

Analytical Comparisons of the PID, ANN, and ANFIS Controllers' Performance in the AVR System

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Abstract:- This research paper thoroughly investigates the performance characteristics of PID, which stands for Proportional-Integral-Derivative, ANFIS, an acronym for Adaptive-Neuro-Fuzzy Inference System, and ANN (Artificial-Neural-Network) controllers in Automatic Voltage Regulator (AVR) systems. This investigation aims to analyze the controller's behavior so that it can be used in any of the other control systems in the power system. Leveraging the power of MATLAB-SIMULINK, the PID controller undergoes meticulous tuning, while the ANFIS and ANN controllers are trained using meticulously curated data from the PID controller. The results exhibit the ANFIS controller's remarkable dominance, showcasing an awe-inspiring performance with an impressively swift settling time of 2.4404 and seconds impeccable 0% overshoot. Although the ANN controller exhibits a reduction in overshoot compared to the PID controller, it falls short with a lengthier settling-time. Based on this comprehensive analysis, it is unequivocally established that the ANFIS controller reigns supreme, closely trailed by the ANN controller and the PID controller. These findings offer profound insights for researchers and practitioners, guiding them in the astute selection of controllers for any control system.

Keywords:- AVR (Automatic-Voltage-Regulator), PID (Proportional Integral Derivative), ANFIS (Adaptive Neuro Fuzzy Inference System), ANN (Artificial-Neural-Network), Simulink, Controller, MATLAB, etc.

I. INTRODUCTION

The regulation and control of complex systems are essential for maintaining stability and achieving desired performance objectives. In the engineering field, the implementation and development of efficient control algorithms have been crucial in various applications, ranging from robotics and manufacturing to industrial processes and power systems. Among the many available control methodologies, proportional-integral-derivative (PID) controllers, artificial-neural-network (ANN) controllers, and adaptive-neuro-fuzzy inference system (ANFIS) controllers

have emerged as popular choices due to their effectiveness and versatility. The purpose of this research content is to compare the effectiveness of PID, ANN, and ANFIS controllers in the setting of an Automatic-Voltage-Regulator (AVR) system. The AVR system plays a critical role in maintaining output voltage stabilizations, thereby ensuring the smooth operation of electrical power systems. Voltage fluctuations can have severe consequences, including disruption of power supply, damage to sensitive equipment, and compromised system reliability. Therefore, it is essential to implement and design control strategies that can robustly modulate the AVR system's output voltage.

By evaluating their performance based on various metrics, such as 'Overshoot', 'Settling time', and 'Rise time'. We aim to provide insights into the limitations and strengths of each controller. This analysis will contribute to the understanding of which control method is better suited for the specific requirements of an AVR system, taking into consideration factors such as model availability, computational efficiency, system complexity, and control performance.

II. MODELLING THE AVR SYSTEM USING PID, ANN, AND ANFIS CONTROLLERS

The three types of controllers (PID, ANN, and ANFIS) are used one after the other in the same Automatic Voltage Regulator (AVR) model. The basic model was the PID controller. The values of P, I, and D were taken by the PID tuning method. As the ANN controller needs input and output data for the ANN training, the data was also taken from the PID controller. (To-Workspace) block is used to get the input and output data from the PID controller for ANN training. For the setup of the (To Workspace) block in Simulink, the 'Save format' option is set to 'Array', and the 'Sample time' is set to -1. And also for the ANFIS controller, the combined input and output are taken from the PID controller. To get the combined input and output data, the MUX is used in Simulink. In every case, the values of P, I, and D were the same. After the successful ANFIS training, the FUZZY block was used for the ANFIS implementation in the model.

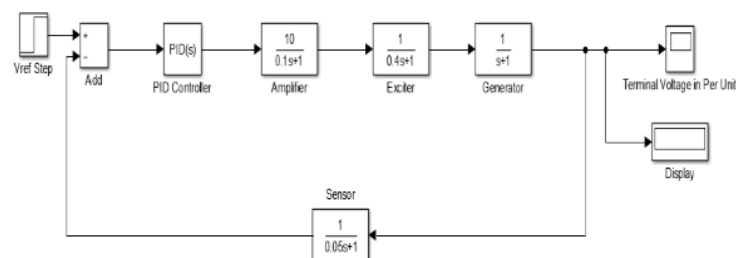


Fig. 1: Diagram of AVR system with PID controller.

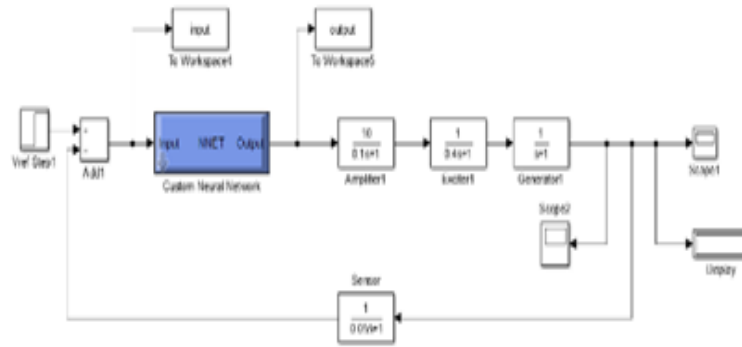


Fig. 2: Diagram of an AVR system with an ANN controller.

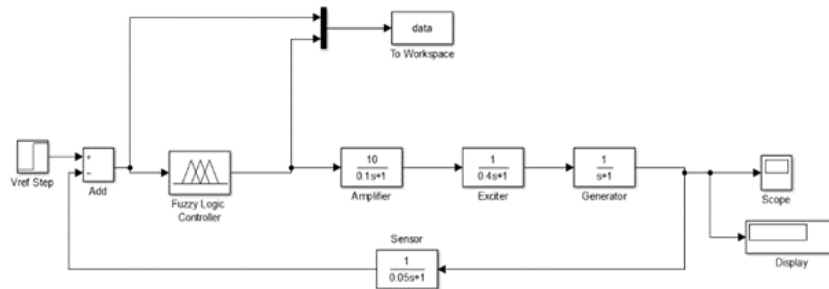


Fig. 3: Diagram of an AVR system with an ANFIS controller.

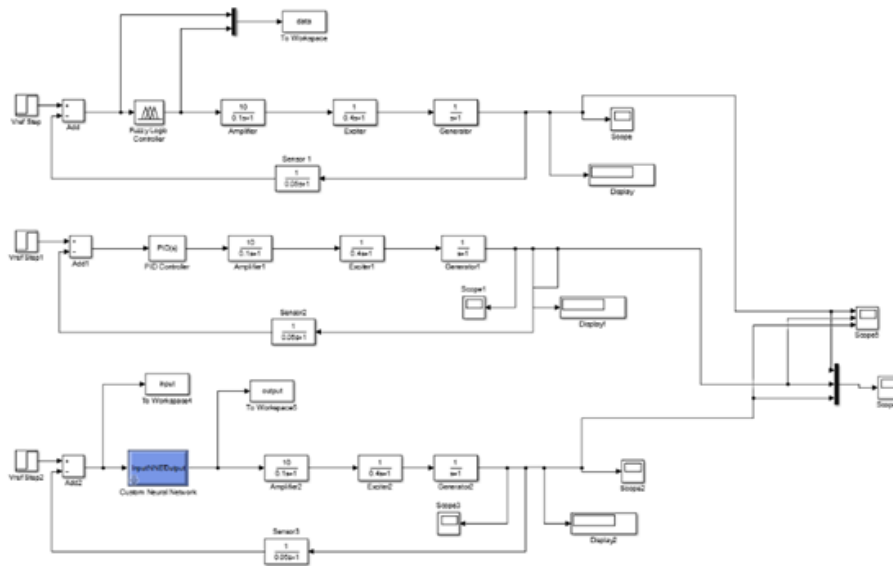


Fig. 4: Diagram of an AVR system with PID, ANN, and ANFIS controllers

III. PID CONTROLLER

A Proportional-Integral-Derivative (PID) controller is an essential control mechanism employed for stabilizing and regulating systems. It computes a control signal output by assessing the discrepancy between a desired set point and the current process value.

The controller is comprised of three fundamental components:

- Proportional (P) Term: Generates an output proportional to the current error, reducing steady-state error and improving responsiveness.
- Integral (I) Term: Integrates the error over time, eliminating steady-state error and long-term errors or correcting for biases.
- Derivative (D) Term: Considers the error's rate of change, stabilizing the system and mitigating abrupt or oscillatory changes.

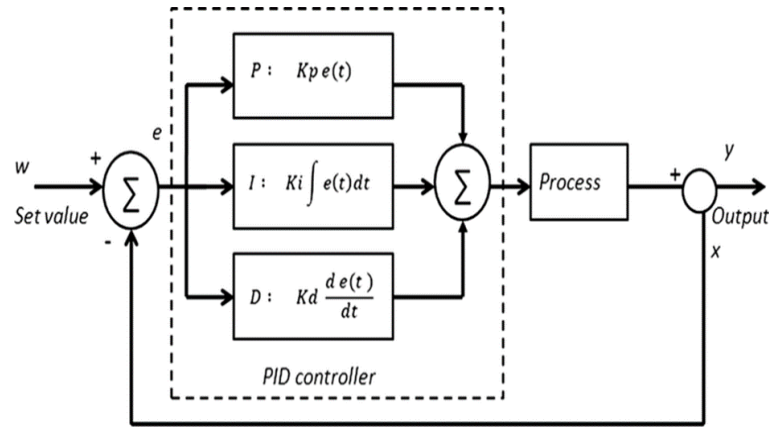


Fig. 5: Block Diagram of the PID Controller

In this investigation, some initial setup of PID is required in Simulink. In this experiment the parallel form PID is used. The time domain is set to 'Continues Time'. And for the Source the 'Internal' option is chosen. The 'Filter-coefficient '(N) is set to 100. The compensator $P + I \frac{1}{s} + D \frac{N}{1+N \frac{1}{s}}$ is used. The value of P, I, and D for this experiment is taken by PID tuning.

- PID Tuning** - PID tuning is the process of selecting the appropriate gains (K_p , K_i , K_d) for a PID controller to achieve desired control performance. It can be done through manual adjustment, using methods like Ziegler-Nichols or Cohen-Coon, or by frequency response techniques or model-based. Proper tuning ensures stability and optimal system response.

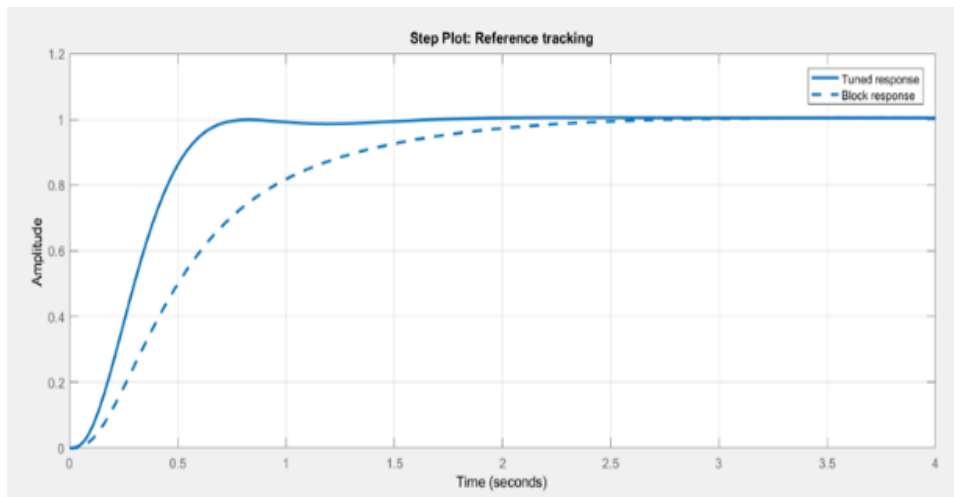


Fig. 6: PID tuning process

After several times of tuning the best value obtained is:

Main	PID Advanced	Data Types	State Attributes
Controller parameters			
Source:	internal		
Proportional (P):	0.214441047073489		
Integral (I):	0.157791984137529		
Derivative (D):	0.0705872353484475		
Filter coefficient (N):	100		

Fig. 7: Tuned value of PID Controller

IV. ANN CONTROLLER

In Automatic-Voltage-Regulator (AVR) systems, artificial-neural-networks (ANNs) are utilized to improve the control capabilities. The use of the ANNs allows for the exploration of non-linear functions through a multi-layer feed-forward technique by adjusting the weights within the network. This flexibility enables ANNs to handle complex mappings and relationships between input control variables and output control values.

The structure of an ANN typically comprises of the three layers input, output, and hidden layers. Every layer consists of interconnected neurons that receive input signals, process them using weighted sums, and apply non-linear activation functions to generate output signals. The weights within the network are iteratively adjusted during the training phase, where the network learns to map input patterns to desired output patterns.

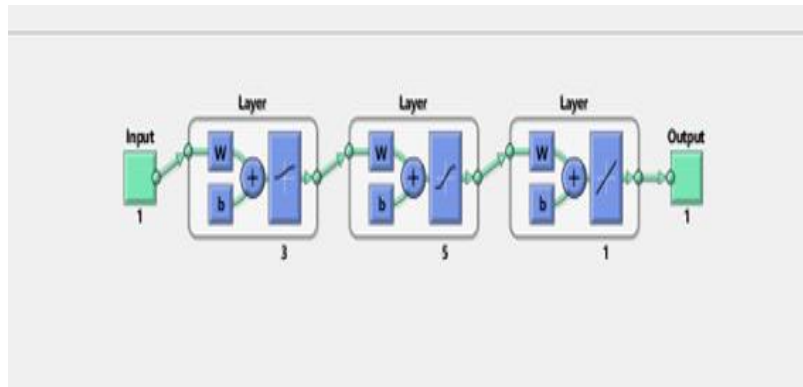


Fig. 8: Architecture of Artificial Neural Network (ANN)

By doing fine-tuning the synaptic connections within the network, ANNs can effectively optimize and adapt the control of AVR systems. This sophisticated and dynamic property, often referred to as gigantic parallelism, allows ANNs to handle a vast number of computations in parallel, facilitating efficient and responsive control.

10000 (Ten Thousand) iterations (shown in Figure 9) were taken for the accuracy of ANN Training. The proficiency of ANNs to acquire and represent non-linear relationships makes them suitable for designing AVR systems, which often involve complex non-linearities and dynamics. By accurately mapping input control variables to appropriate output control values, ANNs contribute to the efficiency, stability, and reliability of AVR systems.

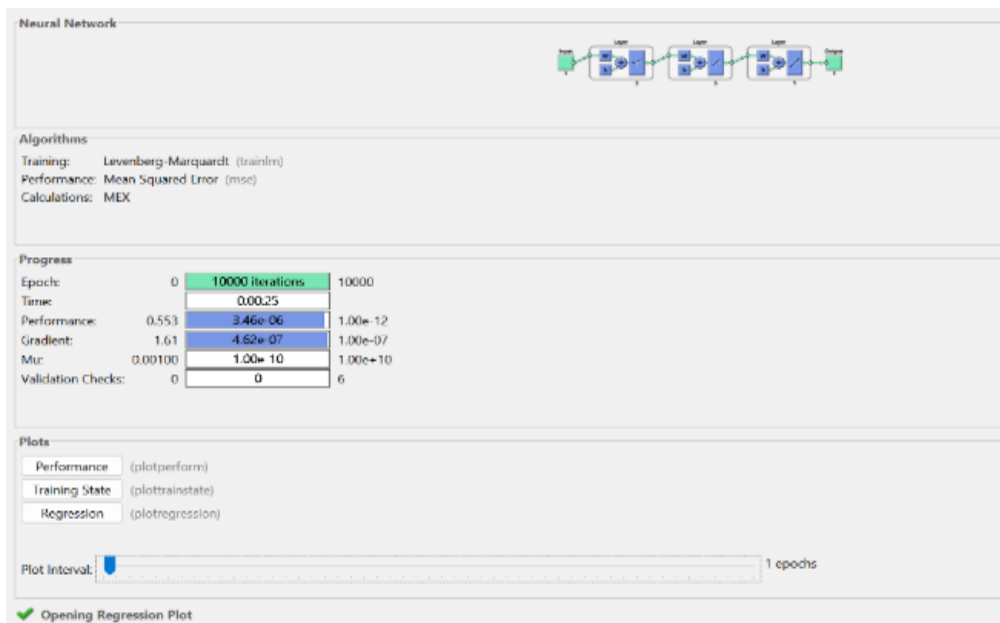


Fig. 9: Training of artificial neural network (ANN).

The criteria for successful ANN training is that the regression must be equal to one. In this investigation, the

regression is 0.99999 which is very close to unity. That means the ANN training is successful.

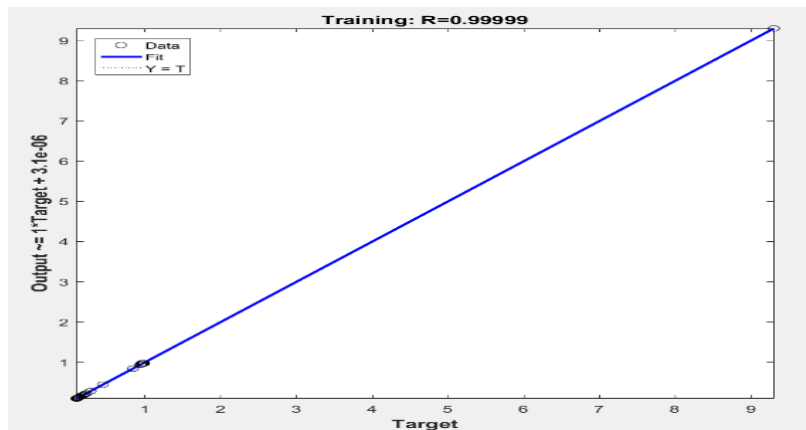


Fig. 10: Regression Graph of ANN Training

After the ANN training, to shift the trained ANN model from the workspace to Simulink the Matlab command ‘genism(net,-1)’ is used.

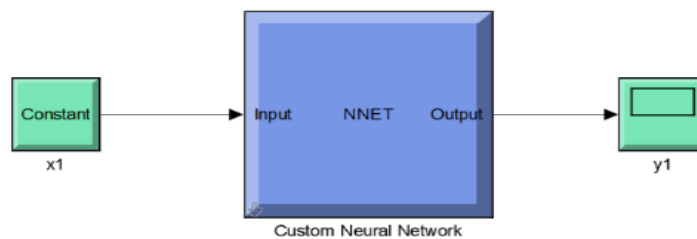


Fig. 11: Trained ANN Model

V. ANFIS CONTROLLER

Fuzzy logic and neural networks combine to form ANFIS. In other words, ANFIS represents an amalgamation of two distinct fields of study, specifically Artificial Neural Networks (ANNs) and fuzzy logic controller that offers the highest level of performance. ANFIS is an extremely effective technique to represent intricate and nonlinear

systems using a minimal amount of training data for inputs and outputs, we require a suitable approach.

It incorporates the benefits of ANN learning capability from the process and Fuzzy logic control in handling ambiguous data. This enables ANFIS to approximate a pure nonlinear mathematical model.

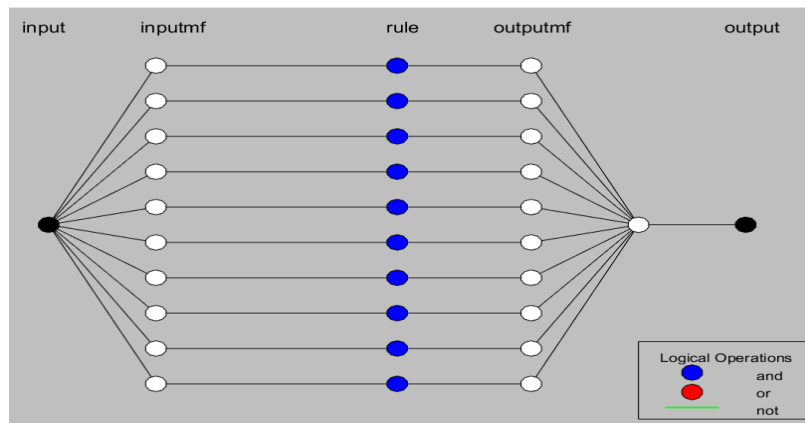


Fig. 12: The Structural Design of ANFIS

ANFIS has five layers, each of which is coupled to the next by weights. The data from the input layer's initial levels are translated into membership functions to establish the degree of membership of that input. Fuzzy rules are used to connect input and output in the second layer. The output is sent to the fourth layer after the third layer has normalized it. The fourth layer provides the output membership function

and transfers the output data. The outputs are combined at the fifth layer to produce a single output.

In this investigation number of MFs is used 10(ten) and the type is ‘trimf’ and constant. The tasting method is selected as ‘Hybrid’ and the epochs are chosen 100 times. The data for the input and output for the training is obtained from the PID controller.

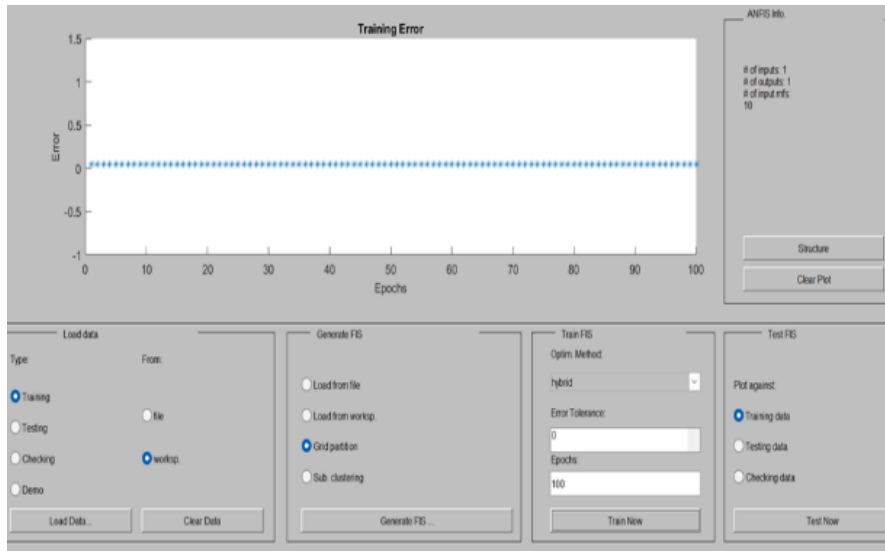


Fig. 13: Training of ANFIS

VI. MATLAB SIMULATION

The simulation model of the AVR system is developed using the numerous toolbox that is offered in MATLAB-SIMULINK.

A. Step1: AVR system design using PID controller

The initial AVR system model was created using a PID controller. To obtain the desired output, the PID tuner is utilized to determine the values of P, I, and D. To measure output data on the command window, the 'To workspace' element is utilized. Fig. 1 depicts a block diagram of the model.

B. Step2: Data generation for ANN and ANFIS training

In this investigation, the PID controller is used for collecting data for ANN and ANFIS training. To obtain the training input and output data, the 'To workspace' block is added to the PID controller's input and output section.

C. Step3: ANN Training Process

For the ANN training input and output data is needed in separate format. A MATLAB code is used to run the training and some basics parameter are used such as the iteration is selected to 10000. The criteria for successful ANN training is that the regression must be equal to 1. The fig.10 shows the regression is 0.99999 which is very close to unity.

D. Step4: Training of ANFIS

For the ANFIS training input and output data are needed in combined format. A MATLAB command (anfisedit) is used to open the training window and some basics parameter is used such as the iteration being selected to 100. The criteria for successful ANFIS training is that the ERROR must be equal to 0. The fig.13 shows the error is almost equal to ZERO.

E. Step4: Comparisons of PID, ANN, ANFIS controller performance

After obtaining all the training results. All three model is taken in a combined platform and added a SCOPE to measure and compare the output signal. The fig.4 shows the block diagram of this.

VII. RESULT AND DISCUSSION

The subsequent demonstration illustrates the performance of PID, ANN, and ANFIS controllers.

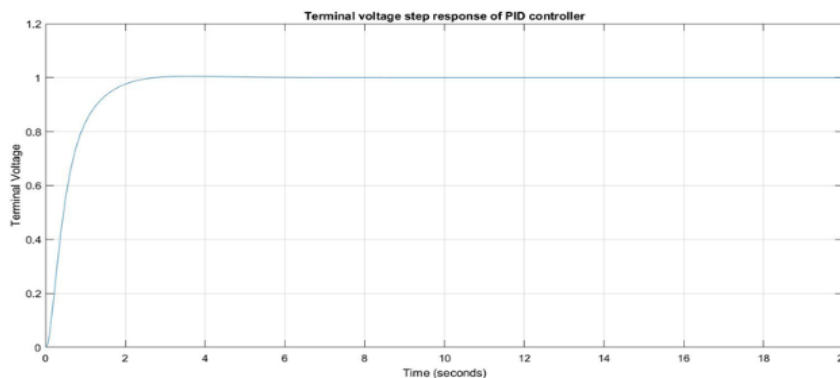


Fig. 14: Terminal voltage in per unit with PID controller

Figure 14 showcases the PID controller response within the system, presenting valuable insights. The graph reveals that the system takes approximately 2.0672 seconds to achieve a state of stability, known as the steady-state condition. Interestingly, during this process, there is a notable

overshoot of 49.87%. This signifies that the system surpasses its target value by almost half, showcasing the dynamic behavior and transient response characteristics of the PID controller in action.

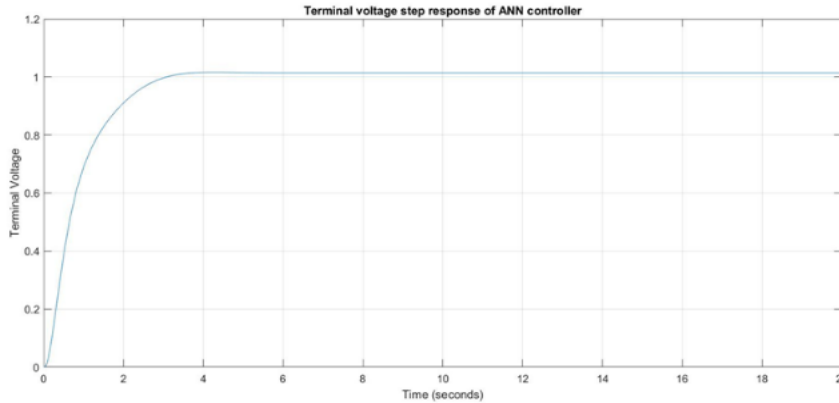


Fig. 15: Terminal voltage in per unit with ANN controller

Figure 15 presents the response of the ANN controller in the system, offering valuable insights. The graph demonstrates that it takes approximately 2.8386 seconds for the system to reach a stable state, known as the steady-state

condition. Interestingly, during this process, there is a notable overshoot of 18.80%, indicating that the system surpasses the desired value temporarily before settling into stability.

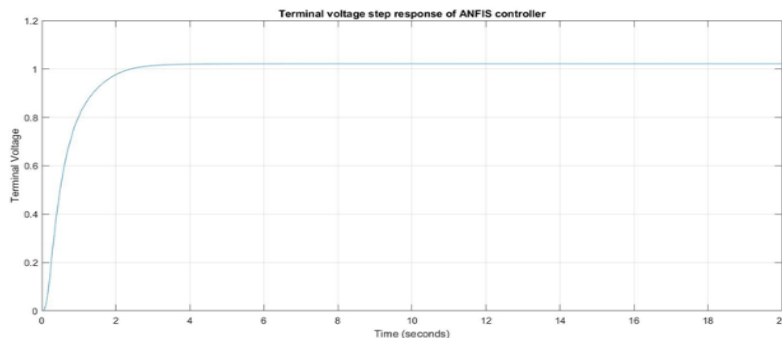


Fig. 16: Terminal voltage in per unit with ANFIS controller

Figure 16 demonstrates the ANFIS controller's response within the system, providing profound insight into its behavior. Notably, the graph reveals an intriguing characteristic: it takes the system approximately 2.4440 seconds to attain a steady state, also known as the steady-state condition. During this process, a remarkable feature emerges

the absence of any overshoot, denoted by a remarkable 0% overshoot. This demonstrates that the system accomplishes its desired state without exceeding the intended parameters, indicating an exceptional level of control and precision in its operation.

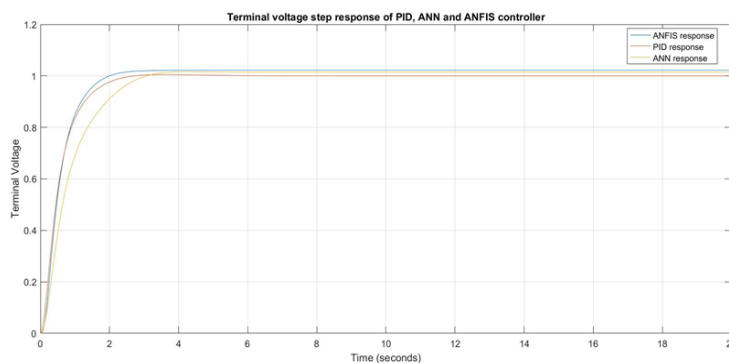


Fig. 17: Terminal voltage in per unit with PID, ANN, and ANFIS controller

A graph depicting the comparative response of the three controllers is depicted in Figure 17. The graph demonstrates that the Artificial Neural Network (ANN) controller demonstrates a lengthier settling period than the other

controllers. In contrast, the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller provides the quickest response, as evidenced by its minimal overshoot and reduced settling time.

Table 1: The time-domain performance specifications (Rise-time, Overshoot, and Settling-time) of the three controllers are:

Controllers	Rise-Time (In sec)	Overshoot	Settling-Time (In sec)
PID	1.1396	0.4987	2.0672
ANN	1.8080	0.1880	2.8386
ANFIS	1.3127	0.00	2.4404

The comparison of 3 Controllers' performance in the AVR system is shown on the graph.

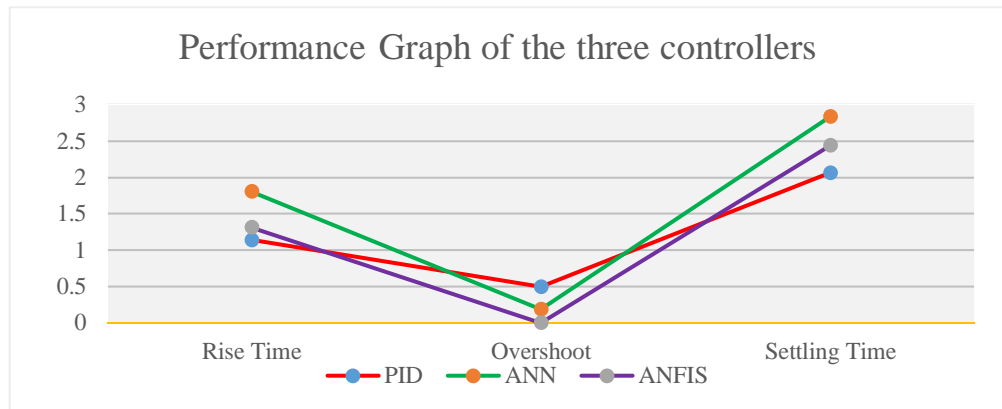


Fig. 18: Performance graph of PID, ANN, and ANFIS controllers

VIII. CONCLUSIONS

This paper is an approach of investigate the performance of PID, ANN, and ANFIS controllers in an AVR system. After doing the experiments on MATLAB/SIMULINK, the time domain performance of PID, such as the ‘Overshoot’ value is found 0.4987. Whereas ANN’s and ANFIS’s overshoots are 62.26% and 100% lower than the PID controller respectively. From this experiment, the ANFIS controller’s performance is found the best with the 0% overshoot and 2.4404 sec. of settling time. Though the ANN controller’s overshoot is lower than the PID controller the settling time is 37.23% higher than it. This study determined that the ANFIS controller is superior to all other controllers, followed by the ANN controller and the PID controller.

IX. FUTURE SCOPE

The effectiveness of the PID controller greatly influences the terminal voltage response of the power system. As a result, there is a possibility to enhance or substitute the PID controller with more advanced intelligent controllers that employ various techniques. Consequently, the Automatic Voltage Control (AVR) systems in Hydro/Thermal Power Plants can be enhanced by incorporating RBFNN (Radial Basis Function Neural Network) and PNN (Probabilistic Neural Network). Similarly, the AVR System has the potential to integrate the latest optimization techniques like Ant Colony Optimization (ACO) and Bee Colony Optimization (BCO), among other methods.

APPENDIX A

The following parameters are considered in this AVR system of the Generator:

Parameter	Gain(K)ss	Time-Constant (T)
Amplifier-(A)	10	0.10
Exciter-(E)	01	0.40
Generator-(G)	01	1.00
Sensor -(R)	01	0.05

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