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Research Article

# Optimization of PID controller parameters for an SMIB system using a hybrid butterfly particle swarm optimization approach

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## Abstract
***In light of the critical need for reliable power systems, this research aims to determine the best configuration of proportional, integral, and derivative (PID) controllers for a single-machine infinite bus (SMIB) system. There has been an effort to discover faster, more efficient, and resource-conservative optimization methods since conventional procedures can need more frequently changing working conditions. By filling in the gaps left by previous assessments, this study hopes to increase the accuracy of PID controllers inside the SMIB framework based on the general-purpose simulation system (GPSS). Hybrid butterfly particle swarm optimization (HBPSO) is one of its innovative strategies. The HBPSO algorithm is a huge step forward in developing a more stable and damping system as it optimizes the PID controller's gain settings and overall design. Extensive GPSS simulations prove that the HBPSO-optimized PID controller is functional. The controller significantly improved over previous methods, including the firefly proportional, integral, and derivative power system stabilizer (FPID-PSS) and biogeography-based optimization algorithm (BBO) based PID systems, with a settling time of only 10.10 seconds. There are a lot of cases when the system's operational dependability and transient stability are greatly enhanced by this substantially quicker reaction time. By guiding unstable and weakly damped eigenvalues toward a more desirable stable zone, eigenvalue analysis supports the claim that the PID-modified power system stabilizer (MPSS) model based on HBPSO has better damping performance and dynamic stability. The optimization of PID controllers in SMIB systems using the HBPSO algorithm has proven useful. This technology uniquely optimizes electrical grid systems, leading to more stable, efficient, and reliable future electrical distribution networks, and sets a new standard for attenuation and robustness.***

## Keywords
***BOA, GPSS, HBPSO, PID, PSO, PSS, SMIB.***

## 1.Introduction
Consistent and reliable electrical infrastructure has become increasingly important as power systems have modernized, leading to ongoing improvements in control approaches. Regulating generator excitation, especially in single-machine infinite bus (SMIB) systems, is one of the most significant issues for power system engineers. Stabilizing the rotor angle and reducing oscillations are achieved through effective excitation control [1]. An essential step in accomplishing this objective is incorporating a power system stabilizer (PSS).

A PSS is a crucial device designed to improve the stability of electric power systems by enhancing the damping of oscillations following disturbances.

These disturbances can include sudden shifts in demand, faults in transmission lines, or variations in generator operations, which may lead to instability or inefficiency within the power grid. The PSS achieves its goal by modulating the generator's excitation system based on real-time changes in the power system's dynamics, thereby aiding in the maintenance of synchronous generator (SG) operation across the grid. It operates by monitoring specific parameters, such as changes in a generator's speed or electrical output, and uses this information to produce a corrective control signal. This signal adjusts the level

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of excitation to the generator, neutralizing the destabilizing oscillations and thus helping to stabilize the electric power system. Implementing a PSS is essential for enhancing system response to fluctuations, ensuring the power grid's stable, reliable, and efficient function, particularly in networks characterized by extensive transmission distances or a substantial presence of interconnected renewable energy sources. To reduce low-frequency oscillations and increase the transmission line's overall energy transfer capacity, PSS adjusts the exciter control's voltage reference [2].

The model reference adaptive control (MRAC) technique is one of the controller types used to guarantee system stability [3]. Yet, PID controllers have become quite popular because they effectively reduce the gap between a variable's target and actual values [4–6]. Power systems and control engineers have significantly contributed to the design of traditional PSS, particularly those that use PID controllers, by incorporating complex control theories into their models [7, 8].

Despite improvements in PSS design, further research is needed to systematically compare optimization strategies for PID controllers in SMIB systems [9]. Much prior work has concentrated on optimization algorithms such as the ant bee colony (ABC) algorithm [10], the Archimedes optimization algorithm (AOA) [11], the artificial neural network (ANN) [11], fuzzy logic [12–20], the biogeography-based optimization algorithm (BBO) [21], the firefly optimization algorithm (FOA) [22], the bat algorithm (BA) [23], the iterative linear matrix inequality (ILMI) approach [24, 25], and the craziness particle swarm optimization (CPSO) [26]. Unfortunately, no thorough evaluation of these approaches considering every possible operating configuration and disturbance is currently available in the literature.

The SMIB system's optimization goals focus on improving stability and dynamic performance in response to transient events using the hybrid butterfly particle swarm optimization (HBPSO) approach. The main objective is to adjust the PID controller's settings so that the generator's reaction to disturbances may be reliably and effectively regulated. It is necessary to appropriately modify the gains of the derivative, integral, and proportional functions. The optimization method also seeks to improve transient stability, decrease settling time, and limit overshoot, all while keeping the system under control and responding quickly. The main focus areas are enhancing resilience in various operating circumstances, improving PSS settings, and increasing voltage control. With efficient power transmission and minimal losses, optimum energy transfer is the end goal. The optimization process considers these goals as it strengthens the control strategy by making the SMIB power system more reliable, efficient, and stable.

To address the existing gap in knowledge, this paper creates and tests a new method for optimizing PID controller settings in an SMIB environment. It does this by responding to many issues raised by the existing literature. This is because of the lack of flexible optimization methods that can handle different operations with less resource usage, faster convergence, and more reliability. This work presents and assesses an HBPSO approach to optimize PID controllers for the SMIB system coupled with the general-purpose simulation system (GPSS). It resolves a gap between comparative evaluations of PID controller optimization in SMIB settings and shows that the HBPSO method can consistently increase PID controller performance.

It is clear that further study is needed to compare optimization methods that target PSS parameters, especially PID controllers in SMIB systems, across different operating circumstances and disturbances. Since there has yet to be a thorough evaluation of the effectiveness of different optimization strategies in the current literature, the best and most efficient way to achieve faster convergence is still up for discussion. A thorough and comparative investigation is required to progress in power system stability. Comprehensive research is required to develop improved PSS solutions that enhance the stability of SMIB systems in both steady-state and transient conditions. To optimize the HPSBM's PID controller settings, this work creates and tests a novel HBPSO approach. The goal is to show that the suggested strategy improves power system stability and reliability more than conventional PID controllers and other optimization techniques.

The SMIB system is a well-known standard for analyzing power system stability. The SMIB system's efficiency has been dramatically improved with the recent addition of HBPSO, a PID controller, and a PSS. The PID controller allows for precise and dependable management of the generator's electrical output, while the PSS improves stability by dampening oscillations at low frequencies. The HBPSO approach optimizes the PID controller and

PSS's tuning settings, enhancing performance and reaction times. The combination of PID, PSS, and HBPSO in this Heffron-Phillips model (HPM)-based SMIB system increases its efficiency, stability, and reliability, making it an excellent tool for control design and stability analysis in power systems.

A novel method is introduced as the major contribution in this work to optimize PID controller parameters of power systems and focus on improving stability and damping. This paper presents a consistent way to tune PID controller parameters in SMIB power system using HBPSO algorithm, while previous literature used different techniques that were complex and time-consuming. By utilizing simulation experiments with multiple operating points, this approach proves its better ability in stability metrics, especially settling times. Moreover, in this work, proposed methodology present the construction of an MPSS by relying on the HPM model and evaluate it with HBPSO for robustness index. The contributions of this work findings are important to the power system engineering community in understanding how such stable power systems could be designed in practice.

This paper is structured as follows. Section 2 provides a comprehensive literature assessment emphasizing seminal research on the subject. The paper's framework is laid out in this part. Section 3 outlines the suggested methodology based on the HBPSO algorithm and thoroughly summarizes the study materials and techniques. Section 4 provides a detailed description of the outcomes and assessment of the MATLAB-based exhaustive simulations. Section 5 explains the paper's limitations and briefly summarizes its main results. Finally, the observations are presented in section 6.

## 2.Literature review

Determining how to optimize the efficacy of PSS through parameter design has been the focus of extensive research. Several intelligent optimization methods, such as those based on populations, have been suggested, including ANN, ABC algorithm, fuzzy logic, adaptive fuzzy, neuro-fuzzy, and additional techniques. The butterfly optimization algorithm (BOA) optimized a novel fractional order PID-PSS. The PID-PSS was assessed on an SMIB power system across various operating conditions and disturbances. A robust PID-based PSS that performs admirably in different operating scenarios was described in [24]. Soliman [25] expressed concern regarding the characteristics of plants with a polytopic structure, which can be attributed to fluctuations in load profiles and generation. A generalized static output feedback synthesis was initially implemented to address the PID control issue. Proposed a straightforward analytical technique for determining the three-term components of stable stabilizing PSSs. The proposed interval plant was stabilized utilizing a phase-lead compensator-based phase-shifter (PSS) in conjunction with a phase-independent-detector controller and the extended Kharitonov theorem. This work also established significant and suitable limitations for defining the robust stabilizing three-term controllers by applying the Routh-Hurwitz criteria to several segment/vertex plants. Saini et al. [26] introduced the particle swarm optimization (PSO) algorithm which is a reliable optimization method renowned for its robustness in determining the optimal values for the parameters of a PID controller. For instance, using speed deviation as an input [26] generates a PSO-based optimal PID-PSS. To enhance the stability of an SMIB power system, Abdul-ghaffar et al. [27] optimized its parameters utilizing the hybrid particle swarm-bacteria forging optimization (HPSBFO) method and PID-PSS.

Silaa et al. [28] employed an enhanced grey wolf optimizer (GWO) to optimize the parameters of fractional-order PID (FOPID) for PSSs in SMIB systems. The outcomes demonstrate that this optimization method has less settling time and overshoot than others. The requirement for many iterations to achieve convergence is a notable drawback of this method. Gomez et al. [29] introduced optimal PID settings for stabilizing power systems in SMIB systems by implementing a multi-objective particle swarm optimization (MOPSO) method. According to analyses, the MOPSO algorithm is more efficient in processing time and objective functions than alternative optimization methods. Similar to the preceding method, one drawback is the substantial quantity of iterations required to attain convergence.

To enhance the stability of power systems in SMIB systems, Puangdownreong [30] implemented an enhanced flower pollination algorithm (EFPA) [30] to optimize PID parameters. Evaluations indicate that the approach is more efficient in terms of objective function computation time when compared to alternative optimization methods. However, there is a catch: its effectiveness is entirely predicated on the initial conditions. Likewise, Naresh et al. [31] proposed the utilization of the harmony search algorithm (HSA) to enhance PID parameters in SMIB systems for power system stability [31]. The research findings demonstrate that this optimization strategy exhibits superior overshoot and settling time performance compared to other strategies. However, convergence necessitates a substantial number of iterations, and the method imposes a computational burden. As a final phase, Mishra et al. [32] utilized the teaching-learning-based optimization (TLBO) method to optimize the PID parameters for power system stability in SMIB systems. When considering settling time and overshoot, the research indicates that this optimization strategy is more effective than alternative approaches. However, much like its predecessor, convergence requires substantial computational capacity and many iterations. Improving the effectiveness of PSS has been the focus of extensive research, with numerous studies examining the optimization of PID controller settings in SMIB systems. Several optimization techniques, along with an overview of their processes, outcomes, advantages, and disadvantages, are described in this section.

In the ABC algorithm, the PID parameters of power system regulators in SMIB systems were optimized using the population-based optimization algorithm. The observed enhancements in settling time and overshoot provide evidence of the adequate performance of the approach. An advantage of the ABC method is its rapid and uncomplicated investigation of the solution space. Potential challenges in achieving convergence within satisfactory iterations can be considered constraints [10]. PSO has frequently been employed to optimize PID parameters for power system stability in SMIB systems. Identifying the optimal PID controller configurations was a simple task when using the PSO-based approach, which exhibited notable effectiveness and resilience. Utilizing PSO in a global search for the most effective solutions is beneficial. A considerable quantity of iterations might be required due to a conceivably extended convergence period [26]. GWO was employed to refine the parameters of the SMIB PSS. The result was an overshoot and settling time enhancement that surpassed the performance of alternative optimization techniques. It extends to many iterations and demands substantial processing power [28]. The MOPSO algorithm is described as a way to stabilize power systems in SMIBs, and PID parameters have been optimized using MOPSO. The results demonstrate that efficiency has increased significantly in processing time and objective functions [29].

Excellent at balancing multiple duties simultaneously. Substantial iterations may be required to attain convergence relative to alternative PSO-based methods. The EFPA and SMIB systems have optimized their PID parameters for the stability of the power system. A substantial enhancement in processing time and objective function efficiency is achieved. Performance significantly improves when one commences from the appropriate vantage point. Because of the reliance on initial conditions may compromise reliability, which is a limitation [30]. To improve the stability of power systems in SMIB setups, using the HSA to optimize PID parameters has been suggested. The outcomes demonstrated improved settling time and overshoot. It is suitable for examining possible resolutions. It is computationally intensive and requires many iterations to reach convergence [31]. TLBO, a program utilized to optimize PID parameters for SMIB power systems, has been implemented to stabilize the power system [32].

In conclusion, these optimization methods exhibit superior performance in excess and settlement time compared to alternative approaches. One advantage is the efficiency with which it enhances pre-existing solutions. Constraints include the computational intensity and the quantity of iterations required to achieve convergence. The HBPSO is an innovative optimization method to optimize the PID parameters; the propose HBPSO method which combines the most advantageous aspects of PSO [26] and the BOA [24]. Compared to traditional methodologies, enhanced overshoot and settling time performance were observed. By employing a blend of local and global exploration tactics, HBPSO enhances convergence efficiency. One potential risk associated with the hybrid technique is an escalation in computational complexity.

The literature contains an extensive range of optimization methods for PID controllers in SMIB systems. Each method has distinct merits and demerits regarding its methodology and practical implications. While these solutions demonstrate improvements in stability measurements, it is critical to thoroughly evaluate their advantages and disadvantages in light of the power system's specific requirements and constraints. The continuous pursuit of an ideal optimization approach aims to achieve a harmonious equilibrium among computing resources, dependability, and efficiency.

The primary research gap concerns optimizing PID parameters to improve power system stability. While several optimization strategies have been suggested, more comparative studies should be conducted across different operating conditions and disturbances. Furthermore, there is a need for the development of more reliable and efficient optimization methods that demonstrate better convergence but also require fewer computational resources and offer faster execution times. The primary goal of PID control parameters is to achieve minimal overshoot in the steady-state response and reduce settling time. While two common conventional tuning strategies exist, such as Ziegler Nichols closed-loop oscillation and Cohen-Coon's process reaction curve, the fourth-order Runge-Kutta method [33] and several other methods have been used for tuning [34]. Joseph et al. [34] introduce adaptive fuzzy lead-lag controller structures for PSSs and damping controllers based on flexible alternating current transmission systems (FACTS) to enhance power system stability. The controller parameters are tuned using a modified grasshopper optimization algorithm (MGOA). The results of the proposed MGOA are compared with a conventional lead-lag controller to demonstrate its superiority [35]. Based on the investigation findings, the PSO performs quick and accurate calculations in the fifth iteration with a fitness function value of 0.007813. The PSO aims to reduce the integral time absolute error (ITAE). The case study involves the application of the SMIB technology with a load-shedding instance. The time domain simulation shows the frequency response and rotor angle of the SMIB system. The results indicate that the controller combination offers stability, reduces overshoot oscillations, and enables quick settling times [36]. Another approach involves an antlion-based proportional, integral, and derivative power system stabilizer (ABPID-PSS) designed to improve power system stability during real-time constraints. A modified particle swarm optimization (MPSO) based PID-PSS is compared to the optimized PSS using different performance indices. Simulation results demonstrate the effectiveness of the proposed PSS based on the antlion optimization (ALO) algorithm, providing robust performance compared to traditional PSS. The proposed [37] PSS achieves significant improvement percentages in integrated square error (ISE), integrated absolute error (IAE), integral of time-weighted square error (ITWSE), and integral of time-weighted absolute error (ITWAE) [37].

A novel power system oscillation damping controller design is presented by Han and Stanković, based on a data-driven model-predictive control (MPC) approach. Two controllers, a standalone PSS and an integrated automatic voltage regulator (AVR) + PSS, are proposed and tested on the SMIB system, Kundur two-area system, and IEEE 39-bus system. The performance is compared with conventional power system stabilizers (CPSSs) under various test scenarios [38]. Another novel control strategy, Jacobian gain control (JGC), is proposed to improve the stability and performance of the linear feedback control (LFC) by addressing the nonlinearity of a SG. JGC utilizes the Jacobian function for control, and its performance is verified through various time-domain simulations on two-area and IEEE 39-bus systems configured by MATLAB/Simulink [39]. The paper introduces a new bare-bones PSO variant called bare-bones particle swarm optimization with crossed memory (BPSO-CM). Experimental results show that BPSO-CM provides highly accurate results for global optimization problems [40]. A method based on an improved PSO algorithm is constructed to optimize drone selection and trajectories in unmanned aerial vehicle (UAV) swarms. Simulation experiments show that the proposed method can determine and optimize drone trajectories in real time [41]. To improve the performance, robustness, and stability of PID parameter auto-tuning, a new stable particle swarm optimization (NSPSO) is proposed. An NSPSO addresses the system's instability. Comparative performance analysis is conducted using various fitness functions and assessing the robustness and changed operation points of the direct current (DC) motor [42].

An exponential particle swarm optimization (ExPSO) presents comparisons and statistical results that demonstrate that the exponential search strategy significantly contributes to the search process, proving the superiority of ExPSO in terms of convergence velocity and optimization accuracy [43]. The literature reviews recent studies utilizing PSO for feature selection problems and provides eight potential research directions to enhance PSO’s performance [44]. A novel multi-objective optimizer leveraging PSO with evolutionary game theory (EGT) is proposed in this paper [45]. Non-parametric analysis results show that the proposed method outperforms contenders over 16 benchmarks.

The investigation addresses electro-mechanical oscillations' havoc caused by electric network and generator power fluctuations. The study considers classical PSS, PID, and FOPID to dampen oscillations. The paper discusses the proposed methods' effectiveness through comparative computer simulations [46]. This article introduces an integral dynamic learning network (IDLN) to address the general time-varying Lyapunov matrix equation (TVLME). The proposed IDLN [47] is verified for effectiveness, stability, and practicability through comparative computer simulations and its application to the voltage stability analysis in an SMIB system [47]. The paper proposes an adaptive dynamic power reduction (DPR) scheme for Type-3 wind turbine generators (WTGs) to enhance the transient stability of SGs. The DPR controller's ability to prevent transient instability is demonstrated in a two-area system [48].

Optimizing the PID controller parameters enhances the stability of power systems. Many optimization techniques are commonly implemented to enhance the performance of PID controllers. Implementing the HB-PSO method optimizes the PID controller parameters for an SMIB system connected via GPSS. By integrating the most advantageous aspects of PSO and BOA, the HBPSO algorithm generates a hybrid optimization approach. It employs two mechanisms—the butterfly optimization for local exploitation and the particle swarm for global exploration. The HB-PSO algorithm locates the optimal solution by dividing the search space into smaller regions and assigning a unique location to each particle. Subsequently, the optimization procedure is refined by implementing the butterfly optimization mechanism, which modifies the particle placements to accelerate convergence and improve precision.

The proposed technique of utilizing the HBPSO algorithm to optimize the PID controller parameters of the Heffron-Phillips SMIB model has been validated through an exhaustive series of simulations. The outcomes demonstrate that the proposed approach outperforms alternative optimization strategies, such as conventional PID controllers. It may improve the transient and steady-state stability of the SMIB system by accurately identifying the optimal values of the PID parameters. Improving stability is essential for the dependability and security of the electrical system.

## 3.Materials and methods

### 3.1Proposed methodology

A streamlined power system model is the typical method when using the GPSS-connected SMIB system for transient stability assessments. A PID controller might adjust the generator's excitation voltage to enhance the system's transient responsiveness. Optimization methods are typically used to alter the controller settings for optimal performance. Combining the best features of both the PSO method and the butterfly optimization process, the HBPSO is an optimization hybrid. This system guarantees the power supply's frequency, maintenance, and stability under varying operating circumstances. *Table 1* shows the procedures used to improve the GPSS-SMIB model's PID parameters using the HBPSO algorithm: The PID controller settings are adjusted step by step to achieve the desired system response using the HBPSO algorithm in this approach. The method tunes the PID controller settings based on the swarm's optimal location determination. It also updates particle positions and velocities, followed by simulating the system response. Monitoring the function's value and iteration count ensures the algorithm's convergence. The process involves modeling the system, setting up the PID controller, starting the algorithm, evaluating the fitness function, tweaking swarm and PID controller parameters, validating and testing optimized controller performance, and then testing the system response to confirm convergence. The iterative process of the HBPSO algorithm enables enhanced system performance optimization and minimization of function by identifying PID controller settings.

**Table 1** Steps of optimizing PID Controller parameters using HBPSO

| Step numbers | Operation of steps | Description of steps |
|---|---|---|
| Step 1 | Problem formulation | To mitigate the discrepancy between estimated and actual system reactions, the issue associated with optimization must be pinpointed. |
| Step 2 | Model the GPSS-connected SMIB system. | To develop a mathematical model of the SMIB system, one must input the appropriate equations into the system description section. The MATLAB/Simulink simulation tools are used to program the model. |
| Step 3 | PID controller design | A PID controller may alter the system's frequency by modifying the generator's |

| Step numbers | Operation of steps | Description of steps |
|---|---|---|
| | | excitation voltage. The controller consists of three parameters: $K_P$ for proportional gain, $K_I$ for integral gain, and $K_D$ for derivative gain. |
| Step 4 | HBPSO algorithm initialization | To use the HBPSO algorithm, insert the basic controller configurations acquired in step 3. Several algorithm parameters must be defined, comprising population size, maximum number of iterations, and convergence criterion. |
| Step 5 | Fitness function evaluation | Apply the target function specified in the initial phase to each swarm particle's fitness function. |
| Step 6 | Swarm update | Make sure to update the particle locations and velocities constantly. |
| Step 7 | PID controller parameter update | After the swarm has found the best spot, tweak the PID controller settings as needed. |
| Step 8 | Evaluate the system response | Evaluate the system's performance by modeling its reaction with the adjusted PID controller settings. |
| Step 9 | Convergence check | If the goal function's value is inside a specific tolerance range or the maximum number of iterations is reached, convergence has been achieved. |
| Step 10 | Repeat Steps 5-9 | Continue iterating through stages 5–9 until convergence is achieved if the initial attempt fails. |
| Step 11 | Validation and Testing | Evaluate the upgraded PID controller's function by examining how the system responds to various loads and power outages. Confirming the results using the original PID controller design or other well-established refining approaches is recommended before making any changes to the system. To achieve peak efficiency, the improved PID controller must reduce steady-state error, overshoot, and settling time more than the original design or traditional methods. |

#### 3.1.1GPSS-SMIB system

A streamlined power system modification, the GPSS-connected SMIB system is synchronously connected to an infinite bus via a transmission connection. Exploiting the model broadly in power system stability studies, which observe the system's reaction to numerous operating conditions and turbulences, is crucial. The mathematical invention of the GPSS-Connected SMIB system originated from the following equations:

***Rotor Angle Equation:*** The rotor angle is signified by the variable δ and is specified by the Equation 1. Equation 1 represents the rate of change of the rotor angle (δ) with respect to time (t), which is equal to the angular velocity ($\omega$) of the rotor in radians per second. In simpler terms, it describes how fast the rotor angle is changing over time. This equation is fundamental in the dynamics of rotating machines, particularly in electrical power systems where SGs are used. The angular velocity indicates how quickly the rotor is rotating, and the rate of change of the rotor angle reflects how the rotor angle is evolving as the machine operates. Understanding this relationship is crucial for analyzing the behavior and stability of power systems.

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

***Rotor speed equation:*** The rotor speed is epitomized by the variable ω and is specified by the Equation 2. This equation describes the dynamic equilibrium of a rotating machine, such as a generator in an electric power system. This equation states that the product of the generator's moment of inertia (M) and the rate of change of its angular velocity ($\frac{d(\omega)}{dt}$) is equal to the difference between the mechanical power input ($P_m$)and the electrical power output ($P_e$). This equation is fundamental in understanding the dynamics of rotating machines in power systems and is crucial for analyzing their stability and performance.

$$M \times \frac{d(\omega)}{dt} = P_m - P_e \quad (2)$$

***Electrical power output equation:*** The electrical power output is specified by the Equation 3. This equation describes the describes the electrical power output ($P_e$) of a generator in an electric power system. The equation states that the electrical power output of the generator is proportional to the product of the magnitudes of the generator's voltage ($E_f$) and the infinite bus voltage ($V_f$) multiplied by the sine of the phase difference between the rotor angle (δ) and the angle of the infinite bus voltage ($\theta_f$). Essentially, it quantifies the amount of electrical power generated by the generator, taking into account the voltage magnitudes and phase angles. This equation is fundamental in analyzing the behavior and performance of generators in power systems.

$$P_e = E_f \times V_f \times \sin(\delta - \theta_f) \qquad (3)$$

***Mechanical Power Input Equation:*** The mechanical power input is specified by the Equation 4. This equation represents the mechanical power input ($P_m$) to a generator in an electric power system. The equation states that the mechanical power input to the generator is equal to the difference between the turbine's power output ($P_{turb}$) and the product of the damping coefficient ($D$) and the angular velocity of the generator ($\omega$). In simpler terms, it quantifies the net mechanical power supplied to the generator's shaft after accounting for the turbine's output and the damping effects on the rotor's rotational speed.

$$P_m = P_{turb} - D \times \omega \qquad (4)$$

***Excitation System Model:*** The excitation system of the generator is denoted by the Equation 5. This equation represents the generator's field voltage ($E_f$) in an electric power system. The equation states that the generator's field voltage ($V_r$) is determined by a combination of two terms: an integral term, and a derivative term. These terms represent how the excitation system adjusts the field voltage to regulate the generator's voltage magnitude ($V_r$) relative to the reference voltage ($V_f$). This equation is fundamental in controlling the generator's output voltage and ensuring stable operation of the power system. $K_a$, $K_b$, and $K_c$ are the excitation system constants.

$$E_f = K_a \times V_r + K_b \times integral(V_r - V_f) + K_c \times \frac{d(V_r - V_f)}{dt} \qquad (5)$$

Modeling the GPSS-Connected SMIB system may implicate relating several numerical methods, such as the Runge-Kutta method [33] and numerical integration methods [50]. One can estimate a system's stability by scrutinizing its responses to varied operating situations and turbulences, such as fluctuations in mechanical power input or glitches in transmission lines. A stability investigation promises that the power system remains operational and stable beyond any specified condition. *Figure 1* shows the PID controller optimization movement chart exhausting the suggested algorithm HBPSO for the SMIB system model. In *Figure 1*, before parameter optimization for the SMIB system, it is compulsory to modify the HBPSO algorithm. The process needs to launch the fitness function criteria and the initial population of particles, as explained in the flow diagram. Subsequently, an initial set of probable solutions is generated, comprising fundamentally distinct parameter combinations for the PID controller and PSS. The fitness of each particle is determined by a predetermined fitness function that signifies optimization objectives such as overshoot minimization and settling time. As the optimization cycle advances, the particle positions suffer nonstop changes. The composite methodology employs PSO for the manipulation of tenacities and butterfly-inspired procedures for exploration. By pointing particles toward optimal solutions with butterfly-inspired motions, PSO algorithms extend the search space. A dynamic balance between examination and manipulation is sustained through the implementation of adaptive adaptations. Once the convergence conditions are satisfied, the algorithm repeatedly polishes the particle locations until it has acknowledged the optimal formations for the PID controller and PSS in the SMIB system. By incorporating both tactics, the objective is to improve the performance and stability of the control parameters through careful optimization.

### 3.1.2 PID controller

By using a PID controller, the system becomes more efficient and stable. An integral part of the PID system is the PID controller. The proportional term modulates the controller's output as the present system output deviates from the desired set point. The integral term incorporates the cumulative mistake when monitoring the controller's output. By modifying the system output, the derivative term modulates the controller output. Equation (6) defines the PID controller as follows:

$$u(t) = K_p \times e(t) + K_i \times integral(e(t)) + K_d \times derivative(e(t)) \qquad (6)$$

Where,

$$integral(e(t)) = integral(e(t-1)) + e(t) \times dt \qquad (7)$$

$$derivative(e(t)) = \frac{(e(t) - e(t-1))}{dt} \qquad (8)$$

Where $u(t)$ is the controller output, $e(t)$ is the error signal (i.e., the difference between the desired setpoint and the actual system output), $K_p$ is the proportional gain, $K_i$ is the integral gain, $K_d$ is the derivative gain, $dt$ is the sampling time, and $integral$ e(t), and $derivative\ e(t)$ are the integral and derivative terms, respectively.The PID controller is shown in *Figure 2*. It shows a PID controller's block diagram. It describes a control system's essential parts. It is part of the set point, process, and error calculation blocks. A set point is the intended state of a system, while a process is the system under control. The PID controller relies on PID terms fundamentally. The derivative looks ahead to potential patterns in mistakes, the integral deals with previous errors, and the proportional term reacts to the current error. The sum of these variables constitutes the control signal communicated with the process. A feedback loop records a portion of the system's output to provide ongoing modification based on natural reactions. The block diagram shows the signal flow, highlighting how the PID controller keeps the system in the intended state by tweaking the parameters optimally. The PID controller modifies the mechanical power input to the generator ($P_m$) based on the error signal e(t), which is typically the difference between the specified and realized rotor angles. Finding the best possible values of $K_P$, $K_I$, and $K_D$ to minimize the objective function is done using the HBPSO approach. Utilizing the butterfly operation to explore the search space, the software iteratively changes the particle locations and velocities according to their individual and global optimum positions.

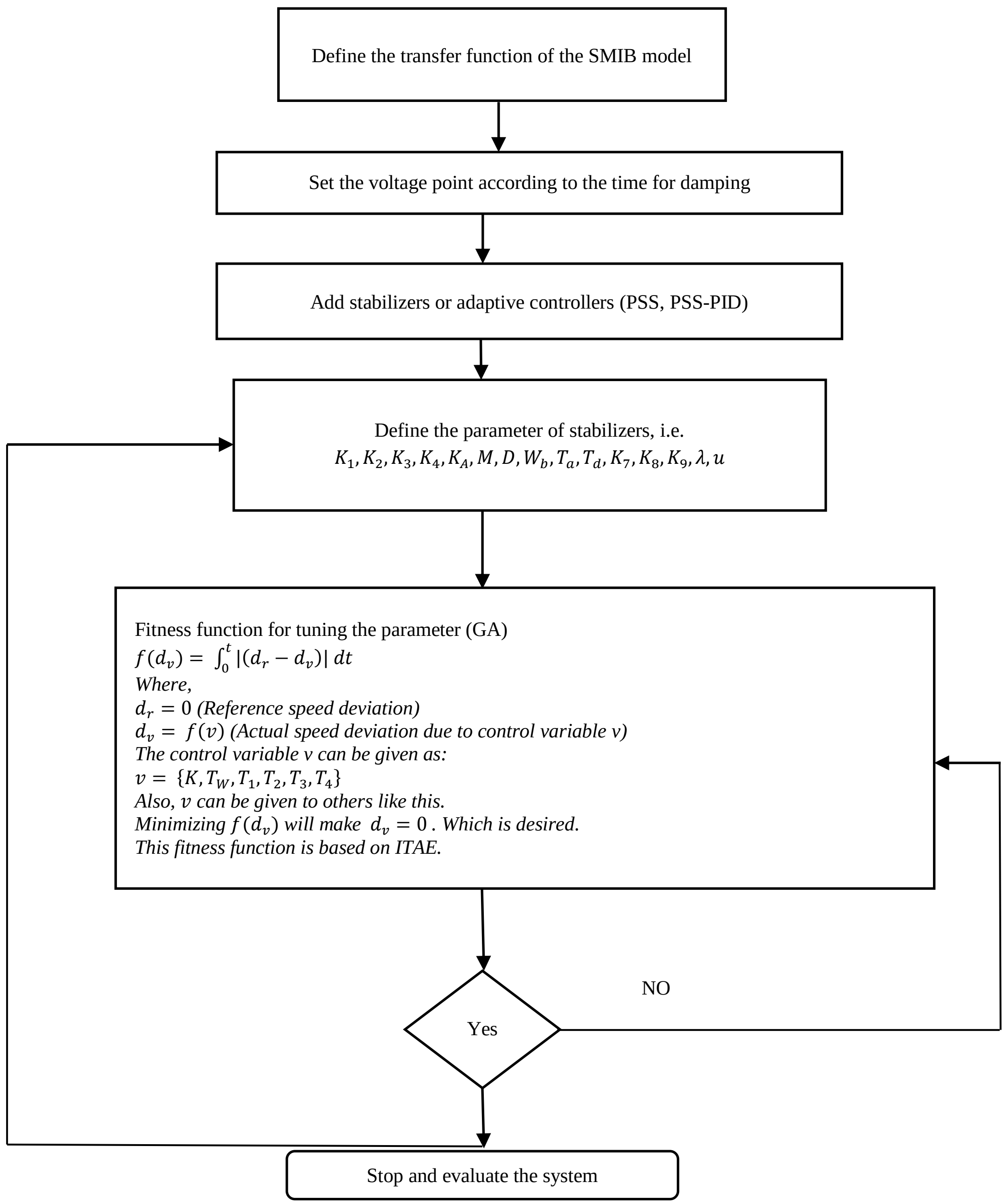



**Figure 1** Flow chart of the parameter optimization of the proposed SMIB system model

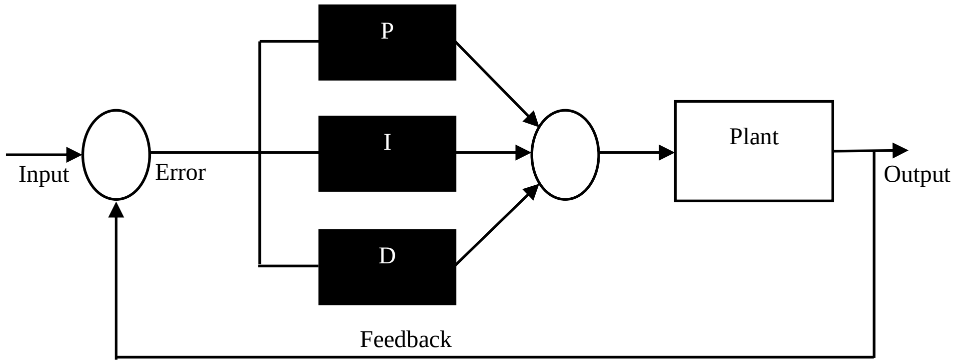



**Figure 2** Block diagram for PID Controller

## 3.2 Proposed method

### 3.2.1Objective function

The HBPSO algorithm is used to optimize the PID controller gains. Fitness Function for PID

$$f(d_v) = \int_0^t |(d_r - d_v)|\, dt \qquad (9)$$

where $d_r = 0$ (Reference speed deviation) and $d_v = f(v)$ (Actual speed deviation due to control variable v).

The control variable v can be given as:

$v = \{kp, ki, kd\}$

Also, v can be given to others like this.

Minimizing $f(d_v)$ will make $d_v = 0,$ which is desired. This fitness function is in terms of ITAE.

The performance response of the rotor speed and angle in three distinct operating modes is evaluated under defective conditions. Further examination of the power system is conducted by employing simulation techniques and linear and nonlinear programming. As determined by the nonlinear analysis, PID-PSS decreases the oscillation frequency of rotor speed, rotor angle, and time-response factors, including overshoot and settling time. Illustrated in *Figure 3* is the procedure by which the optimal PID controller parameters are determined. Obtain the initial values of the machine's parameters (k1–k10). After that, the system matrix A must be calculated. One can discern the system's fundamental dynamics by examining the eigenvalues of damping factor matrix A, which comprises elements of real and imaginary varieties. The initialization of an optimization technique is then used to improve the proportional (P), integral (I), and derivative (D) elements of the PID controller. The best values for each parameter of the PID controller are produced by running the optimization procedure. This work observes the effects of the optimized PID controller on the system dynamics by revising system matrix A with these revised values. *Figure 3* shows the last steps of optimizing the PID controller settings, leading to a more efficient control system.

### 3.2.2 HBPSO optimization of PID parameters

The HBPSO approach is an astute combination of two renowned optimization techniques: PSO and the BOA. The graceful flight of a butterfly while it searches for food and the synchronized wingbeats of a flock of birds are the building blocks of this naturalistic method. BOA is renowned for its graceful search space exploration, reminiscent of a butterfly's activity, while PSO is lauded for its straightforwardness and effectiveness in resolving a range of optimization issues, modeled by the cooperative flight of birds. The uniqueness of the HBPSO method lies in the fact that it uses BOA to do exhaustive searches within smaller portions of the search area, rather than tackling the space as a whole. In the PSO framework, the information about the optimal solutions is used to modify the locations and velocities of the particles based on this extensive investigation. This approach converges to the optimal solution more effectively by balancing broad exploration with targeted exploitation of the best options.

The HBPSO approach is beneficial for modifying the PID controller constants in systems such as the GPSS-SMIB, a power system model. The formulation of the HBPSO algorithm for this purpose is detailed in *Table 2*. *Table 2* provides the HBPSO algorithm for optimizing PID controller constants in the GPSS-SMIB system, which operates through distinct steps. As a first step, it disperses a group of particles throughout the search area; each particle represents a different PID constants collection. After that, it simulates the GPSS-SMIB system and compares the results to the target to determine how well each particle performs. Following this first assessment, the search space is subdivided into smaller manageable chunks, and BOA is used to thoroughly investigate each chunk. Then, using the optimal results from BOA, PSO revises the particle motions and trajectories. This two-step optimization technique accelerates Finding the optimal solution, which guarantees rapid exploration and comprehensive exploitation. The process ends when a threshold is reached, such as the maximum number of iterations or the particle's fitness level. Particularly for complex jobs like fine-tuning PID controller constants in power system simulations, this novel HBPSO approach shows how integrating algorithms inspired by nature may improve optimization results.

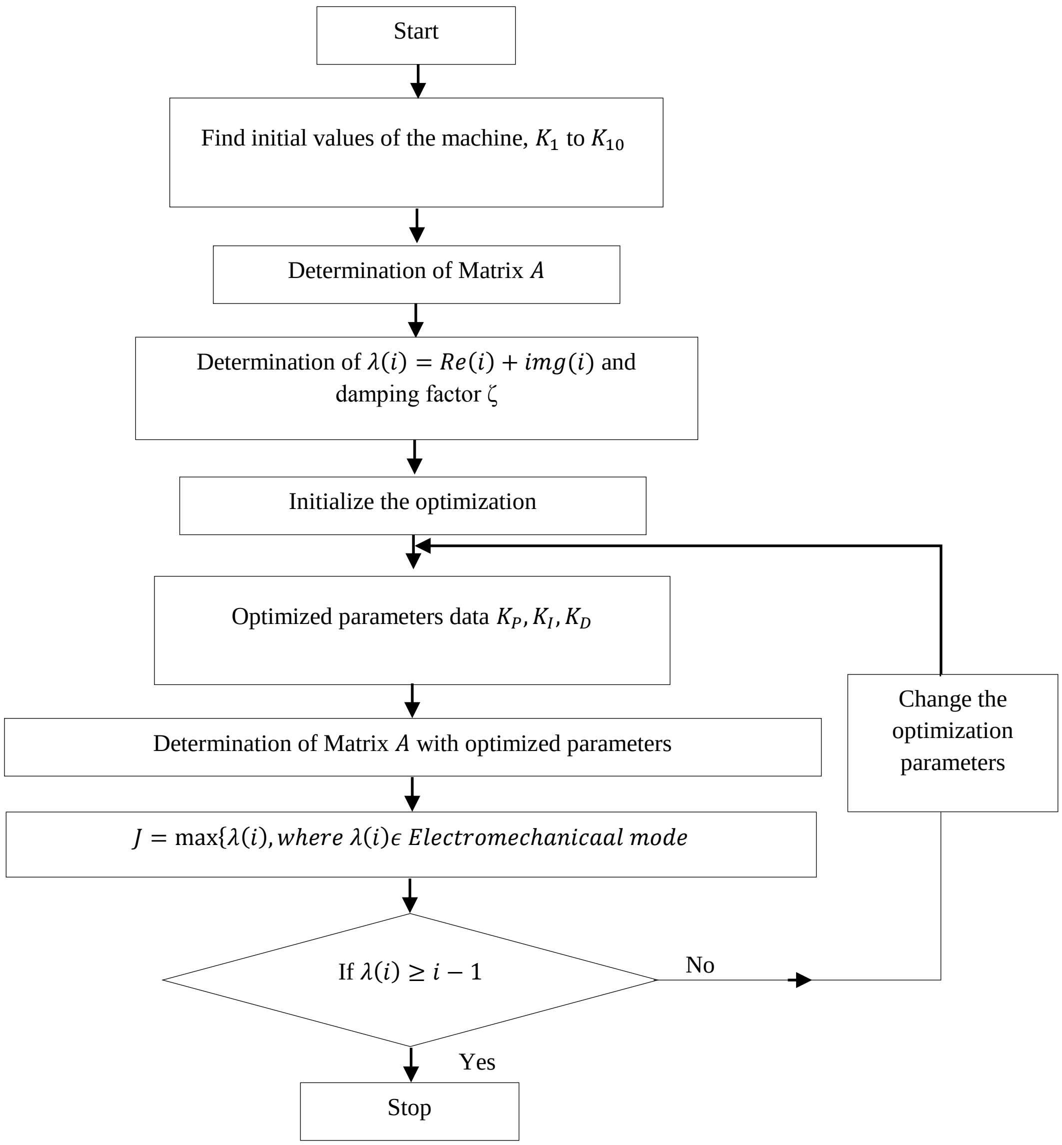



**Figure 3** Flowchart for PID-PSS for tuning $K_P, K_I, K_D$.

**Table 2** Formulation of HBPSO algorithm

| Step numbers | Operation of steps | Description of steps |
|---|---|---|
| Step 1 | Initialization | The technique commences by arbitrarily sowing the search space with a particle population. In place of constants, particles are exploited by a PID controller. |
| Step 2 | Evaluation | Using the consistent PID controller parameters, a GPSS-SMIB system simulation is accompanied to regulate the fitness value for each particle. Typically, the fitness function is abstracted as the difference between the actual and envisioned output of the system. |

| Step numbers | Operation of steps | Description of steps |
|---|---|---|
| Step 3 | Butterfly optimization | Multiple subspaces are spawned from the search space by retaining a BOA search procedure. Associated to traditional optimization methods, the BOA algorithm is executed in every subspace to augment the efficiency and efficacy of search space exploration. The BOA method modernizes the positions of all particles by consuming a local search procedure. |
| Step 4 | PSO | The PSO algorithm informs the position and velocity of particles based on the optimal solution attained from each BOA search procedure after the BOA search phase. The PSO algorithm repositions particles to confirm they all arrive at the optimal location resolute by the swarm. The HBPSO algorithm can swiftly convergently locate the optimal solution by conserving a healthy balance between exploring and exploiting the search space. |
| Step 5 | Termination | The algorithm will occasionally dismiss when the maximum number of repetitions is accomplished or when the fitness value of the optimal particle spreads a scheduled threshold. |

The mathematical formulation of the HBPSO algorithm can be epitomized as follows:
Each particle $i$ in the swarm's position and velocity are represented as $x_i$ and $v_i$, respectively. The personal best position of particle $i$ is defined as $p_i$ and the global best position of the swarm is represented by $p_g$.
Equation 10 shows the position update equation of the BOA algorithm for particle $i$ is given by:

$$x_i(t+1) = x_i(t) + v_1(t) \times D_1\big(p_i(t) - x_i(t)\big) + v_2(t) \times D_2\left(p_g(t) - x_i(t)\right) \quad (10)$$

Where $t$ is the current iteration, $v_1(t)$ and $v_2(t)$ are the random weight factors, $D_1$ and $D_2$ are the distance vectors, and $p_i(t)$ and $p_g(t)$ are the personal best and global best positions, respectively.

The velocity update Equation 11 of the PSO algorithm for particle $i$ is given by:

$$v_i(t+1) = w(t) \times v_i(t) + c_1 \times r_1(t) \times \big(p_i(t) - x_i(t)\big) + c_2 \times r_2(t) \times \left(p_g(t) - x_i(t)\right) \quad (11)$$

Where $w(t)$ is the inertia weight, $c_1$ and $c_2$ are the acceleration coefficients, and $r_1(t)$ and $r_2(t)$ are random values.

The HBPSO technique recognizes the particle with the lowest fitness value as the optimum solution. The HBPSO technique shortens the optimum PID controller coefficients for the GPSS-SMIB system by joining the aids of the BOA and PSO algorithms. The consequences of convergence and effectiveness of the HBPSO technique are meaningfully prejudiced by the early parameters working during optimizing the PID controller outlines in the SMIB system. An optimum population size is attained by efficiently examining and abusing the solution space while maintaining efficiency. The iteration count influences the convergence behavior and computational efficiency in a manner that strikes a gentle symmetry between thorough investigation and early convergence. Adjusting the inertia weight (w) is necessary to preserve a balanced state between exploration and exploitation. This parameter ascertains the extent to which the present positions of the particles are influenced by their previous velocities. The cognitive and social coefficients (c1 and c2) regulate the influence of personal and global information to strike a balance between particles' independent exploration and cooperative behavior. These coefficients are initialized to specified values. The butterfly spread factor (α) governs the optimization component's exploration capability by the intended level of exploration and problem-specific characteristics. These choices in the HBPSO method are determined by meticulously examining the complexities inherent in the optimization problem to ensure that the PID controller settings are optimal for enhanced transient stability in the SMIB system.
Numerical practices and simulation tools are developed in this study to examine the SMIB system's vigorous features and assess the optimization method's efficiency. The Runge-Kutta numerical method is extensively engaged in this study to resolve the differential equations governing the system's dynamics. These numerical techniques and simulation tools were founded on their established effectiveness in demonstrating the complicated dynamics of power systems and their suppleness and consistency. In distinction to more frank methodologies like Euler's method, the Runge-Kutta numerical method is notorious for creating numerical solutions for ordinary differential equations (ODEs) that are more accurately intended.

This method is highly appropriate for simulating the complicated dynamic behavior of the SMIB system across numerous operating conditions and turbulences due to its capability to balance computational efficiency and precision.

The numerical practices and SMIB system model are performed within the MATLAB/Simulink simulation environment. The graphical user interface of Simulink restructures the process of making and performing dynamic models, whereas MATLAB delivers an intelligible environment for inspecting power system stability. Due to Simulink's modular component architecture, the PID controller, PSS, and HBPSO optimization algorithms are upfront to implement. This link delivers an inclusive evaluation of the optimization outcomes and the system's response to disruptions. To construct Simulink blocks, differential equations describing the mathematical model of SMIB must be applied. The optimization procedure and control methodologies are concurrently represented in the Simulink environment using the PID controller, PSS, and HBPSO algorithm. Simulink's Runge-Kutta method obtains numerical solutions to the differential equations while simulating the dynamic reaction of the SMIB system. The widespread application of MATLAB/Simulink in the study of power systems provides validation for its selection as the simulation tool. The software facilitates dynamic modeling, simulation, and analysis through its intuitive interface. These tools are highly effective in evaluating power system transient stability and optimization alternatives due to MATLAB's robust numerical and mathematical computation capabilities and the intuitive graphical user interface of Simulink. The comprehensive simulations conducted using MATLAB/Simulink and the Runge-Kutta numerical method unveiled novel observations regarding the SMIB system's dynamics, the HBPSO algorithm-optimized PID controller outcomes, and the improvement of transient stability.

## 4.Results

This section examines the simulation results to assess the stability of the SMIB system. A vigorous PSS is precisely built using the PID controller. Enhancing the controller's limits with the HBPSO technique improves the system's performance and strength in various circumstances. Complete testing is accomplished concerning the fleeting impulses of the recognized and original PSS controllers. Perilous performance indicators underpin this evaluation, including peak overshoot and settling time. Moreover, a complete assessment of the stability of the pertinent power systems is carried out utilizing several metrics, such as eigenvalues, damping ratios, and eigenvalues. The meticulous MATLAB/SIMULINK development and examination of the SMIB system are noteworthy.

### 4.1Simulation parameters

Associated with the non-regulating system, the excitation controller has meaningfully augmented the system's steadiness and effectiveness. Overall, it badges the execution of considerable diminution constants, which promises exactness by making rapid response times with fewer static mistakes. In electro-mechanical attenuation, the excitation controller has accomplished remarkably well justifying fluctuations throughout the momentary fields. For the PID controller and the system, *Table 3* identifies all the essential limits. The PID controller constants, whose values are exhaustive in the first eight entries ($K_1$–$K_6$), determine how the controller acts. Other system parameters sheltered in entries nine through sixteen include the following: feedback gain ($K_F$), feedback time constant ($T_F$), stabilizing gain ($K_E$), stabilizing time constant ($T_E$), derivative time delay ($T'_d$), inertia constant (M), exciter gain ($K_A$), exciter time constant ($T_A$), damping factor (D), and system frequency (ӫ). These factors broadly define a controlled system's dynamics and response characteristics. As it provides insight into the numerical values allocated to each parameter for specific system configurations, the table is a significant reference for engineers and researchers who develop and analyze PID-controlled systems. *Table 4* shows the improved PID controller settings obtained using the HBPSO method. Optimal values for the PID controller gains are 98.244, 2.6946, and 97.3093 for the $K_P$, $K_I$, and $K_D$, respectively. As a result of the HBPSO optimization procedure, these numbers reflect the optimized parameters that improve the control performance of the system. Engineers and researchers may use this table to adopt these optimized PID controller advantages to increase the overall functioning of their systems.

The transient stability of the system has reached stages not understood earlier, particularly since the application of the PID controller. So, the system showed visible improvements in all features, highlighting low-energy situations such as the station's indolent state (under-excited condition). The system exhibits minimal setup times, almost no static errors, and recuperates from slight fluctuations to its early state.

**Table 3** System parameters

| S. No. | PID controller parameters | Actual values | S. N | PID controller parameters | Actual values |
|---|---|---|---|---|---|
| 1 | PID Controller Constant $K_1$ | 1.4479 | 9 | Feedback Gain $K_F$ | 0.025 |
| 2 | PID Controller Constant $K_2$ | 1.3174 | 10 | Feedback Time Constant $T_F$ | 1.0 |
| 3 | PID Controller Constant $K_3$ | 0.3072 | 11 | Stabilizing Gain $K_E$ | -0.17 |
| 4 | PID Controller Constant $K_4$ | 1.805 | 12 | Stabilizing Time Constant $T_E$ | 0.95 |
| 5 | PID Controller Constant $K_5$ | 0.0294 | 13 | Derivative Time Delay $T'_d$ | 5.9 |
| 6 | PID Controller Constant $K_6$ | 0.5257 | 14 | Inertia Constant M | 4.74 |
| 7 | Exciter Gain $K_A$ | 400 | 15 | Damping Factor D | 0 |
| 8 | Exciter Time Constant $T_A$ | 0.05 | 16 | System Frequency ω | 377 |

**Table 4** Optimized parameters using HBPSO

| S. No. | PID controller gain | Actual values |
|---|---|---|
| 1 | $K_P$ | 98.244 |
| 2 | $K_I$ | 2.6946 |
| 3 | $K_D$ | 97.3093 |

### 4.2Initial results derived from the phase of implementation

At this stage, numerous precarious actions were confirmed:

- The hybrid controller, PSS, and PID were all applied as control plans for the system.
- Conception was accomplished on the controlling performance of the system and simulation results.
- Determining the system's behavior needs the cunning of its dynamic properties.
- To confirm the reliability of the system, inclusive stability testing was shown.

Broad investigations were accompanied on the system in three separate cases:

1. Unsophisticated operation of an open-loop system.
2. To operate using standard PSS and PID controllers in a closed loop.
3. Thirdly, a hybrid (PSS+PID) controller is implemented when the loop is closed.

- Furthermore, this research implemented controlled disruptions by manipulating the external network parameters ($X_L$), including a 15 % variation in the turbine's torque at time t = 0.2s.

4. Simulations were performed on various external network configurations to generate four distinct operating modes:

- Traveling at maximum pace.
- During off-peak hours, reactive power returned to the network (Q = 0).
- Generation of an excessive amount of reactive energy (Q > 0) during periods of elevated demand.

### 4.3 Simulation results

The performance of the controllers is assessed by using two vital metrics: perilous clearance time and ITAE. The previous enumerates the accumulative response error over time, while the latter quantifies the time obligatory for the power system to reinstate itself from a disruption. The objective is to prove the critical development in system stability shown by the joint PSS-PID controller through a side-by-side comparison of the two controllers. An investigation of the effects of different optimization approaches on controller performance will also be delivered. The resulting evaluation revision is carefully assessed and deliberated to ascertain how the new approach enhance power system stability.

A fascinating vigorous is obvious when inspecting the PSO-PID controller's response to a spontaneous defect at t=5 seconds, as demonstrated in *Figure 4*. The deviation value specifies an extensive deviance of the generator's speed from its steady-state features. In the following illustration, this alteration quickly spreads the PID controller, showing an error with a non-zero nonconformity; the PSO-PID controller then pledges the refinement process. Unpredictably, the image exemplifies that these errors incline to steady at about 5 seconds, a timeframe that is both acceptable and commendable. The results prove that the PSO-PID controller efficiently alleviated the troublesome influence of the outage and punctually reestablished the power system to its typical operational state. This detection indicates the PSO-PID controller's capability to withstand system stability and transient approachability in the face of unexpected errors. The controller proves its extraordinary efficiency by improving system performance and accelerating recovery.

*Figures 5(a)* and *5(b)*, demonstrating the phase and rotor angles changes when the PID-PSO controller involves an unexpected failure at t = 10 seconds. A fault disruption continues for a protracted period of 50 seconds without a controller. The PSS and PID controllers alleviate the fault's significance within a single sample period, easing its quick determination. As soon as the defect begins, the generator rotor diverges pointedly from its steady-state speed; the unrushed deviation intensifies this aberration. The instant importance of this aberration is a sampling error in the instant interval that does not equal zero. This error quickly spreads to the PID controller. As a result, the PID controller proceeds to implement the essential compensatory processes. According to the statistics, the PSS controller corrects the aberrations to zero in four seconds, a curiously remarkable performance. Painstaking by all, this validates the effectiveness and punctuality of the controller. This feature improves the performance and sturdiness of the system in the face of impetuous failures, highlighting the competence of the PSS controller to reestablish stability and alleviate transient disturbances promptly.

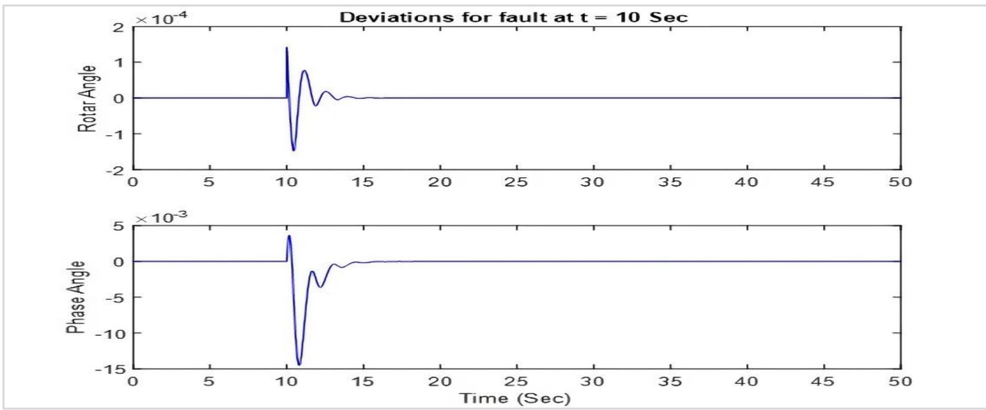
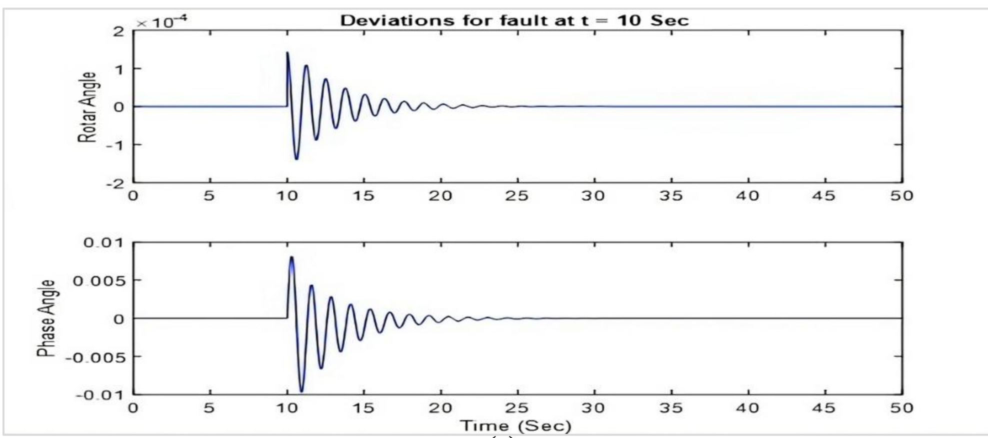
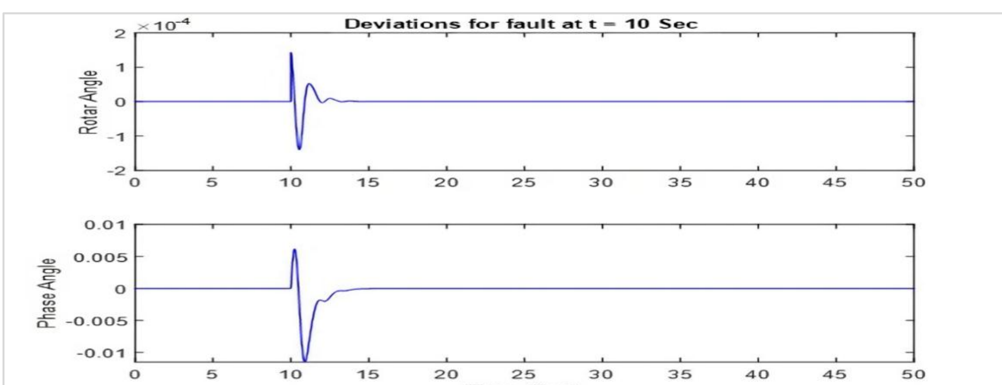



**Figure 4** Differential angles in hybrid PSO-PID model




(a)




(b)

**Figure 5** Response of rotor and phase angles within the hybrid model (PSO-PID) a) Deviations settled down 0 to 5 seconds b) Impulsive fault occurs at t = 10 seconds

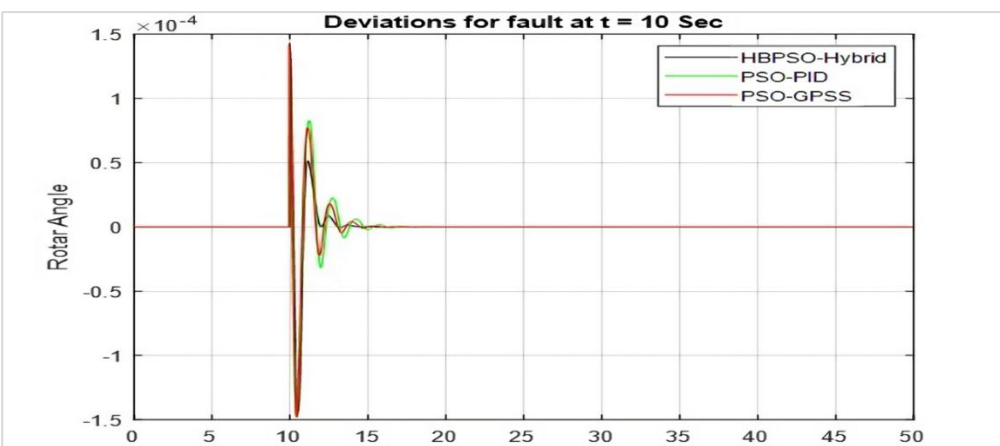
*Figures 6(a) and (b)* illustrate the dynamic response of the hybrid technique based on HBPSO in the event of an abrupt disturbance occurring at t=10 seconds. Surprisingly, the disruptive presence of the defect disappears entirely after a single sampling period. The generator's rotor exhibits a significant deviation from its constant speed at the onset of the defect, as visually depicted in *Figure 6*. This deviation, which becomes apparent as a non-zero deviation error throughout the sampling period, promptly notifies the PSS, which is obliged to initiate a compensatory response. Remarkably, the variances return to zero in only three seconds, demonstrating this method's speed and efficacy. The phase angle stabilizes during the same brief period due to its close tracking of rotor deviation. This results from the HBPSO algorithm modifying the gain parameters of the PSS and PID controllers with extreme precision. Implementing this optimization procedure accelerates both system stability and reaction times. The findings of this inquiry provide robust evidence in favor of the notion that excitation controllers, particularly the PSS, PID, and hybrid controllers, substantially enhance the stability and performance of the system in comparison to an unregulated system. Significant improvements in transient regime accuracy and a reduction in static errors are prominent results of the shortened reaction times enabled by these excitation controllers' more significant attenuation coefficients.

In addition, these excitation controllers significantly increase the electro-mechanical damping of electro-mechanical oscillations, even during critical phases like station rest (under-excited conditions). As a consequence, transient regimes across all system parameters are improved. The system's lightning-fast reaction time is indisputable; it returns to its initial configuration with lightning-fast accuracy following minor oscillations, exhibiting extremely brief startup periods and few static errors. Utilizing excitation controllers, particularly PID and hybrid variants, ultimately enhances a dynamic system's stability, accuracy, and reaction times and increases its resilience.

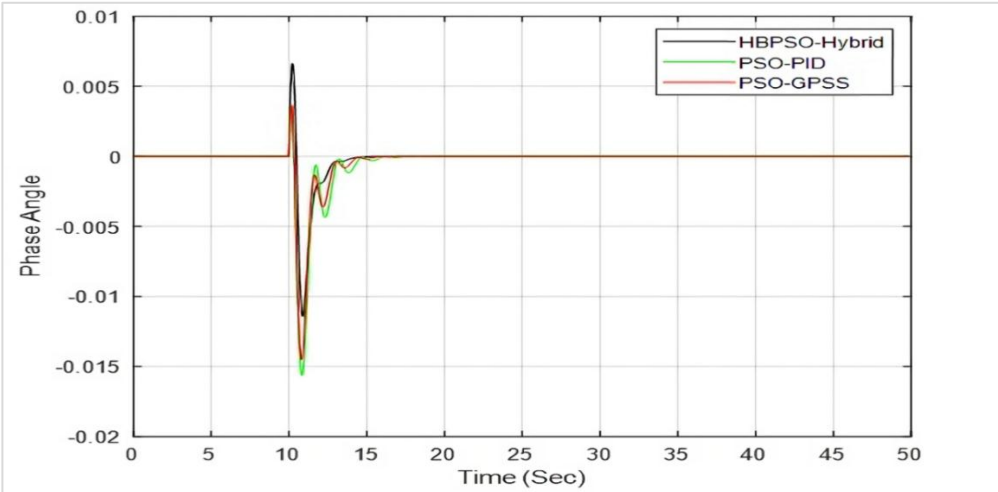
#### 4.3.1Load change stability evaluation in SMIB system

A comprehensive valuation examined the SMIB mathematical model system's stability. There were 5%, 10%, and 15% incremental changes in the system's load. For the most part, the evaluation focused on PSSs that used PID controllers and the groundbreaking HBPSO optimization technique. The appraisal's goal was to regulate the PSS recital under different loads.

*Table 5* shows a comprehensive investigation into the stability of the electro-mechanical methods based on their eigenvalues and damping properties. To control the electro-mechanical modes to the left of the S-plane, the projected controller can regulate their eigenvalues. Enhancing the attenuation characteristics and, by extension, the system's stability verifies the controller's capability. This work empirically evaluated the controller's performance, keeping measures like peak overshoots and settling durations to further prove its superiority. *Figure 7 a) and b)* shows the bar charts of settling time and overshoot time in seconds of HBPSO, PSO, and BOA optimization methods. The results of this study, show that the HBPSO-optimized PID-PSS controller outperforms the alternative controllers that were considered. The bar charts also suggest that HBPSO consistently outperforms PSO and BOA in stabilizing the power system across all tested scenarios of load changes. This could indicate that HBPSO is more robust and adaptable to different degrees of system disturbances compared to the other methods.




(a)

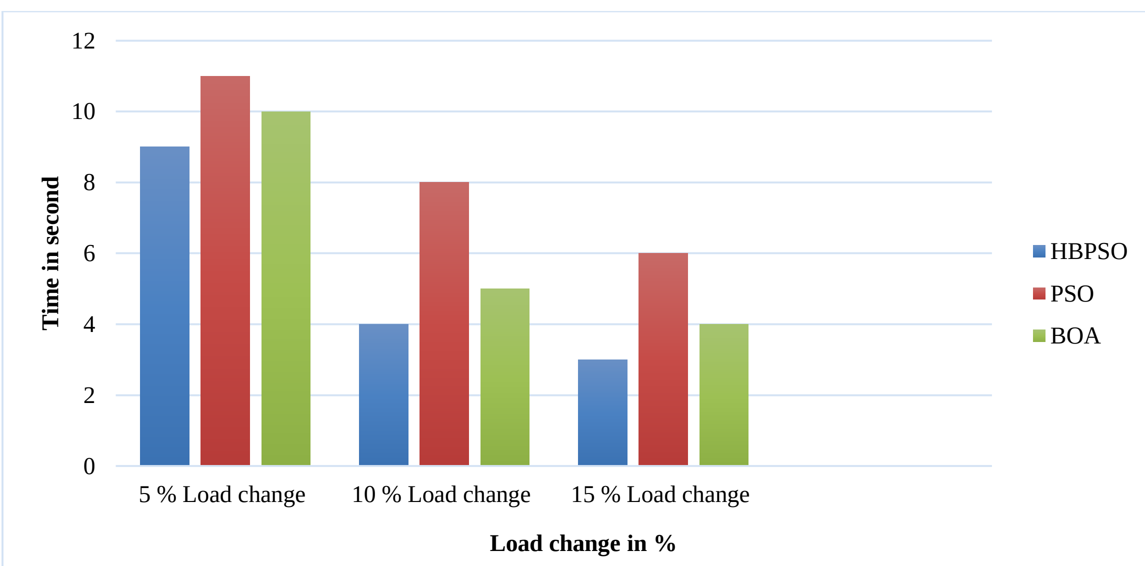



(b)

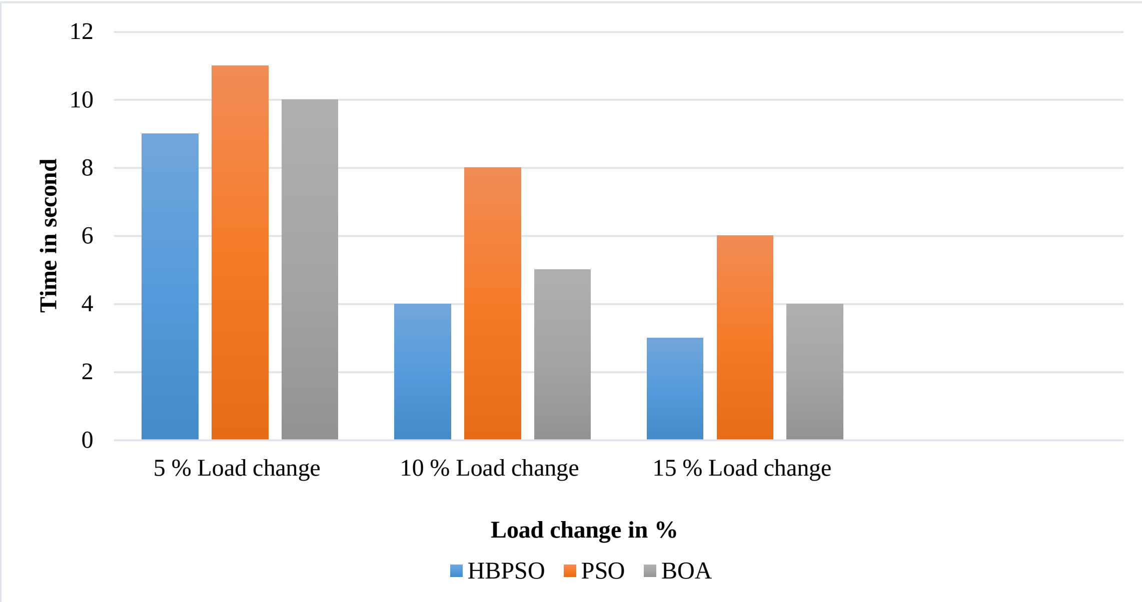
**Figure 6** Comparative assessment of variations in SMIB a) Rotor angle b) Phase angle

**Table 5** Stability assessment of diverse controllers

| Load changes | Optimized controller | Eigenvalue | Damping ratio |
|---|---|---|---|
| 5 % step decreases | HBPSO-PID-PSS | -1.59 ± j4.34 | 0.298 |
| | BOA-PID-PSS [15] | -0.74± j3.91 | 0.198 |
| | PSO-PID-PSS [36] | -0.49 ± j3.37 | 0.174 |
| 10 % step decreases | HBPSO-PID-PSS | -1.28 ± j4.21 | 0.213 |
| | BOA-PID-PSS [15] | -0.56 ± j3.54 | 0.151 |
| | PSO-PID-PSS [36] | -0.26± j2.46 | 0.124 |
| 15 % step decreases | HBPSO-PID-PSS | -1.14 ± j2.74 | 0.196 |
| | BOA-PID-PSS [15] | -0.43 ± j2.13 | 0132 |
| | PSO-PID-PSS [36] | -0.19 ± j1.93 | 0.105 |




(a)




(b)

**Figure 7** Comparison Chart depicting a) Settling time b) Overshoot time

As a performance metric, this simulation utilized ISE. The output of the open-loop system's speed deviation (Δϋ) was consistently modified when the mechanical torque deviation (ΔTm) was altered as input by 0.05 per unit (pu) in the transfer function. The hybrid controller should be implemented to enhance the SMIB system's stability and performance, as demonstrated by these outcomes. The rapid and enormous oscillations produced by input modifications validate the system's inherent recurrence. MATLAB permits the analysis and replication of the exciter and stabilizer, two dynamic components of the system. The system's stability and transient reactivity could be investigated with a performance evaluation method that employs the ISE as the designated performance metric. This platform strives to simplify the process of modifying the excitation control settings so that the requisite system performance can be achieved.

**Table 6** Comparative analysis with prior studies

| Applied method's | Settling time (S) |
|---|---|
| Fuzzy System [16] | 19 |
| BBO-based PID [21] | 11.5 |
| Firefly-PID-PSS [22] | 11.001 |
| Proposed HBPSO-PID | 10.10 |

A comparison of various methodologies is presented in *Table 6*, with settling time (S) serving as a crucial metric that indicates the rate at which the power system reacts to fluctuations in stability. There have been implemented, among other systems, a Firefly-PID-PSS [22], a BBO-based PID [21] with a settling time of 11.5, and a fuzzy system [16] with a settling time of 19. In contrast to the alternative approaches, the proposed solution demonstrates a significantly reduced settling time of 10.10 seconds by implementing HBPSO on the PID controller. The proposed HBPSO-PID method achieves a more stable power system than the alternatives that have been previously examined because a shorter settling time results in a more rapid response and enhanced transient stability.

## 5.Discussion

This research demonstrates a thorough method for improving power system dynamic stability using a modified HPM. Transient stability and peak duration response are significantly enhanced by combining the MPSS design with an HBPSO method, which optimizes the settings of the PID controller. The suggested strategy is effective in part because of the HBPSO algorithm's hybrid character, which combines features of PSO and BOA. The GPSS-SMIB model provides a well-organized and systematic approach to improving PID parameters with the help of the HBPSO algorithm. Effective optimization methods in power system stability analysis are needed, and this paper introduces the HBPSO algorithm to fill that need. The suggested HBPSO-based PID controller is further supported by the comparison study with other optimization approaches, demonstrating a markedly decreased settling time and improved transient stability. The utilization of HBPSO optimization on the PID controller offers several advantages over earlier methods. Firstly, the method consistently achieves superior stability performance across various load change scenarios, as evidenced by the higher damping ratios and more favorable eigenvalues. This indicates the robustness and effectiveness of the approach in enhancing transient stability and system response. Additionally, the reduced settling time achieved by the method demonstrates its ability to quickly restore system stability following disturbances, which is critical for maintaining reliable power grid operation. Furthermore, the approach showcases flexibility and adaptability, outperforming alternative methodologies like BOA-PID-PSS and PSO-PID-PSS across different load change magnitudes. However, it's essential to acknowledge the potential limitations of the approach. While HBPSO optimization yields significant improvements in stability and response time, it may come with increased computational complexity and implementation challenges compared to more straightforward control strategies. Additionally, generalizing the findings beyond the studied SMIB system may require further validation in more complex power grid models. Nonetheless, the comprehensive analysis presented in this study contributes to advancing the understanding of power system stability optimization techniques and lays the foundation for future research to address these challenges and further refine the approach for real-world application.

### 5.1Key findings

Numerous noteworthy results show that the technique recommended in this study recovers the performance and stability of the SMIB system. The paper first presents the HBPSO method to optimize the PID controller's settings. The study shows that the HBPSO method effectively reaches suitable PID settings, which recover the system's transient stability via extensive simulations. One of the study's essential achievements is finding that the PID controller optimized using the HBPSO algorithm may attain a settling time of 10.10 seconds. This finding proves that higher reactivity to power system shocks improves transient stability. In addition, the research associates and dissimilarities several optimization methods, including Firefly-PID-PSS and BBO-based PID, with the recommended HBPSO-PID technique. It has been shown that the HBPSO-PID approach attains stability during variations better than others, and this is the most vital discovery supporting this claim. Further, testing the recommended HBPSO-based PID-MPSS design against standard MPSS layouts shows better damping performance in terms of peak length and settling time. This work designates how the hybrid method might increase dynamic stability. The research also proves that the HBPSO-PID-PSS controller competently replies to various situations when power system loads fluctuate, emphasizing its adaptability to changing load conditions.

The study highlights the significance of the HBPSO algorithm's optimized parameters for the PID controller and the MPSS. These changed parameters suggestively influence the enhanced stability and performance of the SMIB system. When examining optimization results and seizing the complex dynamics of the SMIB system, the research highlights the effectiveness of simulation tools, especially MATLAB/Simulink and the Runge-Kutta numerical approach. The study finishes by discussing the methodology's potential applications in the power system sector and contributing proposals for further research, such as examining the methodology's applicability to more complicated power systems. The consecutive essential results show that the recommended approach is robust and can handle stability issues in the SMIB system.

### 5.2Comparison of result with existing methods

Various strategies were assessed in the research under discussion to determine their efficacy in stabilizing power networks in the face of abrupt fluctuations in power demand. The term used to describe these sudden modifications is "step reductions." An approach that was examined was referred to as HBPSO-PID-PSS. This approach demonstrated considerable efficacy in maintaining the stability of the power system, notwithstanding substantial fluctuations in power demand (5%, 10%, or 15% below the system's design capacity). The evaluation of the efficacy of these approaches involves the examination of two metrics: the rate at which the system reverts to equilibrium following a disturbance (referred to as the "settling time") and the degree of smoothness exhibited by this return to stability (referred to as "eigenvalues" and "damping ratios").

In addition to stabilizing the power system more swiftly than the preceding methods, the HBPSO-PID-PSS strategy ensured that the operation ran effortlessly. This information compares different methodologies, with settling time (S) being a crucial metric indicating how quickly the power system responds to stability fluctuations. Among the systems examined are a Firefly-PID-PSS [22], a BBO-based PID [21] with a settling time of 11.001 seconds and 11.5 seconds, respectively, and a fuzzy system [16] with a settling time of 19 seconds. In contrast to these alternative approaches, our proposed solution significantly reduces settling time to 10.10 seconds by implementing HBPSO on the PID controller. This HBPSO-PID method results in a more stable power system compared to previously examined alternatives, as a shorter settling time leads to a quicker response and enhanced transient stability.

The stability assessment of various controllers under different load change scenarios is summarized in the table. When faced with 5% step decreases, the HBPSO-PID-PSS controller exhibits an eigenvalue of -1.59 ± j4.34 and a damping ratio of 0.298, outperforming the BOA-PID-PSS [15] and PSO-PID-PSS [36] controllers which have eigenvalues of -0.74 ± j3.91 and -0.49 ± j3.37 respectively. For 10% step decreases, the HBPSO-PID-PSS controller maintains superior stability with an eigenvalue of -1.28 ± j4.21 and a damping ratio of 0.213 compared to the BOA-PID-PSS and PSO-PID-PSS controllers. Similarly, under 15% step decreases, the HBPSO-PID-PSS controller demonstrates better stability with an eigenvalue of -1.14 ± j2.74 and a damping ratio of 0.196 compared to its counterparts. Overall, the HBPSO-PID-PSS controller consistently outperforms the others across all load change scenarios, indicating its effectiveness in enhancing system stability.

### 5.3Limitations

Despite the promising results, identifying specific study limitations remains risky. The proposed HBPSO method's efficacy is affected by the startup parameters used in PID controller tuning. Careful examination and adjustment of these parameters are necessary for optimal convergence and efficiency. The specific characteristics of the optimization issue must also be thoroughly assessed when choosing the butterfly spread factor (α) for the HBPSO method. In addition, although the SMIB system serves as a good starting point, it would be beneficial for future studies to test the efficacy of the proposed approach on more complex power systems with interdependent parts. More studies are necessary to control the generalizability and robustness of the HBPSO-PID controller in different power system configurations. Even though the GPSS-SMIB model is widely used and successful, the simulation environment relies on several assumptions and simplifications that are part of it. Power systems in the actual world are complex; thus, the suggested approach may not work there. More complicated system models combined with real-world data should be considered for future research to evaluate the proposed strategy thoroughly.

A complete list of abbreviations is shown in *Appendix I*.

## 6.Conclusion

Based on a modified HPM, this study proposes a design for HBPSO-PID-GPSS that enhances the dynamic stability of the power system via the HBPSO method. The proposed MPSS design depends on local information because, unlike conventional designs, it employs the secondary bus voltage of the generator side transformer as a point of reference instead of external data.

To optimize the gain settings of the PID controller and MPSS parameters, the modified HPM is fitted with the devised HBPSO algorithm. The proposed method's effectiveness is confirmed by examining diverse operational scenarios. The simulation results indicate that the proposed HBPSO-based PID-MPSS provides superior damping performance in peak duration and settling time compared to conventional MPSS. Eigenvalue analysis is applied to every operational circumstance to validate the results further. The findings indicate that the proposed HBPSO-based PID-MPSS architecture brings the unstable and weakly damped eigenvalues closer to the ideal stable region. The suggested approach could improve the dynamic stability of the power system across various operational scenarios, surpassing the performance of traditional MPSS designs.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### Conflicts of interest

The authors have no conflicts of interest to declare.

### Data availability

None

### Author's contribution statement

**Yogesh K. Kirange:** Conceptualization, data collection, investigation, data curation, writing – original draft, writing – review and editing. **Pragya Nema:** Interpretation of results, study conception, design, supervision, investigation of challenges, and draft manuscript preparation.

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## Appendix I

| S. No. | Abbreviation | Description |
|---|---|---|
| 1 | ABC | Ant Bee Colony |
| 2 | ABPID-PSS | Antlion-Based Proportional, Integral, and Derivative Power System Stabilizer (ABPID-PSS) |
| 3 | ALO | Antlion Optimization |
| 4 | ANN | Artificial Neural Networks |
| 5 | AOA | Archimedes Optimization Algorithm |
| 6 | AVR | Automatic Voltage Regulator |
| 7 | BA | Bat Algorithm |
| 8 | BBO | Biogeography-Based Optimization Algorithm |
| 9 | BOA | Butterfly Optimization Algorithm |
| 10 | BPSO-CM | Bare-Bones Particle Swarm Optimization with Crossed Memory |
| 11 | CPSO | Craziness Particle Swarm Optimization |
| 12 | CPSS | Conventional Power System Stabilizers |
| 13 | DC | Direct Current |
| 14 | DPR | Dynamic Power Reduction |
| 15 | EFPA | Enhanced Flower Pollination Algorithm |
| 16 | EGT | Evolutionary Game Theory |
| 17 | ExPSO | Exponential Particle Swarm Optimization |
| 18 | FACTS | Flexible Alternating Current Transmission System |
| 19 | FOA | Firefly Optimization Algorithm |
| 20 | FOPID | Fractional-Order PID |
| 21 | GWO | Grey Wolf Optimizer |
| 22 | GPSS | General-Purpose Simulation System |
| 23 | HBPSO | Hybrid Butterfly Particle Swarm Optimization |
| 24 | HPM | Heffron-Phillips Model |
| 25 | HPSBFO | Hybrid Particle Swarm Bacteria Forging Optimization |
| 26 | HSA | Harmony Search Algorithm |
| 27 | IAE | Integrated Absolute Error |
| 28 | IDLN | Integral Dynamic Learning Network |
| 29 | ILMI | Iterative Linear Matrix Inequality Approach |
| 30 | ISE | Integrated Square Error |
| 31 | ITWAE | Integral of Time-Weighted Absolute Error |
| 32 | ITAE | Integral Time Absolute Error |
| 33 | ITWSE | Integral of Time-Weighted Square Error |
| 34 | JGC | Jacobian Gain Control |
| 35 | LFC | Linear Feedback Control |
| 36 | MGOA | Modified Grasshopper Optimization Algorithm |
| 37 | MPSS | Modified Power System Stabilizer |
| 38 | MOPS | Multi-Objective Particle Swarm Optimization |
| 39 | MPC | Model-Predictive Control |
| 40 | MPSO | Modified Particle Swarm Optimization |
| 41 | MRAC | Model Reference Adaptive Control |
| 42 | NSPSO | New Stable Particle Swarm Optimization |
| 43 | ODE | Ordinary Differential Equations |
| 44 | PD | Proportional Derivative |
| 45 | PI | Proportional Integral |
| 46 | PID | Proportional, Integral, and Derivative |
| 47 | FPID-PSS | Firefly Proportional, Integral, and Derivative Power System Stabilizer |
| 48 | PSO | Particle Swarm Optimization |
| 49 | PSS | Power System Stabilizer |
| 50 | SG | Synchronous Generator |
| 51 | SMIB | Single-Machine Infinite Bus |
| 52 | TLBO | Teaching-Learning-Based Optimization |
| 53 | TVLME | Time-Varying Lyapunov Matrix Equation |
| 54 | UAV | Unmanned Aerial Vehicle |
| 55 | WTG | Wind Turbine Generators |