Innovative Approach to Enhance Stability: Neural Network Control and Aquila Optimization Integration in Single Machine Infinite Bus Systems

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Abstract

This paper highlights the need to improve the stability of single-machine infinite-bus (SMIB) systems, which is crucial for maintaining the dependability, efficiency, and safety of electrical power systems. The changing energy environment, characterized by a growing use of renewable sources and more intricate power networks, is challenging established stability measures. SMIB systems exhibit dynamic behavior, particularly during faults or unexpected load variations, requiring sophisticated real-time stabilization methods to avert power failures and provide a steady energy supply. This paper suggests a complex approach that combines power system stability analysis with a neural network controller enhanced by the Aquila optimization algorithm (AOA) to address the dynamic issues of SMIB systems. The study shows that the AOA-optimized neural network (AOA-NN) controller outperforms in avoiding disruptions and attaining speedy stabilization by exhaustively examining electrical, mechanical, and rotor dynamics. This method improves power system resilience and operational efficiency as demands and technology expand.

Keywords: Aquila optimization algorithm, electrical power systems, neural network, power system stabilizers, single machine infinite bus

1. Introduction

The stability of single-machine infinite-bus (SMIB) systems is crucial in the dynamic energy industry since they are essential for facilitating effective energy transmission in electrical grids. Conventional techniques for preserving SMIB system stability face difficulties due to contemporary power grids' intricate and ever-changing characteristics, underscoring the need for creative solutions. This paper presents a new approach that combines neural network control with the Aquila optimization algorithm (AOA) to improve the resilience and flexibility of SMIB systems. This study aims to use sophisticated artificial intelligence and optimization approaches to provide a solution that exceeds traditional stability tactics, guaranteeing that SMIB systems can adapt to the evolving power environment. This method substantially enhances operational efficiency and resilience, signifying a crucial change in the quest for dependable energy delivery.

1.1. Background

In the ever-evolving landscape of global power networks, compounded by factors like renewable energy integration and unpredictable outages, SMIBs demand cutting-edge stability solutions [1]. Traditional linear control methods fail to address the need to address the nonlinear and time-varying dynamics inherent in SMIBs [2]. Urgency arises for innovative methodologies capable of navigating the intricate nature of these systems [3]. This study assesses stability analysis and

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control strategies in the context of SMIB systems, essential models for broader power systems [1]. While conventional power system stabilizers (PSSs) prove valuable in mitigating oscillations [4], the escalating uncertainties and dynamic elements necessitate a closer look at advanced control methods [5]. With their ability to grasp complex data relationships, neural networks (NNs) and artificial intelligence emerge as promising tools [6]. Integrating NNs into PSSs enhances adaptability by capturing nonlinearities [7].

1.2. The significance of the proposed research

The uniqueness of the proposed research lies in its ability to address the deficiencies in the current body of literature by integrating an SMIB with a PSS enhanced by using an AOA-optimized neural network (AOA-NN). This approach aims to improve power system stability by combining the advantages of SMIB systems, current PSS, and the optimization capabilities of AOA. Unlike earlier methods, this research introduces a comprehensive framework that ensures precision in presenting results and explores the potential of optimization algorithms and fuzzy neural network (FNN) controllers. This integration is expected to improve electrical power systems' overall stability significantly. It will provide a more robust and adaptable solution to address issues arising from adverse operating conditions. Consequently, the proposed method is the first to connect the existing research with a more comprehensive and practical approach to ensuring power system stability.

This paper is organized as follows: Section 2 gives a detailed literature review which includes research gaps. Section 3 delves into the specifics of the proposed methodologies. The results obtained from the MATLAB simulations are then shown in Section 4, followed by a comprehensive analysis. Section 5 offers a concise overview of the findings and concludes the study with some last reflections.

2. Literature Review

Kalegowda et al. [1] proposed an innovative way to analyze power system stability that differs from conventional methodologies in 2022. Their innovative approach integrates robust Taguchi design with particle swarm optimization (PSO), as seen in Fig. 1. The Taguchi-PSO tuning approach improves system settings by creating a target function and recognizing changeable factors as particles in a swarm. Initialization includes configuring PSO parameters and simultaneously establishing Taguchi parameters for experimental design. Taguchi optimization is used to assess fitness to determine important parameter values that direct updates in PSO. The process stops when it converges or reaches the iteration limit. Validated optimized parameters via real-world testing to ensure improved performance meets the defined goal function.

In 2013, Kahl and Leibfried [2] emphasized the need to use sophisticated methods in power systems to tackle nonlinear dynamics and low-frequency oscillations under adverse circumstances. A control approach that uses phase data from many units to reduce inter-area oscillations was suggested. In 2020, Yang et al. [3] proposed a model predictive controller for managing oscillations by using a unified power flow controller (UPFC) to regulate impedance, phase angle, and voltage magnitude accurately, reducing oscillations. Model predictive control (MPC) is a sophisticated control technique in diverse engineering applications. MPC often includes forecasting a system's future actions, creating an optimization challenge, and resolving it to get the best control input. The pseudocode describes an MPC [3] technique. The system constantly observes, forecasts, and optimally modifies control inputs in real-time. The system uses a predictive model, cost function, and constraints to determine the best control sequences, assuring efficient operation and meeting specified requirements at each time step.

Shetgaonkar et al. [4] explored the use of MPC to reduce synchronism loss in high voltage direct current (HVDC) systems in 2023. Their method utilized event tree search in an open-loop scenario to enhance control techniques and improve the system's ability to withstand disturbances. In 2020, Karamanakos et al. [5] showed that a thyristor-controlled series capacitor (TCSC) can enhance transient stability in an SMIB setup. Peng et al. [6] confirmed the advantages of utilizing

FACTS devices with nonlinear MPC to preserve stability in difficult situations and manage disruptive occurrences in 2024. During the COVID-19 pandemic, Therattil et al. [7] introduced a discrete-time nonlinear MPC method that utilizes phasor measurements and TCSC to stabilize multi-machine power systems. In 2022, Kamarposhti et al. [8] investigated strategies to improve PSSs, showing a preference for ant colony optimization (ACO) compared to PSO and genetic algorithms (GA). Wang et al. [9] successfully integrated MPC with a digital signal processor (DSP) in mid-2009, achieving real-time stability and speed optimization, which led to a reduction in inter-area oscillations.

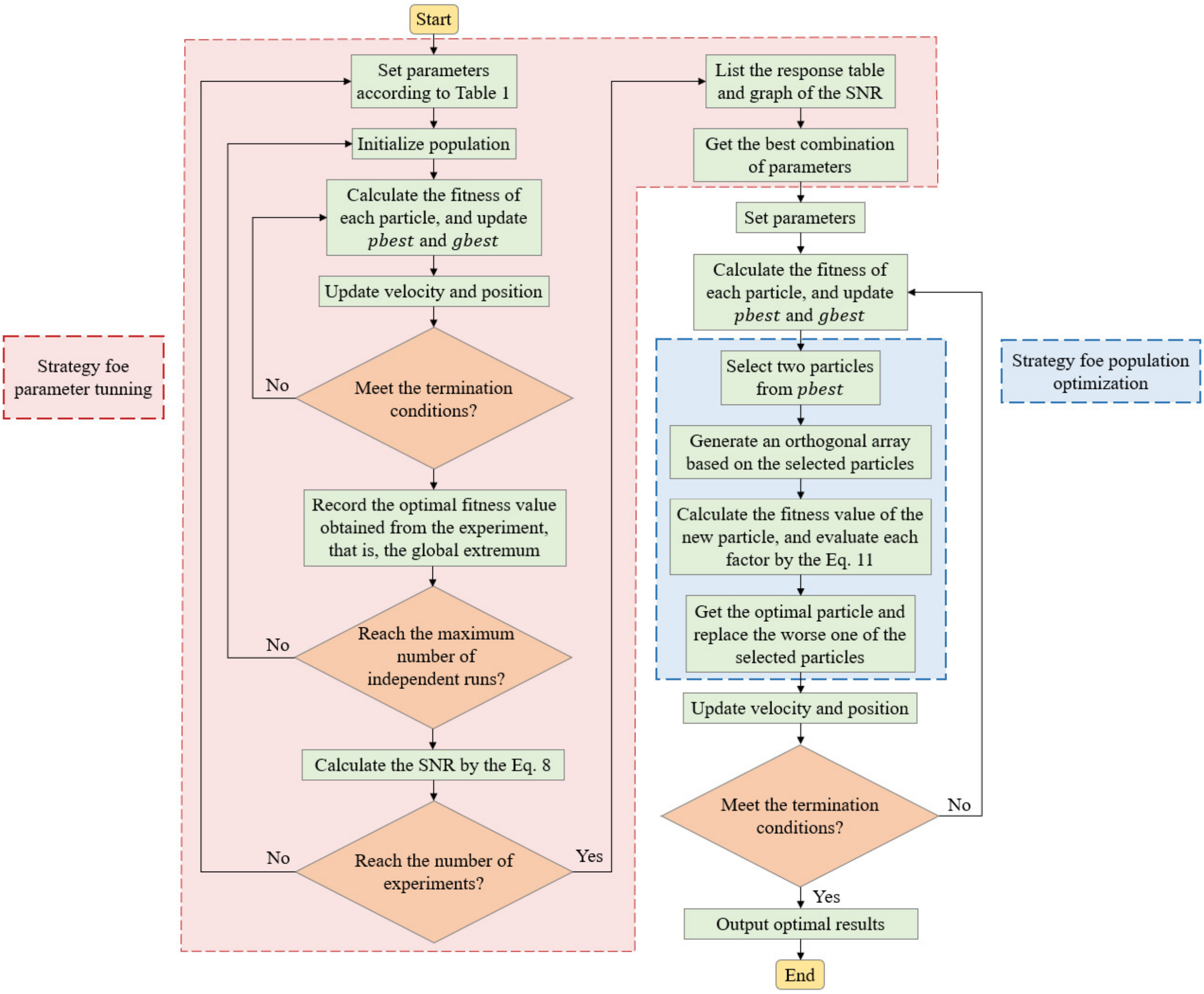

Fig. 1 Flow chart of Taguchi particle swarm optimization algorithm [1]

Rosle et al. [10] and Sabo et al. [11-12] explored NN controllers and suggested integrating PSO with a multi-level neuro-fuzzy power system stabilizer (MLNFPSS) for power system stability in 2018, 2020, and 2021. Ray et al. [13] and Ramshanker and Chakraborty [14] introduced a three-phase series hybrid active filter (SHAF) combined with a photovoltaic (PV) system in 2019 and 2022. Compared to traditional controllers, they demonstrated improved harmonic correction using a robust extended complex Kalman filter (RECKF). In 2017 and 2019, Srinivasarao et al. [15] and Oraibi et al. [16] improved PSSs for multi-machine configurations by employing adaptive neuro-fuzzy inference systems, while Saleem et al. [17] presented an adaptive neuro-fuzzy-based recurrent wavelet control (ANRWC) to boost stability.

In 2022, Cheng et al. [18] developed a hybrid Taguchi-PSO method to optimize reactive power in submersible pumps. Abualigah et al. [19], Zhao et al. [20], and Aribowo et al. [21] studied the Aquila optimization technique for optimizing PID controller settings of DC motors. Wu and Feng [22] in 2018 examined the development of NNs in wireless communication, while Islam et al. [23] in 2019 outlined their significant impact in several fields. Gupta [24] investigated the flexibility of NNs in complex systems, highlighting their ongoing improvement and growing influence on artificial intelligence in 2013.

The research gap in power system stability focuses on the unexplored incorporation of modern technologies like NN control and Aquila optimization, particularly in SMIB systems. The existing research mainly uses traditional methodologies. Hence, it is essential to investigate further the combined benefits these new approaches might provide. It is crucial to address these deficiencies to improve adaptive stability and optimize performance in the changing energy environment. The literature review has found twelve notable research deficiencies. The work on Taguchi-PSO tuning [1] demands a thorough investigation of its performance under various operating situations due to its new methodology.

Further research is required to explore the problems and limits of the complete control technique for inter-area oscillations [2], explicitly focusing on voltage angle fluctuations. The integration of MPC and UPFC [3] for SMIB stability must be thoroughly investigated in the findings, requiring comprehensive performance measurements for practical feasibility. A thorough comparison of optimization criteria and stability indices is needed to properly appreciate the effectiveness of the discrete-time MPC for HVDC control [4]. Extensive validation is needed for the nonlinear MPC [6] for transient stability under various system circumstances, whereas research on real-world application is required for the TCSC-based nonlinear MPC [7].

Additionally, the utilization of ACO for PSS tuning [8] needs comparison with well-established techniques, whereas generator excitation control using DSP-based MPC [9] necessitates further real-time implementation and validation. Investigating the computational complexity and training time required for applying an NN controller [10] to improve SMIB dynamics is necessary. FNN [11] controllers for stability must include sensitivity to uncertainty. The hybrid strategy combining FNNs with PSO [12] must clarify computing requirements and convergence speed. Investigating these factors would significantly improve these advanced methodologies' practical viability and effectiveness in power system stability research.

3. Methods

To fill these deficiencies, this research work presents a study that combines an SMIB with a PSS improved by an AOA-NN. This proposed method offers a comprehensive and better solution for power system stability by integrating the strengths of SMIB systems, modern PSS, and the optimization capabilities of AOA. This work introduces a unified framework that guarantees the presentation of rigorous results and investigates the unrealized potential of FNN controllers in combination with optimization methods, which differs from previous techniques. This integration will significantly enhance the overall stability of electrical power systems, offering a more resilient and flexible solution to the difficulties caused by unfavorable operating circumstances. As a result, the technique is a first step in bridging the gap between current research and a more thorough and efficient strategy for power system stability.

3.1. SMIB system

The SMIB setup is a fundamental model for analyzing transient reactions and stability in power systems. In this configuration, a synchronous generator is connected to an infinite bus, representing the broader power grid. Understanding the functioning of the SMIB system is essential for comprehending the mechanisms by which power systems manage transient stability. Below is the mathematical representation of the SMIB system:

The swing equation typically represents the temporal variation of the rotor angle (δ) and characterizes the dynamics of the SMIB system. This equation, is denoted as:

$$M\frac{d^2\delta}{dt^2}+D\frac{d\delta}{dt}=P_{mech}-P_e \tag{1}$$

Eq. (1) reflects the balance between mechanical input and electrical output, determining the angular motion of the generator rotor.

The swing equation's Laplace transform yields the SMIB system's transfer function. Assuming minor deviations from the equilibrium, the transfer function is expressed as:

$$\frac{\delta(s)}{P_{mech}(s)} = \frac{1}{Ms^2 + Ds - P_e} \tag{2}$$

Eq. (2) is the transfer function of the Laplace transform of the swing equation, which relates the rotor angle deviation to the mechanical power input in the frequency domain, providing insights into the system's response to disturbances.

The stability analysis of the SMIB system typically involves eigenvalue analysis. The stability characteristics of the system are determined by examining the eigenvalues of the system matrix, which is derived from the linearized equations of motion. The eigenvalues are expressed as:

$$\lambda = \frac{-D \pm \sqrt{D^2 - 4MP_e}}{2M} \tag{3}$$

Stability is determined by the genuine parts of these eigenvalues, with negative real parts indicating stability. The solution to the swing equation provides insights into the dynamic behavior of the SMIB system over time. The trajectory of the rotor angle illustrates how the system responds to disturbances and how quickly it returns to a stable state. The SMIB system is a benchmark for stability analysis and control strategy development. Its mathematical representation, through the swing equation and associated transfer functions, enables engineers to understand the transient stability of power systems. Analyzing the dynamic behavior and stability characteristics of the SMIB system is foundational for designing effective control mechanisms, such as PSSs, to ensure the reliable operation of the broader power grid.

3.2. Power system stabilizer (PSS)

The PSS is a crucial component of a generator's excitation system. It is a significant control device that enhances the dynamic stability of a power system. The system's primary purpose is attenuating oscillations and maintaining stability, particularly in the SMIB system. To maximize the stability of the excitation system, the PSS deliberately inserts an extra stabilizing signal. The mathematical representation of the PSS is as follows:

In the SMIB system, the dynamics of the PSS can be described by a differential equation. Considering a first-order lag model, the dynamic behavior of the PSS is given by:

$$T_{PSS}\frac{dV_{PSS}}{dt} = -V_{PSS} + K_{PSS}\left(V_{\delta} - V_{PSS}\right) \tag{4}$$

This equation captures the dynamic response of the PSS to changes in the rotor angle (V_{δ}). Taking the Laplace transform of the differential equation, to obtain the transfer function representation of the PSS:

$$G_{PSS}(s) = \frac{V_{PSS}(s)}{V_{\delta}(s)} = \frac{K_{PSS}}{1 + T_{PSS}(s)} \tag{5}$$

This transfer function relates the PSS output to changes in the rotor angle in the frequency domain. The PSS signal (V_{PSS}) added to the excitation system is given by:

$$V_{PSS} = G_{PSS}(s)V_{\delta}(s) \tag{6}$$

Substituting the transfer function expression:

$$V_{PSS} = \frac{K_{PSS}}{1 - T_{PSS}(s)}V_{\delta}(s) \tag{7}$$

This equation emphasizes that the PSS signal is proportional to the rate of change of the rotor angle, reflecting the PSSs role in responding to dynamic deviations. The PSS gain and time constant are vital parameters that determine the behavior of the PSS. A higher gain increases the influence of the PSS on the system, while the time constant dictates the speed of response to changes in the rotor angle. The PSS contributes a supplementary stabilizing signal to the excitation system, helping dampen oscillations and improve transient stability in the SMIB system. The tuning of PSS parameters is critical to power system analysis and design, ensuring optimal performance under various operating conditions. Dynamic equations, transfer functions, and critical parameters characterize the PSS in the SMIB system. Its role is to enhance the dynamic stability of the power system by responding to changes in the rotor angle and providing additional control signals to the excitation system. The careful design and tuning of PSS parameters are essential for achieving optimal stability performance in power systems.

3.3. Neural network (NN)

NNs are computational models inspired by the human brain's complex architecture and operations. NNs are used in power system stabilization to give the control system flexibility and learning capabilities. NNs are made up of nested nodes that are coupled with predetermined weights and biases. Employing a methodical training procedure, these networks can understand complex relationships from the supplied data. An initial input layer, intermediate hidden layers, and a final output layer comprise a NN's architecture. Signal reception occurs in the input layer; after which it is processed further in the hidden levels. The output layer then generates the final output. A distinct weight characterizes each connecting link between nodes, and each node has an associated bias.

The activation function (f) in a NN is a crucial component that introduces non-linearity to the model. It determines the output of a neuron, helping the network to learn complex patterns and relationships in the data. In the general equation of an NN, the activation function is applied to the weighted sum of inputs and biases before being passed to the next layer. The mathematical representation is often denoted as,

$$y = f(\sum_{i=1}^{n} w_i x_i + b) \tag{8}$$

The role of the activation function is to introduce non-linearities, enabling the NN to learn and approximate complex functions. Without activation functions, the NN would behave like a linear regression model, irrespective of the number of layers, as the composition of linear functions remains linear. Following are some common examples of activation functions in NN:

Sigmoid function (Logistic): The formula below gives output values between 0 and 1. It is often used in the output layer of binary classification models.

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Hyperbolic tangent function (tanh): The hyperbolic tangent function is similar to the sigmoid but outputs values between -1 and 1, making it symmetric around the origin. Mathematically, it is represented as:

$$f(x) = \frac{e^{2x}-1}{e^{2x}+1} \tag{10}$$

Rectified linear unit (ReLU): The ReLU outputs the input for positive values and zero for negative values, as represented by the following equation. It is widely used in hidden layers due to its simplicity and effectiveness.

$$f(x) = \max(0, x) \tag{11}$$

Leaky rectified linear unit (Leaky ReLU): The Leaky ReLU, represented by the equation below, is similar to Eq. (11) but allows a small, non-zero gradient for negative inputs, preventing dead neurons, where, α is a small positive constant.

$$f(x) = \max(\alpha x, x) \tag{12}$$

Activation functions play a crucial role in determining the NN's capability to model complex relationships and improve its overall performance in various tasks. The choice of activation function depends on the specific requirements and characteristics of the problem at hand. The activation function (f) gives the network a hint of non-linearity, which helps it understand complex interactions. The NN is trained to reduce the difference between the expected and actual outputs by exposing it to input-output pairings and fine-tuning the weights and biases. This is usually achieved utilizing optimization techniques, among which gradient descent is famous. An essential technique for training NNs, backpropagation coordinates the backward propagation of mistakes across the network. This entails methodically reducing the total error by repeatedly modifying the weights and biases at each layer.

In the context of the PSS, the NN serves as an adaptive component capable of learning and adapting to the dynamic behavior of the power system. By incorporating an NN into the PSS design, the control system becomes more flexible and capable of capturing non-linear relationships and dynamic interactions within the power system. The NN is integrated into the PSS design to enhance its adaptability and learning capabilities. The PSS, augmented with NNs, becomes more adept at responding to varying operating conditions, capturing non-linearities, and providing an improved supplementary stabilizing signal to the excitation system. The weights and biases of the NN are optimized during the training process. The choice of optimization algorithms, such as gradient descent or metaheuristic algorithms like AOA, plays a crucial role in fine-tuning the NN for optimal performance in the PSS.

3.4. Aquila optimization algorithm (AOA)

The AOA is a nature-inspired optimization technique that mimics the hunting behavior of eagles, particularly the Aquila genus. It combines exploration and exploitation strategies to efficiently search for optimal solutions in optimization problems. The optimization problem being addressed typically involves an objective function that needs to be minimized or maximized. This function quantifies the quality of a solution based on its parameters. In the algorithm, equations representing the objective function are utilized to evaluate the effectiveness of potential solutions (positions of eagles) within the solution space. Equations governing the movement of eagles can be derived from their hunting behavior. For instance, the equations might determine the velocity and direction of eagles' movements during contour flights and short glide attacks. These equations guide the exploration and exploitation phases, ensuring a balanced search process.

To adapt and refine the search strategy over iterations, adaptation equations can be employed. These equations might adjust parameters such as exploration rate, exploitation rate, or the intensity of short glide attacks based on the success or failure of previous iterations. This adaptive mechanism enhances the algorithm's ability to efficiently explore and exploit the solution space. Below is the mathematical representation of the AOA:

The high soar with vertical stoop equation shows the hunting technique of a bird of prey, possibly a falcon or an eagle. These birds use a high soar to gain altitude, then perform a vertical stoop, diving sharply down to catch their prey with great speed and precision. It's a remarkable display of their aerial hunting skills. This equation is denoted as:

$$x_i(t+1) = x_i(t) + r_1\left[gbest(t) - x - x_i(t)\right] + r_2 rand(0,1) \tag{13}$$

The above equation provides the high soar with a vertical stoop that mirrors the algorithm's ability to swiftly navigate vast solution landscapes.

The following equation represents contour flight refers to the exploration phase where the algorithm searches the solution space methodically and efficiently, akin to an eagle circling an area to survey its surroundings. Also, the short glide attack represents the exploitation phase, where the algorithm converges towards promising solutions with a rapid and targeted approach, resembling the quick, precise dives of an eagle when it spots prey.

$$f(x_i) = f\left[x_i(t)\right] + c\left[gbest(t) - x_i(t)\right]^2 \tag{14}$$

The above equation also provides its adeptness at honing in on promising regions with precision. The following equation also mentions another hunting strategy employed by certain birds of prey, where they fly close to the ground or water surface, gradually descending while scanning for prey. This step allows them to approach their target stealthy and precisely before launching their attack. This equation reflects the algorithm's meticulous approach to refining solutions.

$$lbest(t) = \arg\min_{i=1ton} f\left[x_i(t)\right] \tag{15}$$

The swooping by walk and grab prey equation describes the hunting behavior of some birds, particularly, herons and egrets. These birds often use a scooping motion with their long bills to catch fish or other prey in shallow water. The by-walk refers to their slow and deliberate movement as they stalk their prey, often forming a distinctive y shape with their neck and body. Once they spot their target, they use their sharp bill to grab and secure the prey before swallowing it whole or carrying it away. This following hunting technique highlights their patience, precision, and adaptability to different environments.

$$x_i(t+1) = x_i(t) + r_3\left[lbest(t) - x_i(t)\right] + r_4 rand(0,1) \tag{16}$$

The algorithm continues its repeated operation until a predefined stopping condition is met. Commonly used thresholds for stopping include achieving a specific level of precision or finishing a predetermined maximum number of iterations.

The following steps show the AOA:

Step 1. High soar with vertical stoop: Begins by initializing a population of candidate solutions. Identifies the global best solution within the population in Eq. (9).

Step 2. Contour flight with short glide attack: Updates the positions of candidate solutions towards the global best solution, introducing a random perturbation to explore the search space and avoid local minima in Eq. (10).

Step 3. Low flight with slow descent attack: Evaluate the fitness of candidate solutions and identify the best local solution based on fitness in Eq. (11).

Step 4. Swooping by walk and grab prey: Updates candidate solution positions towards the local best solution, incorporating a minor random perturbation to exploit the search space around the local best solution in Eq. (12).

The proposed approach stands out for its user-friendliness, simplicity, and efficiency in identifying effective solutions. Despite potential challenges like susceptibility to local minima and convergence speed, its resistance to noise and flexibility in addressing various optimization problems make it a favorable choice. Precise parameter selection is crucial, but overall, the advantages outweigh the drawbacks, making it well-suited for optimization tasks when managed effectively.

3.5. Research directions

(1) Avoiding local minima: Develop methods to prevent the algorithm from getting trapped in local minima.

(2) Convergence speed: Improve the algorithm's convergence speed.

(3) Robustness: Enhance the algorithm's robustness to noise and ill-conditioned problems.

(4) Theoretical properties: Study the theoretical properties of the algorithm to gain deeper insights.

With its inspiration from nature, the AOA demonstrates effectiveness in solving optimization problems. Its simplicity, efficiency, and adaptability make it a promising approach, while ongoing research aims to address its limitations and further understand its theoretical foundations.

4. Proposed Methodology

Power system stability is crucial for maintaining the dependable and secure operation of electrical networks. It is crucial for maintaining ideal voltage and frequency levels, minimizing chain reactions of failures that might result in widespread power outages, and facilitating the efficient transmission of vast amounts of electricity over long distances. Power system stability is essential for enhancing generator and network component performance, enabling the incorporation of renewable energy sources, and averting voltage instabilities like collapses or sags. An established power system improves grid resilience, enabling it to manage better disruptions from natural disasters, equipment failures, or deliberate assaults, and reduces economic losses linked to power failures. Industries, organizations, and families depend on a consistent power supply to operate without interruptions, highlighting the importance of power system stability in maintaining continuous and reliable energy delivery. Table 1 indicates the research work carried out on various techniques with its limitations as given below.

Table 1 Limitations of existing work carried out

Ref.	Research work carried out	Limitations
Kalegowda et al. [1]	• Developed a detailed power system model, including PSS. • Identified critical PSS parameters affecting stability. • Used PSO for parameter optimization, with the Taguchi method to evaluate parameter effects systematically.	• Effectiveness relies on the accuracy of power system modeling. • May not address extreme or rapidly changing conditions thoroughly. • Specific findings might not apply universally across different systems or conditions.
Kahl and Leibfried [2]	• Modeled the power system for MPC application. • Designed a decentralized control scheme. • Developed MPC algorithms for each subsystem. • Tested via simulations under various conditions.	• Scalability issues in large systems. • High computational demand of MPC. • Dependence on reliable communication between components. • Need for accurate system models for effective control. • Challenges in responding to rapid system changes.
Yang et al. [3]	• Modeled MMC-UPFC and grid. • Designed MPC for MMC-UPFC. • Analyzed unbalanced grid scenarios. • Simulated control performance. • Evaluated effectiveness and stability. • Compared with traditional controls.	• Success hinges on precise MMC-UPFC and grid modeling. • High computational requirements may hinder real-time deployment. • Predicting performance in highly variable unbalanced conditions is complex. • More complex than traditional control systems. • Might need adjustments for different grid scenarios.
Shetgaonkar et al. [4]	• Detailed system modeling. • Integrated of MPC into MTDC. • Designed of protection mechanisms. • Simulated for performance testing. • Dynamic response analysis. • Effectiveness evaluation for stability. • Compared with traditional methods.	• Success tied to accurate modeling of MMC-based MTDC systems. • MPC may pose computational challenges for real-time implementation. • Adapting to rapid power system changes may be complex. • Integrating protection within MPC adds system complexity. • Applicability might vary across diverse MTDC system setups.
Karamanakos et al. [5]	• Detailed system modeling. • Optimized control horizon. • Tuned parameters for improved performance. • Simulated studies for analysis. • Explored real-world challenges. • Evaluated results and discussed encountered challenges.	• Accuracy relies on detailed power electronic system modeling. • MPC might demand significant computational resources, impacting real-time use. • Performance is sensitive to changes in system parameters. • Balancing accuracy and computation time in control horizon selection. • Adapting theoretical models to real-world scenarios can be challenging.

Table 1 Limitations of existing work carried out (continued)

Ref.	Research work carried out	Limitations
Peng et al. [6]	• Detailed system modeling. • Implemented estimated MPC: considering real-time LCC-HVDC stability. • Considered harmonizing control decisions with real-time stability. • Tuned parameter systematic for enhanced control. • Addressed real-world applicability and practical challenges. • Assessed how the proposed control affects system stability. • Analyzed and interpreted outcomes to gauge control strategy effectiveness.	• Precision relies on accurate AC/DC hybrid power system modeling. • Estimated Model Predictive Control (MPC) may have computational challenges. • Incorporating real-time LCC-HVDC stability adds complexity. • Performance may vary with changes in system parameters. • Findings may be more relevant to certain AC/DC system configurations.
Therattil et al. [7]	• Non-linear system modeling. • Integrated hybrid control with facts devices. • Analyzed parameter sensitivity. • Studied different system configurations. • Simulation studies for performance evaluation. • Analyzed computational load.	• Precision relies on effective non-linear modeling. • Integrating FACTS devices adds complexity. • Performance varies with system parameter changes. • Effectiveness may differ across system configurations. • Hybrid control may have computational requirements.

Fig. 2 illustrates the flow from power system stability analysis to the NN-based controller, incorporating the AOA. Each block represents a significant step in the methodology and is described in the following subsections. In Fig. 2, this proposed method endeavors to enhance the stability of power systems by utilizing control signals and an immediate response to changes in system conditions.

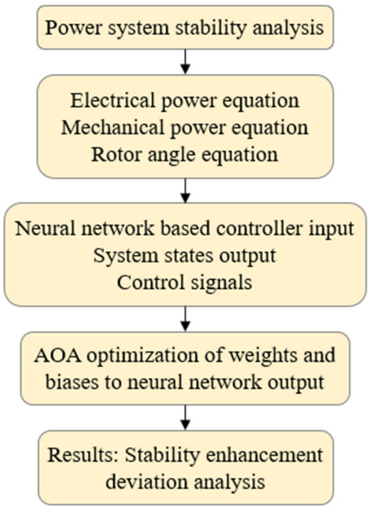

Fig. 2 Flow diagram for proposed SMIB-PSS using AOA-NN

Constant power supply maintenance is contingent upon a dependable power system. When discussing the electrical grid, stability refers to its capacity to return to its original state after a disturbance. Utilizing active control mechanisms, the SMIB-PSS system is designed to restore this stability rapidly. The system dynamics can be simulated by employing equations that illustrate the machine's electrical power output and mechanical power input accordingly. The imbalance between the mechanical and electrical energies, which influences the rotor's acceleration and deceleration, impacts the system's stability. P_e, which stands for electrical power, is determined by several factors, including the generator's output voltage, current, and power factor. The input power from the prime mover is referred to as mechanical power (P_m), which is typically constant over the short term. The equation representing the relationship between the rotor angle and time is denoted by δ. Evaluation of a system's stability is dependent on it. The equation can be derived through the application of the swing equation, which takes into account damping effects and inertia while establishing a relationship between the rotor's acceleration and the net power.

The proposed configuration is complete with the NN-based controller. Inputted into the system are conditions such as rotor angle and rotor speed, while control signals are generated in response. To ensure the preservation of system stability, these control signals are employed to modify the PSS parameters in real-time. To optimize the weights and biases of the neural network, the AOA method is implemented. The objective is to determine which values of the NN parameters have the most significant impact on PSS stability enhancement. AOA was motivated by the realization that an optimal angle exists at which a wing can traverse air with the least amount of resistance. The objective of AOA optimization remains consistent to identify the set of parameters that reduce inaccuracy or optimize performance. Deviation analysis and stability enhancement are utilized to evaluate the effectiveness of the proposed SMIB-PSS system. The system's efficacy is assessed under various disturbance conditions in the presence and absence of the AOA-NN-based PSS. Crucial metrics may include an increase in settling time, a reduction in rotor angle deviation, and overall system stability enhancement under dynamic conditions.

4.1. Power system stability analysis of the SMIB

Power system stability analysis is crucial to understanding the dynamic behavior of the SMIB system. Stability is assessed by analyzing the system's response to disturbances and ensuring the synchronous machine returns to a stable operating point. The electrical power (P_e) equation represents the power generated by the synchronous machine. It is given by:

$$P_e = \frac{VE\sin(\delta)}{X_s} \tag{17}$$

The mechanical power input (P_m) is the sum of the electrical power and the damping power. It is given by:

$$P_m = P_e + D\omega \tag{18}$$

The rotor angle (δ) equation describes the rate of change of the rotor angle concerning time. It is given by:

$$V_\delta = \omega - \omega_s \tag{19}$$

4.2. Neural network-based controller

Implementing the NN controller is a deliberate move intended to improve the SMIB system's stability. Using the system states as inputs, this inventive controller produces control signals that improve the system's dynamic response. The NN's design consists of an input layer, hidden layers for complex processing, and an output layer that terminates. The first input layer processes the system states, and the output layer sends the resulting control signals.

$$u = f(WX + b) \tag{20}$$

4.3. Optimization of neural networks using AOA

The AOA is employed to optimize the weights (W) and biases (b) of the NN, enhancing its capability to stabilize the SMIB system. The fitness function (F) is designed to evaluate the NN's performance based on its weights and biases. It measures the deviation between the predicted ($\hat{y}$) and desired (y) rotor angles.

$$F(W,b) = \frac{1}{2}\left(y - \hat{y}\right)^2 \tag{21}$$

The objective function (J) is formulated as the fitness function to minimize the deviation between the predicted and desired rotor angles across the training dataset. The objective function is the sum of the fitness function overall training instances:

$$J(W,b) = \sum_{i=1}^{N} F(W,b) \tag{22}$$

4.4. AOA application

The AOA updates the weights and biases iteratively using the following equations:

$$W_{ij}(t+1) = W_{ij}(t) + r_1\left[gbest(t) - W_{ij}(t) + r_2 rand(0,1)\right] \tag{23}$$

$$b_i(t+1) = b_i(t) + r_3\left[lbest(t) - b_i(t) + r_4 rand(0,1)\right] \tag{24}$$

The optimized weights and biases are then integrated into the NN, enhancing its control capabilities. The AOA updates the weights and biases until a stopping criterion is met, optimizing the NN's performance and stabilizing the SMIB system. This detailed methodology combines the power system stability analysis, NN-based control, and the AOA to achieve enhanced stability in the SMIB system.

4.5. Pseudocode for AOA algorithm

Table 2 indicates the pseudocode of AOA and NN for enhancing power system stability. The following pseudo-code provides a high-level overview of the methodology. The pseudo-code explains optimizing an NN controller with an approach similar to PSO to stabilize the power system. Power system characteristics are first set to their default values. These include voltage, internal generator voltage, rotor angle, synchronous reactance, damping coefficient, synchronous speed, and rotor speed. These characteristics, coupled with the rotor angle rate, are used to determine the mechanical and electrical powers, which help to understand the system's dynamics. After an NN is initialized, its weights and biases are updated iteratively in a loop that keeps going until a stopping threshold is reached. To optimize the NN's parameters, this loop iteratively updates the global and local best solutions, evaluates the fitness of the system's stability under the current NN parameters, and then integrates these optimized parameters back into the NN. The goal of this optimization loop is to optimize the NN controller so that it can stabilize the power system. It uses global and local search capabilities to identify the optimal solution, which is then tested through a stability study.

Table 2 Pseudocode for improving power system stability with AOA and NN

Line no.	Pseudocode	Explanations
1	V, E, δ, X_s, D, ω, ω_s = *initialize_power_system_parameters*() P_e = *calculate_electrical_power*(V, E, δ, X_s)	*# Power system stability analysis of SMIB*: *# Electrical power equation*:
2	P_m = *calculate_mechanical_power*(P_e, D, ω)	*# Mechanical power equation*:
3	$\dot{\delta}$ = *calculate_rotor_angle_rate*(ω, ω_s)	*# Rotor angle equation*:
4	W, b = *initialize_neural_network*()	*# Neural network-based controller*: *# Neural network initialization*:
5	$gbest$, $lbest$ = *initialize_global_local_best*()	*# Aquila optimization algorithm*
6	r_1, r_2, r_3, r_4 = *initialize_random_numbers*()	
7	*while not stopping_criterion_met*:	*# Optimization loop*:
8	W, b = *update_weights_and_biases*(W, b, $gbest$, $lbest$, r_1, r_2, r_3, r_4)	
9	*fitness* = *evaluate_fitness* (W, b)	
10	*update_global_local_best* (*gbest, lbest, fitness*)	
11	*integrated_*W, *integrated_*b = *integrate_optimized_weights_biases* (W, b)	*# Integrated neural network*:
12	*perform_stability_analysis*(V, E, δ, X_s, D, ω, ω_s, *integrated_*W, *integrated_*b)	*# Research main function* *# Perform stability analysis with neural network control*

The provided Pseudocode in Table 2 clearly outlines a power system stability analysis for an SMIB system. It initializes parameters, calculates power components, and determines rotor angle dynamics. Using an NNC and an AOA, it iteratively updates weights and biases until a stopping criterion is met. The integrated NN is then employed for stability analysis in the SMIB system, showcasing the fusion of NN control and optimization for power system stability assessment.

5. Results and Discussion

The Simulink model and its associated simulation results offer a holistic view of the proposed SMIB-PSS system. They serve as essential tools for assessing the system's stability and the efficacy of the NN controller, guiding researchers and practitioners in refining control strategies for optimal power system performance. Fig. 3 illustrates a Simulink diagram depicting the proposed SMIB-PSS with a NN controller. Within the diagram, various components of the SMIB system are depicted. The NN controller, a crucial element of the proposed system, is integrated into the Simulink framework to demonstrate its role in regulating the stability of the power system. This visualization aids in understanding the dynamics and behaviors of the system under different operating conditions, facilitating analysis and potential improvements.

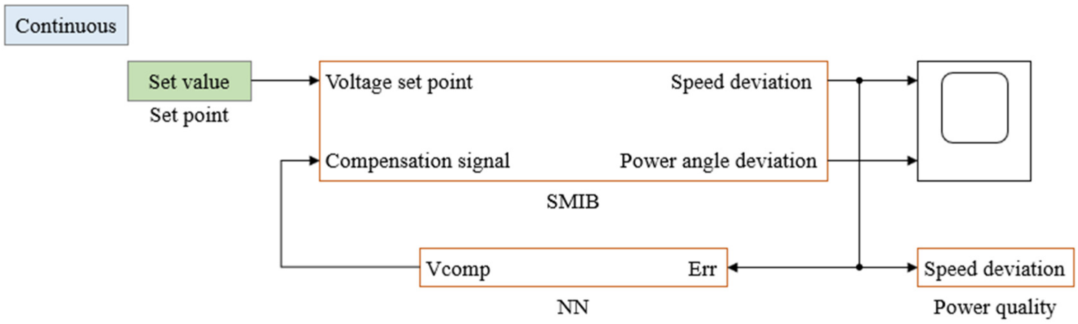

Fig. 3 Simulink diagram for proposed SMIB-PSS with NN controller

Fig. 4 presents a Simulink diagram illustrating the architecture of the NN employed within the SMIB-PSS system. The diagram details the structure and connections of the NN model utilized for controlling the power system stability. It included layers representing input nodes, hidden layers, and output nodes, along with connections indicating the flow of information between them.

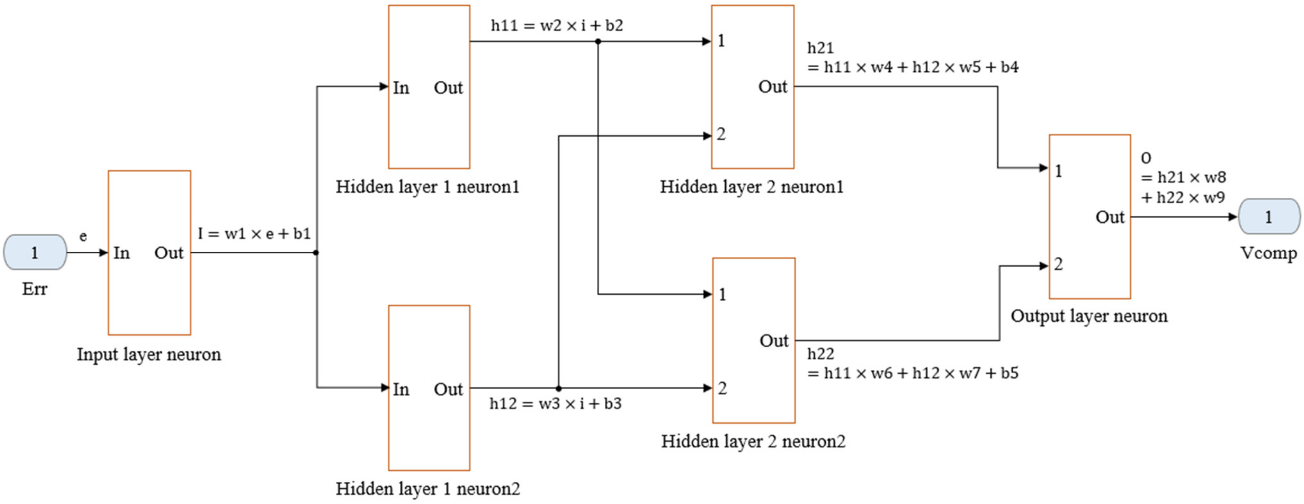

Fig. 4 Simulink diagram for NN architecture

Fig. 5 provides a comparison of phase angle deviations between two different control approaches, namely the NN and the AOA-NN, within SMIB-PSS. The plot shows the deviation of phase angles from their nominal values over time, specifically focusing on a fault occurrence at t = 10 seconds. For the NN approach, the plot demonstrates how the phase angle deviation evolves following the fault event, highlighting the effectiveness (or lack thereof) of the NN controller in stabilizing the system under such transient conditions. On the other hand, the AOA-NN approach was also depicted in the same plot, showcasing its performance in mitigating phase angle deviations post-fault. After analyzing Fig. 4, it was found that the AOA-NN consistently outperforms the standard NN approach. The AOA-NN demonstrates significantly reduced phase angle deviations following the fault event at t = 10 seconds, indicating superior stability enhancement capabilities compared to the conventional NN control strategy.

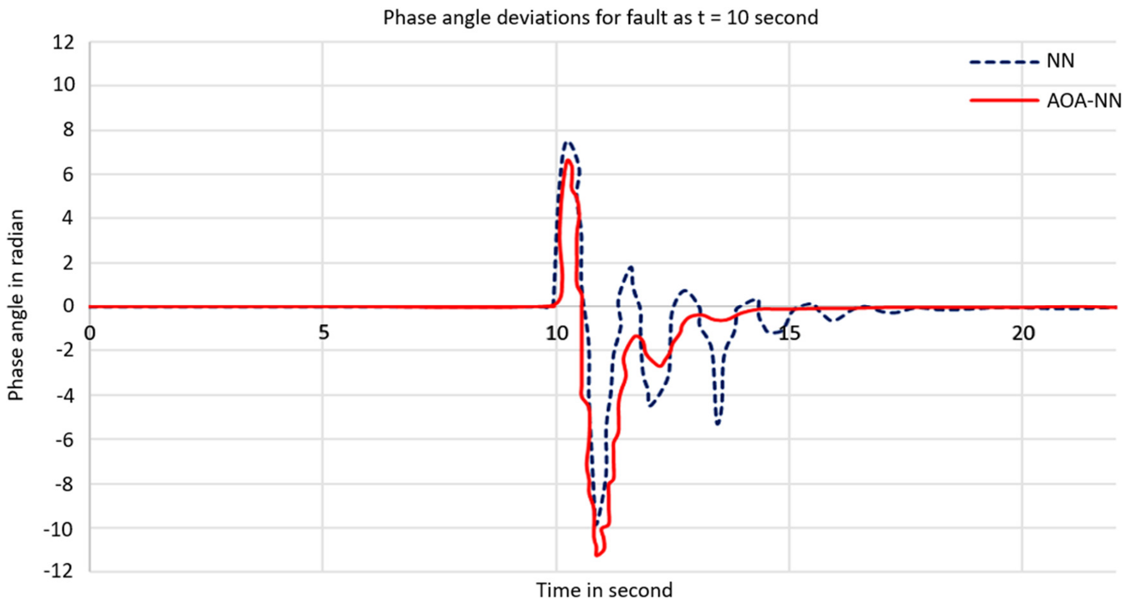

Fig. 5 Phase angle deviation comparison between NN and AOA-NN in SMIB-PSS

Fig. 6 shows a comparison of rotor angle deviations between two control strategies: the NN and the AOA-NN within SMIB-PSS. The plot illustrates the deviation of rotor angles from their nominal values over time, with a focus on a fault occurrence at t = 10 seconds. It was found that AOA-NN surpasses the NN approach in performance. The AOA-NN exhibits notably reduced rotor angle deviation post-fault, indicating its superior capability in stabilizing the SMIB-PSS system compared to the conventional NN control strategy. This observation underscores the effectiveness of leveraging optimization algorithms to enhance the performance of NN-based control systems in SMIB-PSS applications.

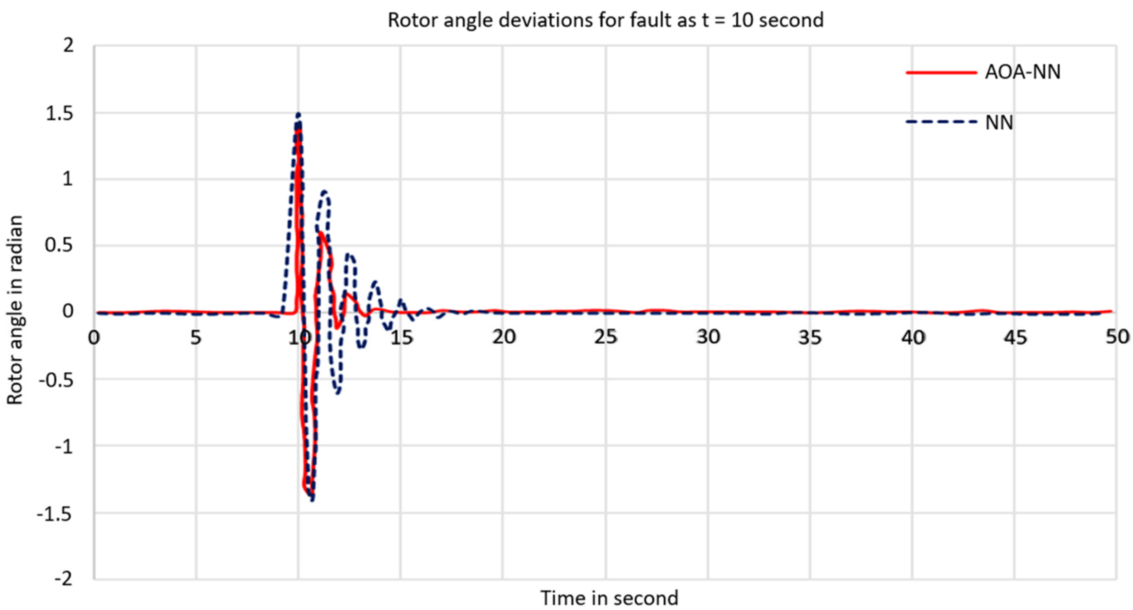

Fig. 6 Rotor angle deviation comparison for NN and AOA-NN in SMIB-PSS

Table 3 provides a comprehensive comparative analysis of the results obtained from previous research works, focusing on the performance evaluation of PSSs and their optimization using various NN-based algorithms. Table 3 includes key metrics related to speed response (overshoot, undershoot, and settling time) and rotor angle response (undershoot and settling time). After analyzing the findings in Table 3 it was found that the STSA-NN PSS achieved an overshoot of 0.0267 and an undershoot of -0.1304 with a settling time of 488 units for speed response, while for rotor angle response, it demonstrates an undershoot of -0.3990 and a settling time of 646 units. Remarkably, the Proposed AOA-NN stands out with the lowest overshoot of 0.012, a negligible undershoot of -0.080, and a relatively faster settling time of 400 units for speed response, coupled with a minimal undershoot of -0.050 and a settling time of 550 units for rotor angle response. These results indicate the superior performance of the proposed AOA-NN method compared to the other techniques analyzed in the table, highlighting its effectiveness in enhancing PSSs. The proposed AOA-NN method can reduce the overshoot speed with an average value of 79.1946% and the overshoot rotor angle with an average value of 87.8634%.

Table 3 Comparative analysis of results with previous research works

Method	Speed response			Rotor angle response	
	Overshoot	Undershoot	Settling time	Undershoot	Settling time
Sine tree-seed algorithm-feed-forward neural network (STSA-NN PSS) [13]	0.0267	-0.1304	488	-0.3990	646
Archimedes optimization algorithm-neural network (AOA-NN PSS) [13]	0.0211	-0.1129	517	-0.4016	630
Distributed time delay with neural network (DTD-NN) [14]	0.4354	-0.8211	107.36	-3.2207	145.02
Tunicate swarm algorithm-feed forward neural network (TSA-FFNN) [14]	0.3055	-0.7226	112.44	-2.8748	146.25
Proposed Aquila optimization algorithm-neural networks (AOA-NN)	0.012	-0.080	400	-0.050	550

6. Conclusion

A complete solution that blends power system stability analysis, NN-based regulation, and the AOA to stabilize SMIB systems was successfully implemented. This novel technique uses the AOA to optimize NN parameters and increase performance to comprehend the SMIB system's behavior. It may increase power system stability, but it has some drawbacks. Power system model quality greatly affects AOA accuracy. Defects in the model may affect performance. Optimizing NNs for real-time applications is computationally difficult. The AOA unique technique based on the Aquila birds' hunting behavior enhances NN flexibility to provide a cost-effective SMIB stability solution.

The study improved SMIB system dynamics stability using power system stability analysis, NN-based control, and AOA. The AOA algorithm improves NN performance and system stability by fine-tuning parameters. This study encourages more research on the technique's flexibility in complicated power systems and grid conditions, opening the path for future advancement. The research investigates the AOA's scalability and robustness in large-scale power networks to highlight its potential for development. The study admits restrictions such as power system model precision and NN real-time optimization. The AOA algorithm enhances NN parameter flexibility by using the Aquila birds' hunting behavior. The AOA and NN control may improve power system stability and control, providing a flexible foundation for varied power system installations. To make it more practicable for large-scale power networks, the technique will be improved, validated, and scaled. Despite limitations, the strategy can improve power system resilience and effectiveness, promoting power system management solutions and grid dependability.

Conflicts of Interest

The authors declare no conflict of interest.

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Appendix: -I List of Symbols

S.N.	Symbol	Description of symbols used in equations	SI units
1	M	inertia constant of the machine	kg.m2
2	D	damping factor or coefficient	dimensionless quantity
3	δ	rotor angle	radian (rad)
4	P_{mech}	mechanical power input	watt
5	P_e	electrical power output	watt
6	T_{PSS}	time constant of the PSS	seconds
7	V_{PSS}	output signal of the PSS	volt or amp
8	K_{pss}	PSS gain	dimensionless quantity
9	V_δ	rate of change of the rotor angle	radian per second (rad/s)
10	f	activation function	--
11	w_i	weights	--
12	x_i	inputs	--
13	b	bias vector	--
14	$x_i(t)$	position of the i^{th} candidate solution at iteration t	--
15	$gbest(t)$	global best solution at iteration t	--
16	r_1 and r_2	random numbers in the range [0,1]	--
17	$rand(0,1)$	random number in the range [0,1]	--
18	$f(x_i)$	fitness of the i^{th} candidate solution	--
19	c	constant	--
20	$lbest(t)$	local best solution at iteration t	dimensionless quantity
21	n	number of candidate solutions in the population	--
22	P_e	electrical power	watt
23	V	terminal voltage	volt
24	E	synchronous machine voltage	volt
25	X_s	synchronous reactance	ohm
26	P_m	mechanical power	watt
27	ω	angular speed	radian per second (rad/s)
28	ω_s	synchronous speed	revolutions per minute (rpm) or radians per second (rad/s).
29	u	control signal	--
30	W	weight matrix	--
31	X	input vector	--
32	F	fitness function	--
33	y	desired rotor angle	radian per second (rad/s)
34	$\hat{y}$	predicted rotor angle based on the neural network with weights W and biases b	radian per second (rad/s)
35	W_{ij}	weight matrix element	--
36	b_i	bias element	--
37	r_3 and r_4	random numbers in the range [0,1]	--
38	N	number of training instances	--