Research Article

CONTROL AND IDENTIFICATION OF SINGLE MACHINE INFINITE BUS WITH NEURAL NETWORK FOR SYSTEM STABILITY

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Abstract. *This paper deals with implementing artificial neural networks for the identification and control Investigating the stability and stabilization of a single machine connected to an infinite bus through a transmission line (SMIB) system. Artificial Neural Network (ANN) employs a multi-layer feedforward network trained using the Backpropagation (BP) algorithm by simulations using MATLAB/Simulink. Weight coefficients of the ANN are determined using the Levenberg-Marquardt algorithm. The proposed approach uses two types of neural networks: neural controller and neural identification, neural network control is a single device on an infinite bus instead of the PID-PSS controller, to improve the performance of the SMIB system, and neural identification to emulate the characteristics of the single machine infinite bus (SMIB) system These neural networks model system dynamics and nonlinear for selection and control purposes. The primary objective is to develop a neuronal identification model that accurately equals the characteristics of the single machine infinite bus (SMIB) system and a neuro-controller is implemented to replace traditional controllers such as Power System Stabilizers (PSS) and Automatic Voltage Regulators (AVR). Simulations are performed to examine the system under various conditions, evaluating rotor speed deviation, stator voltage, and rotor angle delta.*

Keywords

Neuro-Identifier and Neuro-controller, Single Machine Infinite Bus, Automatic Voltage Regulators, Power System Stabilizers

1. Introduction

When an electric power system is subjected to an external disturbance, the ability to recover its original operational equilibrium and stay in its equilibrium state is referred to as power system stability [1]. The power system has grown in size and complexity in recent years, necessitating strong instruments to address pertinent issues. The generator excitation system's two primary parts the Automatic Voltage Regulator (AVR) and the exciter play an active part in keeping the stability of the power system. It is a device that automatically regulates the output voltage generator to keep it at a relatively fixed value. This is done by comparing the voltage output with a voltage reference and, of the variation (or error); making the indispensable modification in the current field to get the voltage output nearer to the wanted value and control the exciter output, the terminal generator voltage is measured and compared with the reference voltage. After any malfunction, the damper and field waveform attempt to dampen the rotor swing. The negative damping torques generated by the AVR counter the damping system [2]. The power system could become unsynchronized or produce undesirable oscillations. The Power System Stabilizer (PSS) was extended and updated technologically to address this issue. It provides a damping component with phase and rotor speed variations, which serves as the primary signal generator in the system excitation, by adding a signal extra. Therefore, installing the PSS device would improve system stability [3]. As a result of this problem Artificial Neural Networks (ANN) techniques were demonstrated to become active implements for determining large power system problems and they could become widely actual when properly connected with conventional mathematical approache [4]. Artificial Neural Networks (ANN) is a popular solution tool because of their capacity to understand complex non-linear correlations and their ability to handle applications with a large amount of historical data [5]. ANN is made up of various simple nodes (neurons) such as joined to make either a single or multiple layers. It is indispensable to study the weights that exist among neurons [6]. Connections among different layers and connections into the same layer are referred to as feedback connections. There are many varieties of Neural Networks (NNs). A feedforward network is termed by the continuous forward propagation of input and intermediate signals. In this method, the information at all times gets about from the input to the output out of the hidden layers in a forward direction [7] So, ANN more effective gadget that utilizes identification and control for system complex due to the properties of the non-linear chart to the neural networks. When the neural network training is very well and enough to give results, a controller may be used instead of PSS [8] Adjust different operating conditions and obtain satisfactory results, to control different operating conditions and get very good results; the network must be trained under different conditions. The use of backpropagation and learning networks leads to continuous interference problems [9]. The main suggestion of this work is that utilizing neural network-instituted controllers and identification might highly become better the stability and execution of SMIB systems compared to conventional control techniques. So, it is very important for the competition of high speed and the ability for learning and generalization [10]. This new study advances with comprehensive system networks within the SMIB framework, which previous research has not extensively explored. Through careful design of the complex interactions and dynamics between the generator and the infinite bus, the grid system sports approved voltage stability and alleviation of terminal damage to voltage equipment. Several studies have focused on this study of NN in power systems [11]. Reference [12] includes the advanced transient stability assessment (TSA) method of CNN+GRU, which includes convolutional neural networks and gated recurrent units, and the advanced focal loss (FL) function that can apply self-adaptive changes according to neural network training and model training ordered for guidance.In reference [9] intends to explicate and explore the application of artificial neural networks to enhance the probabilistic transient stability of the electric power system assessment process. In reference [8] to manage the low-frequency oscillation that exists in the single-machine infinite bus system (SMIB), a PSS based on neural networks is developed in this research. Neuro-PSS consists of two neurons: Neuro-identity, which simulates power flow, and the Neuro-Controller, which generates additional excitation signals. Reference [13] study uses multilayer perceptron (MLP) neurons to offer an approach for determining the normalized transient stability margin. The neural networks are used to construct the intricate link between the input and output variables. The MLP neural network is used to construct the nonlinear mapping relationship between the normalized transient stability margin and the operating circumstances of the power system. In [14] study the load margin in power systems using artificial neural networks (ANN) and genetic algorithms occurs in the publication. The load margin is an indicator that shows how close the system is to instability. Voltage stability requirements are often considered in load margin calculations; however low-frequency oscillation modes with slow damping rates can also have an impact on system performance. The suggested approach monitors the load margin by synchronizing data from Phasor Measurement Units (PMUs), considering the need for voltage stability and small-signal stability. A technique based on genetic algorithms is utilized to choose a smaller number of buses for the ANN input layer. The outcomes show that the approach can be used to track the load margin in real-time. In [15] the review of power systems for voltage stability using artificial neural networks (ANN) is covered in this article. The authors stress the need for voltage stability evaluation in maintaining the secure functioning of power systems, particularly in light of the rising demand for electricity and the scarcity of available power sources. In this study, several line voltage stability indices are introduced, and the IEEE 9-Bus and IEEE 14-Bus systems are used to test each of them. A real-time voltage stability monitoring system employing ANN is also shown, illustrating the value of computed and estimated indices in foretelling voltage breakdown. According to the results, operators can take the required steps to stop voltage collapse mishaps. This paper is organized as follows Section 2 is a review of recent literature on stability and control of power systems with a comparison of all methods for ANN by using control and Identification, Section 3, introduction to power system control, Section 4, is methodology contained system dynamic modeling, the architecture of the Neural Network design in SMIB, Process of System Identification, Architecture and training for Neural Identifier (NI), detailed with the design system controller, training of the Neural Controller (NC), Section 5, Studies and Simulation Results, Section 6 Simulation and results of the Neural Identifier (NI), Section 7, Simulation and results of the Neural Controller (NC), Section8, Simulation Training of the Neural Identifier and Neural Controller (NINC) that will be a comparative plant with and without NINC, Section 9, Conclusions this all results.

2. Recent Works

The AVR and PSS applied procedures have helped to give noticeably improved stability, especially while running in normal and minor-disturbance situations. To improve stability conditions and control systems under operating systems, more effective controller parameters must be sought. It is important to note that, as was already said, several unique optimization techniques have been explored in the pertinent literature. A sizable collection of generators, transmission lines, transformers, safety equipment, and other related components make up an electric power system. A power system's primary function is to generate, move, and distribute electrical energy. The system's end users can be linked at different voltage levels (such as subtransmission, primary distribution, and secondary distribution), and they control the necessary generation needs through their continually shifting demand [1] and [2]. Reference][16] shows how to develop feedforward and feedback controllers for discrete and continuous-time dynamical systems using the ideas of recurrent neural networks and reinforcement learning. An elegant foundation for system identification and control design is provided by neural networks. Neuro controllers or neural controllers are often created utilizing a feedforward-feedback control rule, which uses a stabilizing controller and model compensation provided by any neural network structure.In [17] research on the nonlinear control of a single-machine infinite-bus (SMIB) system for steady-state and transient stability is presented in this publication. The research looks at how the system responds to making a difference can be life changing. The findings demonstrate that the method produces accurate and reliable information on transient stability. Control methods applied to power systems to improve transient stability are also include in the paper. Reference [18] study looked at how artificial neural networks (ANNs) may be used to identify different types of faults in electric power system transmission lines. The ANN network architecture chosen for each stage of detection was trained and simulated using the two versions of the parameters. The findings demonstrate that the system experienced three line-ground faults, three line-line faults, three double-line-ground faults, and one three-phase fault. Reference [19] discusses the application of an artificial neural network (ANN) neuro controller for the control of a hydropower plant (HPP). The study compares the performance of the neuro controller with a conventional PID controller. The neuro-controller, based on the NARMA-L2 technique, offers faster system stabilization and better dynamic performance. The results show that the neuro-controller outperforms the PID controller in terms of rise time, stability, and response speed. The study highlights the potential of using neurocontrollers in complex non-linear systems like HPPs. In [20] artificial neural network (ANN)–based black-box modeling strategy for synchronous generators is presented in this article. The performance of the ANN is evaluated in comparison to other nonlinear models after it has been trained using experimental data from an actual generator. The suggested ANN model exceeds the competition and displays great accuracy. The study also provides a test method that does not call for extra tools or disconnecting the generator from the grid. The issue of oscillations in a synchronous generator connected to an endless bus through transmission lines is covered in this article. It suggests using simulated annealing (SA) and artificial neural networks (ANN) as online control approaches to eliminate these oscillations. Through the suppression of low-frequency oscillations brought on by disruptions from power grid faults, the control techniques try to avoid system instability. The simulation results demonstrate that both the SA and NN controllers successfully increase the stability of the synchronous generator while solving optimization difficulties. In [21] the necessity of an intelligent excitation control system in power plants is covered to maintain the generator's terminal voltage. To get around the problems of time delay, nonlinearity, and load variations, it suggests a unique architecture utilizing a neural controller. Through simulation, the suggested system's performance is assessed and contrasted with traditional controllers. The benefits of the intelligent controller over current controllers are emphasized. In [22] the construction of a Simple Neural Network stabilizer (SANN-PSS) for a synchronous machine in a power system is covered in the publication. It highlights the problems with conventional power stabilizer design based on linearized models and suggests using an artificial neural network to enhance system dynamics and adjust to shifting operating circumstances. The article discusses the SANN-PSS's design and comparison to a traditional Lead-Lag PSS, as well as the mathematical model of the power system. The suggested SANN-PSS outperforms other systems in terms of overshoot, settling time, and dependability, according to digital simulation findings. Paper [23] examines the use of artificial intelligence (AI) methods in the design of power system stabilizers (PSS), including fuzzy logic, neural networks, and optimization algorithms. It draws attention to the drawbacks of conventional control systems and the advantages of employing AI-based PSS to increase system performance and stability. The study examines several AI methods used in PSS design, such as controllers based on artificial neural networks, fuzzy logic, and optimization.In [24] used the artificial neural networks (ANNs) for system stability is covered in the publication. It suggests replacing traditional power system stabilizers with a predictive controller based on two neural networks. MATLAB and DIgSILENT PowerFactory exchange data to represent the control hierarchy. The simulation results show how effective the suggested structure. In [25] it is based on a combination of Convolutional Neural Network (CNN) and Graph Attention Network (GAT), and this paper shows that the multi-task transient energy analysis method captures time change properties captured by CNN time feature types, and correlations between objects associated with the embedded map are fetched using GAT. To identify the important characteristics affecting transient stability and to improve power grid operators' perceptions of stability conditions, the model further applies the Shapley additive explanation (SHAP) method. Materials findings indicate that the proposed model has strong topographic generalisation, interpretable analysis, and accuracy. In [26, 27] and [28] the article examines the use of a neuro-controller in the context of hydropower plant control, drawing a comparison with the standard PID controller. The focus studied on the examination of dynamics system behavior and the formulation of mathematical models. The controllers are simulated and compared using the MATLAB/Simulink program. The findings indicate that the implementation of the neuro-controller yields superior outcomes in terms of system stabilization speed and dynamic performance when compared to the PID controller. In reference [29] discuss power system transient stability improvement through STATCOM (static synchronous compensator) and neural networks. The authors propose an auxiliary controller for the STATCOM that adjusts the shunt sensitivity based on the device angle and speed severity The control method is applied to a New England 10-machine, 39-bus test system, and simulation results are shown STATCOM according to the system operation point to obtain the critical time you want to fix it. The controller must adjust the gain A multilayer perceptron neural network-based method is proposed to speed up the gain estimation process in online applications. Simulation results obtained by the proposed method are also presented and discussed. In general, monitoring the synchronous alternator has always been crucial to the proper operation of the generator. Load angle and other parameters of SG affect alternator output; however, when the parameter is increased, the power system's security reaches its maximum level. As a result, generators are operated much below their steady state stability limit for the secure running of a power system. An effective instrument for operating and managing power systems, the artificial neural network (ANN) is proliferating. Weight tuning for ANN takes a lot of work, but once done correctly, it runs quickly and accurately. Previously, ANNs have been trained either online or in a high-dimensional input space. As a result, either taking a long time to produce the control signal or using it in associated power systems is a little unsafe [20].

This paper's goal is to investigate and then provide a solution to improve transient stability and stabilization regulation while removing steady-state faults. It focuses on designing two neural networks (the neuro-identifier and the neuro-controller) of nonlinear systems. Both identification and control are emphasized. This object has two principal objectives. The first and most important objective is to suggest neural identification to emulate the result of the generator, and the other is neuro controller is applied to replace a PSS/AVR with a PID controller (E_{fd}) to provide a neuronal identification model that accurately emulates the characteristics of the single-machine infinite bus (SMIB) system. It focuses on designing two neural networks for nonlinear dynamical systems' steady-state stability and voltage regulation of nonlinear dynamical systems.

3. Power System Control

Numerous interrelated components make up an electrical power system. Several of these pieces are incredibly nonlinear, and some of them like synchronous and induction machines, are made up of a combination of mechanical and electrical parts. Thus, the operation and control of power systems have evolved into complex systems with various unstable properties [30]. These systems are vulnerable to various interruptions because they diffuse across such large geographic regions. Systems become considerably more brittle as a result of generators working under these disturbances having smaller stability margins [31]. A wide range of issues have started to surface with the introduction of the connectivity of massive electrical power networks. Some of these issues are caused by the oscillations (inter-area oscillations) between electrical power subsystems connected to huge networks [32]. It may be said that a system is stable if an oscillation brought on by a disturbance in the power system quickly stabilizes. If not, the system is unstable. An average power system is a multivariable system that is influenced by a variety of devices with various dynamic properties. The nature of the disturbance, operating mode, and system architecture all affect how instability manifests

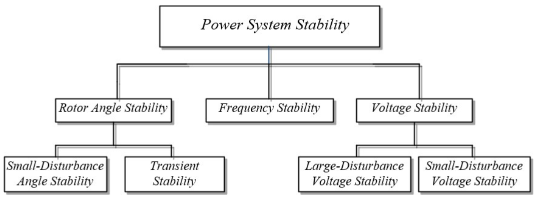


Fig. 1: Classification of power system stability.

itself. The system will typically return to normal operating conditions with the help of automated controls and/or operator intervention. Power system stability is categorized, with its categories and subcategories, in Fig. 1. The classification of power system stability makes it easier to spot instances of instability, decide how to effectively handle them, and use the right analysis techniques [33] and [34]. The power system's capacity to return to synchronism after a small disruption, such as a slight change in the loads, is known as small signal stability. In this case, the nonlinear equations of the system may be linearized to a point of equilibrium. The period for this type of stability that is important is ten to twenty seconds after a disturbance. In transient stability investigations, the time window of interest is typically 3 to 5 seconds after the disturbance; however, it might go up to 10 or 20 seconds for large systems. Voltage stability is described as a power system's ability to keep the voltage level of all busbars within an acceptable range under varying operating conditions. The most typical result of voltage instability is loading loss, which is accompanied by the tripping of transmission lines and other elements by their protective systems, resulting in cascading outages. Voltage stability may also be classified as either a significant disruption in voltage stability or a minor disturbance in voltage stability, depending on the type of disturbance. This type of stability issue can be classified as either short-term or long-term, depending on the period of interest, which ranges from a few seconds to 10 minutes. The capacity of a power system to maintain a steady frequency in the face of major supply and demand imbalances is referred to as frequency stability. It is stated if this is a short-term or long-term phenomenon. Because more than one form of instability may be seen in a power system, there is some overlap between the many types of instability [33, 34] and [35].

4. Methodology

4.1. System Dynamic Modelling

The power system is a highly complex, non-linear system; thus, when choosing a power system, the stability of the rotor angle and generator voltage management

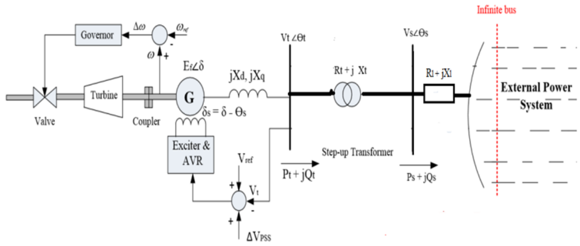


Fig. 2: Single-line diagram of the power system under study.

should be taken into consideration. Because of this, the power system has an Automatic Voltage Regulator (AVR) to control generator voltage and ensure the stability of the power system, as well as a power system stabilizer (PSS) [36] and [37]. This research takes into consideration the single-machine connected to infinite-bus (SMIB) power system configuration shown in Fig. 2 [38, 39, 40, 41] and [42]. The synchronous generator model is a seventh-order detailed dynamic model, but the excessively used model third order is still a very important tool for control and stability analysis once the generator is coupled to the power system, as stated in [33] and [34].

$$\frac{d\delta(t)}{dt} = \omega(t) - \omega_0 \tag{1}$$

$$\frac{d\omega(t)}{dt} = \frac{KD}{2H}[\omega(t) - \omega_0] + \frac{\omega_0}{2H}[Pm - Pe(t)] \tag{2}$$

$$\frac{dE'_q(t)}{dt} = \frac{1}{T'_{do}}\left[E_{fd}(t) - E_q(t)\right] \tag{3}$$

In which δ relates to the rotor angle of the generator, ω the speed deviation between the synchronism and the generator, $\mathrm{P_e}$ is the generator-delivered electrical output power, The transient EMF on the q-axis is $\mathrm{dE_q^{'}}$, the input mechanical power is P_m, E_{fd} is the input voltage excitation. The values of $\mathrm{T_{do}^{'}}$ and $\mathrm{K_D}$, H, denotes the system components that correspond to the excitation circuit time constant, dumping torque coefficient, and inertia constant respectively. Other algebraic equations are:

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

$$E_q(t) = \frac{X_{ds}}{X_{ds}}E_q(t) - \frac{X_d - X'_d}{X_{ds}}V_s cos\delta(t) \tag{5}$$

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

$$\left. V_t(t) = \tfrac{1}{X_{ds}}\begin{array}{l}\left[(X_s^2 E_{q'}(t) + X_s^2 X_d^2 + 2X_s X_d V_s E_q)\right. \\ \qquad \left. + (t)cos\delta(t))^{\frac{1}{2}}\right.\end{array}\right\} \tag{7}$$

where $X_s = X_T + \frac{X_L}{2}$, $X_{ds} = X_d + X_s$, $X'_{ds} = X'_d + X_s$. The terminal voltage magnitude is $V_t(t)$, V_s is the voltage to the infinite bus, X_q and X_d are the (q-d-axises) synchronous reactance, X'_d is the transient reactance at the d-axis, X_L and X_T denoted to the single-line reactance and the transformer. While the active electrical power, $P_e(t)$, is genuinely measure in practice, the generator's internal transient voltage. Therefore, in the system dynamic related to Eq. (1), the differential of $E'_q(t)$ might be replace by the electrical power differential (see equation (8)):

$$\left.\begin{array}{l} \frac{dP_e(t)}{dt} = \frac{1}{T'_{do}}\frac{V_s}{X'_{ds}}\sin(\delta)E_{fd}(t) + \frac{X_d - X'_d}{X'_{ds}X_{ds}}V_s^2\omega\sin^2(\delta) \\ \frac{X_d - X'_d}{X'_{ds}X_{ds}}V_s^2\omega\sin^2(\delta) + \left(\omega\cot(\delta) - \frac{X_{ds}}{X'_{ds}}\frac{1}{T'_{do}}\right)P_e(t) \end{array}\right\} \tag{8}$$

Eq. (1) and (2) provide a comprehensive description of the rotor dynamics, which include a known inertia constant. The control action E_{fd} that adjusts the field voltage to stabilize the system. We can use a combination of PID control and PSS control to achieve this. Let's denote the PID controller as u_{PID} and the output of the PSS controlle u_{PSS}. The control law for the combined control system can be formulated as: Where TA and KA denote, respectively, gain constant of the exciter time constant and the exciter gain constant and:

$$U(t) = u_{PSS} + u_{PID} \tag{9}$$

Consequently, the emphasis of this research is on the use of neural networks to analyze nonlinear power systems. The analysis uses a single-machine infinite bus (SMIB) model in the power system, which interfaces with artificial neurons generated in MATLAB using the neural interface toolbox. A time-delayed feedforward neural network is used to capture the nonlinear dynamics of the system. Notably, the discrete model is important for the training process [25]. Let us consider a system with general nonlinear discontinuity-time dynamics represented by:

$$y_{(k+1)} = f\left(y_{(k)}.., y_{(k-n+1)}, u_{(k)}, ..u_{(k-m+1)}\right) \tag{10}$$

Where y and u represent scaler output and input variable respectively. The function f: $R^n \to R$ is believed to possess differential ability with respect to its inputs The discrete time for the third-order model with sampling time T_s of the generator electrical and rotational dynamics equations is represented as:

$$\delta_{(k+1)} = \delta_{(k)} + T_s \tag{11}$$

$$\omega_{(k+1)} = \omega_k + T_s\left(\frac{1}{2H}\left(P_m - P_e - D(\omega_k - \omega_s)\right)\right) \tag{12}$$

$$E'_{q(k+1)} = E'_q + T_s.\frac{1}{T'_{do}}[E_{fd(k)} - E_{q(k)}] \tag{13}$$

Where:
(k) represents the discrete time step.
(K+1) represents the discrete next time step
Ts is the sampling time.

This research uses neural networks with two types, the neuro (identifier and controller). The architecture of the multi-layer neural network, trained using the backpropagation (BP) technique, is characterised by a feedforward network. This network exhibits a nonlinear behaviour, as it operates with inputs and outputs. The model consists of weight parameters and neurons, each of which employs a nonlinear sigmoid function.

4.2. Neural network design in SMIB

This study demonstrates the effectiveness of neural network implementation in single-machine infinite bus (SMIB) systems. We utilize two neural networks, identifiers, and controllers to capture the dynamics of nonlinear systems. It focuses on developing appropriate models for system identification and control. A feedforward neural network trained with a backpropagation algorithm can accurately represent a model of a nonlinear dynamical system. Effective training requires discrete modeling. This study presents two multilayer feedforward neural networks: one for the neural identifier and the other for the neural controller. The multilayer neural system includes nonlinear functions that capture the system's dynamics [17]. In this work, we suggest a Feedforward Neural Network (FNN) construction with a Backpropagat algorithm. A FNN is one of the modest and extremely widely utilized kinds of artificial neural networks, especially for tasks such as classification and regression. The structure of an FNN combined with backpropagation for training forms a fundamental building block in the field of neural netwoWe suggest training methods for neural networks, including Feedforward Neural Networks (FNNs), so they are critical for adjusting the network's weights to minimize the error between predicted and actual output [43]. The Levenberg-Marquardt (trainlm) method compares with two other methods Bayesian Regularization (trainbr) and Scaled Conjugate Gradient (trainscg) methods. The neural network proposed was trained using the training data set. Tab. 1 and 2 summarizes the results of training the proposed network using the three training algorithms discussed in this paper. Each entry in the table represents 50 different trials, with random initial weights taken for each trial to rule out the weight sensitivity of the performance of the different training algorithms. The table is shown below for the control and identifier. At this network when training it, the Levenberg–Marquardt algorithm takes the least value of time on average. Otherwise, the Scaled Conjugate Gradient Descent algorithm takes the most time on average. The Bayesian Regularization-based training algorithm varies its execution function more often than the Levenberg-Marquardt algorithm; thus, it takes longer. yet, this method takes a lot less time than the Scaled Conjugate Gradient Descent method.

Tab. 1 and 2 explain that the Levenberg-Marquardt method performs better than all other training algorithms calculated, in this investigation of the expression of speed when training a neural network to recognize the multimachine power system.

4.3. System identification

The neuro-identifier is designed as a multilayer feedforward neural network. We utilize the multi-layer neural network with a feedforward network trained with the BP algorithm. This training algorithm contains a delay component to increase the network's capacity to catch the behavior systems' tentative aspects. The process training employs discrete modeling to enhance the neural network to efficaciously learn and generalize the implicit patterns of the SMIB system. The training system of the Neuro-Identifier model is determined as described in Fig. 3. To train this NN model, it is necessary to have enough sets of input-output patterns and trained around stable operating points. The training procedure of a multi-layer neural network model in capturing the complex dynamics of power systems via the Levenberg-Marquardt algorithm. It is used to train the neural network efficiently and is renowned for its versatility and quick convergence in non-linear optimization system issues. The multi-input multi-output (MIMO) model proposed in ANN utilizes the multi-layer neural network with a feedforward network trained with the BP algorithm by trial and error test. For each input sample, perform forward propagation to compute the outputs of the network. So the input variables are ($\Delta\omega$, $\Delta \mathrm{E_q}$, $\Delta\delta$, $\Delta \mathrm{P_m}$, $\mathrm{E_{fd}}$) with a set of the delay values to the input layer of the neural network and the output variables ($\Delta\omega$, $\Delta\delta$, $\Delta \mathrm{E_q}$) to the output layer of the neural network.

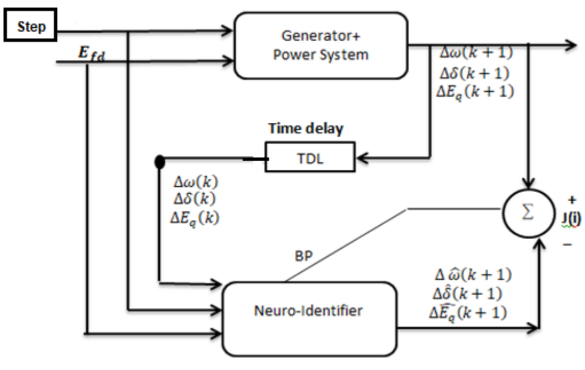


Fig. 3: Block diagram for training the neuro-identifier.

4.4. Architecture and training for NI

We utilize the multi-layer neural network with a feedforward network trained with the BP algorithm. So, the neuro-identifier is composed of two hidden layers and three output neurons, and the number of hidden neurons will be constant in later learning trials the activation function for the hidden layer is that of a sigmoid and the linear for input and output, the output of the neuron at each layer by expression the following:

$$a_i^{(k)(id)} = f\left(\sum w_{ij}^{(k)(id)} a_{(id)(k-1)}\right) \tag{14}$$

In which f is the activation function. In order to training procedure of a multi-layer neural network model in capturing the complex dynamics of power systems. The neural model has been trained around some stable operating points and after training trails, the better option artificial for data set requires are 16 inputs based on the number of delays, two hidden layers, each having 10 neurons, the algorithm for backpropagation is utilized for train the neuro-identifier. The Neuro-Identifier is placed in parallel with the system and has the following input: $[\Delta\omega, \Delta\omega(\mathrm{k}-1), \Delta\omega(\mathrm{k}-2), \Delta\omega(\mathrm{k}-\mathrm{m}),..., \Delta\mathrm{E_q}, \Delta\mathrm{E_q}(\mathrm{k}-1), \Delta\mathrm{E_q}(\mathrm{k}-2), \Delta\mathrm{E_q}(\mathrm{k}-\mathrm{m}),..., \Delta\delta, \Delta\delta(\mathrm{k}-1), \Delta\delta(\mathrm{k}-2), \Delta\delta(\mathrm{k}-\mathrm{m}), \mathrm{P_m},..., \mathrm{u}(\mathrm{k}), \mathrm{u}(\mathrm{k}-1),..., \mathrm{u}(\mathrm{k}-\mathrm{n})]$. Where $\Delta\omega$ is the generator speed deviation, $\Delta\mathrm{E_q}$ a q-axis component of the steady-state internal emf proportional to the field winding self-flux linkages, $\Delta\delta$ rotor angle, u(k) is the output of the neuro controller (generator input and neuro-identifier input) and it is referred to $[\mathrm{E_{fd}}]$, it is noted that $\mathrm{P_m}$ is the input mechanical power, and $\mathrm{E_{fd}}$ the input excitation voltage. The multi output of the identifier is the predicted ($\Delta\omega$ speed deviation, $\Delta\delta$ rotor angle, $\Delta\mathrm{E_q}$). This model is a comprehensive nonlinear framework that accounts for the interconnected nonlinear relationship between the output of the plant and previous values of both plant inputs and outputs. The backpropagation algorithm regulates the network for the weights to reduce the error among the actual system responses and the predicted outputs. One reason for choosing different values for time steps is that a third model of the system is sufficient to study the transient stability. Another reason is that more time delay means more computation previous studies have shown that differences in time delays are larger for such problems [44]. The cost function used for the NI is:

$$J_i = \left.\begin{array}{c} \frac{1}{2}\sum_i \left(e_i\left(k\right)\right)^2 = \frac{1}{2}\sum_i \left(\left(\Delta\omega(k) - \Delta\widehat{\omega}(k)\right)^2 + \right. \\ \left.\left(\Delta\delta(\mathrm{k}) - \Delta\widehat{\delta}(\mathrm{k})\right)^2 + \left(\Delta\mathrm{E_q}(\mathrm{k}) - \Delta\widehat{\mathrm{E_q}}(\mathrm{k})\right)^2\right) \end{array}\right\} \tag{15}$$

The learning rate for this data set to 0.01 to control the step size through weight updates, and the data under study is typically divided into; Training data typi-

Tab. 1: Statistical comparison of different training algorithms for the identifier.

Training Algorithm	Average Time (s)	Maximum Time (s)	Minimum Time (s)	Standard Deviation
Levenberg Marquardt	7.1867	13.803	0.05	4.0405
Scaled Conjugate Gradient Descent	78.344	151.38	0.063	42.796
Bayesian Regularization	41.364	82.677	0.06	23.997

Tab. 2: Statistical comparison of different training algorithms for the control.

Training Algorithm	Average Time (s)	Maximum Time (s)	Minimum Time (s)	Standard Deviation
Levenberg Marquardt	0.1246	0.147	0.08	0.074
Scaled Conjugate Gradient Descent	0.23	0.353	0.082	0.5165
Bayesian Regularization	0.494	0.862	0.092	0.5165

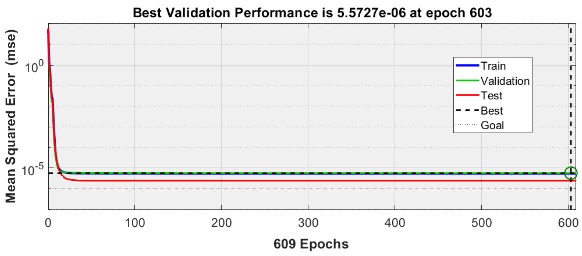


Fig. 4: Evolution of the mean square learning errors for NI.

cally comprising 70%, validation data typically makes 15% and test Data makes 15%, also measured the performance in expression of mean squared error. The evolution of these mean square learning by the Levenberg-Marquardt algorithm and the best validation performance is an average of 5.5727e-06 at epoch 603 at Fig. 4.

4.5. System controller

In a single machine infinite bus (SMIB) system, the main components include a synchronous generator, power system stabilizer (PSS), excitation system, turbine and governor system, and load dynamics. The synchronous generator is responsible for converting mechanical energy into electrical energy [44]. The PSS helps in stabilizing the system by adjusting the generator's excitation level. The excitation system regulates the terminal voltage and reactive power output of the generator. The turbine and governor system maintain the rotor speed at the desired level. Finally, load dynamics refer to the behavior of loads connected to the system that may cause fluctuations in the power output. These components collectively contribute to the functioning and stability of the SMIB system [45]. The role of the neuro-controller in regulating system parameters is essential to achieving stability and optimal performance in the single-machine infinite bus system. Various training methods can be employed for the development of a neuro-controller in the context of a SMIB. One approach is the supervised learning technique. So, this work role of the Neuro-Controller is applied to replace a PSS/AVR and PID controller to provide E_{fd}. The neuro- controller is also design from a multilayer feedforward neural network. We utilize the multi-layer neural network with a feedforward network trained with the BP algorithm.

4.6. Architecture for NC

The network has multiple layers and is feed-forward. The expected voltage at instant (k+1) in the future, the real voltage at the end, and the generator deviation speed make up its input. The neural controller emits the actual energy that excites the machine. The NN controller takes as its inputs either the delayed values of the neural network's outputs either the control signal or the system output or both. The network is trained to reproduce the given target (control signal). In this case, the difference between the NN output and the reference is used for adjusting weights during training. We utilize the multi-layer neural network with a feedforward network trained with the BP algorithm. So, the neuro controllers are composed of one hidden layer and one output neurons and with three inputs $(\omega\left(\mathrm{k}\right), \delta\left(\mathrm{k}\right), \mathrm{E}_q\left(\mathrm{k}\right))$ number of hidden neurons will be constant in later learning trials the activation function for the hidden layer is that of a sigmoid and the linear for input and output linear. Architecture of the neural control suggested in Fig. 4 the output of the neuron at each layer by expression the following:

$$a_i^{(k)(co)} = f\left(\sum w_{ij}^{(k)(co)} a^{(co)(k-1)}\right) \tag{16}$$

4.7. Training of the NC

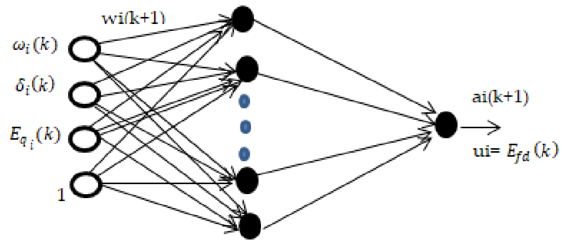


Fig. 5: Structure of Neural controller.

A simulation approach is employed to assess the performance of a neuro-controller in regulating SMIB system is shown in Fig. 5. NC is designed as a multi-layer feedforward neural network trained using the Levenberg-Marquardt backpropagation algorithm (trainlm) method. With three input, twelve hidden layer, and one output layer. The NC cascades with the training of the NI during this part the input to the NC are (rotor speed deviation (ω), load angle (δ), and stator voltage (**Eq**) and output is to generate the control signal $\mathrm{E_{fd}}$, it is then sent to the neuro identifier, which compares it to the target. The desired control signal is calculated through the neuro-identifier by comparing it with the desired response of the system through the neuro-identifier. Simulations are conducted using MATLAB/Simulink, with the neuro-controller replacing (PSS) and (PID) controllers or Automatic Voltage Regulator (AVR) controllers. The objective function used to train the neuro of the controller is given by:

$$J(k) = \frac{1}{2}\sum\nolimits_{1}^{k} \left(y_d\left(k+1\right) - y(k+1)\right) \tag{17}$$

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

$$w_i(k+1) = w_i(k) - \varepsilon\frac{\partial J(k)}{\partial w_i(k)} \tag{18}$$

$$\frac{\partial \mathrm{J(k)}}{\partial \mathrm{w_i(k)}} = \frac{\partial \mathrm{J(k)}}{\partial \mathrm{E_{fd}(t)}}\frac{\partial \mathrm{E_{fd}(t)}}{\partial \mathrm{w_i(k)}} \tag{19}$$

Where ε is the learning rate for this data set to 0.01 to control the step size through weight updates, and the data under study is typically divided into; training data typically comprising 70%,validation data typically makes 15% and test data makes 15% also, measured the performance in expression of mean squared error. The evolution of these mean square learning by the Levenberg-Marquardt algorithm and the best validation performance is an average of 1.2748e-07 at epoch 200 at Fig. 6. This section presents simulation results obtained through a specialized learning approach for neural networks. To develop a neural network controller, the initial step involves defining appropriate network architecture by specifying the number of layers and neurons in each layer. Following several learning trials, the number of hidden neurons remains constant, and the architecture that yields the fewest errors is chosen. For the hidden layer, the sigmoid activation function is commonly employed, while the input and output layers typically utilize the linear activation function.

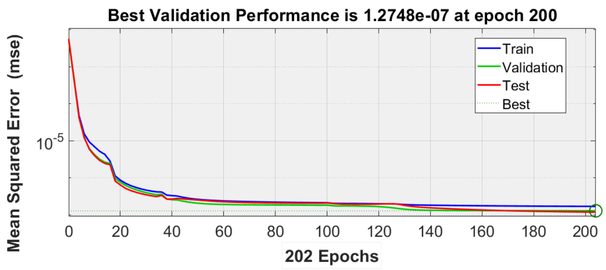


Fig. 6: Evolution of the mean square learning errors for NC.

5. Studies and Simulation Results

In this part, the performance and reliability of the system controller shown in Fig. 2 is assessed using a single generator linked via a transformer to an infinite number of buses. The assumed values for the voltage excitation are as follows:
$\mathrm{E_{fd}min} = -4\mathrm{p.u.}$ and $\mathrm{E_{fd}max} = 4\mathrm{p.u.}$

The system operates at a steady state and becomes result as follow:
$\delta_0 = 55.1\,\mathrm{deg}, E_{q0} = 1.57\mathrm{p.u.}, E_{fd0} = 1.82\mathrm{p.u.},$
$P_{e0} = 0.75\mathrm{p.u.}, P_{m0} = 0.75\mathrm{p.u.}, V_{t0} = 1\mathrm{p.u.}, V_s = 1\mathrm{p.u.},$
$T_e = 0.7516$ pu and $\omega_m = 1$ (p.u).

This result was obtained by using a steady-state condition design for (SMIB) by using solver types of Simulink with the following choices: solver (ode4 Runge-Kutta), type (fixed step) and the primary sample time (10-4 s). At steady state (before fault) and the transient stability based on a three-phase short circuit applied at the system of the infinite bus with the comparison of the system responses cases, which are described as follows:

The system is exposed to a three-phase short circuit fault that occurred near the infinite bus at t= 3m s and cleared at 100ms by the disconnection of the faulted and the result shows the rotor speed deviation (ω), load angle (δ), and stator voltage ($\mathrm{E_q}$) is shown in Fig. 7(a, b, c) respectively.

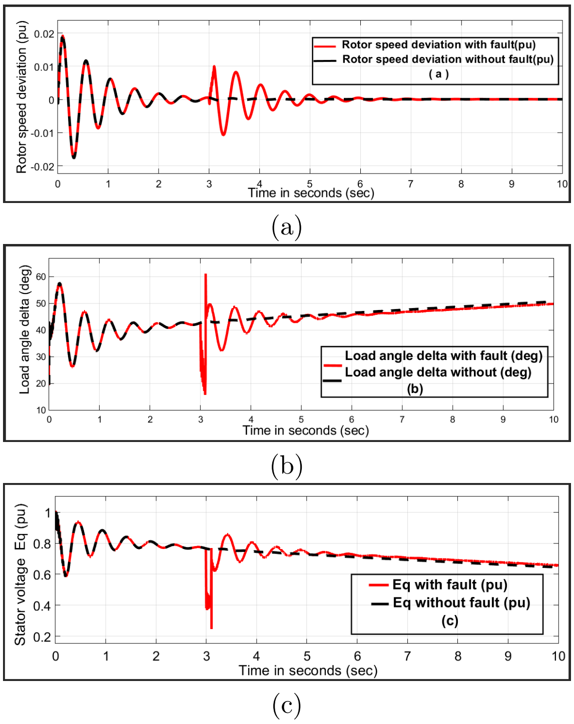


Fig. 7: Three-phase short-circuit responses of the case with and without fault: (a) Rotor speed deviation; (b) load angle delta(c) stator voltage.

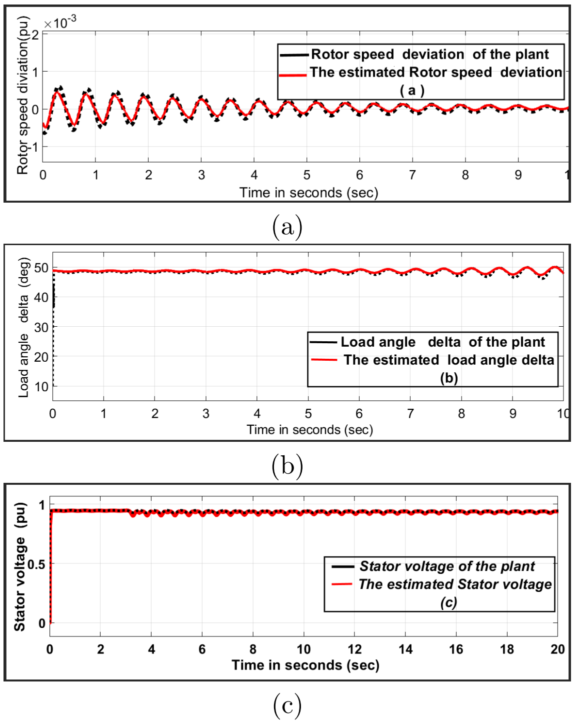


Fig. 8: The result from the training of the Neuro-Identifier case 1: (a) Rotor speed deviation (b) load angle delta (c) stator voltage.

6. Simulation of the NI

The neural model has been trained around some stable operating points. The artificial neural network (ANN) requires 16 inputs based on the number of delays. The network design includes two hidden layers, each having 10 neurons, which helps capture intricate patterns and correlations present in the data. The proposed framework has a hierarchical learning procedure, with the first hidden layer capturing intermediate characteristics and the second hidden layer amalgamating these features to generate more abstract representations. This can potentially improve the network's capacity to generalize and acquire complex associations within the input data and we suppose two cases:

Case 1: Suppose the system has a fixed mechanical power (P_m) and the field voltage is variable. The results of training the neuro-identifier are shown in Fig. 8.

Case 2: When power mechanical (P_m) is variable and field voltage is variable. The result from the training of the NI is shown in the Fig. 9.

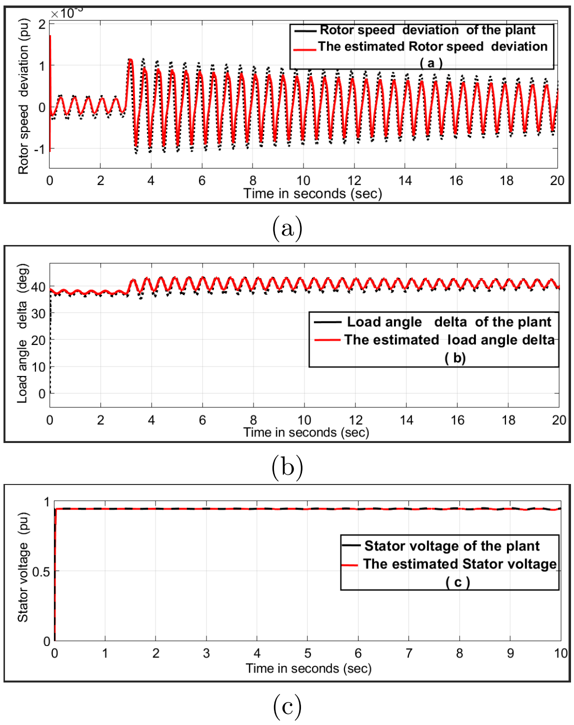


Fig. 9: The result from the training of the Neuro-Identifier case 2: (a) Rotor speed deviation (b) load angle delta (c) stator voltage.

7. Simulation of the NC

In this study, a simulation approach is employed to assess the performance of a neuro-controller in regulating SMIB system is shown in Fig. 10. With three neurons in the input layer, twelve neurons in the hidden layer, and one neuron in the output layer. The NC cascades with the training of the NI during this part the input to the NC are rotor speed deviation (ω), load angle (δ), stator voltage (**Eq**) and output is to generate the control signal E_{fd}, it is then sent to the neuro identifier, which compares it to the target. The desired control signal is calculated through the neuro-identifier by comparing it with the desired response of the system through the neuro-identifier. Simulations are conducted using MATLAB/Simulink, with the neuro-controller replacing (PSS) and (PID) controllers or Automatic Voltage Regulator (AVR) controllers. This section presents simulation results obtained through a specialized learning approach for neural networks. To develop a neural network controller, the initial step involves defining appropriate network architecture by specifying the number of layers and neurons in each layer. Following several learning trials, the number of hidden neurons remains constant, and the architecture that yields the fewest errors is chosen, it is essential to select a suitable structure for the neural network.

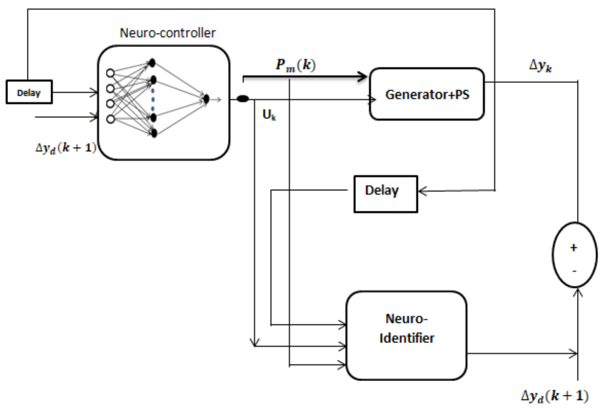


Fig. 10: The neural network controller of training proceses.

8. Simulation training of the (NINC)

A simulation is performed for the several types of faults in the system. The training process of the NINC takes place in both. neuro-controller with the training of the neuro-identifier in cascade shown in Fig. 11 during this stage, the input to the neuro-controller is (ω), (δ), and (**Eq**) and the output is the (E_{fd}). which is then fed to the NI and plant system, the output signals are calculated through the NI by comparing the output of the neuro identifier and output signals of the plant. The process of training the neuro-controller and neuro-identifier is conducted for various operating points and

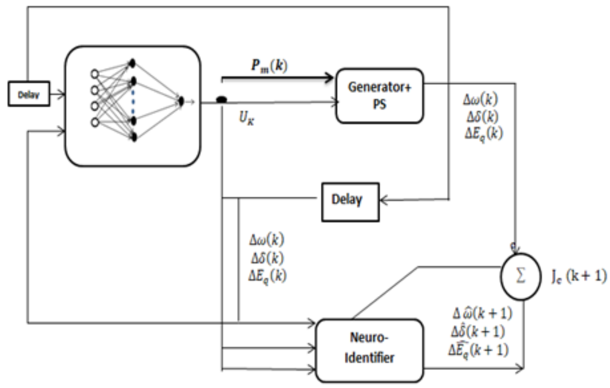
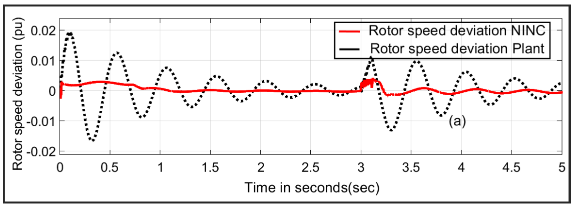
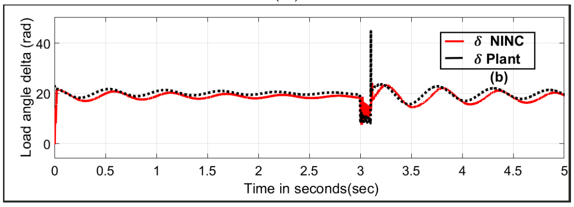


Fig. 11: Block diagram for training the NINC.

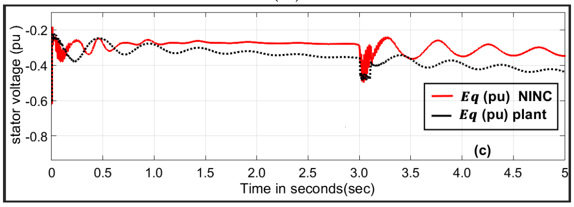
system configurations until the weights of the neuro-controller reach convergence. So, to assess the efficacy of the neuro-controller, it is necessary to analyze the system response of the NINC. The investigation occurs inside various disturbances. These disturbances are the three-phase to ground fault at the infinite bus. The comparison is carried out under two types of faults. The system is subjected to a three-phase to ground fault that occurred near the infinite bus at t= 3 ms and cleared at 100 ms by the disconnection of the faulted, it can be seen that the result of the NINC for the rotor speed deviation (ω_i), load angle (δ), and stator voltage (E_q) is better than the output of the plant without the result shows the rotor speed deviation (ω_i), load angle (δ), and stator voltage (E_q) is shown in Fig. 12 and the neuro controller improves its performance on the design. Neuro-Identified Neuro-Controller (NINC) objects show how well they work to improve the stability and performance of power systems in a range of operating conditions and disturbances. It is clear from the simulations and tests that the NINC works better than the uncontrolled plant because it lessens the effects of disturbances like three-phase ground faults near the infinite bus. When there are different problems, the NINC can handle them without any problems and does a great job of keeping the system stable and reducing changes in important variables like rotor speed deviation, load angle, and stator voltage. Also, the NINC's training process, which includes training the NINC's training program continues in both directions. The neuro-controller is accompanied by the training of the one after the other, causes the weights to converge, which shows that the system has learned and adapted to its surroundings. This shows that the approach is a good one for controlling and managing power systems because it is more stable, flexible, and effective than traditional control methods. As evidenced by the varying system response between different fault-clearing times, the NINC represents a promising approach for power system control and management, offering en-



(a)



(b)



(c)

Fig. 12: Three-phase short-circuit responses of the case NINC: (a) Rotor speed deviation (b) load angle delta (c) stator voltage.

hanced stability, adaptability, and performance compared to traditional control strategies.

9. Conclusions

This study produced a power system design was complex which included a single generator equipped with an IEEE type-1 excitation system. The system was simulated and designed to utilize MATLAB Simulink. The detection made in this research displays that the employ of this pattern allows for the evaluation of power system stability over a broad spectrum of operational scenarios. Additionally, it is crucial to incorporate additional controllers for the excitation system of the synchronous generator, commonly known as Power System Stabilisers (PSS and PID), to improve its stability and increase the maximum limit of power transmission capacity in response to changes in load conditions. It is easier for the artificial neural network (ANN) to adapt and use in different situations, which means it can manage a wider range of problems that can happen in power systems at various times. The results show that the suggested artificial neural network (ANN) controller and identifier could work well in a wide range of situations because they are very accurate, have a quick response time and can change with the situation. Hence, the suggested artificial neural network (ANN) controller is seen to be more appropriate for addressing the issue of tiny signal stability in power systems.

Author Contributions

Shaimaa Shukri developed the methodology, and simulation with wrote the entire paper. Wissam Bahloul was responsible for validating the research results. Nabil Derbel contributed to reviewing and editing the manuscript. Supervised the research by Mohamed Chtourou.

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