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FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY (DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

Optimal ANFIS Based Automatic Generation Control for Steam Power Plant

A Thesis for the Partial Fulfillment of

Master of Science (MSc) in Electrical Automation and Control Technology Management

By,

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ADDIS ABABA, ETHIOPIA

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TECHNICAL AND VOCATIONAL TRAINING INSTITUTE (TVTI)

FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY

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Thesis 0n

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APPROVED BY THESIS ADVISORY COMMITTEE

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DECLARATION

I hereby declare that the work presented in this thesis entitled "**Optimal adaptive neuro-fuzzy inference system (ANFIS) based automatic generation control for steam power plant"** is my Owen original work, has not been presented for a degree in this or other universities and all sources of materials used for this thesis work have been fully acknowledged.

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Place: Addis Ababa

Date of Submission: March 9, 2026

This thesis submitted for examination with my approval as a TVTI advisor.

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ABSTRACT

The growing complexity, nonlinear characteristics, and continuous load variations in modern power systems require advanced control techniques to ensure reliable operation and maintain frequency stability. Automatic Generation Control (AGC) plays a crucial role in balancing power generation with load demand and in maintaining system frequency within acceptable limits. Although conventional controllers such as PID and FLC have been widely used in AGC applications, their performance often decreases under nonlinear operating conditions and load disturbances. This can result in higher overshoot, longer settling time, and reduced robustness. This thesis proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based AGC scheme for a steam power plant. The proposed approach integrates the learning capability of neural networks with the reasoning ability of fuzzy logic for effectively handle system nonlinearities and uncertainties. A detailed mathematical model of single-area steam power plant, including the governor, turbine, and generator-load dynamics, is developed and implemented in the MATLAB/Simulink. The performance of the proposed controller evaluated under both steady-state conditions and different load disturbance scenarios, including load addition and load rejection. The results compared with those obtained PID and FLC controllers. Simulation results show that the proposed ANFIS controller significantly improves overall system performance. The ANFIS-based control achieved lower percentage overshoot of 0.5%**,** faster settling time of 4.2s and shorter rise time of 0.3s. In comparison, the FLC produced 3.2% overshoot, 7.3s settling time, and 1.25s rise time**,** while the PID controller resulted in 4.8% overshoot**,** 8.7s settling time**,** and 1.5s rise time**.** These findings confirm the ANFIS-based approach provides reliable, efficient, and intelligent solution for AGC in steam power plants. It demonstrates superior performance compared with PID and FLC strategies in terms of dynamic response and system stability**.**

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS), Automatic Generation Control (AGC), steam power plant, frequency regulation.

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Contents

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Acronym

A list of acronyms used in this thesis along with their corresponding meanings presented below:

Acronym	Full Form
AGC	Automatic Generation Control
LFC	Load Frequency Control
ANFIS	Adaptive Neuro-Fuzzy Inference System
FLC	Fuzzy Logic Controller
IMC	Internal Model Controller
AVR	Automatic Voltage Regulator
PID	Proportional–Integral–Derivative
NN	Neural Network
FIS	Fuzzy Inference System
ANN	Artificial Neural Network
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
IGSA-BPSO	Improved Gravitational Search Algorithm – Binary Particle Swarm Optimization
RSO	Rat Swarm Optimization
PAPC	Predictive Adaptive Predictive Control
ZN	Ziegler–Nichols
TPGS	Thermal Power Generating Station
HTPS	Hydro Turbine Power System
CCPP	Combined Cycle Power Plant
RTDS	Real-Time Digital Simulator
HP	High Pressure
LP	Low Pressure
Pf	Power–Frequency
QV	Reactive Power–Voltage
MW	Megawatt
pu	Per Unit
Hz	Hertz
MATLAB	Matrix Laboratory

CHAPTER ONE

INTRODUCTION

1.1 Background

The rapid economic growth of modern societies has led to a significant increase in electrical energy demand, as electricity has become an essential and economically valuable component of daily life. An electric power system designed to convert energy from naturally available sources into electrical form and deliver it to end users. Although electricity is transmitted in electrical form, it is rarely consumed directly; instead, it is converted into other forms such as heat, light, and mechanical energy [4].

A modern power system network (PSN) typically consists of several interconnected control areas linked by tie lines, where each area is equipped with its own generating units to supply local load demands. Power systems may include various types of generating sources, such as steam power plants, hydroelectric plants, thermal power plants, and renewable energy sources like solar power.

Among these sources, steam power plants remain one of the dominant methods of large-scale electricity generation. In a steam power plant, high-pressure and high-temperature steam is expand through a turbine to convert thermal energy into mechanical energy, which is then transforms into electrical energy by a generator. The generated electricity is transmit and distribute to meet diverse consumer demands. However, the continuous growth in load demand often creates a mismatch between power generation and consumption, making system control increasingly challenging.

Frequency and voltage are critical operational parameters in power plants, and maintaining their stability is a primary concern. System frequency is directly dependent on active power balance and must remain constant under varying operating conditions. In interconnected grid systems, any change in generation or load at one location can affect the overall system frequency. Consequently, frequency regulation is a key indicator of power quality and system reliability.

A steam power plant operates based on thermodynamic principles, where fuel sources such as coal, natural gas, oil, or nuclear energy are uses to produce high-pressure steam. This steam drives a turbine connected to a generator through a shaft, converting thermal energy into mechanical energy and subsequently into electrical energy via electromagnetic induction[1].

Automatic Generation Control (AGC) is employ to automatically regulating the power output of generators in order to maintain the balance between electricity supply and demand. AGC plays a vital role in stabilizing system frequency and controlling power exchanges among interconnected areas. By continuously monitoring load variations and frequency deviations, AGC enhances system stability, reliability, and economic performance.

The primary function of AGC is to maintain system frequency within specified limits and to ensure scheduled power interchange between control areas. To achieve these objectives effectively, AGC systems must incorporate advanced and intelligent control techniques capable of responding to dynamic operating conditions [5]. In steam power plants, AGC is essential for mitigating the effects of random load disturbances, maintaining system frequency within standard limits (50 Hz or 60 Hz), and ensuring safe and reliable operation. This highlights the close relationship between frequency regulation and active power control.

Any imbalance in active power within the power system manifests as a frequency deviation across the network. Therefore, generating units are equipped with speed governors to regulate turbine speed and control frequency. Load variations are manages by adjusting the reference settings of the speed controller, which operates through a steam turbine governor to regulate turbine speed in response to changes in system load.

Basic Requirements for Power Generating Unit

An imbalance between generated power and load demand in a power system results in a variation in system frequency. For a power system to operate reliably and efficiently, the system frequency must be maintain within acceptable deviation limits around its nominal value. These limits are define by international standards and utility practices. The commonly accepted admissible frequency ranges used in power system operation and AGC studies are as follows [6].

1Nominal system frequencies

- 50 Hz systems: most of the world (Europe, Asia, Africa, -including Ethiopia)
- 60 Hz systems: North America, parts of Japan.

2Admissible frequency deviation ranges

A, Normal (steady state) operation it means no disturbance

Table: 1.1

Table 1 Admissible frequency deviation ranges for steady state

Nominal frequency	Admissible range	Deviation
50 Hz	49.95 – 50.05 Hz	± 0.05 Hz
60 Hz	59.95 – 60.05 Hz	± 0.05 Hz

B, continuous operation/small disturbance (small load changes)

Table 2 Admissible frequency deviation ranges for small load changes

Nominal frequency	Admissible range	Deviation
50 Hz	49.8 – 50.2 Hz	± 0.2 Hz
60 Hz	59.8 – 60.2 Hz	± 0.2 Hz

C, Emergency/ short time operation (large load disturbance)

Table 3 Admissible frequency deviation ranges for large load changes

Nominal frequency	Admissible range	Deviation
50 Hz	49.0 – 51.0 Hz	± 1 Hz
60 Hz	58.8 – 61.2 Hz	± 1.2 Hz

For reliable and stable operation of a power system, the frequency deviation must be maintain within ±0.05 Hz under normal operating conditions and within ±0.2 Hz during continuous operation. In emergencies, the permissible deviation may extend up to ±1 Hz for a short duration. To satisfy these requirements, generating units must be equipped with speed governors that provide the necessary speed control action. The relationship between turbine speed and load demand can be adjust by modifying the load reference set point of the speed controller or through a power control mechanism. In steam power plants, the control system mainly consists of a steam turbine governor and an excitation control system. The steam turbine governor regulates system frequency by controlling the turbine speed in response to variations in load demand, while the excitation system manages the reactive power requirement of the generator[6].

This thesis presents the modeling of Automatic Generation Control (AGC) for a steam power plant and evaluates the performance of different control strategies, including the conventional PID controller, Fuzzy Logic Controller (FLC), and the proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. The primary objectives of AGC are to regulate the system frequency to its nominal value, maintain the scheduled power interchange, and ensure stable distribution of generation among the units. Therefore, an effective control system in a steam power plant is essential to cancel the effects of random load disturbances and to keep the system frequency within the standard operating range of 50 Hz or 60 Hz.

1.2 Problem of Statement

The rapid economic and social development of modern society has led to a continuous increase in the demand for electrical energy. Modern power systems are required to operate under strict technical and operational constraints to ensure a reliable and high-quality electricity supply. However, growing and highly variable consumer load demands often drive power system networks into stressed operating conditions, creating the need for more efficient and robust generation control strategies. Variable load variation conditions and improper tuning of control parameters can result in undesirable frequency fluctuations, which negatively affect system stability and power quality. Although generating units automatically adjust their output in response to frequency changes, effective Automatic Generation Control (AGC) is essential to maintain frequency within acceptable limits. Conventional control approaches, particularly PID and Fuzzy Logic Controllers, have been widely used to regulate frequency and power output in power plants. Nevertheless, under rapidly changing load conditions these controllers exhibit significant limitations, including high fluctuations, high overshoot, long settling time, and excessive peak deviation. To address these challenges, this thesis proposes the design of an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based controller to improve frequency regulation and enhance active power delivery. The proposed approach adaptively adjusts the generator speed governor in accordance with actual load demand, thereby providing faster and more accurate frequency response compared to conventional methods.

1.3 Objectives

1.3.1 General Objective

The primary aim of this thesis is to design and simulate an Adaptive Neuro-fuzzy inference system/ANFIS/-based Automatic generation control for a steam power plant to effectively maintain stable system frequency under varying load conditions, while ensuring coordinate changes in generation among units to achieve optimum active power output.

1.3.2 Specific Objective

- To adopt an appropriate mathematical model representing the dynamics of a steam power unit
- To design and determining required parameter of PID, Fuzzy Logic, and ANFIS-based control mechanisms in the context of automatic generation control (AGC) for steam power systems.
- To build up a comprehensive simulation model of the steam power unit using MATLAB/SIMULINK software.
- To evaluate the proposed ANFIS-based automatic generation controller within the MATLAB/ SIMULINK environment.
- To compare the performance of PID and Fuzzy controllers against the proposed ANFIS method, using defined performance metrics such as stability, accuracy, and adaptability.

1.4 Methodology

The research methodology of this thesis consists of several steps carried out to achieve the study objectives. The first step is to identify the problem and clearly define the research objectives. This is follow by a review of relevant literature related to automatic generation control in steam power plants including a comparison with previous similar studies. A detailed mathematical model of the steam power plant unit is then developed. A brief explanation and design of the proportional-integral-derivative (PID), fuzzy logic controller (FLC) and adaptive neuro-fuzzy inference system (ANFIS) is also provide. MATLAB/Simulation are carrying out for proportional-integral-derivative (PID), fuzzy logic controller (FLC) and the adaptive neuro fuzzy inference system /ANFIS/ and compared their simulation result to show the performance control mechanisms. The final stage is the conclusion, based on the research findings and recommendations suggest for future research and practical implementation.

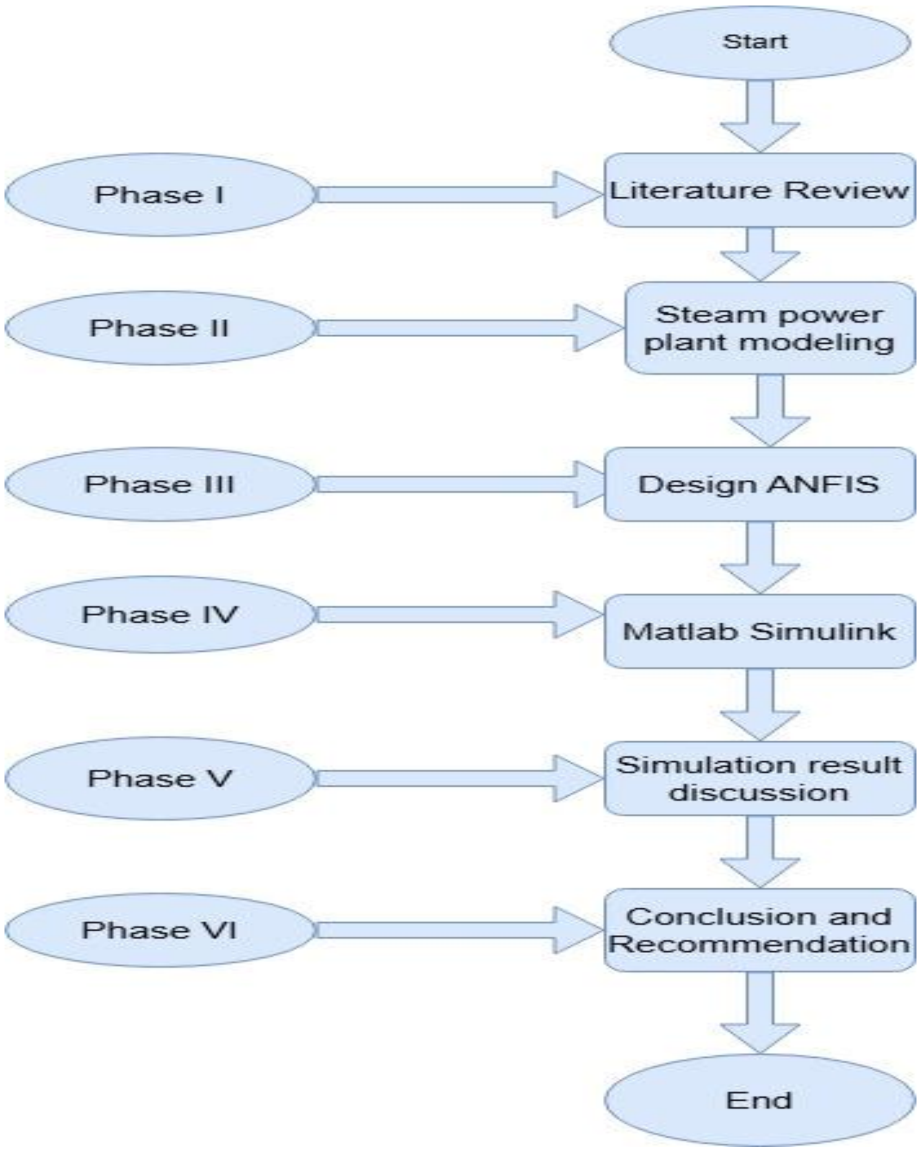

Figure 1 Flow Chart of the thesis research methodology

1.5 Scope of the Thesis

The scope of this thesis is structure into four main components as follows:

1st A comprehensive review and synthesis of relevant literature related to automatic generation control and steam power plant systems is conduct.

2nd A detailed mathematical model of a steam power plant is developed to represent its dynamic behavior.

3rd The conventional control strategies, including PID and FLC controllers are design and incorporated into the steam power plant model. The system performance is then evaluate through simulations carried out in the **MATLAB/Simulink** environment.

Finally, an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller is developed and integrated into the system, and its performance is analyze using MATLAB-based simulation results.

1.6 Thesis Outline

This thesis is organize into six chapters, each addressing a specific component of the research work.

Chapter one: introduces the introduction, problem statement, objectives of the thesis and the Methodology adopt to accomplish the thesis goals.

Chapter Two: provides a detailed review of existing literature related to automatic generation control in steam power plants and other relevant studies.

Chapter Three: focuses on the development of the mathematical model of the steam power plant. This chapter includes the modeling of key components such as the governor system, turbine, and generator**.** A complete SIMULINK block diagram of the system is also present with detailed explanations of its operational components.

Chapter Four: describes the brief explanation and design of the PID controller, Fuzzy Logic Controller (FLC), and Adaptive Neuro-Fuzzy Inference System (ANFIS) applied to the steam power plant.

Chapter Five: presents the simulation results obtained using MATLAB/Simulink environment, along with a detailed discussion and comparative analysis of controller performance.

Chapter Six: presents the conclusion, based on the research findings and recommendations suggest for future research and practical implementation.

1.7 limitations

Despite the Adaptive Neuro-Fuzzy Inference System (ANFIS) demonstrates promising results and improved performance in controlling automatic power generation in a steam power plant, several limitations that need to be acknowledge:

- ✓ This study is limited to a single-area, non-reheat type power system modeled.
- ✓ The ANFIS controller was compared against conventional controllers like PID and FLC,
- ✓ The research remains at the simulation level, and no physical hardware or real-time control implementation been performed to validate the theoretical outcomes in practice.
- ✓ Only the step load disturbances are consider in the simulation. Other types of disturbances, such as persistent load variations, which commonly occur in real power systems, have not been test.

CHAPTER TWO

LITERATURE REVIEW

2.1 Related Works

This chapter presents reviews of various control strategies used for automatic generation control (AGC) in steam power plants. It discusses the fundamental concepts of different controllers, provides an overview of the simulation software used in this study, and summarizes previous research related to load frequency control. Based on this review, the research gap addressed in this thesis is also identify.

Controllers in power generation systems must be design to meet load demand while ensuring the safe and reliable operation of the power plant**.** At the same time, the design should consider the operational safety and lifespan of key plant components. One of the major challenges in power system operation is maintaining the system frequency within acceptable limits, since frequency stability is directly relate to the balance between generated power and load demand.

Steam power plants play an important role in electricity generation and support many industrial applications. In these plants, steam is produce by heating water inside a boiler drum. When heat is applied, the water circulating within the drum tubes evaporates and forms steam. This steam is then supply to the turbine to generate mechanical power, which is later convert into electrical energy.

Several researchers have investigated different controller designs for AGC and load frequency control (LFC). A study on a two-area power system implemented PI, fuzzy logic, and hybrid PI–fuzzy controllers to regulate system frequency. The controllers evaluated under different simulation conditions, including operation without a controller and with each control strategy. The results indicated that the fuzzy logic controller performed better than both the PI controller and the uncontrolled system in maintaining frequency stability[7]. However, the fuzzy controller exhibited excessive overshoot and longer settling time, indicating limited effectiveness in achieving fast and well-damped dynamic responses.

Another study applied PID, PD–PID, and fuzzy PI controllers to a two-area reheat thermal power system for load frequency control. The results demonstrated that the fuzzy PI controller achieved better performance compared with the PID and PD–PID controllers[8]. Nevertheless, the fuzzy PI approach still resulted in relatively large settling times, limiting its suitability for fast dynamic response requirements.

An artificial neural network (ANN)-based load frequency control strategy proposed for multi-area power systems. The study showed that the ANN-based controller improved frequency regulation and power delivery compared with conventional ANN and PID approaches. The controller also achieved a minimum time multiplied absolute error of approximately 3.45

seconds[9]. Despite these advantages, the controller showed reduced robustness under nonlinear operating conditions and fault scenarios.

A particle swarm optimization tuned PID (PSO–PID) controller was developed to improve load frequency control in interconnected thermal power systems. Simulation results showed that the PSO–PID controller provided faster settling performance compared with conventional PID, genetic algorithm (GA)-based PID, and differential evolution (DE)-based PID controllers. The performance improvements were reported as 79% compared to conventional methods, 55% compared to GA, and 24% compared to DE[10]. However, oscillations persisted for up to 39 seconds, highlighting limitations in transient performance improvement.

Another research study implemented a fuzzy logic–based power system stabilizer (FLPSS) for the Tana Beles hydropower plant to enhance transient stability. The results showed that the fuzzy stabilizer significantly improved oscillation damping and reduced settling time compared with an automatic voltage regulator (AVR) based excitation system[11]. Nonetheless, active power exhibited noticeable oscillations and a settling time of approximately 9 seconds, and overshoot reduction remained insufficient.

Dynamic modeling and simulation of the Basochhu Hydropower Plant were also investigate under islanded operation and grid restoration conditions. The study emphasized the importance of accurate simulation models for analyzing the dynamic and static behavior of hydropower plants. The results indicated that grid disturbances caused significant active power oscillations and deviations in generator speed**,** suggesting weaknesses in the governor control system[12]. The study revealed significant active power oscillations and frequency deviations during disturbances, indicating weak governor performance. The findings emphasized the need for improved governor control to enhance transient and dynamic stability.

An improved gravitational search algorithm–binary particle swarm optimization (IGSA-BPSO) tuned PID controller was proposed for AGC in interconnected multi-source power systems. Simulation results demonstrated that this controller provided better settling time and damping performance compared with GSA-PID and PSO-PID controllers[13].However, high overshoot and instability under nonlinear load variations limited its robustness.

Another work introduced a Rat Swarm Optimization (RSO)-based PID controller for load frequency control in a single-area thermal power plant. The results showed that the RSO-based controller outperformed the firefly algorithm (FFA) and Ziegler–Nichols tuning techniques[14]. Despite these improvements, the controller exhibited large oscillations, poor settling time, and negative frequency overshoot under load disturbances, posing risks to system stability.

A study investigating AGC performance under varying generation schedules analyzed the behavior of a thermal power plant over a 24-hour load cycle. The results indicated that AGC performance deteriorates when the operating level deviates from the rated generation capacity due to changes in turbine parameters[3]. However, From a research gap perspective, although improvements in overshoot reduction and settling time minimization are reported, there is insufficient in-depth analysis of robustness, sensitivity to parameter uncertainties, damping characteristics, and stability margins under nonlinear operating conditions. Furthermore, the optimization of rise time versus overshoot trade-offs is not thoroughly explored, and no detailed investigation of controller performance under large disturbance constraints is provided. Therefore, future research should focus on multi-disturbance testing, robustness analysis, and comprehensive stability metrics evaluation to strengthen proposed control approach.

Additional research compared PID, internal model control (IMC), and IMC-based PID controllers for a hydro turbine power system. The IMC controller demonstrated faster settling performance compared with the other methods[15]. However, all controllers showed reduced effectiveness in handling nonlinearities and external disturbances, indicating limited adaptability to realistic operating conditions.

Fuzzy logic control has also been widely applied to multi-area to load frequency control systems. Simulation results showed that fuzzy controllers significantly reduced overshoot and settling time compared with conventional PI controllers[16]. Nonetheless, the fuzzy controller struggled fully address nonlinear dynamic behavior, restricting its effectiveness under varying load conditions.

A predictive controller proposed for turbine-generator regulation and compared with a conventional PID controller. Simulation results indicated that the predictive controller achieved improved settling time and reduced overshoot for both small and large disturbances[17]. However, performance degradation observed under extreme operating conditions, indicating limited robustness.

A neuro-fuzzy controller also proposed for load frequency control of a two-area power system. The results showed that the neuro-fuzzy approach provided better dynamic stability compared with PI and fuzzy controllers [18]. Despite these improvements, complete robustness under all operating scenarios not achieved.

A comprehensive review of robust control strategies and optimization techniques for AGC highlighted the advantages of fuzzy logic controllers in managing nonlinear systems without requiring precise mathematical models. The review indicated that fuzzy–PID controllers outperform conventional PID controllers by reducing overshoot and improving oscillation damping [19]. Despite these advantages, the review identifies several critical limitations. Conventional controllers struggle to achieve an optimal balance between overshoot reduction and settling time minimization when operating under nonlinear and uncertain conditions. Moreover, Type-I fuzzy controllers exhibit limited robustness against severe uncertainties and parameter variations, which constrains their applicability in modern, highly dynamic power systems. The paper further emphasizes the absence of unified optimization frameworks capable of simultaneously addressing overshoot minimization, fast settling time, and robustness under nonlinear system constraints.

Another study proposed a fuzzy logic–based AGC scheme for multi-area power systems, which improved frequency response compared with conventional controllers. However, the system still experienced high overshoot and large settling times, indicating that fuzzy logic alone may not completely solve frequency deviation problems. An ANFIS-based AGC controller was also developed and experimentally tested for a hydropower plant. The results demonstrated that the ANFIS controller significantly reduced frequency deviation and improved settling time compared with PID and fuzzy controllers[20]. However, the study was limited to hydropower plants and did not consider steam power plant applications.

Finally, research on ANFIS-PID and fuzzy-PID controllers for AGC and load frequency control of a two-area reheat thermal power plant showed improved dynamic responses. Simulation results indicated that these hybrid controllers reduced settling time to approximately 10–15 seconds, demonstrating improved system performance [21].

2.2 Summary of literature review

Here is the reviewed gap analysis in clear table format**,** summarizing each study, its contribution, limitations, and the identified research gap.

Table 4 reviewed gab analysis

L.R. No.	Author/ Year	Method / Controller Used	Key Findings	Identified Limitations	Research Gap
1	Nilay N. Shah (2012)	PI, Fuzzy, PI–Fuzzy for two-area AGC	Fuzzy controller performs better than PI	High overshoot and long settling time	Need controllers that reduce overshoot and settling time simultaneously
2	Anita Pritam (2017)	PID, PD-PID, Fuzzy PI	Fuzzy PI performs best	Fuzzy PI shows long settling time	Requires an improved controller with better dynamic response
3	Sadeq D. Al-Majidi (2022)	ANN-based optimal LFC	ANN improves frequency adjustment and minimizes error	Poor performance under some nonlinear or fault conditions	Need an more robust ANN-hybrid approach for nonlinearity handling
4	Boopathi Dhanasekaran	PSO-PID	Faster response and improved	Settling time still large (39	Need an optimization technique with faster

	(2023)		% performance	s)	stabilization
5	Gedef Yirgalem (2021)	Fuzzy Logic PSS (Hydro)	Improves damping and reduces settling time	Active power settling time = 9 s; overshoots remain	Need an advanced controller minimizing oscillation & overshoot
6	Cheku Dorji et al. (2022)	HPP dynamic model & tests	Identified weak governor control	Significant oscillations during disturbances	Need robust governor control and dynamic stability enhancement
7	Kumar et al. (2022)	IGSA-BPSO-PID	Best settling time among methods	High overshoot; unstable under nonlinearities	Need improved multi-objective optimization addressing overshoot & nonlinear dynamics
8	Pasala Gopi (2024)	RSO-based PID	Outperforms FFA and ZN	Large oscillations, poor settling time, negative overshoot (frequency rise)	Need a safer, more stable controller under load change
9	Bhura (2024)	PID, IMC, IMC-PID	IMC has fast settling under disturbance	Poor handling of nonlinearities	Need nonlinear-adaptive or predictive controllers
10	Panwar & Chahar (2016)	Fuzzy vs PI	Fuzzy reduces overshoot & settling time	FLC struggles with nonlinear dynamics	Need a hybrid fuzzy-based system to address nonlinearity
11	Xiao et al. (2015)	NN-based One-Step-Ahead Predictive Control	Better than PID in some cases	Poor performance for both small and large disturbances	Need predictive controller with improved robustness
12	P. O. Oluseyi (2019)	Neuro-fuzzy LFC	Neuro-fuzzy outperforms PI and FLC	Still lacks complete stability under all conditions	Need enhanced neuro-fuzzy model with better generalization
13	Amit Panwar (2016)	Fuzzy for multi-area LFC	Better than conventional methods	High overshoot & large settling time remain	Need controller reducing both overshoot & settling time effectively

14	TilahunWeldcherkos(2021)	ANFIS for hydro power plant system	Works well for a system with nonlinearities	experimented only with hydro power plant system	experimented with stem power plant system
15	Kavita Choudhary(2019)	ANFIS and Fuzzy- PID controllers	significant improvements of dynamic responses	High settling time	Needs improved settling time
16	Prakash Chandra Sahu (2025)	fuzzy–PID	FLCs ability to handle nonlinearities	Overshoot, settling time, under nonlinear constraints.	Needs optimization framework addressing overshoot, settling time, and robustness
17	Nikhil Pathak (2016)	power generation levels/schedules	AGC dynamic performance to changes in steam turbine dynamics	High overshoot, rise time and settling time	Analysis limited to critical performance such as overshoot, settling time, rise time, and overall stability not evaluated

Different control methods proposed in the literature to improve the system frequency and active power stability in power generation systems, including PID controllers optimized with IGSA-BPSO and RSO, Fuzzy Logic Controllers, IMC-based methods, and neural network-based predictive control. Each control method demonstrates specific advantages, such as reduced overshoot or improved settling time. However, limitations remain in handling nonlinearities, dynamic load changes, and adaptability. Specifically Classical and many advanced PID variants still exhibit relatively long settling times (>10–40 s) and/or significant overshoot/undershoot. Pure Fuzzy Logic controllers dramatically reduce overshoot but often at the cost of longer settling time and residual oscillation.

These challenges have motivate the use of ANFIS, which offers a hybrid intelligent control system capable of learning, adapting, and managing nonlinear dynamics more effectively than conventional methods (PID and FLC). This study plans to effectively handle plant non-linearity, which is achieving settling times within 5–10 seconds accompanies by minimal overshoot or undershoot.

CHAPTER THREE

POWER GENERATION PROCESS AND DYNAMIC MODELING OF STEAM POWER PLANT

3.1 Introduction

This chapter describes the procedures involved in power generation and the equipment used in the process. First, the basic operating principle of the steam power system is briefly discuss. Next, the process and stages of steam generation are explained, along with the main components that drive the system for electricity production. In addition, the mathematical modeling of the main sub-systems and the combined cycle model adopted for the study are present.

The steam power plant model considered in this work is implemented using MATLAB/Simulink software. The model consists of the following dynamic sub-models:

- ✓ Governor system model
- ✓ Turbine model
- ✓ Generator and load model

The block diagram of the complete system, including its sub-models, is illustrate in Figure 3.1.

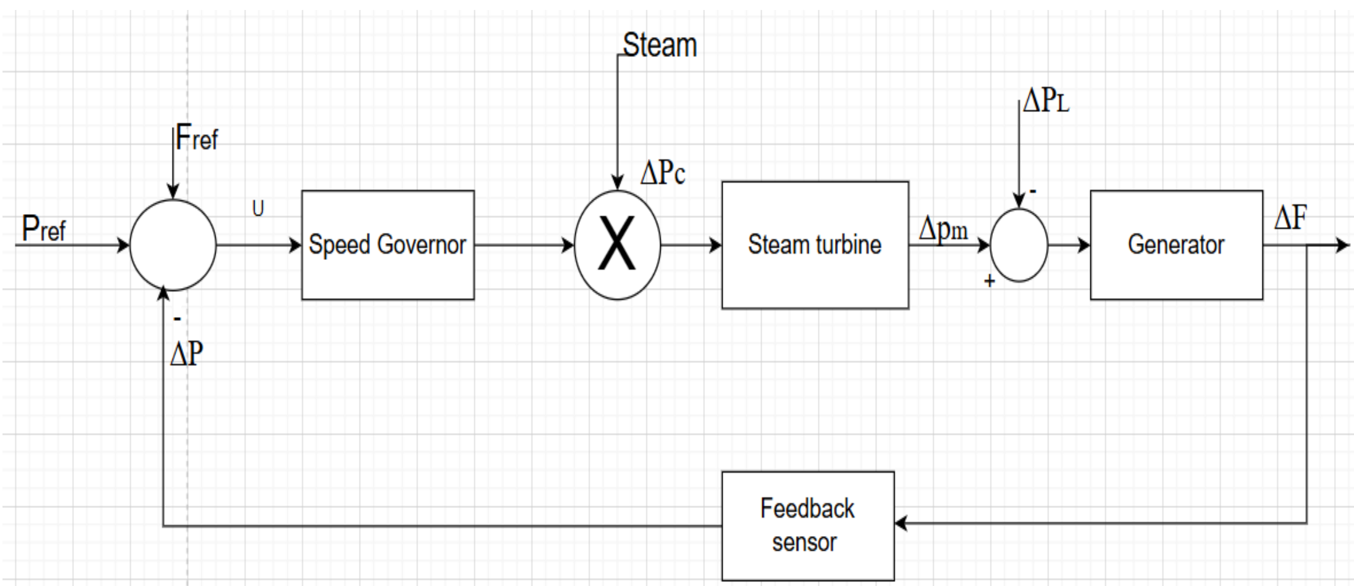

Figure 2 Block diagram of the complete model with its sub models

3.2 Working Principle of Steam Generation Process

The fundamental principle of steam generation is simple and straightforward. In this process, the boiler functions as a closed vessel in which water is stored and heated. Fuel, commonly coal, is burn in a furnace to produce hot gases. These gases meet the water container, transferring their heat energy to the water. As a result, the water is convert into steam inside the boiler. The generated steam is then directed through pipes to the turbine of the steam power plant, as illustrated in Figure 3.1[1].

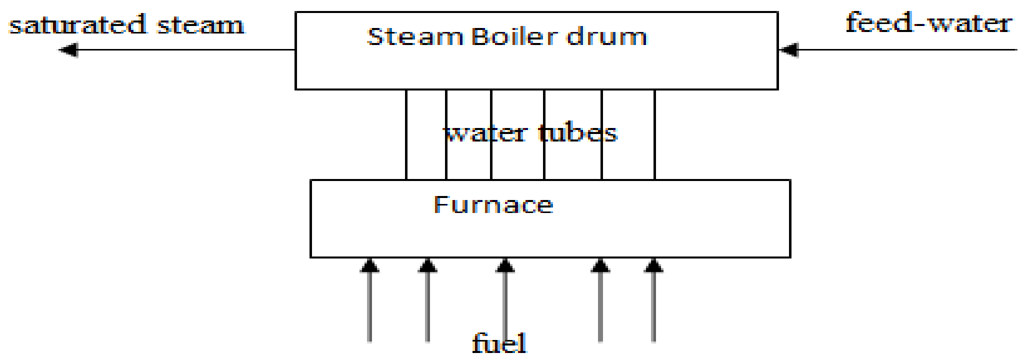

Figure 3 working principles of steam generation process **[1]**.

Elements of a steam power plant

Heater Fuel Unit: - Heaters in a steam power plant may operate using a single fuel or a combination of fuels such as natural gas, refinery gas, fuel oil, or pulverized coal. The fuel supply system ensures that fuel oil and other fuels are delivers to process heaters and steam generators at the required temperature and pressure levels to support efficient combustion.

Feed-Water Unit: - The feed-water system plays a critical role in steam generation. To maintain continuous operation, the quantity of water entering the boiler must be equal to the amount of steam leaving the system. Proper feed-water control ensures stable steam production and prevents damage to boiler components.

Water Tubes: - Water tubes are straight or curved hollow tubes through which a mixture of water and steam circulates. These tubes are classify into two main types: down-comers and risers. Together, the down-comer and riser arrangement form the evaporator section, also referred to as the boiler proper, where the phase transformation from water to steam takes place.

A. Down comer Water Tubes

Down comers are water tubes that carry water from the steam drum downward to the mud drum. During this process, only saturated water should flow through the down comers, and the presence of vapor bubbles must be avoid. If vapor bubbles enter the down comers, the density difference between the tubes will decrease, which in turn reduces the pressure head required for natural circulation[1].

B. Risers Water Tubes

Risers are the tubes that transport the steam–water two-phase mixture from the mud drum upward to the steam drum at saturation temperature. These tubes are generally positioned near the furnace so that they can absorb heat effectively, whereas the down comers are located farther away from the furnace region[1].

Steam Boiler Drum

The boiler drum plays an important role in separating steam from water and maintaining an adequate water inventory to handle operational variations. Water flows through the riser tubes where it is heat and gradually changes from a single-phase liquid into a mixture of saturated water and steam. As the heat input increases, the amount of steam produced in the riser tubes also increases.[1].

3.3 Stages in Steam Generation Process

The feed water and steam circuits of a boiler consist of several key components, including the economizer, boiler drum, evaporator, water tubes, and super heater. The production of high-pressure steam is accomplished through the coordinated operation of both high-pressure and low-pressure drum boiler units, as explained in the following section.[1].

1. **Economizer stage:** In this stage, feed water supplied by the pump preheated before entering the boiler drum to improve thermal efficiency and reduce overall fuel consumption. The economizer consists of water tubes positioned in the path of hot flue gases leaving the evaporator section. These tubes, typically made of steel or cast iron, designed to withstand high temperatures and pressures. By raising the feed-water temperature, the economizer minimizes thermal stress on the evaporator tubes and enhances system efficiency.

2. **Evaporator stage:** Water flows downward through the down-comer and rises through the riser tubes in a closed circulation loop due to gravity and density differences. During this process, heat absorption converts the water from a liquid state into saturated steam. The evaporator tubes commonly installed along the boiler floor (water floor) and walls (water walls). The generated saturated steam then directed toward the steam drum before supplied to the super heater.

3. **Super Heater Stage:** Saturated steam exits the steam drum and flows through the super-heater, where it heated further to produce superheated steam. The super-heater functions as a heat exchanger that raises the steam temperature beyond saturation, thereby increasing thermal efficiency and turbine performance. Super-heater tubes exposed to extremely high steam

pressures and temperatures internally, as well as high flue gas temperatures externally, making them one of the most critical components of the steam power plant.

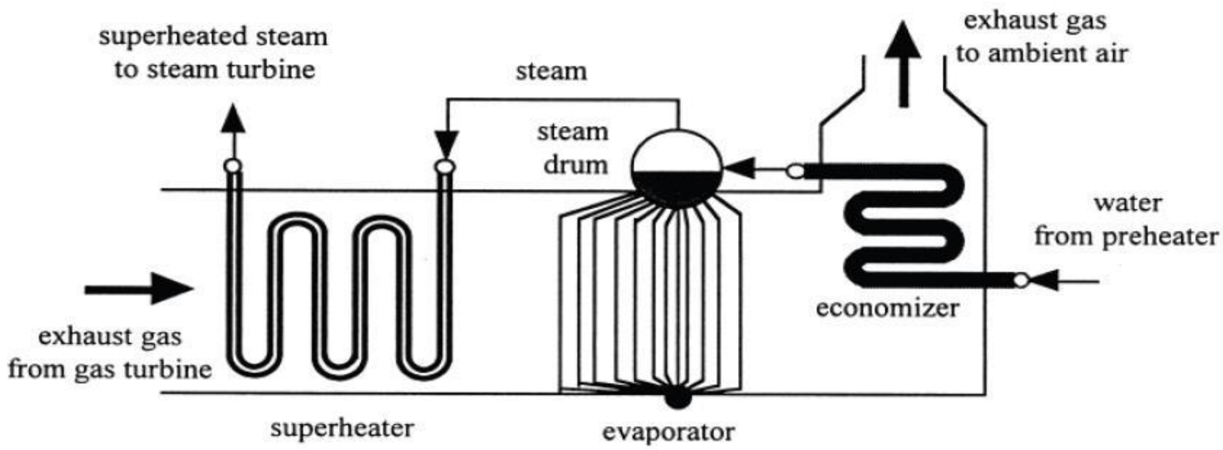

Figure 4 Heat Recovery Steam Generator [1].

3.4 Mathematical Modeling of the Steam Power Plant

3.4.1 Power plant model

The power generating unit system control task of a steam power plant are divide into two main control channels:

- Power – frequency(Pf) control and
- Reactive power – voltage (QV) controls[4].

1. The turbine-governor model, which considers:

The Pf control channel is responsible for regulating the turbine shaft power to maintain the system speed and frequency, while also controlling the active power output of the generator [4].

2. Generator and excitation system model:

The QV control channel regulates the generator terminal voltage and controls the reactive power output of the system[4].

The steam power plant model use in this work is develop using MATLAB/Simulink software and consists of the following dynamic sub-models:

- Speed governor
- Steam Turbine
- Generator load dynamics

The block diagram of the complete system, including its sub-models, is shown in Figure 3.3[4].

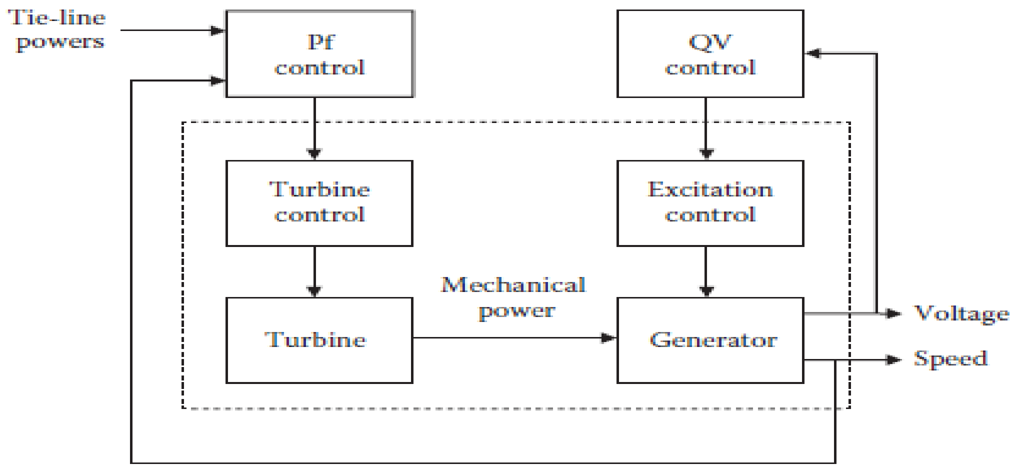

Figure 5 control loops of a power generating unit [2].

3.4.2 power- Frequency Control Channel

Maintaining a stable system frequency is a fundamental requirement for the reliable and efficient operation of electric power systems and is particularly critical for industrial processes and production facilities. System frequency expected to remain constant or exhibit only small deviations around its nominal value, as specified by power utility standards. Frequency stability is directly link to the balance between active power generation and load demand. Any change in active load at a bus introduces a mismatch between generated power and consumed power. This imbalance is initially compensate by the kinetic energy stored in the rotating masses of the generators, causing a reduction in generator speed and, consequently, a decrease in system frequency[4].

The resulting frequency deviation is detect and fed back to the turbine speed governor, which adjusts the inlet valve position of the turbine. This modification alters the mechanical power input to the turbine and, in turn, the electrical output of the generator, thereby reducing the active power imbalance. This mechanism refers to as primary control and provides a rapid but limited correction of frequency deviations. The dynamic response of this control loop is constrained by the turbine's inherent time constant[4].

3.4.3 Basic mathematical models of a typical steam power plant

Before developing the model of a complete turbine system, it is necessary to first derive the transfer function of a steam vessel and determine the expression for the power produced by a turbine stage.

Figure 6 A vessel provided with openings for the inflow and outflow of steam **[3]**.

The continuity equation for the vessel is

$$\frac{dw}{dt} = \mathrm{v}\frac{d\rho}{dt} = Q_{in} - Q_{out} \qquad (3.1)$$

Where:

W = mass of steam contained in the vessel (kg) = vρ

V = volume of the vessel (m^3)

ρ = steam density ($^{kg}/_{m^3}$)

Q = mass flow rate of steam (kg/s)

T = time (S)

It assumed that the steam flow leaving the vessel is directly proportional to the pressure inside the vessel:[5].

$$Q_{out} = \frac{Q_o}{p_o}\mathrm{P} \qquad (3.2)$$

Where

P = pressure of steam in the vessel (kpa)

p_o = Rated pressure

$Q_o = rated\ flow\ out\ of\ vessel$

With constant temperature in the vessel,

$$\frac{dp}{dt} = \frac{dp}{dt}\frac{\partial\rho}{\partial p} \qquad (3.3)$$

The variation of steam density with respect to pressure ($^{\partial\rho}/_{\partial p}$) at a constant temperature can be obtained from standard steam tables[5].

By combining equations (3.1), (3.2) and (3.3), we obtain:

$$Q_{in} - Q_{out} = \mathrm{v}\frac{\partial\rho}{\partial p}\frac{dp}{dt}$$

$$Q_{in} - Q_{out} = \mathrm{v}\frac{\partial\rho}{\partial p}\frac{p_o}{Q_o}\frac{dQ_{out}}{dt}$$

$$Q_{in} - Q_{out} = T_v\frac{dQ_{out}}{dt} \qquad (3.4)$$

$$\text{Where } T_v = \frac{p_o}{Q_o}\mathrm{v}\frac{\partial\rho}{\partial p} \qquad (3.5)$$

Taking the Laplace transform of equation (3.4) gives:

$$Q_{in} - Q_{out} = T_v\, s\, Q_{out}$$

$$\frac{Q_{out}}{Q_{in}} = \frac{1}{1+T_v s} \qquad (3.6)$$

3.4.3.1Model of the Primary Control Action (speed governor System)

The governor is a device connected to the turbine that regulates the mechanical input power supplied to the generator. The input signal to the governor is the **speed deviation (**Δω) which occurs due to load variations in the system. This deviation is define as the difference between the actual generator speedand the reference speed ω*r*[4].

$$\Delta\omega = \omega a - \omega r \qquad (3.7)$$

This deviation signal is amplify and integrate to produce the actuating valve or gate signal Δ*Pg*. The signal Δ*Pg* adjusts the inlet steam flow to the turbine, thereby controlling the turbine power output. The governor action can be represent by the block diagram shown in Figure 3.6. For proper load sharing among generators operating within the same power system, each governor is design with a speed regulation characteristic, where the generator speed decreases slightly as the load increases. This behavior, known as speed droop, is obtain by introducing feedback around the integrator, as indicated by the dotted lines in Figure 3.6.[4]

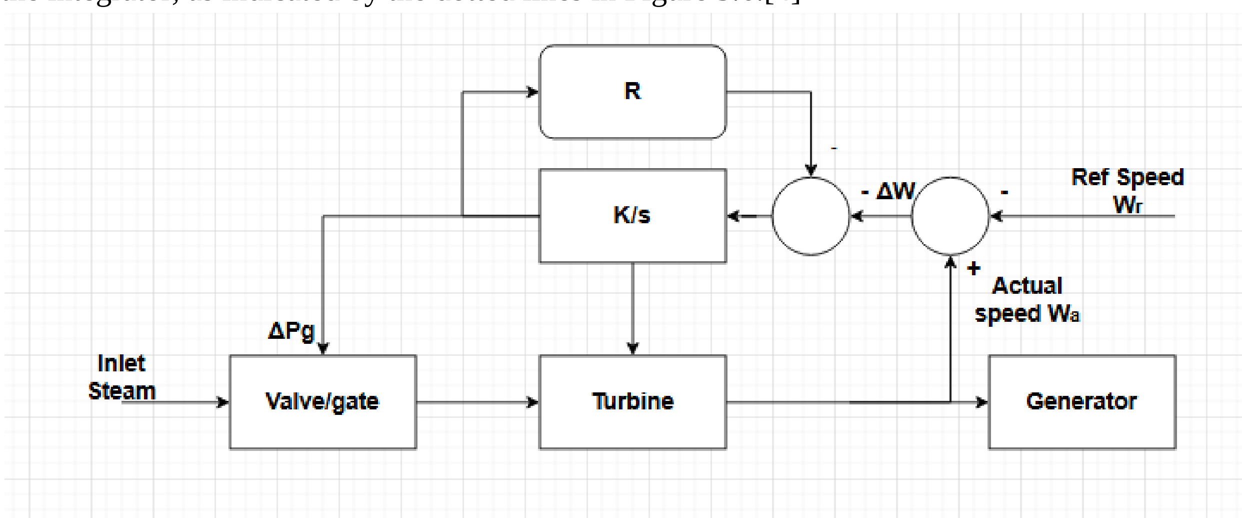

Figure 7 Block diagram of the governor action

In steady state, the governor follows speed droop control:

$$\Delta P_g = \frac{-1}{R}\Delta W \qquad (3.8)$$

Where:

R = speed droop (Hz/pu mw)

Negative sign → increase in speed reduces power

In reality (Introduce governor dynamics), the governor valve/servomotor cannot respond instantly.

It is modeling as a first-order system**:**

$$T_g \text{ d} \frac{(\Delta P_g)}{dt} + \Delta P_g = \frac{-1}{R} \Delta W \qquad (3.9)$$

Where:

- Tg = governor time constant (seconds),represents mechanical delay

Take Laplace transform, assuming zero initial conditions:

$$T_g \text{ (s) } \Delta P_g(s) + \Delta P_g(s) = \frac{-1}{R} \Delta W(s) \qquad (3.10)$$

Factor ΔPg(s):

$$\Delta P_g(s)\ (1 + sT_g) = \frac{-1}{R} \Delta W(s) \qquad (3.11)$$

$$\frac{\Delta P_g(s)}{\Delta W(s)} = \frac{-1/R}{1 + sT_g}$$

Thus, the transfer function of the governor with speed droop becomes:

$$\frac{\Delta P_g}{\Delta W} = - \frac{1/R}{1+ST_g} \qquad (3.12)$$

Where:

- Tg = $1/KR$ = governor time constant
- R = speed droop regulation constant

From the steady-state relationship illustrated in Figure 3.6 that

$$\Delta w = -R\ \Delta Pg \qquad (3.13)$$

This indicates that the change in valve opening (ΔPg), and consequently the generator power output (ΔP), is directly proportional to the frequency deviation (Δw). Therefore, the relationship between generator frequency and power output can be express as[4]:

$$f = -R \qquad (3.14)$$

This relationship is illustrate in figure 3.7, where f_0 and f_{f1} represent the no-load and full-load frequencies, respectively, and Po denotes the full-load power. The unit of R *is* express as Hz per P_U MW.

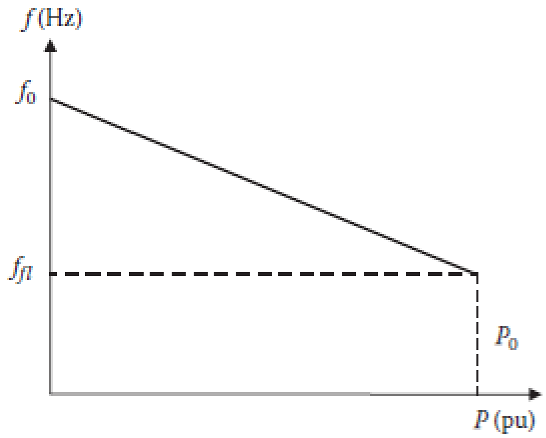

Figure 8 the characteristic of speed governor frequency droops[4].

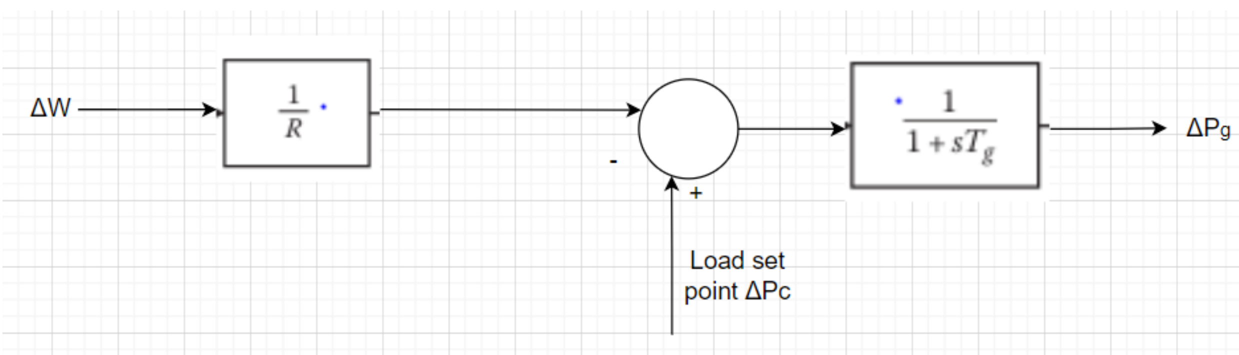

Figure 9 a simplified Transfer function model of a typical governor model [4].

3.4.3.2 Steam turbine model

The turbine converts the valve or gate position signal into mechanical power, which drives the generator shaft. Among the different types of turbines used in power systems, steam turbines are widely used in thermal power plants[4].

A steam turbine transforms the thermal energy of high-pressure, high-temperature steam into mechanical energy. Steam turbines are commonly classify as reheat turbines or non-reheat turbines**.** In a reheat turbine**,** steam leaving the high-pressure (HP) stage is return to the boiler for reheating before entering the intermediate or low-pressure (LP) turbine stage. This reheating process improves the overall efficiency of the turbine.

A reheat turbine has two power-producing sections**:**

High – pressure (HP) turbine

- ✓ Respond fast
- ✓ Fraction of power = 1-K

Low – pressure (LP) turbine (reheat stage)

- ✓ Slower response (due to reheat)
- ✓ Fractional of power = K

So total mechanical power is:

$$\Delta P_m = \Delta P_{HP} + \Delta P_{LP} \tag{3.15}$$

The steam chest (HP turbine) behaves like a first-order system**:**

$$\frac{\Delta P_{HP}\ (s)}{\Delta P_g\ (s)} = \frac{1-k}{1+ST_l} \tag{3.16}$$

The re-heater introduces an additional lag (Re-heater + LP turbine dynamics):

$$\frac{\Delta P_{LP}\ (s)}{\Delta P_g\ (s)} = \frac{k}{(1+ST_l)\ (1+ST_r)} \tag{3.17}$$

Total mechanical power output (Add HP and LP contributions):

$$\frac{\Delta P_m\ (s)}{\Delta P_g\ (s)} = \frac{1-k}{1+ST_l} + \frac{k}{(1+ST_l)\ (1+ST_r)}$$

$$\frac{\Delta P_m\ (s)}{\Delta P_g\ (s)} = \frac{(1-k)\ (1+ST_r)+K}{(1+ST_l)\ (1+ST_r)}$$

$$\frac{\Delta P_m\ (s)}{\Delta P_g\ (s)} = \frac{1+ST_r\ (1-k)}{(1+ST_l)\ (1+ST_r)} \tag{3.18}$$

Define re-heater gain parameter

$$\text{Let, Kr} = 1-\text{K} \tag{3.19}$$

$$\frac{\Delta P_m\ (s)}{\Delta P_g\ (s)} = \frac{1+SK_rT_r}{(1+ST_l)\ (1+ST_r)}$$

Then the simplified transfer function of a reheat steam turbine becomes:

$$\frac{\Delta P_m}{\Delta P_g} = \frac{1+sKT_r}{(1+sT_t)\ (1+sT_r)} \tag{3.20}$$

Where

ΔPm = change in turbine mechanical power output

ΔPg = change in steam valve position

K = fraction of power generated by the HP turbine

Tr = re-heater time constant

Tt = turbine time constant

For a non-reheat turbine, where K =0, Tr = 0, the transfer function reduces to

$$\frac{\Delta P_m}{\Delta P_g} = \frac{1}{1+sT_t} \tag{3.21}$$

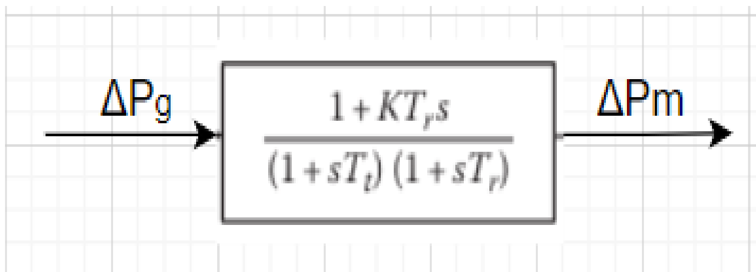

Figure 10 simplified Transfer function model of a reheat type steam turbine model [4].

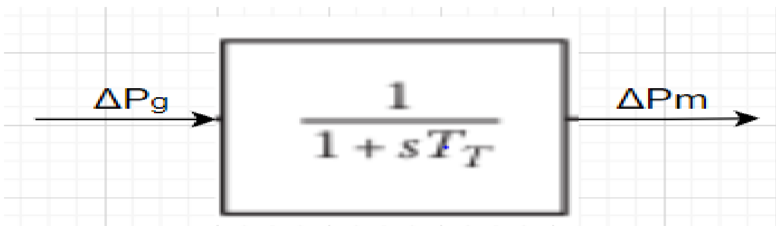

Figure 11 simplified Transfer function model of a non-reheat type steam turbine model [4].

3.4.3.2 Generator and load model

In load frequency control (LFC) studies, all generators within a control area are assume to operate in a coordinated manner. When a load disturbance occurs in the area, all generators respond collectively. Therefore, the entire group of generators can be represent by an equivalent generator model**.** Assume that the system experiences a load change $\Delta\bar{P}_l$. Due to the actions of the governor and turbine, the generator mechanical power changes by $\Delta\bar{P}_m$. The incremental power balance ($\Delta\bar{P}_m - \Delta\bar{P}_l$) will be acting as an accelerating power and dissipated in increasing the area kinetic energy $\bar{W}$ at a rate d$\bar{W}$/dt and in increasing the load consumption. Since most of the power system loads are motors, the load consumption increase is assumed as $\bar{D}\Delta\bar{f}$, where $\bar{D}$ = ∂PL/∂f is the load damping constant expressed in MW/Hz and $\Delta\bar{f}$ is the frequency change in Hz. Thus, the power balance equation written as[4]:

$$\Delta\bar{P}_m - \Delta\bar{P}_l = \frac{d\bar{W}}{dt} + \bar{D}\Delta\bar{f} \tag{3.22}$$

The kinetic energy of the system is proportional to the square of frequency (or speed), that is,

$$\bar{W} = W_0\left(\frac{\bar{f}}{f_0}\right)^2 \tag{3.23}$$

Where $W0$ and $f0$ are the nominal kinetic energy and nominal frequency respectively. Assuming $\bar{f}$ = $f0$ + $\Delta\bar{f}$ and neglecting the second-order term, one can write (3.23) as

$$\bar{W} = W_0\ (1+2\frac{\Delta\bar{f}}{f_0}) \tag{3.24}$$

There fore

$$\frac{d\bar{W}}{dt} = 2\frac{W_0}{f_0}\frac{d\Delta\bar{f}}{dt} \tag{3.25}$$

Dividing both sides of (3.25) by the base MVA (BMAV), we get

$$\frac{dW}{dt} = 2\frac{W_0}{BMVA}\ \frac{d}{dt}(\frac{\Delta\bar{f}}{f_0}) \tag{3.26}$$

Where $\frac{dW}{dt} = \frac{1}{BMVA}\ \frac{d\bar{W}}{dt}$. The inertia constant H of the combined generator and turbine is define as

$$\mathrm{H} = \frac{W_0}{BMVA}\mathrm{S}$$

In per unit, equation (3.26) rewritten in the form

$$\frac{dW}{dt} = 2\mathrm{H}\frac{d}{dt}\ \Delta\mathrm{f} \tag{3.27}$$

Where Δf is the frequency change in pu. Dividing both sides of (3.22) by the BMVA and using equation (3.27), we get the pu power balance equation

$$\Delta P_{\ m} - \ \Delta P_l = 2\mathrm{H}\frac{d}{dt}\ \Delta f + D\ \Delta f \tag{3.28}$$

Where $D = \frac{\bar{D}f_0}{BMVA}$ is the Pu load damping constant. The simplified transfer function representation of generator-load block diagram shown in Figure 3.11.

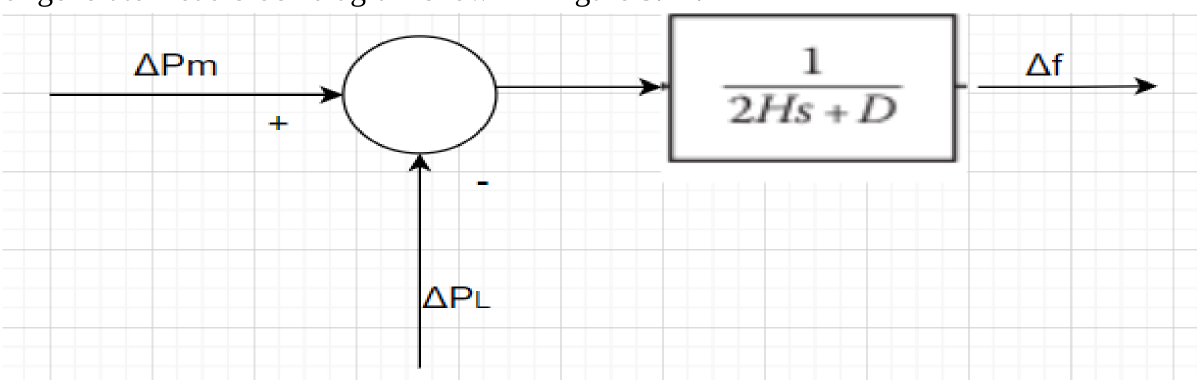

Figure 12 simplified transfer function of a generator–load model block diagram [4].

Combined Cycle over all model

A combined steam power plant includes the typical governor, steam turbine (ST), and an electric generator- load.

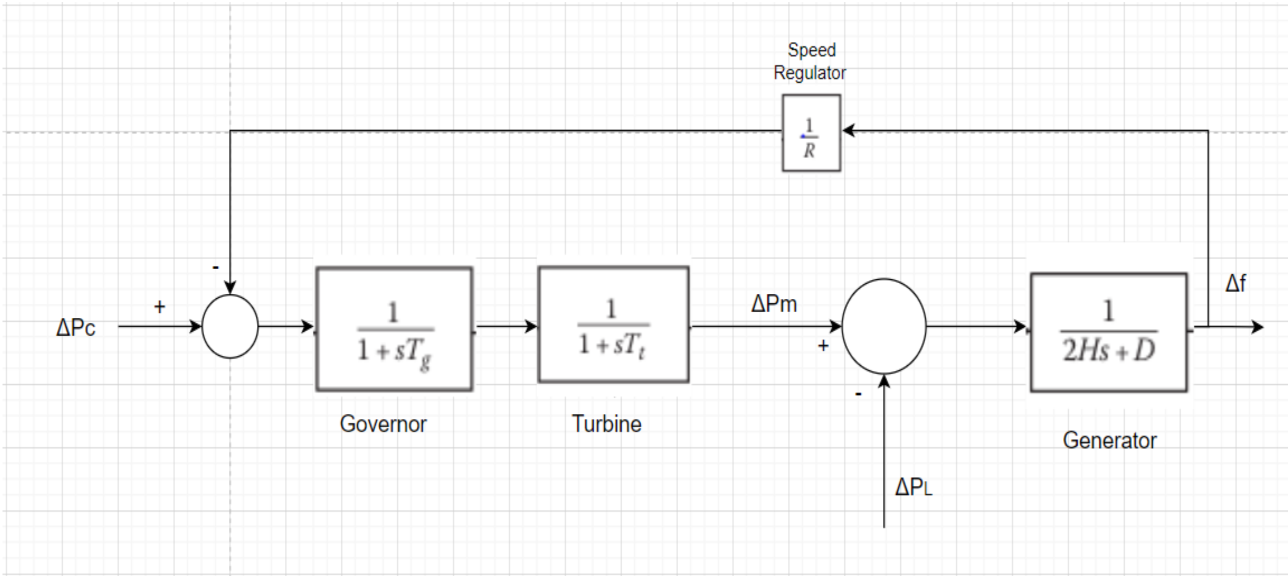

Figure 13 A combined simplified transfer function model of the non-reheat type steam turbine model[4].

Operating Principle and Overall Configuration of the interconnected system

This thesis investigates the dynamic behavior of a single-area isolated power system comprising five identical generating units operating in parallel. Each generating unit is rates at 50 MW, resulting in a total installed generation capacity of 250 MW, which matches the system load under nominal operating conditions. The inertia constant of each generator is H = 5s, on a 50 MW base, ensuring adequate inertial support for frequency stability.

The system operates at a nominal frequency of 50 Hz, and the overall speed-droop (regulation) characteristic of the generators is represented by a droop constant of R = 0.05 P_U. To evaluate the frequency regulation performance of the system, a sudden load disturbance of 50 MW, corresponding to $0.2P_U$, applied to the system.

The prime mover is modeled as a non-reheat steam turbine, characterized by a turbine time constant of T_t = 0.5 s, while the speed governor is modeled with a governor time constant of Tg = 0.2 s. The equivalent generator inertia constant is taken as H = 5s, and the system load damping coefficient is assumed to be D = $0.8P_U$, accounting for the natural frequency-dependent load behavior.

Based on these system parameters and assumptions, a single-area automatic generation control (AGC) model developed. The corresponding simulation block diagram constructed to analyze the frequency deviation and dynamic response of the interconnected generating units under load disturbances [4].

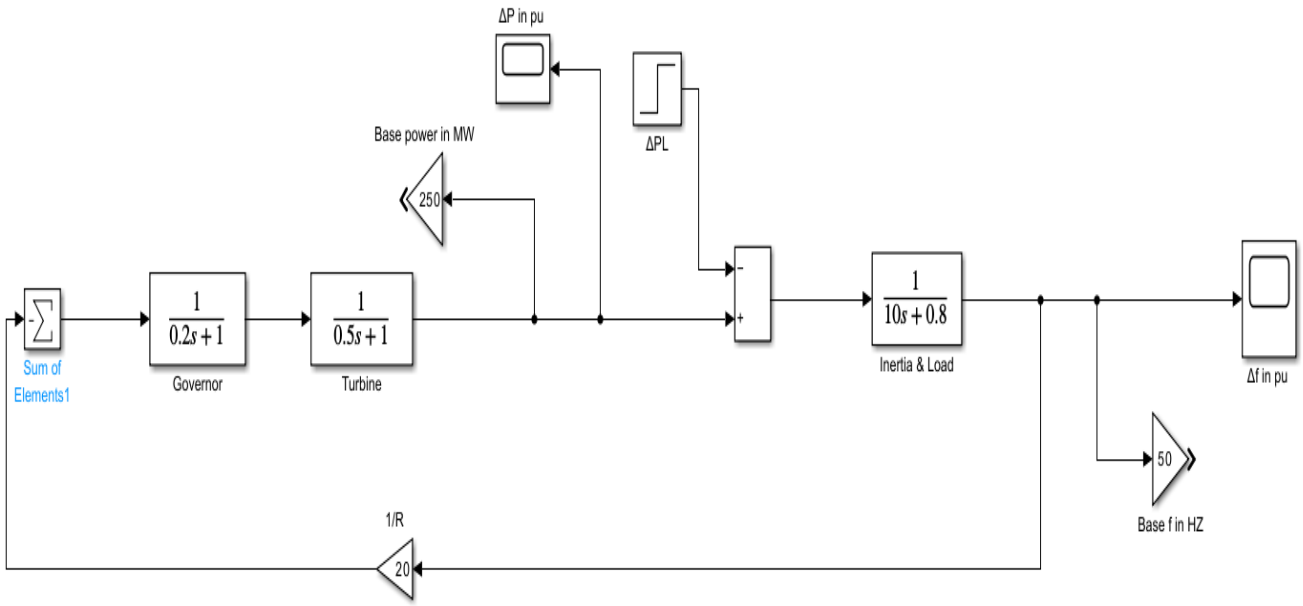

Figure 14 Overall Simplified Model of Interconnected Operation.

The primary control (governor – turbine) response of a single-area non-reheat type steam power generating system following a 0.2 P_U load change, demonstrated system stability, transient oscillation and dynamic response behavior are showed in figure 3.14 as follows.

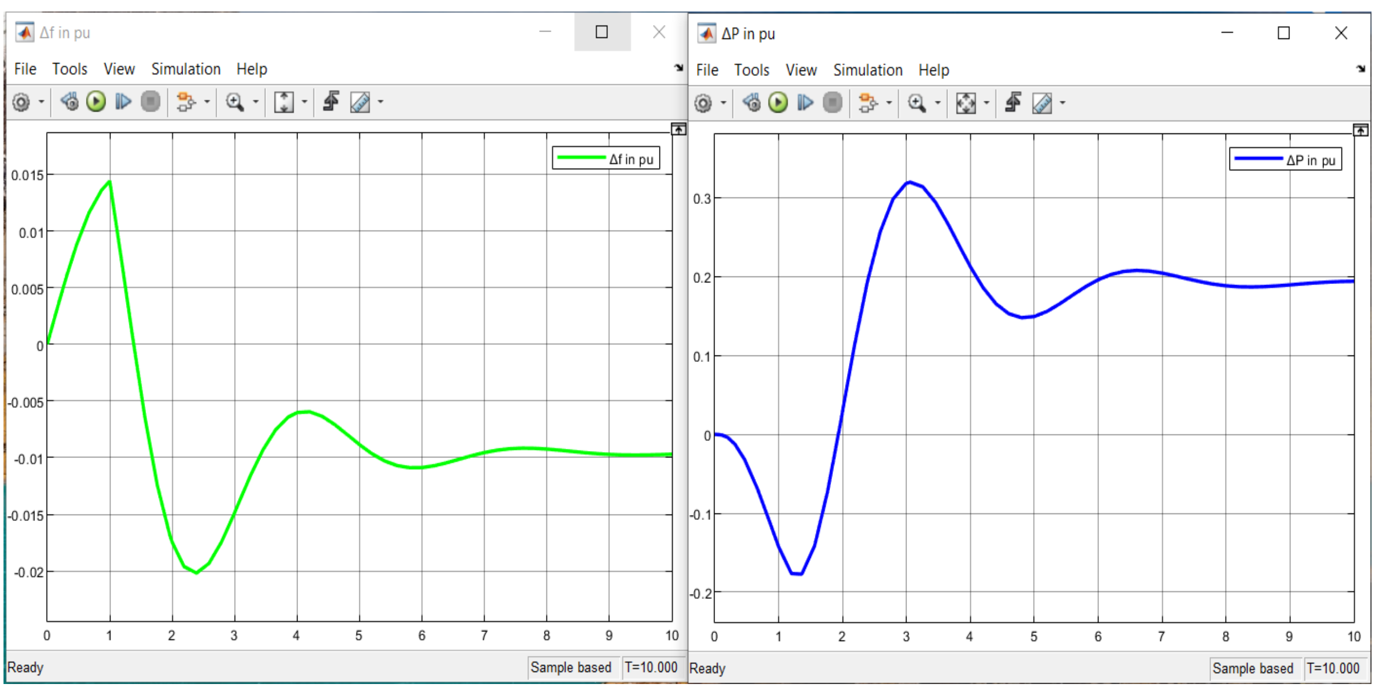

Figure 15 step response with the primary control action (without secondary control)

The left plot shows the frequency deviation (ΔF inP_U) following a sudden load increase of $0.2P_U$. Immediately after the disturbance, the system experiences a frequency drop due to the power imbalance. The oscillatory behavior indicates the dynamic interaction between the governor, turbine, and generator inertia. Over time, the oscillations damped, and the frequency deviation settled to a small steady state offset, which is expect in a single-area system with droop control ($R \neq 0$) and no secondary control action.

The right plot illustrates the power deviation (ΔP inP_U) of the generating units. After the load change, the generated power increases with an initial overshoot, reflecting the governor and turbine response dynamics. The oscillations gradually decay due to system damping, and the power output settles around the new load demand, sharing the disturbance among the generators according to the droop characteristic.

Overall, the result indicated that the system exhibits poor stability with inadequate damping and failed to effectively regulated frequency following load disturbances. The presence of a significant steady – state frequency deviation clearly demonstrates the necessity of implementing secondary control, such as AGC/ANFIS, to restore the system frequency to its nominal value.

CHAPTER FOUR

CONTROLLER DESIGN

4.1 Introduction

This chapter describes the design and implementation of the proposed Automatic Generation Control (AGC) system to enhance frequency and power stability for a steam power plant using three control techniques such as PID, FLC and the proposed ANFIS controllers, simulated in MATLAB/Simulink environment. The control system receives an error signal generated from an error acquisition unit, where deviations in frequency and active power variation are determined by comparing reference values with actual generator outputs. The sum of frequency deviation and power variation forms the composite error that serves as the input to each controller.

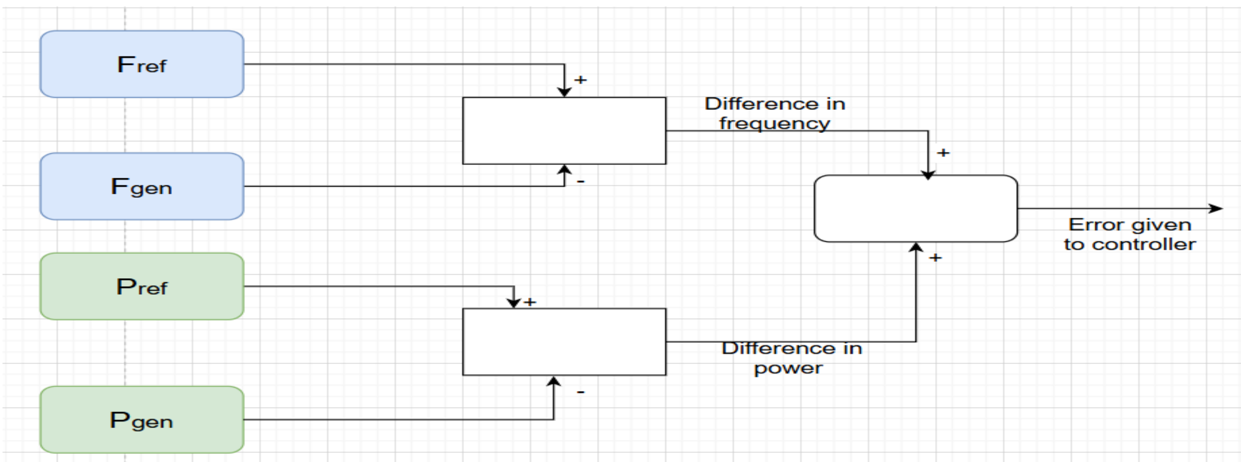

Figure 16 illustrates the structure of the Error Acquisition System

Under normal operation, the error should approach zero; however, any non-zero value indicates system imbalance requiring corrective action. The designing controllers therefore, act to generate appropriate control signals to adjust the turbine governor, thereby restoring system stability and maintaining the nominal frequency.

4.2 Controller Design

In this thesis, three strategies of controllers been designed. The first controller is the Proportional–Integral–Derivative (PID) controller**,** the second is the Fuzzy Logic Controller (FLC)**,** and the third is the proposed optimal control approach based on the Adaptive Neuro-Fuzzy Inference System (ANFIS)**.**

4.2.1 PID controller

The Proportional–Integral–Derivative (PID) controller is a widely used control technique in industrial applications. It determines the appropriate corrective action by combining proportional, integral, and derivative control actions. These three components work together to produce a single control signal that helps regulate and stabilize the system's performance.

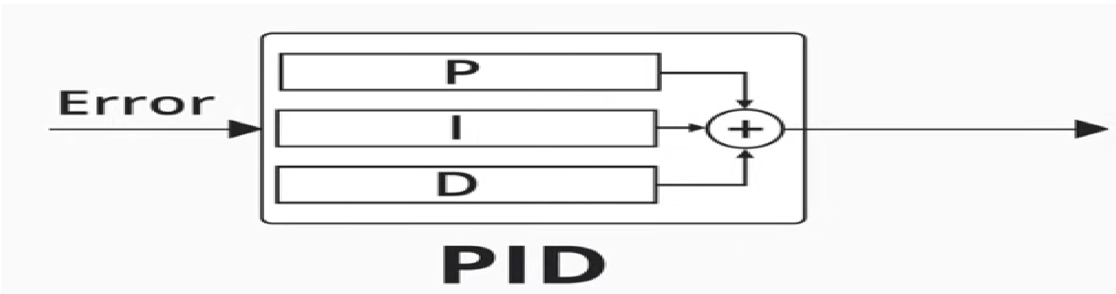

Figure 17 PID controller block diagram

Each component of the PID controller contributes a distinct effect to the overall control output. The controller consists of three main terms: proportional, integral, and derivative.

Proportional Term

The proportional term (often referred to as the gain component) generates an output that is directly proportional to the current error value. This action is achieves by multiplying the error signal by a constant known as the proportional gain(K_P).

Integral Term

The integral term (also called the reset action) considers both the magnitude and duration of the error. It accumulates past errors over time, which helps in eliminating steady-state error in the system. The effect of this component is determine by the integral gain (K_i).

Derivative Term

The derivative component (sometimes- called rate action) predicts the future behavior of the system by evaluating the rate of change of the error. It is obtain by taking the time derivative of the error signal and multiplying it by the derivative gain **(**K_d). This term improves system stability and transient response.

4.2.1.1 Working principles of the Proportional–Integral–Derivative (PID) Controller

The PID controller operates using a closed-loop control mechanism to minimize the difference between the system output (process variable) and the desired reference value (set point). Because of its simple structure, low implementation cost, and ease of use**,** the PID controller is widely applied in many industrial control systems. However, although PID controllers are suitable for many applications, their performance may decline when dealing with highly nonlinear or complex higher-order systems.

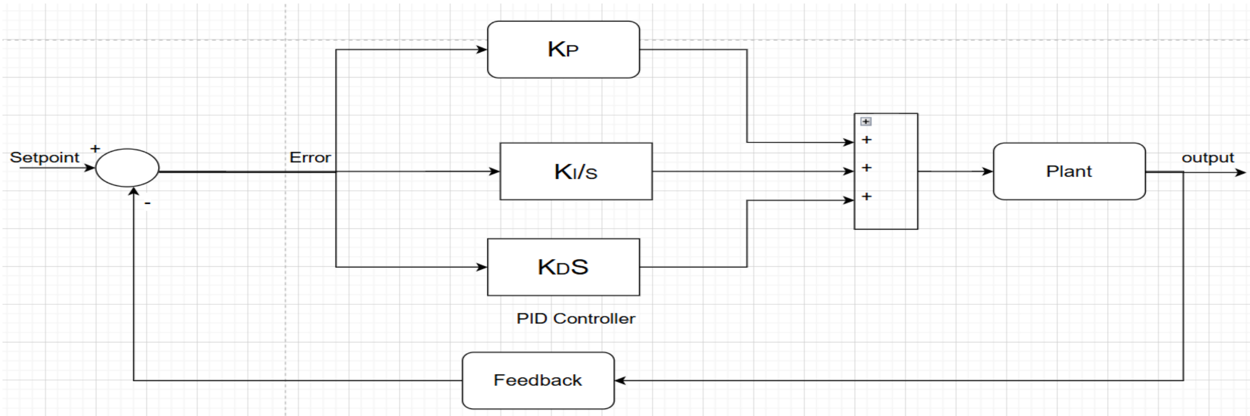

Figure 18 PID plant diagram connected with the plant.

In this thesis, the combined frequency and power deviations are feds into the PID controller to generate corrective control actions that help stabilize both system frequency and power generation. The controller continuously computes the error between the measured output and the reference signal and adjusts the control signal accordingly. The proportional term reacts to the present error, the integral term compensates for accumulated past errors, and the derivative term responds to the rate of change of the error. By appropriately tuning the three gains, the controller aims to minimize the error quickly. However, it should noted that the use of a PID controller alone does not always guarantee optimal performance or complete system stability.

4.2.1.2 PID Controller Tuning Methods

Before implementing a PID controller, proper tuning is required to match the dynamic characteristics of the controlled process. Default values of the proportional, integral, and derivative gains may not yield satisfactory performance and can sometimes result in slow response or system instability. Various tuning techniques have developed to determine suitable gain values, requiring careful selection by the designer.

The Common tuning approaches are includes the trial and error methods and the process reaction curve technique. In this thesis, the PID controller parameters K_P, K_i and K_d are obtained using the trial-and-error method.

Trial- and-Error Method:

The trial-and-error approach is a simple and commonly used PID tuning technique applied while the system is operating. Initially, the integral and derivative gains are set to zero, and the proportional gain is gradually increases until the system begins to show sustained oscillations**.** After that, the integral gain is adjust to reduce or eliminate these oscillations, and finally, the derivative gain is tune to obtain a faster and smoother system response**.**

Table 5 reviewed gab analysis

parameter	value
K_P	1.0
K_i	0.25
K_d	0.28

4.3 Fuzzy Logic Controller and Design

4.3.1 Fuzzy Logic Controller

The Fuzzy logic controller (FLC) acquires output data from the plant, compares it with the reference input, and determines the appropriate control action required to satisfy the desired performance objectives. In this thesis, the generated frequency measured from the sensing system compared with the reference frequency to obtain the frequency deviation, which serves as an input to the fuzzy inference system. The resulting control output from the FLC applied to the gate opening mechanism of the steam valve position of the turbine. The gate opening mechanism operated through a servomotor, which adjusts the turbine valve position based on the control signal generated by the FLC. The FLC uses two input variables-error and change in error-to generate an appropriate control output related to the valve gate opening. This output regulates the opening and closing of the guide vanes according to a predefined set of fuzzy rules.

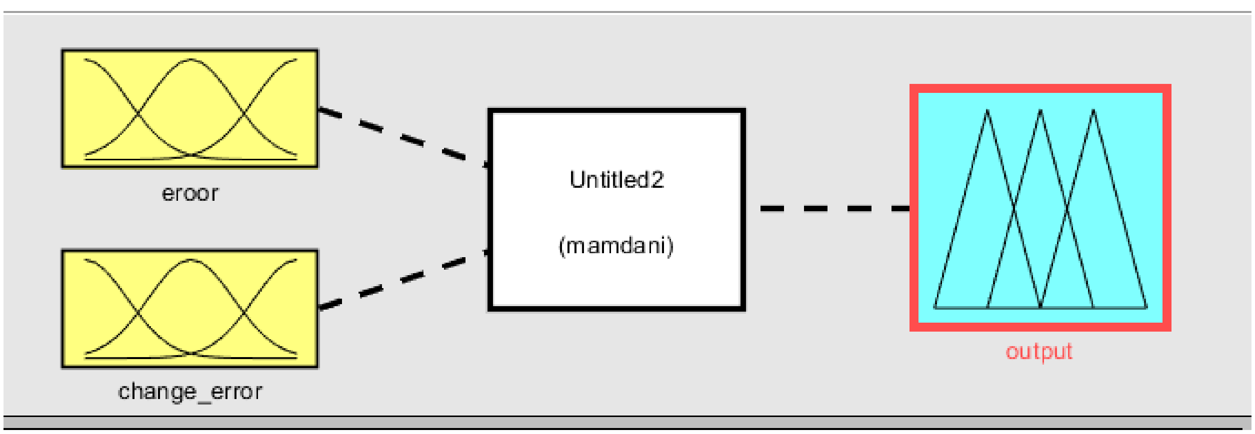

Figure 19 Mamdani Fuzzy Logic Controllers

The fundamental structure of a fuzzy Logic Controller consists of four main components:

1 Fuzzification
2 Fuzzy knowledge base
3 Decision-making Logic (fuzzy reasoning) and
4 Defuzzification

The fundamental structure of a fuzzy logic controller is show in Figure 4.5:

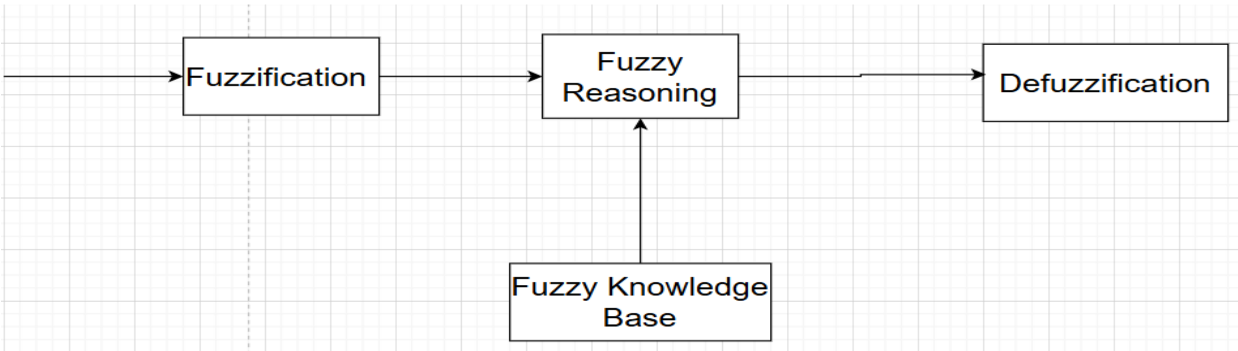

Figure 20 Basic Structure of fuzzy logic controller

These components work together to convert crisp input data into an intelligent control action suitable for nonlinear systems such as steam power plants. Their functions are describing as follows:

1 The Fuzzification:-The fuzzification block transforms precise numerical inputs, such as frequency deviation and its rate of change, into fuzzy linguistic variables using predefined membership functions. This process enables the controller to handle uncertainty and imprecision in system measurements.

2 The Fuzzy knowledge base: - The knowledge base contains the set of linguistic rules and membership function definitions that represent expert knowledge about system behavior. These rules establish the relationship between input conditions and the required control actions.

3 Decision-Making Logic (fuzzy reasoning):- The decision-making mechanism is the core component of the fuzzy logic controller. It imitates human reasoning by evaluating the activated fuzzy rules based on the fuzzified inputs. In the Fuzzy reasoning stage, the inference mechanism evaluates the activated rules based on the fuzzified inputs. It determines the degree to which each rule contributes to the final decision, combining those using logical operations to produce a fuzzy output set.

4 The Defuzzification: - The defuzzification stage converts the aggregated fuzzy result into a crisp control signal that can be applies to the plant actuator. This output represents the appropriate adjustment to the governor or control valve to maintain a stable system frequency. This structure enables the fuzzy logic controller to provide flexible, robust, and human-like decision-making, making it well suited for automatic generation control of steam power plants operating under varying load conditions.

4.3.2 Fuzzy Logic Controller Design

The fuzzy logic control system for the steam power plant is develops to regulate the turbine governor**.** The main function of the governor is to control the turbine speed, thereby maintaining system frequency at a constant nominal value. When a sudden load increase occurs, the system frequency decreases due to the imbalance between generation and demand. This frequency deviation detected by the governor and processed by the FLC, which generates a control signal to increase the turbine valve opening. As a result, the generated power rises to match the increased load demand, restoring the system frequency to its nominal value of 50 Hz.

The following steps applied to design the fuzzy logic controller.

- ✓ Step1: Identify the input and output variables of the fuzzy logic controller.
- ✓ Step2: Define membership functions for each input and output variable.
- ✓ Step3: Form a rule base (develop the fuzzy rule base).
- ✓ Step4: rule evaluation
- ✓ Step5: Defuzzification

4.3.2.1 Input Variables

For effectively regulate system frequency, the controller primarily responds to two important parameters: frequency error and rate of change of frequency error**.** These parameters are select as the input variables for the fuzzy logic controller and can be mathematically express as:

$$E(t) = f_{ref} - f(t) \tag{4.1}$$

$$dE(t) = E(t) - E(t-1) \tag{4.2}$$

Where f_{ref} reference (nominal) frequency

f (t) is the actual system frequency

E (t) is the instantaneous frequency deviation of the power system from its nominal value.

dE (t) is the rate of change of the frequency deviation, describing how fast the error is increasing or decreasing.

Physical meaning:

The error signal (E) indicates the magnitude of imbalance between generated power load powers.

- ✓ E > 0: frequency is below nominal (load increase)
- ✓ E < 0: frequency is above nominal (load decrease)

Physical meaning: The change in error (ΔE) signal provides information about the dynamic trend of the frequency deviation.

- ✓ ΔE > 0: frequency deviation is increasing
- ✓ ΔE < 0: frequency deviation is decreasing

Under normal operating conditions, the system frequency remains at 50 Hz, resulting in zero error. However, during load increment, the frequency decreases and produces positive error values, while load decrement leads to negative error values. If considering the huge increase or decreases in load demand operating scenarios, the system frequency may reduce or increase to very low/high value resulting in a frequency deviation varying approximately between −2 Hz and +2 Hz. Therefore, the universe of discourse for the input variable frequency change is selecting as [−2, +2].

Seven linguistic membership functions are assigning to represent the input variables: Negative-Big (NB), Negative-Medium (NM), Negative-Small (NS), Zero (Z), Positive-Small (PS), Positive-Medium (PM), and Positive-Big (PB). These membership functions enable the controller to interpret different degrees of frequency deviation and respond with appropriate control actions.

1 Membership function of error (E):

The limits of the power system frequency error (Δf)) are determined based on the expected variation of system frequency in existing power system as shown in Figure (4.6).

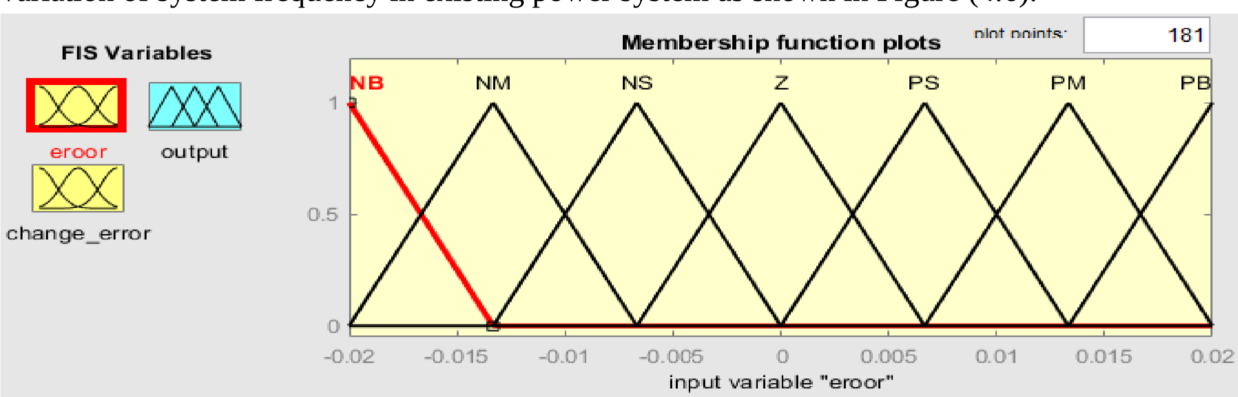

Figure 21 Error Input Fuzzy membership function system

2, Membership function for rate change of error (E (t))

The rate of change of error helps predict future system behavior by analyzing the current slope of the error signal. The universe of discourse for this variable is select within the range -0.02 to 0.02 as shown in Figure (4.7).

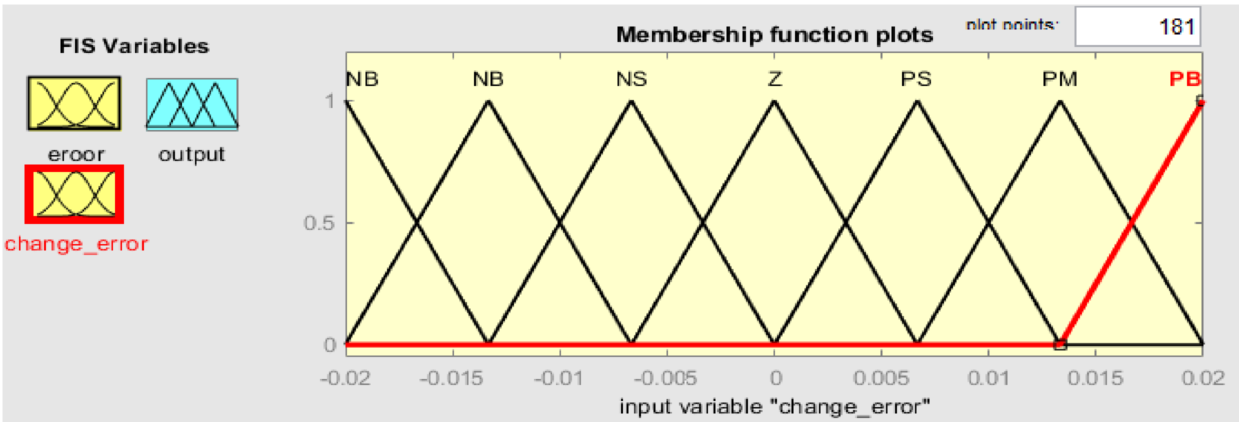

Figure 22 Changes in Error Input Membership function system

4.3.2.2 Output Variable

The output variable U (t) is the control action generated by the controller to correct frequency deviation. The control signal adjusts the reference power setting of the governor or steam valve position, thereby regulating the mechanical input power of the turbine.

U (t) $\longrightarrow \Delta P_m$

Where ΔP_m = change in turbine mechanical power

The valve position ranges is from 0 to 1, where:

0 represents the fully closed position, and

1 represents the fully open position.

To ensure smooth and flexible control, the output variable is also divided into seven linguistic terms similar to the input variables: Fully Closed (NB), Mostly Closed (NM), Half Closed (NS), Normal (Z), Half Open (PS), Mostly Open (PM), and Fully Open (PB).

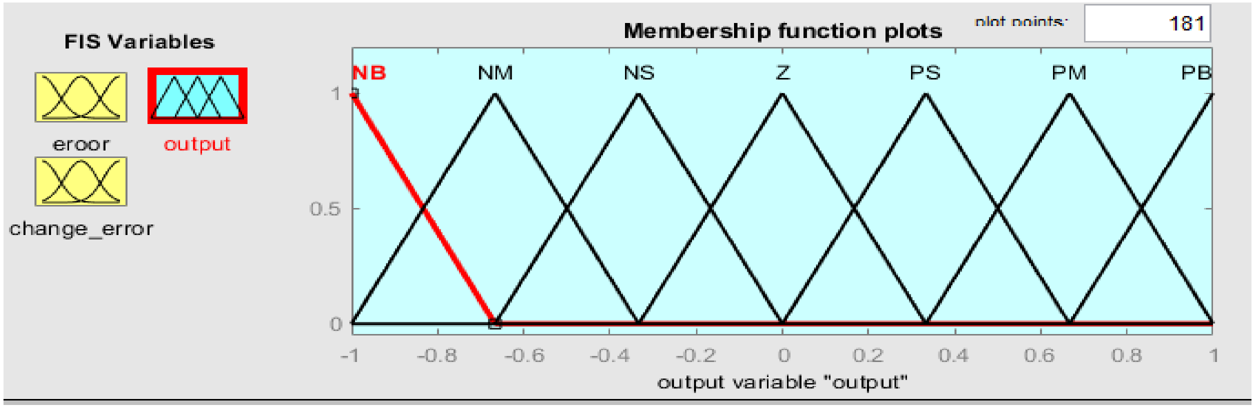

Figure 23 output membership functions

4.3.2.3 Fuzzy control rules

Fuzzy control rules represent the knowledge and experience of experts in the application domain. These rules are typically express in IF–THEN form and describe the control action that should take based on the observed system conditions.

In this thesis, identical membership functions are employs for both input and output variables, with seven triangular membership functions assigned to each input, as previously described. Since the fuzzy logic controller utilizes two input variables and each input is characterizes by seven membership functions, 49 fuzzy inference rules are constructed. These rules, summarized in Table 4.2, collectively govern the operation of the fuzzy logic controller.

The fuzzy rules are formulated using IF–THEN logic combined with an AND operator for rule aggregation. In the FLC control scheme, the error and cumulative error (or change in error) serve as the input variables of the fuzzy logic controller, and the rule base defines the corresponding control actions for all possible input combinations.

Table 6 rule base of fuzzy membership

		Error change						
		NB	NM	NS	Z	PS	PM	PB
Error	NB	NB	NB	NM	NB	NM	NS	Z
	NM	NB	NB	NM	NM	NS	Z	PS
	NS	NB	NM	NM	NS	Z	PS	PM
	Z	NM	NM	NS	Z	PS	PM	PM
	PS	NM	NS	Z	PS	PM	PM	PB
	PM	NS	Z	PS	PM	PM	PB	PB
	PB	Z	PS	PM	PB	PB	PB	PB

Based on the combination of input membership functions, 49 fuzzy inference rules are formulate to establish the relationship between frequency deviation and valve position. This structured definition of input-output variables and rule base enables the fuzzy logic controller to provide intelligent and robust control performance for automatic AGC of the steam power plant.

If error is NB and the change error is NB, then output is NB

If error is NB and the change error is NM, then output is NB

If error is NB and the change error is NS, then output is NM

If error is NB and the change error is Z, then output is NB

If error is NB and the change error is PS, then output is NM

If error is NB and the change error is PM, then output is NS

If error is NB and the change error is PB, then output is Z

If error is NM and the change error is NB, then output is NB

If error is NM and the change error is NM, then output is NB

If error is NM and the change error is NS, then output is NM

If error is NM and the change error is Z, then output is NM

If error is NM and the change error is PS, then output is NS

If error is NM and the change error is PP, then output is Z

If error is NM and the change error is PB, then output is PS

If error is NS and the change error is NB, then output is NB

If error is NS and the change error is NM, then output is NM

If error is NS and the change error is NS, then output is NM

If error is NS and the change error is Z, then output is NS

If error is NS and the change error is PS, then output is Z

If error is NM and the change error is PM, then output is PS

If error is NM and the change error is PB, then output is PM

If error is Z and the change error is NB, then output is NM

If error is Z and the change error is NM, then output is NM

If error is Z and the change error is NS, then output is NS

If error is Z and the change error is Z, then output is Z

If error is Z and the change error is PS, then output is PS

If error is Z and the change error is PM, then output is PM

If error is Z and the change error is PB, then output is PM

If error is PS and the change error is NB, then output is NM

If error is PS and the change error is NM, then output is NS

If error is PS and the change error is NS, then output is Z

If error is PS and the change error is Z, then output is PS

If error is PS and the change error is PS, then output is MM

If error is PS and the change error is PM, then output is PM

If error is PS and the change error is PB, then output is PB

If error is PM and the change error is NB, then output is NS

If error is PM and the change error is NM, then output is Z

If error is PM and the change error is NS, then output is PS

If error is PM and the change error is Z, then output is PM

If error is PM and the change error is PS, then output is PM

If error is PM and the change error is PM, then output is PB

If error is PM and the change error is PB, then output is PB

If error is PB and the change error is NB, then output is Z

If error is PB and the change error is NM, then output is PS

If error is PB and the change error is NS, then output is PM

If error is PB and the change error is Z, then output is PB

If error is PB and the change error is PS, then output is PB

If error is PB and the change error is PM, then output is PB

If error is PB and the change error is PB, then output is PB

Rule Viewer in MATLAB Software

All fuzzy rules implemented using the MATLAB fuzzy logic toolbox, and the graphical representation of these rules can observed through the Rule Viewer interface. The visualization of the complete rule set is illustrate in Figure 4.9**.**

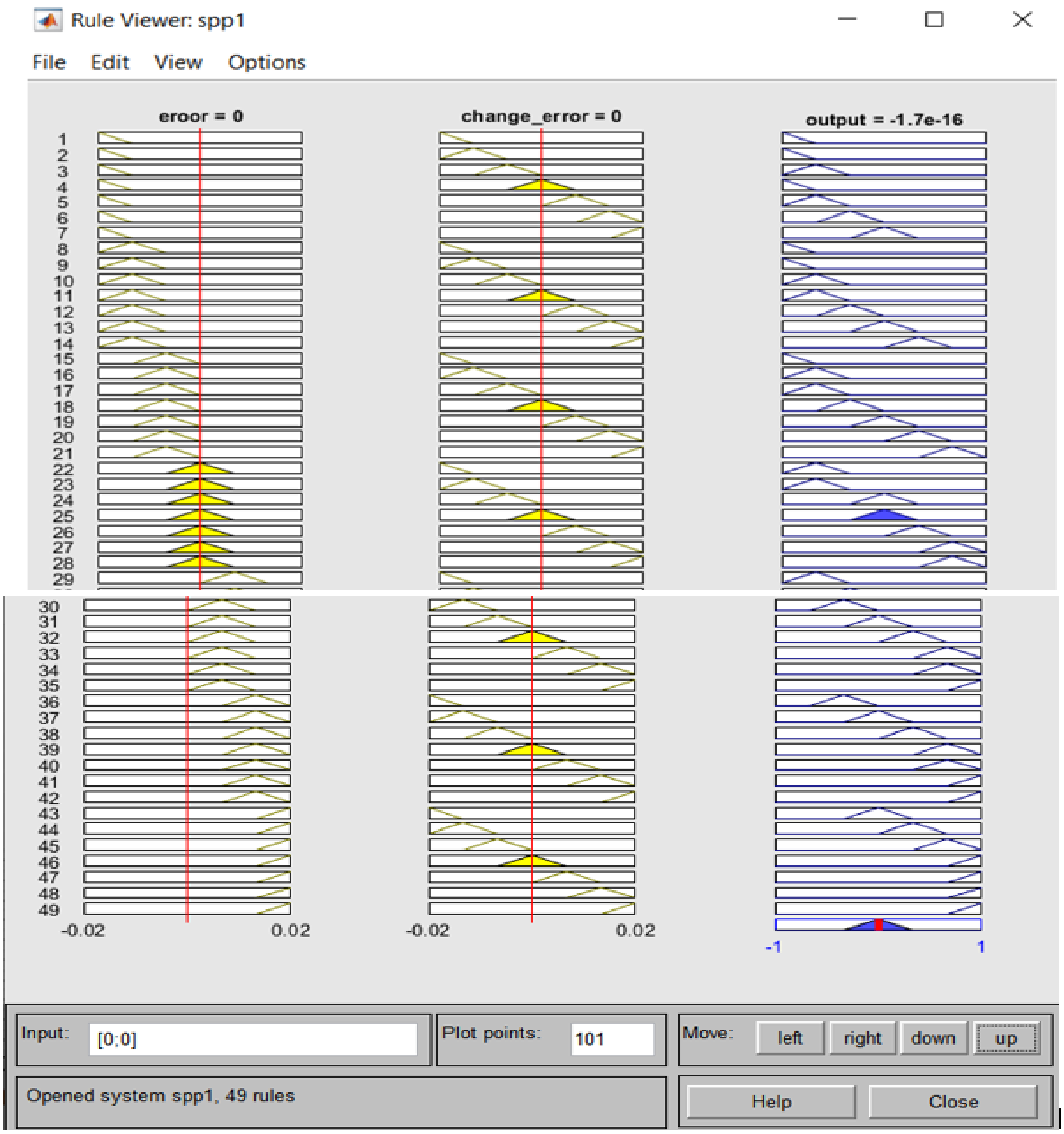

Figure 24 Rule viewer for steam power plant

The Rule Viewer shown in Figure 4.9 presents the complete set of 49 fuzzy rules developed for the ANFIS-based controller of the steam power plant. The two input variables frequency error and change in error are display in the first two columns, while the third column represents the corresponding output control signal. The red vertical lines indicate the current operating point where both inputs are zero [0 0], and the resulting output is approximately -1.7×10^{-16}, which is practically zero.

From the viewer, it can be observe that multiple rules are activate simultaneously with different firing strengths, represented by the shaded yellow regions. This confirms that the controller uses a smooth inference mechanism rather than a single dominant rule. The gradual variation of the output membership functions demonstrates that the defuzzification process produces a continuous and stable control action.

The symmetrical distribution of activated rules around the zero operating point indicates that the rule base is well balances for both positive and negative frequency deviations. This behavior is essential for automatic generation control, as it ensures proportional corrective action for load increases and decreases. The Rule Viewer therefore verifies the correctness of the fuzzy rule structure and confirms that the ANFIS model responds logically to variations in system frequency and its rate of change.

4.3.2.4 Defuzzification

Defuzzification is the final stage of the fuzzy inference process, in which the inferred fuzzy output transformed into a precise control signal. Since practical control systems require a numerical output, the aggregated fuzzy output set must be convert into a single crisp value. In the proposed model, the defuzzification process takes the combined fuzzy output as its input and produces a single control action. The Centre of Area (COA) method employed for this purpose, as it provides a smooth and representative crisp output based on the weighted average of the fuzzy set.

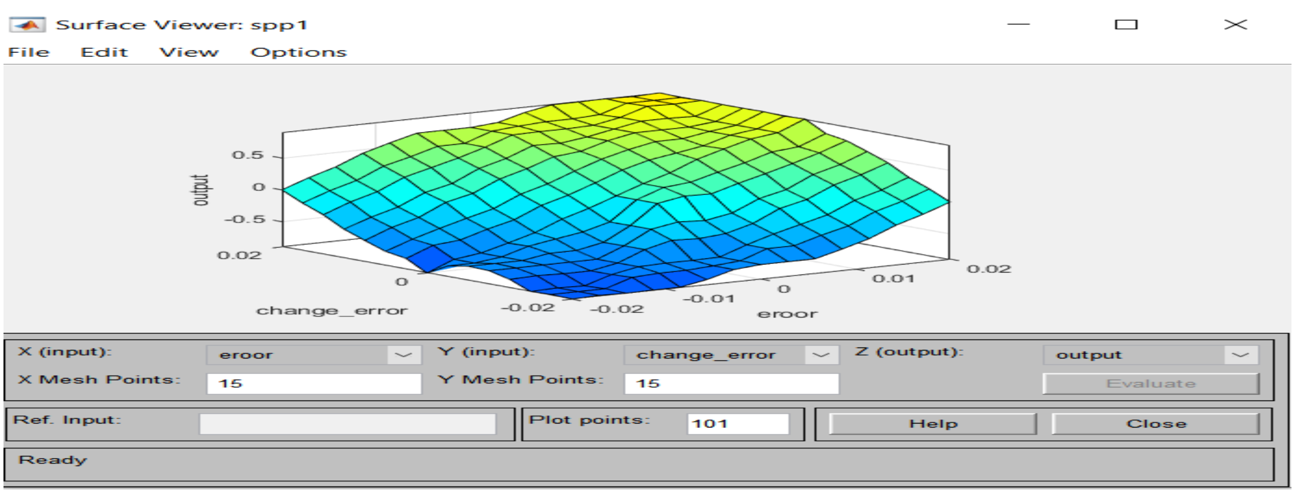

Figure 25 Surface viewers

The Surface Viewer illustrated in the figure 4.10 represents the defuzzified output of the ANFIS controller with respect to the two input variables: frequency error and change in error. The three-dimensional surface demonstrates the nonlinear mapping between the inputs and the power control signal.

The smooth and continuous nature of the surface confirms that the defuzzification process successfully converts the fuzzy inference results into a precise crisp output. There are no abrupt jumps or discontinuities, which indicates proper tuning of the membership functions and effective learning of the input–output relationship. This behavior is essential for automatic generation control, as it ensures gradual and stable adjustment of the governor signal in response to load variations.

From the surface trend, it can be observe that positive frequency errors produce positive control actions, while negative errors generate negative outputs. Similarly, the slope of the surface along the change-in-error axis shows that the controller considers the dynamic behavior of the system, not only the steady-state deviation.

Overall, the Surface Viewer validates that the defuzzification mechanism provides a coherent and well-distributed control surface, suitable for maintaining system frequency within acceptable limits under varying operating conditions.

4.3.2.5 Limitation of Fuzzy logic controller

The Fuzzy Logic Controller (FLC**)** has certain limitations, mainly because it does not possess expert knowledge by itself. Instead, it relies on human expertise to define appropriate rules and membership functions in order to achieve good system performance. If the expert-defined rules are not properly designed, the fuzzy logic controller may produce unsatisfactory results, sometimes even performing worse than a conventional PID controller.

In many practical situations, sufficient knowledge about the system behavior may not be available. As a result, when implementing a fuzzy logic controller, it is often difficult to determine the most appropriate rule set. Consequently, the rules are frequently develop using a trial-and-error approach to obtain acceptable system performance.

To overcome these limitations, advanced techniques has introduce to enhance the intelligence of fuzzy logic controllers. One such approach is the integration of Artificial Neural Networks (ANN) with fuzzy logic systems. Neural networks enable the controller for automatically learn from data rather than relying entirely on expert knowledge. Since ANN requires only input and output data for training, it can learn the system behavior and adjust the control rules accordingly.

Based on the system input–output data, the neural network identifies the appropriate relationships within the system, determines suitable fuzzy rules, and optimizes the membership function parameters to achieve improved performance. Among these intelligent techniques, the Adaptive Neuro-Fuzzy Inference System (ANFIS**)**-which combines fuzzy logic with neural network learning capability-can automatically learn and adapt the fuzzy rules. As a result, ANFIS is considers a highly effective and accurate method for obtaining optimal control performance.

4.4 Adaptive neuro- fuzzy inference system (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the principles of artificial neural networks (ANNs) with fuzzy logic control. This hybrid approach combines the learning capability of neural networks with the reasoning ability of fuzzy logic, making ANFIS an effective tool for modeling nonlinear and complex systems using relatively small training datasets. By incorporating fuzzy inference with neural learning, ANFIS is able to manage system uncertainties and nonlinearities without relying on precise mathematical models.

ANFIS applies neural network learning mechanisms for automatically generate fuzzy membership functions and inference rules based on collected input–output data. Through supervised learning, the system captures the dynamic behavior of the plant and adjusts control parameters accordingly. The ANFIS structure used in this work consists of a five-layer network, as illustrated in Figure 4.11.

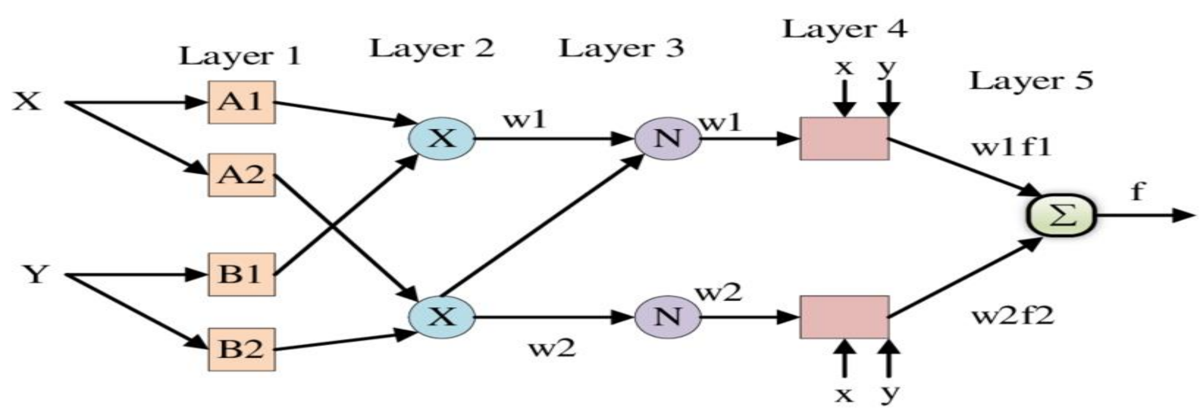

Figure 26 ANFIS model architecture.

In the ANFIS architecture, square nodes represents as a collection of the parameters of the membership functions (MFs) for Takagi–Sugeno Kang (TSK) inference system. These parameters adjusted during the training process. Circular nodes, on the other hand, are fixed and not adjustable/tuned and perform logical operations such as max/min computations. In this structure, *n* denotes the normalization operation, while W_1 and W_2 represent network weights. The following assumptions made for the ANFIS structure shown in Figure 4.11[20].

The system has two-input variables, X and Y, and one-output variable (f). Each input describes by two fuzzy sets (A_1, A_2 for X and B_1, B_2 for Y). The result/output represents by a first order polynomial (f). The ANFIS shown in the figure 4.11 governed by two rules, which are Sugeno's rule base of the fuzzy inference system. These rules given as follows[20]:

Rule 1: if X is A1 AND Y is B1, THEN f1 = p1X + q1Y + r1

Rule 2: if X is A2 AND Y is B2, THEN f2 = p2X + q2Y + r2

In general, for 'i' rule, the above first order polynomial function written as:

If X is Ai AND Y is Bi, THEN fi = piXi + qiXi + ri.

Here, A_i and B_i represent fuzzy sets associated with the input variables X and Y, respectively. Fi- is the output of fuzzy set within the specified areas by the fuzzy rules, and the parameters p_i, q_i, and r_i are consequent parameters that optimized during the training phase[20].

ANFIS Layer Description

The Sugeno-type ANFIS model consists of five layers, each performing a specific function:

Layer 1 - Input Membership Layer: This layer maps each crisp input to its corresponding membership functions. It contains adaptive nodes that define the premise parameters of the fuzzy sets and directly transfer the input signals to subsequent layers.

Layer 2 -Fuzzification Layer: In this layer, membership values of the inputs are calculated. The T-norm operator is applies to determine the firing strength of each rule's antecedent.

Layer 3 - Rule Layer: This hidden layer represents the fuzzy rules. It normalizes the firing strengths obtained from the previous layer and prepares them for consequence evaluation. The product operator commonly used to model the intersection of fuzzy sets.

Layer 4 - Normalization and Consequent Layer: Nodes in this layer compute the normalized firing strength for each rule and apply the corresponding consequent functions. The firing strength of each rule expressed as the ratio of its activation level to the sum of all rule activations.

Layer 5 - Defuzzification Layer: The final layer aggregates the outputs of all rules to produce a single crisp output. The overall output obtained using a weighted average method, commonly based on centroid defuzzification, which ensures smooth and accurate control action.

The ANFIS output calculated using consequent parameters identified during the forward pass of training, while parameter updates carried out through a back-propagation algorithm in the backward pass. Since membership functions cannot optimally selected by visual inspection alone, their parameters must tuned to achieve the best system performance.

To accelerate convergence and improve accuracy, a hybrid-learning algorithm employed. This approach combines the Least Squares Estimation (LSE) method for identifying linear consequent parameters with the steepest descent (back propagation) method for updating nonlinear premise parameters. The forward pass estimates consequent parameters using LSE, while the backward pass adjusts premise parameters using back-propagation. In this thesis, generalized bell-shaped membership functions selected due to their smooth and continuous characteristics, which enhance gradient-based learning performance.

For the proposed AGC application, the frequency error and the rate of change of frequency error used as inputs to the ANFIS controller, while the control command signal serves as the output.

4.4.1 Procedures to model the ANFIS controller for the AGC system

In the AGC system, the steps describe the main stages used to build the ANFIS controller for the AGC system are:

Step 1: Load data and normalize: The input–output data taken from the PID controller are import into MATLAB. The data are then normalize to a suitable range so that all variables have comparable values and the ANFIS training becomes stable and faster.

Step 2: Build the initial fuzzy system: A basic fuzzy inference structure is create, number of rules (such as 7×7) and the type of membership functions for each input are selected to represent the relationship between frequency deviation, its rate of change, and the control signal.

Step 3: Train the ANFIS model: The ANFIS is train using the prepared data. Training parameters like the number of epochs and allowable error are set, and the hybrid learning algorithm adjusts the membership functions and rule parameters to minimize the training error.

Step 4: Test and verify performance: The trained model is check with testing data. The estimated output of ANFIS is compare with the actual control signal, and the error is evaluate to confirm that the controller performs accurately.

4.4.2 Training of the ANFIS model

The ANFIS learning algorithm adjusts both premise and consequent parameters to achieve optimal control performance. The training and testing stages are critical in defining the accuracy and reliability of the developed controller. While training data used to tune the ANFIS parameters, testing data employed to evaluate the generalization capability of the model.

The training performance is evaluated using the Root Mean Square Error (RMSE) between the ANFIS output and the desired control signal over successive training epochs. Initially, the RMSE is relatively high due to untrained parameters. As training progresses, the error decreases significantly, indicating successful learning of the AGC control law. A low final RMSE confirms that the ANFIS controller can effectively generate appropriate governor control signals to suppress frequency deviations caused by load disturbances.

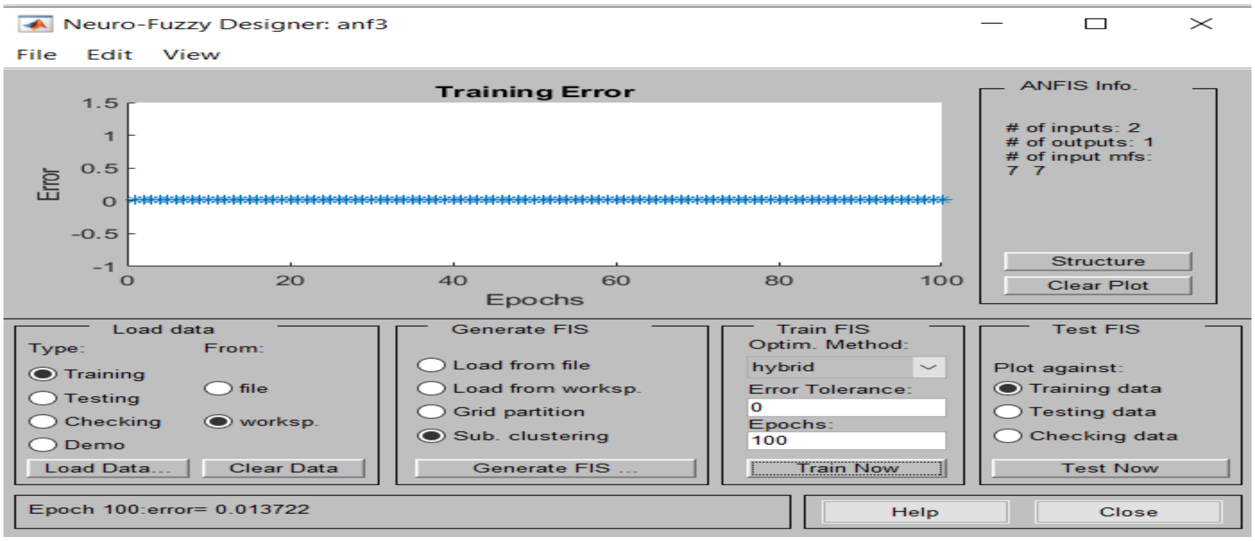

Figure 27 training error vs Epochs

Checking (Validation) Error vs Epochs

This plot shows the checking (validation) error obtained using an independent testing dataset. Unlike the training curve, this plot reflects the generalization capability of the ANFIS model to unseen operating conditions. The checking error decreases and remains stable without significant oscillations, which indicates that over-fitting has not occurred. The minimum checking error represents the optimal stopping point of training. This behavior verifies that the ANFIS controller will perform reliably under real-time load variations in the steam power plant and can maintain accurate frequency regulation beyond the training data.

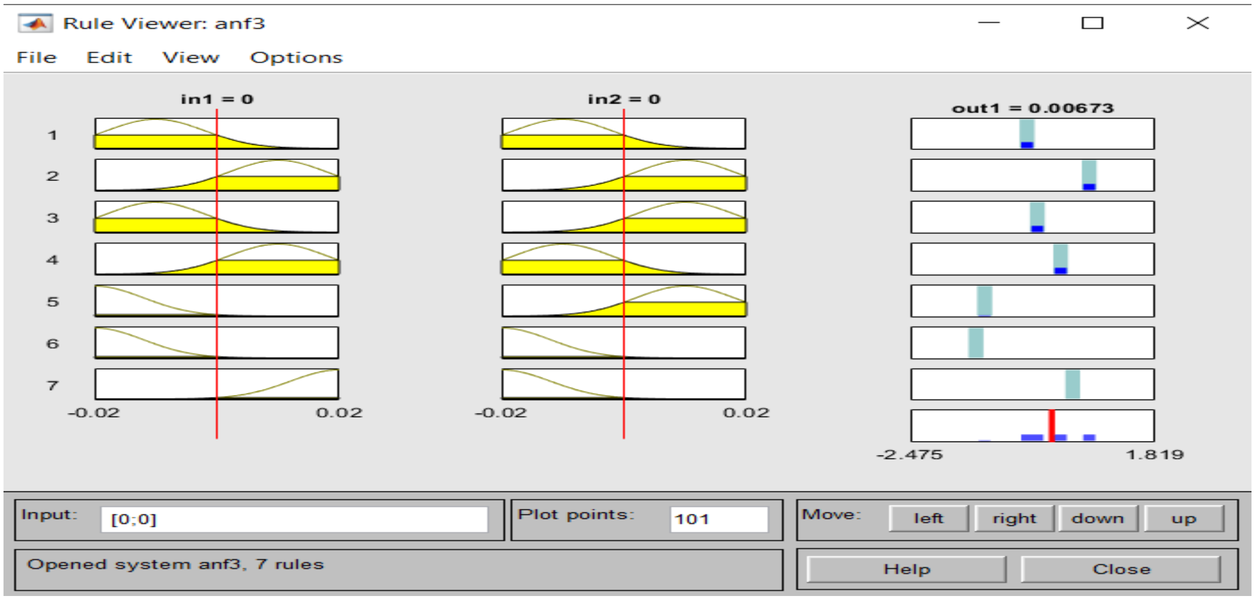

Figure 28 checking (validation) error vs Epochs

ANFIS predicted output: - This plot shows Target output (desired AGC control signal) and ANFIS predicted output Confirms correct mapping between (Error, Δ Error) → control output.

This figure validates that ANFIS can:

- ✓ Correctly adjust turbine valve position
- ✓ Restore frequency to nominal value (50 Hz)
- ✓ Maintain power balance after load changes

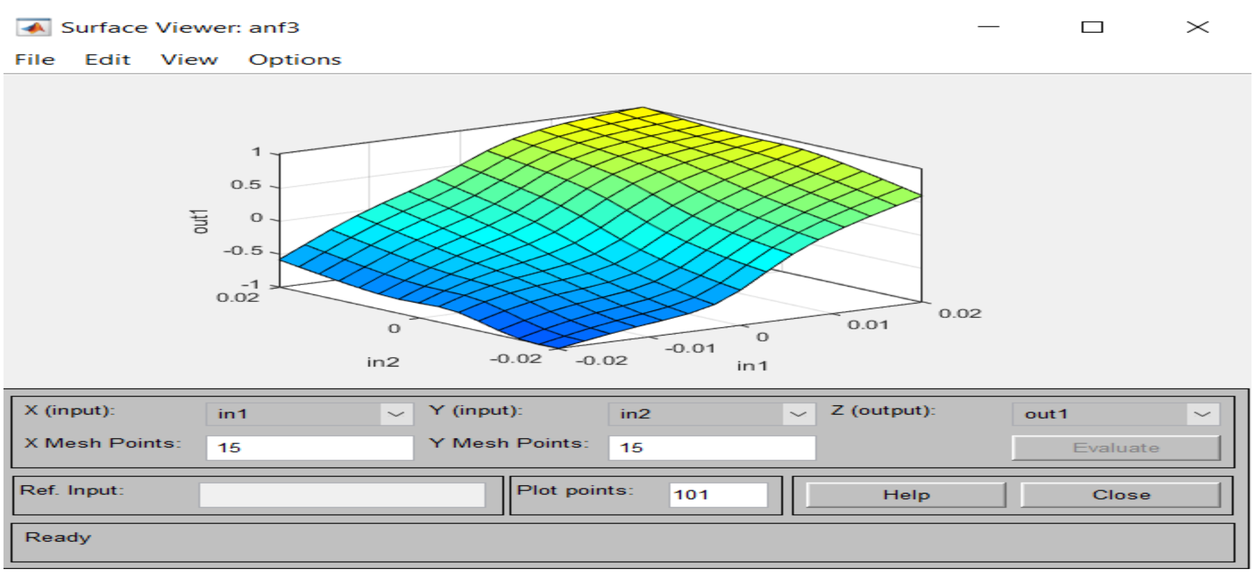

Figure 29 ANFIS predicted output

This Figure compares the target control signal with the output predicted by the trained ANFIS model. The two curves closely overlap, showing that the ANFIS has successfully captured the nonlinear relationship between frequency error inputs and the required governor action. The small deviation between desired and predicted responses confirms high modeling accuracy. This result validates that the proposed controller can correctly adjust turbine valve position to counteract load disturbances, restore system frequency to the nominal 50 Hz, and maintain active power balance. The figure therefore demonstrates the effectiveness of ANFIS as an alternative to conventional FLC and PID control.

ANFIS model structure (membership function after training)

This figure illustrates the membership function structure after the completion of ANFIS training. The shapes and positions of the membership functions are automatically tune from their initial values based on the learning algorithm. The smooth and well-distributed membership functions indicate proper adaptation to the system dynamics. This tuning process eliminates the need for manual rule adjustment required in classical fuzzy controllers. The figure confirms that the neuro-fuzzy system has optimized its internal parameters to provide precise and continuous control action, which contributes to improved stability and faster response of the automatic generation control system.

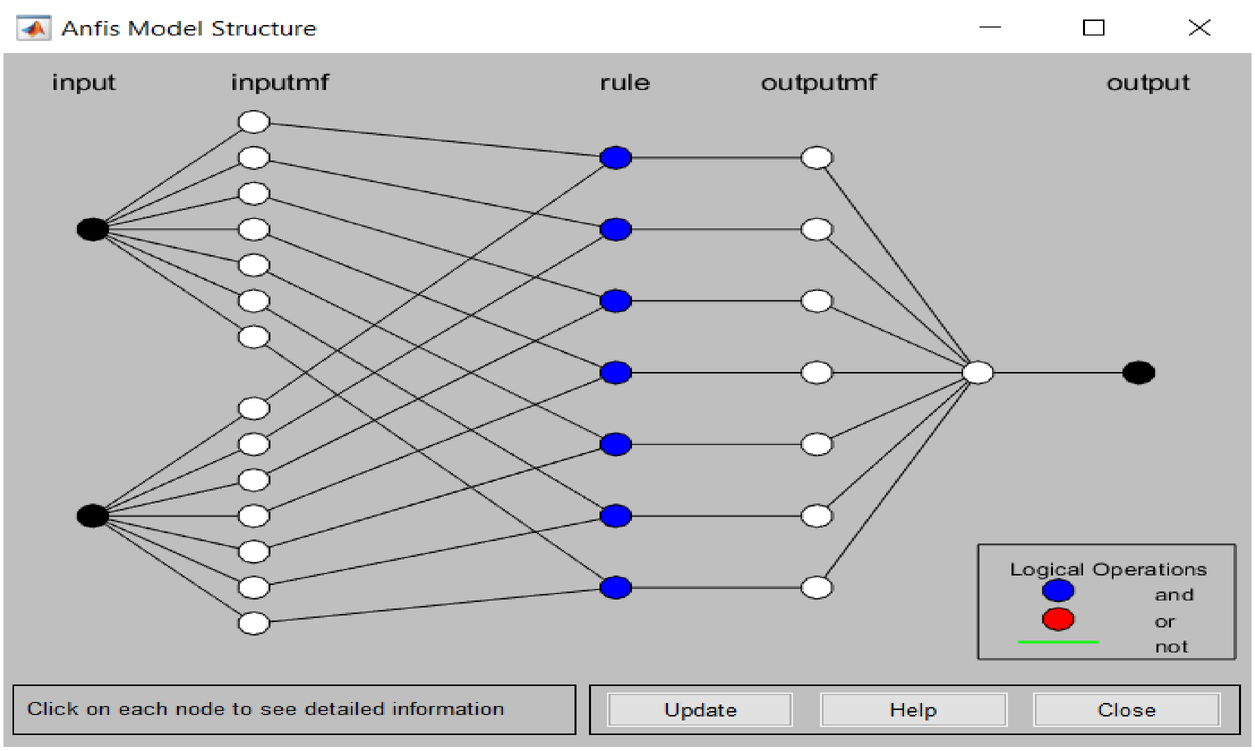

Figure 30 ANFIS model structure

The ANFIS training figures collectively demonstrate the effectiveness of the proposed ANFIS-based AGC controller for a steam power plant. The reduction in training and checking errors confirms successful learning and generalization capability.

4.4.3 Limitations of the Adaptive Neuro-Fuzzy Inference System (ANFIS)

Although the Adaptive Neuro-Fuzzy Inference System (ANFIS) provides effective learning and adaptive capabilities, it also has some limitations:

1, ANFIS is primarily designs to operate with Takagi–Sugeno type fuzzy inference systems, which restricts its application to this specific fuzzy model structure.

2, The ANFIS architecture is generally configures for single-output systems, meaning that it is typically applies to problems where only one output variable is required.

CHAPTER FIVE

SIMULATION RESULT AND DISCUSSION

5.1 Introduction

This chapter presents the simulation results obtained from performance evaluations of a steam power plant model developed in MATLAB/Simulink. The system is testes under three different control strategies: the Proportional-Integral-Derivative (PID) controller, the Fuzzy Logic Controller (FLC), and the proposed Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. The main objective of this analysis is to assess and compare the dynamic and steady state performance of the power system under these three control approaches. The Simulink model illustrated in Figures (5.1, 5.2 and 5.3) used to perform the simulation studies and facilitate a comprehensive performance comparison of the three controllers.

5.2 MATLAB Simulation Model

MATLAB/Simulink-based Models develops to achieve nominal frequency regulation and generation load balance under three different control configurations. First, the steam power plant model with a conventional PID controller was design. Second, the plant model incorporating a Fuzzy Logic Controller (FLC) is developed. Finally, the plant model was integrate with the proposed ANFIS controller implemented.

5.2.1 MATLAB/Simulation Model of the steam power plant with PID Controller

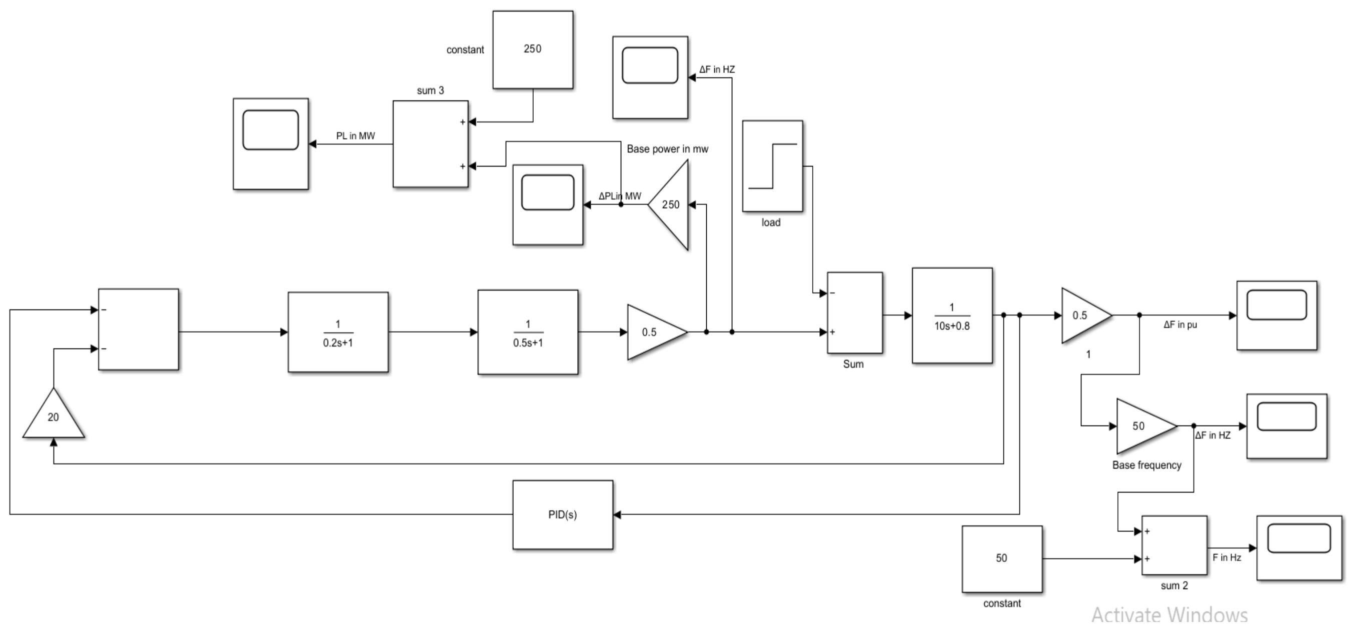

Figure 31 MATLAB /Simulink model of AGC for steam power plant with PID controller

5.2.2 MATLAB/Simulation Model of the steam power plant with FLC Controller

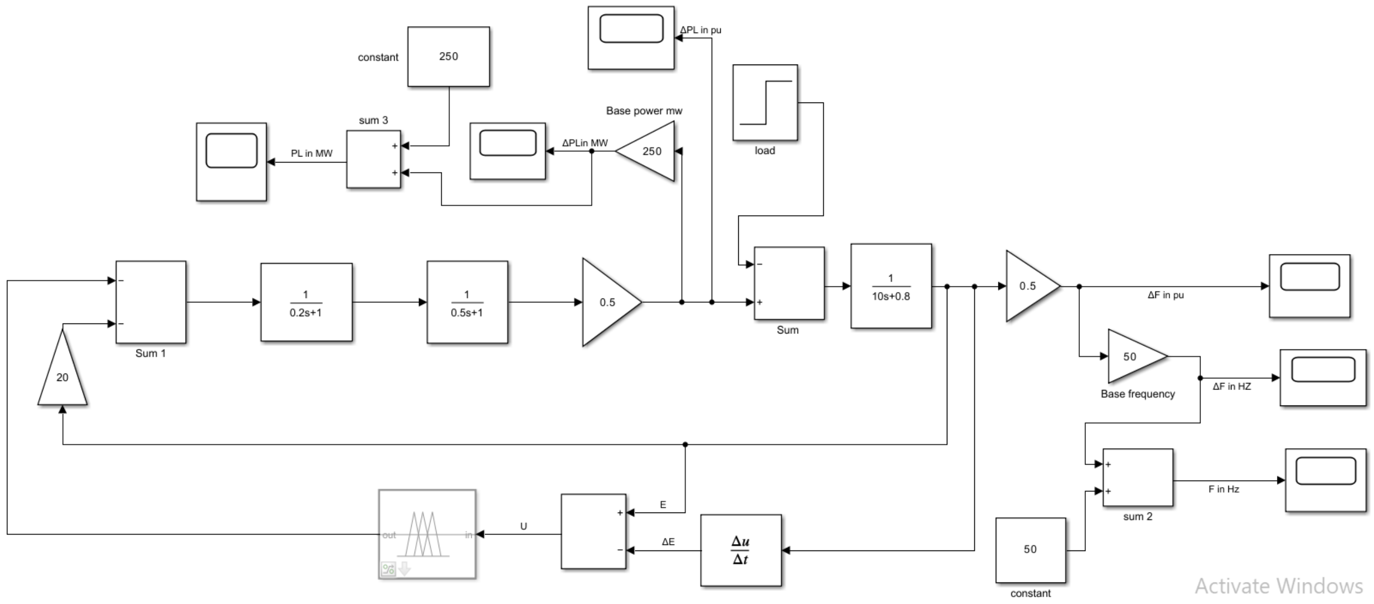

Figure 32 MATLAB /Simulink model of AGC for steam power plant with FLC controller

5.2.3 MATLAB/Simulation Model of the steam power plant with ANFIS controller

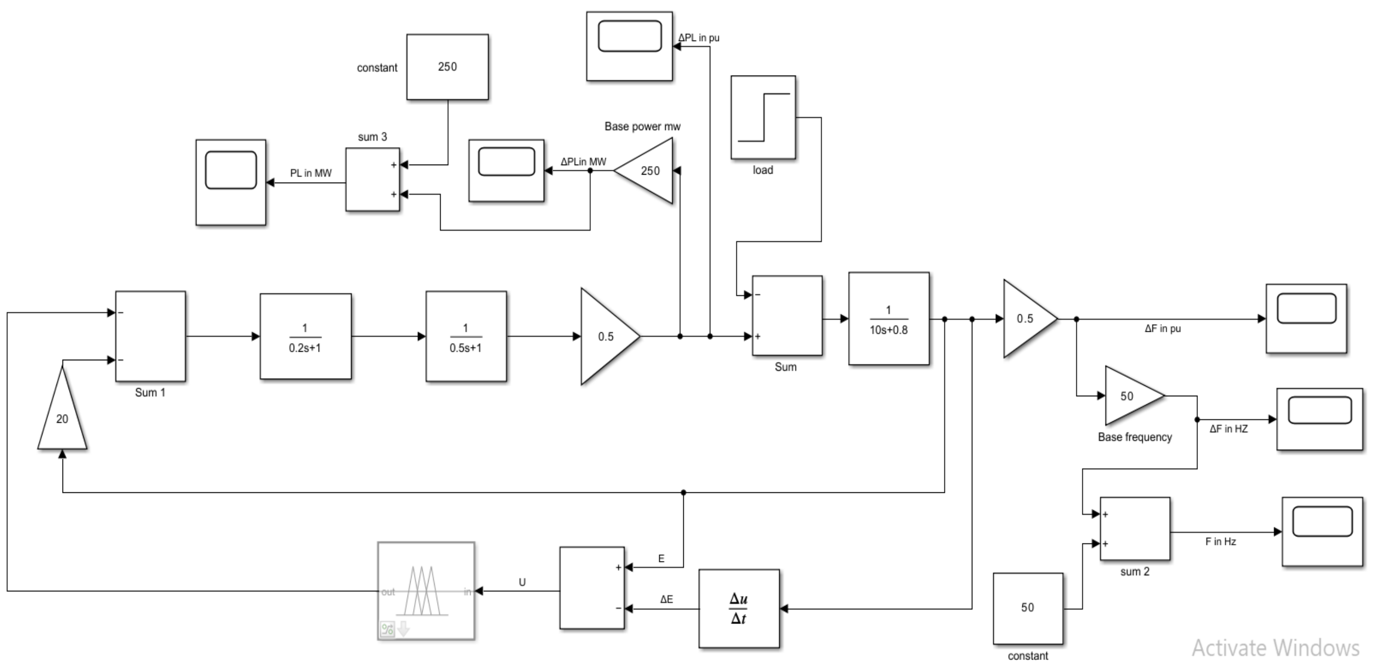

Figure: 5.3 MATLAB/Simulink Model of AGC for steam power plant with ANFIS controller

5.3 Simulation Result

At this section, the output responses of each control scheme observed and analyzes over different time intervals. At the initial stage, the system response exhibits transient characteristics, which used to assess system stability and speed of response. As the simulation time progresses, the response converges to their steady state values, which indicate the accuracy and effectiveness of each control strategy in regulating the steam power plant. The responses of frequency and power are evaluate in both per-unit and actual quantities for clearly describe the dynamic behavior of the steam power plant under different operating conditions.

The equations used to compute the actual frequency and power values corresponding to the simulation per-unit results at steady state and under various load addition and rejection, scenarios are compute based on the following formulations.

The relationship between the per–unit frequency deviation and the actual frequency deviation is express as:

$$\Delta \mathrm{f}_{actual} = \Delta \mathrm{f}_{pu} * \mathrm{f}_{Base} \tag{5.1}$$

Accordingly, the actual operating frequency of the system is obtain as:

$$\mathrm{f}_{actual} = \mathrm{f}_{nominal} + \Delta \mathrm{f}_{Actual} \tag{5.2}$$

For a system with a nominal frequency of 50 Hz, this becomes:

$$\mathrm{f}_{actual} = 50\ HZ + \Delta \mathrm{f}_{Actual} \tag{5.3}$$

Where the per-unit frequency deviation ($\Delta \mathrm{f}_{pu}$) obtained from the simulation result.

Load disturbances applied to the system are define in per–unit form as ΔP_L in (P_U) and converted to actual megawatt values using the base power of the plant. The conversion given by:

$$\Delta P_L\ (P_U) = \frac{\Delta \mathrm{P}_l\ (MW)}{\mathrm{P}_{\mathrm{base}}} \tag{5.4}$$

And conversely,

$$\Delta P_L\ (\mathrm{MW}) = \Delta P_L\ (P_U) \times P_{base} \tag{5.5}$$

After a disturbance, the total system load is determined as:

$$P_L\ (\mathrm{New}) = P_L + \Delta\ P_L(\mathrm{MW}) \tag{5.6}$$

For a system with under nominal operating conditions installed generation capacity of 250 MW,

$$P_L \text{ (New)} = 250 \text{ MW} + \Delta\, P_L(\text{MW}) \qquad (5.7)$$

Where a positive value of ΔP_L (MW) represents load addition and a negative value represents load rejection.

5.3.1 Simulation results at steady state operation (without load demand variation)

Under steady - state operating conditions and the absence of load demand variation, the system exhibits a small frequency deviation (~ 0 HZ). This result indicates that, in the absence of load disturbance, the system reaches a stable steady state condition with a slight reduction in frequency, which remains within acceptable operation limits, confirming the inherent stability of the system under nominal operating conditions.

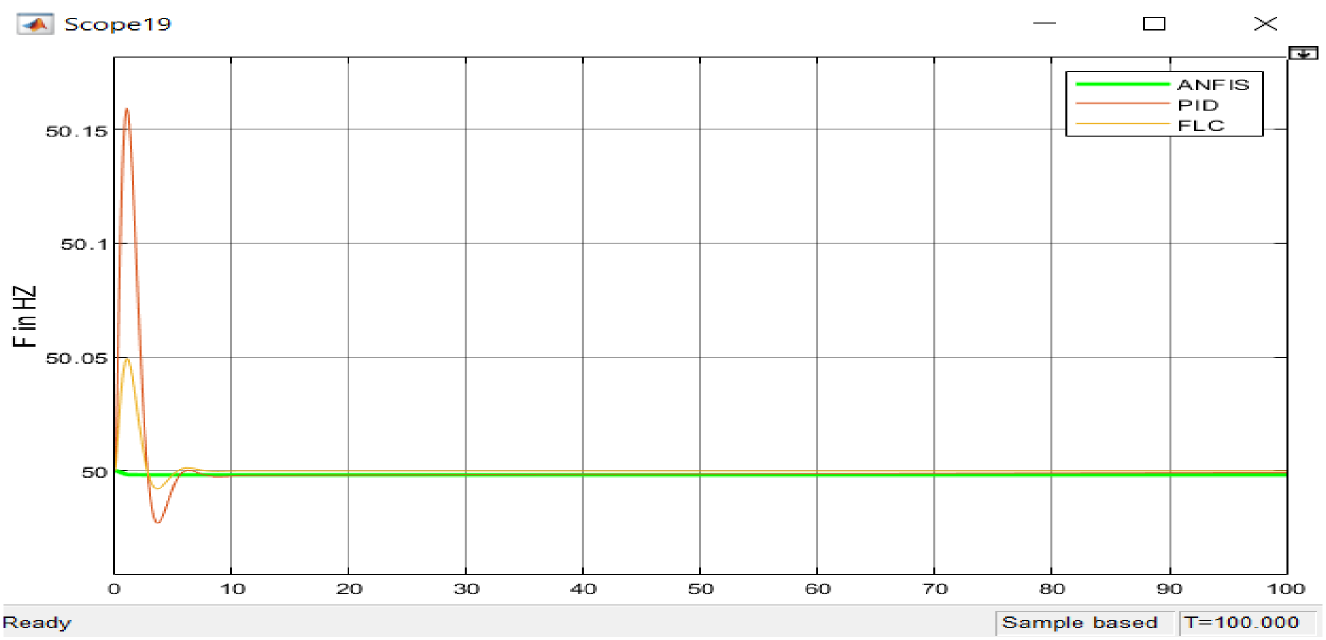

Figure 33 Graph system frequency at steady state condition

Under steady state operating conditions, with no variation in load demand, the dynamic response of the turbine–generator unit and over all power system is analyze. Since the load remains constant, the incremental load change is zero (0 MW) and in addition, the total system load remains at its nominal valueP_L, (250 MW).

The simulation results show that the turbine-generator unit reaches equilibrium and delivers a constant power output equal to the steady state load demand. Consequently, no active power imbalance exists between generation and load, and the turbine output power settles at its rated value without oscillations.

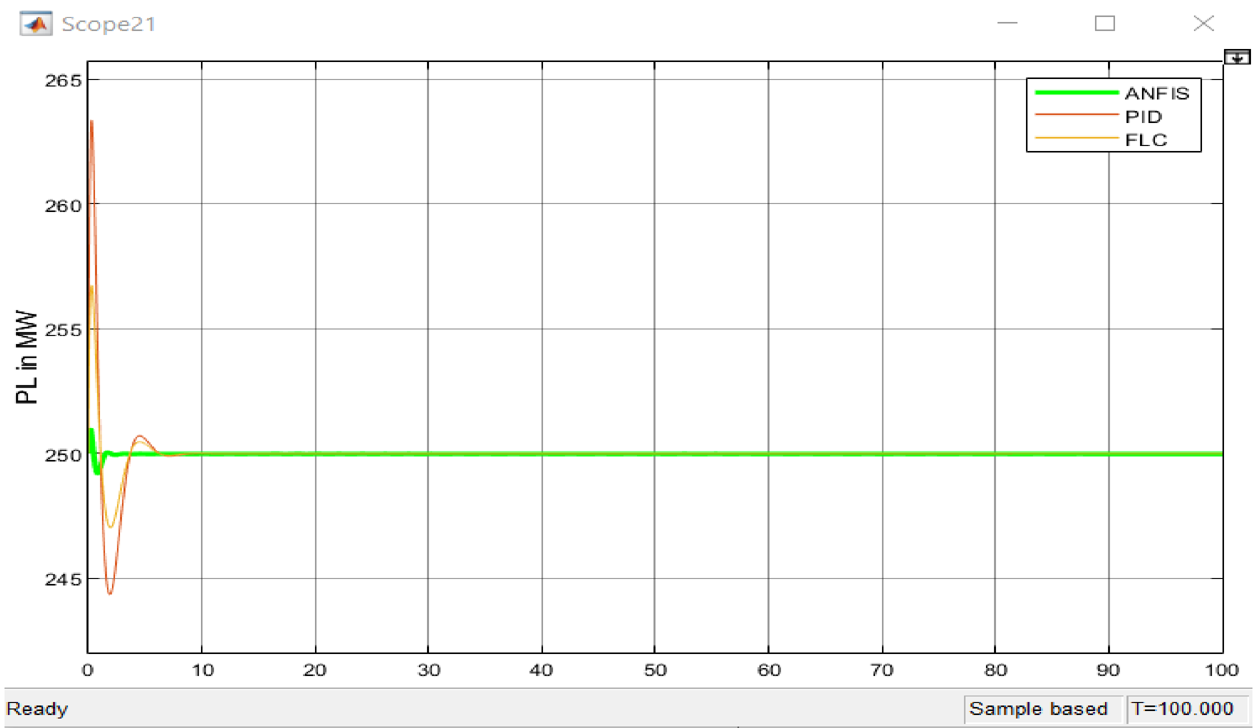

Figure 34 Graph power generation at steady state condition

Table 7 system frequency deviation, actual frequency values and Time-response specifications of without load variation.

Controller	Δf_{pu}	Δf_{Actual}(HZ)	f_{actual} (HZ)	Settling time(s)	Overshoot (%)	Rise time (s)
PID	0	0	50	8.7	4.80	1.5
FLC	0	0	50	7.3	3.20	1.25
ANFIS	0	0	50	4.2	0.50	0.3

5.3.2 Simulation results with 0.1pu (25MW) load addition to the system Network

To evaluate the dynamic performance of the power system under load disturbance conditions, a step increase of 0.1 P_U (25 MW) load is applied to the system network. This disturbance cause an immediate imbalance between generation and demand, resulting in a decrease in system frequency. This reduction in frequency indicates that the system is unable to maintain its nominal frequency immediately after the load increment without appropriate control action.

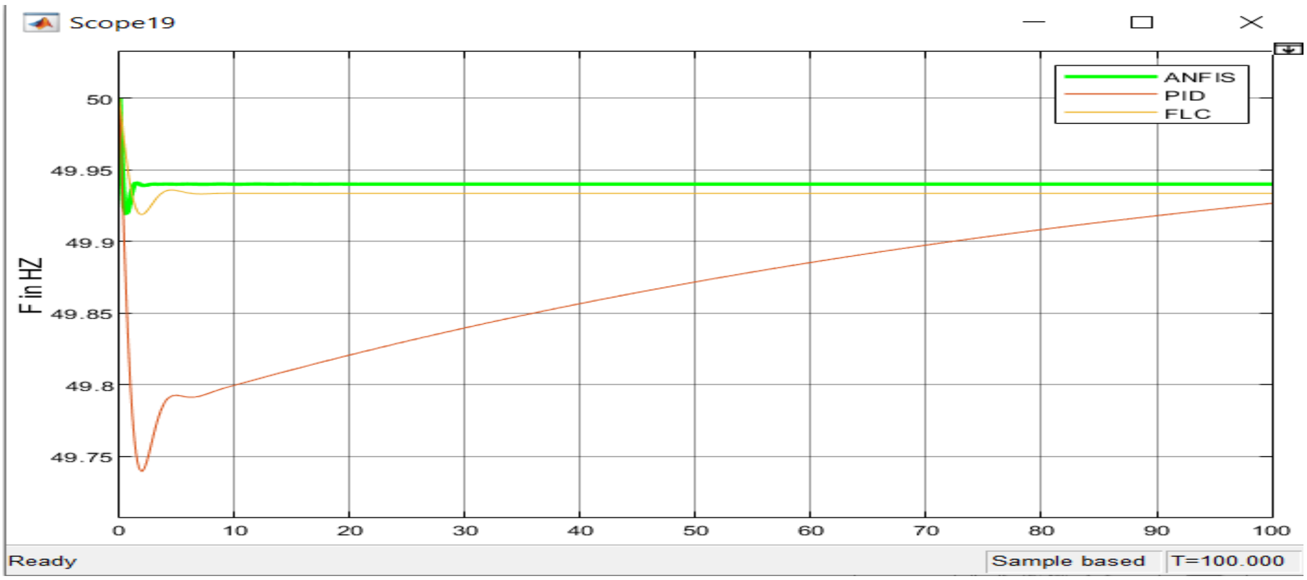

Figure 35 Graph system frequency at 0.1 P_U load added

To restore the system frequency to its nominal value of 50 HZ, the turbine-generator unit must increase its power output by an amount equal to the applied load disturbance (25MW). Therefore, the required new total system load becomes 275 MW. The automatic generation control (AGC) response of the system for this load disturbance under different control strategies is illustrate in figure 5.7.

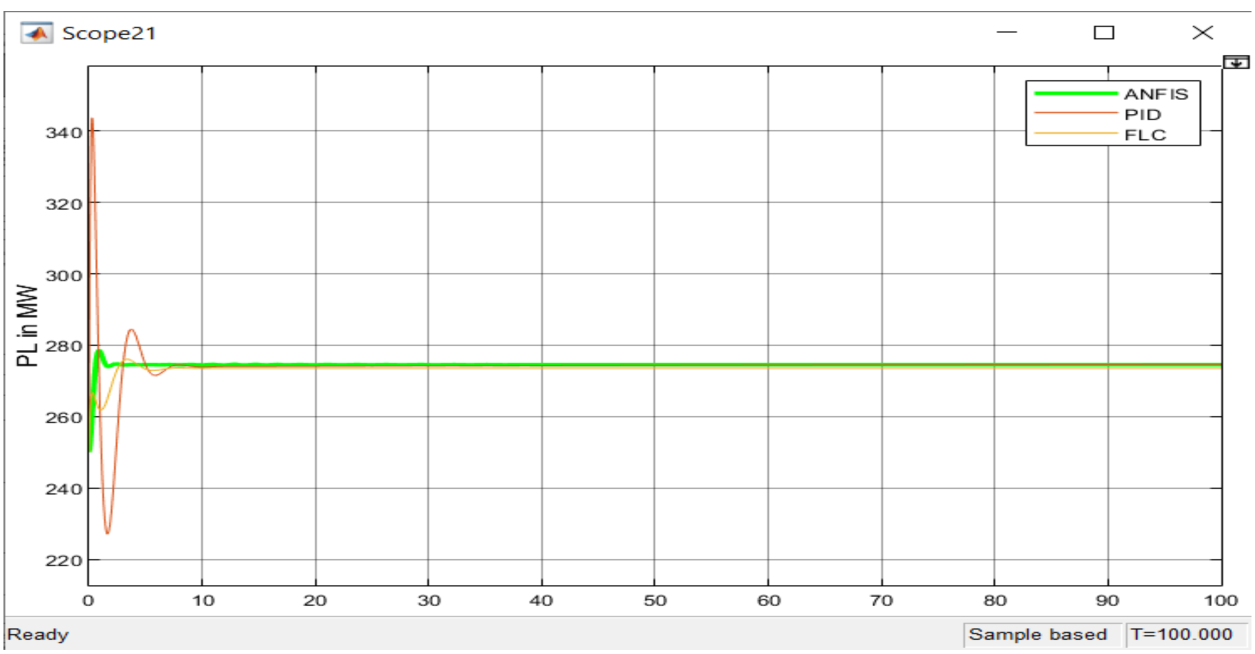

Figure 36 Variation of generated power when a 0.1 p.u load disturbance applied to the system

To quantitatively asses the effectiveness of each controller, key Time domain performance indices such as settling time, overshoot, and rise time evaluated and summarized in table 5.2.

Table 8 system frequency deviation, actual frequency values and time-response specifications for 0.1pu load addition.

Controller	Δf_{pu}	Δf_{Actual}(HZ)	f_{actual} (HZ)	Settling time(s)	Overshoot (%)	Rise time (s)
PID	-0.0014	-0.070	49.93	10	36.8	1.55
FLC	-0.0012	-0.060	49.94	8.5	35.6	1.33
ANFIS	-0.0011	-0.0550	49.945	5.5	7.2	1.3

5.3.3 Simulation results with 0.2pu (50MW) load addition to the system Network

To further investigate the dynamic behavior and robustness of the power system, a step increase of 0.2 P_U (50 MW) load is applied to the system network. This large load disturbance creates a more severe generation-load imbalance, leading to a noticeable reduction in system frequency. This frequency reduction indicates that, without appropriate control action, the system cannot maintain its nominal frequency under increased load conditions.

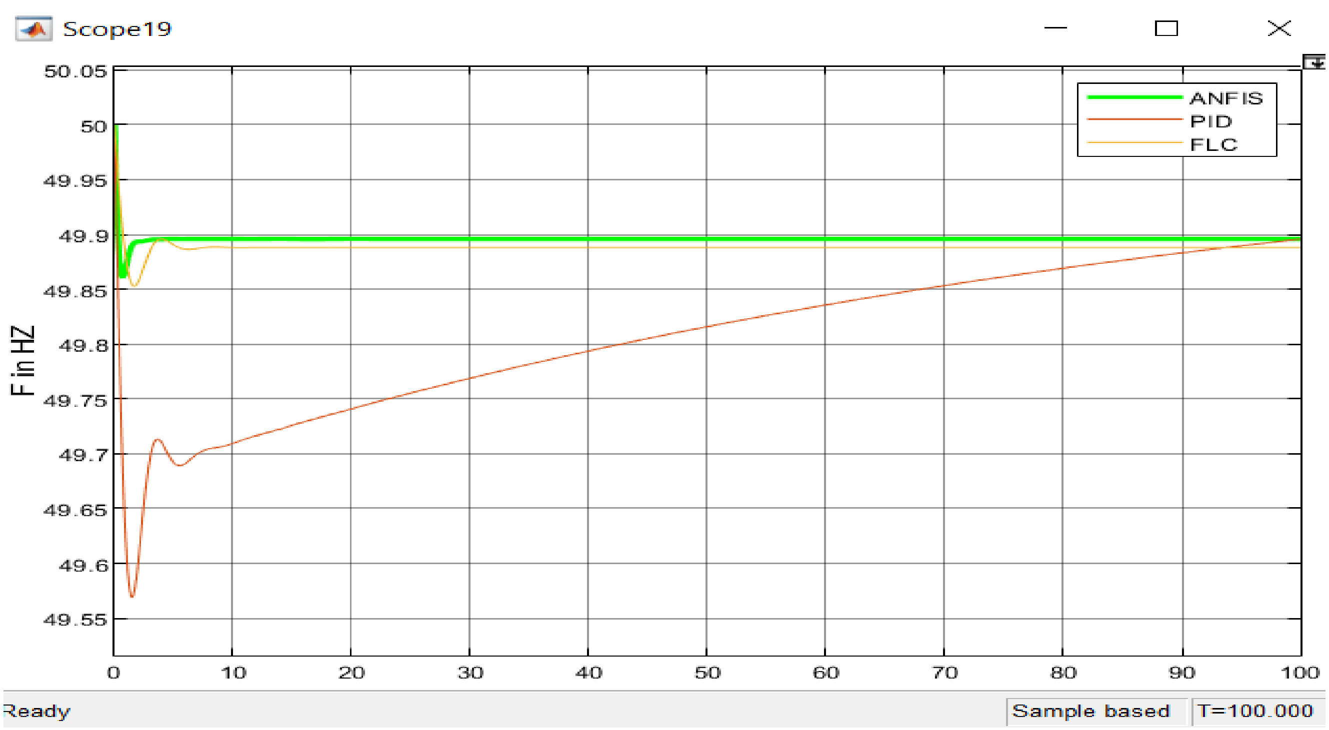

Figure 37 Graph system frequency at 0.2 P_U load added

To restore the system frequency to the nominal of 50 HZ, the turbine – generator unit must increase its power generation by an amount equal to the applied load increment (50MW). Hence, the required total system load becomes 300 MW.

The automatic generation control (AGC) responses of the system under different control strategies for this disturbance illustrated in figure 5.9.

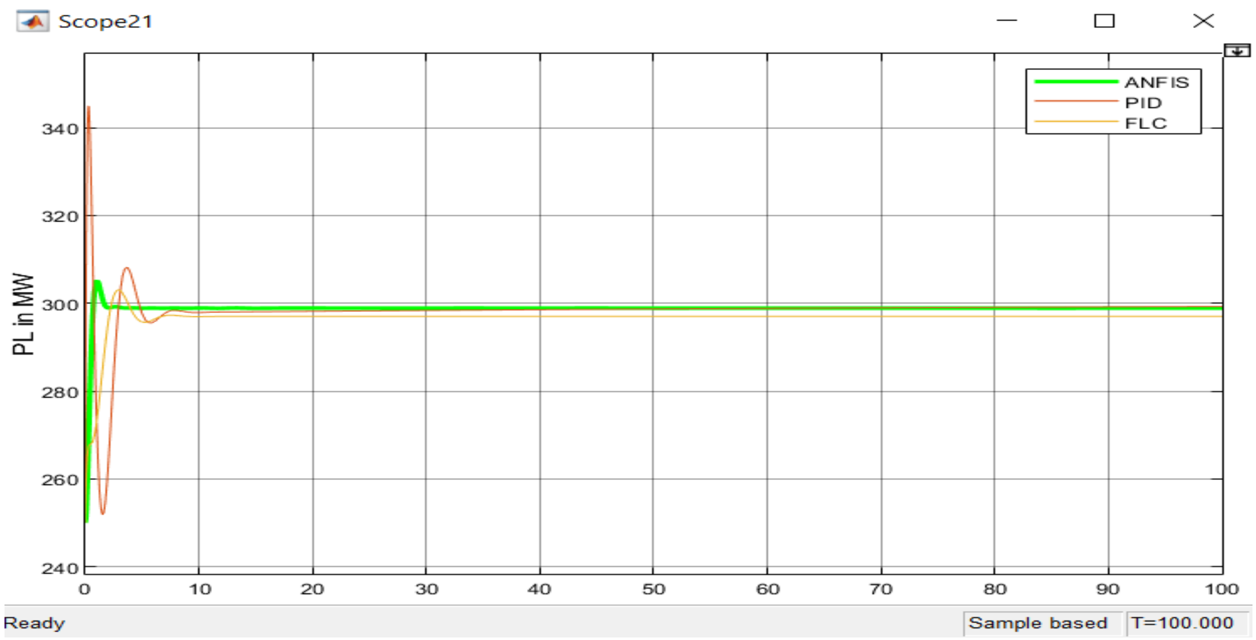

Figure 38 Variation of generated power when a 0.2 p.u load disturbance applied to the system

To evaluate and compare the dynamic performance of the controllers, Time domain performance indices such as settling time, overshoot, and rise time extracted from the simulation results and summarized in table 5.5.

Table 9 system frequency deviation, actual frequency values and Time-response specifications for 0.2pu load addition.

Controller	Δf_{pu}	Δf_{Actual}(HZ)	f_{actual} (HZ)	Settling time (s)	Overshoot (%)	Rise time(s)
PID	-0.0024	-0.12	49.88	11	39.2	1.59
FLC	-0.0022	-0.11	49.89	9.3	37.6	1.38
ANFIS	-0.0020	-0.10	49.90	6.1	19.4	1.32

5.3.4 Simulation results for Load rejection of 0.1pu (25MW)

To analyze the system response under load rejection conditions, a sudden reduction of 0.1 P_U (25 MW) load is applied to the system network. The removal of load creates a temporary surplus of generation, which results in an over-frequency condition in the power system. This increase in frequency indicates that, immediately after load drop, the generated power exceeds the system demand.

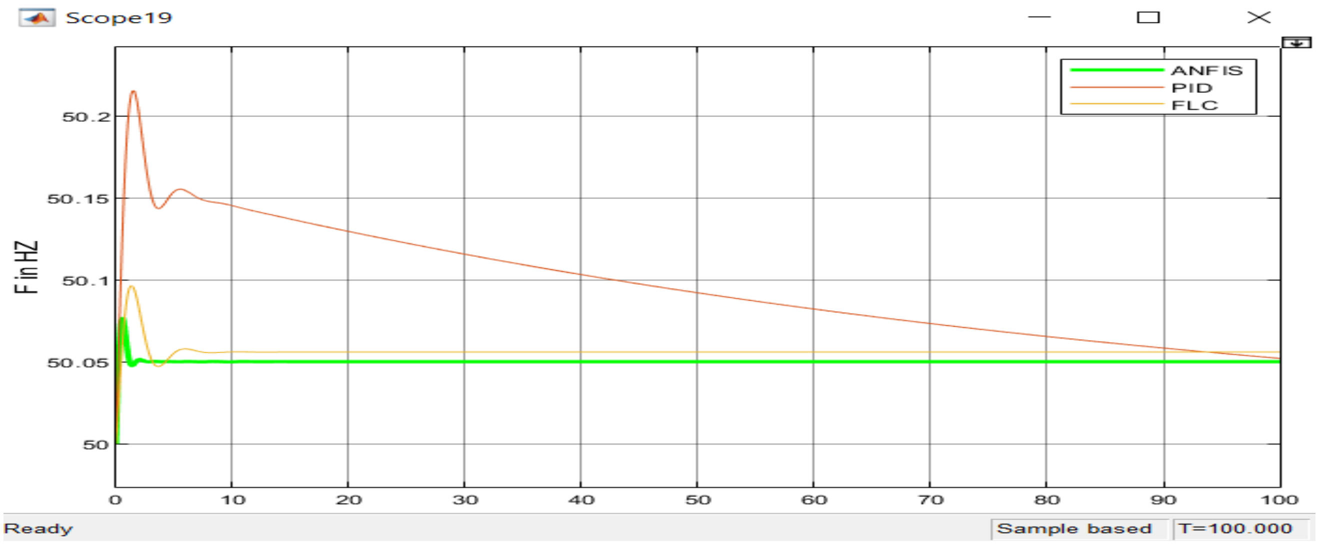

Figure 39 Graph system frequency at 0.1 P_U load rejection

To restore the system frequency to its nominal value of 50 HZ, the generating unit must reduce its output power by an amount equal to the load (-25MW). Hence, the required, new steady state system load becomes 225 MW. The automatic generation control (AGC) response of the system under different control strategies for this load rejection scenario illustrated in figure 5.11.

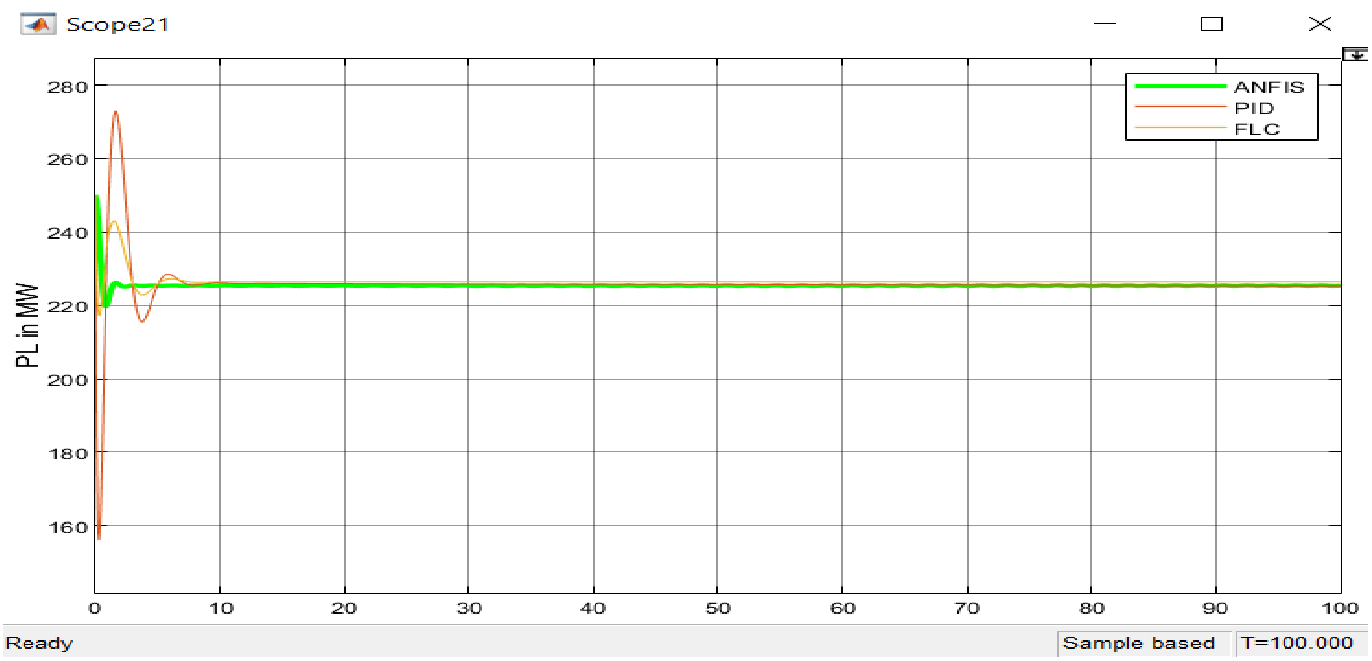

Figure 40 Variation of generated power when a 0.1 p.u load rejection from the system

To assess the dynamics performances of each controller, key time domain indices such as settling time, undershoot, and fall time were extract from the simulation results and summarized in table5.4.

Table 10 system frequency deviation, actual frequency values and Time-response specifications for 0.1pu load rejection.

Controller	Δf_{pu}	Δf_{Actual}(HZ)	f_{actual} (HZ)	Settling time(s)	Undershoot (%)	Fall time (s)
PID	+0.00116	+0.058	50.057	10.3	35.7	1.57
FLC	+0.00114	+0.057	50.058	8.8	34.8	1.35
ANFIS	+0.001	+0.05	50.05	5.9	8.4	1.31

5.3.5 Simulation results for Load rejection of 0.2pu (50MW)

For further evaluate the system performance under severe disturbance conditions a sudden load rejection of 0.2 P_U (50 MW) is applied to the system network. The removal of this load results in an excess of generated power, causing the system to experience an over frequency condition. This rise in frequency indicates that, immediately after the disturbance, the generated power exceeds the system load demand.

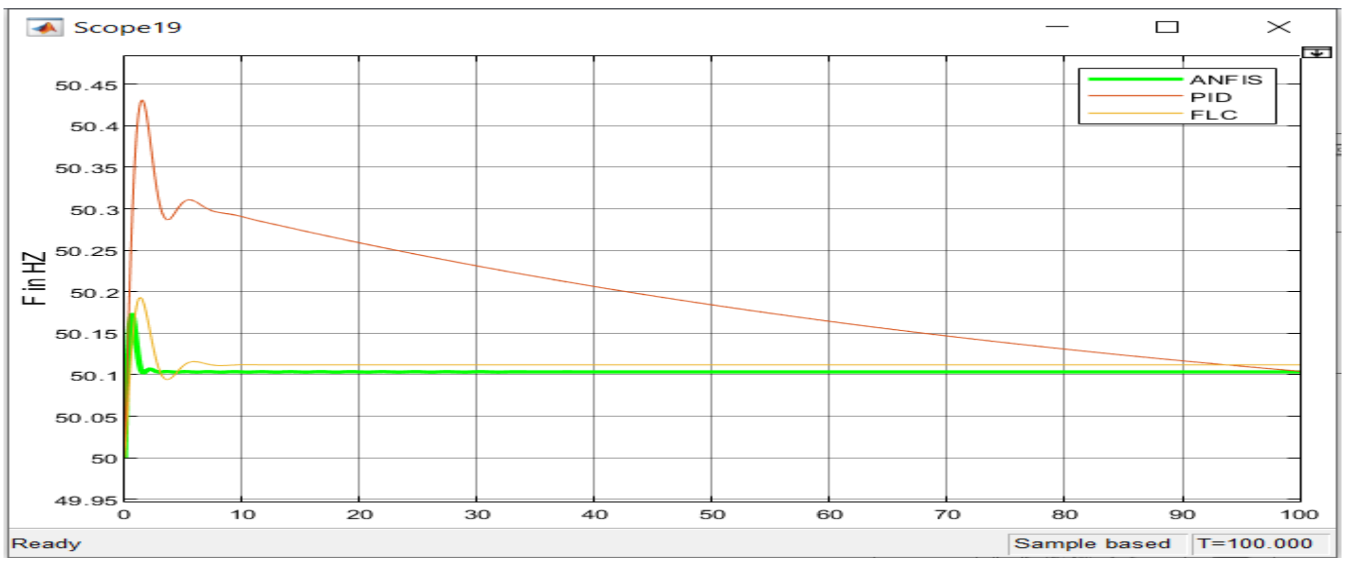

Figure 41 Graph system frequency at 0.2 P_U load rejection

To restore the system frequency to its nominal value of 50 HZ, the generating unit must decrease its output power by an amount equal to the rejection load (-50MW). Therefore, the required new steady state system load becomes 200 MW. The automatic generation control (AGC) response of the system under different control strategies for this load rejection scenario illustrated in figure 5.13.

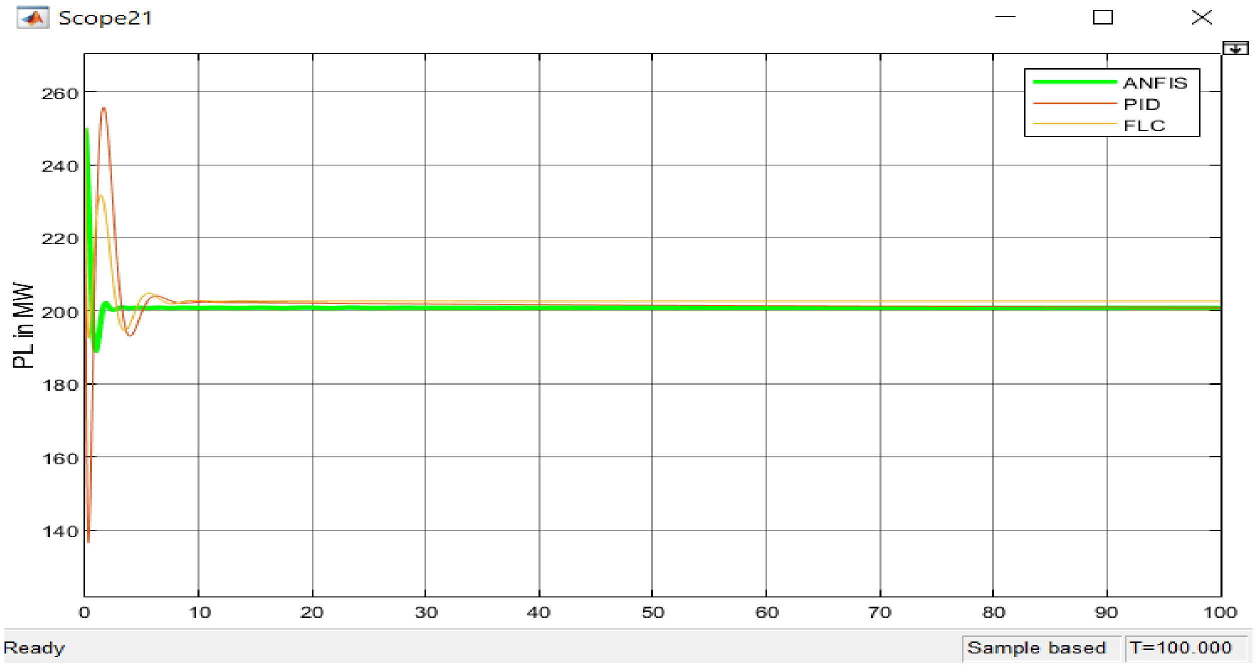

Figure 42 Variation of generated power when a 0.2 p.u load rejection from the system

The dynamic performance of the controllers is evaluated using time domain indices such as settling time, overshoot, and rise time, which summarized in table 5.5.

Table 11 system frequency deviation, actual frequency values and time-response specifications for 0.2pu load rejection

Controller	Δf_{pu}	Δf_{Actual}(HZ)	f_{actual} (HZ)	Settling time(s)	Undershoot (%)	Fall time(s)
PID	+0.0024	+0.12	50.12	11.2	39.9	1.58
FLC	+0.0022	+0.11	50.11	9.5	38.4	1.37
ANFIS	+0.002	+0.1	50.1	6.3	19.7	1.33

5.4 Discussion

The primary objective of the control system in an Automatic Generation Control (AGC) scheme is to ensure that the system output closely tracks the desired reference value while minimizing the error between the set point and the feedback signal under both steady state and transient operating conditions. In this thesis, the dynamic behavior of a steam power plant analyzed under various load disturbances using three different control strategies; the PID controller, the Fuzzy Logic Controller (FLC), and the proposed Adaptive Neuro-Fuzzy Inference System (ANFIS). The simulation results demonstrate that the developed models respond in accordance with the principle of stable power system and frequency control theory. Under steady-state conditions with no load variation, the system maintains stable operation with only a small frequency deviation, confirming the inherent stability of the plant and the adequacy of the control structures. When load disturbances introduced; either in the form of load addition or load rejection, the system experiences frequency deviations proportional to the magnitude and direction of the disturbance. An increase in load results in a frequency drop due to a temporary generation-load imbalance, whereas a decrease in load causes a rise in frequency because of excess generated power.

In all simulated disturbance scenarios, the controllers act to restore the system frequency to its nominal value by appropriately adjusting the turbine input through the governor mechanism. The control action increases power generation during load addition and reduces generation during load rejection, thereby re-establishing the balance between generation and demand. This behavior was consistently observe across all operating cases, confirming the correctness of the developed simulation models.

A comparative evaluation of the controllers indicates significant differences in their transient performance. The conventional PID controller, while capable of restoring system stability, exhibits relatively larger overshoot or undershoot, longer settling time, and slower rise or fall time, particularly under higher load disturbances. These limitations mainly attributed to its fixed gain parameters, which restrict its adaptability to nonlinear system dynamics and varying operating conditions.

The Fuzzy Logic Controller shows improved performance compared to the PID controller. It provides reduced overshoot, faster settling time, and better damping of oscillations due to its rule-based structure and nonlinear control capability. This indicates that the FLC is more robust than the PID controller in handling system nonlinearities and load uncertainties is.

The proposed ANFIS controller demonstrates the best overall performance among the three control strategies. Across all tested scenarios; steady-state operation, load addition of 0.1 P_U and $0.2P_U$, and load rejection of $0.1P_U$and $0.2P_U$; the ANFIS controller consistently achieves the fast settling time, less overshoot or undershoot, and smoother dynamic response. The superior performance of the ANFIS controller can attributed to its hybrid learning capability, which combines the human-like reasoning of fuzzy logic with the adaptive learning features of neural networks. This enables the controller for effectively adapt to system nonlinearities and changing operating conditions.

Overall, the discussion of simulation results confirms that while all controllers are capable of maintaining system stability, the ANFIS-based AGC provides enhanced dynamic performance and robustness compared to the conventional PID and FLC approaches. Therefore, the ANFIS controller is more suitable for frequency regulation of steam power plants operating under varying load conditions.

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

6.1 Conclusion

This thesis investigated the application of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Automatic Generation Control (AGC) of a steam power plant with to improving frequency regulation and active power control under varying load conditions. A detailed mathematical model of a single-area non-reheat steam power plant, including the governor, turbine, and generator-load dynamics, is developed and implemented in the MATLAB/Simulink environment.

The performance of the proposed ANFIS-based AGC was evaluated and compared with conventional PID and Fuzzy Logic Controllers (FLC) under steady-state operation as well as different load disturbance scenarios, including load addition and load rejection of 0.1 pu and 0.2 pu. The comparative analysis was carry out using standard performance indices such as peak frequency deviation, overshoot, settling time, and dynamic response behavior.

Simulation results clearly demonstrate that the conventional PID controller suffers from relatively large overshoot, longer settling time, and reduced robustness when subjected to step load changes. The Fuzzy Logic Controller provides better performance than PID by reducing overshoot; however, it still exhibits slower dynamic response and residual oscillations under larger disturbances. In contrast, the proposed ANFIS controller consistently delivers superior performance by effectively handling system nonlinearities and uncertainties. It achieves minimal frequency deviation; faster settling time, improved damped of oscillations, and enhanced adaptability under all tested operating conditions.

Based on the obtained results, it can be conclude that the ANFIS-based AGC significantly improves the frequency stability and dynamic performance of the steam power plant compared to traditional control techniques (PID and FLC). Therefore, ANFIS represents a robust and intelligent control strategy suitable for modern power systems where nonlinear behavior and rapid load variations are unavoidable.

6.2 Recommendation

Although the proposed ANFIS-based Automatic Generation Control (AGC) has shown promising performance, demonstrated significant improvements in frequency regulation and dynamic performance of the steam power plant, the following recommendations suggested for future research and practical implementation.

As future works:

- Multi-Area Power System Extension

The present study is limited to a single-area and no-reheat type steam power plant. Future work should extend the proposed ANFIS controller to multi-area interconnected power systems and the reheat type steam power plant model system to evaluate its effectiveness in regulating tie-line power and inter-area frequency oscillations.

- Real-Time and Hardware Implementation

The current work is-based on simulation studies only. Practical implementation using real-time digital simulators (RTDS) recommended validating the controller's performance under real operating conditions.

- Integration of Automatic Voltage Regulator (AVR)

The present work focuses primarily on active power and frequency control through AGC. Future research should incorporate an Automatic Voltage Regulator (AVR) and excitation system to simultaneously controlling voltage and reactive power. Coordinated design of ANFIS-based AGC and AVR would provide comprehensive power system control, improve voltage stability, enhance transient performance, and ensure overall system reliability.

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