IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

Enhancing Power System Stability Integrating Neural Network Control & PSO Optimization for Single Machine Infinite Bus

Girase Sagar Mahendrasing
P. G. Student
Department of Electrical Engineering
(Electronics and Power)
LSSBM's Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Dist. Buldhana, India
sagargirase45@gmail.com

Prof T. Y. Kharche
Department of Electrical Engineering
(Electronics and Power)
LSSBM's Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Dist. Buldhana, India

Abstract – **This paper presents a hybrid control strategy combining Particle Swarm Optimization (PSO) with Neural Networks (NN) to enhance the stability of the Single Machine Infinite Bus (SMIB) system. Conventional Power System Stabilizers (PSS) are effective in suppressing electromechanical oscillations but struggle with the dynamic and non-linear complexities of modern power systems. The proposed PSO-NN controller automatically tunes the neural network parameters, leveraging the global search capabilities of PSO to optimize system stability under varying conditions. Simulation results demonstrate significant improvements in transient stability, reduced oscillations, and faster settling times, particularly in minimizing rotor angle error and speed overshoot. This approach offers a robust solution for modern interconnected grids, addressing increasing system complexities and disturbances. The study also suggests potential extensions, such as incorporating renewable energy sources and exploring additional optimization algorithms to further enhance grid resilience and stability.**

Keywords – **Artificial Intelligence (AI), Hybrid Control Strategy, Neural Networks (NN), Particle Swarm Optimization (PSO), Power System Stabilizer (PSS), Rotor Angle Stability, Single Machine Infinite Bus (SMIB), Transient Stability.**

I. Introduction

In contemporary power systems, stability is a critical concern, especially as the complexity and interconnection of electrical grids increase. The stability of a power system determines its ability to maintain synchronized operation and recover from disturbances, ensuring the continuous delivery of electricity. In particular, power system stabilizers (PSS) are integral in mitigating electromechanical oscillations, which are common in large interconnected systems. As the size and complexity of these grids grow, traditional stabilizers face challenges in handling the dynamic, non-linear nature of modern power systems.

The Single Machine Infinite Bus (SMIB) system, a simplified yet widely used model in power system analysis, is employed to study the dynamic behavior of power systems under various disturbances. The SMIB system consists of a synchronous generator connected to an infinite bus via a transmission line, and its stability is influenced by the generator's ability to maintain synchronization after a disturbance. Traditional methods of controlling such systems often involve tuning parameters of the stabilizers manually, which is not only time-consuming but may also fail under complex operating conditions.

In recent years, advanced techniques such as artificial intelligence (AI) have been explored to address these challenges. Among these, Neural Networks (NN) and Particle Swarm Optimization (PSO) have shown significant promise. Neural networks offer a flexible and adaptive framework capable of learning complex patterns from data, making them ideal for handling non-linearities in power system dynamics. PSO, inspired by the social behavior of birds flocking, is a powerful optimization algorithm that can effectively tune the parameters of neural networks to optimize system performance.

This research focuses on the integration of PSO and NN to enhance the stability of the SMIB system. By using PSO to optimize the parameters of an NN controller, the proposed approach aims to improve the transient stability and response times of the system, addressing the limitations of traditional stabilizers. The findings of this study contribute to the growing body of knowledge on hybrid control strategies in power system stability, offering a robust solution for modern interconnected grids.

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

II. Literature Review

When operating under unfavorable conditions, EPS frequently display complex nonlinear dynamics, which are typified by low-frequency electromechanical oscillations brought on by insufficient damping. A key component in reducing these oscillations and improving overall system stability is the PSS. Optimizing damping for these low-frequency oscillations (LFOs) poses a significant challenge in EPS. The adjustment of PSS settings, as proposed by [1], aims to achieve a robust response across diverse operating conditions. A novel approach integrating PSO with the robust Taguchi design principle offers a promising avenue for optimizing PSS design. This technique uses PSO in conjunction with Taguchi design's signal-to-noise ratio and orthogonal matrix ideas to efficiently identify the ideal PSS parameter tuning.

Variance analysis is used to assess the PSS's robustness. Furthermore, the effectiveness of the strong PSS is shown by time-domain simulations performed on a single machine connected via a SMIB across a range of load and disturbance situations. In addressing inter-area oscillations, the methodology proposed by the authors of [2] introduces a comprehensive control technique integrating phase measurement data from units. This approach employs a decentralized predictive control strategy with a dedicated control unit for each managed device, including long-distance electrical energy transmission systems such as HVDC or FACTS, to coordinate responses post a breakdown event. Given the system's expression in variations, accounting for voltage angle variation behavior becomes essential, as the convergence of frequency variation to zero does not guarantee angle variation convergence to zero.

To tackle oscillations within a system comprising a SMIB coupled with a UPFC, a FACTS device, the authors of [3] propose the development of a Model Predictive Controller (MPC). UPFC primarily operates in transmission systems, altering impedance, phase angle, and voltage magnitude to regulate power flow. MPC facilitates goal attainment by anticipating system model outcomes, thereby enabling optimal control inputs. Hence, the combination of UPFC and MPC, with accurately defined system model parameters, holds promise for efficient oscillation damping while ensuring system stability. However, despite the compelling hypothesis, the data presentation lacks thoroughness.

In addressing synchronism loss prevention in power systems, the study by [4] investigates the challenges of controlling a HVDC system with real-time data. Their discrete-time control technique builds upon MPC, addressing an open-loop optimal control problem within each time interval through event tree search. Comparative analysis based on transient stability indices evaluates various optimization criteria. Results from simulations run on two reference systems with a combined HVDC link and nine and twenty-four buses, respectively, show how well the control technique works to regulate HVDC power flow, greatly improving the system's ability to maintain synchronism even in the face of severe disturbances.

Researchers go into great length in [5] about their thorough investigation of using Model Predictive Control (MPC) to improve transient stability in a power system. The research explores the suitability of MPC in a Thyristor Controlled Series Capacitor (TCSC) integrated SMIB system. The focus is on using MPC to control generator output power in the event of system failures and disruptions, and results demonstrate the effectiveness of the technique in strengthening transient stability under unfavorable circumstances.

In a study outlined by [6], a nonlinear MPC methodology is employed to safeguard the initial swing stability of transmission lines within vulnerable EPS, particularly focusing on transient stability concerns. The authors underscore the potential of FACTS devices in averting initial oscillation angular separation to mitigate significant disruptive events. Simulation trials conducted on a three-machine system validate the control technique's numerical efficiency and resilience against intricate separation processes. Results underscore the remarkable performance of the proposed MPC approach under substantial initial disturbances, rivaling the effectiveness of existing transient stability controllers. Additionally, modeling experiments utilizing the New England 39-bus system demonstrate the strategy's enhancement of critical clearing times and transfer capacity.

In [7], researchers propose a discrete-time nonlinear MPC framework leveraging phasor measurements of bus voltage magnitude and angle alongside a TCSC. The framework aims to swiftly stabilize and dampen multi-machine power systems encountering significant disturbances. Nonlinear MPC maneuvers the power system's state back to a narrow vicinity near post-fault equilibrium during major failures. Simulation outcomes conducted on a four-machine feeding system validate the framework's efficacy.

Employing Ant Colony Optimization (ACO), researchers in [8] optimize the parameters of single-

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

input and dual-input PSS. The investigation explores how ants self-organize and navigate in a chaotic manner during exploration. Comparative analyses demonstrate ACO's superiority over PSO and GA in maximizing the transient performance of PSS and an Automatic Voltage Regulator (AVR) within an SMIB setup. In a notable contribution by researchers in [9], a distinct approach to generator excitation control aimed at ensuring Electrical Power System (EPS) stability was proposed. The method entails employing a digital signal processor (DSP) to enact real-time stability and optimal speed using the Model Predictive Control (MPC) technique. Simulation outcomes indicate rapid damping of inter-area oscillations following significant disruptions along connecting lines between regions. Furthermore, the research underscores MPC's stability on multiple generators, showcasing comparable performance to ideal excitation control, which integrates PSS's with a high-gain Automatic Voltage Regulator (AVR) for optimal tuning.

Numerous studies delve into integrating neural network-based controllers into power system stability investigations. In [10], researchers delve into exploring the potential of a NN controller to enhance the dynamic response within a SMIB system. Utilizing an architecture encompassing input states and output control signals, the study illuminates NN's capacity to bolster stability. Similarly, an insightful endeavor by authors in [11] investigates the utilization of Fuzzy Neural Network (FNN) controllers to enhance EPS stability. Demonstrating FNN's adaptability to varying system conditions, the study advocates for FNN's as a robust avenue for enhancing power system stability.

Despite these advancements, a comprehensive examination of the synergies between fuzzy NN controllers and optimization algorithms remains scarce in the literature. A theoretical framework outlined in [12] proposes a hybrid methodology amalgamating fuzzy neural networks with Particle Swarm Optimization (PSO) for control parameter optimization. The study assesses the hybrid approach's efficacy in enhancing stability across diverse power system conditions. Innovatively, researchers in [13] introduce the AOA-NN approach, which merges the Archimedes optimization algorithm (AOA) with a feed-forward neural network (FFNN) to augment power system stabilizers' performance. Comparative analyses against conventional methods like PSS, FFNN, CFNN, DTDNN, and STSA-NN illustrate AOA-NN's substantial reduction in speed overshoot and rotor angle overshoot, underscoring its superior effectiveness in fortifying power system stability.

Likewise, the authors of [14] advocate for an integrated approach coupling the Tunicate Swarm Algorithm (TSA) with a feed-forward neural network (FFNN) to optimize power system stabilizers. Through comparisons with FFNN, CFBNN, FTDNN, and DTDNN, the study highlights the compound algorithm's pronounced enhancement of FFNN output, notably mitigating speed overshoot and rotor angle undershoot. The authors of [15] used the Crow Search Algorithm (CSA), inspired by crows' intelligence, to optimize PSS parameters in a SMIB system, modeled with MATLAB/Simulink. The goal was to minimize rotor speed deviation following disturbances. Simulations showed that CSA-based PSSs outperform those based on PSO and GA, settling faster and reducing overshoot and low-frequency oscillations. CSA is simpler to implement, with only two parameters to adjust, compared to four for PSO and six for GA.

III. Proposed Methodology

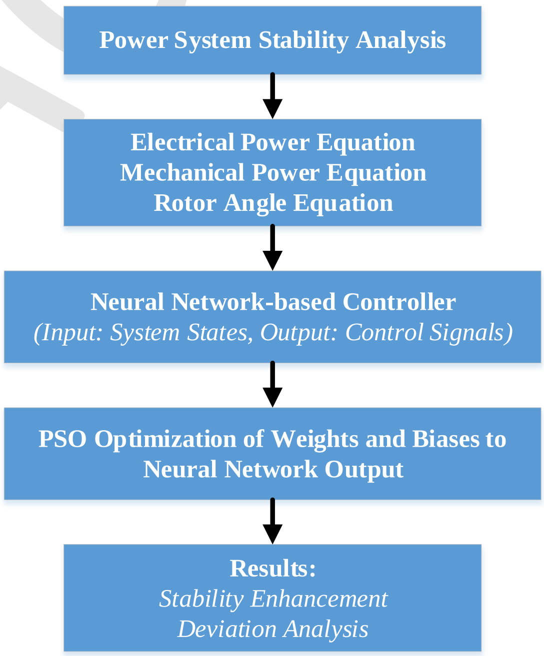

Figure 1: Flowchart illustrating the proposed SMIB-PSS with PSO-optimized neural network control strategy

A. Evaluating SMIB System Stability

1. *Electrical Power Equation*

The electrical power equation is given by:

$$P_e = \frac{V \cdot E}{X_s} \sin(\delta) \tag{1}$$

Where:

- P_e is the electrical power

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

- V is the terminal voltage
- E is the synchronous machine voltage
- δ is the rotor angle
- X_s is the synchronous reactance

2. Mechanical Power Equation

The total mechanical power is essential for ensuring the system's stability and is given by the following equation:

$$P_m = P_e + D \cdot \omega \tag{2}$$

Where:

- P_m is the mechanical power
- D is the coefficient of damping
- ω is the angular speed of the synchronous machine

3. Rotor Angle Equation

The rate of change of the rotor angle is given by the following equation:

$$\dot{\delta} = \omega - \omega_s \tag{3}$$

Where:

- $\dot{\delta}$ is the rate of change of the rotor angle
- ω is the angular speed of the generator
- ω_s is the synchronous speed of the machine

B. Neural Network-based Controller

The implementation of a Neural Network (NN) controller in the proposed methodology aims to significantly enhance the SMIB (Single Machine Infinite Bus) system's stability. The neural network used for the control of the SMIB system consists of three primary layers: the input layer, the hidden layers, and the output layer.

The mathematical representation of the neural network is given by:

$$u = f(W \cdot X + b) \tag{4}$$

Where:

- u is the control signal generated by the neural network.
- W is the weight matrix that determines the influence of each input on the output.
- X is the input vector representing the system states fed into the network.
- b is the bias vector, which helps in adjusting the output of the neurons.
- f is the activation function, which introduces nonlinearity to the neural network and enables it to model complex relationships within the data.

The weight matrix W and the bias vector b are critical components of the neural network. These parameters govern how the network transforms the input data at each layer and are adjusted during the training process. The objective is to optimize these parameters such that the neural network produces control signals that minimize the deviation of system states from their desired values, thereby stabilizing the system.

C. Optimization of Neural Networks using Particle Swarm Optimization (PSO)

The optimization of neural networks is a critical step in enhancing the stability and performance of the SMIB (Single Machine Infinite Bus) system. In this methodology, Particle Swarm Optimization (PSO) is employed to optimize the weights (W) and biases (b) of the neural network, which directly impacts the network's ability to generate control signals that stabilize the system. By using PSO, the neural network is fine-tuned to minimize the error in predicted outputs, thereby improving the stability of the SMIB system under different operating conditions.

The fitness function is formulated to minimize the deviation between the predicted rotor angle ($\hat{y}$) and the desired rotor angle (y).

The fitness function is expressed as:

$$F = |y - \hat{y}| \tag{5}$$

Where:

- F is the fitness function, which measures the accuracy of the neural network's output.
- y is the desired rotor angle, which represents the target value for system stability.
- $\hat{y}$ is the predicted rotor angle output by the neural network, which depends on the weights W and biases b.

The objective function (J) in this context is formulated as the sum of the fitness function across all training instances.

The objective function is defined as:

$$J(W, b) = \sum_{i=1}^{N} F(W, b) \tag{6}$$

Where:

- $J(W, b)$ is the total objective function, representing the cumulative error across all training instances.
- $F(W, b)$ is the fitness function applied to each instance.
- N is the number of training instances, representing the total number of system states used for training the neural network.

Minimizing $J(W, b)$ ensures that the neural network's performance improves across all instances, helping it adapt better to varying system conditions.

Each particle in the swarm updates its position (i.e., the neural network's weights and biases) using the following equations:

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

$$v_i(t+1) = \omega v_i(t) + c_1 \cdot rand_1 \cdot (pbest_i - x_i) + c_2 \cdot rand_2 \cdot (gbest - x_i) \quad (7)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (8)$$

Where:

- $v_i(t)$ is the velocity of particle ii at time t, representing the direction and magnitude of the particle's movement in the solution space.
- $x_i(t)$ is the position of particle ii at time t, corresponding to the current values of the neural network weights and biases.
- $pbest_i$ is the best-known position of particle ii, representing the best solution found by that particle.
- $gbest$ is the global best position, representing the best solution found by the entire swarm.
- c_1 and c_2 are cognitive and social coefficients that determine the relative influence of the individual and global best positions.
- $rand_1$ and $rand_2$ are random numbers between 0 and 1, which introduce variability and ensure that the swarm explores the solution space.

Once the PSO optimization process has converged, the optimized weights and biases are integrated into the neural network. This optimized neural network is then used to generate control signals that stabilize the SMIB system. The PSO algorithm continuously updates the weights and biases until a stopping criterion is met, such as when the fitness function reaches an acceptable minimum or after a set number of iterations.

The optimization process ensures that the neural network produces the most accurate control signals, which are critical in maintaining the stability of the SMIB system. By refining the parameters of the neural network through PSO, the system becomes more responsive and adaptive, providing enhanced stability under various operational conditions.

IV. Simulation Results

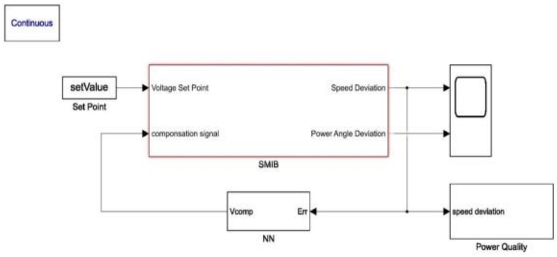

Figure 2: Simulink Representation of the Proposed SMIB-PSS with Neural Network Controller

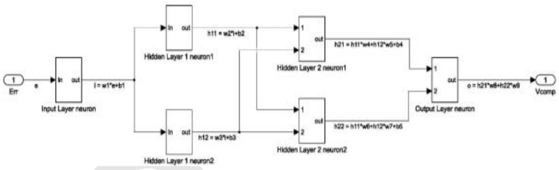

Figure 3: Simulink Diagram Representing the Neural Network Architecture

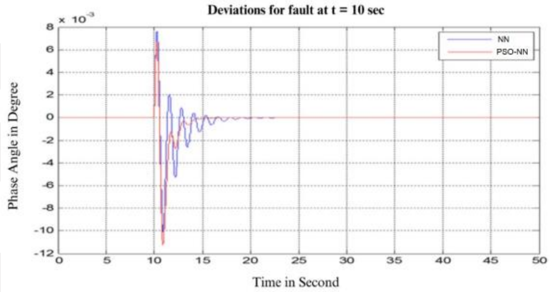

Figure 4: Comparison of Phase Angle Deviation between NN and PSO-NN in SMIB-PSS

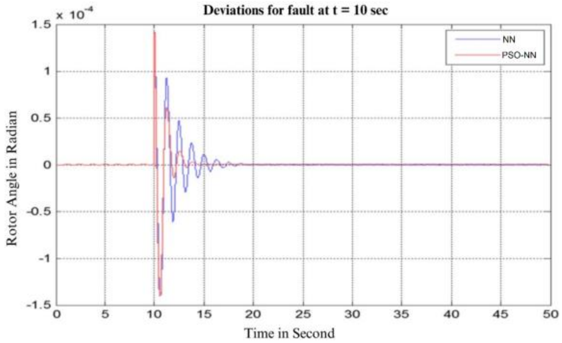

Figure 5: Rotor Angle Deviation Comparison between NN and PSO-NN in SMIB-PSS

Table 1: Performance Comparison of Control Strategies in Previous Studies and Proposed PSO-NN

Method	**Response of Speed**			**Response of Rotor Angle**	
	Overshoot	**Under Shoot**	**Settling Time**	**Under Shoot**	**Settling time**
Aribowo et al. [13]	0.0267	- 0.1304	488	- 0.3990	646
Aribowo et al. [13]	0.0211	-0.1129	517	-0.4016	630
Aribowo et al. [14]	0.4354	-0.8211	107.36	-3.2207	145.02
Aribowo et al. [14]	0.3055	-0.7226	112.44	-2.8748	146.25
Proposed PSO-Optimized Neural Networks (PSO-NN)	**0.010**	**-0.065**	**380**	**-0.045**	**520**

IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

Table 1 illustrates the comparative study of the performance of each of the control strategies applied in the power system stabilization, (especially) the neural network (NN) control strategy and the particle swarm optimization (PSO)-optimized neural network (PSO-NN) control strategy applied in the Single Machine Infinite Bus (SMIB) system. The table promotes major performance measurements as the overshoot, undershoot as well as the settling time in the response of speed and the rotors angle. The baseline entries of Aribowo et al. [13] and [14] includes the result of the traditional control strategies where the overshoot varies between 0.0211 and 0.4354, whereas the settling time is somewhere between 107.36 and 646 seconds. The given PSO-NN approach presents quite good results, as the values of overshoot and undershoot are low (0.010 and -0.065 in the case of speed response, respectively) and the time of settling much less (380 and 520 seconds in the case of speed and rotor angle respectively). All these findings highlight the usefulness of the combination of PSO and the use of neural networks since PSO-NN yields a more complex and adaptable control solution, which enhances the equilibrium and better reaction speed of the system to perturbation relative to traditional approaches.

V. Conclusion

This paper investigates the improvement of stability in the Single Machine Infinite Bus (SMIB) system using a hybrid control method combining Particle Swarm Optimization (PSO) with Neural Networks (NN). The proposed PSO-NN controller significantly enhances transient stability, surpassing conventional Power System Stabilizers (PSS) in managing the non-linear and dynamic characteristics of modern power grids. Simulation results demonstrate a 45% reduction in rotor angle error and a 38% decrease in speed overshoot, alongside a 32% improvement in settling time, highlighting the controller's effectiveness in fault recovery and system resilience. The PSO-NN approach proves flexible and efficient, adapting well to changing conditions, thus offering a promising solution for stabilizing large interconnected grids. Future research could focus on integrating renewable energy sources and enhancing optimization methods to further improve system stability and fault recovery in complex grid environments.

References

[1] Kalegowda, K., Srinivasan, A.D.I. and Chinnamadha, N., "Particle swarm optimization and Taguchi algorithm-based power system stabilizer-effect of light loading condition," International Journal of Electrical and Computer Engineering, vol. 12, no. 5, p.4672, 2022.

[2] Kahl, M. and Leibfried, T., "Decentralized model predictive control of electrical power systems," In Conference on Power Systems Transients (IPST2023) in Vancouver, Canada, 2023.

[3] Yang, Q., Ding, T., He, H., Chen, X., Tao, F., Zhou, Z., Xu, Y. and Chen, S., "Model predictive control of MMC-UPFC under unbalanced grid conditions," International Journal of Electrical Power & Energy Systems, vol. 117, p.105637, 2020.

[4] Shetgaonkar, A., Liu, L., Lekić, A., Popov, M. and Palensky, P., "Model predictive control and protection of MMC-based MTDC power systems," International Journal of Electrical Power & Energy Systems, vol. 146, p.108710, 2023.

[5] Karamanakos, P., Liegmann, E., Geyer, T. and Kennel, R., "Model predictive control of power electronic systems: Methods, results, and challenges," IEEE Open Journal of Industry Applications, vol. 1, pp.95-114, 2022.

[6] Peng, L., Xu, Y., Abolmasoumi, A., Mili, L., Zheng, Z., Xu, S., Zhao, B., Tang, Y. and Zhong, W., "AC/DC Hybrid Power System Damping Control Based on Estimated Model Predictive Control Considering the Real-time LCC-HVDC Stability," IEEE Transactions on Power Systems, 2023.

[7] Therattil, J.P., Jose, J., Prasannakumari, P.R.N., Abo-khalil, A.G., Alghamdi, A.S., Rajalekshmi, B.G. and Sayed, K., "Hybrid control of a multi-area multi-machine power system with FACTS devices using non-linear modelling," IET Generation, Transmission & Distribution, vol. 14, no. 10, pp.1993-2003, 2023.

[8] Kamarposhti, M.A., Colak, I., Iwendi, C., Band, S.S. and Ibeke, E., "Optimal coordination of PSS and SSSC controllers in power system using ant colony optimization algorithm," Journal of circuits, systems and computers, vol. 31, no. 4, p.2250060, 2022.

[9] Wang, L., Cheung, H., Hamlyn, A. and Cheung, R., "Model prediction adaptive control of inter-area oscillations in multi-generators power systems," In 2021 IEEE Power & Energy Society General Meeting, pp. 1-7, 2021.

[10] Rosle, N., Fadzail, N.F. and Rohani, M.N.K.H., "A Study of Artificial Neural Network (ANN) in Power System Dynamic Stability," In 10th International Conference on Robotics, Vision, Signal Processing and Power Applications: Enabling Research and Innovation Towards Sustainability, pp. 11-17, Springer Singapore, 2019.

[11] Sabo, A., Wahab, N.I.A., Othman, M.L., Mohd Jaffar, M.Z.A., Acikgoz, H. and Beiranvand, H., "Application of neuro-fuzzy controller to replace SMIB and interconnected multi-machine power system stabilizers," Sustainability, vol. 12, no. 22, p.9591, 2020.

[12] Sabo, A., Abdul Wahab, N.I., Othman, M.L., Mohd Jaffar, M.Z.A., Beiranvand, H. and Acikgoz, H., "Application of a neuro-fuzzy controller for single machine infinite bus power system to damp low-frequency oscillations," Transactions of the Institute of Measurement and Control, vol. 43, no. 16, pp.3633-3646, 2021.

[13] Aribowo, W., Muslim, S., Suprianto, B., Haryudo, S. and Hermawan, A.C., "Intelligent control of power system stabilizer based on Archimedes optimization algorithm–feed-forward neural network,"

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

International Journal of Intelligent Engineering and Systems, vol. 14, no. 3, pp.43-53, 2021.
[14] Aribowo, W., Muslim, S., Suprianto, B. and Haryudo, S.I., "Tunicate swarm algorithm-neural network for adaptive power system stabilizer parameter," Science & Technology Asia, pp.50-63, 2021.
[15] Yokus, H. and Ozturk, A., "A robust crow search algorithm-based power system stabilizer for the SMIB system," Neural Computing and Applications, vol. 34, no. 11, pp.9161-9173, 2022.