Advanced Control Strategies for Mitigating Frequency Deviations in Electric Vehicle Connected Power Systems

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Abstract - The rising demand for electric vehicles (EVs) is driving up the demand for electrical charging stations, which presents serious threats to the stability of the power system, including frequency variations that go beyond allowable bounds. In response, this paper proposes advanced control techniques to regulate the governor of generators and mitigate frequency deviations in EV-connected power systems. Specifically, the utilization of Proportional-Integral (PI) controllers for governor control and the integration of Artificial Neural Networks (ANN) with fuzzy logic are explored to develop a robust control strategy. The proposed control system dynamically adjusts generator parameters in response to varying EV charging demands, leveraging ANN's adaptive learning capabilities and fuzzy logic's linguistic reasoning to enhance grid stability and ensure frequency within acceptable limits. Through simulation studies and performance evaluations using MATLAB/SIMULINK tools, the efficacy of the proposed approach is demonstrated, offering a promising solution to mitigate adverse effects of EV-induced power imbalances on power system frequency.

Keywords: Multi- Area Power System, Load Frequency Control (LFC), Artificial Neural Networks (ANN), Adaptive Neuro Fuzzy Inference Systems (ANFIS).

I. INTRODUCTION

The continuous adoption of electric vehicles (EVs) represents a significant shift towards sustainable transportation, offering numerous environmental and economic benefits. However, the quick rise in EVs presents new difficulties for power system management, especially when it comes to controlling the rising demand for electricity needed for vehicle charging. When electric vehicles are added to the grid, the imbalance between reactive and active power introduced into the system during charging can lead to frequency deviations. These deviations pose a threat to power system stability and reliability, if they are beyond acceptable limits.

To address this issue and enhance power system resilience, power system operators can develop proactive measures to maintain grid stability amidst evolving energy consumption patterns. This can be achieved by understanding the underlying causes of frequency deviations and exploring advanced control techniques, such as PI controllers and the integration of ANN with fuzzy logic.

This paper aims to use Hybrid Intelligent Controllers to the power system's load frequency regulation in the subsequent steps:

(1) To create a two-
area power system's transfer function
Model for load frequency control.

(2) Design intelligent controllers based on the following techniques:
   (a) Adaptive Neuro-fuzzy Inference System (ANFIS).
   (b) Artificial Neural Network.

(3) To assess the performance of the designed controllers against conventional ones (such as PID).

Simulations have been conducted for both the designed and existing controllers.

II. LITERATURE SURVEY

The research concerning load frequency control (LFC) in power systems incorporating electric vehicles (EVs) provides valuable perspectives on different control tactics and modeling methods. Studies by Sharma et al. [1] and Neofytou et al. [3] explored hybrid controllers and distributed resource utilization for frequency regulation respectively. Annamraju and Nandiraju [2] propose coordinated control for conventional power sources and plug-in hybrid EVs.

Sundaram and Jayabarathi [5] investigated ANN controllers, Additionally, Tawfiq Hussein and

Awad Shamekh [4] and S. K. Jain et al. [7] presented fuzzy logic-based control strategies. V. S. Sundaram and T. Jayabarathi [12] Utilized artificial neural network (ANN) controllers tuned with proportional-integral-derivative (PID) parameters for load frequency control. Poonam Rani and Mr. Ramavtar Jaswal [9] discussed automatic control using ANN controllers and genetic algorithms. Additionally, Tawfiq Hussein and Awad Shamekh [4] discussed PI fuzzy logic gain scheduling load frequency control in two-area power systems, while S. K. Jain, A. Bhargava, and R. K. Pal [8] presented a three-area power system load frequency control using fuzzy logic controllers. Moreover, V. S. Sundaram and T. Jayabarathi [12] explored load frequency control using PID-tuned ANN controllers in power systems, and Poonam Rani and Mr. Ramavtar Jaswal [9] discussed automatic load frequency control of multi-area power systems using ANN controllers and genetic algorithms.

III. ELECTRIC VEHICLE CONNECTED POWER SYSTEM

Battery-powered Plug-in Electric Vehicles (PEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are increasingly popular technologies aimed at reducing greenhouse gas emissions and air pollution. PEVs are vehicles that recharge from an external power source, such as the electric grid.

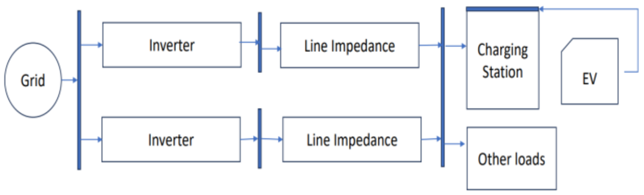


Fig.1. Block Diagram of Electrical vehicle Connected Power System.

Conversely, PHEVs integrate plug-in electric vehicle systems for charging from an electrical power source with a petrol/diesel engine, which acts as a backup power source to charge the battery and power the electric motor of the vehicle

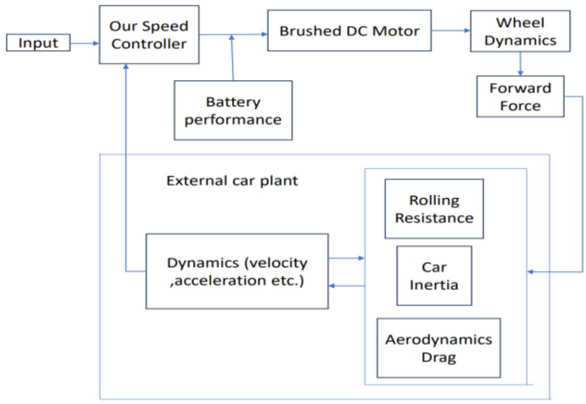
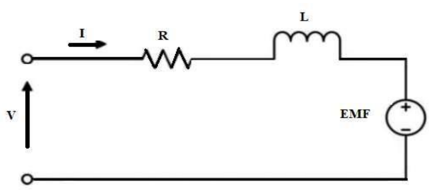


Fig.2. Model diagram of Electrical Vehicle.

A block diagram of EV connected to grid is shown in fig.1. To connect EVs to the electric grid, power electronics controllers based on Electric Vehicle Supply Equipment (EVSE) are required. An EV consist of DC motor, speed controller and feedback parameters etc. as shown in fig.2. Recently, a lot of new EV charging technologies are being developed and deployed commercially across the globe [9]. This enables EVs to get charged at a very fast rate. Although the fast-charging may pose a lot of challenges in the smooth functioning of the electrical power distribution system (EPDS). Moreover, the simultaneous charging of a significant number of EVs from the grid can pose several operational challenges for the power system, including frequency deviations due to increased peak load demands and system harmonics. Hence, it is essential to assess the impact of widespread EV charging on the EPDS.

(a) *Mathematical Modeling of EVs:*



(b) Fig.3. Equivalent circuit of DC motor.

(c) With K_E the back EMF constant and $\omega(t)$ the rotational speed of the motor in rad/s. Hence, applied voltage can be written as:

$$V(t) = I(t) * R + L * \frac{dI}{dt} + K_E * \omega(t) \quad (1)$$

And the Torque equation can be written as:

$$T(s) = K_T * \frac{V(s) - K_E * \omega(s)}{sL + R} \quad (2)$$

Further the power requirement on charging station can be calculated as:

$$P = \mathrm{T}(s).\,\omega(s) \quad (3)$$

Here,

I(t)- Current,
K_T- Torque constant
P - Power requirement on charging station

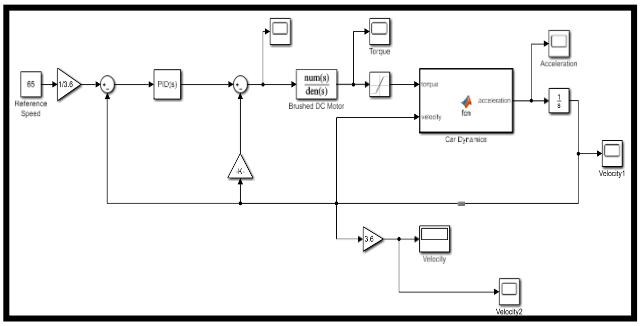


Fig. 4. Simulink model of EV

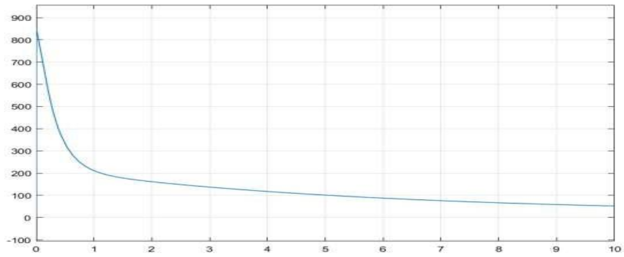


Fig.5. EV Torque Characteristic

A Simulink model of EV is shown in fig. 4 and the torque characteristics with respect to time is shown in fig. 5, this Simulink model is used as an EV load in ANFIS Controller-Based LFC Model.

When the torque demand increases due to rise in EV demand, the power demand on the charging stations also increases which further leads to imbalance in active and reactive power which results as frequency deviations below acceptable limits.

(d) LFC Problem in Two Area Power System

In interconnected electric power systems covering large areas, LFC plays a crucial role in maintaining system frequency and inter-area tie power close to scheduled values. The input mechanical power supplied to the generators is adjusted to regulate the frequency of the output electrical power.

One key goal of AGC (Automatic Generation Control) is to sustain the system frequency at a designated nominal value, typically 50 Hz. During standard operation, the controller is configured to accommodate minor fluctuations in load demand while ensuring that voltage and frequency remain within predetermined limits. However, if operating conditions change due to any factor, the controller must be adjusted. The frequency is detected through a frequency sensor, while alterations in frequency and tie-line real power are gauged by changes in rotor angle (δ). The load frequency controller magnifies and converts the error signal, represented as Δf_i, into a real power command signal, ΔP_{ci}. This signal is then transmitted to the prime mover through the governor, which regulates the valve mechanism, this whole mechanism is explained in block diagram shown in fig. 6.

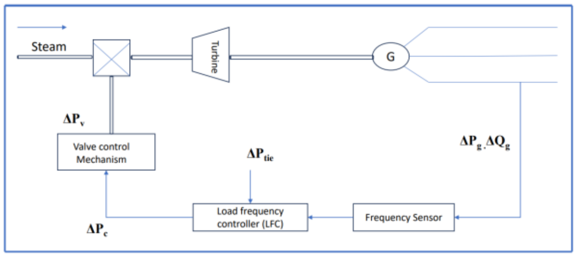


Fig.6. Block diagram Load frequency control.

To initiate an increase or decrease in torque, the prime mover adjusts to balance the output of the governor, thereby compensating for the error signal represented by Δf. This iterative process persists until deviations in the form of Δf_i and ΔP_{tie} align within the specified tolerance limits.

This study primarily centers on the controller unit within a two-area power system.

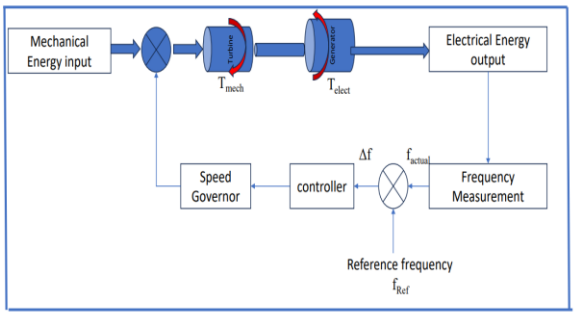


Fig.7. The AGC system

Fig. 7 displays a comprehensive block diagram illustrating an isolated power system, including the turbine, generator, governor, and load. In this scenario, no controller action is implemented, reflecting the actual system response to a step change in load.

The dynamic behavior of the nominal system, particularly concerning frequency variation, is represented through models such as the Hydraulic Amplifier, Turbine, and Generator, as shown in the fig. 8.

Fig. 8 can be represented in state-space form using the following matrix equation.

$$\dot{x} = Ax + Bu + F\rho \tag{4}$$

Here,

$$A = \begin{bmatrix} -\frac{1}{T_p} & \frac{K_p}{T_p} & 0 \\ 0 & -\frac{1}{T_t} & \frac{1}{T_t} \\ \frac{1}{RT_H} & 0 & -\frac{1}{T_H} \end{bmatrix} \tag{5}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{T_H} \end{bmatrix} \tag{6}$$

$$f = \begin{bmatrix} -\frac{K_p}{T_p} \\ 0 \\ 0 \end{bmatrix} \tag{7}$$

$$\rho = [\Delta P_E] \tag{8}$$

Here,

x^T= State vectors, $[\Delta f \quad \Delta P_T \quad \Delta P_H]$

u = Control vector, it is zero in uncontrolled case.

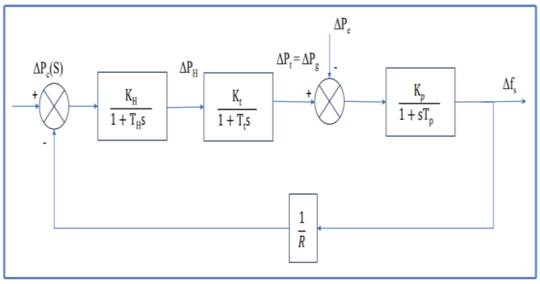


Fig.8. Block Diagram of Load Frequency Control

IV. ANFIS BASED FREQUENCY CONTROL

This section deals with different control techniques for load frequency control. The methods are divided into two categories.

Conventional and Intelligent techniques. Conventional controllers are comprised of P, PI, and PID, whereas few of the intelligent techniques are Fuzzy, ANN, and ANFIS controllers.

Artificial Neural Networks: ANNs are computational models inspired by the architecture and behavior of biological neural networks observed in the human brain. Typically, ANNs consist of input, hidden, and output layers [5]. Data travels through the network from the input layer, traverses the hidden layers where computations occur, and results in an output at the output layer

Fuzzy Logic: Fuzzy Logic is a mathematical approach that deals with uncertainty and imprecision in decision-making processes [4]. Unlike classical logic, which operates in binary terms (true or false), fuzzy logic allows for degrees of truth, where propositions can be partially true or partially false.

Adaptive Neuro-Fuzzy Inference System: ANFIS integrates the principles of ANNs with those of fuzzy logic to create a hybrid intelligent system [6]. It utilizes the learning capabilities of ANNs to adaptively tune fuzzy inference systems based on input-output data pairs. ANFIS is capable of modeling intricate nonlinear relationships between inputs and outputs.

(a) Mathematical Modeling of ANFIS

While there are several algorithms to train the ANN/ANFIS model, yet one of the fastest and most efficient algorithms is the Levenberg Marqardt (LM) algorithm which is a modified version of the steepest gradient descent. The steepest descent algorithm is 1st order derivative of the minimization function which makes it an asymptotic convergence. Taking into account the gradient of the error concerning weights for a loss minimization, we obtain the derivative gradient as:

$$g = \frac{\partial E(x,w)}{\partial x} = \begin{bmatrix} \frac{\partial E}{\partial w_1} & \frac{\partial E}{\partial w_2} & \dots & \frac{\partial E}{\partial w_N} \end{bmatrix}^T \tag{9}$$

Considering the loss/cost function as the mean squared error, the weight update rule for LM algorithm is:

$$w_{k+1} = w_k - [J_k J_k^T + \mu I]^{-1} J_k^T e_k \qquad (10)$$

Here,
k is the iteration number
w_{k+1} - weight (next iteration),
w_k - weight (present iteration)
J_k - The Jacobian Matrix and is given by the terms $J_k = \frac{\partial^2 e}{\partial w^2}$ i.e. the second order rate of change of errors with respect to weights
J_k^T - Transpose of Jacobian Matrix
e_k - Error of Present Iteration
μ is step size i.e. amount by which weight changes in each iteration
I is an identity matrix, with all diagonal elements equal to 1 and other elements 0.
The training is truncated as the cost or loss function is stable or the maximum iterations are over. The cost or loss function is defined as:

$$MSE = \frac{1}{N}\sum_{t=1}^{N} {e_t}^2 \qquad (11)$$

The mean absolute percentage error can also be computed as:

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{|V_t-\hat{V}_t|}{V_t} \qquad (12)$$

(b) Methodology:

The control methodology employed in this paper is ANFIS, it involves taking a fuzzy inference system (FIS) and refining it using a backpropagation algorithm with a set of input-output data. This enables the fuzzy systems to adapt and learn from the provided data.

Membership Functions used: The inputs are ACE (area control error) and Change in ACE, two linguistic variables of the inputs and two linguistic variables of the output using the Neuro-Fuzzy Analyzer toolbox. Only fixed and somewhat arbitrarily selected membership functions have been taken into account. Additionally, fuzzy inference is solely employed for modeling systems with rule structures essentially predetermined by the user's understanding of variable characteristics in the model. Typically, the shape of membership functions relies on adjustable parameters that can be modified to alter the function's shape. These parameters can be automatically adjusted based on the data used for modeling.

The complete implementation and validation of the results can be performed by sequentially implementing the steps in the flowchart of the proposed system shown in fig. 9.

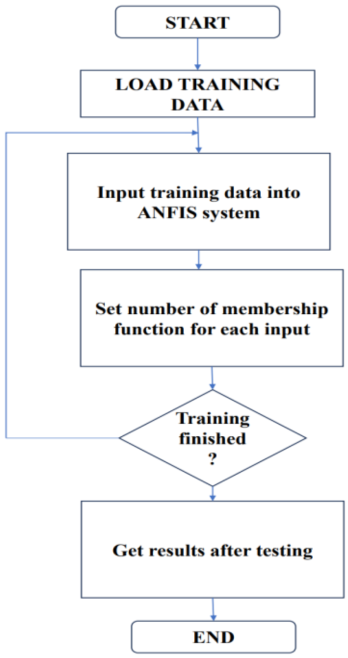


Fig.9. ANFIS Flowchart

V. SIMULATION RESULTS & DISCUSSION

Two different control techniques Post mathematical modeling are implemented in MATLAB/Simulink and their models are simulated for the 20s to observe the ability of controllers in maintaining the frequency of generator concerning variation in load. Post simulation different parameters of response are also calculated for the controller to find the best out of them.

(a) ANN tuned PI controller Based LFC Model:

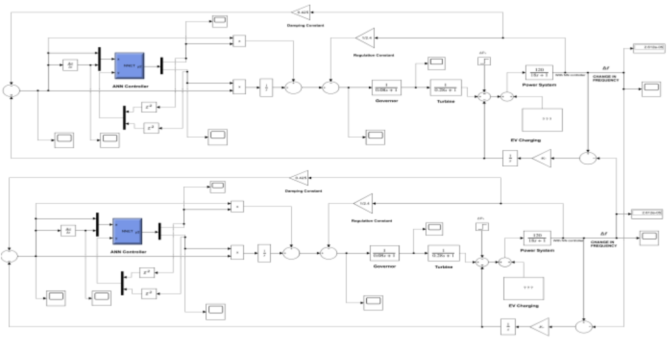


Fig. 10. ANN-PI Controlled LFC Model

The Simulink model of ANN-PI Controller is shown in fig. 10. The training is performed using the LM training algorithm. The technique runs for nine iterations. Two inputs are fed to ANN model: ACE and change in ACE. Along with these two, two-step, the delay signal is also provided at the input end of the model. The output signal from the trained model is used as a gain to the PID model, which further generates the control signal for the model. The output frequency variation curve is shown in fig.11.

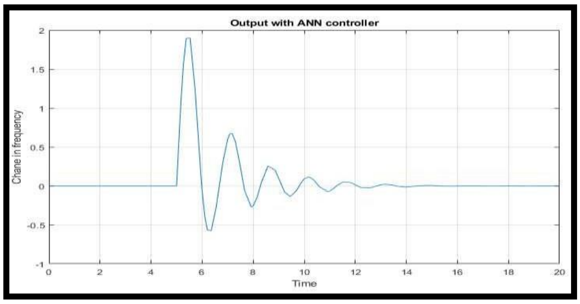


Fig. 11. Change in Frequency (Δ_f) for ANN-PI controller

TABLE 1. FREQUENCY RESPONSE PARAMETERS

ACE	Change in ACE	Proportional (Prop)	Integral (Int)
-9.75E-05	-0.5084	1	1.4
-9.75E-05	-2.43196	1	1.4
-9.75E-05	-2.69166	1	1.4
-0.18414	-2.66934	1	1.4
0.000908	0.013986	1.78	2.492
0.003438	0.010092	1	1.4
0.003155	-0.0013	1	1.4
0.001371	-0.00843	1.24	1.736
-0.00061	-0.0086	0.28	0.392
-0.0015	-0.004	1	1.4
-0.00103	0.002012	0.5	0.7
-0.00058	0.003995	0.94	1.316
-0.00058	0.004795	0.94	1.316
-0.00058	0.007978	1.26	1.764

TABLE 2 LOAD (EV) PARAMETERS

Parameters	Value
Simulation Time	20s
Load connected at	5s
Inputs to ANN	ACE & change in ACE
Range of ACE	-1 TO 0.4
Change in ACE	-2.5 TO 2.5 (NS), (NB)
Membership Function	(PS), (PB), (ZO)

Table 1 represents the frequency response parameters for the ANN-PI controller and Table 2 represents the parameters and their respective values, and. Based on these parameters, a comparison among the three controllers is conducted to evaluate their performance.

(a) ANFIS Controller-Based LFC Model:

The fig. 12 shows the Simulink model for load frequency control employing the ANFIS controller. The output signal from the controller block, following subtraction from the frequency regulator value, is directed to the Governor Block. Subsequently, the output from this block is fed into the turbine block. The resulting output, subsequent to deduction of the change in power value and additional EV charging load, is transmitted to the power system block to regulate the output power, thereby maintaining a constant frequency value.

Membership functions would be defined for ACE (fig. 13) and change in ACE (fig. 14). These functions would partition the input space into fuzzy sets, representing different degrees of ACE and its rate of change. The ANFIS model would be trained using the collected data. Once trained, the ANFIS model can be deployed for real-time operation. It takes current values of ACE and change in ACE as inputs, applies the fuzzy inference rules to determine the required control action, and adjusts generation accordingly to mitigate frequency deviations.

When the load demand increases the ACE falls down to negative value (-0.8 pu) as shown in fig 13, Similarly change in ACE falls down to -2.54 pu as shown in fig. 14.

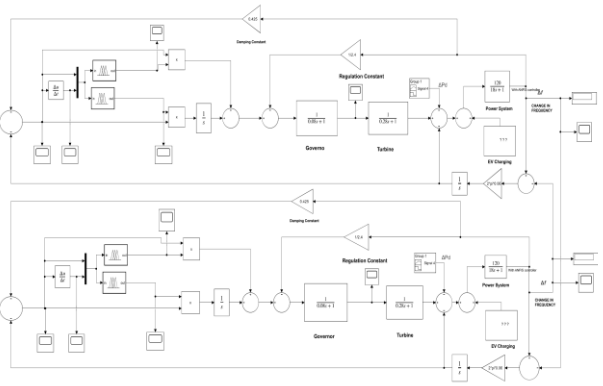


Fig. 12. Simulink model of LFC using ANFIS controller

When the steam input increases to compensate this demand the frequency of the system also shoot up to peak value 51.9579 Hz. This frequency deviation settles down in 11.0145 sec as shown in fig 15.

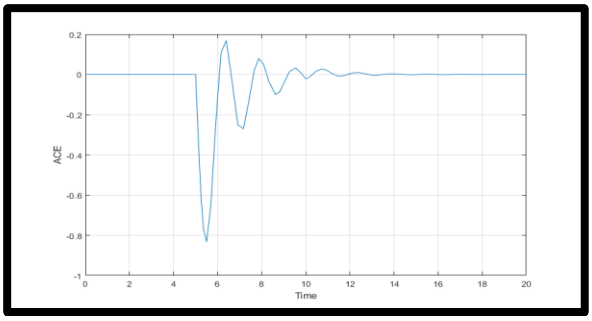


Fig. 13. ACE for ANFIS Controller

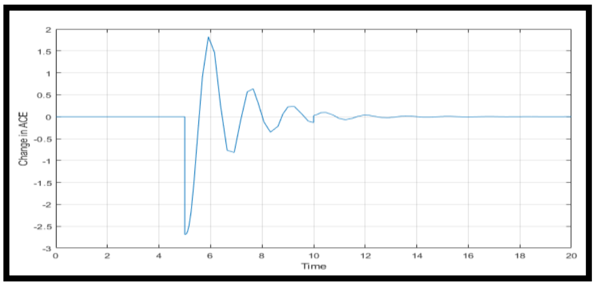


Fig. 14. Change in ACE for ANFIS Controller

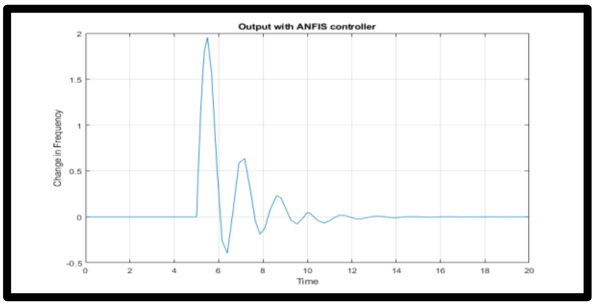


Fig. 15. Change in Frequency *(Δf)* for ANFIS Controller

(a) Comparative Analysis:

The summary of results for LFC response parameters of both ANN and ANFIS controllers is compared in Table 3, The output of both models is shown together in fig. 16 Where the blue line represents the change in frequency response from the ANFIS-PI controller, while the red line indicates the change in frequency response from the ANN-PI controller.

TABLE 3. COMPARATIVE ANALYSIS OF ANN & ANFIS

Parameter	ANN	ANFIS
Rise Time:	1.5593e-05 sec	1.3832e-05 sec
Settling Time:	11.8526 sec	11.0145 sec
Settling Min:	-0.5747 Hz	-0.3966 Hz
Settling Max:	1.8975 Hz	0.6361 Hz
Overshoot:	7.2653e+06	6.6417e+05
Undershoot:	2.2007e+06	3.2790e+06
Peak:	1.8975 Hz	1.9579 Hz
Peak Time:	5.5281 sec	5.4959 sec

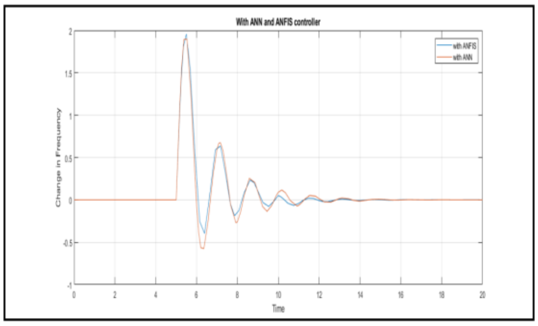


Fig. 16. Comparative graph of Change in frequency (Δf) for all techniques

VI. CONCLUSION & FUTURE SCOPE

LFC is utilized to manage and regulate the frequency of electrically generated power within a specific area, adjusting in response to variations in system loads. This paper examines the impact of electric vehicles on load frequency deviation. The study presents a case scenario involving the design of a controller capable of achieving optimal outcomes in a two-area power system under varying input parameters. Two LFC methods were investigated within an isolated power system. The efficacy of the controller under examination is assessed and validated using MATLAB/SIMULINK tools.

On comparison, it was found that ANFIS has

minimum settling time **(**11.0145 sec**)** out of two, it enables the power system to recover quickly from disturbances, thereby minimizing the duration of frequency deviations. This is crucial for maintaining grid stability and ensuring the reliable operation of interconnected power systems.

It was also found that ANFIS has **minimum** percentage overshoot **(**6.6417e+05**)** out of the two, it is essential for preventing excessive frequency deviations and maintaining system stability. Excessive overshoot can lead to oscillations, instability, and potential cascading failures in the power grid.

In the future scope, a signal processing tool can be utilized to check their effect on results. Some of the Hybrid techniques like Wavelet Neural Network etc. can be checked to see improvement in results. By adding generation control and governor dead band into the system the system will look more realistic and nonlinear.

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