkage between the rotor and the stator. Over-fluxing will overheat the entire core of the generator. When flux value is exceeded, the core will overheat due to increased eddy current. This paper also discusses about PSS (Power system stabilizer). The PSS is only responsible for the oscillatory stability the oscillatory stability is related to the interaction between torque angle and power supplied to the system. Both the torque angle and the power supplied affect each other in a way that cause power and torque angle oscillation. The PSS job is to boost the magnetic link at the right point of time to suppress the torque angle oscillations. So, when the torque angle is increasing, the PSS will boost the DC field current to strengthen the magnetic link to slow the rate of increase.

Mehdi Rahbar explain effect of various control systems such as constant IGV, constant TIT and constant TET on the performance of Siemens V94.2 gas turbine and specially the fuel consumption and its costs at the control systems in simple and combined cycle power plants are considered and the results are explained. According to the analysis the IGV constant control system has the lowest fuel consumption and the highest efficiency rather than the two other systems in open cycle. In the combined cycle this control system has the lowest efficiency and also has the lowest fuel consumption. Also due to the decrease in the turbine temperature in IGV constant control system the cost of maintenance of hot section of turbine will be reduced. The TIT constant control system has the highest fuel consumption rather than the two other control systems.

2.3 Neural Network

Identification and control of dynamic system using neural network is explained deeply by Kumpati S. Narendra and Kannan Parthasarthy (1990). The paper explains that the NN can be used effectively for dynamical system control. It demonstrates two different methods for back-propagation algorithm: Static and dynamic. It also gives overview of the need for these two methods. Unified approach for creating multilayer and recurrent NN is introduced. Simulation results shows identification and control schemes suggested are practically possible.

Chapter 3

Problem Identification and Analysis

3.1 Analysis of field data

Analysis of the field data has been done for four different load select operations- at part load, at base load, at variable peak and at peak load of operation as shown in fig: 3.1. Throughout fluctuations in plant output (MW) is observed.

It is also observed that effectors like Fuel flow and Angle of IGVs are also fluctuate at part load. At part load operation, fuel is controlled through FSRN. At base load and peak load fuel is controlled through FSRT loop. And at variable peak load operation IGVs are at its maximum position and load is purely controlled through FSRN. From observation of site trend (Fig:3.1), it is seen that fluctuation range is higher while running on part load and variable peak load selects but megawatt output fluctuates lesser while operating on base load and peak load selects. So from this observation, it is concluded that at part and variable peak, when FSRN controls, the fluctuations are higher than when (at base and peak) FSRT controls. So the conclusion had been made that 'FSRT loop offers tighter control than FSRN loop.

3.2 Root cause

In order to find the root cause behind fluctuations in FSRN loop, inputs to FSRN loop are observed in the software. After the analysis has been done on FSRN loop, it is observed that FSRN directly depends on turbine shaft speed and turbine shaft speed is fluctuating. Even in field data, same thing is observed. In the field data, the range of shaft speed fluctuations is $\pm$ 0.2% of the rated speed is observed. So whenever turbine shaft speed goes up, megawatt output goes down in order to maintain grid frequency and vice versa. It could be also translated as the power delivered is higher than the power demanded by grid. During part load operation, turbine shaft speed fluctuates and because of that FSRN also fluctuates, that leads to fluctuations in plant megawatt output.

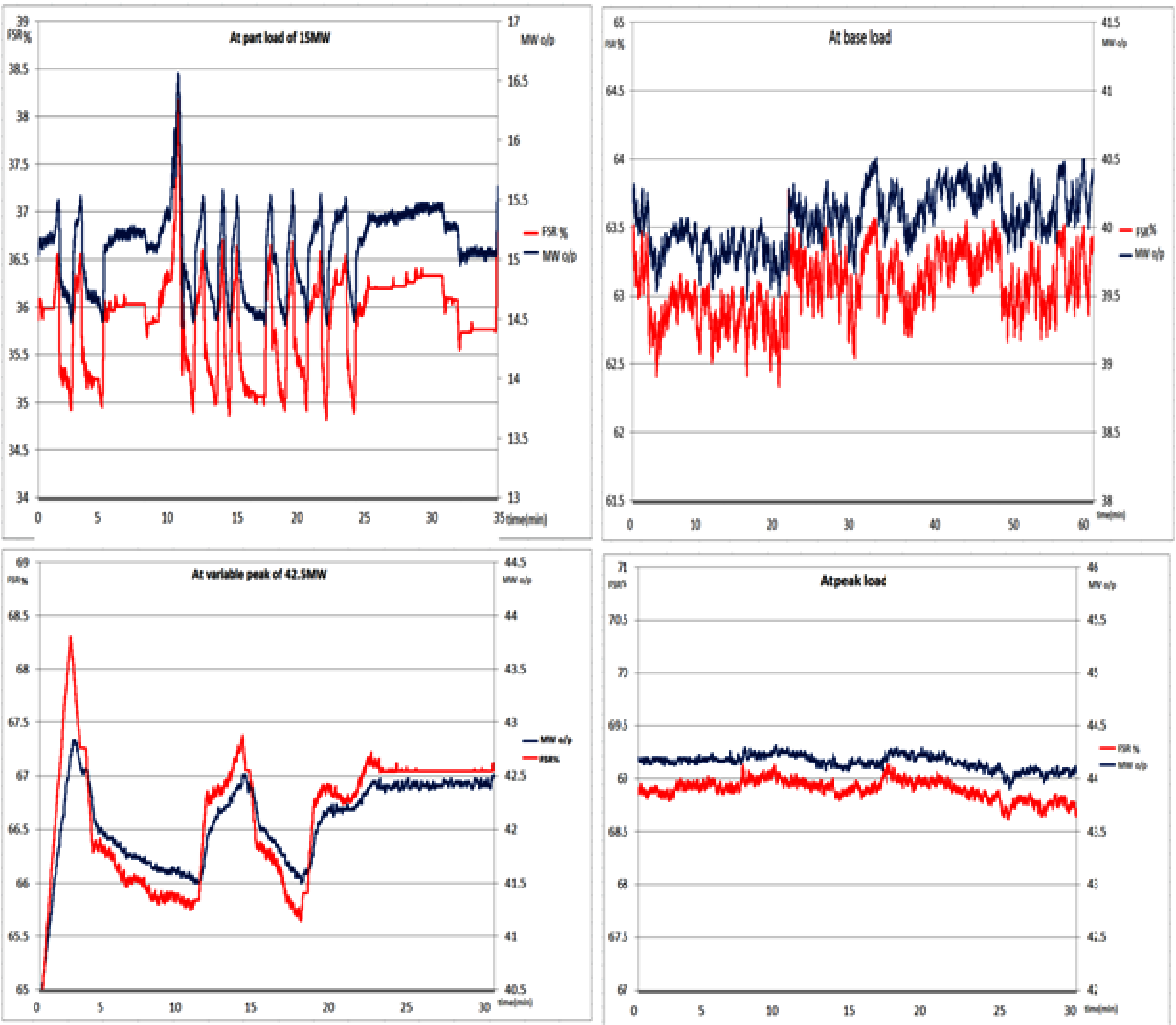


Figure 3.1: Comparison of plant output fluctuation

As shown in Fig: 3.2 that turbine shaft speed fluctuates, and because of that fluctuations FSRN loop reacts. The control action is taken by FSRN loop if the error between reference turbine shaft speed and original turbine shaft speed increases above the defined dead band. The manipulating variable of FSRN loop is FSRN and controlled variable is megawatt output. So because of change in manipulating variable (FSRN) controlled variable (plant megawatt output) fluctuates.

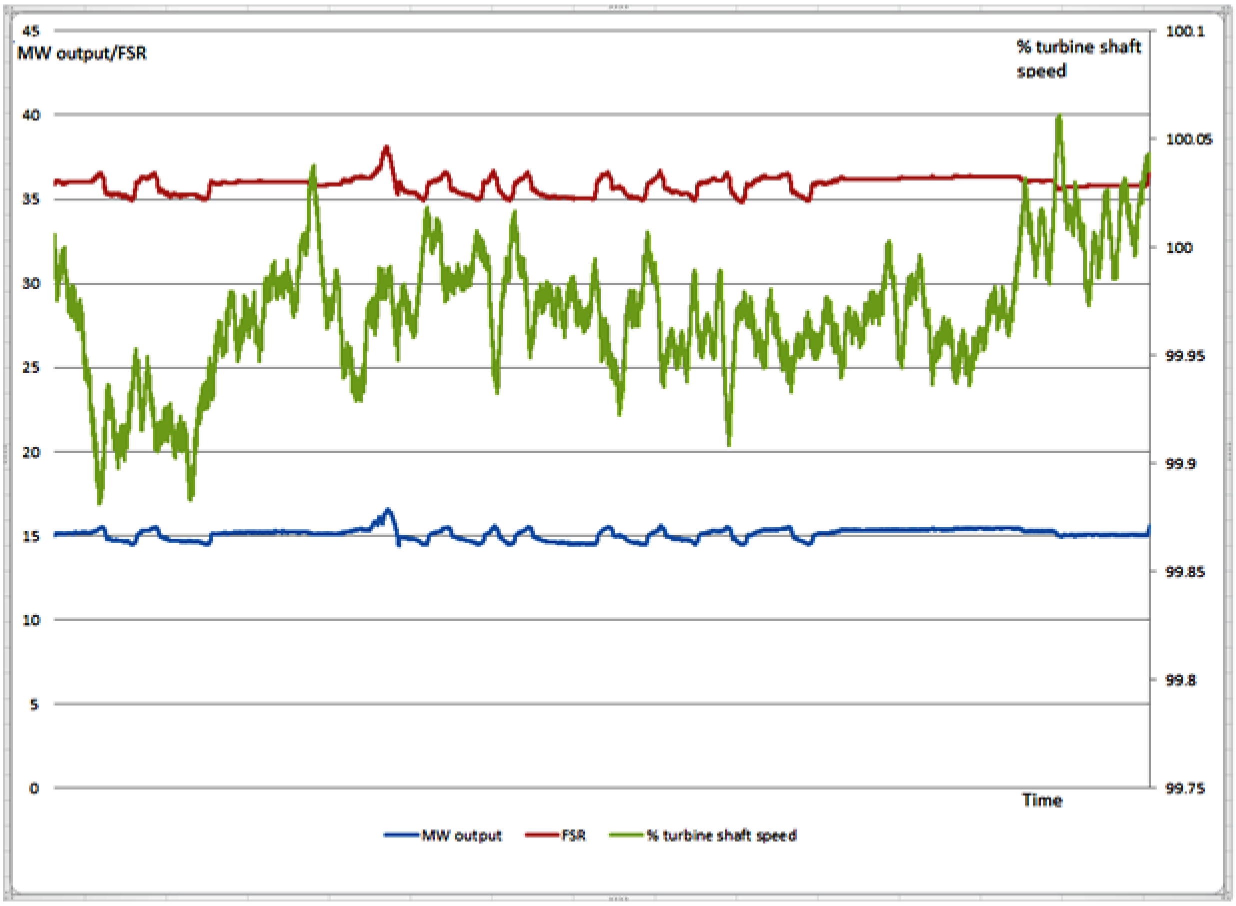
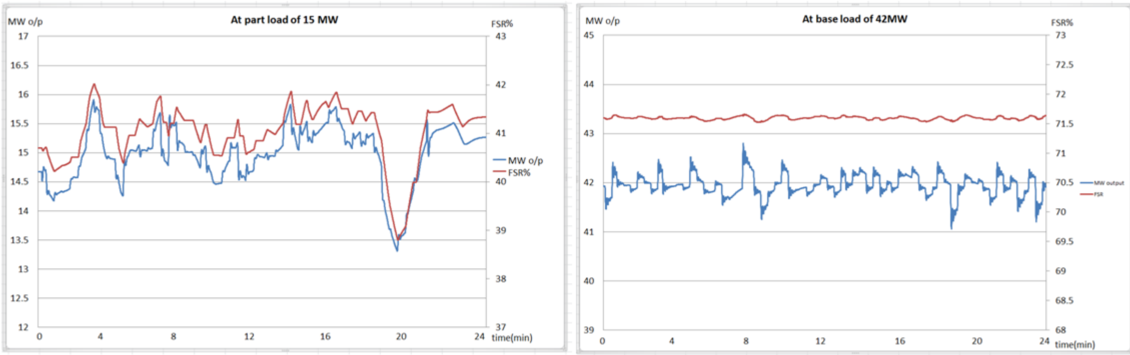


Figure 3.2: Observed % turbine shaft speed fluctuations in field data

3.3 Replicating the fluctuations and analysis

After knowing the root cause behind the fluctuations, replicating those fluctuations in simulation environment was the next challenging task.

The root cause has been found is turbine shaft speed fluctuations. To replicate the fluctuations in simulation environment random noise is added to the turbine shaft speed in the model of gas turbine. The random noise function generator generates noise in the



(a) Part Load

(b) Base Load

Figure 3.3: Simulation results with added noise

defined range. The noise has been injected in part load as well as base load. So that effect of noise can be observed for both FSRN as well as FSRT loop. The results of simulation are shown in fig: 3.3(a) & (b). From both the results it can be seen that MW output fluctuates more at part load (2.57MW) than at base load (1.5MW). Even FSR fluctuations are less at base load region because the effect of shaft speed fluctuations on FSRT loop is less.

FSRT loop works on temperature reference and grid fluctuations doesnt affect FSTR loop directly because turbine shaft speed is not a direct input to the FSRT loop. But some fluctuations are still observed in base load and peak load region. These fluctuations are indirect effect of turbine shaft speed fluctuations. When turbine shaft speed fluctuates it affects compressor parameters like compressor discharge pressure. Compressor discharge pressure has direct effect on MW output. That is the reason behind base and peak load fluctuations in MW output. But range of base and peak load fluctuations are in range and somehow tolerable.

In variable peak region where fluctuations are same as part load, IGVs are at their maximum angle and FSRN loop controls the MW output. From the discussion, it is proved that FSRT offers tighter control then FSRN loop.

Chapter 4

Proposed Solution

4.1 Control of variable peak through FSRT

FSRT loop takes temperature reference as an input and generates FSRT to maintain exhaust temperature as per reference temperature which is shown in fig: 4.1. Exhaust temperature is measured through array of thermocouples. When base load and peak load are commanded, fuel is controlled through FSRT loop. Since FSRT is less affected because of turbine shaft speed fluctuations, it could be a solution to control variable peak.

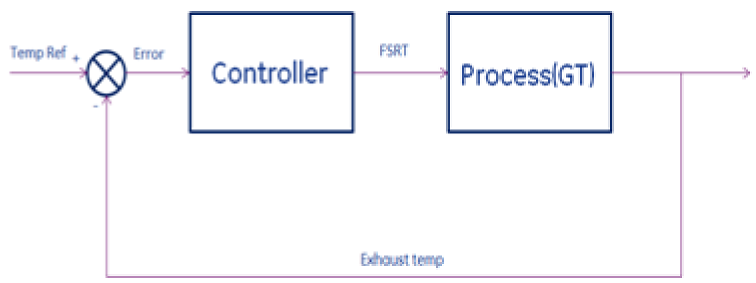


Figure 4.1: Actual FSRT Loop

If exhaust temperature reference can be generated as per MW set point given by operator and if FSRT loop tries to maintain exhaust temperature as per megawatt set point, then better control can be achieved. The modified FSRT loop for variable peak is shown in fig: 4.2. In the figure: 4.2 control algorithm that is generating exhaust temperature reference as per MW set point should be adaptive to variations in ambient temperature and fluctuations in compressor parameters. Megawatt output is a function of ambient temperature and compressor discharge pressure. To generate exhaust temperature reference as per MW set point, ambient temperature and compressor parameter, some adaptive control is needed.

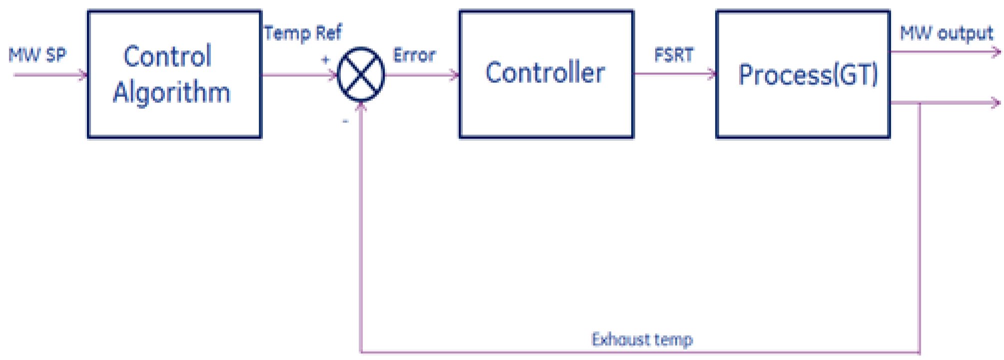


Figure 4.2: Modified FSRT Loop for Variable Peak

4.2 Neural network as an adaptive control

Consider that the input data shown in fig: 4.3 to generate temperature reference are known. For fixed ambient, exhaust temperature reference is also a fix value (for fixed MW set point). In this situation where input and output data is known, neural network can be the suitable adaptive algorithm to generate temperature reference as per inputs.

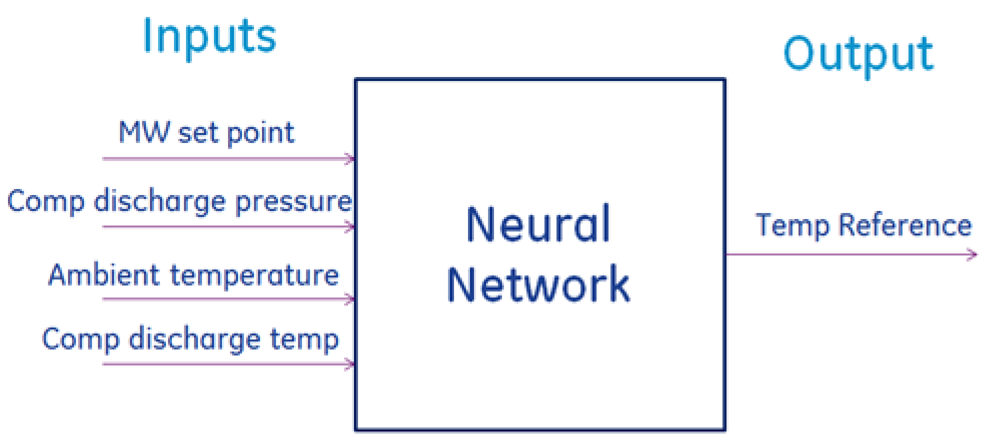


Figure 4.3: Input and output of Neural Network

By giving input and output data, the neural network can be trained and after training it can be used in modified FSRT loop to control megawatt output. As shown in fig: 4.3 MW set point, compressor discharge pressure, compressor discharge temperature and ambient temperature will be the inputs for NN and temperature reference will be the output from NN.

4.3 Implementation

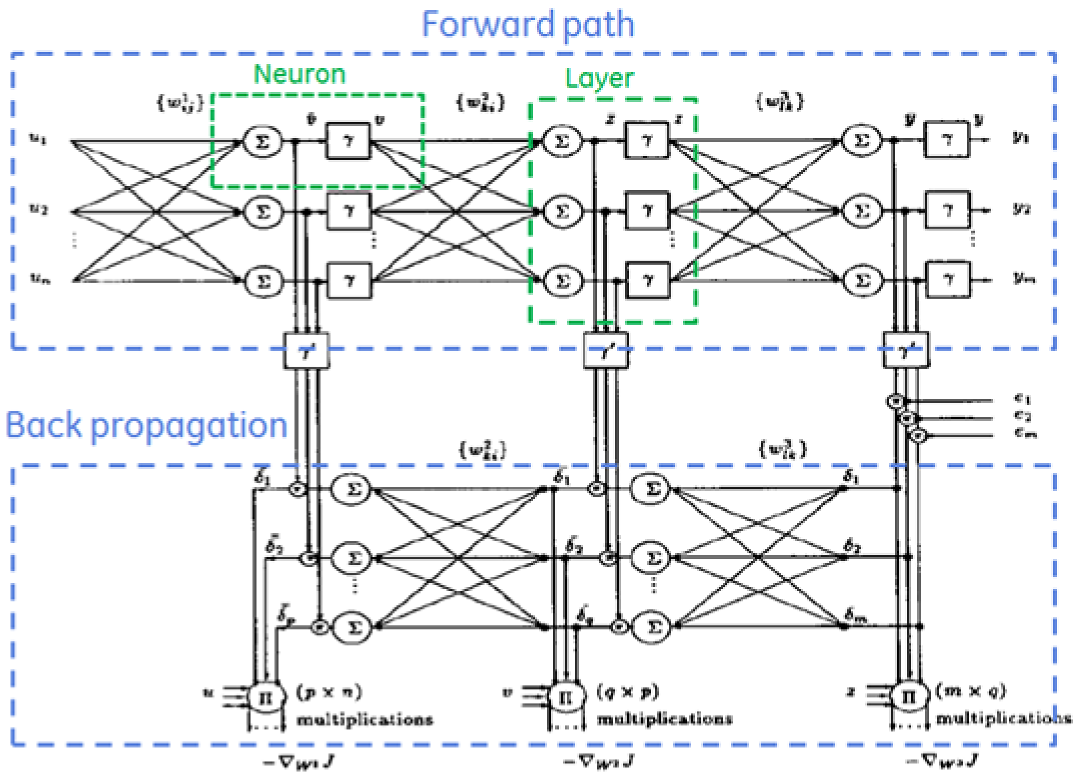


Figure 4.4: Block diagram of neural network algorithm with back-propagation*

***Source:** *Identification and control of dynamical system using NN by Narendra and Parthasarthy (fig 7)*

As discussed in chapter 2 about neural network implementation in control system application by Narendra and Parthasarthy fig 4.4 is showing the internal structure of neural network. Neural network has one forward path and one weight update rule algorithm which is shown in fig 4.4. As shown in the fig 4.5 by combining matrix algebra and activation function one neuron can be built and by combining more than one neurons one layer of neural network can be built.

As shown in fig 4.5, inputs and weights are the inputs for neuron. If the structure has n inputs it must have n weights (multiplying factors) related with inputs. Dot multiplication

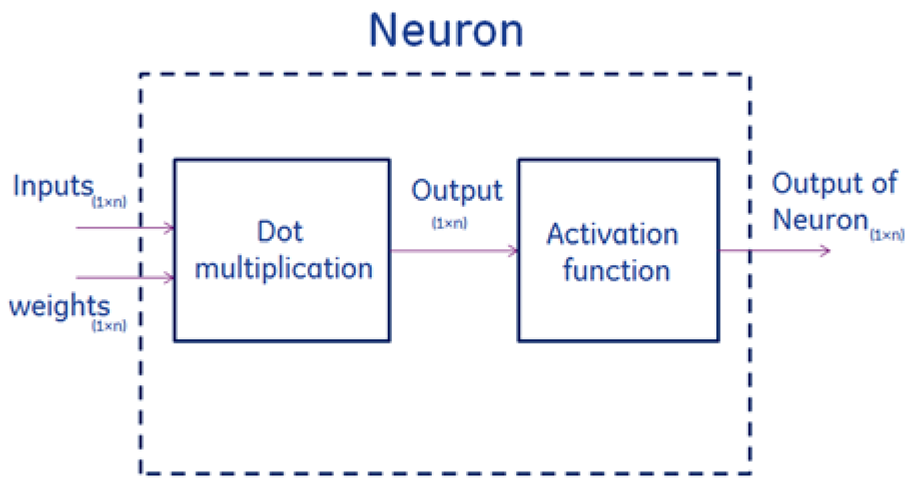


Figure 4.5: Simulation result at part load with added noise

of inputs with weights will give output matrix of $1X$n. The output matrix of $1X$n will pass through activation function which can be linear or nonlinear (sigmoidal or tanh). The output of activation function will be the output of one neuron.

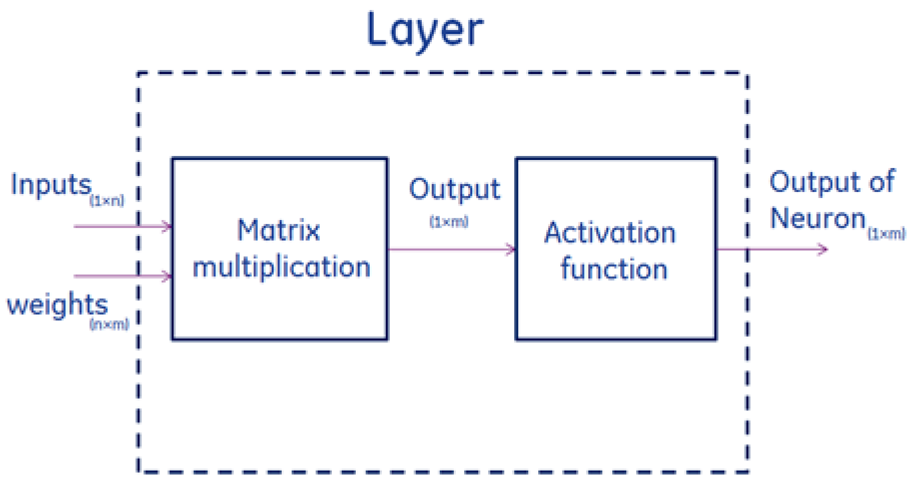


Figure 4.6: Simulation result at part load with added noise

As shown in fig 4.4 by combining more than one neuron layer can be made. Layer structure is shown in fig 4.6. Here, n is number of inputs to the layer (if it is a first layer) or number of outputs from previous layer (if it is a hidden layer or output layer), m is number of neurons in the layer.

4.4 Implementation of NN in ToolboxST®

Initial attempt is tried to make the NN with just 2 hidden layer (each hidden layer has 2 neurons), one output layer, and learning parameter= 0.7. Activation function for all neurons is tanh function.

$$tanh(x) = \frac{e^x - e^{-x}}{e^x - e^{-x}} \tag{4.1}$$

The NN has 6 inputs and one output. The inputs are MW set point, humidity, ambient temperature, Compressor discharge pressure, Compressor discharge temperature and Inlet flange temperature. NN output is ‘Required temperature reference. These inputs and output have different scales though they are different physical quantity. So it is needed to normalize those values in the input range of tanh function [-1, 1].

Training of NN is conducted for variable peak region and for ambient of 59 F. 3 Inputs (humidity, Inlet flange temperature and ambient temperature) are held constant while MW set point is changed. The effect of changed MW set point can be observed in compressor discharge pressure and compressor discharge temperature.

To train the NN it is needed to give the steady state values of input and output variable to the NN. Sampling of the input data has been done before passing the input to the NN. Testing data covers the whole range of variable peak region.

During training, it is observed that the error is not converging towards its optimum value. So the learning is not actually happening in the NN.

After analyzing the NN, it is found that number of neurons needs to be increased. The inputs are 6 and total neurons used are only 5, so tuning is not occurring in the NN. To minimize the error to its optimum value, more tuning parameters (weights) are needed.

After getting this solution, NN is made with 9 hidden layers and one output layer, each hidden layer containing 6 neurons with learning parameter= 0.7. Training is conducted for the expanded NN. During training, it is observed that error is converging to the zero value. But after sometime Neural network output saturates to the maximum value of tanh function which is 1 and -1. After doing some literature survey, it is found that the learning parameter value is comparatively large and that is causing the saturation in input of tanh function and because of the saturation of tanh function, NN output saturates. The learning parameter value is changed from 0.7 to 0.07. Again the training is initiated. During training it is found that now error is converging towards zero value and activation function doesnt saturate. After 50 times of training of neural network through loading and unloading in variable peak region, the final updated weights are with us.

With the final updated weights testing of NN has been conducted. Whatever data has been given during training should not contain the testing data points into it. Testing data have to be different than testing data. So the training has been done for MW set points of 42, 43 and 45 but not for 44. During training, weight update algorithm is attached with forward path and weight update occurs in the direction to minimize the square of error. The observations are made during testing is shown in fig: 4.7.

Training data			Testing Data			Results		
MW SP	Temp Ref	Amb Temp	MW SP	Temp Ref	Amb Temp	MW SP	NN_OP	ACTUAL_OP
42	1014	59	42.2	1018	59	42.2	1068	1018
42.5	1024	59	42.7	1028	59	42.7	1068	1028
43	1034	59	43.2	1038	59	43.2	1068	1038
43.5	1044	59	43.7	1048	59	43.7	1068	1048
44	1054	59	44.2	1058	59	44.2	1068.8	1058
44.5	1064	59	44.7	1068	59	44.7	1069	1068
45	1074	59	44.9	1070	59	44.9	1070	1070

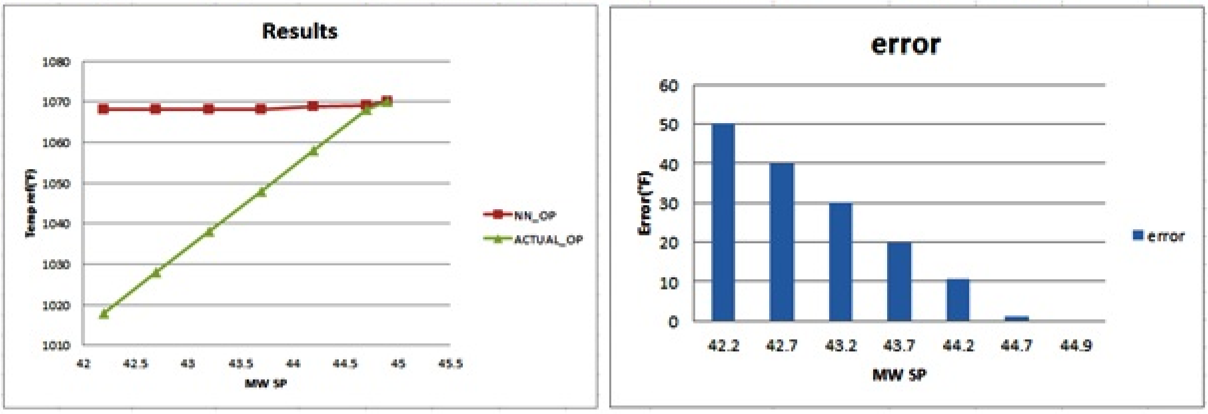


Figure 4.7: Reults of NN

For testing it is needed to disengage the weight update algorithm. MW set point 44, compressor discharge pressure and compressor discharge temperature values for 44 MW are applied as test data. But couldnt get expected temperature reference. After that, all the data points, which are not used in the training, are applied as testing data. The resultant curve is shown in figure 4.7. In the result graph, the curve Actual_OP is showing the output expected from the neural network and NN_OP is showing the results after this attempt. From the error graph in fig 4.7, it is seen that for last sample error is zero.

- NN forgot the past samples because the input fed to it was scalar value. So at an instance it is just one sample that is going in the NN and it generated the scalar error which is tried to minimize at that instance by updating the weights.
- But here, NN is used for function approximation (as curve fitting tool) thats why it

Number of Samples	MW_SP	CTD	CPD	CTIM	ATID	CMHUM
1	42	677.8	171.33	58.77	58.77	0.0064
2	42.5	678.7	171.83	58.77	58.77	0.0064
3	43	679.09	171.9	58.77	58.77	0.0064
4	43.5	680.2	172.5	58.77	58.77	0.0064
5	44	680.4	172.5	58.77	58.77	0.0064
6	44.5	681.3	173.02	58.77	58.77	0.0064
7	45	681.9	173.3	58.77	58.77	0.0064

Temp_Ref	1014	1024	1034	1044	1054	1064	1074

Table 4.1: Training Data of NN

is needed to feed all the data point as a vector at each instance to fit the curve. By feeding the inputs as a vector at each instance, error would be a vector.

- If the error is a vector, weights will be updated such that they can minimize the sum of square of error for the whole variable peak region and not only for one point.

The input should not be a column vector but had to be the matrix of m X n, which covers the whole input range and can give the error at each point over the curve. Here m = number of samples and n = number of inputs.

After getting the results, it is concluded that NN is minimizing the error at one point and not over the entire range of the curve. The reason is it was given scalar inputs and not the samples of inputs over the curve. So the modifications are made to the algorithm. Samples of input are taken over the entire range of the curve. Samples of MW set point, Compressor discharge pressure, Compressor discharge temperature and Inlet flange temperature has been taken over the entire range of the curve is shown in the table 4.1.

The matrix made up of the input samples (7 X 6) is fed to the NN. The table 4.1 is showing the input training data. For this vector configuration of NN, every time the same matrix of input data and same matrix of output data would be the training data for NN. Here, only 7 samples are fed to the NN but training could be better if number of samples could be more. If each and every data point can be fed then NN could fit the curve with optimum error.

Training is initiated for the modified NN. The results are shown in fig: 4.8

As shown in result graph of fig: 4.8 NN was minimizing the error at the midpoint of

Training data			Testing Data			Results		
MW SP	Temp Ref	Amb Temp	MW SP	Temp Ref	Amb Temp	MW SP	NN_OP	ACTUAL_OP
42	1014	59	42.2	1018	59	42.2	1048	1018
42.5	1024	59	42.7	1028	59	42.7	1048	1028
43	1034	59	43.2	1038	59	43.2	1048	1038
43.5	1044	59	43.7	1048	59	43.7	1048	1048
44	1054	59	44.2	1058	59	44.2	1048	1058
44.5	1064	59	44.7	1068	59	44.7	1048	1068
45	1074	59	44.9	1070	59	44.9	1048	1070

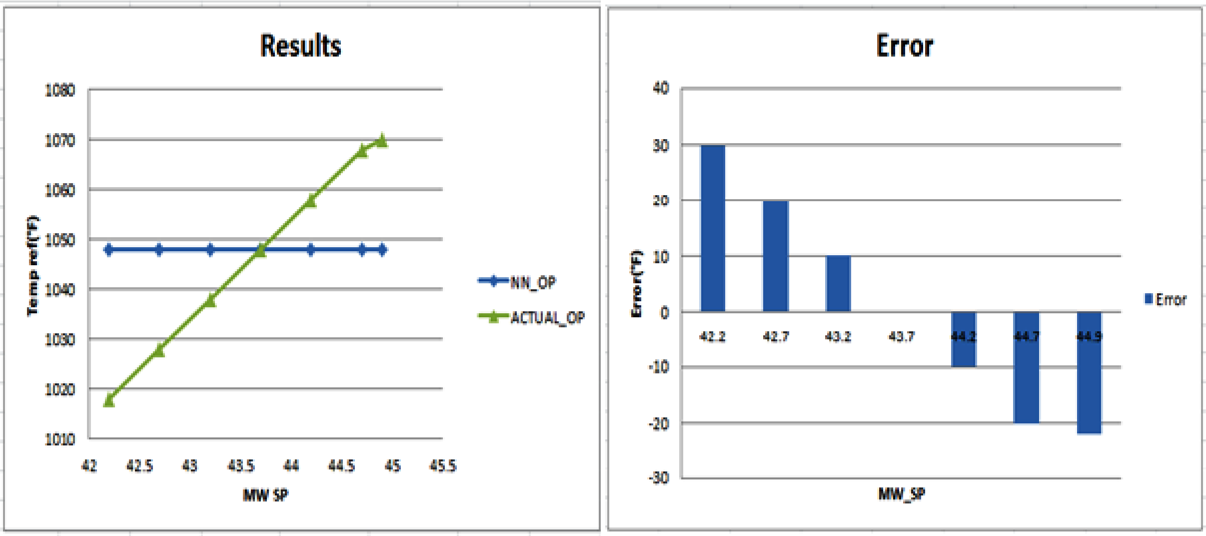


Figure 4.8: Reults of NN

the curve. In other words, NN is giving the straight line passing through the midpoint of training curve as an output. Essentially, the 7 element output vector of NN has same value for every element.

After the analysis of the NN has been done, it is observed that activation function used in neural network is getting saturated during training. The straight line is coming as an output of NN because of saturation of activation function. To resolve this issue, possible solution could be use of scalable tanh function instead of using same activation function in each layer of NN.

If activation function is

$$f(x) = atanh(bx) \tag{4.2}$$

Then

$$f'(x) = \frac{d}{dx}f(x) = \left(\frac{b}{a}\right)(a^2 - f^2(x)) \tag{4.3}$$

Here 'a and 'b are two coefficients of tanh function and $f'(x)$ can be used in back propagation algorithm. In f(x), 'a can be any real value, and 'b can be any value less than 1. Coefficient 'a is used to increase the output magnitude of tanh function and 'b is used to limit the input of tanh function so it wont create saturation of tanh function. Using scalable tanh function, layers of NN are created. Coefficients of tanh function are stated as A=1 and B=2/3, for 9 hidden layers as well as for output layer.

During training, the issue is found that NN is giving the straight line after doing some iteration. So NN tries to fix the curve. But weight update occurs in such manner that at the end NN gives straight horizontal line. In the input data matrix, the column of humidity, ambient temperature and Inlet flange temperature contain same data over the entire range. They are 3 input data columns form 6. It covers almost 50% of the data, which was constant. The issue is that in NN, constant inputs ruled on the weight update and they pull some of the weights to constant value and dont allow the NN to fit the curve.

So the conclusion made after facing this issue that the input samples should not contain constant value over the entire range of the curve rather changing inputs can train the NN better than constant inputs.

Discarding the two constant inputs (humidity and Inlet flange temperature) new NN is made. So now, the NN have 4 inputs (MW SP, ambient temperature, compressor discharge pressure, compressor discharge temperature). Among these four inputs only ambient temperature is held constant at 59. So after making the modifications, input matrix formed was of $7X4$.

During training, it is observed that error vector is converging towards optimum value. But all the elements of the error vector couldnt achieve almost zero error. Some offset is there between the expected output from NN and the actual output got from NN.

Research paper by Yann LeCun [2] on efficient back-propagation explains about what should be the initial weights, how normalization of inputs and outputs should be done. It also gives idea about the activation function saturation problem and the solutions are discussed in detail.

Some of the important points learned from the paper are mentioned below.

- Coefficient of the activation function should be in ascending order to prevent saturation of activation function.
- Ideal value of the learning parameter is in between 0.05 to 0.07.
- Initial weights should not be a very high value because that may cause saturation of activation function.
- If the function, for which NN is implemented, is linear it is better to use linear function with bias (y=mx+c) as an activation function of last output layer.

So based on these points, changes are made to the NN. The coefficient of tanh function for each layer is changed. B remains constant for each layer. (B=0.4)

Layer	1	2	3	4	5	6	7	8	9
Coefficient	1	1.7195	2.5	3	3.5	4	4.5	4.8	5.5

Table 4.2: tanh function coefficient for each layer

The outer layer activation function is changed with linear.

$$y = mx \tag{4.4}$$

where, m = 1

After making these changes the resultant curve found is shown in figure 4.9. Some offset is still there between the desired output and NN output. The solution to make the best curve fit is to add bias to activation function. Adding the fixed bias to the activation function helps to reduce the error. But the value of bias cant be changed after training has been

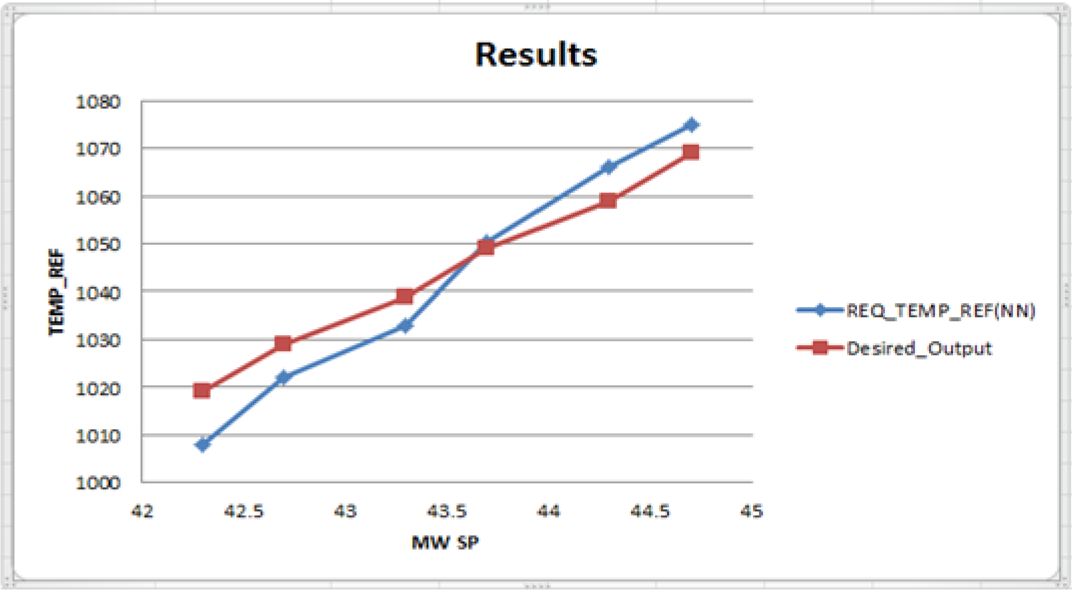


Figure 4.9: Reults of NN

done. The value given to NN as bias remains same for the entire operation of training as well as testing. So the bias is added to the outer layer of NN.

$$y = mx + c \tag{4.5}$$

Value for c is mentioned in the table 4.3.

Bias	C1	C2	C3	C4	C5	C6	C7
Value	-1.7	-1.2	-0.6	-0.08	0.4	1	1.6

Table 4.3: Bias values for linear activation function

The results are shown in figure 4.10 after adding the bias.

The results achieved after adding bias are satisfactory for linear curve fit. But it is required to check that if NN can give the satisfactory curve fit even for nonlinear functions. So the input and output data are changed. Input/output data is mentioned in the table 4.4.

After training the NN with the input/output data shown in table 4.4, testing of NN has been done. The figure 4.11 shows the testing results after training the NN with nonlinear data.

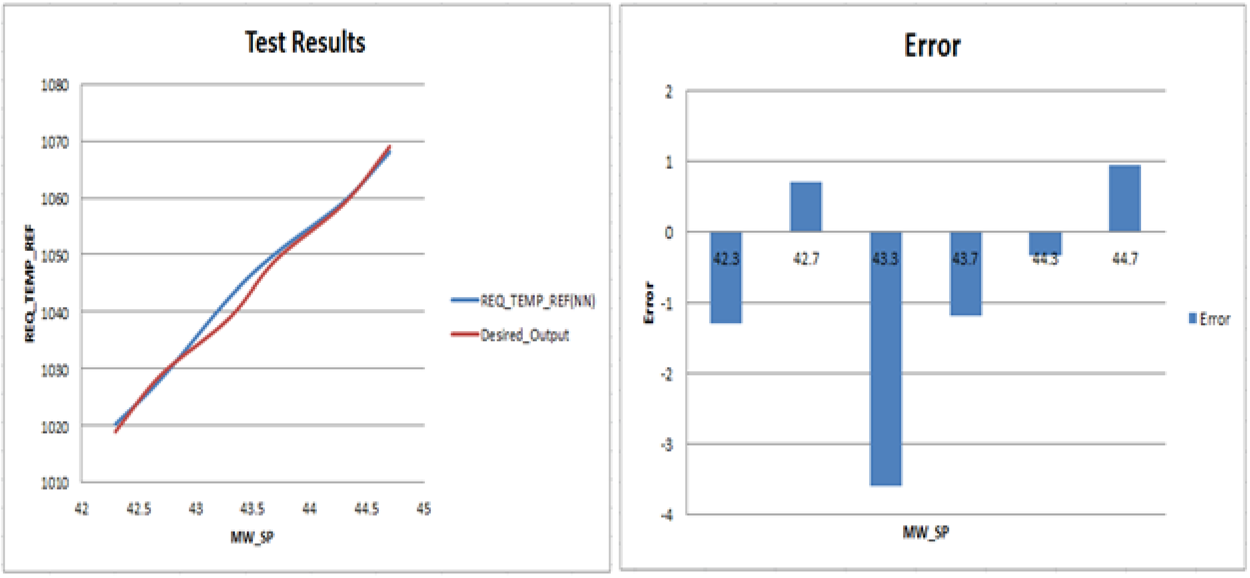


Figure 4.10: Results for linear curve fit

ATID	30	40	50	60	70	80	90
MW_SP	46.5	44.4	43	42	40.4	39.2	37.8
CPD	180.91	176.65	173.07	171.33	165.9	162.6	159.01
CTD	645.32	656.17	667.81	677.81	692.35	704.95	717.29
Temp_Ref	1030	1015	1022	1014	1044	1050	1060

Table 4.4: Training Data of NN (with different ambient temperature)

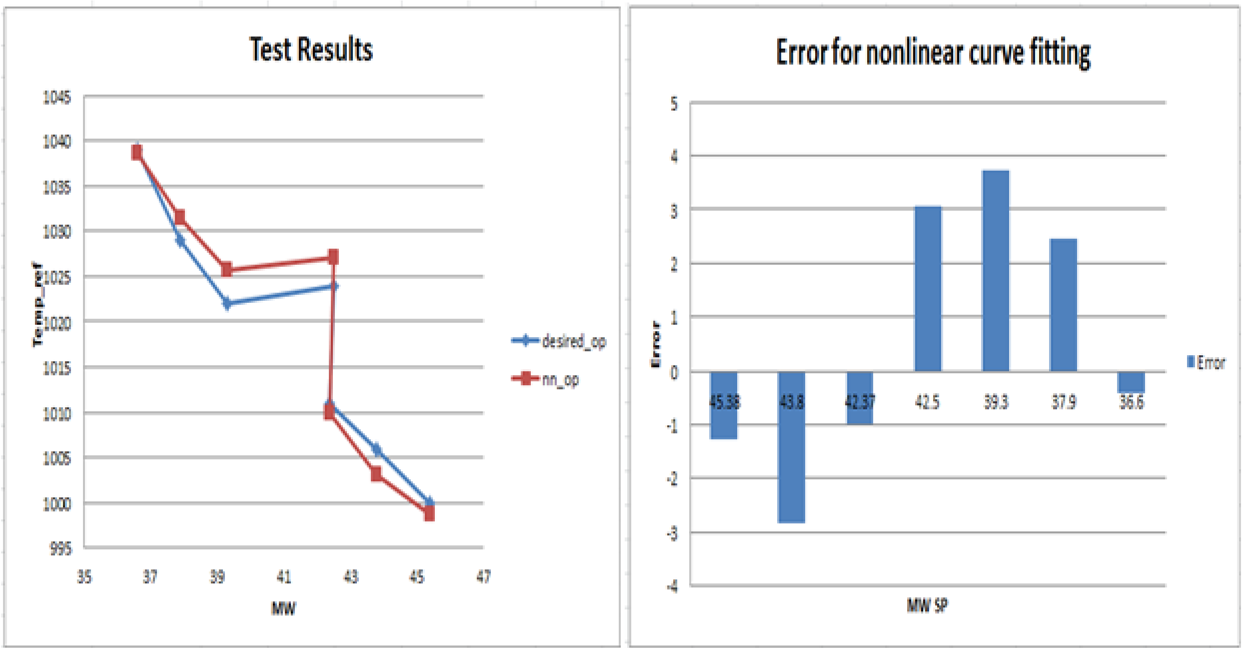


Figure 4.11: Results for non-linear curve fit

Chapter 5

Results and Discussion

5.1 Neural network in FSRT loop

In the previous chapter, neural network and results obtained from NN are discussed. After getting satisfactory results from neural network, the next task is to put the implemented NN block in the FSRT loop. From the results of NN, it is seen that NN is learning and giving the best possible function approximation for linear and nonlinear functions. NN is giving temperature reference for variable peak region. As shown in figure 4.2, NN is placed in FSRT loop. The NN placed in FSRT loop have updated set of weights and throughout the operation weights will remain same.

The inputs are MW set point, compressor discharge temperature, compressor discharge pressure and ambient temperature. Inputs are applied to the FSRT loop online in variable peak region. For different scenarios, the results are observed. First scenario is observed, keeping the ambient temperature constant and changing MW set point. Other scenarios are observed, changing ambient temperature as well as changing MW set point.

MW Set point	42	42.5	43	43.5	44	44.5

Table 5.1: MW set points (Fix ambient: 59^oF)

In the figure 5.1, trends are shown for four variables (MW set point, temperature reference, MW output, and exhaust temperature). In the table 5.1, the MW set points are shown. Ambient temperature is kept constant during simulation. As soon as the operator gives command of MW set point change, NN generates temperature reference according to the MW set point given by operator. Exhaust temperature starts following the tempera-

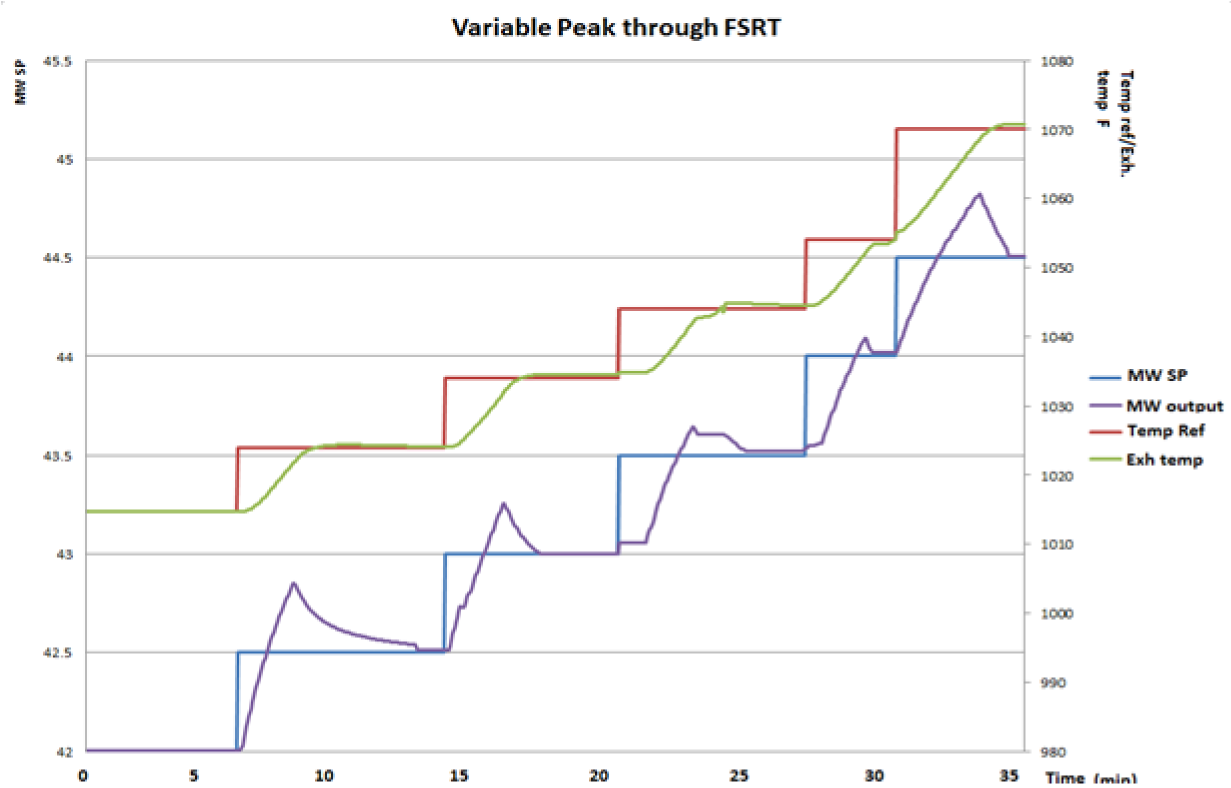


Figure 5.1: Results for MW output (Fix ambient: 59^o F)

ture reference given by NN. MW output also starts following the MW set point and settles down at the set point. Here, fuel is controlled through FSRT loop at variable peak region, at fixed ambient temperature of 59 ^{o}F.

Amb_temp(F^o)	30	40	50	60	70	80	90
MW set point	45	44	42	41	39.5	38	36.5

Table 5.2: MW set points (increasing ambient temperature)

In figure 5.2, trends are shown for five variables (MW set point, temperature reference, ambient temperature, MW output, and exhaust temperature). These trends are showing the effect of ambient change with MW set point change. The simulation is run by changing MW set point and increasing ambient temperature. The effect of change in temperature reference change due to increasing ambient temperature can be seen in the figure 5.2. So it is seen that NN is giving satisfactory results while increasing ambient temperature. Here, fuel is controlled through FSRT. Exhaust temperature is following the temperature reference given by NN during variable peak region.

Table 5.3 is showing the MW set point given by the operator to the NN while decreasing

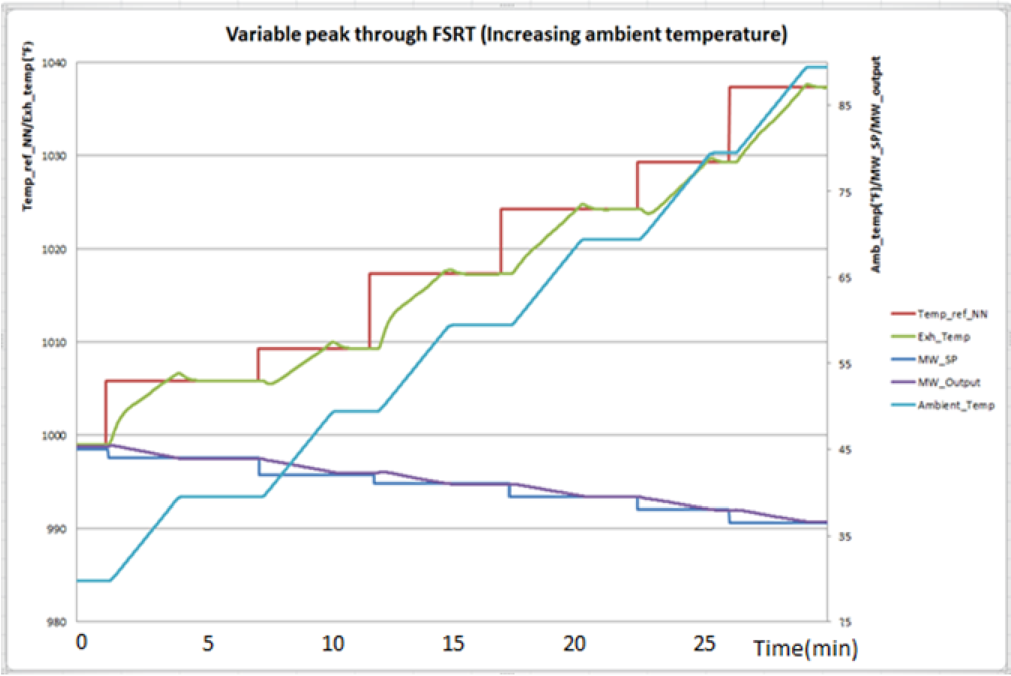


Figure 5.2: Results for MW output (At different ambient, increasing ambient)

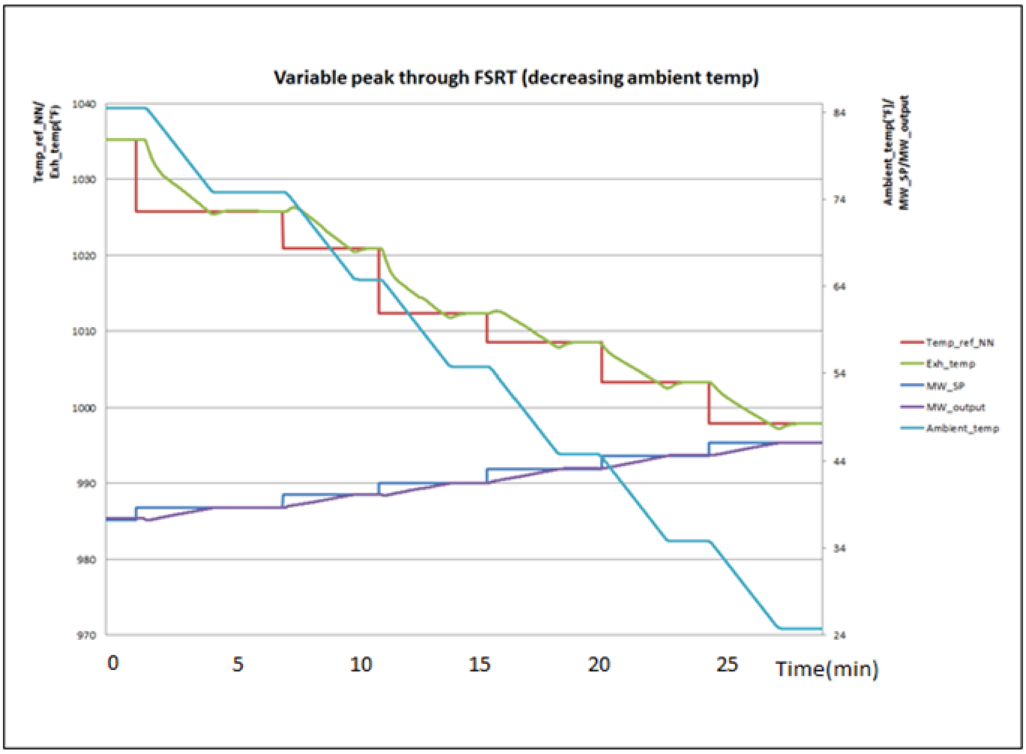


Figure 5.3: Results for MW output (At different ambient, decreasing ambient)

Amb_temp(^{o}F)	85	75	65	55	45	35	25
MW set point	37.2	38.6	40.1	41.1	43	44.6	46.1

Table 5.3: MW set points (decreasing ambient temperature)

ambient tem-perature. The trends in figure 5.3 are showing the effect of ambient change with MW set point change. The simulation is run by changing MW set point and decreasing ambient temperature. The effect of change in temperature reference change due to decreasing ambient temperature can be seen in the figure 5.3. From the results of figure 5.3 and 5.2, it is seen that NN can give temperature reference as per ambient change. (Increasing or decreasing)

In the last two cases, the ambient temperature was changed in ascending and descending order. NN was giving the desired temperature reference. MW output was satisfactory following the MW set point given by the operator. Now, it is tried to change MW set point as well as ambient temperature in random manner the data given to the NN is shown in table 5.3. MW output follows MW set point is shown in figure 5.4.

Figure 5.5 shows that even during random change of ambient, NN gives the satisfactory

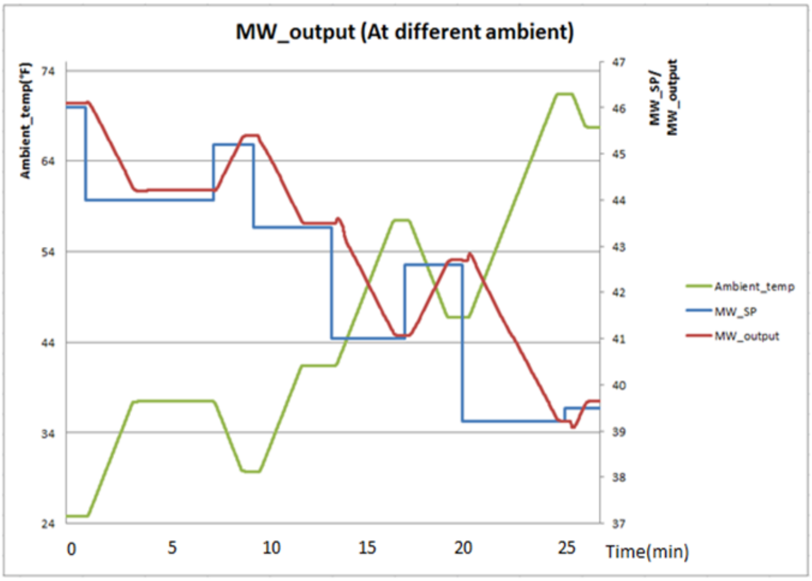


Figure 5.4: Results for MW output (At different ambient)

temperature reference as per MW set point and it also considers ambient conditions.

Amb_temp(^{o}F)	25	37	29	41	57	46	71	67
MW set point	46	4	45.2	43.4	41	42.6	39.2	39.5

Table 5.4: MW set points (decreasing ambient temperature)

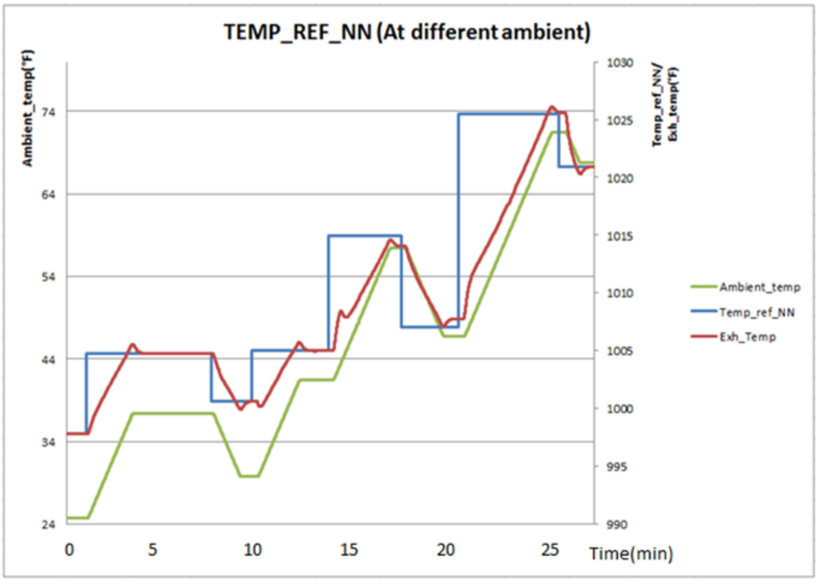


Figure 5.5: for TEMP_REF_NN (At different ambient)

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

1. After understanding the issue and analyzing it, some of the conclusions are made.
    - Fluctuations in MW output of gas turbine are observed.
    - In the simulation environment, plant output doesnt fluctuate.
    - MW output fluctuates more at part and variable peak region than base and peak load region.
2. During part load and variable peak, FSRN loop controls MW output and during base and peak load, FSRT controls MW output.
3. The root cause is turbine shaft speed fluctuations.
4. At base and peak load, MW output fluctuations are the effect of the fluctuations in compressor discharge pressure. Compressor discharge pressure fluctuates because of the fluctuations in turbine shaft speed.
5. Turbine shaft speed is one of the inputs to FSRN loop, which initiates fluctuations in MW output. The noisy MW output goes as a feedback in FSRN loop, which adds more fluctuations in MW output.
6. FSRT loop works on temperature control and shows less sensitivity to turbine shaft speed fluctuations than FSRN loop. (FSRT dont have turbine shaft speed as an input.)
7. The proposed solution could be:
    - Control the fuel through exhaust temperature reference.
    - Instead of controlling variable peak through FSRN, control it using FSRT.

8. By using neural network as a function approximator, temperature reference can be generated as per MW set point given by operator. Generation of temperature reference should also consider the ambient condition changes, because ambient conditions could affect MW output. (Considering that the temperature reference is available for MW set point at different ambient)

9. From the results obtained by using NN in FSRT loop, it has been concluded that MW output can be controlled by controlling exhaust temperature.

10. By controlling through FSRT, better control of MW output can be achieved than FSRN loop.

6.2 Future Scope

- To add the MW error (MW Error=MW set point - MW output) as one of the inputs to the NN to generate temperature reference.
- To implement neural network by using different weight update rules.
- To make the neural network generic, scalable and flexible.

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