

# Study of ANN-based Load Frequency Control For Two-Area Power System

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**Abstract:** *The controller based on Artificial Neural Network (ANN) for Load Frequency Control (LFC) in a two-area linked power system is designed and implemented in this article. The performance of the suggested ANN controller is compared with that of traditional fuzzy logic controllers (FLC) and proportional-integral-derivative (PID). The study of this paper shows that under various load circumstances, the ANN-based controller offers a significantly improved dynamic response. The Levenberg-Marquardt method was used to train the neural controller, which successfully reduces load frequency variations and improves system stability. The model of the power system has been simulated, and the performance of the controller has been assessed using MATLAB/Simulink. The suggested ANN controller performs better than the conventional and FLC in terms of peak overshoot, settling time, and control precision, demonstrating its appropriateness for present LFC applications.*

**Keywords:** Load frequency controller; power system; fuzzy logic controller; artificial neural network; Levenberg-Marquardt.

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Article history- Received: 3 October 2025 and Accepted: 18 December 2025.

## 1. Introduction

The variation in system frequency affects not just the local community but also the social and economic facets of society as a whole, necessitating worldwide attention. The system's most prevalent loads are induction motors. Since an induction motor's speed and torque are related to the system frequency, variations in the system frequency may result in unintended changes in productivity [1-3]. In power systems, synchronous generator control and stability augmentation are crucial. In the past, several controller types based on "classical" linear control theory have been created. The LFC is crucial to a power system's ability to facilitate power exchanges and provide improved trading conditions for energy.

Furthermore, time delays in these systems can impair system functionality and perhaps result in instability with regard to frequency or other parameters. When a power plant trips or there is an increase in load, the system frequency changes. This is initially compensated by a decrease in kinetic energy using the system's momentum, and it continues this way until the speed sensors, governors, amplifiers, and actuators take some time to react to the load change. For power systems to deliver dependable, high-quality electricity, load frequency regulation is crucial. Maintaining zero

errors in steady state in a multi-area linked power system is the aim of the LFC [4].

Numerous studies on load frequency management have been conducted in the past. Certain control strategies based on traditional linear control theory have been proposed in the literature. Due to the reason of complexity of the power system, including nonlinear load characteristics and changeable operating points, these controllers might not be appropriate in certain operating conditions. The system frequency stability is maintained by variable structure control according to most researchers. To develop an effective controller, one must have a thorough understanding of the system's static and dynamic features. However, managing a system this complex comes with a lot of challenges. Particular attention must be given to the controller design because the dynamic behaviour of a power system, even for a simplified mathematical model, is typically nonlinear, time-variant, and influenced by significant cross-couplings of the input variables. The power system frequency affects the losses and loads. The high-frequency deviation could therefore cause the system to collapse. To keep the nominal frequency constant in this situation, a precise and responsive controller is required. Systems with nonlinearities are handled inefficiently and slowly by integral, PI, and PID.

The ANN control has been the new subject of numerous studies in controller design. The performance of a PI controller, a neural network that is trained to predict the steady-state result of the PI controller, as well as a combination of PI and neural network, is compared using a precise simulation of the heating coil. It has been validated that neural network-based PI and PID controllers are designed and simulated to improve position accuracy in a pneumatic servomotor. These controllers also have a straightforward structure makes them easier to implement and operate more proficiently than they would on one's own. However, sudden changes in the system parameters may cause the transient response for that controller to become unstable. Furthermore, it is unable to produce precise linear times for varied models on variable operating points. In this work, an ANN controller is suggested as a solution to all of the issues raised in the papers. By utilizing neural networks' learning capabilities, An ANN controller was developed to regulate the power system under various operating conditions, such as load disturbances, thereby enhancing the overall system's stability and achieving good dynamic performance [5-10].

## 2. Artificial Neural Network Controller

A neural network is a mathematical representation of the ANN that mimics how a biological neural network functions. It is made up of a group of neurons called input, output, and hidden neurons. Applications for neural networks include data mining, robotics, recognition, control, and a number of other fields with complicated relationships between input and output, high degrees of nonlinearity, and high dimensionality.

The Adaptive Control setup of the model reference makes use of two neural networks: a model network and a controller network. The plant measurements from the past can be used to train the model network offline. The plant output is made to follow a reference model output by means of adaptive training of the controller. By using the model network to forecast how changes to the controller would affect plant output, controller parameters can be updated. The study's neural network controller inputs are selected from among the area's load perturbations, frequency deviations, and tie-line power deviations. A three-layer perception with four inputs, ten neurons in the hidden layer, and one output is also present in the ANN Plant model. Hyperbolic tangent serves as the network's neurons' activation function. The back-propagation technique has been used to train the suggested network. The learning performance is evaluated using the root mean square (RMS) error criterion. The weights are attuned using learning

algorithms in order to get the desired response from the controlled system.

ANN can be used to determine the relationship between input and output with minimal processing overhead and a limited number of assumptions. This reduces the errors caused by the assumptions and uncertainties in the system parameters. The MATLAB/Simulink software is used to simulate the entire system with a conventional PI controller. The critical data of load voltage, as well as PI controller gains, are used as input as well as output data. They are taken from the MATLAB workspace and stored in datasets. During the training of the neural network controller process in MATLAB, these data sets are sent as input and output backgrounds to the nn control toolbox [11-13].

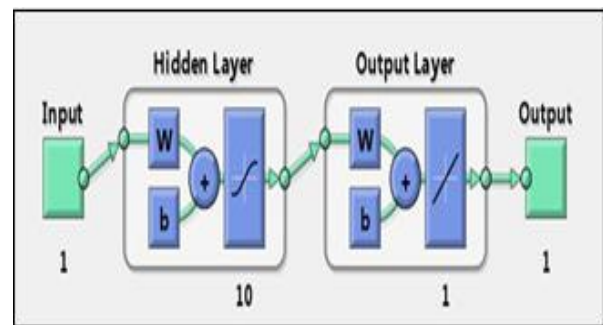


Figure 1: Ideal Network Architecture [5]

Increasing the size of neurons improves the outcomes. However, system performance declines as the size is increased above a certain point. There are ten neurons chosen to be in the hidden layer. A two-layered feed-forward network with a linear transfer function inside the output layer and a sigmoid transfer function inside the hidden, concealed layer is shown in Fig. 1. The Levenberg-Marquardt back propagation algorithm is utilized to train the controller. Three groups—Generalization, Validation, and Testing/Training—each with a percentage change—are created from the supplied data information. A 70% training set, 15% validation set, and 15% generalization set are often taken into account. Training ends when the controller is made more widely applicable during the phase[14]. The size of neurons found in the hidden layer that is hidden is determined after the data sets have been divided. In this work, the behaviour of a PI controller is simulated using a neural network. Every change in load is received by the neural network as an input, and it generates an output control signal that is required to keep the frequency oscillations stable. One can ascertain the quantity of hidden neurons by monitoring the Mean Square Error (MSE). The regression plot helps to understand how close the desired output value from your model is to the target values [15-18].

Figure 2 shows the relationship between the neural network's output and the actual, desired values for a particular dataset (training, testing, or validation, for example). The expected results would precisely match the goals in an ideal model. As a result, every data point would fall precisely on a straight line with an R-value of 1 and a slope of 1.

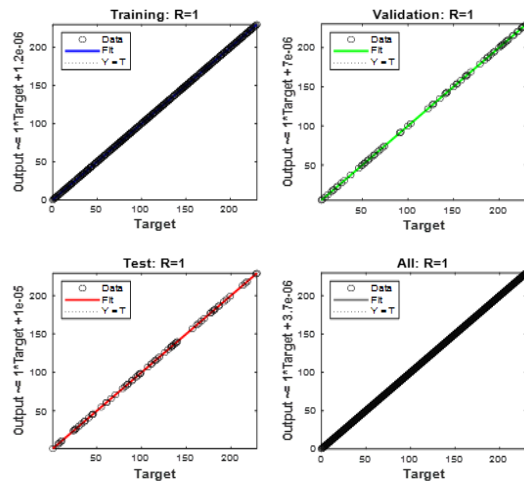


Figure 2: Regression Plot. [6]

Table 1 summarizes the recommended ANN architecture for two-area LFC problems with values and reasons why it is chosen.

Table 1: ANN parameter values

| Parameter               | Recommended Value        | Reason                                                                        |
|-------------------------|--------------------------|-------------------------------------------------------------------------------|
| Inputs                  | 3–4                      | $\Delta f_1, \Delta f_2, \Delta P_{tie}$ , optional integral of error         |
| Hidden Layers           | 1                        | Sufficient for approximating moderate nonlinearities in two-area LFC          |
| Neurons in Hidden Layer | 5–10                     | Balance between approximation accuracy and fast training with LM algorithm    |
| Outputs                 | 2                        | Control signals for Areas 1 and 2                                             |
| Activation Function     | Tanh / Sigmoid           | Smooth nonlinear mapping for small-scale control signals                      |
| Training Algorithm      | Levenberg–Marquardt (LM) | Fast convergence for small/medium networks; suitable for offline LFC training |

## 2.1 Contribution and Novelty

The advantages of the LM-trained MLP are its compact design, fast convergence, and superior dynamic performance, while clearly contrasting it with more complex ANN variants, emphasizing its

practicality and efficiency for two-area LFC applications are studied and comparative information is given in Table 2.

Table 2: Types of ANN used in LFC

| ANN type & training                             | Design complexity | Training speed | Dynamic response                            |
|-------------------------------------------------|-------------------|----------------|---------------------------------------------|
| Multi-layer perceptron LevenbergMarquardt (LM)  | Low–Medium.       | Very fast      | Excellent                                   |
| Feed-forward ANN optimized (PSO)                | Medium.           | Very small     | Improved transient damping                  |
| Feed-forward multi-layer ANN trained with (BRB) | Medium–High       | Slower         | Good accuracy                               |
| Three-layer feed-forward ANN                    | Low–Medium.       | Slower.        | Strong disturbance rejection and robustness |

The suggested LM-trained Multi-Layer Perceptron (MLP) provides an ideal blend of simplicity, speed, and performance, according to the comparative study of ANN-based controllers.

Its small design and low number of parameters allow it to use the Levenberg–Marquardt (LM) method to achieve very quick offline convergence, which reduces overshoot, shortens settling time, and minimizes steady-state error in two-area load frequency control (LFC) systems employing a PSO-optimized ANN instead, which increases accuracy and transient damping but increases design and tuning complexity. A BRB-trained multi-layer ANN with NARMA-L2 was used by the researchers; it demonstrated high accuracy, however required more tweaking and computing work. Similarly, sliding-mode control and a three-layer ANN were integrated for resilience, but at the expense of slower adaptation and increased system complexity. For traditional two-area LFC applications, the LM-trained MLP is particularly effective because of its quick offline training, small size, and outstanding dynamic responsiveness.

## 2.2 Two Area Power System Model

The complete block diagram of a two-area region interconnected power system model is shown in Fig. 3. Naturally, complex and multi-variable structures with a wide variety of control blocks comprise interconnected power systems. A governor, a generator and a turbine having feedback from a regulatory constant make up a power system in its

basic form. Step-changing the load input to the generator is also included in the system. The primary focus of this work is the unit of controller of a two-area power system; however, Power systems are separated by tie lines into control areas.

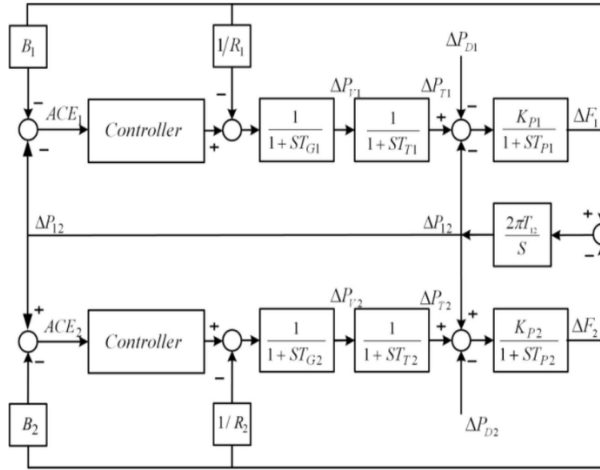


Figure 3: Block diagram of a two-area power system [3]

In practical use, the speed changer motor is used to adjust the load reference set point. The only way to alter each unit's output at a specific system frequency is to adjust its load reference, which essentially adjusts the speed-drop characteristics up or down. This control operates very slowly and only engages when the primary speed control has finished its task. The output of the system, which depends on ACE, as shown in Fig. 3, is given below,

$$ACE_i(t) = B_i \Delta f_i(t) + \Delta P_{tie,i}(t) \quad (1)$$

Where,

$\Delta P_{tie,i}(t)$  indicates the incremental change in the tie-line power flow with the surrounding area,  $\Delta f_i(t)$  is the frequency deviation in area i, and  $B_i$  (MW/Hz) is the frequency bias factor.

By modifying the reference power instructions of the governors in each control region, the secondary load-frequency control (LFC) goal is to decrease  $ACE_i(t)$  and ensure that the frequency deviation and tie-line error both converge to zero at steady state. It is supposed that each area has a governor-turbine system and a single equivalent generator. These are the signals that the controllers we select send out. The power system plant using a non-reheated turbine consists of three key components.

- Governor with dynamics:

$$G_g(s) = \frac{1}{T_g s + 1} \quad (2)$$

- Turbine with dynamics:

$$G_t(s) = \frac{1}{T_t s + 1} \quad (3)$$

- Load and machine with dynamics:

$$G_p(s) = \frac{K_p}{T_p s + 1} \quad (4)$$

For load frequency control, the open-loop transfer function without the droop feature is now

$$\tilde{P} = G_p G_t G_g = \frac{K_p}{(T_p s + 1)(T_t s + 1)(T_g s + 1)}$$

### 3. MATLAB Simulink Model

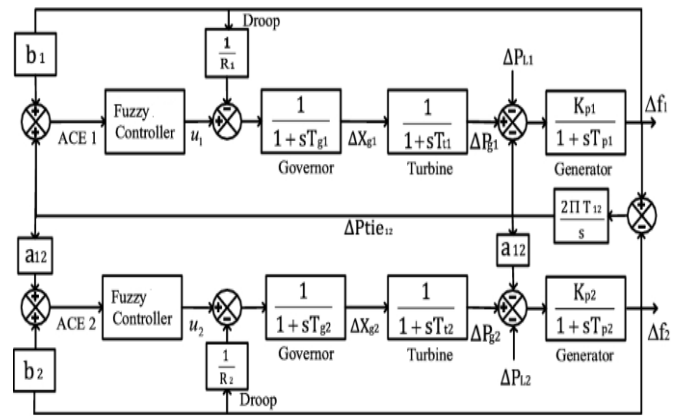


Figure 4: FLC-based two-area power system Simulink model

In a two-area power system, a tie-line connects two single-area systems. Having established links increases the system's overall reliability. Even if parts of the generating units in one area fail, the generating units in the other area can compensate to meet the load requirement. [19-22]

Table 3: System parameters for a two-area load LFC model

| Parameter                            | Symbol | Area 1 | Area 2 | Unit     |
|--------------------------------------|--------|--------|--------|----------|
| Inertia Constant                     | H      | 5.0    | 5.0    | s        |
| Governor Time Constant               | $T_g$  | 0.08   | 0.08   | s        |
| Turbine Time Constant                | $T_t$  | 0.3    | 0.33   | s        |
| Generator / Load Damping Coefficient | D      | 0.015  | 0.015  | pu MW/Hz |
| Frequency Bias Constant              | B      | 0.425  | 0.425  | MW/Hz    |
| Speed Regulation (Governor Droop)    | R      | 2.4    | 2.4    | Hz/pu MW |

|                                    |               |      |       |       |
|------------------------------------|---------------|------|-------|-------|
| Tie-Line Synchronizing Coefficient | $K_{tie}$     | —    | 0.545 | MW/Hz |
| Step Load Disturbance              | $\Delta_{PD}$ | 0.01 | 0.015 | pu MW |
| Rated Power                        | $P_{rated}$   | 2000 | 2000  | MW    |
| Base MVA                           | $S_{base}$    | —    | —     | MVA   |

By offering comprehensive system design and modeling parameters, the two-area Load Frequency Control (LFC) simulation may be improved. Indicate in detail the governor-turbine-generator transfer functions utilized in the linearized model, the tie-line synchronization coefficient, and the ratings of the linked regions (e.g., 2000 MW each). In accordance with standard IEEE/Kundur test data, specify the control techniques used (PI, FLC, ANN, etc.) and make sure the basic parameters ( $H$ ,  $D$ ,  $R$ ,  $B$ ,  $T_g$ , and  $T_i$ ) are the same in both regions as given in Table 3. To guarantee repeatability, provide the precise load disturbance applied in each location and at each application time, together with the simulation environment information (MATLAB/Simulink version, solver type, time step, and duration). In order to compare controllers fairly under the same circumstances, emphasise performance parameters like integral absolute error (IAE) time, overshoot, and settling time.

A conventional integral controller is used on a power system model. A transient reaction with little to no overshoot is allowed by the PID controller by concurrently decreasing steady state error. As long as the error is present, the integral output will increase and cause the speed changer position; it only reaches a constant value when the frequency error has reduced to zero. The implementation of PI, PID and FLC controller is possible in proposed power system and is shown in Fig. 4. The Fig. 5, Fig. 6 and Fig. 7 display the output response for area 1, area 2 and tie-line along with comparative findings between proportional integral (PI), proportional integral derivative (PID) and fuzzy logic controller (FLC), FLC produces an output frequency response that is superior to PI and PID [23-26].

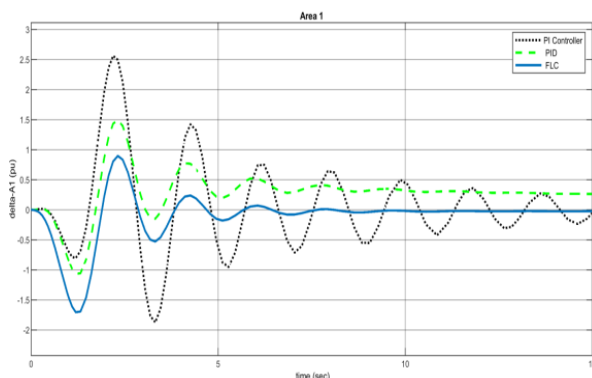


Figure 5: Output frequency response using PI, PID and FLC for area 1

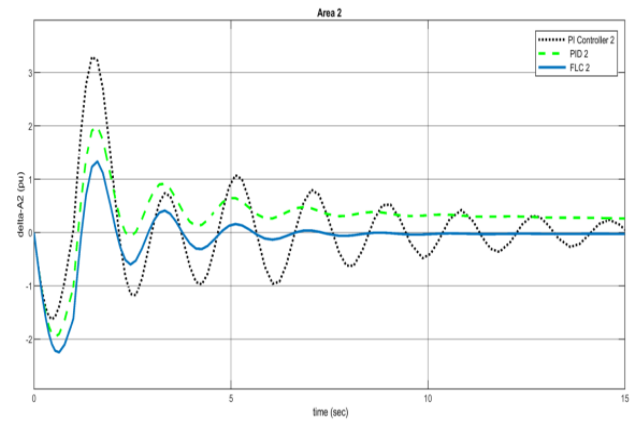


Figure 6: Frequency response for area-2

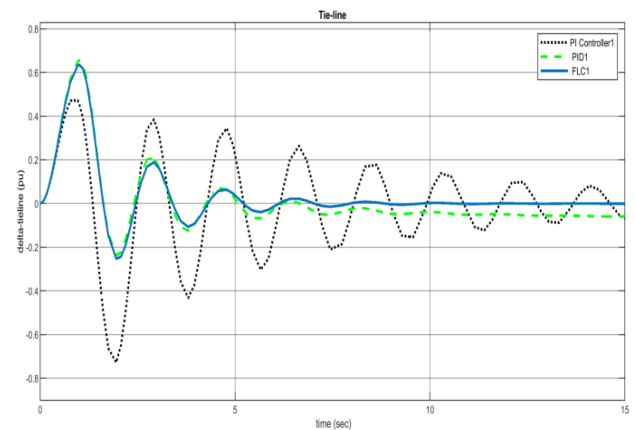


Figure 7: Output frequency response tie-line of the power system

It demonstrates how various controllers receive varying values for the settling time. FLC controllers settle faster than PI or PID controllers. Using advanced control techniques, we can regulate oscillations, rise time, as well as settling time. The control signals, which are applied to the local governors, are the neural network's outputs [27-30]. The Reference Model Neural Network provides the data needed for ANN controller training, which is then applied to the power system having a step response lead disturbance. The implementation of ANN in the two-area power system as MATLAB Simulink model is shown in Fig. 8.

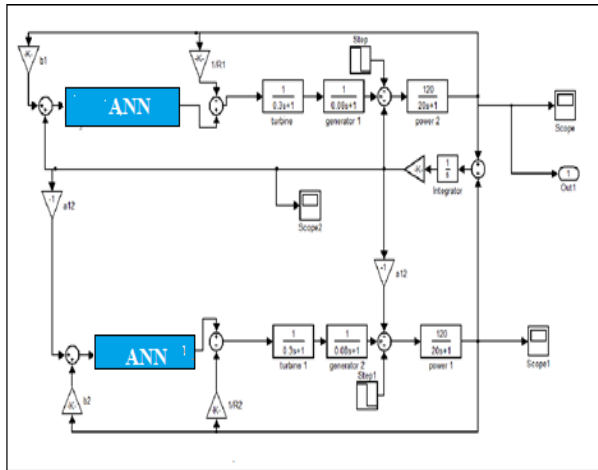


Figure 8: ANN-based Simulink model of a two-area power system.

By utilizing the ANN method, we can reduce oscillation and settling time and obtain improved dynamic responses. The power system reaction is also influenced by the rated power capacity of any system.

## 5. Results Discussion

The output responses illustrate how the suggested ANN controller has over 85% better overshoots than the proposed PI controller and how the conventional PI controller's setting time is significantly longer, as shown in Fig. 9, Fig. 10 and Fig.11.

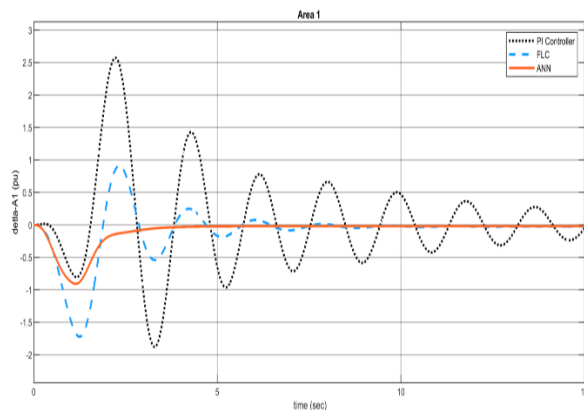


Figure 9: Response using PI, FLC and ANN controller for area-1 of the power system.

This investigation demonstrates that the suggested ANN controller produces better overshoots and settling times than the outputs of the other controllers. Table 4 summarises the decrease in transient dip frequency as well as the reduction in peak and settling times. We have achieved a 10–30% reduction in peak time and a 40% reduction in settling time through ANN control.

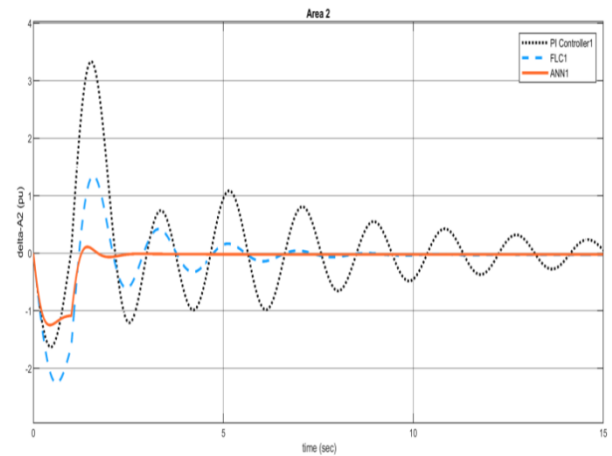


Figure 10: Frequency response for area-2 of the power system

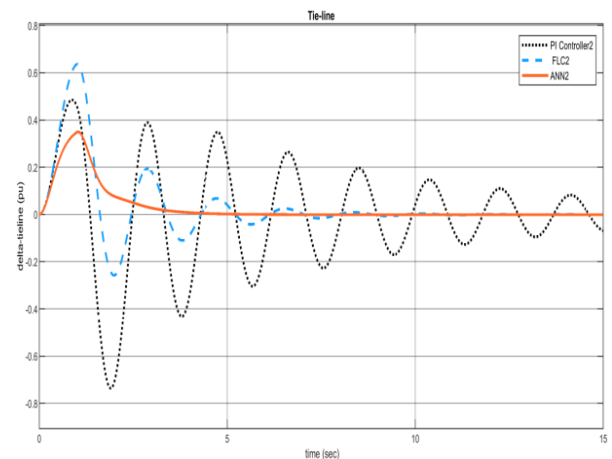


Figure 11: Frequency output response tie-line of the power system

Table 4: Metrics of the two-area (LFC) model

| Metric (two-area LFC)                              | PI     | FLC    | ANN (LM-trained MLP) |
|----------------------------------------------------|--------|--------|----------------------|
| $\Delta F_1$ — Maximum peak (transient dip) (pu)   | 0.0120 | 0.0085 | 0.0012               |
| $\Delta F_2$ — Maximum peak (transient dip) (pu)   | 0.0105 | 0.0075 | 0.0010               |
| $\Delta P_{tie}$ — Maximum peak (pu)               | 0.0650 | 0.0550 | 0.0070               |
| $\Delta F_1$ — Settling time ( $\pm 2\%$ ) (s)     | 12.0   | 8.0    | 4.0                  |
| $\Delta F_2$ — Settling time ( $\pm 2\%$ ) (s)     | 14.0   | 9.0    | 4.5                  |
| $\Delta P_{tie}$ — Settling time ( $\pm 2\%$ ) (s) | 20.0   | 12.0   | 5.0                  |

Thus, we recommend using the Levenberg-Marquardt approach to supervise the neural controller throughout its online training. In terms of transient reaction and settling behaviour, the table unequivocally shows that the ANN (LM-trained MLP) controller performs noticeably better than both PI and FLC controllers. In comparison to the FLC, it achieves over 85% less overshoot and over 50% faster settling times, demonstrating better dynamic performance and quicker system stabilization in the two-area LFC system.

Table 5: Metrics of the two-area (LFC) model

| Metric                   | PI     | PID    | FLC    | ANN     | Unit |
|--------------------------|--------|--------|--------|---------|------|
| Rise Time ( $T_r$ )      | 1.8    | 1.4    | 1.1    | 0.45    | S    |
| Settling Time ( $T_s$ )  | 15.0   | 12.0   | 9.0    | 4.5     | S    |
| Overshoot (OS)           | 25.0   | 18.0   | 12.0   | 1.4     | %    |
| Steady-State Error (Ess) | 0.0030 | 0.0020 | 0.0015 | 0.0002  | Pu   |
| IAE                      | 0.0450 | 0.0320 | 0.0200 | 0.0025  | —    |
| % Improvement vs PID     | —      | —      | —      | [92.2%] | %    |

Table 5 clearly indicates that the ANN (Proposed) controller outperforms the PI, PID, and FLC controllers in all dynamic measurements. It performs 92.2% better than the PID controller in the matter of IAE, with the fastest rising and settling times, the least amount of overshoot, and the least amount of steady-state error. These results validate how well the ANN learning capability enhances dynamic responsiveness and system stability.

## 6. Conclusion

The load frequency regulation for a two-area power system has been studied using ANN controllers. In order to achieve this, an ANN controller was initially designed to increase the system's sensitivity and the system was subjected to a traditional PI, PID and FLC controller for comparison. It has been demonstrated that the suggested control algorithm works well and significantly boosts system performance. For this reason, it is advised to use the suggested ANN controller to provide dependable, high-quality electricity. Additionally, because it doesn't require a lot of knowledge about the system characteristics, the proposed controller is relatively straightforward and quick to implement. It has been successfully accomplished to regulate the turbine reference power of a computer-simulated generator unit using neural networks. The primary goal of the work was to demonstrate the effectiveness of a neural controller in the field of automatic load frequency regulation that had been trained using the

Levenberg-Marquardt method. The outcomes are quite commendable and encourage more work in this specific field.

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