# A Neural Controller Design for Enhancing Stability of a Single Machine Infinite Bus Power System

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## ABSTRACT

**This paper examines the formulation and implementation of a neuro-controller for the excitation system of synchronous generators in a Single-Machine Infinite Bus (SMIB) power system. The SMIB model is employed as a fundamental model of a power system, thereby facilitating the assessment and comparison of disparate control strategies with the objective of enhancing system stability. The goal of this study is to enhance the stability of the SMIB power system through the implementation of an Artificial Neural Network (ANN) neuro-controller, providing a comparison of its performance to that of a Power System Stabilizer (PSS) and a Proportional-Integral-Derivative (PID) controller. The proposed neuro-controller will be integrated into the generator's excitation system and will be designed to regulate the excitation voltage in response to fluctuations in the system's operational parameters. To this end, an ANN is calibrated to account for the singularity of the generator's excitation level and terminal voltage. The Levenberg-Marquardt algorithm is employed to ascertain the optimal weight coefficients for the ANN. To assess the performance of the neuro-controller, simulations were conducted using MATLAB/Simulink. The simulations encompass a comprehensive range of operational scenarios, including diverse disturbances and alterations in the reference voltage level. Subsequently, the neuro-controller's outputs are evaluated in comparison to the PSS and PID controllers, as these are the prevailing controllers used to enhance voltage regulation and transient stability in power systems. This paper presents the results of an analysis of the neuro-controller's impact on the system's robustness, voltage variation amplitude, and generator dynamic performance during faults. Simulation results demonstrate that the application of an ANN-based neuro-controller yields superior outcomes in voltage regulation and transient stability compared to the conventional controllers PSS and PID. Furthermore, the neuro-controller is distinguished by accelerated response times and enhanced precision in voltage level regulation. The neuro-controller represents a superior approach to the control of a power system, particularly in the context of SMIB, which would ultimately result in enhanced performance and stability.**

***Keywords-neural controller; Single-Machine Infinite Bus (SMIB); power system stability; Power System Stabilizer (PSS); Proportional-Integral-Derivative (PID) controller; Artificial Neural Networks (ANNs); Levenberg-Marquardt-algorithm***

# I. INTRODUCTION

The stability of the power system is of great importance when considering the credibility of active operation, particularly in the context of SMIB systems. They serve as foundational models for investigating power system stability, encompassing pivotal components, such as synchronous generators, excitation systems, turbine and governor systems, load dynamics, and PSS [1, 2]. The synchronous generator represents the core of the SMIB system, responsible for the conversion of mechanical energy into electrical energy. Nevertheless, the participation in a settled operation necessitates the precise regulation of numerous parameters, including voltage terminal, output reactive power, and rotor speed (3). The process is facilitated by the system excitation, which regulates the generator's excitation level to ensure optimal reactive power control and voltage regulation [4, 5]. Furthermore, the governor systems and turbine play a significant role in maintaining rotor speed within the desired limits, which contributes to the overall stability of the system. Furthermore, fluctuations in connected loads can impact the system's power output and stability, introducing additional complexities to the system dynamics [6-8]. In recent years, there has been a growing interest in the use of previous control techniques, such as neural network-based controllers, to enhance the stability of power systems. Neuro-controllers offer the advantage of modification and robustness, making them a potentially suitable means of regulating system parameters in SMIB systems [9, 10]. There has been a growing benefit to leveraging advanced control techniques, such as neural network-based controllers, to further improve power system stability. Neuro-controllers demonstrate the advantages of modification and robustness, making them a potentially suitable means of adjusting system parameters in SMIB systems [11, 12]. Based on a comprehensive simulation learning and comparative analysis, the proposition that neuro-control may offer a potential advantage in SMIB systems is put forth, thereby contributing to the advancement of control techniques for power system stability [13].

This study focuses on the advancement of control methods in power systems, with a particular emphasis on the integration of neural network-based controllers with existing control methods to enhance reliability and stability. The results demonstrate that employing an ANN instead of a PSS with a PID and an AVR enhances the stability of the power system. By deploying a multi-layer neural network trained to use the Backpropagation (BP) algorithm and the Levenberg-Marquardt optimization technique, the efficacy of neuro-control in enhancing stability is analyzed and compared to conventional control approaches using MATLAB modeling to examine the distinctions in performance. The term "power system stability" is defined as the capability of an electric power system to restore its initial operational balance and remain in a state of equilibrium when it experiences an external disruption [14]. The electrical system has undergone a notable expansion in both size and complexity in recent times, thereby facilitating the deployment of robust instruments for the effective management of pertinent issues. The system responsible for generating the excitation signal depends on two principal components: the Automatic Voltage Regulator (AVR) and the exciter. The regulated output of the exciter is determined by measuring the terminal generator voltage and comparing it to a reference voltage. The damper and the field winding are designed to mitigate the effects of rotor oscillations following any disturbance. The AVR generates negative damping torques that impede the damping process [15]. The power system is susceptible to the potential loss of synchronization or the generation of undesired oscillations. To address this issue, the PSS has undergone an expansion and enhancement process using advanced technology. The PSS incorporates a damping element that is synchronized with fluctuations in rotor speed. This element serves as the primary signal generator for the system excitation, introducing an additional signal. Therefore, the installation of the PSS device would serve to enhance the stability of the system [16]. ANNs are frequently employed due to their capacity to comprehend intricate nonlinear relationships and their ability to process applications that include a substantial volume of past data [17, 18]. This research project is designed to examine the advancements in control methodologies for power systems, with a particular emphasis on the integration of neural network-based controllers with existing control techniques to enhance reliability and stability. The results demonstrate that employing an ANN instead of a PSS with a PID and an AVR for an infinite bus single-machine enhances the stability of the power system. The deployment of the AVR and PSS has led to a discernible enhancement in stability, particularly in normal and minor disturbance scenarios. In order to enhance stability and control within operational systems, it is essential to identify more effective controller parameters. It is important noting that a number of distinctive optimization techniques have been investigated in the relevant academic literature. A substantial assortment of generators, transmission lines, transformers, safety apparatus, and additional pertinent components constitute the power system of an electric utility. The principal function of a power system is to generate, transmit, and distribute electrical energy. The system's end users can be interconnected at disparate voltage levels, such as sub-transmission, primary distribution, and secondary distribution, and they regulate the requisite generation needs through their continually shifting demand [14, 15]. Authors in [19], studied an ANN-based AVR equipped with a synchronous generator. In contrast to conventional AVR systems that depend on PID controllers, the proposed AVR system employs ANN to guarantee a constant output voltage despite load fluctuations.

The system uses synchronous generators, induction motors, and experimental data gathered from the design, encompassing frequency converters and weight groups. Three distinct learning methods in MATLAB are employed to train the ANN with experimental data on the snow. Subsequently, the trained ANN models are tested individually and their performances are compared in order to evaluate the optimal control of the generator output power. Authors in [20] proposed a novel robust PSS, designated as the Fractional Order PID Controller-PSS (FOPID-PSS). This system integrates fractional order PID control with PSS, thus achieving enhanced robustness. The Integral of the Error Squared (ISE), the measured absolute Error Average Over Time (ITAE), and the squared error multiplied by the Interpolated Time Element (ITSE) are effective criteria for evaluating the control performance. The Bat algorithm (BA), which is driven by echolocation behavior, is employed to ascertain optimal stability features. Authors in [21] employed, an ANN to enhance the dynamic stability of power systems. The model utilizes post-fault generator rotor angle trajectories as input to forecast the ultimate values and time for failure of substantial generator stability with precision. Authors in [22] investigated the use of ANN for the detection of faults in power lines. The simulations in MATLAB employ real 132 kV line data from the Enugu station of the transmission line, along with both real and synthetic parameters. The ANN is trained and designed to detect a variety of fault types, including line-to-ground, line-to-line, and line-to-line-ground faults. The results of the performance analysis demonstrate that ANN-based methods are an effective approach for accurate fault detection. Authors in [23], analyzed the electronic design process, and the use of ANN was employed to enhance the analytical process. This analysis incorporates several unknown variables, including the contained fault mode, fault type, fault location, and fault resolution time. The proposed method has been proven to accurately predict the short-term stability of large-scale power systems. Authors in [24], proposed the optimal advantages of equations as a means of designing a PSS to address the issue of slow (LFOs) in power systems. The performance of PSS is compared to that of ANN methods, with a particular emphasis on efficiency and effectiveness in the stabilization of power systems. Authors in [25] propose the use of integrating decentralized control in a multi-machine power system as the focus of this work. A model was constructed for each machine within the grid using the Blondel diagram. This is primarily due to the fact that the system is nonlinear, necessitating the use of a Takagi-Sugeno (TS) fuzzy logic controller, which was demonstrated to provide relatively good performance. A significant advantage of the proposed control system is its reduced susceptibility to disturbances. This is further evidenced by the simulation results on a nine-node Western System Coordinating Council (WSCC) test grid. The indices of system damping, matrix page size, transient stability, and voltage regulation were optimized by minimizing the ITAE for the optimization criterion. Synchronous numerical simulations have been conducted on a SMIB system, taking into account various fault and fault-cleared scenarios [26]. The results demonstrate the efficacy of the proposed approach in comparison to traditional PSS methodologies. While the precise degree of improvement may vary depending on the specific circumstances, the asserted outcomes include a 5% reduction in overshoot, an 87% decrease in transient time, and the absence of steady-state error.

## II. SYSTEM DYNAMIC MODELLING

The nonlinear power system is a highly intricate and sophisticated entity. Therefore, when selecting a power system, it is essential to consider the stability of the rotor angle and the management of generator voltage. Consequently, an AVR is employed to regulate the generator voltage and guarantee system stability, in conjunction with a PSS [27, 28]. This research considers the single-machine connected to SMIB configuration, as shown in Figure 1 [29-33]. The synchronous generator model is a seventh-order detailed dynamic model. However, the third-order model remains a valuable tool for control and stability analysis of generators associated with power systems [34]:

$$\frac{d\delta(t)}{dt} = \omega(t) \tag{1}$$

$$\frac{d\omega(t)}{dt} = \frac{\omega}{2H}\ [Pm\ - Pe\ (t)] - \frac{KD}{2H}[\omega(t)] \tag{2}$$

$$\frac{dE_q'(t)}{dt} = \frac{1}{T_{do}'}\left[E_{fd}(t) - E_q(t)\right] \tag{3}$$

where, $\delta$ is associated with the rotor angle of the generator, $\omega$ with the speed deviation between the synchronism and the generator, and $P_e$ with the electrical power output delivered by the generator. The transient Electromagnetic Force (EMF) on the q-axis is represented by $dE_q'$, the input mechanical power is represented by $P_m$, and $E_{fd}$ is the input voltage excitation. The values of $T_{do}'$, $K_D$, and $H$ denote the system components that correspond to the excitation circuit time constant, damping torque coefficient, and inertia constant, respectively. Additional algebraic equations are:

$$\mathrm{E_{fd}}(t) = K_A\ E_F\ (t) \tag{4}$$

$$\mathrm{E_q(t)} = \frac{\mathrm{X_{ds}}}{\mathrm{X_{ds}^{`}}}\mathrm{E_q^{`}(t)} - \frac{\mathrm{X_d - X_d^{`}}}{\mathrm{X_{ds}^{`}}}\mathrm{V_S}\ \mathrm{cos\delta(t)} \tag{5}$$

$$P_e(t) = \frac{E_q(t)V_S}{X_{ds}} sin\delta(t) \tag{6}$$

$$V_t(t) = \frac{1}{X_{ds}}\sqrt{X_s^2E_q^2(t) + X_s^2X_d^2 + 2X_sX_dV_sE_q(t)cos\delta(t)} \tag{7}$$

where, $\mathrm{X_s = X_T + \frac{X_L}{2}, X_{ds} = X_d + X_s,\ X_{ds}' = X_d' + X_s}$ . The terminal voltage magnitude is represented by $V_t(t)$. $V_S$ is the voltage to the infinite bus, $X_q$ and $X_d$ are the (q-d-axes) reactance and synchronous reactance, respectively. $X'_d$ is the transient reactance at the d-axis, while $X_L$ and $X_T$ are the single line reactance and transformer, respectively. Although the electrical active power, $P_e(t)$, is accurately measured in practice, the generator's internal transient voltage is not. Consequently, in the system dynamic related to (1), the differential of $E'_q(t)$ may be replaced by the following electrical power differential equation:

$$\frac{dP_e\,(t)}{dt} = \frac{1}{T_{do}^{`}}\frac{V_S}{X_{ds}^{`}}sin(\delta)\,E_{fd}(t) + \frac{X_d - X_d^{`}}{X_{ds}^{`}X_{ds}}V_s^2\ \omega sin^2(\delta) + \left(\omega cot(\delta) - \frac{X_{ds}}{X_{ds}^{`}}\frac{1}{T_{do}^{`}}\right)P_e\,(t) \tag{8}$$

The control action is represented by $E_{fd}$ that adjusts the field voltage to stabilize the system. A combination of PID control and PSS control can be used to achieve this. Let us denote the PID controller as $u_{PID}$ and the output of the PSS controller as $u_{PSS}$. The control law for the combined control system is:

$$\frac{dE_{fd}\,(t)}{dt} = \frac{1}{T_A}\ [K_A\,(V_{ref}\ \ - V_t(t) + U(t) - E_{fd}(t))] \tag{9}$$

where the gain constant exciter is $K_A$ and the time exciter constant is $T_A$ and:

$$U(t) = (u_{PSS} + u_{PID}) \quad (10)$$

The objective of this research is to demonstrate the efficacy of employing a neural network to analyze a nonlinear power conclusion system. The study employs a SMIB model within the power system, interfaced with an artificial neural network developed in MATLAB using the Neural Network Toolbox. In order to maintain the nonlinear dynamics of the system, a feedforward neural network with time delays is deployed. It is noteworthy that a discrete model is a prerequisite for the training process [33].

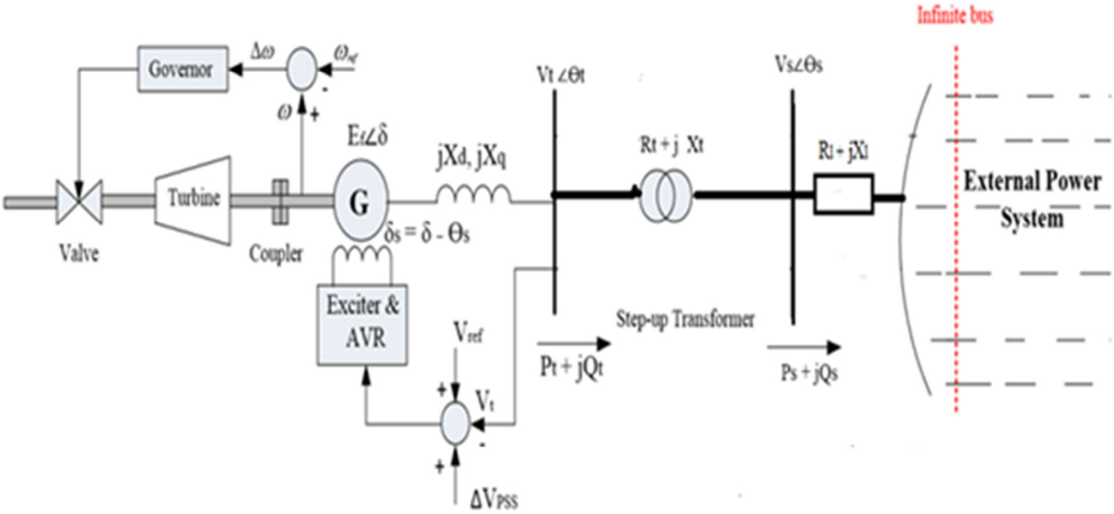



Fig. 1. Power system under study: single line diagram.

The model state space for the power system exhibits nonlinear behavior, which can be described as:

$$\left.\begin{array}{c}\dot{X} = X(t), \emptyset(t)X(t) + u(t) \\ Y(t) = N((X(t), \emptyset(t)\end{array}\right\} \quad (11)$$

where $X(t)$ is a vector representing the three states, $Y(t)$ is a vector representing the output, and $\emptyset(t)$ is the vector parameter for all function parameters. Consequently, these equations describe the state vector, output vector, and parameter vector. The state vector $X(t) = [\ \delta(t), \omega(t), E'_q(t)]$, $Y(t) = [\omega(t), V_t(t)]$, $\emptyset(t) = [X_S, V_S]$.

The discrete time for the third-order model with a sampling time $T_s$ of the generator electrical and rotational dynamics using Euler approximation can be:

$$X(k+1) = T_s \,.\, X(k) + T_s \,.\, u(t) \quad (12)$$

$$\delta_{(k+1)} = \delta_{(k)} + T_s\,(\omega_s + \omega_k) \quad (13)$$

$$\omega_{(k+1)} = \omega_k + T_s\,(\tfrac{1}{2H}\,(P_m - P_e - D(\omega_k - \omega_s)\,) \quad (14)$$

$$E^{`}_{q\,(k+1)} = E^{`}_{q\,(k)} + T_s \,.\, \frac{1}{T^{`}_{do}}\left[E_{fd(k)} - E_{q(k)}\right] \quad (15)$$

where $k$ is the discrete time of the step, ($k$+1) is the discrete time of the next step, and $Ts$ is the sampling time. This research uses the neuro-controller, and the architecture of the multi-layer neural network, employing the BP technique, which is characterized by a feedforward network. This network exhibits a nonlinear behavior as it operates with many inputs and outputs.

## III. MODELING OF PID CONTROLLER WITH PSS

The operation of power plants is subject to a number of uncertainties, including those pertaining to the conditions under which they are operated and the potential for disruption. The deployment of a PSS is essential for ensuring equipment efficiency, given that oscillatory stability [32] is maintained within an optimal operational range. The stratification of damping torque for an electrical damping torque ($\Delta T_m$) in conjunction with the PSS through the speed variation ($\Delta\omega$) serves to reduce oscillations in the power system. The study employs an active method that uses the PID controller to precisely adjust the tuning parameters of the PID-type PSS novel design structure, thereby determining the optimal PID-PSS configuration for a SMIB power system [36]. The principal objective of a PSS is to enhance the stability of a generator by controlling its excitation through the introduction of stabilizing signals, which serve to minimize oscillations in the rotor. The stabilizer generates electrical torque that is synchronized with every variation in the rotor speed, thereby providing damping [37]. A PID is a type of control loop feedback mechanism that addresses the issue of variability between different operational parameters and the desired input. It accomplishes this by identifying the underlying issue and transmitting a corrective signal to optimize the process. In general, a controller PID can be expressed as: $u_{(PID)} = K_p + K_i + K_d$, where $K_p$ is the proportional gain, $K_i$ is the integral gain, and $K_d$ is the derivative gain. The algorithm comprises three principal parameters: proportional, integral, and derivative values and oversees the implementation of the desired output [38]. The Simulink block set has been developed using

MATLAB software for the analysis and performance evaluation of the PSS. As evidenced in Figure 2, the PID controller and PSS validation have been evaluated under different operational conditions [39]. The stabilizer's input signal provides the speed deviation (*Δω*) and it is recommended for a PSS in conjunction with a PID controller to be employed to enhance the system's stability and performance, particularly in comparison to existing power systems. The response of the controller can be evaluated in terms of the achievement of the error controller, the points at which the controller exceeds the set point, and the degree of system oscillation [40].

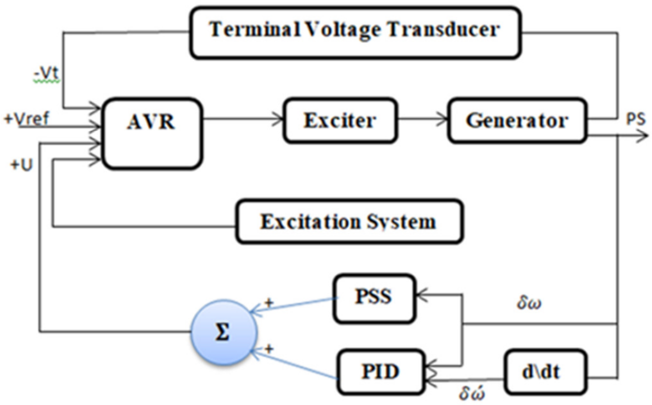



Fig. 2. Block diagram of PID-PSS.

## IV. DESIGN OF THE NETWORK WITH ANN

In light of the ongoing advancement of power systems and the growing necessity for high-quality energy, it is imperative to undertake a comprehensive examination of contemporary control approaches. ANNs are particularly well-suited for addressing complex problems in a manner that is more effective than other techniques. This analysis examines ANN models and then engages in a comprehensive discussion of many key aspects. ANNs have been increasingly used in a variety of power systems to address a range of issues, including load forecasting, security assessment, fault detection, system identification, operation, planning, protection, and alarm processing [41, 42]. In a SMIB, the principal components are a synchronous generator, a PSS and an excitation system, a turbine and a governor system, and load dynamics. The synchronous generator is the component responsible for the conversion of mechanical energy into electrical energy. The PSS assists in maintaining system stability by regulating the excitation level of the generator. The excitation system is responsible for regulating the terminal voltage and reactive power output of the generator. The turbine and governor system are responsible for maintaining the rotor speed at the desired level. Finally, load dynamics pertain to the behavior of loads connected to the system that may result in fluctuations in the power output. These components, in combination, facilitate the functionality and stability of the SMIB system [2]. The neuro-controller plays a crucial role in regulating system parameters, which is essential for achieving stability and optimal performance in a single-machine infinite bus system [43]. A variety of training methods may be used for the development of a neuro-controller within the context of a single-machine infinite bus system. One approach is supervised learning. The neural controller offers several advantages over traditional controllers for power systems, especially in terms of self-tuning capabilities and its ability to handle nonlinear characteristics inherent to power systems. This is achieved with notable success in minimizing overshoot, reducing settling time, and enhancing overall system stability at varying fault levels. However, it is not without its limitations, including the necessity for extensive learning datasets, heightened model complexity, and augmented processing demands, as well as the potential for overlearning. Additionally, it appears to be more of an opaquer system rather than a conventional controller, which may limit its transparency. Nevertheless, the potential of the neural controller is evident, and this forms the basis for its use as an enhanced tool in power system control.

### A. *Architecture and Training of the Neural Controller*

The Neuro-Controller is employed to supplant both a PSS/AVR and a PID controller, hence facilitating the provision of $E_{fd}$. ANN employs a multi-layer neural network with a feedforward network trained using the BP algorithm. The neuro controllers are composed of one hidden layer and one output neuron, with two inputs: rotor speed deviation ($\Delta\omega_t$) and voltage terminal ($V_t$). In subsequent learning trials, the number of hidden neurons remains constant. During these trials, the activation function for the hidden layer is that of a sigmoid, while the activation functions for the input and output layers are linear. The Levenberg-Marquardt algorithm is employed to efficiently train the neural network, and is renowned for its versatility and rapid convergence in nonlinear optimization systems. Therefore, it can be concluded that this algorithm is the most optimal among those that have been proposed so far. The network is trained to reproduce the specified target, or control signal. In this case, the discrepancy between the NN output and the reference is employed for the purpose of adjusting weights during the training process. The neural control system architecture, as presented in Figure 3, comprises a neuron at each layer, with the output of each neuron expressed by:

$$a^i(k) = f^{k+1}\left(\sum w^k\ a^i\ (k-1)\right) \tag{16}$$

where f is the activation function. The neural controllers that are connected to the single machine are subjected to a comprehensive examination. The network comprises multiple layers and is feed-forward. The anticipated voltage at the subsequent instant (k+1) in the future, the actual voltage at the conclusion, and the generator deviation velocity constitute the input. The neural controller is responsible for emitting the actual energy that excites the machine. The NN controller accepts inputs from either the delayed values of the neural network's outputs (or the control signal), the system output, or both. The network is trained to reproduce the specified target, which is also referred to as the control signal. In this context, the discrepancy between the NN output and the reference (target) is employed for the purpose of adjusting weights during the training process. The network is trained with the Levenberg-Marquardt backpropagation algorithm, which uses the trainlm algorithm. The neural controller is composed of three inputs, one hidden layer, and one output neuron. The activation function for the hidden layer is the sigmoid function, while the activation functions for the input and output layers are linear. Following the learning trials, the number of hidden neurons is fixed.

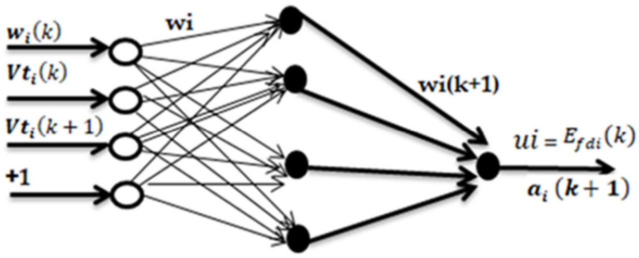



Fig. 3. Structure of the neural controller.

In order to develop a successful neural controller through training, the value of the parameters from the machine is taken and used to train the neural controller. The data set is provided from SMIB. It should be noted that the parameter values in the system are updated in a dynamic model when the system training algorithm is in operation. The neural controller training was evaluated for different initial conditions, and is given by:

$$J(k) = 0.5 \sum [\, y_d(k+1) - y(k+1)]^2 \quad (17)$$

The gradient descent of the error for the network weights is a function of the back-propagation method:

$$W_{ij}(k+1) = w_{ij}(k) - \varepsilon \frac{\partial J(k)}{\partial w_{ij}(k)} \quad (17)$$

$$\frac{\partial J(k)}{\partial w_i(k)} = \frac{\partial y(k+1)}{\partial ui(k)} \frac{\partial ui(k)}{\partial w_i(k)} \quad \partial J(k) \quad (18)$$

where $u(k)$ is the output of the neural controller, which refers to the $E_{fd}$ , and $\varepsilon$ is the learning rate, a hyperparameter controlling the step size during weight updates. The simulation results were obtained through the implementation of a specialized learning approach for neural networks. The initial step in developing a neural network controller is to define an appropriate network architecture, which involves specifying the number of neurons and the number of layers in each layer. A typical neural controller comprises a single output neuron and a single hidden layer. Following several learning trials, the number of hidden neurons remains constant, and the architecture that yields the fewest errors is selected. In regard to the hidden layer, the sigmoid activation function is a standard approach, whereas the input and output layers typically employ the linear activation function.

It is therefore imperative to select an appropriate structure for the neural network. The training of the NN commences with a predefined number of neurons, and its performance is assessed through the recording of outcomes. In the event that the performance of the neural network fails to achieve the desired level of precision and accuracy, an additional neuron is added to the network, followed by retraining. This process is repeated until either the mean squared error reaches a sufficiently low level or no substantial improvement is observed when the neural network is expanded. To assist in the selection process, numerous trials have been based on the aforementioned process, resulting in a final NN structure comprising three inputs, 12 neurons in the hidden layer, and a single output. Following the training trials, the optimal configuration is determined to be a network with three neurons in the input layer, twelve neurons in the hidden layer, and one neuron in the output layer. The data set comprises 2,000 samples, each of which was captured with the values of the state variables of the system and the corresponding control action taken at that time. The learning rate for this data set is set to 0.01, which allows for the control of the step size through weight updates. The data under study are typically divided into three categories: training data, which constitute 70% of the total data set, validation data, which typically constitute 15% of the data set and test data, which make up the remaining 15% of the data set. The performance is also measured in terms of the mean squared error. The mean square learning process, conducted using the Levenberg-Marquardt algorithm, yielded an average of 5.5727e10$^{-6}$ at epoch 603, representing the optimal validation performance, as depicted in Figure 5.

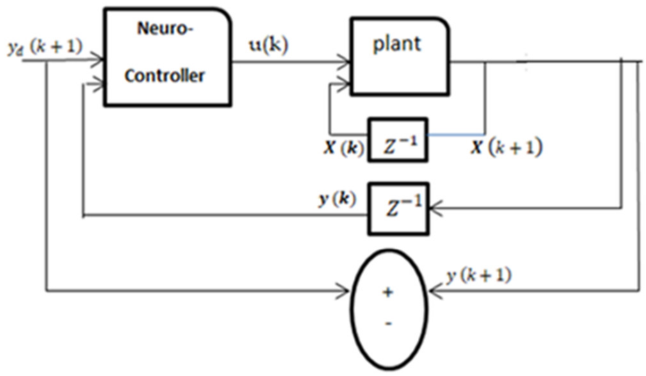



Fig. 4. Neural network controller of the training process.

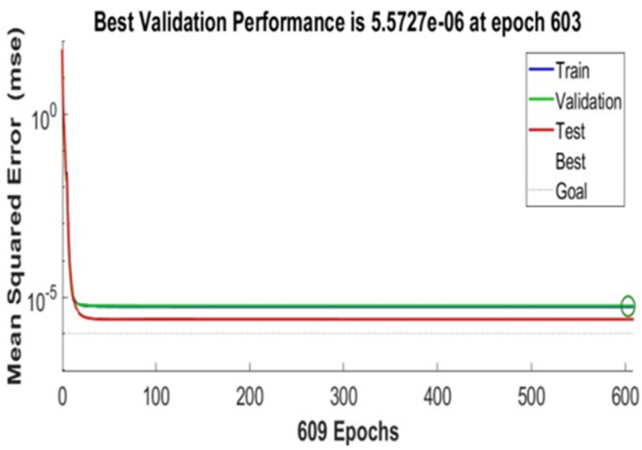



Fig. 5. Feedforward NN performance.

The process for validating the neural controller in the SMIB system presents a planned approach to ensuring its functionality and stability, particularly with regard to the voltage terminal. The process commences with the enhancement of an intricate SMIB model, which includes the dynamics of the synchronous generator. The subsequent phase of the process entails the design of a neural controller that optimizes the performance of the excitation system under a range of operational scenarios. The training process for the neural controller entails the usage of a dataset for the purpose of acquiring an understanding of the intricate relationship between the state system and the desired control inputs. The test validation encompasses the examination of the system under steady-state and transient conditions, in addition to a robustness assessment of the parameters. A comparative analysis should be conducted with traditional control strategies, with the performance metrics of voltage deviation and settling time evaluated. The validation findings are meticulously documented in order to highlight the strengths and limitations of the neural controller, thereby providing insights for further refinement and optimization.

### *B. Simulation Results*

The power system under consideration is a single-machine system. The stability of a single-machine transmission system is analyzed in Figure 6.

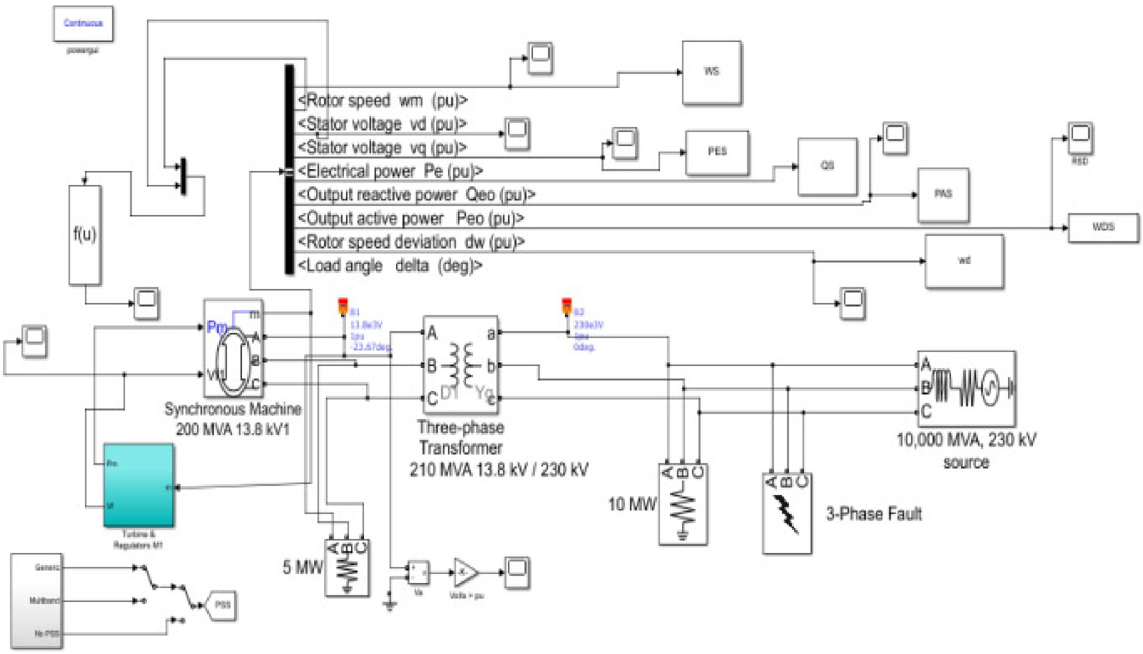



Fig. 6. Model under study in power system.

The simulations are conducted using MATLAB (R2019a), and the simulation approach is employed to assess the performance of a neuro-controller in regulating a SMIB system. The neuro-controller is designed as a multi-layer feedforward neural network, trained using the Levenberg-Marquardt backpropagation algorithm (trainlm) method. Following the training trials, the optimal configuration was determined to be a neuro-controller with three neurons in the input layer, twelve neurons in the hidden layer, and one neuron in the output layer. The neuro-controller receives inputs, including rotor speed deviation ($\Delta\omega_t$) and voltage terminal ($v_t$), along with a previous value of $v_t$, to generate the control signal $E_{fd}$. Simulations are conducted using MATLAB/Simulink, with the neuro-controller serving as a substitute for the PSS or AVR controllers. An ANN is used to replace a PSS/AVR controller in the machine, therefore enhancing both steady-state stability and voltage regulation in the power system. The simulation is conducted for the various types of controllers, including AVR without PSS, AVR with PSS and PID, and AVR with ANN, and both steady-state conditions and dynamic responses to disturbances are examined, with a comparison of the performance of the neuro-controller against that of traditional control methods. The system was subjected to a three-phase to ground fault at two different times. The first and second faults occurred near the load at $t$=1 s and cleared at 100 ms and 300 ms, respectively, by the disconnection of the faulted line. The results demonstrated the terminal voltage ($v_t$), rotor speed deviation ($\omega$), and load angle ($\delta$), as illustrated in Figures 7 and 8.

The simulation results display the differences between the neuro-controller and other neural controllers, including the PID and PI controllers. The objective of this study is to conduct a comprehensive analysis with the aim of evaluating the efficiency of the neuro-controller in enhancing the system stability and the response characteristics. The incorporation of ANN has resulted in a notable reduction in the system's growing and settling times, when compared to traditional control methods, such as AVR+PSS with PID and AVR. It is evident that upon the removal of the short circuit and subsequent alteration of the topology, the system reverts to its equilibrium state. The employment of a conventional AVR+PSS controller results in the destabilization and fragmentation of the system. It is evident that the implementation of neural controllers in power systems leads to a discernible enhancement in transient stability, particularly in the context of fault conditions.

(a)
(b)
(c)

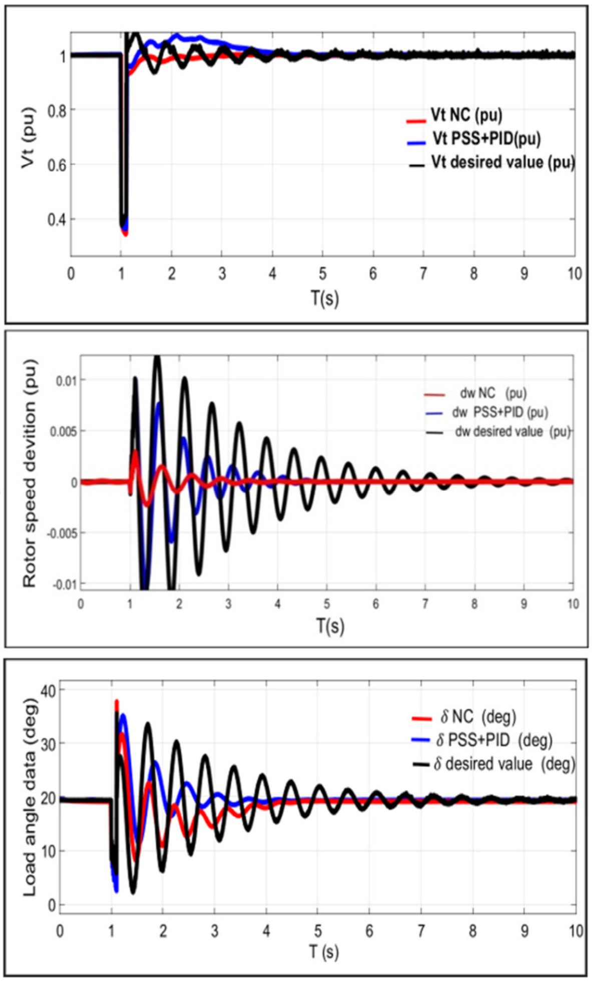
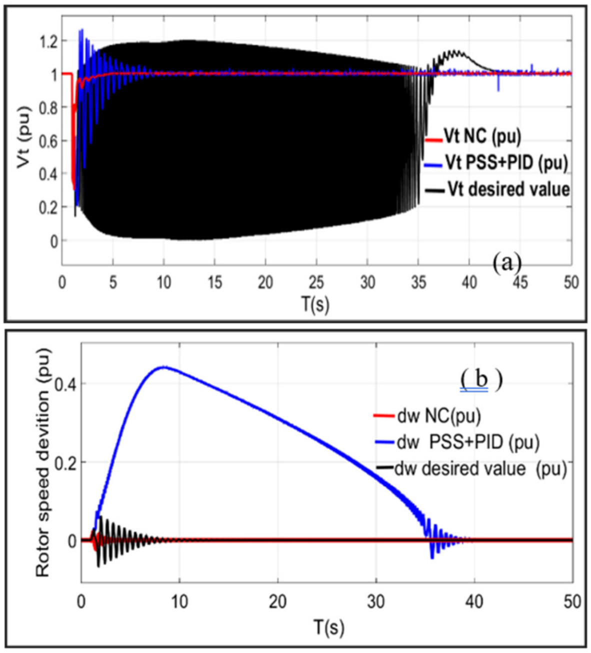



Fig. 7. Simulation results at fault t=1 and cleared at 100 ms: (a) field voltage,(b) Rotor speed deviation, (c) load angle delta.

(a)
(b)




(c)

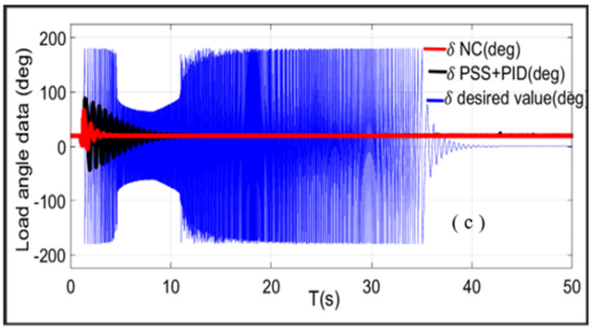



Fig. 8. Simulation results at fault t=1 and cleared at 300ms:(a) field voltage,(b) Rotor speed deviation, (c) load angle delta.

## V. CONCLUSIONS

This paper presents the design of a novel neuro-controller developed for the control of the excitation system of synchronous generators in the Single Machine Infinite Bus (SMIB) power system. The main contribution of this work is the use of the Levenberg-Marquardt algorithm for training the weight coefficients of the Artificial Neural Network (ANN), which has not been tried in power system control. Compared with Power System Stabilizer (PSS) and Proportional-Integral-Derivative (PID) controllers, this paper proposes an effective control method that improves the transient stability and voltage regulation, and simulations are performed in MATLAB/Simulink under different operating situations. Compared with other similar works that aim to analyze the conventional control approaches, the present work shows that the proposed ANN-based neuro-controller exhibits faster response, higher precision and better generalization ability. Thus, the results presented in this paper indicate that the proposed ANN controller offers improved performance as well as more stability of power system operation in a wider range of disturbed conditions. This paper contributes to the use of neural networks in power system control and provides practical means to advance the conventional approaches for further development of the subject.

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