

RESEARCH ARTICLE

Design of Power System Stabilizer Using Harris Hawk Optimizer for 150 kV Sulselrabar Electricity System

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Abstract

In this paper, design of the Power System Stabilizer (PSS) using Harris Hawk Optimizer (HHO) is proposed to improve stability of the 150 kV interconnected electricity system in South, Southeast, and West Sulawesi (Sulawesi Selatan, Tenggara, dan Barat – Sulselrabar), as one of the large-scaled electricity of Indonesia. The simulation and optimization are performed in Simulink/MATLAB software. HHO is used to find the optimal parameter of PSS based on the Critical Damping Index (CDI) calculation. For investigating the performance, load changes are subjected to the power system. Based on the results, HHO achieved the best stability improvement compared to the Cuckoo Search Algorithm (CSA). Based on the time domain simulation analyses, the PSS-HHO design reduced overall oscillation by 83.81%, and reduced settling time by 57.9%. Based on the Integral Time Absolute Error (ITAE) calculation, the PSS-HHO design also reduced the average error by 67.34%.

Keywords: harris hawk optimization, large-scaled electricity system, power system stabilizer

I. INTRODUCTION

Maintaining and improving the stability is crucial to maintain the reliability of a large-scaled electricity system [1]. One of the example is the South, Southeast, and West Sulawesi (*Sulawesi Selatan, Tenggara, dan Barat* – Sulselrabar), as one of the large-scaled electricity system of Indonesia, consisting of multiple machines in interconnected areas. This system covers the electricity for the provinces of South, Southeast, and West Sulawesi of Indonesia. This system faces a stability problem in several generators, named Barru and Tello Lama generators, when sudden load changes occur, resulting in rotor angle deviation and slow recovery to their steady-state responses. This condition leads to synchronization reduction and operation standard violation, indicating the urgency of improving the stability [2].

To mitigate this problem, a Power System Stabilizer (PSS) is implemented to increase the stability limits of the generators, especially during dynamic disturbances like sudden load changes. To increase the performance, the PSS design should be optimized to ensure the parameters give the optimum stability improvement. One of the viable options is to perform PSS design optimization using an Artificial Intelligence (AI) method. Recently, an AI-based metaheuristic algorithm has rapidly developed due to offering simplicity for solving power electricity system cases [3], [4].

Metaheuristic algorithms are also widely used for PSS design optimization, due to their advantage of exploring the candidate optimal solution of PSS. For instance, Equilibrium Optimizer Algorithm (EOA) [5], Black Widow Optimization

Algorithm (BWOA) [6], Mayfly Optimization Algorithm (MOA) [7], Grey Wolf Optimizer (GWO) [8], Gravitational Search Algorithm (GSA) [9], and Gorilla Troops Optimizer (GTO) [10], have been demonstrated in PSS design optimization. Among the algorithms, Harris Hawk Optimizer (HHO) has attracted researchers with its strong exploration and exploitation capabilities, fast convergence, and high accuracy [11-14]. Despite its demonstrated efficacy in diverse power system optimization problems, including Power System Stabilizer (PSS) design optimization, the application of Harris Hawks Optimization (HHO) for conventional PSS tuning within large-scale, multi-machine power systems has seen limited exploration. While HHO has been implemented for PSS design, these applications have predominantly been confined to test systems like the Single Machine Infinite Bus (SMIB). This study seeks to address this research gap by rigorously evaluating the performance of a pure HHO algorithm in enhancing the transient stability of the SULSELBAR electrical grid, as the HHO implementation for PSS design in a real system-based model is currently lacking.

This paper proposes a design of the PSS using HHO to improve a real system-based model from the Sulselrabar electricity system. The simulation and optimization are performed in Simulink/MATLAB software. HHO is used to find the optimal parameter of PSS based on the Critical Damping Index (CDI) calculation. To validate the improvements, HHO is compared to CSA as a settled algorithm. Both algorithms have a similar structure and use, allowing a fair comparison between them. HHO and CSA PSS designs are evaluated by using statistical analyses and time domain simulations under different dynamic disturbance conditions. The stability improvement is focused

on the overshoot reduction, settling time, and error calculation in the frequency and rotor angle responses. To calculate the error, the Integral Time Absolute Error (ITAE) calculation is used [15].

II. SYSTEM MODELLING

In this section, the fundamental concepts and techniques of system modeling is described. Furthermore, the proposed approach and methodology used to create accurate and useful representations of complex systems also explained.

A. Generator Modeling

Modeling a linear synchronous generator is essential for analyzing changes in frequency response and power affect the rotor angle [16]. By using Transformation Park, the synchronous generator can be represented by a mathematical model, which is then linearized as shown in Equation (1) below [17].

$$\begin{bmatrix} \Delta v_d \\ -\Delta v_F \\ 0 \\ \Delta v_q \\ 0 \\ \Delta T_m \\ 0 \end{bmatrix} = - \begin{bmatrix} r & 0 & 0 & \omega_0 L_q & \omega_0 k M_Q & \lambda_{q0} & 0 \\ 0 & r_F & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\omega_0 L_d & -\omega_0 k M_F & -\omega_0 k M_D & r & 0 & -\lambda_{d0} & 0 \\ 0 & 0 & 0 & 0 & 0 & r_Q & 0 \\ \frac{\lambda_{q0} - L_q i_{q0}}{3} & \frac{-k M_F i_{q0}}{3} & \frac{-k M_D i_{q0}}{3} & \frac{-k M_Q i_{d0}}{3} & \frac{k M_Q i_{d0}}{3} & -D & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta i_d \\ \Delta i_F \\ \Delta i_D \\ \Delta i_q \\ \Delta \omega \\ \Delta \delta \end{bmatrix} \quad (1)$$

$$- \begin{bmatrix} L_d & k M_F & k M_D & 0 & 0 & 0 & 0 \\ k M_F & L_F & M_R & 0 & 0 & 0 & 0 \\ k M_D & M_R & L_D & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & L_q & k M_Q & 0 & 0 \\ 0 & 0 & 0 & k M_Q & L_Q & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -T_j & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta i_d \\ \Delta i_F \\ \Delta i_D \\ \Delta i_q \\ \Delta \omega \\ \Delta \delta \end{bmatrix}$$

In this framework, v_d and v_q correspond to the stator voltage components along the d-q axis, while v_F represents the voltage in the rotor field. Meanwhile, v_D and v_Q refer to the rotor voltages along the same d-q axis. Additional parameters in this system include r , which denotes the stator resistance L_d and L_q for the rotor inductances along the d-q axis, and λ_{q0} and λ_{d0} for the initial flux values along the d-q axis. The term $k M_F$ represents the rotating magnetic field, and M_D and M_Q indicate the mutual inductance. Furthermore, Δi_d and Δi_q represent the stator currents along the d-q axis, with i_F denoting the rotor field current, and Δi_D and Δi_Q representing the rotor currents along the d-q axis. Finally, ω signifies the change in the generator's speed, and δ indicates the variation in the generator's rotor angle.

B. Excitation Modeling

The excitation system consists of equipment designed to manage the generator's output parameters, such as voltage, current, and power factor [18]. These parameters are controlled by modifying the field flux within the generator. In this study, a fast exciter is used as the excitation system, which is recognized for its rapid response time as in Equation (2). With K_A is gain parameter, and T_A is time constant value [19] and it's illustrated as shown in Fig. 1

$$E_{fd} = K_A \left(\frac{V_t - V_{ref}}{1 - T_A s} \right) \quad (2)$$

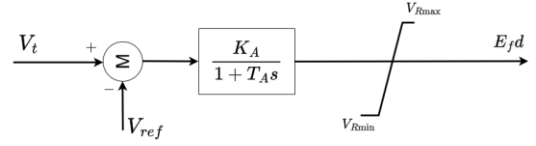


Fig. 1 Fast Exciter Block Diagram

C. Governor Modeling

The governor is essential for regulating the mechanical torque generated by the generator, ensuring it stays within the required limits for stable and efficient power system operation. The extent of variation in mechanical torque (ΔT_m) is determined by the constant associated with the speed reduction, the governor's transfer function, and the available energy source. These changes in (ΔT_m) occur as a result of fluctuations in speed, variations in load, and adjustments made to the speed reference set by the Governor Speed Changer (GSC) [20]. When the generator rotor speed changes, the governor quickly responds by sending feedback signals that help the system reach a new equilibrium point. This process ensures that the system remains stable and responsive to such changes. To better understand the functioning of the governor, a block diagram illustrating its operation can be found in Figure 1 [19]. As illustrated in the Fig. 2, a change in ($\Delta \omega_d$) leads to a corresponding change in the machine's mechanical torque (ΔT_m).

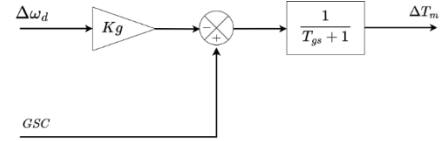


Fig. 2 Governor Block Diagram

D. Power System Stabilizer (PSS)

The design of PSS generally involve frequency response techniques focused on improving torque damping. The PSS transfer function is tuned to provide the appropriate phase lead needed to compensate for the phase lag between the Automatic Voltage Regulator (AVR) reference input (Δv_s) and the electrical torque [21]. Consequently, the electrical torque component becomes in phase with speed variations, enhancing system damping. By utilizing a simplified mathematical model of the PSS, the mathematical representation of the PSS can be formulated as in Equation (3) [22].

$$V_s = K_{pss} \frac{T_w s}{1 + T_w s} \left[\frac{(1 + s T_A)(1 + s T_C)}{(1 + s T_B)(1 + s T_D)} \right] \omega \quad (3)$$

Assuming that the PSS output is V_s with $\Delta \omega$ as the input, Equation (3) can be depicted in the block diagram presented in Fig. 3

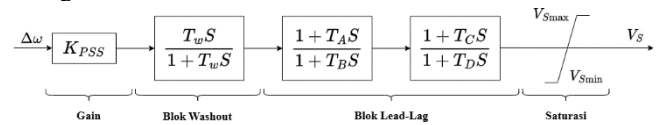


Fig. 3 PSS Block Diagram

E. Sulsebar Electricity System

The Sulsebar electricity system connects the areas of South Sulawesi, Southeast Sulawesi, and West Sulawesi. It comprises 46 transmission lines and 16 generators that link

the main load centers with 14 PSS. Operating at a voltage of 150 kV, the system includes 37 buses. To aid in the analysis, a bus numbering scheme is implemented, as shown in Fig. 4.

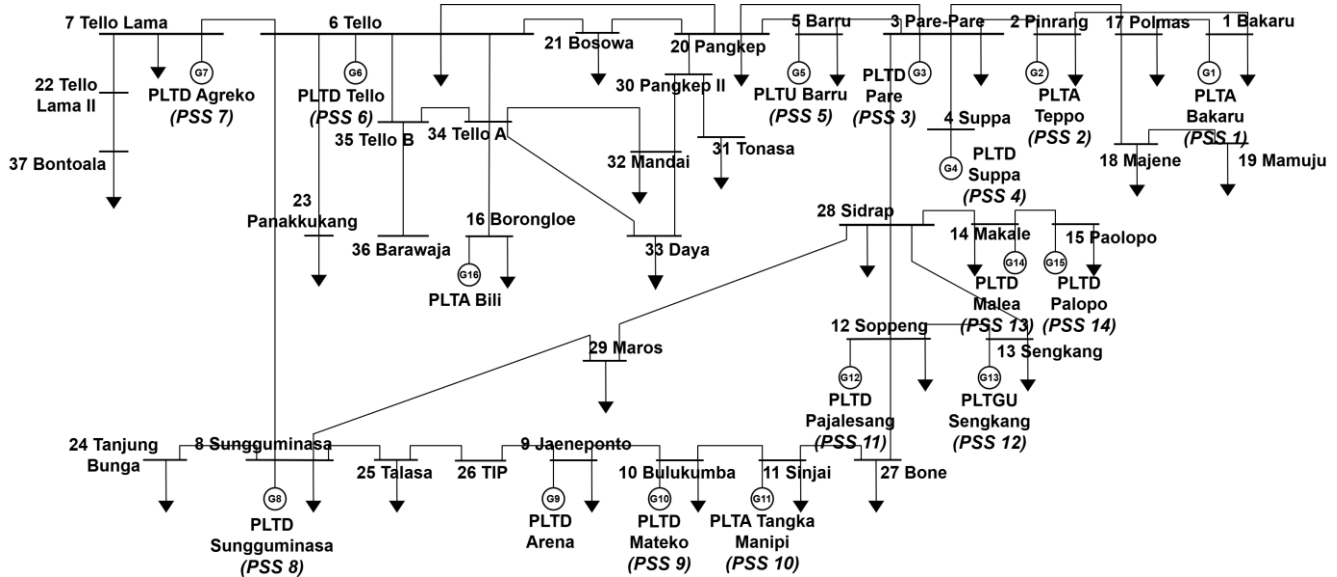


Fig. 4 Single Line Diagram Sulsebar Electricity System

III. RESEARCH METHOD

In this section a comparison of different methods for optimizing the ideal PSS parameters based on the algorithms are discussed. It also outlines the method is implemented using an objective function for optimization. The underlying theory of this approach is as follows.

A. Harris Hawk Optimization (HHO)

This algorithm, based on characteristics of Harris Hawks' unique hunting strategies, is a population-based metaheuristic method focused on capturing their target [11]. The fundamental process that underpins this algorithm is explained in detail in the following section.

1) Exploration Phase

The HHO algorithm is developed by replicating the hunting strategy of Harris Hawks, based on their natural instincts. The initial phase of the algorithm is known as the exploration phase, where the hawks waiting, selecting, observing, and tracking their prey. In this phase, the hawks are modeled as candidate solutions, and the best solution found at each iteration tends to be the optimal one. The hawk's behavior of perching in random areas during exploration is linked to parameter q . If $q \geq 0.5$, the hawk waits on a randomly chosen high tree within the search area with its family. If $q < 0.5$, the hawk perches near its family and prey. The position vector and the average position, which determine the hawk's next move, are given in Equation (4) and (5).

$$X(It+1) = \begin{cases} X_{rand}(It) - r_1 |X_{rand}(It) - 2r_2 X(It)|, & q \geq 0.5 \\ X_{rabbit}(It) - X_m(It) - r_3 (L_b + r_4 (U_b - L_b)), & q < 0.5 \end{cases} \quad (4)$$

$$X_m(t_{HHO}) = \frac{1}{N_{HHO}} \sum_{i=1}^{N_{HHO}} X_i(t_{HHO}) \quad (5)$$

With, X indicates the position vector of the hawk, X_m signifies the average position within the hawk population, X_{rand} indicates a hawk chosen at random, X_{rabbit} represents the position of the rabbit, $r_1 - r_4$ are random values ranging from 0 to 1, It denotes the iteration number, N refers to the total number of solutions; and U_b and L_b represent the upper and lower limits of the variables.

2) Transition Phase

The hunting group of the hawks observes and estimates the rabbit condition. In HHO, this behavior belongs to the transition phase. The transition in HHO is influenced by E_o and E as shown in Equation (6) and Equation (7).

$$E_o = \begin{cases} E_o, 0 >> 1, \text{the rabbit has a lot of energy} \\ E_o, 1 << 0, \text{the rabbit is run out of energy} \end{cases} \quad (6)$$

$$\text{phase}(E) = \begin{cases} |E| \geq 1, \text{phase} >> \text{exploration} \\ |E| < 1, \text{phase} >> \text{exploitation} \end{cases} \quad (7)$$

In Equation (40), the increase in E_o from 0 to 1 represents that the rabbit still has a lot of energy and confidence. Whereas the decrease in E_o from 1 to 0 represents the rabbit is running out of energy and exhausted. If $|E| \geq 1$, then the hawks are still in the exploration phase. While $|E| < 1$, then the hawks advance to the exploitation phase.

3) Exploitation Phase

The exploitation phase is further classified into four distinct conditions, which depend on the values of r and $|E|$. The following sections explain these conditions in detail, showing how each scenario influences the algorithm's behavior and adjustments based on the specific values r and $|E|$. Each condition plays a critical role in determining the next steps and optimizing the process accordingly.

a) Soft besiege, its represented by $r \geq 0.5$ and $|E| \geq 0.5$. A group of hawks uses the soft besiege strategy when the rabbit is still energetic and tries to escape. They surround it and take turns attacking to weaken it before a surprise strike.

The soft besiege mathematical model is shown in Equations (8) and (9), with J calculated in Equation (10).

$$X(t_{HHO} + 1) = X(t_{HHO}) - E|JX_{rabbit}(t_{HHO}) - X(t_{HHO})| \quad (8)$$

$$\Delta X(t_{HHO}) = X_{rabbit}(t_{HHO}) - X(t_{HHO}) \quad (9)$$

$$J = 2(1 - r_5) \quad (10)$$

b) Hard besiege, its represented by $r \geq 0.5$ and $|E| < 0.5$. A group of hawks initiates the hard besiege when the rabbit shows signs of fatigue, surrounding it with heavy and sudden attacks. The hard besiege mathematical model is shown in Equation (11).

$$X(t_{HHO} + 1) = X_{rabbit}(t_{HHO}) - E|X(t_{HHO})| \quad (11)$$

c) Soft besiege with progressive rapid dives, its represented by $r < 0.5$ and $|E| \geq 0.5$. This condition reflects the rabbit still having high energy and escaping using random Levy Flight (LF) movements. Hawks estimate the rabbit's path (Y) using Equation (12), and if hawks fail to catch rabbit, perform random dives to remap the path (Z) as shown in Equation (13). LF is modeled in Equation (14), and the attack pattern updates follow Equation (15).

$$Y = X_{rabbit}(t_{HHO}) - E|JX_{rabbit}(t_{HHO}) - X(t_{HHO})| \quad (12)$$

$$Z = Y + S \times LF(D) \quad (13)$$

$$LF(x) = 0.01 \times \left(\frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}} \right) \times \sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{\frac{\beta-1}{2}}} \right) \quad (14)$$

$$X(t_{HHO} + 1) = \begin{cases} Y & \text{if } F(Y) < F(X(t_{HHO})) \\ Z & \text{if } F(Z) < F(X(t_{HHO})) \end{cases} \quad (15)$$

d) Hard besiege with progressive rapid dives, its represented by $r < 0.5$ and $|E| < 0.5$. This condition occurs when the rabbit lacks energy after attempting to escape. Similar to the soft besiege, hawks reduce their distance before launching a surprise attack. The attack pattern is determined by Equation (15), with updated Y and Z rules in Equations (16) and (17).

$$Y = X_{rabbit}(t_{HHO}) - E|JX_{rabbit}(t_{HHO}) - X_m(t_{HHO})| \quad (16)$$

$$Z = Y + S \times LF(D) \quad (17)$$

B. Objective Function

The damping ratio (ξ) is defined in Equation (18), and it serves as a key parameter for evaluating the damping characteristics of the system. To gain a more comprehensive understanding of the system's overall damping behavior, the value of the Comprehensive Damping Index (CDI) is used. The Comprehensive Damping Index (CDI) is used as an aggregate measure of the system's damping performance, where a lower CDI indicates better stability. In this study, the HHO algorithm indirectly minimizes CDI by optimizing the PSS parameters to increase the damping ratios of oscillatory modes. As the HHO searches for the best parameter set, it enhances system damping, thereby reducing the CDI value across generators. The overall damping performance of a system can be assessed using CDI, giving a broader perspective on the damping effectiveness throughout the entire system.

The parameters limit of pss are determined based on practical considerations derived from standard PSS design, for lower bound $K_{pss} = 10$, T_1 and T_2 are 0.01, T_3 and T_4 are 0.5, for lower bound $K_{pss} = 50$, T_1 and T_2 are 0.05, T_3 and T_4 are 1. The following parameters were used in the

implementation of the HHO method for optimizing the PSS settings are $N = 15$, $It = 50$, $X_{rabbit} = 10$, $r_1 - r_5 = \text{rand}[0,1]$. Additionally, the parameter T_w is set with values ranging from $T_{w1} - T_{w16}$ is 10.

$$\zeta_i = \frac{-\sigma_i}{\sqrt{\sigma_i^2 + \omega_i^2}} \quad (18)$$

$$CDI = \sum_{i=1}^n (1 - \zeta_i) \quad (19)$$

IV. RESULT AND ANALYSIS

In this section, the results of tuning PSS tuning are discussed, which were performed using several optimization methods, HHO and CSA. The results from these algorithms are compared with the output of the system without the PSS. The analysis compares the performance of the three methods based on the minimum Integral of Time Absolute Error (ITAE) using Simulink blocks in MATLAB. Where the ITAE can be represented by,

$$ITAE = \left(\sum_0^t t \times |e(t)| dt \right) \quad (20)$$

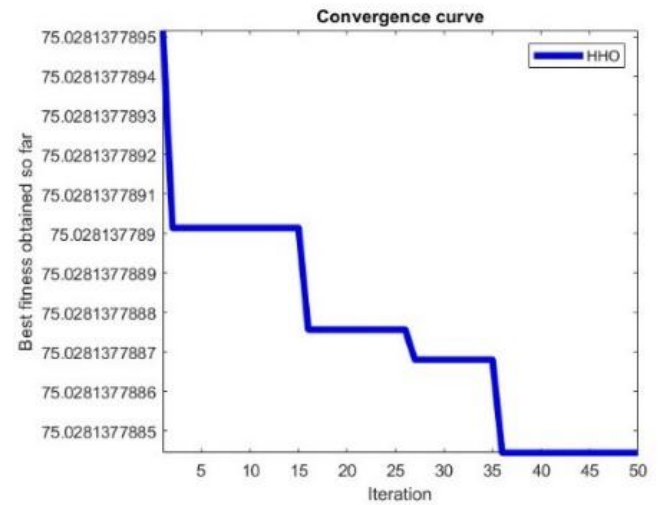


Fig. 5 Converge Curve of HHO

The study case used in this research involves a disturbance in the form of load variations within the system, followed by an analysis of the frequency response and rotor angle of the Barru generator, both before and after the implementation of a PSS tuned using CSA and HHO. The Barru generator is one of 16 generating units within the Sulselrabar power system. Generator Barru was chosen as the sample in this study because it exhibited the most satisfactory results, as reflected in its frequency response and rotor angle response, both of which showed significant improvements in stability and damping performance. The parameters of the PSS include K_{pss} , T_1 , T_2 , T_3 , and T_4 is presented in Table II. Fig 4 presents the convergence curve of the HHO algorithm applied to the optimization of the Sulselrabar system. The convergence curve shows that the HHO algorithm quickly improves the fitness value in the early iterations, then stabilizes around 75.0281. This indicates that the algorithm reached an optimum early, with little to no improvement afterward, suggesting either premature convergence or that the optimal solution was found. The tuning process for these parameters was carried out using HHO.

TABLE I TUNING RESULTS OF PSS PARAMETER

Generator	K_{pss}	T_1	T_2	T_3	T_4
Bakaru	47.9172	0.010824	0.022188	0.746147	0.865454
Pinrang	47.437	0.021031	0.016062	0.947076	0.965215
Pare-Pare	11.2242	0.011712	0.037435	0.567099	0.873027
Suppa	23.526	0.011218	0.01713	0.856002	0.888663
Barru	47.7097	0.011713	0.011468	0.951783	0.703536
Tello	19.7454	0.002221	0.002345	0.084643	0.917525
Tello Lama	11.3379	0.011321	0.046483	0.920244	0.770188
Sungguminasa	26.3328	0.023500	0.012134	0.760212	0.464732
Bulukumba	44.9262	0.011712	0.011713	0.647786	0.647783
Sinjai	47.9315	0.011059	0.012766	0.842273	0.961812
Soppeng	11.2266	0.011216	0.012279	0.880427	0.640396
Sengkang	11.2226	0.018102	0.048064	0.865949	0.654073
Makale	11.2221	0.018416	0.011214	0.78098	0.725513
Palopo	31.6582	0.027423	0.035912	0.72661	0.842117

TABLE II FREQUENCY OF BARRU GENERATOR

Method	Overshoot (p.u)	Undershoot (p.u)	Settling Time (s)	CDI
No PSS	0.03654	-0.08482	16.678	79.2312
PSS Cuckoo	0	-0.033810	7.365	75.7440
PSS HHO	0	-0.027910	4.194	75.0281

TABLE III ITAE PARAMETER

Generator	ITAE		
	No PSS	Cuckoo	HHO
Bakaru	0.05174	0.02036	0.01367
Pinrang	0.07447	0.02367	0.01512
Pare-Pare	0.05489	0.02021	0.01293
Suppa	0.07252	0.02428	0.01581
Barru	0.19510	0.08661	0.08499
Tello	0.17940	0.17130	0.16890
Tello Lama	0.53800	0.21650	0.12550
Sungguminasa	0.03429	0.03189	0.02691
Jeneponto	0.05347	0.02000	0.01321
Bulukumba	0.08606	0.02960	0.01652
Sinjai	0.13930	0.04607	0.02280
Soppeng	0.10420	0.02912	0.01737
Sengkang	0.08557	0.02655	0.01655
Makale	0.23330	0.06279	0.03080
Palopo	0.25800	0.07063	0.03236
Borongloe	0.05142	0.03944	0.03537

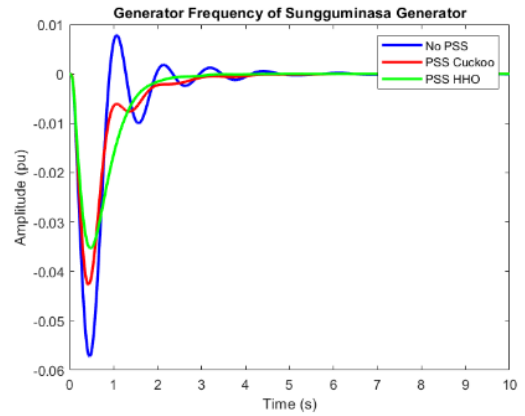


Fig. 6. Frequency of Sungguminasa Generator

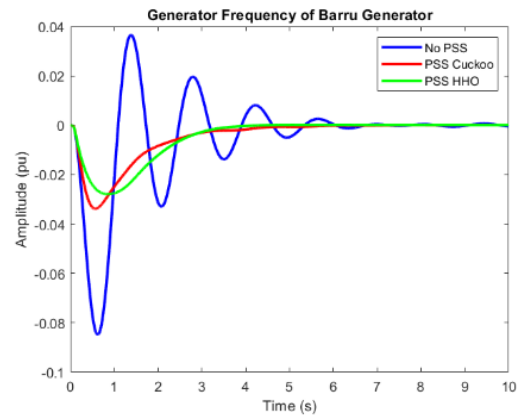


Fig. 7. Frequency of Barru Generator

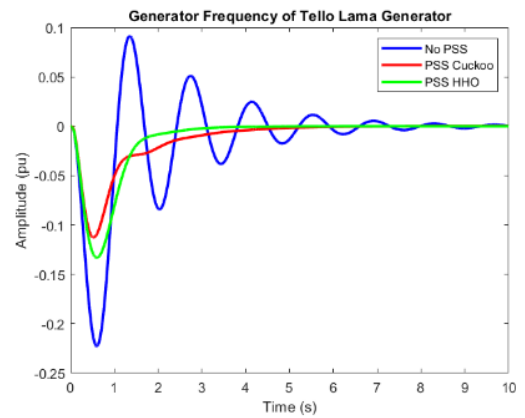


Fig. 8 Frequency of Tello Lama Generator

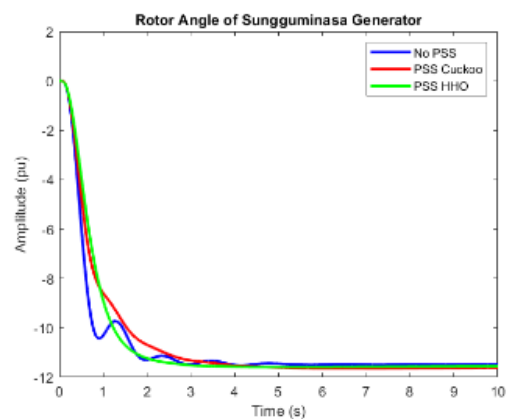


Fig. 9 Rotor Angle of Sungguminasa Generator

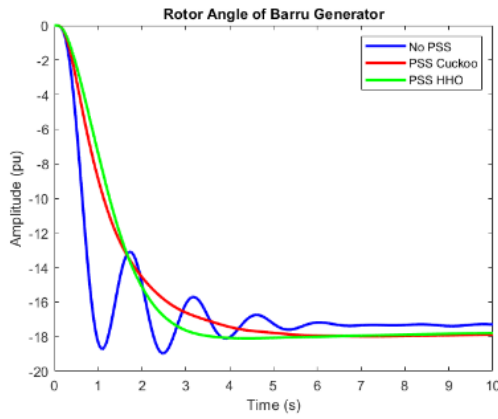


Fig. 10 Rotor Angle of Barru Generator

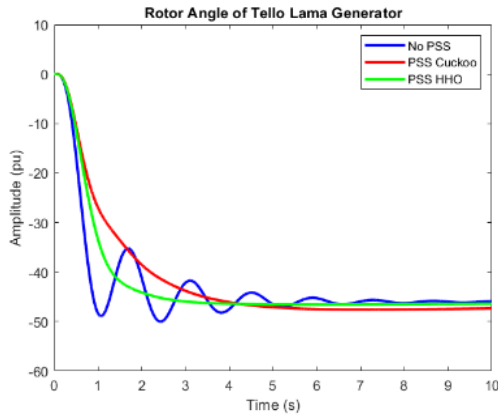


Fig. 11 Rotor Angle of Tello Lama Generator

The results of the Comprehensive Damping Index (CDI) as shown in Table II analysis demonstrate that the system equipped with a PSS tuned using the Harris Hawk Optimization (HHO) algorithm achieves the lowest CDI value compared to both the No PSS and CSA-based PSS scenarios. This lower CDI value indicates superior damping of electromechanical oscillations and reflects a more stable dynamic response.

The generator's speed response under load variation is essential to assess system stability and control performance. When the active power exceeds the mechanical power of the generator, the initial rotor speed tends to decrease, as indicated by the simulation results in Fig. 4 – Fig. 11. In this scenario, the rotor experiences deceleration due to the imbalance between active and mechanical power, resulting in a negative rotor angle response. Based on the observation of speed and rotor angle deviation graphs for each generator under fault conditions particularly when a disturbance is applied to the Bakaru generator it is evident that the amplitude of oscillations or overshoot is significantly reduced after the installation of a Power System Stabilizer (PSS). Moreover, the recovery time to reach a steady-state condition, or settling time, is considerably shorter when employing the Harris Hawk Optimization (HHO) algorithm-based control method compared to the Cuckoo Search Algorithm (CSA) and systems without any stabilizing control. The analysis confirms a substantial improvement in the system's dynamic performance following the optimal placement of Power System Stabilizers. The optimal PSS installation locations are identified at Bakaru, Pinrang, Pare-

Pare, Suppa, Barru, Tello, Tello Lama, Sungguminasa, Bulukumba, Sinjai, Soppeng, Sengkang, Makale, and Palopo.

These tuning parameters as presented in Table I are crucial in ensuring that the power system returns to its normal operating condition promptly. Therefore, the findings confirm that the HHO tuned PSS significantly enhances the overall stability of the Sulselrabar power system. In a system without PSS (No PSS), the overshoot reaches 0.03654 p.u., this indicates that the system, in the absence of a PSS, is in a critical state and susceptible to generator trips due to underfrequency protection activation. Excessive overshoot can cause voltage levels to exceed safe operational limits, potentially damaging electrical equipment and prolonging system recovery time. To address this issue, PSS parameter optimization was performed using two metaheuristic methods: CSA and HHO. By applying the CSA, overshoot was successfully reduced by 93.41%, demonstrating an improvement in the system response to disturbances as presented in Table II.

This significant reduction proves that the CSA effectively optimizes PSS parameters, enhancing system stability when facing load changes. However, despite the considerable reduction in overshoot, residual oscillations may still impact system stability under certain operating conditions. Meanwhile, the HHO exhibited a more optimal performance than the CSA. According to simulation results, this approach completely eliminated overshoot (100% reduction) as shown in Fig 5-7, meaning the system could achieve stability without facing excessive voltage spikes, as rotor angle response shown in Fig 8-10, HHO reduced the oscillation. The superior performance of the HHO can be attributed to its more adaptive exploration and exploitation mechanisms, enabling more precise and optimal PSS parameter tuning to minimize voltage oscillations. By eliminating overshoot entirely, the system becomes safer and more efficient in adapting to load changes. The application of HHO significantly reduced the system's settling time from 16.678 seconds to 4.194 seconds. This demonstrates that HHO-optimized PSS not only dampens oscillations effectively but also accelerates the return of the rotor angle to stable synchronization ($\Delta\delta \rightarrow 0$). This capability is particularly important in multimachine systems like Sulselrabar, where poor synchronization among generators can lead to widespread instability. Based on the ITAE parameter, the simulation results indicate that the Pare-Pare generator exhibit relatively good performance with PSS-HHO, and in Janeponto generator with PSS-Cuckoo, as presented in Table III. Overall, the findings of this study confirm that metaheuristic-based PSS parameter optimization significantly improves power system stability, by reducing the overshoot with the percent average is 83.81%, improved the settling time by 57.9%, and achieved an improvement of 67.34% in the ITAE value. HHO has been proven to be a more effective and efficient approach than CSA, making it a more optimal solution for addressing power system stability challenges, particularly under conditions of load variations and complex operational disturbances.

V. CONCLUSION

This result highlights the effectiveness of HHO in optimizing PSS parameters, allowing the system to recover more rapidly and efficiently after disturbances. These findings confirm that HHO is more effective than CSA in reducing both overshoot and settling time, making it a more optimal approach for PSS tuning in power systems. The ability of HHO to eliminate overshoot entirely while significantly shortening settling time underscores its potential as a superior optimization technique for improving power system stability.

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REFERENCES

- [1] P. Stoffel, L. Maier, A. Kümpel, T. Schreiber, and D. Müller, "Evaluation of advanced control strategies for building energy systems," *Energy Build.*, vol. 280, p. 112709, 2023, doi: 10.1016/j.enbuild.2022.112709.
- [2] C. Wang, Z. Lei, and H. Huo, "Transient Stability Control Strategy Based on Uncertainty Quantification for Disturbances in Hybrid Energy Storage Microgrids," 2024.
- [3] V. Tomar, M. Bansal, and P. Singh, "Metaheuristic Algorithms for Optimization: A Brief Review," *Eng. Proc.*, vol. 59, no. 1, pp. 1–16, 2023, doi: 10.3390/engproc2023059238.
- [4] A. M. Nassef, M. A. Abdelkareem, H. M. Maghrabie, and A. Baroutaji, "Review of Metaheuristic Optimization Algorithms for Power Systems Problems," *Sustain.*, vol. 15, no. 12, pp. 1–27, 2023, doi: 10.3390/su15129434.
- [5] M. A. Prakasa and I. Robandi, "Power System Stabilizer Tuning Improvement for Single-Machine Infinite Bus using Equilibrium Optimizer Algorithm," 2022 *Int. Semin. Intell. Technol. Its Appl. Adv. Innov. Electr. Syst. Humanit. ISITIA 2022 - Proceeding*, pp. 320–325, 2022, doi: 10.1109/ISITIA56226.2022.9855203.
- [6] M. T. I. Hidayat, I. Robandi, R. S. Wibowo, M. A. Prakasa, and M. R. Djalal, "Optimal Tuning of Power System Stabilizer and Virtual Inertia Control Based On Black Widow Optimization Algorithm," 2024 *Int. Semin. Intell. Technol. Its Appl.*, pp. 65–70, 2024, doi: 10.1109/ISITIA63062.2024.10668177.
- [7] M. R. Djalal, I. Robandi, and M. A. Prakasa, "Stability Enhancement of Selselrabar Electricity System Using Mayfly Algorithm Based on Static Var Compensator and Multi-Band Power System Stabilizer PSS2B," no. June, pp. 57319–57340, 2023.
- [8] Z. Sun, Y. Cao, Z. Wen, Y. Song, and Z. Sun, "A Grey Wolf Optimizer algorithm based fuzzy logic power system stabilizer for single machine infinite bus system," *Energy Reports*, vol. 9, pp. 847–853, 2023, doi: 10.1016/j.egy.2023.04.365.
- [9] F. D. Pramudhita, I. Robandi, A. Priyadi, M. A. Prakasa, and M. R. Djalal, "Hybrid Tuning for Parameters of Power System Stabilizer and Virtual Inertia Based on Super Conducting Magnetic Energy Storage Using Gravitational Search Algorithm," *Proc. Int. Conf. Comput. Eng. Netw. Intell. Multimedia, CENIM 2024*, pp. 1–6, 2024, doi: 10.1109/CENIM64038.2024.10882670.
- [10] M. A. El-Dabah, M. H. Hassan, S. Kamel, M. A. Abido, and H. M. Zawbaa, "Optimal Tuning of Power System Stabilizers for a Multi-Machine Power Systems Using Hybrid Gorilla Troops and Gradient-Based Optimizers," *IEEE Access*, vol. 11, no. March, pp. 27168–27188, 2023, doi: 10.1109/ACCESS.2023.3250384.
- [11] M. Almas Prakasa, I. Robandi, R. Nishimura, and M. Ruswandi Djalal, "A New Scheme of Harris Hawk Optimizer With Memory Saving Strategy (HHO-MSS) for Controlling Parameters of Power System Stabilizer and Virtual Inertia in Renewable Microgrid Power System," *IEEE Access*, vol. 12, no. June, pp. 73849–73878, 2024, doi: 10.1109/ACCESS.2024.3385089.
- [12] M. A. Prakasa and I. Robandi, "Tuning Improvement of Power System Stabilizer using Hybrid Harris Hawk Optimization-Equilibrium Optimizer Algorithm," *Proceeding - 6th Int. Conf. Inf. Technol. Inf. Syst. Electr. Eng. Appl. Data Sci. Artif. Intell. Technol. Environ. Sustain. ICITISEE 2022*, pp. 553–558, 2022, doi: 10.1109/ICITISEE57756.2022.10057700.
- [13] M. Almas Prakasa, I. Robandi, R. Nishimura, and M. Ruswandi Djalal, "A Hybrid Controlling Parameters of Power System Stabilizer and Virtual Inertia Using Harris Hawk Optimizer in Interconnected Renewable Power Systems," *IEEE Access*, vol. 12, no. May, pp. 76219–76243, 2024, doi: 10.1109/ACCESS.2024.3405994.
- [14] M. A. Prakasa, I. Robandi, A. Borghetti, M. R. Djalal, and W. Himawari, "Coordinated Design of Power System Stabilizer and Virtual Inertia Control Using Modified Harris Hawk Optimization for Improving Power System Stability," *IEEE Access*, vol. 13, no. December 2024, pp. 2581–2603, 2024, doi: 10.1109/ACCESS.2024.3522291.
- [15] D. Murugesan, K. Jagatheesan, P. Shah, and R. Sekhar, "Optimization of Load Frequency Control Gain Parameters for Stochastic Microgrid Power System," *J. Robot. Control*, vol. 4, no. 5, pp. 726–742, 2023, doi: 10.18196/jrc.v4i5.19772.
- [16] J. Boboulov and B. Narzullayev, "Development of a model for diagnosing rotor conditions in the parallel connection of synchronous generators with the network," *E3S Web Conf.*, vol. 525, 2024, doi: 10.1051/e3sconf/202452506001.
- [17] Z. M. Gao, J. Zhao, Y. R. Hu, and H. F. Chen, "The improved harris hawk optimization algorithm with the tent map," 2019 *IEEE 3rd Int. Conf. Electron. Inf. Technol. Comput. Eng. EITCE 2019*, pp. 336–339, 2019, doi: 10.1109/EITCE47263.2019.9095091.
- [18] A. Fathollahi and B. Andresen, "Adaptive Fixed-Time Control Strategy of Generator Excitation and Thyristor-Controlled Series Capacitor in Multi-Machine Energy Systems," *IEEE Access*, vol. 12, no. July, pp. 100316–100327, 2024, doi: 10.1109/ACCESS.2024.3430199.
- [19] C. B. Pop *et al.*, "Review of bio-inspired optimization applications in renewable-powered smart grids: Emerging population-based metaheuristics," *Energy Reports*, vol. 8, pp. 11769–11798, 2022, doi: 10.1016/j.egy.2022.09.025.
- [20] N. Du Nguyen-Hoang *et al.*, "Operation Method of Energy Storage System Replacing Governor for Frequency Regulation of Synchronous Generator without Reserve," *Energies*, vol. 15, no. 3, 2022, doi: 10.3390/en15030798.
- [21] R. Khezri, A. Oshnoei, A. Yazdani, and A. Mahmoudi, "Intelligent coordinators for automatic voltage regulator and power system stabiliser in a multi-machine power system," *IET Gener. Transm. Distrib.*, vol. 14, no. 23, pp. 5480–5490, 2020, doi: 10.1049/iet-gtd.2020.0504.
- [22] M. R. Djalal and I. Robandi, "Dual Input Power System Stabilizer in Selselrabar System Based on Mayfly Optimization Algorithm," *Proc. - ISMODE 2022 2nd Int. Semin. Mach. Learn. Optim. Data Sci.*, pp. 76–81, 2022, doi: 10.1109/ISMODE56940.2022.10181005.