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Original Article

Improving Frequency Control Strategy of Interconnected Power Systems with Renewable Energy Integration Using an Adaptive Neuro-Fuzzy Inference System Controller

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Abstract *- Maintaining frequency stability within a power system can be a critical criterion for ensuring reliable and secure grid operation. This challenge is particularly pronounced in today's wide-ranging and interconnected systems, where the presence of non-linear properties and the increasing integration of renewable energy sources introduce significant complexities. This work is a new approach to using an Adaptive Neuro-Fuzzy Inference System (ANFIS) methodology to achieve robust frequency control in such environments. The proposed approach is evaluated within a three-area interconnected power system model incorporating diverse turbine types, Governor Dead-Band (GDB), Generation Rate Constraint (GRC), and renewable energy sources. The effectiveness of the ANFIS controller is subsequently validated through comparative analysis with existing control strategies, as evidenced by the superior performance demonstrated in numerical simulation results.*

Keywords *- GRC, GDB, ANFIS, Interconnected power system, LFC.*

1. Introduction

Modern electrical power systems comprise a vast network of interconnected elements, forming a unified infrastructure. This intricate system incorporates numerous components such as power generation plants, transmission lines, and transformer stations, each playing a critical role in the delivery of electrical energy. Within this framework, power quality is paramount, ensuring the consistent and reliable provision of electricity. Two key parameters utilized in the evaluation of power quality are voltage and frequency.

Frequency, in particular, exhibits a systematic characteristic. Deviations from the nominal frequency value arise due to imbalances between electricity production and consumption. These imbalances can be attributed to fluctuations in power demand. As consumption patterns shift throughout the day, the system frequency experiences corresponding variations, momentarily deviating from the standard value. However, these deviations are only temporary, and the system should have an inherent control mechanism to maintain the net frequency at the nominal values.

This phenomenon emphasizes the importance of maintaining the right balance between production and consumption in an interconnected power system. When these two factors are not in equilibrium, imbalances arise, manifesting as frequency deviations. The ability to effectively manage and regulate these imbalances is essential for ensuring optimal power quality and system stability.

From this point of view, maintaining frequency stability within interconnected power systems is a crucial aspect of ensuring reliable and efficient power delivery. Numerous research efforts have been undertaken to develop and evaluate various control strategies for mitigating frequency deviations. In [1], authors proposed an online intelligent controller that combines adaptive algorithms for stabilizing the frequency of a four-region system encompassing three heat recovery turbine regions and one hydraulic turbine region. The specific details regarding "suspected bats and fuzzy" are unclear and require further investigation.

Report [2] explored the application of a PID hierarchical frequency controller within a four-area interconnected power system, evaluating its performance under different operating conditions. Research [3] investigated an optimized sliding mode control (SMLFC) method to control load frequency ($H\infty$) in interconnected power systems that incorporate time delays.

In [4], the authors presented an approach based on fuzzy logic to determine the optimal PID controller parameters for frequency regulation in a three-area system. Next, the article [5] introduces a neural network controller designed to continuously adjust the parameters of the PID controller based on real-time changes in Area Control Errors (ACE).

The authors in [6] focused on designing a Model Predictive Controller (MPC) for a multi-areas power system with 4 areas and 8 generators. This approach considers load variations and uncertain factors that can influence frequency stability. Report [7] delves into the building of a neural controller applied for an interconnected power system comprising non-reheat, reheat, and hydraulic turbine configurations.

Several studies have investigated control strategies for power systems connected to conventional generating sets. Research [8] proposed a load frequency controller for a two-zone system using the Bacteria Search Optimization Algorithm (BFOA) to deal with significant frequency deviations. In [9], the authors presented a hybrid controller that combines Particle Swarm Optimization (PSO) and Differential Evolution (DE) optimization methods with fuzzy logic for frequency stabilization in a two-zone system. with three transmitters per zone.

Research [10] explored a frequency controller for a two-zone, non-reheat turbine system using a hybrid approach combining BFOA and PSO. This study emphasizes the simplicity of the considered system with minimal constraints. The paper [11] studied a control strategy for a two-zone, non-reheat turbine system, incorporating consideration of uncertainties.

The growing demand for electricity has led to the widespread adoption of renewable energy sources in power systems. Although these sources provide environmental benefits, their integration poses challenges related to system nonlinearity.

Research [12] addresses this problem by proposing a Terminal Sliding Mode Control (T-SMC) strategy for a multi-connected, two-zone power system coupled with wind turbines. Other research explores an adaptive model predictive controller designed for systems with renewable energy sources, such as wind power [13].

Recent research delves into advanced control methods for managing large power systems with diverse renewable energy sources. For example, one study investigated the application of the Fractional Order Derivative Control (FODC) method to large-scale systems incorporating renewable energy sources such as wind power, photovoltaic systems, and solar panels. Superconducting Magnetic Energy Storage (SMES) [14].

Meanwhile, a study [15] proposed a virtual inertial controller for frequency stabilization in a two-zone power system connected to wind and solar renewable energy sources.

This overview highlights the evolution of control strategies for frequency regulation in interconnected power systems. The integration of renewable energy sources necessitates the development of increasingly sophisticated control methods to maintain grid stability and ensure reliable power delivery.

The present paper presents the Adaptive Fuzzy Inference System (ANFIS) control method as a new approach for frequency regulation in a three-zone connected power system. The proposed method specifically addresses the challenges related to system nonlinearity and the increasing involvement of renewable energy sources.

The remainder of this article is structured as follows:

Section 2: ANFIS Controller Design - This section delves into the detailed design of the ANFIS controller, including its integration with the fuzzy logic structure.

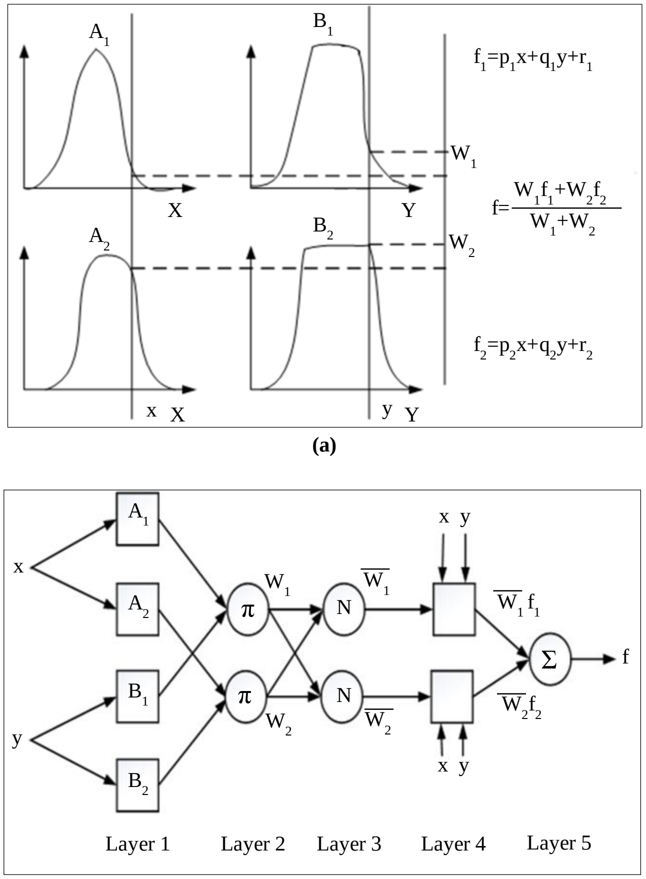
Section 3: System Modeling and Simulation Results- This section focuses on the modeling of a three-area power system and the simulation of frequency response under various load conditions, encompassing different load shapes and magnitudes. Furthermore, the simulation results obtained using MATLAB/Simulink software with significant comments verifying the applicability and effectiveness of the proposed ANFIS control methodology will be introduced in this section.

Section 4: Conclusion and Future Work – This final part summarizes the main findings of the paper and highlights the potential benefits of the ANFIS control approach for frequency regulation in systems which are connected to electricity with integrated renewable energy. Additionally, some directions related to future work will be presented.

2. Design of ANFIS Controller

The ANFIS leverages principles from both artificial neural networks and fuzzy logic, offering a unified framework that capitalizes on the strengths of each approach. ANFIS builds upon the Takagi-Sugeno fuzzy inference system, inheriting its interpretability and rule-based structure.

Additionally, by incorporating elements of neural networks, ANFIS gains the ability to learn and adapt to complex nonlinear relationships within the data. A key advantage of this neuro-fuzzy system lies in the reduced number of membership function inputs and outputs, leading to a more parsimonious model compared to traditional fuzzy logic systems (see Figure 1).



(b)

Fig. 1 The ANFIS structure (a) Sugeno fuzzy model, and (b) Architecture of ANFIS.

The design of an ANFIS controller involves a series of sequential steps:

- Data Acquisition: The initial step entails acquiring system data, potentially by leveraging a Fuzzy PSO controller as described in [16]. This data serves as the foundation for training the ANFIS model.
- Input and Output Definition: The ANFIS controller is configured with two primary inputs: Area Control Error (ACE) and its rate of change (dACE). The controller's output represents the control signal denoted by u(t).
- ANFIS Model Creation: The ANFIS Editor (ANFISEDIT) software is employed to construct an ANFIS model file in the *.fis* format.
- Training Data Loading and Membership Function Selection: The data collected in step 1 is loaded into the ANFIS model. Subsequently, the model utilizes Gaussian bell-shaped membership functions (*gbell MF*) to represent the fuzzy sets within the system.
- Model Training: The ANFIS model undergoes a training process using the acquired data and a predefined target output. This training process refines the model's parameters to achieve optimal performance.
- Model Saving: Upon successful training, the final ANFIS model is saved as a *.fis* file. This file embodies the neuro-fuzzy enhanced ANFIS controller, ready for deployment in the power system.

When implemented using the MATLAB Fuzzy Logic Toolbox, an ANFIS structure takes the form depicted in Figure 2. It is noted that for the LFC problem, the Area Control Error (ACE) signals are used for the inputs of the controller. Hence, they are also used for the ANFIS model in this study.

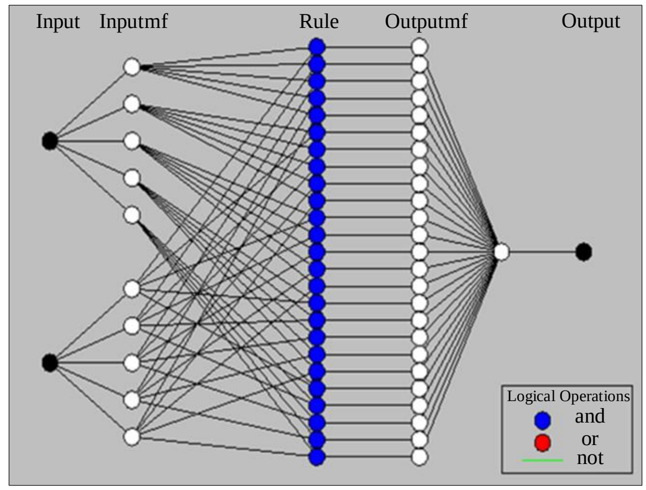


Fig. 2 Structure of the ANFIS built-in MATLAB

It can be seen that membership functions with necessary parameters for two inputs and one output are shown in Figures 3 and 4 and Table 1.

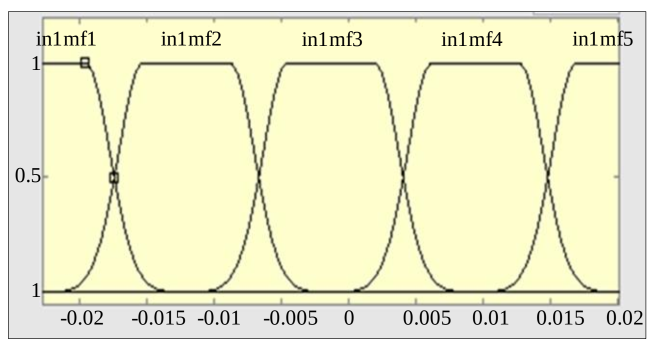


Fig. 3 The membership functions of ACE - input 1

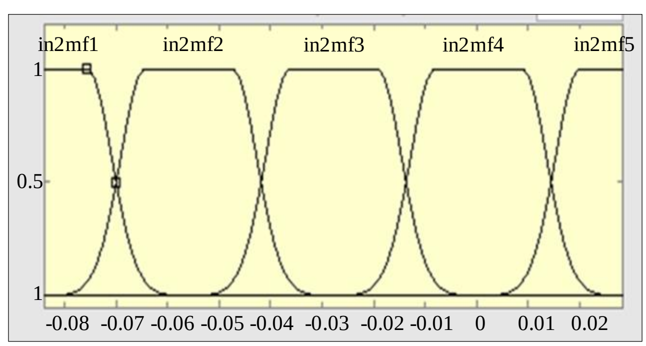


Fig. 4 The membership functions of dACE - input 2

Table 1. The output function values

-0.0214	10.9	0.2012	0.111	0.012
-0.67	0.293	0.1819	0.071	-0.01
0.341	0.6686	0.1204	0.088	-0.092
2.794	7.944	0.08	-0.048	-0.077
-0.0866	-0.07	0.8343	-0.04	-0.09

A significant advantage of the neuro-fuzzy design approach, compared to traditional fuzzy logic methods, lies in its ability to handle systems with limited input data and a small number of output Membership Functions (MFs). When dealing with such scenarios, fuzzy logic systems typically require a high number of rules to achieve the desired accuracy. This, in turn, results in a large and complex rule base that consumes significant memory resources.

For instance, consider the example presented in [16]. The fuzzy set, in that case, employs three inputs three outputs, and necessitates 49 fuzzy rules for effective operation. In contrast, the ANFIS approach adopted in this article utilizes a model with only two inputs, one output, and a considerably smaller set of 25 fuzzy rules. This reduction in rule base size translates to a more compact and efficient model, requiring less memory for storage and execution.

Table 2. Training and checking data of ANFIS

Sum of Nodes	75
Sum of Linear Parameters	25
Sum of Nonlinear Parameters	20
Sum of Epoch	45
Sum of Training Data Pairs	1198
Sum of Checking Data Pairs	0
Sum of Fuzzy Logic Rules	25

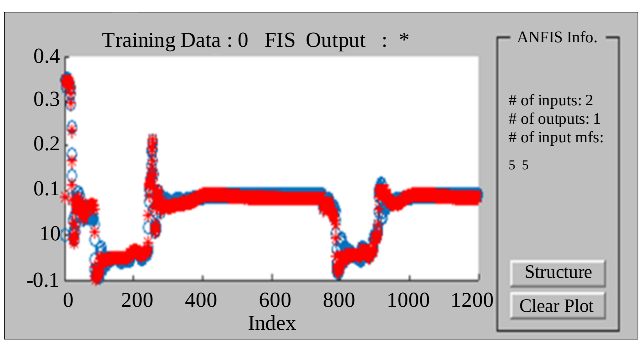


Fig. 5 The training data and FIS output

The optimal number of training epochs for the ANFIS model is determined based on a combination of the formula mentioned above parameters, error measures, and, potentially, user-defined adjustments. The specific training and testing data sets employed for model development are presented in Table 2. The training process successfully converged, achieving a minimal error value of 0.008861106.

3. System Modelling under Study and Numerical Simulations

3.1. System Modelling

Modern electrical power systems are characterized by extensive networks that encompass numerous interconnected sub-regions. These sub-regions are linked via transmission lines, facilitating the bidirectional flow of electrical energy throughout the entire system. Each sub-region typically incorporates a collection of essential components that contribute to both the generation and regulation of electrical power. These components can be categorized as follows:

3.1.1. Governors

These control systems regulate the flow of the working fluid (e.g., steam, water) directed towards the prime mover (turbine) within a power generation facility. This regulatory action directly influences the amount of electrical power generated.

3.1.2. Turbines

These machines function by converting the energy inherent within the working fluid into mechanical energy. The mechanical energy output from the turbine is then used to drive the generator. Different types of turbines exist, each designed for specific operating conditions and fuel sources. Common examples include Non-reheat turbines, Reheat turbines, Hydraulic turbines, Gas turbines, etc.

3.1.3. Generators

These devices are responsible for converting the mechanical energy provided by the turbine into electrical energy. This transformation enables the delivery of power to the interconnected grid. Detailed illustrations depicting models that utilize these various turbine types are presented in Figures 6, 7, and 8, respectively. The presence of nonlinear factors within a power system significantly influences the frequency stability of individual interconnected areas. These nonlinearities can arise from various sources, including Governor Deadband (GDB) and Generation Rate Constraints (GRC). An example of the GRC model is shown in Figure 9.

The interconnected electric power grid being studied is a three-zone system consisting of three separate turbine types. This configuration represents a large and complex electrical network. The system combines nonlinear elements such as GDB and GRC with the participation of renewable energy sources. These factors contribute to frequency instability in each region. The diagram of the entire system in this study is presented in Figure 9.

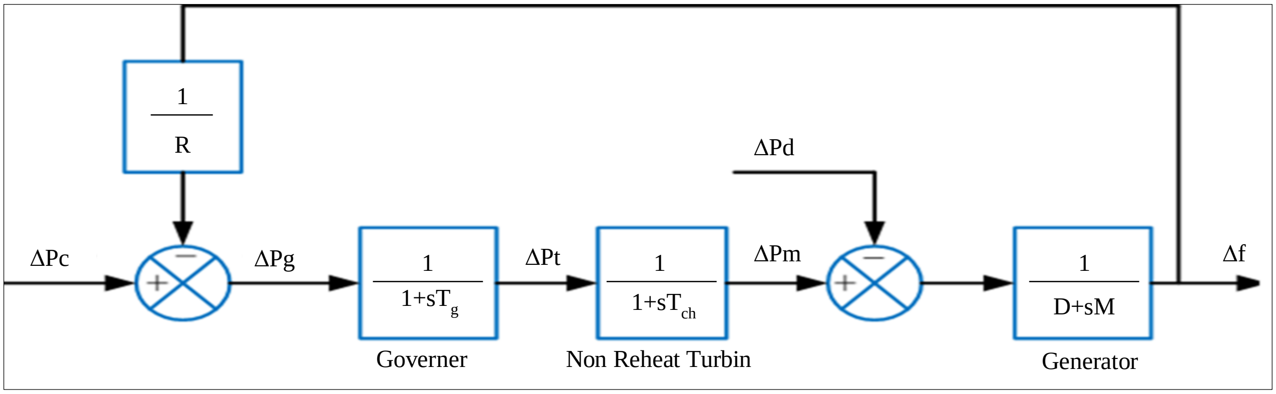


Fig. 6 A typical block diagram of a non-reheat turbine area

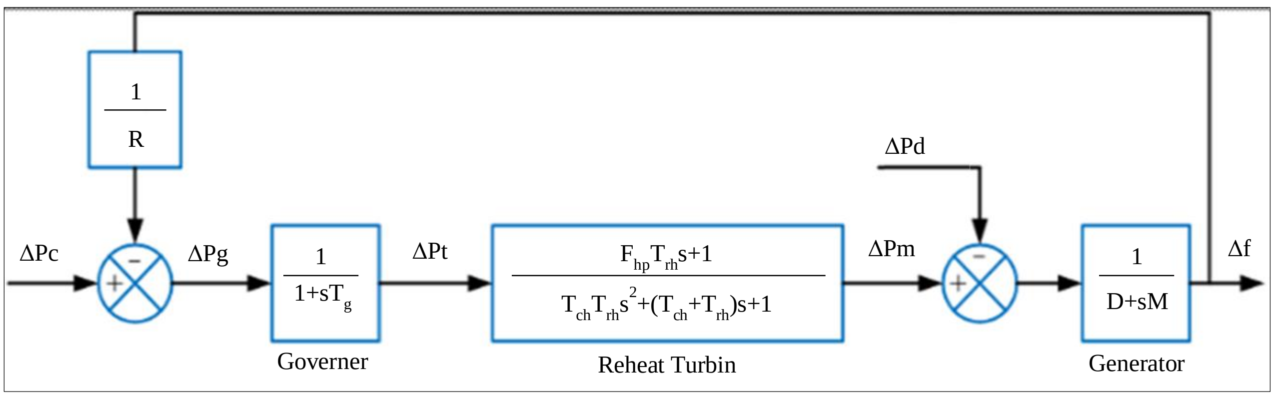


Fig. 7 A typical block diagram of a reheat turbine area

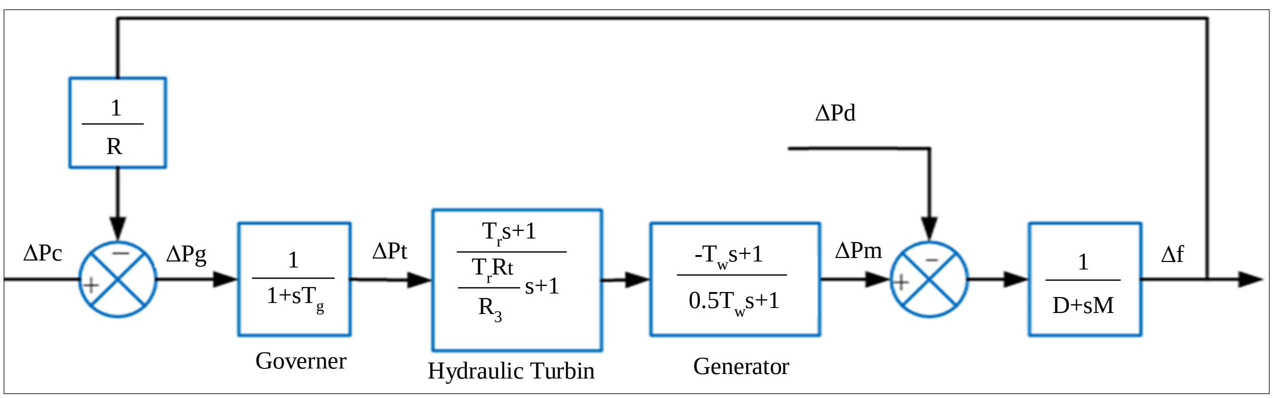


Fig. 8 A typical block diagram of a hydraulic turbine area

Mathematical models employing transfer functions depict the behavior of renewable energy sources, as presented in the subsequent formulas.

$$\frac{\Delta P_{wtg}(s)}{\Delta P_{wt}(s)} = \frac{1}{T_{wts}s+1} \tag{1}$$

$$\frac{\Delta P_{spv}(s)}{\Delta P_{sp}(s)} = \frac{1}{T_{spv}s+1} \tag{2}$$

Where, T_{wts}, and T_{spv} are two time constants which can be determined through a proper identification method.

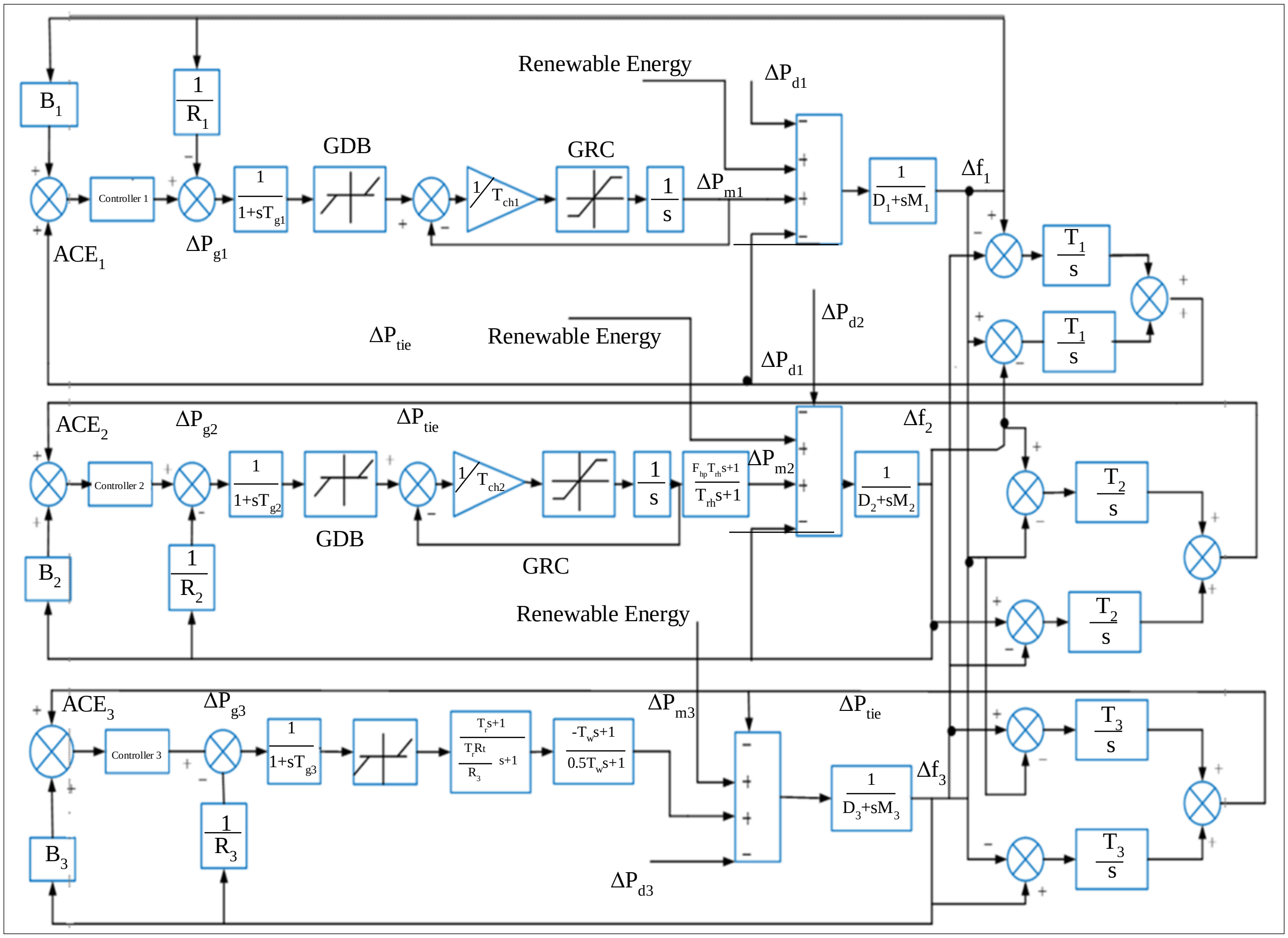


Fig. 9 An interconnected power system model with renewable energy resources and HVDC established in Matlab/Simulink

3.2. Numerical Simulations

This section delves into the analysis of frequency response characteristics within a multi-area power system employing the previously introduced ANFIS controller. To assess the controller's effectiveness in maintaining grid stability, a comprehensive simulation study is undertaken. The simulated power system accurately reflects real-world complexities by incorporating three interconnected areas, each utilizing distinct turbine types. Furthermore, to enhance the model's realism and capture non-idealities present in practical systems, non-linear factors such as GDB and GRC are meticulously integrated.

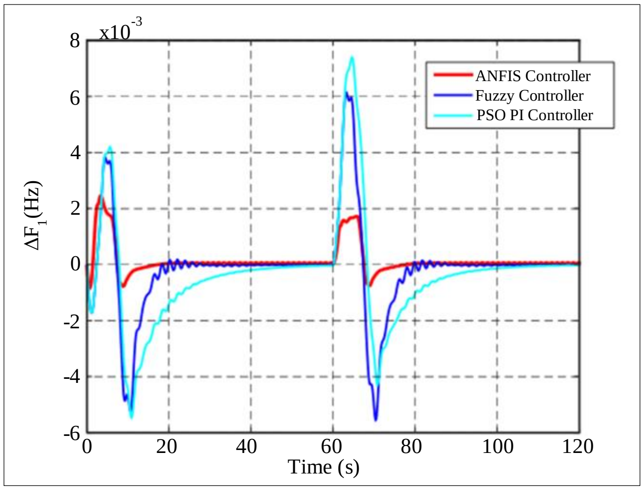
Additionally, the model incorporates the participation of renewable energy sources, reflecting the growing trend towards sustainable power generation. Finally, the performance of the designed ANFIS controller is rigorously evaluated through a comparative analysis against established control strategies, namely Fuzzy PI and PSO PI controllers. It is noted that the PSO algorithm used in this comparison has been modified in the initial phase to enhance the convergence speed.

This comparative analysis will shed light on the advantages of the ANFIS controller in terms of its ability to maintain frequency stability in each area of the connected power system. The simulation parameters can be found in [16]. In this paper, two simulation cases are performed to verify the feasibility of the proposed controller compared to the other two controllers, as mentioned above.

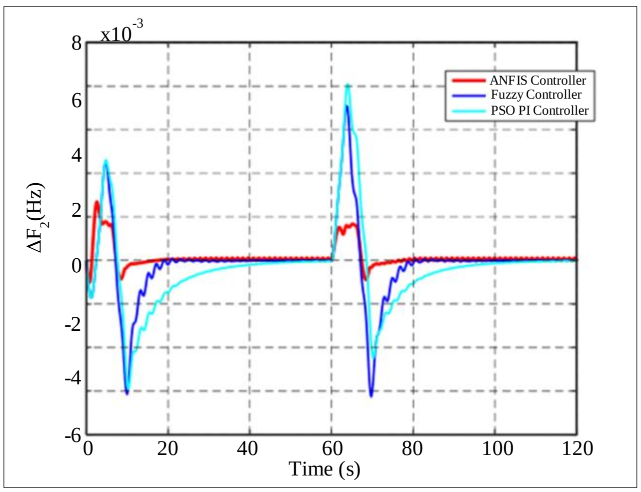
Case 1: $\Delta P_{d1} = 0.03\,p.u.; \Delta P_{d2} = 0.03\,p.u.; \Delta P_{d3} = 0.04\,p.u.$ (Types of step), $\Delta P_{spv} = 0.05$ p.u. (Type of pulse), $\Delta P_{wts} = 0.04$ p.u. (Type of step). Simulation results are illustrated in Figure 10 (a), (b) and (c).

Case 2: $\Delta P_{d1} = \Delta P_{d2} = 0.04$ p.u. (Type of random); $\Delta P_{d2} =$ 0.05 p.u. (Type of random); $\Delta P_{spv} = 0.05$ p.u. (Type of pulse), $\Delta P_{wts} = 0.03$ p.u. (Type of pulse).

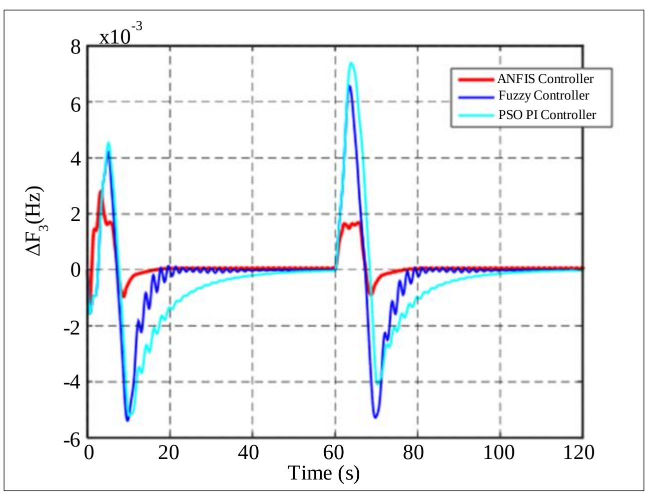
Numerical simulation results are shown in Figure 11 (a), (b) and (c).



(a)

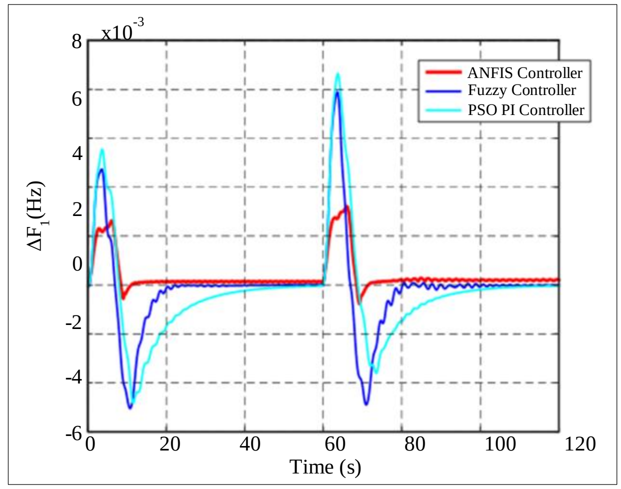


(b)

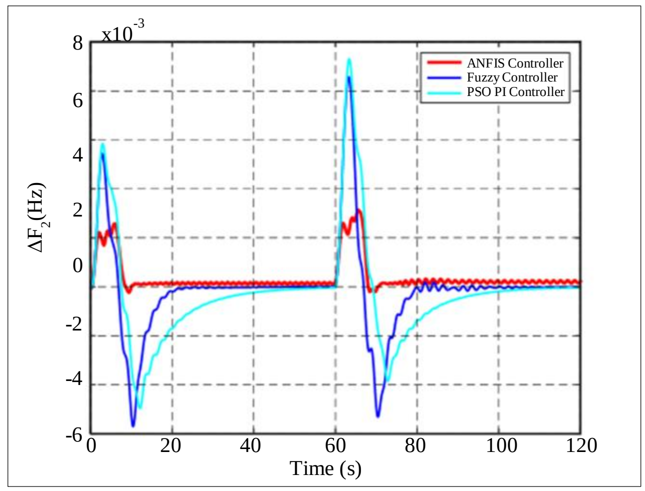


(c)

Fig. 10 Dynamic responses of the network frequency in the whole network (in case 1) (a) ΔF1, (b) ΔF2, and (c) ΔF3.



(a)



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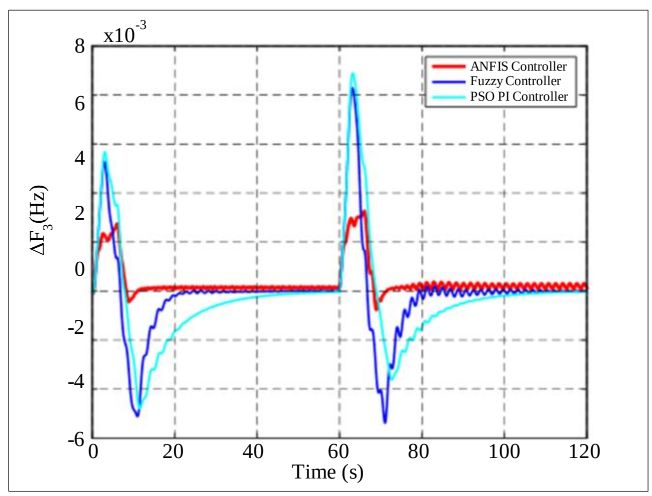

(c)

Fig. 11 Dynamic response frequency in sub-systems (in case 2) (a) ΔF1, (b) ΔF2, and (c) ΔF3.

The evaluation of a power system's frequency response across three distinct regions is a crucial aspect of ensuring grid stability. This paper presents the frequency error responses obtained under two distinct scenarios, as illustrated in Figures 10 and 11. The results demonstrate that the ANFIS controller exhibits superior performance compared to both the Fuzzy PI and PSO PI controllers. As mentioned earlier, the PSO algorithm used in this scenario is an improved one in which its initialization has been modified with a fast optimization mechanism to enhance its convergence speed. This advantageous performance can be attributed to the underlying design philosophy of the ANFIS controller. This philosophy prioritizes minimizing the number of inputs, outputs, and fuzzy rules required for operation. However, this minimalistic approach does not compromise effectiveness, as the ANFIS controller demonstrably achieves superior results in maintaining frequency stability.

4. Conclusion and Future Work

This work presents a novel Load Frequency Controller (LFC) that utilizes an Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture. The proposed controller demonstrates exceptional efficacy in achieving stable frequency responses across individual control areas within a power system. This stability is demonstrably maintained even under the influence of inherent system nonlinearities such as Governor Deadband (GDB) and Governor Rate Change (GRC), as well as the growing integration of renewable energy sources with their inherent fluctuations.

However, it is well recognized that large-scale power systems exhibit significant complexity due to their interconnected nature. Multiple control areas interact dynamically, and numerous exogenous factors beyond those explicitly addressed here can influence frequency regulation. As a result, the development of increasingly sophisticated control strategies remains an active area of research. The primary objective of this ongoing research endeavor is to ensure robust frequency stability across all regions within the interconnected power grid, even in the face of these significant challenges.

Acknowledgments

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