Ain Shams Engineering Journal 16 (2025) 103790

Contents lists available at ScienceDirect

Ain Shams Engineering Journal

journal homepage: www.sciencedirect.com

Full Length Article

Optimal coordinative design of SVC and PSS with the application of neural network to improve power system transient stability

Waseem Akram [a], Aslam Pervez Memon [a], Muhammad Ismail Jamali [a], Mohsin Ali Koondhar [a], Zuhair Muhammed Alaas [b], Ezzeddine Touti [c], Mohammed H. Alsharif [d], Mun-Kyeom Kim [e,*]

[a] Department of Electrical Engineering, Quaid-e-Awam University of Engineering, Science and Technology Nawabshah, Sindh 67450, Pakistan
[b] Department of Electrical and Electronics Engineering, Faculty of Engineering and Computer Science, Jazan University, Jizan 45142, Saudi Arabia
[c] Center for Scientific Research and Entrepreneurship, Northern Border University, Arar 73213, Saudi Arabia
[d] Department of AI Convergence Electronic Engineering, Sejong University, Seoul 05006, the Republic of Korea
[e] School of Energy System Engineering, Chung-Ang University, 84 Heukseok-ro, Dongjak-gu, Seoul 06974, the Republic of Korea

ARTICLE INFO

Keywords:
Power system stability
Transient stability
Voltage regulation
PSS
SVC
ANN
SimPowerSystem

ABSTRACT

This study presents an Artificial Neural Network (ANN)-based coordinated control approach that integrates Static VAR Compensators (SVC) and Power System Stabilizers (PSS) to enhance the transient stability of power systems. The proposed method is tested on a two-area, two-machine, three-bus system supplying a 5000 MW resistive load using MATLAB/Simulink. The system includes two generating plants rated at 1000 MVA and 5000 MVA, respectively. A feedforward ANN with two hidden layers (each containing five neurons) is trained using 60 % of the data and the Levenberg-Marquardt backpropagation algorithm. Simulations involve two main fault scenarios: a single line-to-ground (SLG) fault applied at 4 s and cleared at 4.2 s, and a three-phase-to-ground (LLL-G) fault cleared at 4.1 s. Without any controllers, the system shows significant instability, with rotor angle deviation exceeding 90° and voltage sags of up to 0.5 p.u. When PID-based Generic-PSS is applied, stabilization is observed after 6 s, with residual speed oscillations of ±0.02 p.u. However, the ANN-based Generic-PSS reduces recovery time to approximately 3.2 s, enhances damping by over 40 %, and decreases voltage overshoot by around 25 %. Furthermore, the ANN-based MB-PSS in combination with SVC confines bus voltage deviations to within ±0.01 p.u. and speed deviations below ±0.005 p.u., even during severe LLL-G faults. Overall, the ANN-based controllers outperform conventional PID-based approaches by providing faster damping, improved voltage regulation, and enhanced robustness under fault conditions, making them a promising solution for smart grid applications.

1. Introduction

As the world is growing in populations and regions so that demand of electrical power consumption is also increasing. So it is required to increase in generation of power, its transmission and distribution same way to fulfill the need [1–3]. As power demand has increased in a largish way in recent years while on other side the expansion of power generation and its transmission due to limited resources and environmental restrictions has been severely limited [4]. Due to that increasing demand of energy consumption and the construction of large generating plants mainly due to opening of power electric markets, it becomes highly essential to provide secure, stable, controlled and high quality of electrical energy on today's highly electronic environment [5,6]. Maintaining power system stability has been a significant challenge for secure and controlled operation since the 1920 s [7,8]. Stability in a power system refers to its ability to maintain equilibrium under normal conditions and return to equilibrium after a disruption [9,10]. Stability is crucial to prevent disturbances such as oscillations, faults, voltage sags, and frequency fluctuations [11]. Instability can cause voltage and frequency fluctuations, leading to equipment failure or damage [12]. Power System Stabilizers (PSS) have long been used to dampen electromechanical oscillations and enhance transient stability by generating electrical torque through the generator's excitation system [13,14]. However, PSS alone may be insufficient for inter-zone modes, and their coordination in multi-machine systems is challenging due to potential negative impacts on other modes [15]. The management of reactive

* Correspondence author.
E-mail addresses: malsharif@sejong.ac.kr (M.H. Alsharif), mkim@cau.ac.kr (M.-K. Kim).

https://doi.org/10.1016/j.asej.2025.103790
Received 3 June 2025; Received in revised form 7 August 2025; Accepted 23 September 2025
Available online 8 October 2025
2090-4479/© 2025 The Authors. Published by Elsevier B.V. on behalf of Faculty of Engineering, Ain Shams University. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

power through VAR compensation and the use of FACTS controllers is essential to enhance power system stability [16,17]. As modern power systems face increased demand and overloading of long transmission lines, transient stability becomes a critical concern, requiring robust solutions like PSS and FACTS to maintain stable operation after significant disturbances [18,19]. Flexible Alternating Current Transmission System (FACTS), which can regulate network conditions quickly, increase transient and steady state stabilities, and boost voltage regulation, is presently used to stabilize many complex power systems[20–22].

FACTS controllers offer rapid and efficient control over transmission line parameters, including terminal voltages, line impedances, and voltage angles [23,24]. Their benefits include improved system dynamic response, robustness, and loadability [25–27]. Beyond power flow control, FACTS devices also enhance power system stability, making their installation crucial for optimizing existing systems and increasing transmission capacity [28–30]. With proper control strategies, FACTS devices can interact with one another and coordinate with other systems to stabilize and enhance overall system stability [31–33]. These controllers, classified into series, shunt, combined series-series, and combined series-shunt types, regulate various power system parameters such as oscillation damping, current, voltage, impedance, and line power [34,35]. Recent studies have explored advanced techniques like parameter coordination optimization using BP neural networks [36], Adaptive Rat Swarm Optimization for tuning SVC and PSS parameters [37], and optimized PID controllers using the Archimedes optimization algorithm for transient stability enhancement [38,39]. These advancements reflect the ongoing evolution in power system stability research. In [40] have proposed a research work in which authors presented the modulation and simulation of a SMIB system. The transient stability of the above said system enhanced using power system stabilizer and its coordination with a shunt FACTS controller SVC. The authors have used an optimization-based technique that is Genetic Algorithm to search the ideal parameters of the PSS and the SVC for a SMIB. In [41] different sorts of disturbances that arise in the power systems such as unexpected changes in load, generation and transmission failures, lines switching, etc. can produce an imbalance in the power system's coordinated operation. The authors have discussed the transient stability improvement using PSS of SMIB power system against Electric Vehicle (EV) disturbance. An LQR base PSS was designed for the power system's stability improvement.

The comprehensive literature review highlights the critical role of coordinating shunt FACTS controllers, specifically Static VAR Compensators (SVCs), with traditional Power System Stabilizers (PSSs) employing PID controllers to enhance transient stability in power systems. While PID controllers offer effective control, their limitations in handling non-linearity and gain variations are evident. Consequently, the research indicates the suitability of Artificial Neural Networks (ANNs) as a promising alternative due to their potential to mitigate these limitations and provide improved control strategies for transient stability enhancement. The reliable operation of power systems is of paramount importance, and transient stability plays a pivotal role in ensuring uninterrupted electricity supply to consumers. However, the contemporary power generation and transmission landscape faces multifaceted challenges, including resource limitations and stringent environmental regulations, which limit the expansion of infrastructure. Consequently, heavily loaded transmission lines are increasingly prevalent, elevating the risk of instability in power systems. Addressing this challenge is imperative, as instability can lead to voltage and frequency fluctuations, equipment damage, power outages, and substantial economic ramifications. To maintain the stability of power systems under these evolving conditions, there is a pressing need to explore advanced control strategies, particularly the coordination of FACTS controllers like Static VAR Compensators (SVCs) and Power System Stabilizers (PSSs), augmented by emerging technologies such as Artificial Neural Networks (ANNs). This research aims to investigate and optimize the coordinated deployment of SVCs and PSSs, with the integration of ANNs, to enhance transient stability in power systems, thereby ensuring reliable, efficient, and secure electrical energy delivery. This investigation is motivated by three critical challenges:

i. Equipment Safety and Reliability: The first challenge pertains to safeguarding the safety and reliability of electrical equipment within the power system. Voltage and frequency fluctuations caused by instability can lead to premature equipment failure, damage, and increased maintenance costs, posing a substantial risk to both utilities and consumers.
ii. Operational Costs and Efficiency: The second challenge revolves around the economic implications of power system instability. Instability necessitates costly infrastructure upgrades, emergency measures, and reactive maintenance, straining the financial resources of power utilities and potentially resulting in higher electricity costs for consumers.
iii. Public Safety and Emergency Preparedness: The third concern relates to public safety and emergency preparedness. Power system instability, if left unaddressed, has the potential to trigger widespread blackouts with severe consequences for public safety, particularly in critical sectors such as healthcare and transportation. Ensuring power system stability is essential to mitigate such risks and maintain the uninterrupted functioning of essential services during grid disturbances.

1.1. Related work and novelty Justification

While previous studies have explored the application of artificial neural networks (ANNs) for tuning power system stabilizers (PSS), most have focused on single-machine or simplified system models, or have used ANNs primarily for offline parameter optimization. In contrast, this work proposes a real-time ANN-based control strategy for the coordinated operation of PSS and Static VAR Compensator (SVC) in a two-area, two-machine interconnected power system under both SLG and LLL-G faults. Unlike earlier efforts that often required retraining for new conditions or lacked integration with FACTS devices, the proposed ANN structure dynamically responds to varying fault conditions without manual tuning, demonstrating improved damping, voltage stability, and speed recovery. In[36–38] have applied evolutionary algorithms or optimization heuristics for controller tuning, yet they lack the adaptability and low-latency decision-making of the trained ANN deployed here[4]. This distinction, coupled with extensive scenario-based validation, forms the key novelty of this study.

Main Contributions of the Paper are as follows:

- A novel Artificial Neural Network (ANN)-based coordinated control strategy is developed, combining PSS and SVC, to enhance transient stability in a two-area, two-machine power system.
- The ANN controller is trained using simulation-based data under various fault conditions (SLG and LLL-G), offering real-time control adaptability.
- Comparative performance analysis is carried out among PID-based PSS (Generic and MB-PSS), ANN-based PSS, and combinations with SVC under both SLG and LLL-G fault conditions.
- The ANN-based MB-PSS in coordination with SVC demonstrates significant improvements in damping, voltage recovery, and rotor angle stability achieving $\pm$ 0.01p.u. voltage regulation and $<\pm$0.005p.u. speed deviation under severe disturbances.
- The simulation results validate the superiority of the proposed approach over conventional controllers, making it suitable for future smart grid applications.

The organization of this research is as follows: the Section 1 introduces the power system model used, Section 2 discusses Power System Stabilizers (PSSs), Section 3 covers Static VAR Compensators

(SVCs), and Section 4 explains Artificial Neural Networks (ANNs). Section 5 is subdivided into four subsections, each detailing simulations and results for different fault scenarios, including SLG and three-phase-to-ground faults with PID-based controllers, as well as single-phase-to-ground and LLL-G faults with ANN-based controllers. Finally, Section 6 provides a concluding summary of key findings, implications, and suggestions for future research.

1.2. Problem statement

Modern power networks are under tremendous strain as a result of the restricted growth of generating and transmission infrastructure, which is limited by resource and environmental constraints, and the growing demand for electricity worldwide. Transmission lines get overburdened as a result, and there is a greater chance of instability during disruptions. Improving transient stability is essential to avoiding system failure. Although static VAR compensators (SVC) and traditional power system stabilizers (PSS) are frequently utilized to reduce power oscillations, their effectiveness is frequently constrained in non-linear, dynamic fault scenarios. System response is further hampered by inadequate coordination and adaptive control techniques. To improve damping performance and stability, an intelligent and coordinated control framework incorporating cutting-edge technologies like Artificial Neural Networks (ANNs) is therefore required.

1.3. Research methodology

The proposed methodology involves the development and simulation of an Artificial Neural Network (ANN)-based coordinated control scheme integrating a Static VAR Compensator (SVC) and Power System Stabilizers (PSS) to enhance transient stability in a multi-machine power system. A two-area, two-machine, three-bus system supplying a 5000 MW resistive load is modeled in MATLAB/Simulink. Generating units rated at 1000 MVA and 5000 MVA are considered in the test system, which includes long transmission lines to reflect realistic operational dynamics. The control framework is implemented in two phases. First, conventional PID-based PSS controllers are applied and their performance evaluated under fault scenarios. In the second phase, these PID controllers are replaced with a feedforward ANN controller, trained using the Levenberg-Marquardt backpropagation algorithm. The ANN architecture includes two hidden layers, each with five neurons, and utilizes 60 % of the simulation-generated dataset for training and 30 % for testing. Input features to the ANN include dynamic system parameters such as rotor angle, voltage deviations, and speed differences. Transient faults are introduced at specific intervals: a single line-to-ground (SLG) fault is applied at 4 s and cleared at 4.2 s, and a three-phase-to-ground (LLL-G) fault is applied a 4.1 s and cleared at 4.1 s. System performance is evaluated based on rotor angle stability, speed deviation, voltage recovery, and damping response. Comparative analysis demonstrates that the ANN-based controllers, particularly when combined with SVC and Multiband PSS (MB-PSS), significantly as compared to conventional PID-based schemes in terms of damping efficiency, voltage stability, and resilience under severe fault conditions. This validates the effectiveness of the proposed ANN-SVC-PSS coordination strategy for enhancing power system transient stability.

1.4. Power system model

A multi-machine power system is used as a test model, which is shown in Fig. 1. It consists of a two-machine, two-area, three-bus power system with two power transformers and a resistive load of 5000 MW connected. A 1000 MVA hydraulic generation plant (machine M1) is connected to a load center through a long 500 kV, 700 km transmission line. The load center is modeled by a 5000 MW resistive load. The load is fed by the remote 1000 MW plant and a local generation of 5000 MVA (machine M2). The system has been initialized so that the line carries 950 MW which is close to its surge impedance loading (SIL = 977 MW). In order to maintain system stability after faults, the transmission line is shunt compensated at its center by a 200-Mvar Static Var Compensator (SVC). Notice that this SVC model is a phasor model valid only for transient stability solution. The SVC does not have a Power Oscillation Damping (POD) unit. The two machines are equipped with a Hydraulic Turbine and Governor (HTG), Excitation system and Power System Stabilizer (PSS). These blocks are located in the two 'Turbine and Regulator' subsystems. Two types of stabilizers can be selected: a generic model using the acceleration power (Pa = difference between mechanical power Pm and output electrical power Peo) and a Multiband stabilizer using the speed deviation (dw). The stabilizer type can be selected by specifying a value (0=No PSS, 1=Pa PSS or 2 = dw MB PSS) in the PSS constant block.

2. Power system stabilizer (PSS)

For many years Power System Stabilizers (PSS) have been used to dampen electromechanical oscillations in the power system [42–44]. PSS controllers (see Fig. 2) have the ability to improve the stability of the synchronous machine by varying the excitation through using high speed exciters and accordingly, changing the AVRs. These controllers damp out electromechanical oscillations by adding damping to the generator unit's attributes by modulating or changing the excitation of generator to produce the components of electrical torque (damping torque) that are in phase with the rotor speed deviations [45,46]. Thus, the PSS improves the small signal stability of the power system. Generator shaft speed, terminal bus frequency, and electrical or accelerating power are common inputs to the PSS. It includes a high pass filter known as a washout block, and a lead-lag block, a gain block, and other components in a power system. The two types of PSS are used in this research work: Generic PSS and Multiband PSS.

3. Static VAR Compensator (SVC)

Static VAR Compensator (SVC) is a shunt-connected FACTS device connected in parallel to the line [47,48]. It acts as a load or generator that its output is regulated to exchange inductive or capacitive current

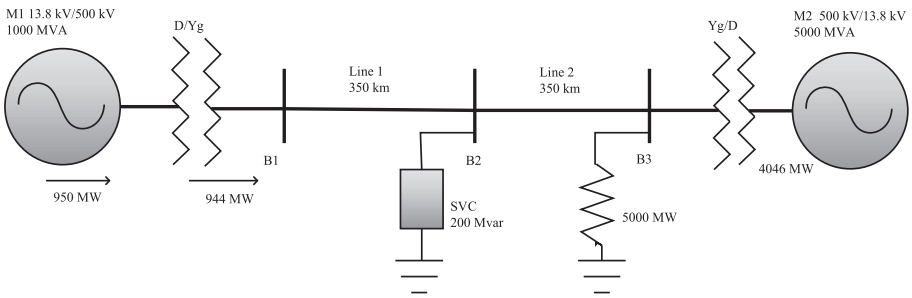


Fig. 1. Single line diagram of under study test system [12].

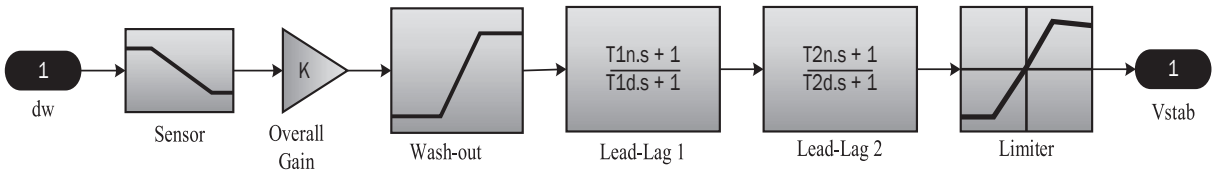


Fig. 2. Block diagram of PSS [9].

so as to maintain or control specified variables of the power system [49–51]. It is connected in the power system and controls voltage and reactive power to enhance transient stability[52,53]. By injecting or absorbing reactive power, the SVC regulates voltage. When the system voltage decreases, the SVC operates in capacitive mode and generates reactive power[54–56]. Conversely, when the power system voltage increases, the SVC operates in inductive mode and absorbs reactive power. As shown in Fig. 3, a typical SVC consists of one or more banks of capacitors and reactors that can be stabilized or controlled by thyristors. The capacitor banks and inductor banks can be switched to change the reactive power. Thyristor switched capacitors (TSC) switch the capacitors ON and OFF, while thyristor-controlled reactors (TCR) control the reactors.

The SVC operates in two modes [25,57];

1. VAR Control Mode (Fixed Susceptance, Bref = 0)
2. Voltage Regulation Mode

A variable susceptance type SVC is employed in this investigation. Conduction angle α and the compensator inductive susceptance B_L have a non-linear relationship for fundamental frequency, given by:

$$B_L(\alpha) = 2\pi - \sin\left(\frac{2\alpha}{\pi}\right)X_s \quad \text{For} \quad \frac{\pi}{2} \le \alpha \le \pi \tag{1}$$

where X_S is the SVC reactance and given by:

$$X_s = \frac{V_s^2}{Q_L}$$

where, V_S is SVC bus bar voltage; Q_L is the MVA rating reactor.

The magnitude of the SVC's total susceptance (B), given by:

$B = (B_L - B_C)$

where, B_C is a base capacitor that permits the compensator's range to enter both the capacitive and inductive sections. The effective shunt admittance for the SVC is given by (2), since the TCR-F_C and F_C are combined in the SVC.

$$B_s = \left[\frac{1}{X_c}\right] - B_L(\alpha) \tag{2}$$

where X_C is capacitive reactance.

As depicted in Fig. 4, the SVC 's control system is composed of a voltage regulator, synchronizing system, and measurement system. The

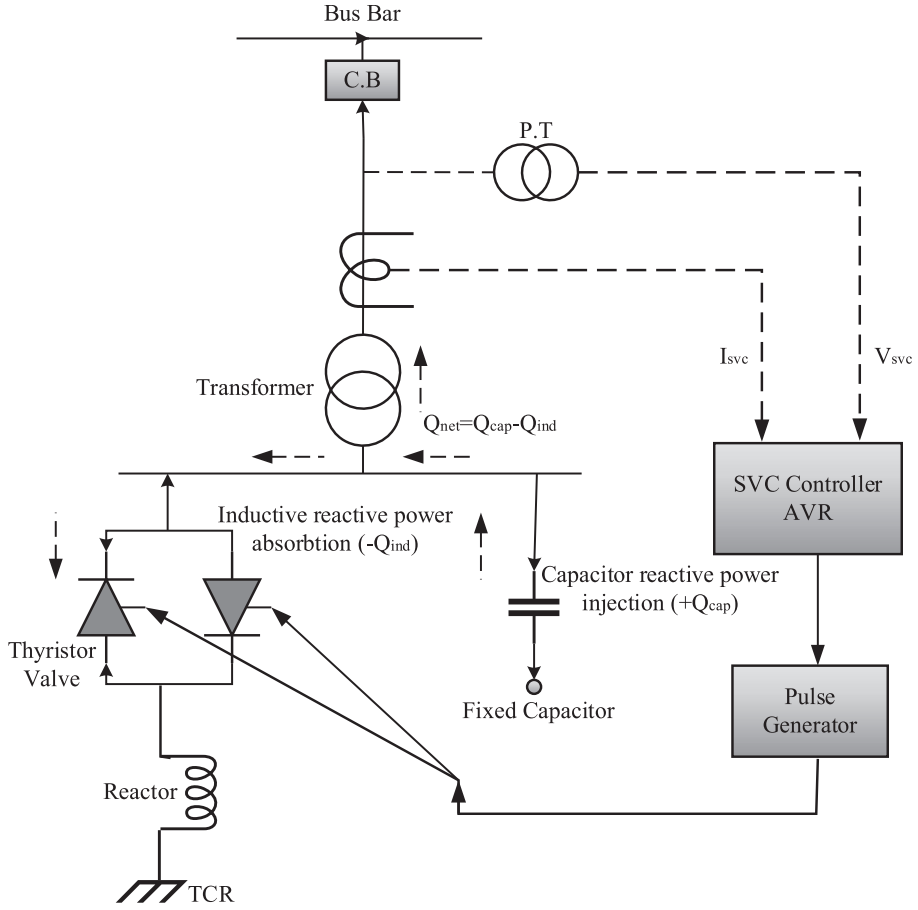


Fig. 3. SVC based control system.

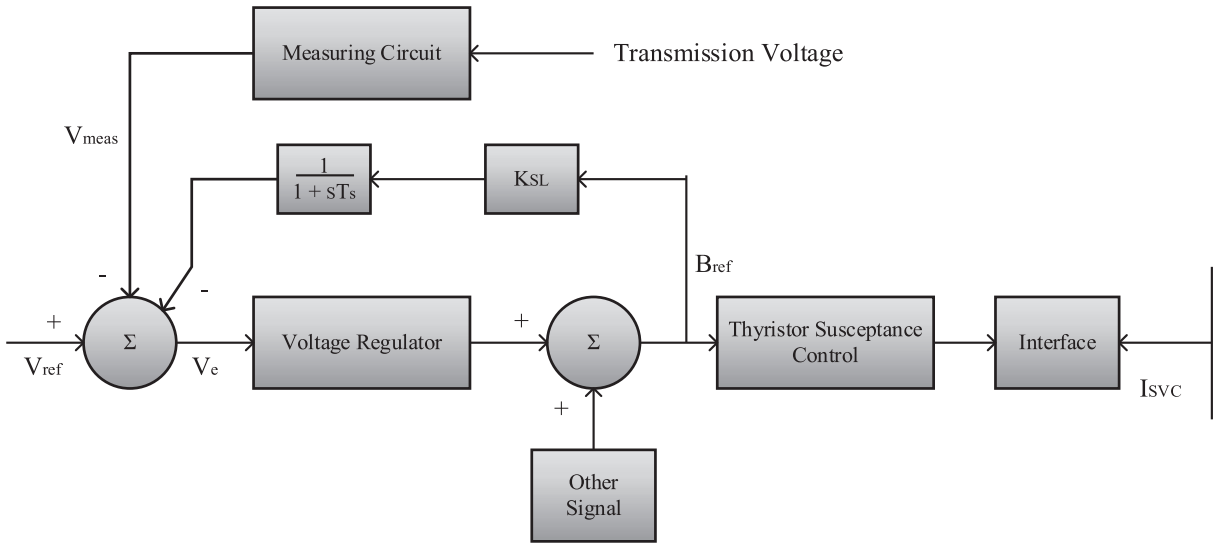


Fig. 4. Control System of SVC [9].

controllable positive sequence voltage is measured by the measurement system. A voltage regulator measurement system that uses the voltage error using the Fourier transformation. The difference between the reference voltage (Vref) and the measured voltage (Vm) determines the SVC suspectance (B). For the system voltage to remain constant, the susceptance (B) is crucial. The distribution unit that calculates the firing angle 'α' of the TSC (and subsequently of the TCR) to be switched IN and switched OUT. A phase-locked loop (PLL) and a pulse generator make up a synchronization system that delivers the proper pulse to the thyristor. Assuming a balanced, fundamental frequency operating with sinusoidal voltages results in the SVC model for transient stability, as shown in Fig. 5. It can be represented by Eqs. (3) and (4):

$$\begin{bmatrix} X_c' \\ \alpha' \end{bmatrix} = f_c\left(X_c, \alpha, V, V_{ref}\right) \tag{3}$$

$$0 = \begin{bmatrix} P - (2\alpha\sin(2\alpha) - \pi) - \pi\left[2\left(\frac{X_L}{X_C}\right)\right]/\pi X_C \\ I - ViB_e \\ I - Vi^2B_e \end{bmatrix} \tag{4}$$

4. Artificial Neural network (ANN)

A feedforward neural network is used in this research. The activation functions are taken as 'logsig', 'logsig', 'tansig' and 'purelin' for the input layer, two hidden layers and output layer, respectively. The Levenberg-Marquardt Backpropagation algorithm is employed as the training algorithm, which employs the gradient descent method to reduce error [58]. The selection of Artificial Neural Networks (ANNs) over traditional optimization techniques such as Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) is based on their superior adaptability and fast response in real-time applications. Once trained, the ANN controller operates with high computational efficiency and minimal processing delay, which is crucial for transient stability control during faults. Unlike conventional methods that often require repeated iterations and are optimized offline, ANNs provide generalized solutions that adapt to non-linear system behavior and fault conditions dynamically. The network architecture in this study, which includes two hidden layers with five neurons each, was specifically designed to balance complexity with computational speed. The training phase used 60 % of the dataset with the Levenberg-Marquardt algorithm to ensure quick convergence and robust learning. Once deployed, the ANN controller demonstrated improved damping, reduced voltage deviations, and faster stabilization compared to PID-based methods, confirming its practical advantages for online power system control. The training process employs the Levenberg-Marquardt backpropagation algorithm due to its fast convergence and robustness in minimizing the mean squared error. This detailed architecture ensures both accurate learning and efficient generalization, making the ANN suitable for real-time transient stability control in dynamic power system environments. Transmission line parameters are applied to the input layer, two hidden layers with five neurons in each. The transmission line parameters are sent to input layer and weights and biases in each hidden layers are modified and tuned using above mentioned activation function [59].

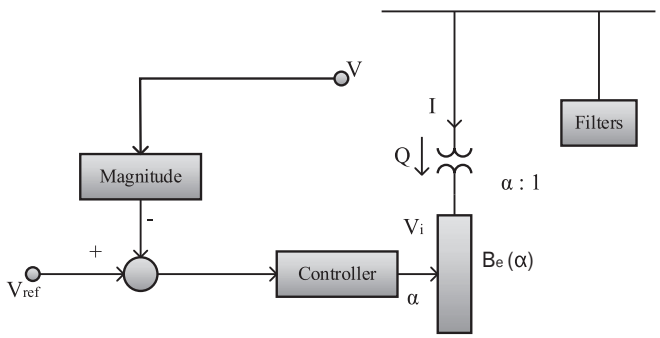


Fig. 5. Transient Stability model of SVC [9].

In this study, the dataset used to train the neural network was generated through extensive simulations of the two-area, two-machine power system model using MATLAB/Simulink under various fault scenarios, including SLG and LLL-G faults. The input features consist of transmission line parameters and system operating conditions, while the target outputs are the optimal control signals for PSS and SVC coordination. A total of 1000 data samples were collected, out of which 60 % were used for training the network, 20 % for validating the network and 20 % for testing the controlle). Before training, the dataset was normalized to ensure consistent scaling, and noise filtering was applied to reduce simulation-induced artifacts. The model's performance was validated by comparing the ANN controller's response to unseen fault conditions against traditional PID controllers, demonstrating improved damping and stability. These details have been added to the manuscript to clarify the data generation and validation strategy.

The weights and biases are adjusted to minimize the error. The number of iterations depends on the fixed number of epochs. At the end

of each epoch, the network's output is calculated, compared to the goal data, and an error is calculated.

The output function of the network is given by Equation (5)

$$Y = f\sum_{i=1}^{n}(w_{ji}x_i + b_j) \tag{5}$$

The output of hidden layer is

$Y = f\sum_{i=1}^{n}(w_{ki}p_i + b_k)$ (6)The output of entire system from (5) & (6)

$$Y = f\sum_{i=1}^{n}[w_{ji} - f\sum_{i=1}^{n}(w_{ki}\,p_i + b_k) + b_j] \tag{7}$$

where w_{ji} is the weight of output layer, w_{ki} is the weight of hidden layer, b_j and b_k represent the bias of hidden and output layer respectively. P_i being the input to the system, x_i being fed to the output layer.

5. Simulation and results

In this section, the simulation of the proposed model is performed in MATLAB/SimPowerSystems and obtained results are discussed. The system is a two-machine, three-bus system. The system's specifications are shown in Table 1. To prove the effectiveness of the controllers under a variety of operating situations and various disturbances, including three phase faults, the simulation results of a two-area, two-machines, three-bus power system for transient stability enhancement employing the PSS, SVC and ANN-based controllers are shown and discussed in this section. The simulations are performed on MATLAB/SimPowerSystems. The Fig. 6 shows the simulation model of the power system under study.

In this study, the coordination between the Static VAR Compensator (SVC) and Power System Stabilizer (PSS) is achieved through an Artificial Neural Network (ANN)-based control strategy that dynamically adjusts their control signals based on system conditions. The ANN is trained to recognize patterns in voltage, rotor angle, and speed deviations, and to generate optimized control actions that are applied simultaneously to both the SVC and PSS. The control synchronization is implicitly handled through the shared input–output learning framework, ensuring both devices respond cohesively to disturbances. The optimization constraints considered include maintaining system voltages within ±5 % of nominal, rotor angle deviation below 90°, and minimizing speed deviation to prevent generator desynchronization. These constraints guide the ANN during training to ensure stable, coordinated operation of the two controllers under a range of fault scenarios.

Table 1
System parameters.

Components	Parameters
Machine 1	1000MVA, 13.8 kV, 60 Hz, Xd = 1.305, X'd = 0.296, X''d = 0.252, Xq = 0.474, X''q = 0.243, XL = 0.18
Machine 2	5000MVA, 13.8 kV, 60 Hz, Xd = 1.305, X'd = 0.296, X''d = 0.252, Xq = 0.474, X''q = 0.243, X_L = 0.18
Transformer T_1	1000 MVA, 13.8 kV/500 kV, 60 Hz
Transformer T_2	5000 MVA, 13.8 kV/500 kV, 60 Hz
Transmission Line1	R/Length = 0.01755 Ω/km X/Length = 0.8737 × 10^{-3}H/Km C/Length = 13.33 × 10^{-9}F/Km T/L Length = 350 Km
Transmission Line 2	R/length = 0.01755 Ω/km X/length = 0.8737 × 10^{-3}H/km C/length = 13.33 × 10^{-9}F/km T/L Length = 350 Km
Surge Impedance Loading	977 MW
Static VAR Compensator	SVC rating = ±200 MVAR Voltage Regulator K_i = 300 Droop X_S = 0.3
Reference/Base Voltage	1.009p.u.
Load	5000 MW

Five graphs with different parameters of the transmission line and the machines (i.e., three Buses Voltages, Line Power, Rotor angle difference, Speed Deviations and Terminals Voltages) are combined in a single figure and the results are discussed. Simulation results of the test system are obtained under different faults and situations and different cases of operation of power system are discussed as follows:

5.1. Single line to ground (SLG) fault with PID based controllers

5.1.1. SLG fault without controllers

A single line to ground (SLG) fault is applied to the transmission line of the power system at 4 sec and is cleared at 4.2 sec. Fig. 7 shows bus voltages, Line power, Rotor angle difference, Speed deviations and terminal voltages of the machines. The first graph in Fig. 7 which depicts three buses voltages show that whenever fault is applied, the voltages of all three buses shoot up and system lost its synchronism. The second graph which shows the Line power and the third graph shows Rotor angle difference or power angle difference. Power transfer is maximum when this angle reaches 90°, which is a good indication of system stability. The machines will lose synchronism and the system will become unstable if this angle difference exceeds 90° for a prolonged period of time. Graph 4 shows speed deviations, graph 5 shows terminals voltages of the machines. From all the graphs of Fig. 7, it is clearly shown that without controllers the system loses its synchronism and becomes unstable with an SLG fault.

5.1.2. SLG fault with a PID-based Generic (PSS) without SVC

Here in this section, an SLG fault has been applied, and only a PID-based generic PSS is connected to stabilize the power system. The Static VAR Compensator (SVC) is kept out of service (i.e., it is set to operate in VAR control mode, where fixed susceptance Bref = 0). The SLG fault was applied at 4 sec and cleared at 4.2 sec. Graph 1 in Fig. 8 shows three buses voltages that arise during a fault but smooth out after some cycles of the waveform with the application of a PID-based generic PSS.

Line power, rotor angle difference, speed deviations, and terminals voltages of machines are shown in Graphs 2, 3, 4, and 5, respectively. In graph 4, which shows speed deviations of the machines at the time of the fault, it is noted that the speed of machine 1 (M1) increases abruptly, because during the fault the mechanical power of M1 is greater than its electrical power. In Fig. 8, it is shown that in an SLG fault, the system remains stable with a PID-based Generic-PSS even without an SVC controller.

5.1.3. SLG fault with PID-based-(MB) PSS without SVC

Here, an SLG fault is applied to the transmission line of the power network, and only the PID-based Multiband-PSS is used to overcome the fault and stabilize the power network, but the SVC is kept out of service. Fig. 9 shows the response of MB-PSS to alleviate the fault effect, and it can be seen that MB-PSS has an improved response compared to Generic-PSS. It can also damp out small frequency oscillations of about 0.8 Hz to 0.025 Hz but the Gen-PSS is unable to damp out these lower-level oscillations.

5.1.4. SLG fault with PID-based Generic-PSS and SVC

In this case, an SLG fault is applied at 4 sec and cleared at 4.2 sec. A PID-based Generic-PSS and SVC FACTS controllers are used to alleviate the effect of the fault and keep the power system operating in a stable condition. In addition to the SVC controller, it shows some improved response. The Fig. 10 shows the simulation results of the following system.

5.1.5. SLG fault with PID-based MB-PSS and SVC

An SLG fault is applied at 4 sec and cleared at 4.2 sec. In this case, a PID-based MB-PSS and an SVC FACTS controller are used to alleviate the

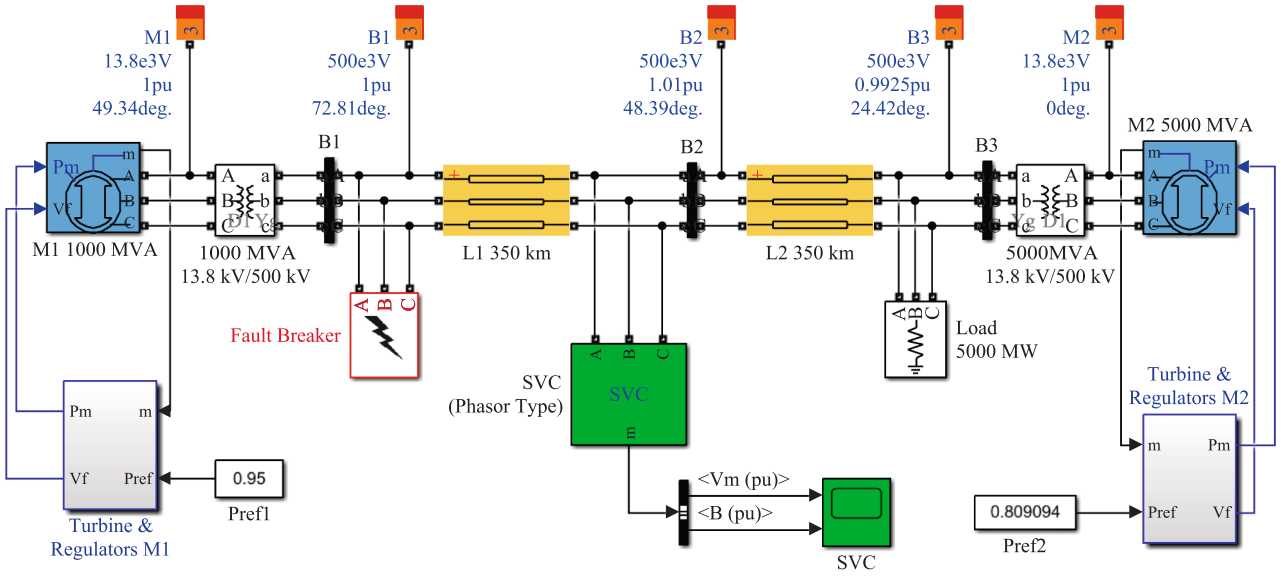


Fig. 6. Simulation model of the power system under study.

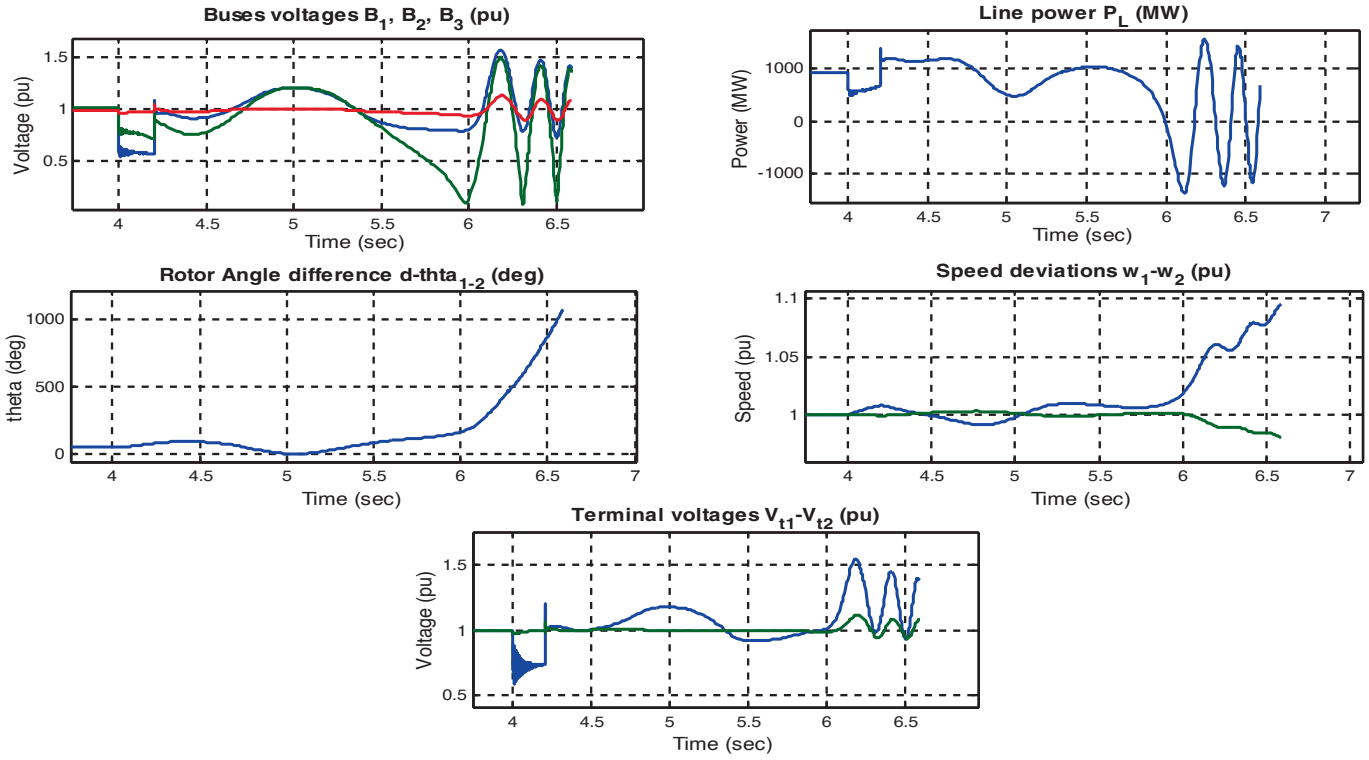


Fig. 7. Shows the bus voltage, line power, rotor angle difference, speed deviations, and terminal voltages of the machines during an SLG fault, without any controller.

effect of the SLG fault and keep the power system operating in a stable condition. Due to the addition of the SVC controller, the system shows some improved response. Fig. 11 shows the simulation results of the test system with an SLG fault.

5.2. *Three-phases-to-ground fault with PID-based controllers*

5.2.1. *Three-phases-to-ground (LLL-G) fault without controllers*

Fig. 12 shows that without controllers, when an LLL-G fault occurs in the transmission system, the power system becomes unstable.

5.2.2. *LLL-G fault with PID based Generic-PSS without SVC and with PID-based MB-PSS without SVC*

In the both above cases i.e., the PID based Generic-PSS and the PID based MB-PSS both without SVC are unable to acquire stable operating position of the power system whenever a three-phases-to-ground (LLL-G) fault occurs). Fig. 13 shows the response of the controllers (i.e., Generic-PSS and MB-PSS) without SVC.

5.2.3. *LLL-G fault with PID-based Generic-PSS and SVC controllers*

Here in this case, an LLL-G fault is applied at 4 s and cleared at 4.1 s

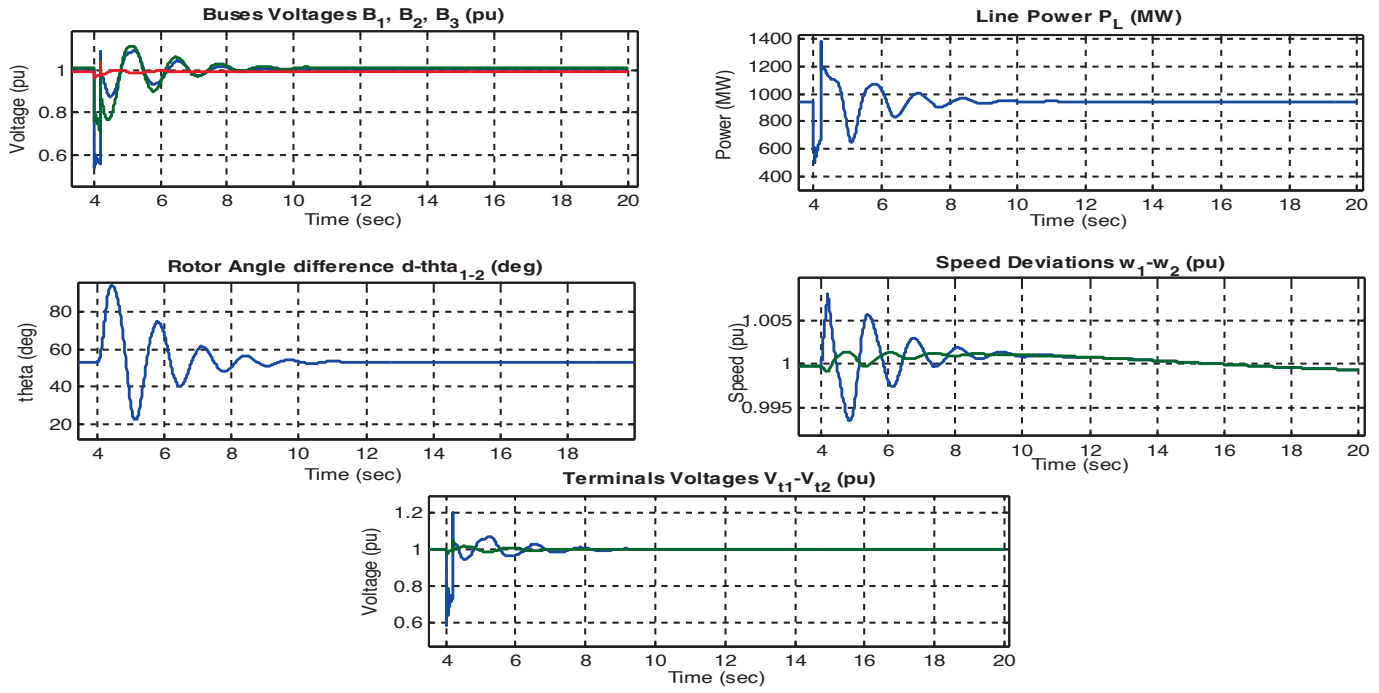


Fig. 8. Shows voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an SLG fault, with PID-based Generic-PSS.

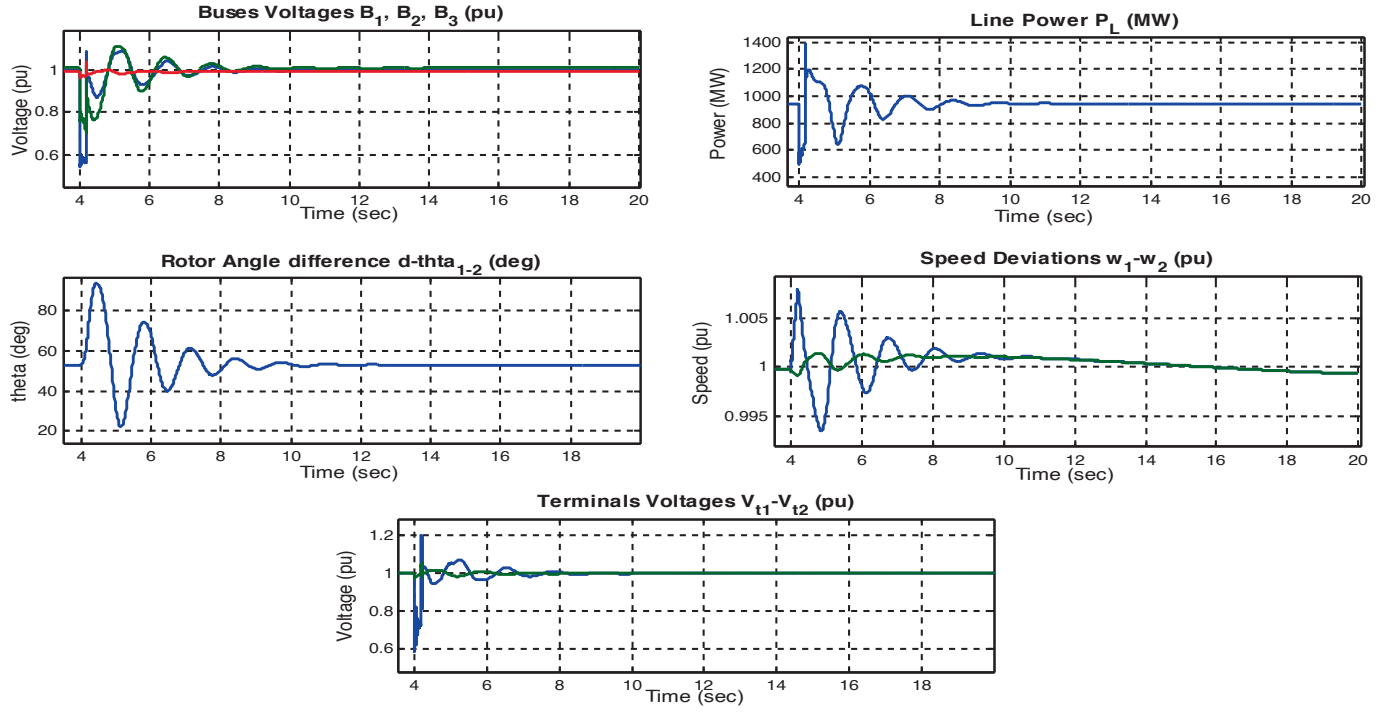


Fig. 9. Shows voltages (buses and terminals), line power, rotor angle difference and speed deviations of the machines during an slg fault, with pid-based multi-band-pss.

to the transmission system of a power network. The power system acquires equilibrium position after being subjected to an LLL-G fault controller when the SVC controller is added to the PID-based Generic-PSS in the system. Fig. 14 shows the response of controllers during the LLL-G fault.

5.2.4. LLL-G fault with PID-based MB-PSS and SVC controllers

Here in this case, the impact of a PID-based MB-PSS in addition to the SVC controller during LLL-G fault is analyzed. The system remains stable by these controllers, even under the application of three lines to ground (LLL-G) fault, as shown in Fig. 15.

5.3. Single phase to ground fault with ANN

5.3.1. SLG fault with ANN-based Generic-PSS without SVC

The PID controller is replaced by an artificial neural network (ANN).

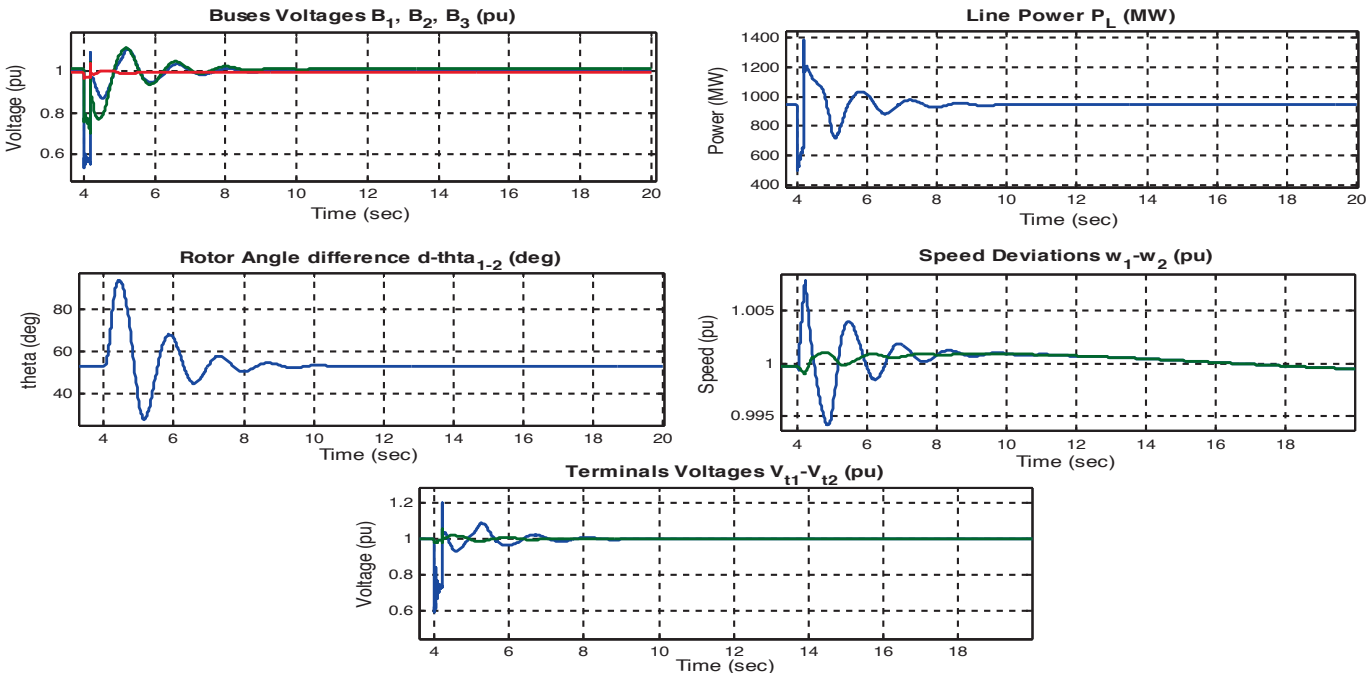


Fig. 10. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an SLG fault, with PID-based Generic-PSS and SVC controllers.

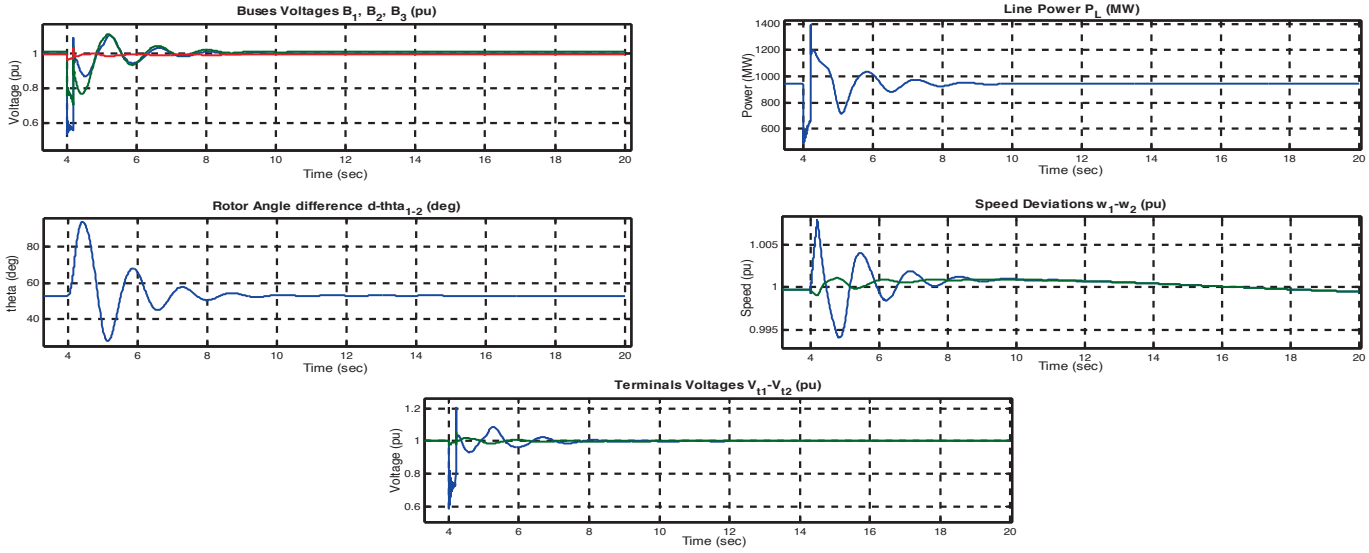


Fig. 11. Shows voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines in SLG fault, with PID-based MB-PSS and SVC controllers.

An SLG fault is created and applied at 4 sec and cleared at 4.2 sec, and only an ANN-based generic PSS is used to clear the fault or enhance the stability of the power system. The SVC is kept out of service in this case. In Fig. 16, it is clearly shown that the ANN-based Generic PSS has a more improved response compared to the PID-based Generic PSS.

5.3.2. *SLG fault with ANN-based MB-PSS without SVC*

An SLG fault is applied to the transmission line of the power system, and an ANN-based MB-PSS is used to overcome the fault. The SVC is set to operate in VAR control mode (i.e., keeping it out of service). Fig. 17 shows an improved response of the power network compared to the PID-based MB-PSS.

5.3.3. *SLG fault with ANN-based Generic-PSS and SVC*

For SLG fault clearing and stability enhancement, ANN-based Generic-PSS in addition to the SVC FACTS controllers are used in this case. Simulation results are shown in Fig. 18.

5.3.4. *SLG fault with ANN-based MB-PSS and SVC*

Fig. 19 shows the response of an ANN-based MB-PSS with an SVC controller. An SLG fault was applied at 4 sec and cleared at 4.2 sec. The response of the controllers is significantly improved, faster and more uniform, even with the SLG fault.

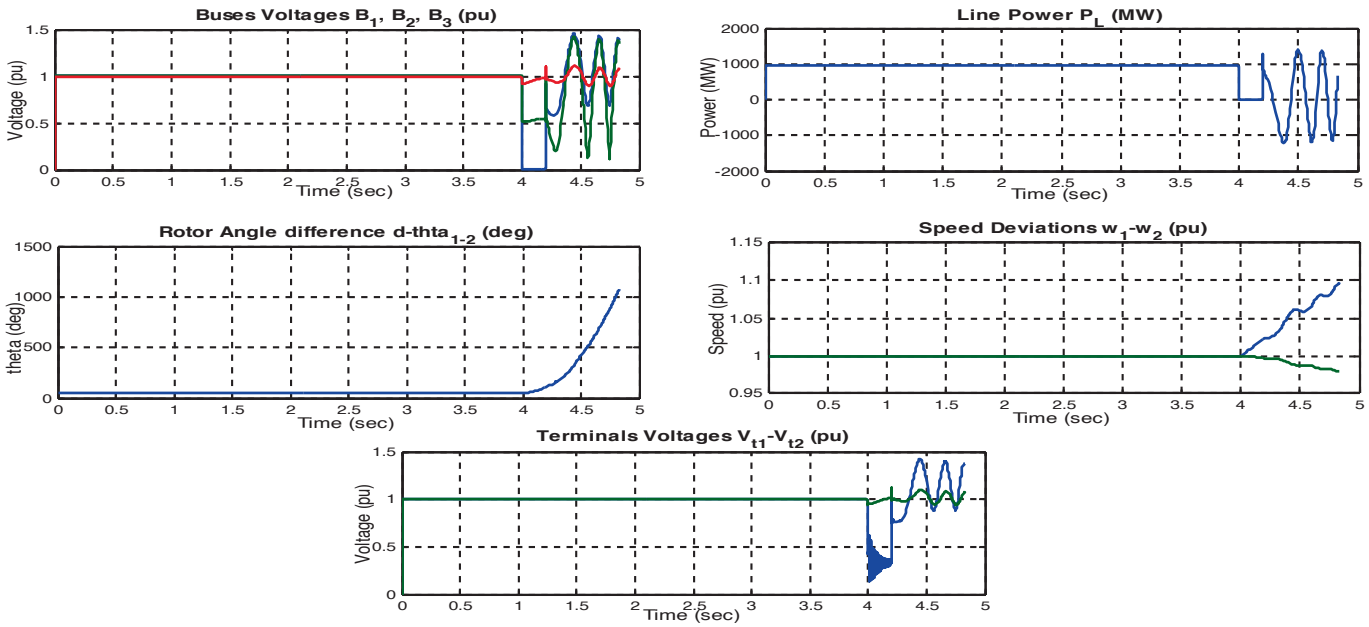


Fig. 12. Shows voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault, without controllers.

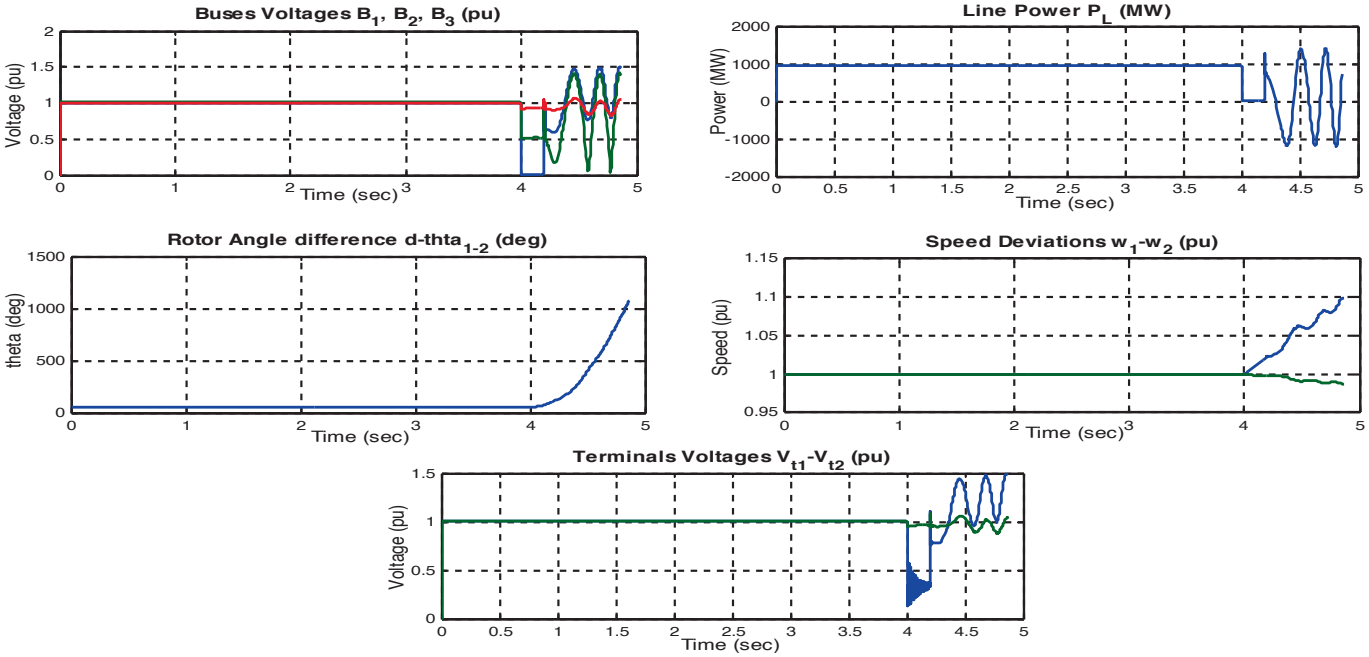


Fig. 13. Shows voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault and the impact with only Generic-PSS and with only MB-PSS, both without the SVC controller.

5.4. LLL-G fault with ANN-based controllers

5.4.1. LLL-G fault with ANN-based Generic-PSS and ANN-based MB-PSS without SVC

When the LLL-G fault is applied to the transmission system, the system becomes unstable, even with ANN-based generic-PSS and also with ANN-based MB-PSS without an SVC controller. The Fig. 20 shows the simulation results.

5.4.2. LLL-G fault with ANN-based Generic-PSS and SVC

Power system remains stable even after three lines to ground (LLL-G) fault occurrence, with the application of ANN-based generic-PSS when the SVC controller is putted in service. Fig. 21 shows the simulation response of the power system.

5.4.3. LLL-G fault with ANN based MB-PSS and SVC

ANN-based MB-PSS, in addition to the SVC FACTS controller, provides more stable and secure operation of the power system even during an LLL-G fault. Fig. 22 shows that controllers damp out oscillations and enhance the stability of the system.

Replacing the PID-based PSS with ANN-based controllers demonstrates significant performance gains. The ANN-based Generic PSS, without SVC, results in faster damping and reduced voltage deviation compared to its PID counterpart. The ANN-based MB-PSS offers even better performance, showing quick stabilization, lower overshoot, and minimal speed deviation. The best results are observed when the ANN-

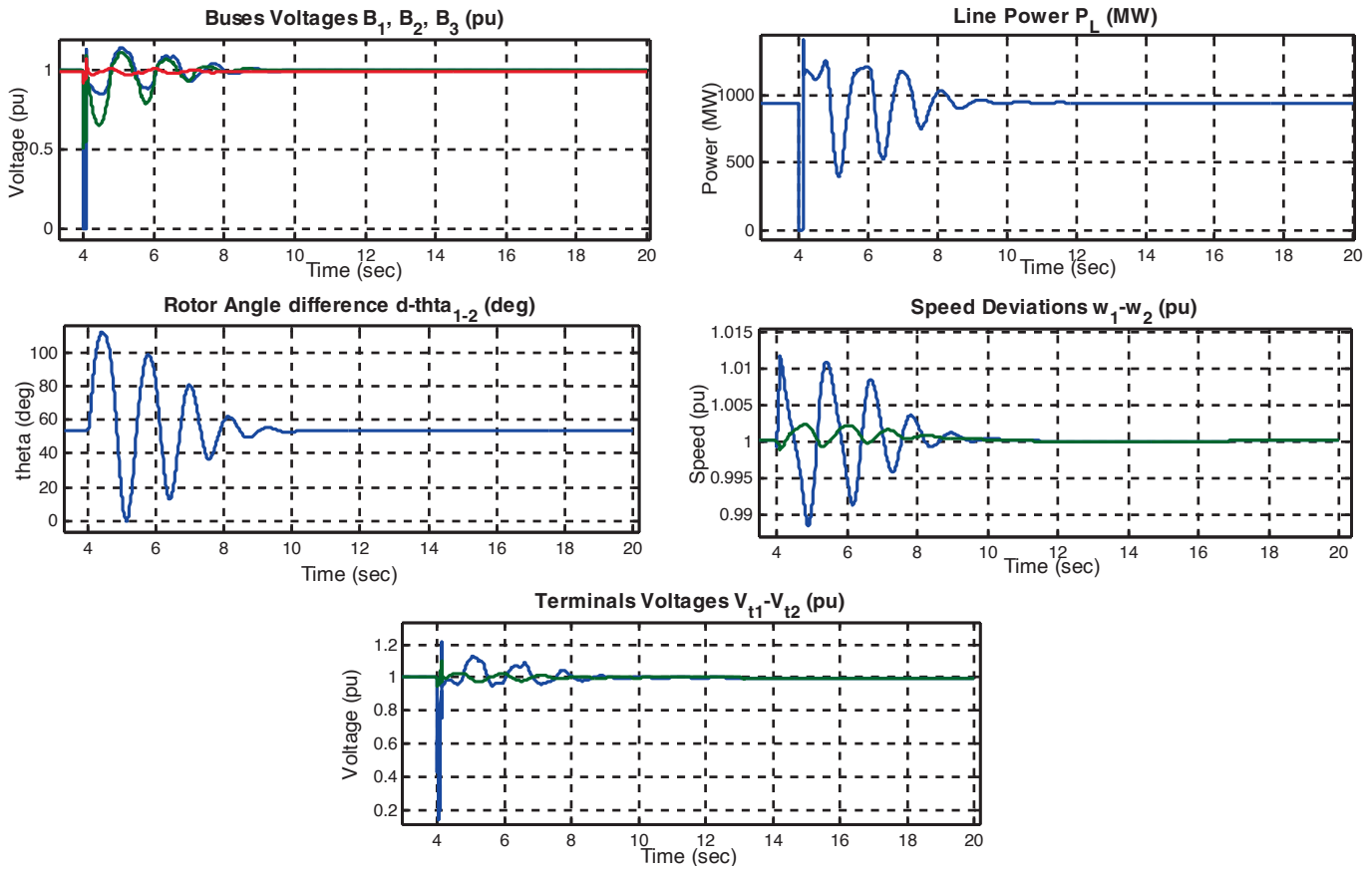


Fig. 14. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during LLL-G fault, with PID-based Generic-PSS and SVC controllers.

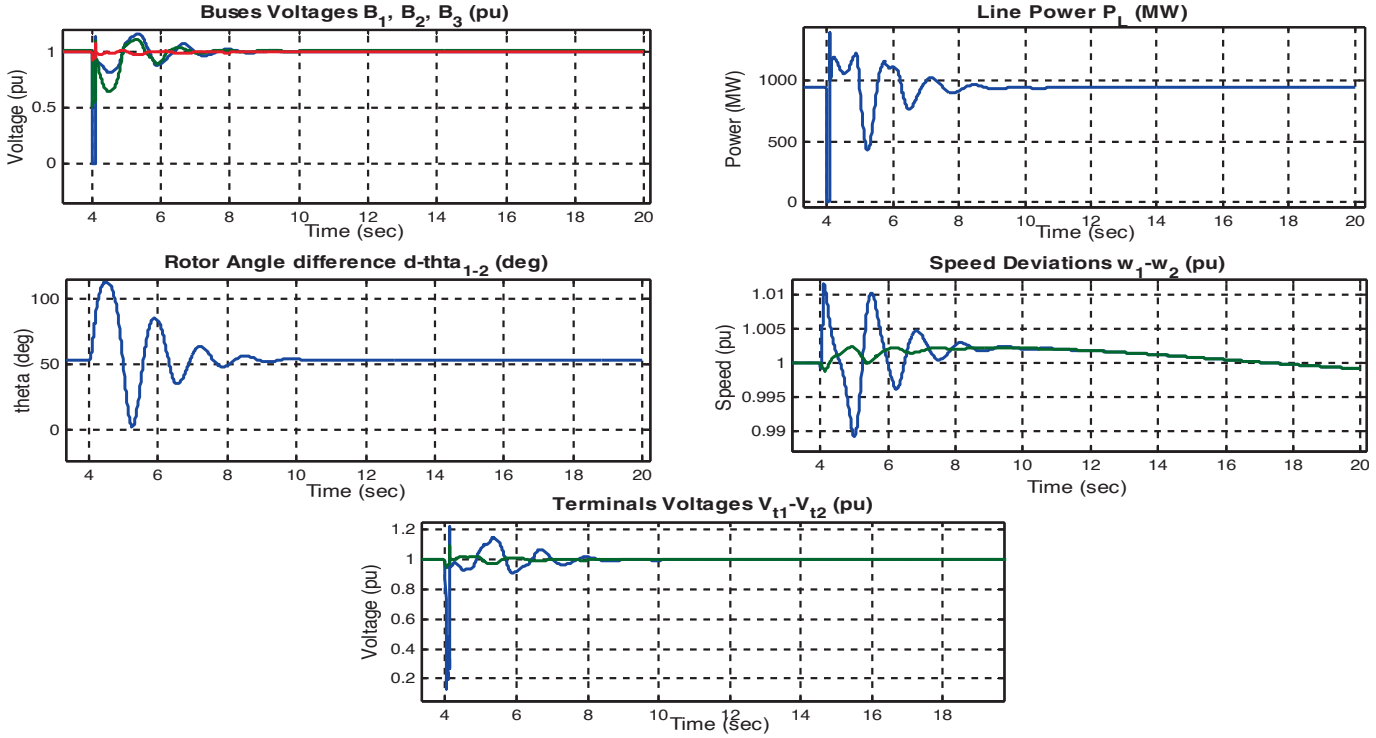


Fig. 15. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault, with MB-PSS and SVC controllers.

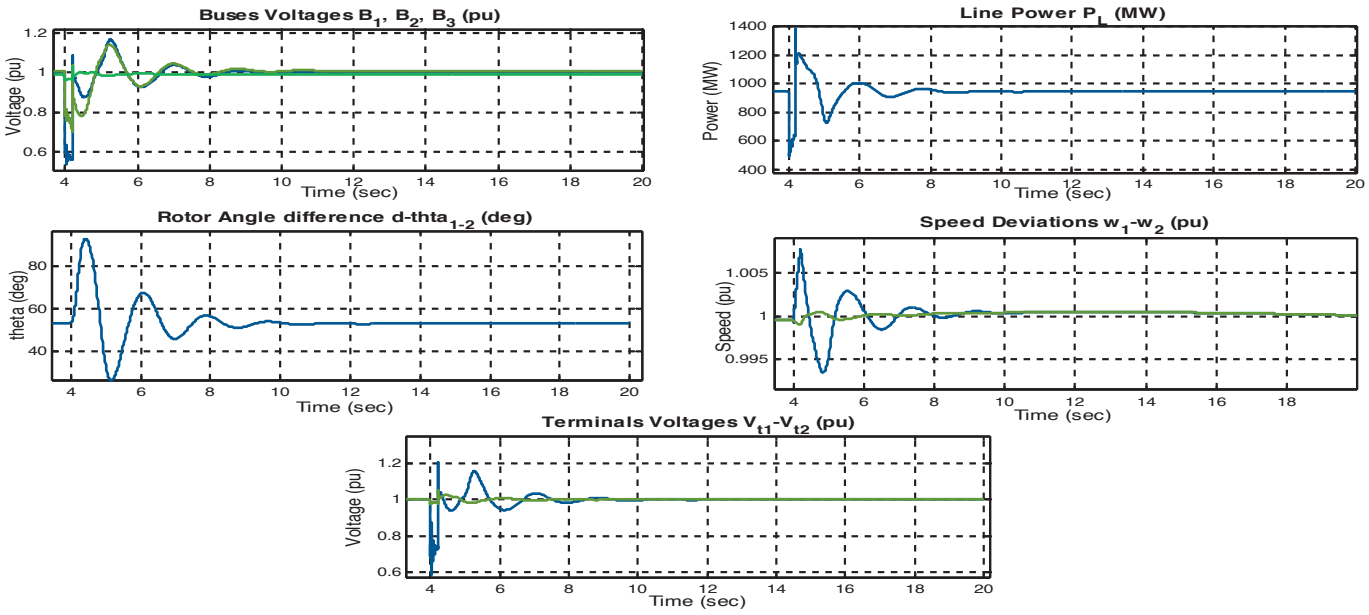


Fig. 16. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an SLG fault, with only ANN-based Generic-PSS.

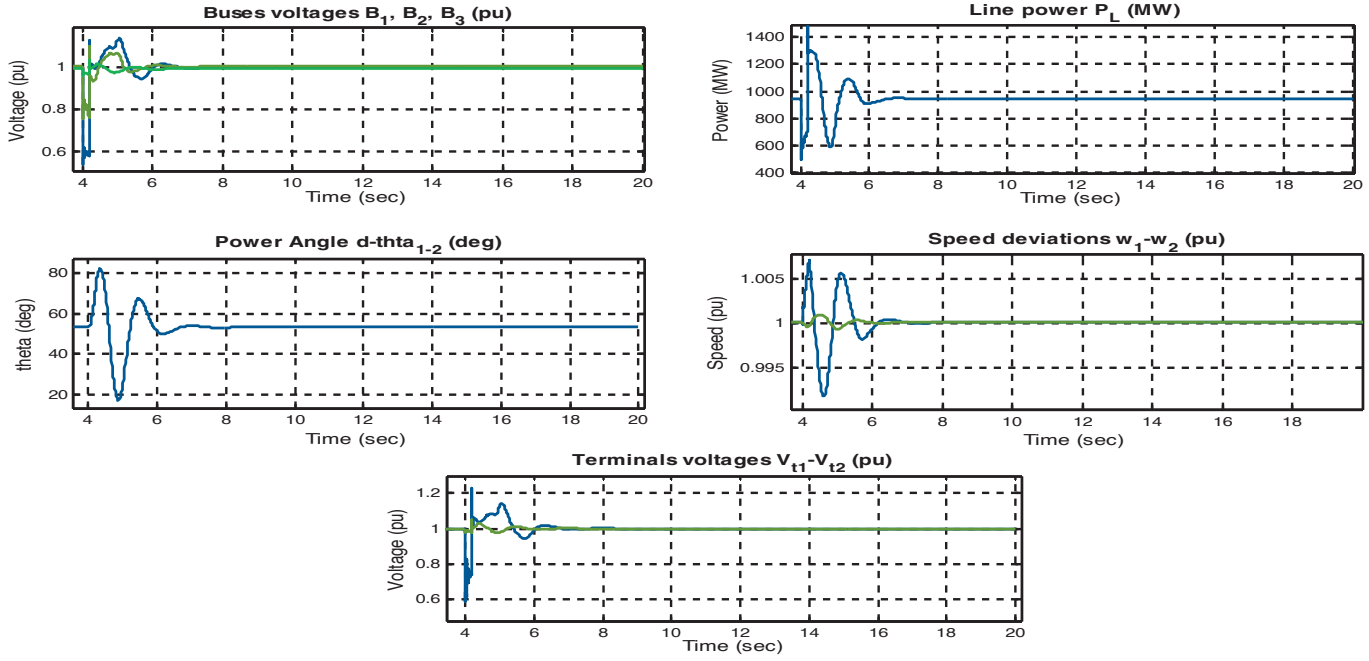


Fig. 17. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an slg fault, only with ann-based mb-pss.

based MB-PSS is used in combination with the SVC. In this case, bus voltage deviations remain within ±0.01 p.u., and speed deviations are controlled within ±0.005 p.u., even during fault conditions. Under the LLL-G fault condition, the system without controllers is highly unstable. PID-based controllers alone, whether Generic or Multiband, are unable to maintain stability without the support of the SVC. When the SVC is introduced alongside PID controllers, the system stabilizes, but with a delayed response and moderate oscillations. ANN-based controllers without SVC also struggle under this severe fault condition. However, the combination of ANN-based PSS (both Generic and MB-PSS) with SVC significantly enhances system robustness. These configurations effectively damp power oscillations, reduce voltage and frequency fluctuations, and restore system equilibrium within a short duration. Overall, the simulation results clearly demonstrate that the proposed ANN-based control strategy, particularly the MB-PSS combined with SVC, outperforms traditional PID-based methods. It provides faster damping, better voltage recovery, and improved synchronization between generator units under various fault conditions. These findings confirm the suitability of the proposed ANN coordination scheme for real-time applications in modern and future smart grids.

5.5. Research outcomes

- Improved Transient Stability

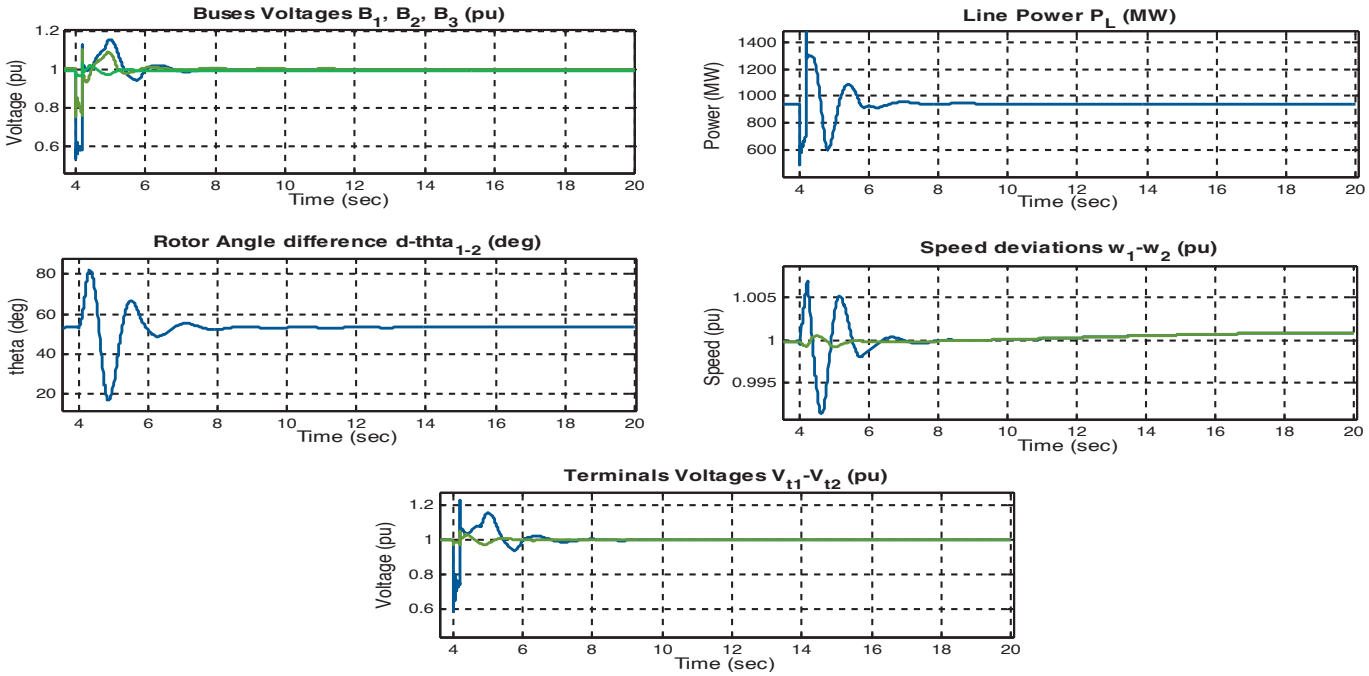


Fig. 18. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an SLG fault, with ANN-based Generic-PSS and SVC.

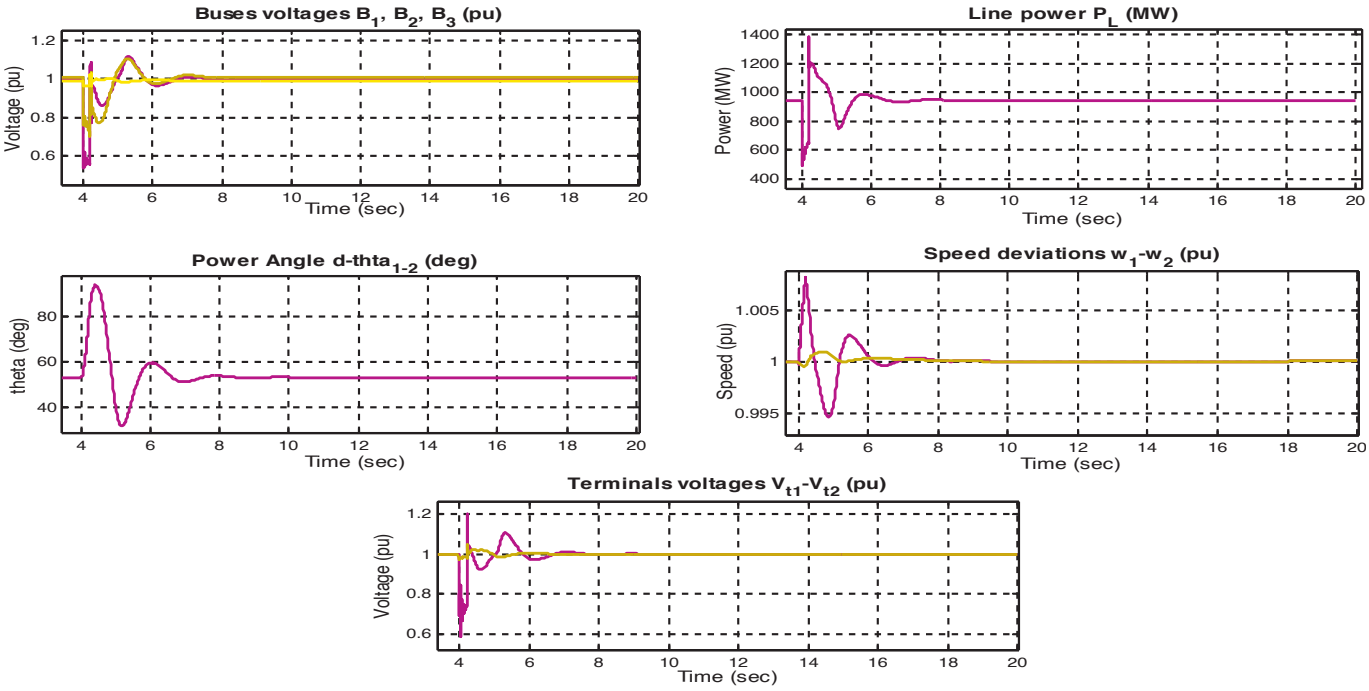


Fig. 19. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an SLG fault, with ANN-based MB-PSS and SVC.

By enabling quicker system recovery following disruptions, the ANN-assisted coordinated operation of SVC and PSS will improve the power system's transient stability.

- Superior Damping of Power Oscillations

Under fault situations, the ANN-based controllers will exhibit a noticeably faster damping rate than the traditional PID-based SVC and PSS controllers.

proposed ANN coordination scheme for realResults from simulations conducted under different fault circumstances (L-G and L-L-L-G) will show that the ANN-based control system is more resilient and flexible when dealing with significant disruptions.

- Adaptive and Intelligent Control

In comparison to fixed-parameter controllers, the ANN will offer real-time, non-linear adaptive control capabilities that can learn system

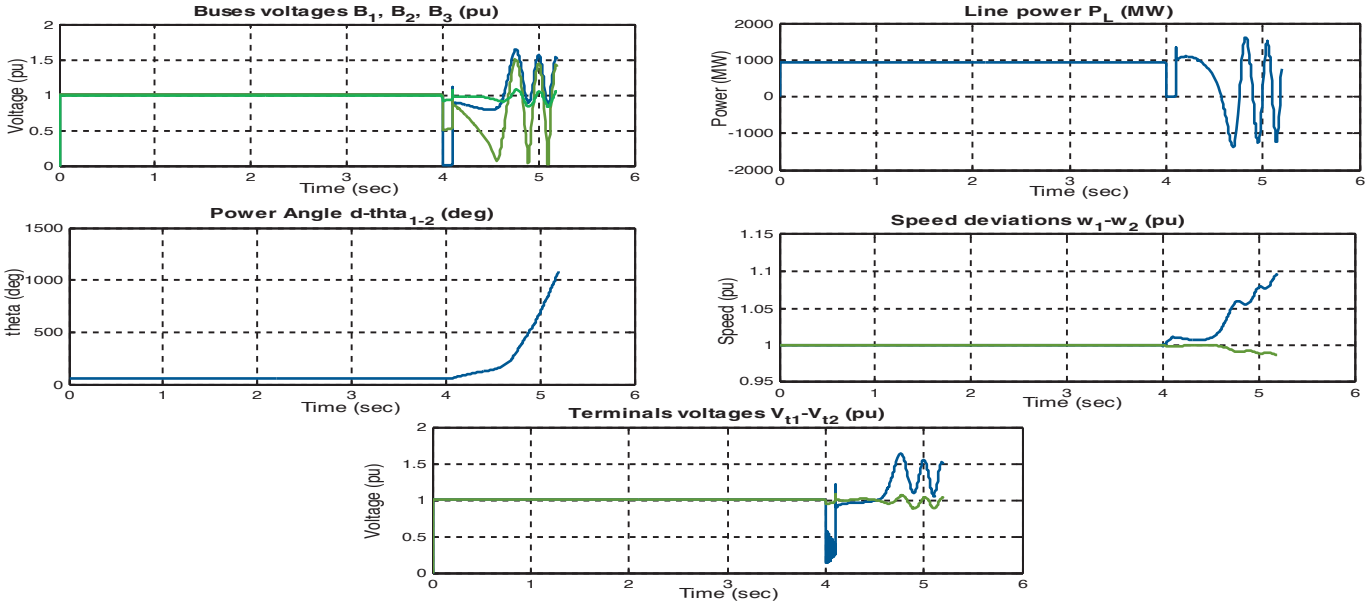


Fig. 20. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault with only ANN-based Generic-PSS and only ANN-based MB-PSS, without SVC.

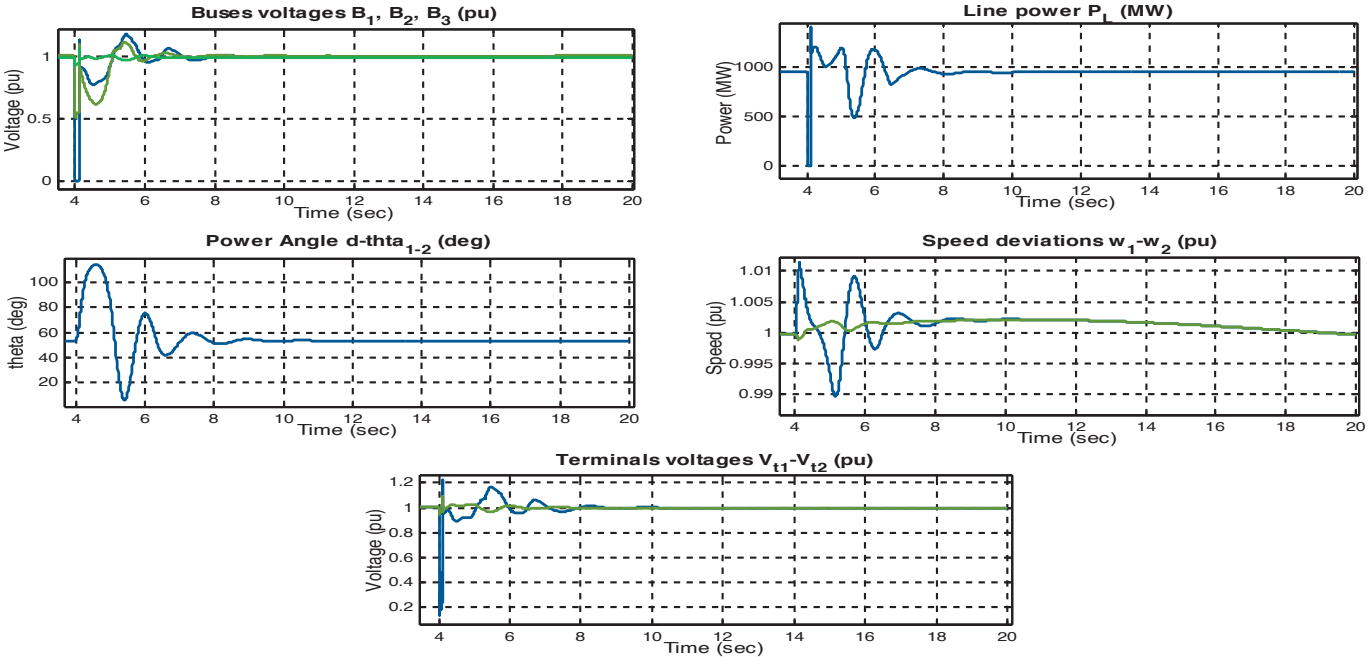


Fig. 21. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault with ANN-based Generic-PSS and SVC.

dynamics and optimize the response.

- Optimal Coordination Between SVC and PSS

The study will demonstrate that better voltage regulation and frequency stability result from coordinated management of SVC and PSS, lowering the possibility of cascading failures.

- Validation through Simulation

The efficiency of the suggested control method will be confirmed through the use of MATLAB/Simulink models, offering a strong foundation for practical deployment in smart grids.

- Contribution to Smart Grid Technologies

By encouraging intelligent, self-correcting systems, the integration of ANN in power system stability control is onsistent with the evolution of the smart grid.

6. Conclusion and future scope

This study presented a coordinated control strategy using Artificial Neural Networks (ANNs) for integrating Power System Stabilizers (PSS)

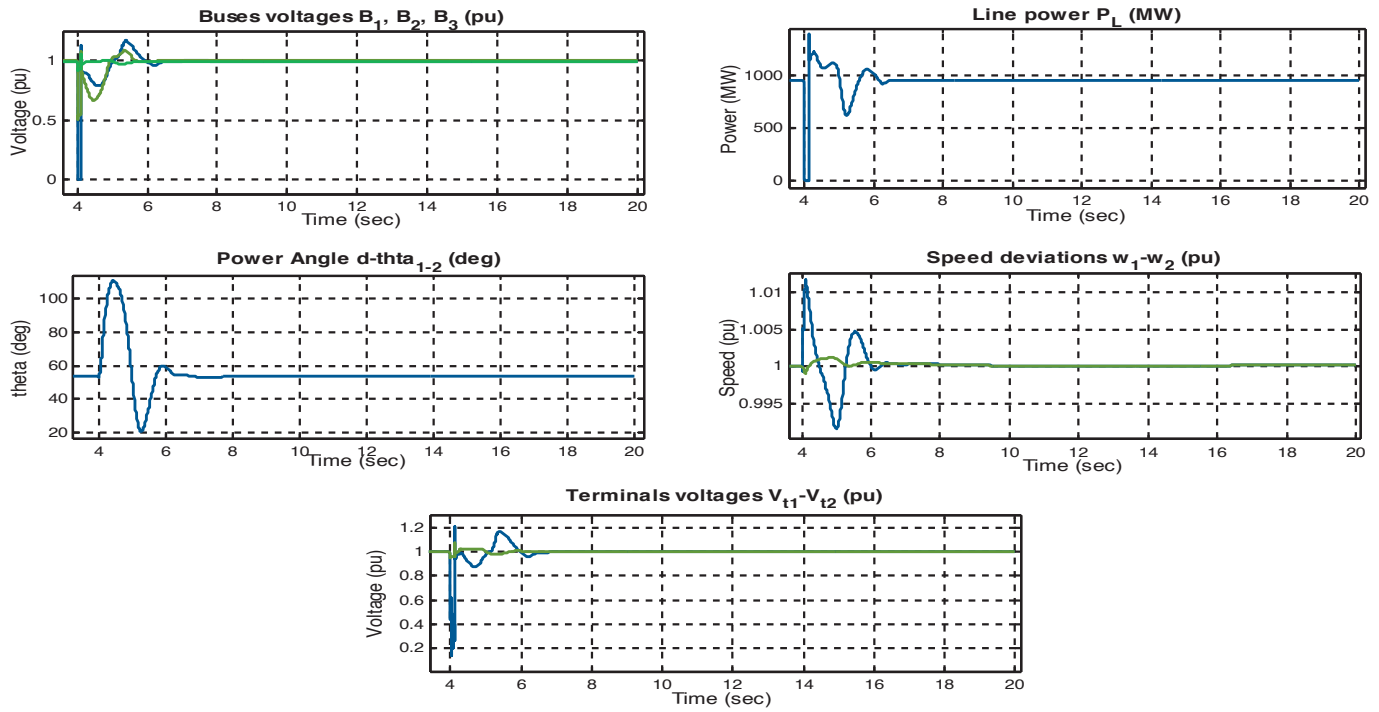


Fig. 22. Shows the voltages (buses and terminals), line power, rotor angle difference, and speed deviations of the machines during an LLL-G fault with ANN-based MB-PSS and SVC.

and Static VAR Compensators (SVC) to enhance the transient stability of a multi-machine power system. The ANN was trained using simulation-based data and tested under critical fault scenarios such as single line-to-ground (SLG) and three-phase-to-ground (LLL-G) faults. Comparative simulations were conducted using PID-based Generic and Multiband PSS controllers, with and without SVC, against the proposed ANN-based approach. The results demonstrated that the ANN-based MB-PSS, particularly when coordinated with SVC, significantly outperformed conventional PID-based controllers. It achieved faster damping, reduced voltage overshoot, and improved synchronization, maintaining voltage deviations within ± 0.01 p.u. and speed deviations within ± 0.005 p.u. under severe fault conditions. The findings confirm that ANN-based coordinated control offers an efficient, adaptive, and real-time capable solution for improving power system resilience during transient disturbances. This makes it a strong candidate for integration into future smart grid control architectures.

Future work can explore the application of deeper neural networks or hybrid AI algorithms such as neuro-fuzzy systems or reinforcement learning to further improve adaptability. Additionally, implementation on larger and more complex power systems with renewable energy sources and testing under stochastic operating conditions could help validate the robustness and scalability of the proposed control strategy.

CRediT authorship contribution statement

Waseem Akram: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Aslam Pervez Memon:** Supervision, Resources, Investigation. **Muhammad Ismail Jamali:** Visualization, Project administration, Data curation. **Mohsin Ali Koondhar:** Project administration, Investigation, Formal analysis. **Zuhair Muhammed Alaas:** Supervision, Software, Investigation. **Ezzeddine Touti:** Software, Resources, Funding acquisition. **Mohammed H. Alsharif:** Methodology, Investigation, Conceptualization. **Mun-Kyeom Kim:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This research was supported by the Chung-Ang University Research Grants in 2025. The authors extend their appreciation to the Northern Border University, Saudi Arabia for supporting this work through project number “NBU-CRP-2025-2448’’.

References

[1] Alsharif MH, Nordin R, Ismail M. Green wireless network optimisation strategies within smart grid environments for Long Term Evolution (LTE) cellular networks in Malaysia. Renew Energy 2016;85:157–70.
[2] Lipu MSH, Karim TF. Effectiveness of FACTS controllers and HVDC transmissions for improving power system stability and increasing power transmission capability. Int J Energy Power Eng 2013;2(4):154–63.
[3] Alsharif MH, Nordin R, Ismail M. Classification, recent advances and research challenges in energy efficient cellular networks. Wirel Pers Commun 2014;77(2):1249–69.
[4] Kar MK, Kumar S, Singh AK, Panigrahi S. A modified sine cosine algorithm with ensemble search agent updating schemes for small signal stability analysis. Int Trans Electr Energy Syst 2021;31(11):e13058.
[5] Kar MK, Kumar S, Singh AK, Panigrahi S, Cherukuri M. Design and analysis of FOPID-based damping controllers using a modified grey wolf optimization algorithm. Int Trans Electr Energy Syst 2022;2022(1):5339630.
[6] Kar MK. Stability analysis of multi-machine system using FACTS devices. Int J Syst Assur Eng Manage 2023;14(6):2136–45.
[7] Kundur P, et al. Definition and classification of power system stability IEEE/CIGRE joint task force on stability terms and definitions. IEEE Trans Power Syst 2004;19(3):1387–401.
[8] Yang M, Guo Y. Wind power cluster ultra-short-term prediction error correction method based on the load peak and valley characteristics. CSEE J Power Energy Syst 2023.
[9] Hatziargyriou N, et al. Definition and classification of power system stability–revisited & extended. IEEE Trans Power Syst 2020;36(4):3271–81.
[10] Wang W, Zheng J, Liu Z, Fang J, Li Z, Wu Q. Hierarchical demand response considering dynamic competing interaction based on multi-agent deep deterministic policy gradient. CSEE J Power Energy Syst 2025.

[11] Ardanza A, Moreno A, Segura Á, de la Cruz M, Aguinaga D. Sustainable and flexible industrial human machine interfaces to support adaptable applications in the Industry 4.0 paradigm. Int J Prod Res 2019;57(12):4045–59.
[12] Sahoo SK, Kar MK, Kumar S, Mahanty RN. Improved sine-cosine algorithm-based power system stability under different fault conditions. Majlesi J Elect Eng 2025;19 (1):1–10.
[13] Kim JJ, Park JH. A novel structure of a power system stabilizer for microgrids. Energies 2021;14(4):905.
[14] Zhang J, et al. Series–shunt multiport soft normally open points. IEEE Trans Ind Electron 2022;70(11):10811–21.
[15] Li S, Zhou J, Zhou F, Niu F, Deng W. A reduced current ripple overmodulation strategy for indirect matrix converter. IEEE Trans Ind Electron 2024.
[16] Dhouib B, Kahouli A, Abdallah HH. A comparative study of performance of multi-band and conventional power system stabilizers to improve transient stability of multimachine power system. in 2016 17th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering (STA), 2016: IEEE, pp. 501–7.
[17] Li N, et al. Single-degree-of-freedom hybrid modulation strategy and light-load efficiency optimization for dual-active-bridge converter. IEEE J Emerg Select Top Power Electron 2024;12(4):3936–47.
[18] Sahare SB, Bonde U. Transient stability enhancement in multi-machine power system by using power system stabilizer (Pss) and static var compensator (Svc). Int J Eng Res 2020;9(2):94–103.
[19] Li N, et al. An improved modulation strategy for single-phase three-level neutral-point-clamped converter in critical conduction mode. J Mod Power Syst Clean Energy 2024;12(3):981–90.
[20] Alsharif MH. Techno-economic evaluation of a stand-alone power system based on solar/battery for a base station of global system mobile communication. Energies 2017;10(3):392.
[21] Zeng Z, Goetz SM. A general modeling and analysis of impacts of unbalanced inductance on PWM schemes for two-parallel interleaved power converters. IEEE Trans Power Electron 2024;39(10):12235–48.
[22] Ding S, Liu C, Fan Z, Hang J. Lumped parameter adaptation-based automatic mtpa control for ipmsm drives by using stator current impulse response. IEEE Trans Energy Convers 2025.
[23] Alsharif MH. Comparative analysis of solar-powered base stations for green mobile networks. Energies 2017;10(8):1208.
[24] Zeng Z, Goetz SM. A zero common mode voltage PWM scheme with minimum zero-sequence circulating current for two-parallel three-phase two-level converters. IEEE J Emerg Selected Top Power Electron 2024;13(2):1503–13.
[25] Benaissa MO, Hadjeri S, Zidi SA. Impact of PSS and SVC on the Power System Transient Stability.
[26] Zhang J, Ji Y, Zhou J, Jia Y, Shi G, Wang H. Cooperative AC/DC voltage margin control for mitigating voltage violation of rural distribution networks with interconnected DC link. IEEE Trans Power Delivery 2025.
[27] Liu Y, Wang Y, Chen S, Zhang J. A novel hybrid neural lyapunov method with low conservatism for power system domain of attraction estimation. IEEE Trans Ind Inf 2025.
[28] Li H, Wu P, Zeng N, Liu Y, Alsaadi FE. A survey on parameter identification, state estimation and data analytics for lateral flow immunoassay: from systems science perspective. Int J Syst Sci 2022;53(16):3556–76.
[29] Wang S, Jiang A, Ma J, Wang P, Zhang R, Liu T. Transient stability analysis for hybrid parallel-connected converters by two-dimensional phase portrait. IEEE Trans Power Electron 2025.
[30] Wang S, Cheng Q, Shangguan B, Ma J, Jiao N, Liu T. Accurate and continuous reactive power control of three-terminal hybrid DC transmission system. IEEE Trans Power Delivery 2024.
[31] Shahgholian G, Mahdavian M, Ganji E, Eshaghpour I, Matouri M, Janghorbani M. Transient stability enhancement of a two-machine power system using SVC and PSS: A comparative study. in 2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2017: IEEE, pp. 103–6.
[32] Singh B, Gyanish BJ. Impact assessment of DG in distribution systems from minimization of total real power loss viewpoint by using optimal power flow algorithms. Energy Rep 2018;4:407–17.
[33] Relić F, Glavaš H, Petrović I, Stojkov M. Historical development and recent advances in FACTS technology for transient stability in power systems. Tehnički Vjesnik 2025;32(1):370–80.
[34] Wang Y, Chen J, Zhao Y, Xu B. Incorporate robust optimization and demand defense for optimal planning of shared rental energy storage in multi-user industrial park. Energy 2024;301:131721.
[35] Yang Y, Zhang Z, Zhou Y, Wang C, Zhu H. Design of a simultaneous information and power transfer system based on a modulating feature of magnetron. IEEE Trans Microw Theory Tech 2022;71(2):907–15.
[36] Yang Y, et al. Parameter coordination optimization of power system stabilizer based on similarity index of power system state-BP neural network. Energy Rep 2023;9:427–37.
[37] Toolabi Moghadam A, Aghahadi M, Eslami M, Rashidi S, Arandian B, Nikolovski S. Adaptive rat swarm optimization for optimum tuning of SVC and PSS in a power system. Int Trans Electr Energy Syst 2022;vol:2022.
[38] Hemeida M, Osheba D, Alkhalaf S, Fawzy A, Ahmed M, Roshdy M. Optimized PID controller using archimedes optimization algorithm for transient stability enhancement. Ain Shams Eng J 2023;14(10):102174.
[39] Lin L, Liu J, Huang N, Li S, Zhang Y. Multiscale spatio-temporal feature fusion based non-intrusive appliance load monitoring for multiple industrial industries. Appl Soft Comput 2024;167:112445.
[40] Keskes S, Bahloul W, Kammoun MBA. Improvement of power system stability by static var compensator and tuning employing genetic algorithm. Int J Mod Nonlinear Theory Appl 2014;2014.
[41] Agrawal N, Gowda M. Power flow enhancement by TCSC using two different types of pulse generators. Int J Recent Eng Sci 2022;9(1):31–8.
[42] Vikhram GR, Latha S. Design of Power System Stabilizer for Power System Damping Improvement with Multiple Design Requirements.
[43] Rong Q, et al. Asymmetric sampling disturbance-based universal impedance measurement method for converters. IEEE Trans Power Electron 2024.
[44] Gao S, Chen Y, Song Y, Yu Z, Wang Y. An efficient half-bridge MMC model for EMTP-type simulation based on hybrid numerical integration. IEEE Trans Power Syst 2023;39(1):1162–77.
[45] El-Moursi M, Bak-Jensen B, Abdel-Rahman M. Novel STATCOM controller for mitigating SSR and damping power system oscillations in a series compensated wind park. IEEE Trans Power Electron 2010;2(25):429–41.
[46] Huo S, et al. Negative differential resistance with ultralow peak-to-valley voltage difference in Td-WTe2/2H-MoS2 heterostructure. Nano Lett 2024;24(38): 11937–43.
[47] Padmavathi SV, Sahu SK, Jayalaxmi A. Modeling and simulation of static var compensator to enhance the power system security. in 2013 IEEE Asia Pacific Conference on Postgraduate Research in Microelectronics and Electronics (PrimeAsia).
[48] Meng Q, Hussain S, Luo F, Wang Z, Jin X. An online reinforcement learning-based energy management strategy for microgrids with centralized control. IEEE Trans Ind Appl 2024.
[49] Bu F, Hu Y, Huang W, Zhuang S, Shi K. Control strategy and dynamic performance of dual stator-winding induction generator variable frequency AC generating system with inductive and capacitive loads. IEEE Trans Power Electron 2013;29(4): 1681–92.
[50] Yang M, Jiang Y, Guo Y, Su X, Li Y, Huang T. Ultra-short-term Prediction of photovoltaic cluster power based on spatiotemporal convergence effect and spatiotemporal dynamic graph attention network. Renew Energy 2025:123843.
[51] Shen Y, Li Z, Zeng Z, Lu Q, Lee CH. Quantitative analysis of asymmetric flux reversal permanent magnet linear machine for long excursion application. IEEE Trans Ind Electron 2024;71(10):12781–92.
[52] Wang H, Wang Y, Xiao X, Ma Z, Xu Q. Harmonic state space based stability analysis of LCC-HVDC system with saturated transformer. IEEE Trans Power Delivery 2025.
[53] Wang Y, et al. Low-frequency oscillation in power grids with virtual synchronous generators: a comprehensive review. Renew Sustain Energy Rev 2025;207:114921.
[54] Zhang W, et al. Reversible manipulation of field-free perpendicular magnetization switching via electric field. Appl Phys Lett 2025;126(17).
[55] Xiao S, et al. Electrical-thermal conduction and distribution characteristics of the catenary system for electrified railway applying electrothermal ice-melting technique. Appl Therm Eng 2025:126809.
[56] Liu Y, et al. Region of attraction estimation for power systems with multiple integrated DFIG-based wind turbines. IEEE Trans Sustainable Energy 2025.
[57] Chen S, Wang Y, Yang M, Xiao X, Gomis-Bellmunt O. Forced oscillation in hybrid system with grid-following and grid-forming inverters. Energy 2025;319:134915.
[58] Pandey DS, Das S, Pan I, Leahy JJ, Kwapinski W. Artificial neural network based modelling approach for municipal solid waste gasification in a fluidized bed reactor. Waste Manag 2016;58:202–13.
[59] Liang Q, Tvete HA, Brinks HW. Prediction of vessel propulsion power using machine learning on AIS data, ship performance measurements and weather data. in J Phys: Conf Ser, 2019;1357(1):012038. IOP Publishing.



Waseem Akram received his B.E degree in Electrical Engineering from Mehran University of Engineering and Technology, Jamshoro, Pakistan. He later completed his M.E degree in Power Engineering from Quaid-e-Awam University of Engineering, Science and Technology, Nawabshah, Pakistan. He was born in Nawabshah, Pakistan. His research interests include FACTS and DC transmission systems, Power System Optimization and Control, Smart Grids and Renewable Energy Integration.



Aslam Pervez Memon is an esteemed academician with over two decades of experience in Electrical Engineering. He earned his Ph.D. in Electrical Power System, M. Phil in Power System, and B.E. in Electrical Engineering from MUET. Dr. Memon's research spans diverse areas, including Electrical Power Quality, Harmonics, Power Electronics, Neural Networks, AC and DC Machines, Wavelet Transformation, and Simulation of Power Systems. Currently, his research focuses on Power Electronics, Power System Protection, Neural Networks, and more. Alongside his research, Dr. Memon passionately imparts knowledge in courses like Power Electronics and Power System Protection. He has contributed significantly to the field with over 30 publications in reputable journals, recognized by HEC, ISI index, and impact factors. As a Permanent Member of the Pakistan Engineering Council and an IEEE and IAENG member, Dr. Memon is dedicated to advancing Electrical Engineering.



Muhammad Ismail Jamali was born in Nawabshah, Sindh, Pakistan. He received the B.E. and M.E. degrees from the Electrical Engineering Department, Quaid-e-Awam University of Engineering, Science and Technology Nawabshah. He is currently working as a Lab Engineer with the Quaid-e-Awam University of Engineering, Science, and Technology Nawabshah. His research interest includes the renewable energy.



Mohsin Ali Koondhar was born in Nawabshah, Sindh, Pakistan, in 1985. He received the B.E. and M.E. degrees from the Electrical Engineering Department, Quaid-e-Awam University of Engineering, Science and Technology Nawabshah, in 2007 and 2016, respectively. He is currently working as a Lecturer with the Quaide-Awam University of Engineering, Science, and Technology Nawabshah. His research interests include the control of dc and ac machines, renewable energy, and programmable logic controllers. He has served as a Reviewer for IET Generation, Transmission and Distribution, and IIUM Engineering Journal Malaysia.



Zuhair Muhammed Alaas (Member, IEEE) received the B.S. degree from the King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia, in 2002, the M.S. degree from the University of Newcastle upon Tyne, Newcastle, U. K. in 2007, and the Ph.D. degree from Wayne State University, Detroit, Michigan, USA, in 2017, all in electrical engineering. From September 2002 to November 2010, he was a Lecturer with the Abha College, Technical and Vocational Training Corporation, Saudi Arabia. From November 2010 to June 2011, he was a Power Transmission Engineer with Saudi Electric Company. Since June 2011, he has been with Jazan University, where he is currently an Assistant Professor and the Department of Electrical Engineering Chairperson. His current research interests include energy storage devices, power electronics, microgrids, alternative/hybrid energy power generation systems, and motor drives.



Ezzeddine Touti received the B.S. degree in electrical engineering from the Higher National College of Engineers of Tunis, Tunisia, in 1997, the master's degree in electrical engineering from the National College of Engineers of Tunis, Tunisia, in 2005, and the joint Ph.D. degree in induction generators wind turbine, power quality and electric drives from the National College of Engineers of Monastir, Tunisia, and Artois University, France, in 2013. In 2005, he joined the Laboratory of Industrial Systems Engineering and Renewable Energies (LISIER), University of Tunis, Tunisia, as a Researcher Faculty Member. Currently, he is an Associate Professor with the College of Engineering, Northern Border University. His research interests include renewable energy, control of electrical systems smart grid, electric vehicles, and power electronics.



Mohammed H. Alsharif is an Associate Professor in the Department of AI Convergence Electronic Engineering at Sejong University, South Korea. He received his M.Sc.Eng. and Ph.D. degrees in Electrical Engineering, specializing in wireless communication and networking, from the National University of Malaysia in 2012 and 2015, respectively. Dr. Alsharif's research interests include Green technology, Green Communications, and Energy Harvesting. He has authored over 160^{+} articles published in prestigious SCI/E journals in Electrical and Electronics/Communications Engineering, including IEEE, Elsevier, Springer, and MDPI. His work has garnered more than $8{,}034^{+}$ citations, with an H-index of 44^{+} and an I-10 index of 118^{+}. Additionally, he has served as a guest editor for several special issues. For five consecutive years (2020–2024), Dr. Alsharif has been recognized as one of the top 2% scientists globally in Stanford University's report.



Mun-Kyeom Kim received the Ph.D. degree from the School of Electrical and Computer Engineering, Seoul National University. He is currently a Professor with the School of Energy System Engineering, Chung-Ang University, Seoul, South Korea. His research interests include the operation techniques in hybrid AC/DC power systems, AI-based smart power networks, big data-based demand response, real-time market design, and multi-agent-based smart city intelligence.