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Design Power System Stabilizer Based on a Novel Improved Red-Tailed Hawk Algorithm

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ABSTRACT

This research proposes the design of a Power System Stabilizer (PSS) using an improved metaheuristic algorithm, the Improved Red-Tailed Hawk Algorithm (IRTH). The main problem in power systems is low-frequency oscillations that arise due to small or large disturbances. These oscillations can disrupt generator synchronization and potentially cause system disturbances and power outages. To overcome this, the PSS is used as an additional device in the generator excitation system to improve dynamic stability and dampen oscillations. The main contribution of this research is the development of the IRTH algorithm, which is an improvement of the Red-Tailed Hawk Algorithm (RTH). This improvement aims to improve global exploration capabilities, accelerate convergence, and reduce the possibility of being trapped in a local optimum. The IRTH algorithm is used to optimize PSS parameters in a single-machine system with the Heffron-Phillips model, and is validated through small-signal and large-signal disturbance simulations. Tests on 23 benchmark functions show that IRTH has excellent performance on unimodal (F1–F7) and multimodal (F8–F13) functions, although its performance is slightly degraded on complex multimodal functions with fixed dimensions (F14–F23). In PSS applications, IRTH-PSS shows the best performance with a settling time of 293 seconds, without overshoot on the rotor angle, and more effective oscillation damping capability compared to RTH-PSS and MPA-PSS, with a settling time reduction of about 15% compared to standard RTH.

1. Introduction

Power system stability is a fundamental requirement for ensuring the reliability and secure operation of modern electric power systems [1]–[4]. One of the major challenges in power system dynamics is the occurrence of low-frequency electromechanical oscillations, which may arise due to small disturbances (such as load variations) or large disturbances (such as faults or sudden generator outages) [5]–[9]. If these oscillations are not adequately damped, they can lead to the loss of synchronism among generators and potentially trigger large-scale blackouts [10]–[13]. To mitigate this problem, the Power System Stabilizer (PSS) has been widely implemented as an auxiliary control device within the generator excitation system [14]–[18]. The primary function of the PSS is to introduce supplementary damping torque to suppress low-frequency oscillations and thereby enhance both small-signal and transient stability of the power system [19]–[21].

Metaheuristic optimization methods have emerged as powerful techniques for solving complex engineering problems characterized by nonlinear, multimodal, and high-dimensional search spaces [22]–[25]. Unlike conventional deterministic optimization methods, metaheuristic algorithms are typically derivative-free and stochastic in nature, enabling them to explore the search space more effectively [26]–[31]. These algorithms employ a balance between exploration, which allows the algorithm to investigate diverse regions of the solution space, and exploitation, which focuses on refining promising candidate solutions [32]–[36]. Many metaheuristic algorithms are inspired by natural phenomena, including evolutionary processes, swarm intelligence, and animal foraging behaviors [37]–[41]. In power system applications, metaheuristic techniques have been extensively used to automatically determine optimal PSS parameters in order to improve damping performance against low-frequency oscillations caused by system disturbances [42]–[46]. Their flexibility and adaptability make them particularly suitable for addressing the nonlinear and multivariable characteristics of modern power system optimization problems [47]–[51].

The design of an optimal PSS requires accurate tuning of controller parameters, which are inherently nonlinear and strongly coupled with system dynamics. Over the past decades, numerous metaheuristic-based optimization techniques such as Genetic Algorithms (GA) [52], [53], Particle Swarm Optimization (PSO) [53], [54], and other nature-inspired algorithms have been applied to determine optimal PSS parameters. Despite their success, several challenges remain, including slow convergence rates, insufficient global exploration capability, and a tendency to become trapped in local optima when dealing with complex optimization landscapes [55]–[58].

The Red-Tailed Hawk Algorithm (RTH), a recently developed metaheuristic optimization technique inspired by the hunting strategies of red-tailed hawks, has demonstrated promising performance in solving various complex optimization problems [59]. The hunting dynamics of red-tailed hawks naturally model a balance between exploration and exploitation, making the algorithm suitable for addressing multimodal and nonlinear optimization problems such as PSS parameter tuning. Nevertheless, the standard RTH algorithm still exhibits certain limitations, particularly in terms of global search capability and population diversity. To overcome these limitations, this study proposes an enhanced version of the algorithm. In this research, an Improved Red-Tailed Hawk Algorithm (IRTH) is developed and applied to optimize the parameters of a Power System Stabilizer. The proposed approach aims to improve the damping performance of power system oscillations while maintaining robustness under different operating conditions.

The main contributions of this study are summarized as follows:

1. Development of the Improved Red-Tailed Hawk Algorithm (IRTH).

   This study proposes an enhanced version of the original RTH algorithm by incorporating improvement mechanisms that strengthen global exploration capability, accelerate convergence speed, and reduce the likelihood of premature convergence to local optima.

2. Application of IRTH for optimal PSS parameter tuning

   The proposed IRTH algorithm is employed to determine the optimal parameters of a Power System Stabilizer in a single-machine power system model. This method enables systematic and adaptive parameter tuning without relying on conventional trial-and-error procedures or complex analytical formulations.

3. Comprehensive validation and performance evaluation.

   The effectiveness of the proposed IRTH-based PSS design is evaluated using a single-machine system subjected to various disturbance scenarios, including both small-signal and large disturbances. A comparative analysis with several state-of-the-art metaheuristic algorithms is conducted, along with robustness testing under different operating conditions, demonstrating the reliability and general applicability of the proposed approach.

The article consists of the method, mathematical formulation, and explanation of the proposed method approach in Section 2. Section 3 is a simulation and discussion. The final section contains the research conclusions.

2. Method

2.1. Red-Tailed Hawk (RTH) Algorithm

The Red-Tailed Hawk (RTH) algorithm is inspired by the hunting behavior of red-tailed hawks in nature. The algorithm models the sequential hunting strategies observed during the predation process. In general, the hunting mechanism consists of three main phases: high soaring, low soaring, and bending–diving attack. These phases represent different exploration and exploitation behaviors during the search process. The RTH algorithm offers several advantages, including a small number of control parameters, simple implementation, and low computational complexity. By mathematically modeling the natural hunting behavior of red-tailed hawks, the RTH algorithm provides an effective optimization framework for solving complex optimization problems. The mathematical formulation of the RTH algorithm based on these hunting behaviors is described as follows.

2.1.1. Soaring High

The Red-Tailed Hawk will fly high into the sky looking for the best location in terms of food availability. Equation (1) represents the mathematical model of this stage:

$$X(t) = X_{best} + (X_{mean} - X(t-1).levy(dim).TF(t) \tag{1}$$

$$Levy(dim) = 0.01 \times \frac{\mu.\sigma}{|v|^{1/\beta}} \tag{2}$$

$$\sigma \ = \left[\frac{\Gamma(1+\beta)\sin(\frac{\alpha\pi}{2})}{\Gamma\left(\frac{(1+\beta)}{2}\right).\beta\, 2^{\frac{(1-\beta)}{2}}} \right] \tag{3}$$

$$TF(t) = 1 + \sin\,(2.5 + \left(\frac{t}{T_{max}}\right)) \tag{4}$$

where $X(t)$ represents the position of the red-tailed eagle at iteration t; X_{best} is the best position obtained in (3); $TF(t)$ denotes the transition factor function that can be calculated based on (4); dim denotes the problem dimension; β is a constant (1.5); μ and v are random numbers [0 to 1]; and T_{max} represents the maximum number of iterations.

2.1.2. Soaring Low

The eagle circles its prey by flying much lower to the ground in a spiral line and the model can be expressed as follows:

$$X(t) = X_{best} + (x(t) + y(t)).Stepsize(t) \tag{5}$$

$$Stepsize(t) = x(t) - X_{mean} \tag{6}$$

where x and y represent directional coordinates which can be calculated as follows:

$$\begin{cases} x(t) = R(t)\,.\sin(\theta(t)) \\ y(t) = R(t)\,.\cos(\theta(t)) \end{cases} \begin{cases} R(t) = R_0\,.\left(r - \frac{t}{T_{max}}\right).rand \\ R(t) = A.\left(r - \frac{t}{T_{max}}\right).rand \end{cases} \begin{cases} x(t) = x(t)/\max|x(t)| \\ y(t) = y(t)/\max|y(t)| \end{cases} \quad \begin{matrix} (7) \\ (8) \end{matrix}$$

where R_0 represents the initial value of the radius [0.5–3]; A represents the angel gain [5–15]; rand is the random gain [0–1]; and r is the control gain [1, 2]. This parameter helps the eagle circle its prey with a spiral movement.

2.1.3. Bending and Swooping

At this stage, the eagle suddenly bends down and attacks its prey from the best position obtained in the low flight stage. This stage can be modeled as follows:

$$X(t) = \alpha(t).X_{best} + x(t).Stepsize1(t) + y(t).Stepsize2(t) \quad (9)$$

$$Stepsize1(t) = X(t) - TF(t).X_{mean} \quad (10)$$

$$Stepsize2(t) = G(t).X(t) - TF(t).X_{best} \quad (11)$$

$$\alpha(t) = sin^2(2.5 - \frac{t}{T_{max}}) \quad (12)$$

$$G(t) = 2.(1 - \frac{t}{T_{max}}) \quad (13)$$

The parameter α is the acceleration of the hawk that depends on time (t), and it increases in each generation to enhance the convergence rate. In contrast, the G represents the gravitational force acting on the hawk (downwards) as in hawk tries to approach prey based on its limit.

2.2. Power System Stabilizers

The primary function of a Power System Stabilizer (PSS) is to enhance the damping of electromechanical oscillations by providing a supplementary stabilizing signal to the generator excitation system [60], [61]. By modulating the generator field excitation in response to rotor speed deviations, the PSS generates an additional electrical torque component that counteracts rotor oscillations. This supplementary control signal improves the damping of low-frequency oscillations and contributes to the overall dynamic stability of the power system. The structure of the PSS used in this study is illustrated in Fig. 1.

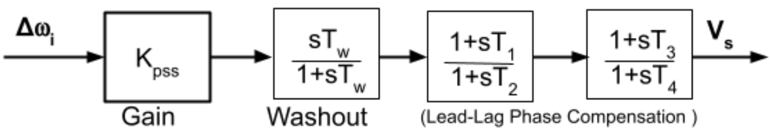

Fig. 1. Illustration of PSS lead-lag type

2.3. Proposed Method

To enhance this method, here we suggest a modification to the RTH algorithm. The modification made to the method consists of introducing parameters for following the progressive increase in exploration by both the number of iterations $\left(1 + \frac{t}{T}\right)$ and the average value of points pertaining to new current solution based on t time iteration $(X(t))$ in (1), (5), and (9). So (1), (5), and (9) becomes (14), (15), and (16). Through introducing dynamic iteration parameters and the effect of the average of group solutions, the algorithm is more flexible and efficient in solving complicated optimization problems like PSS tuning. The flowchart of IRTH can be seen in Fig. 2.

$$X(t) = (X_{best} * \left(1 + \frac{t}{T}\right)) + (X_{mean} - X(t-1).levy(dim).TF(t) \quad (14)$$

$$X(t) = (X_{best} * \left(1 + \frac{t}{T}\right)) + (x(t) + y(t)).Stepsize(t) \quad (15)$$

$$X(t) = \alpha(t).(X_{best} * \left(1 + \frac{t}{T}\right)) + x(t).Stepsize1(t) + y(t).Stepsize2(t) \quad (16)$$

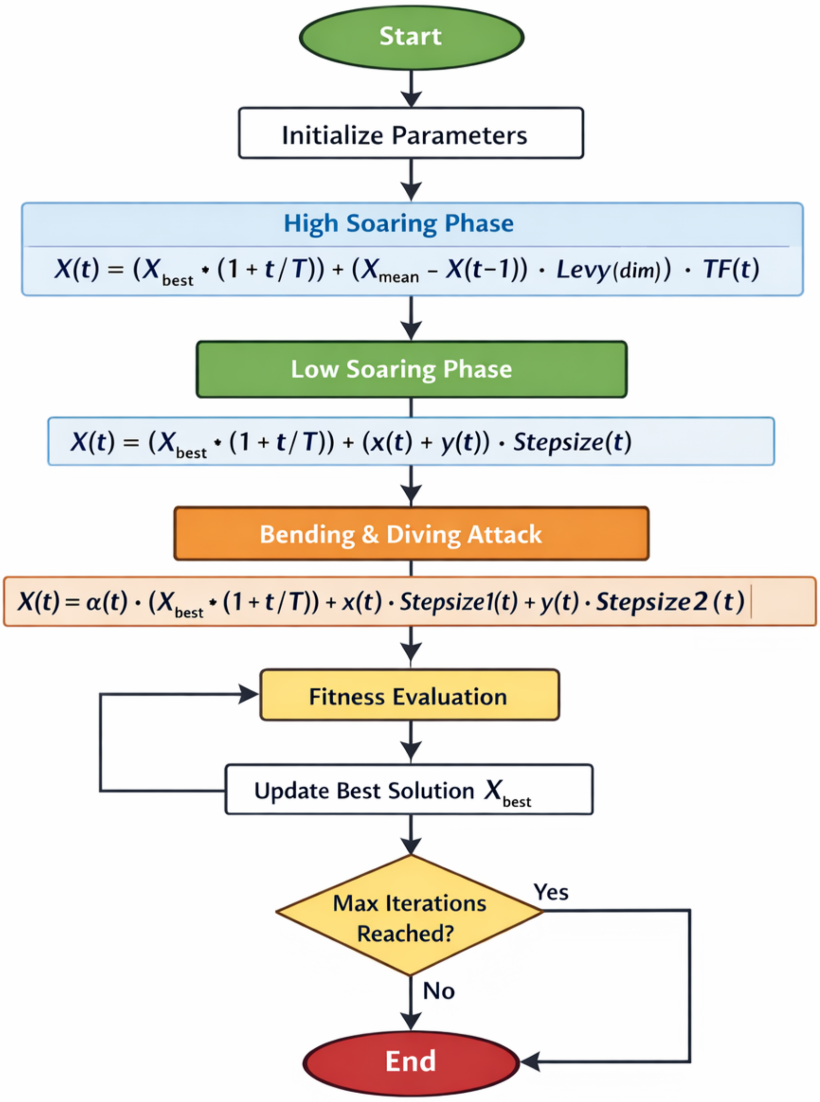

Fig. 2. Illustration of IRTH

3. Results and Discussion

3.1. Convergence Curve

The simulation experiments were conducted using MATLAB/Simulink on a computer equipped with an Intel Core i5-5200 CPU (2.19 GHz) and 8 GB RAM running a 64-bit operating system. To ensure a fair comparison among the optimization algorithms, all methods (IRTH, RTH, and MPA) were evaluated under identical experimental conditions. Each algorithm was executed using the same benchmark functions (F1–F23), identical problem dimensions, search space boundaries, and maximum number of iterations. In addition, the population size and stopping criteria were kept consistent across all algorithms to avoid bias in the performance evaluation. The benchmark function can be divided into the following three classes: unimodal (F1-F7), multimodal (F8-F13) and multimodal with fixed dimensions (F14-F23). All three groups have their characteristics. This unimodal function is a prime candidate for comparing the exploitativity of algorithms as it has one global minimum and no local minima. As the multi-modal function has excessive local optimum points and it is useful to evaluate the exploration and discover the algorithm's local optimal point. The composite function consists of biased, rotated and shifted multi-modal test functions.

Table 1 and Table 2 compares the performance of three optimization algorithms, namely IRTH, MPA (Marine Predators Algorithm), and RTH on 23 benchmark functions (F1–F23) based on the best, average, worst, standard deviation (std), and rank metrics. Smaller values generally indicate better performance, except on maximized functions (F8, F16–F23), where more negative values are more optimal. IRTH and RTH are equally competitive with a total rank of 32 (average 1.391), while MPA is at the bottom (total rank 50, average 2.174). IRTH significantly outperforms on F1–F4, F8, and F10–F13 with near-optimal solutions and high consistency (very small std). However, on complex functions such as F5–F7 and especially F15, RTH outperforms IRTH and even IRTH is in last place on F15. MPA is less competitive in general, although stable on F16–F18. No single algorithm is dominant across all functions; IRTH excels in accuracy and reliability, while RTH excels in certain functions. Algorithm selection should be tailored to the characteristics of the problem, and IRTH has proven highly competitive compared to comparable approaches.

Table 1. Performance comparison of IRTH, RTH, and MPA on 23 benchmark functions.

Function		IRTH	MPA	RTH
F1	Best	1.56E-48	1.88E+01	3.1E-48
	Mean	2.22E-40	5.11E+01	3.6E-39
	Worst	3.81E-39	1.09E+02	9.05E38
	Std	8.81E-40	23.4335	1.4E-38
	Rank	1	3	2
F2	Best	4.94E-26	1.1E+00	2.95E-23
	Mean	2.33E-21	2.7E+00	1.54E-20
	Worst	9.87E-20	4.0E+00	2.21E-19
	Std	1.40E-20	0.58864	3.9E-20
	Rank	1	3	2
F3	Best	1.97E-49	5.02E+02	4.53E-46
	Mean	4.57E-41	2.44E+03	4.09E-38
	Worst	1.06E-39	5.23E+03	1.04E-36
	Std	1.78E-40	1090.538	1.94E-37
	Rank	1	3	2
F4	Best	1.74E-26	4.12E+00	1.00E-23
	Mean	4.76E-22	6.17E+00	5.79E-21
	Worst	5.76E-21	9.10E+00	9.07E-20
	Std	1.11E-21	1.2448	1.63E-20
	Rank	1	3	2
F5	Best	28.5108	213.0381	25.7875
	Mean	28.7402	1004.248	26.7496
	Worst	28.828	3721.421	28.7184
	Std	0.067828	606.5921	0.55268
	Rank	2	3	1
F6	Best	1.1368	19.135	0.00558
	Mean	1.9759	58.8372	0.057434
	Worst	3.1386	151.6262	0.26121
	Std	0.52509	26.918	0.069966
	Rank	2	3	1
F7	Best	3.04E-05	0.007552	2.85E-05
	Mean	0.000685	0.029423	0.000804
	Worst	0.002138	0.08243	0.002692
	Std	0.00048	0.01638	0.000566
	Rank	2	3	1

Function		IRTH	MPA	RTH
F8	Best	-9928.38	-7763.08	-9716.83
	Mean	-6574.09	-5945.01	-8143
	Worst	-3402.26	-4687.25	-5758.33
	Std	1578.303	604.5583	786.3736
	Rank	1	3	2
F9	Best	0	24.4887	0
	Mean	0.000279	83.6776	0
	Worst	0.003818	142.6068	0
	Std	0.000615	28.0435	0
	Rank	1	2	1
F10	Best	8.88E-16	1.89E+00	8.88E-16
	Mean	5.60E-14	3.09E+00	8.88E-16
	Worst	1.21E-12	4.21E+00	8.88E-16
	Std	1.80E-13	0.50251	0
	Rank	1	2	1
F11	Best	0	1.1376	0
	Mean	1.25E-09	1.4727	0
	Worst	6.23E-08	1.8639	0
	Std	8.81E-09	0.17624	0
	Rank	1	2	1
F12	Best	1.62E-07	0.39475	1.44E-04
	Mean	3.48E-06	1.3311	0.0036975
	Worst	1.57E-05	4.2442	0.10414
	Std	4.05E-06	0.67111	0.014595
	Rank	1	3	2
F13	Best	7.02E-07	2.7768	0.046852
	Mean	5.51E-05	5.7664	1.6701
	Worst	0.000250	13.0469	2.9662
	Std	5.79E-05	2.1908	1.0459
	Rank	1	3	2
F14	Best	0.998	0.998	0.998
	Mean	1.7052	1.4345	3.3597
	Worst	6.7194	4.9505	10.7632
	Std	1.4906	0.82882	2.95
	Rank	1	2	1

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Table 2. Performance comparison of IRTH, RTH, and MPA on 23 benchmark functions (continue).

Function		IRTH	MPA	RTH
F15	Best	0.000597	0.000344	0.000307
	Mean	0.007036	0.000717	0.004415
	Worst	0.028717	0.001728	0.020363
	Std	0.006106	0.000272	0.008060
	Rank	3	2	1
F16	Best	-1.0316	-1.0316	-1.0316
	Mean	-1.0238	-1.0316	-1.0316
	Worst	-0.99185	-1.0316	-1.0316
	Std	0.008267	1.52E-10	4.02E-16
	Rank	1	1	1
F17	Best	0.39872	0.39789	0.39789
	Mean	0.42307	0.39789	0.39789
	Worst	0.49636	0.39789	0.39793
	Std	0.024173	5.18E-09	5.79E-06
	Rank	2	1	1
F18	Best	3.0279	3	3
	Mean	3.7517	3	3
	Worst	7.7506	3.0011	3
	Std	0.81912	0.000161	2.68E-15
	Rank	2	1	1
F19	Best	-3.8603	-3.8628	-3.8628
	Mean	-3.6969	-3.8628	-3.8628
	Worst	-3.4417	-3.8625	-3.8628
	Std	0.11086	3.79E-05	2.81E-15
	Rank	2	1	1

Function		IRTH	MPA	RTH
F20	Best	-3.1664	-3.322	-3.322
	Mean	-2.7871	-3.2954	-3.2697
	Worst	-2.173	-3.195	-3.2031
	Std	0.25359	0.04614	0.059616
	Rank	2	1	1
F21	Best	-10.1532	-10.1532	-10.1532
	Mean	-10.1323	-8.9297	-5.7254
	Worst	-10.0318	-5.0552	-2.6305
	Std	0.025482	2.1994	2.0359
	Rank	1	1	1
F22	Best	-10.403	-10.4029	-10.4029
	Mean	-10.382	-9.2317	-6.2294
	Worst	-10.3126	-5.0044	-2.7659
	Std	0.022332	2.2278	2.5848
	Rank	1	2	2
F23	Best	-10.5365	-10.5364	-10.5364
	Mean	-10.5171	-9.6443	-6.0076
	Worst	-10.418	-3.8354	-1.8595
	Std	0.022671	2.0696	2.8868
	Rank	1	2	2
SUM Rank		32	50	32
MEAN Rank		1.391304	2.173913	1.391304

Table 3 compares the performance of the three algorithms IRTH, MPA, and RTH specifically on unimodal functions (F1–F7), which are commonly used to evaluate the convergence ability and accuracy of optimization algorithms. The results show that IRTH clearly excels in this category, with a total sum rank of 8 and a mean rank of 1.14, making it the best algorithm overall (Total Rank = 1). Meanwhile, RTH ranks second with a sum rank of 10 and a mean rank of 1.43, indicating still competitive performance although slightly below IRTH. On the other hand, MPA consistently ranks at the bottom, with the highest sum rank (18) and a mean rank of 2.57, indicating that it struggles to achieve optimal solutions on unimodal functions. Overall, these findings confirm that IRTH is most effective in addressing unimodal optimization problems, thanks to its high ability in fast convergence and solution accuracy.

Table 4 compares the performance of the three algorithms, IRTH, MPA, and RTH, on multimodal functions (F8–F13), designed to test the algorithms' ability to avoid local optimum traps and find global optimums among multiple solution peaks. The results show that IRTH again dominates with the lowest total sum rank of 6 and a perfect mean rank of 1.0, making it the best algorithm overall (Total Rank = 1). This indicates that IRTH consistently ranks first across all tested multimodal functions. RTH comes in second with a sum rank of 9 and a mean rank of 1.5, demonstrating good but not entirely consistent performance like IRTH. Meanwhile, MPA again lags far behind with a sum rank of 15 and a mean rank of 2.5, meaning it almost always ranks last on these functions. Overall, these findings confirm that IRTH not only excels on unimodal functions but is also highly effective in handling the complexity of multimodal functions, thanks to its ability to globally explore the solution space and accurately exploit optimal solutions.

Table 5 shows a comparison of the performance of the three algorithms, namely IRTH, MPA, and RTH on fixed-multimodal functions (F14–F23), which are generally complex benchmark functions with many local optima and challenging structures, often used in competitions such as CEC to test the robustness of optimization algorithms. Different from the previous results on general unimodal and multimodal functions, this time RTH emerged as the best algorithm with a total sum rank of 12 and the lowest average rank (mean rank), namely 1.2, thus occupying a Total Rank of 1.

MPA was in second place with a sum rank of 10 and a mean rank of 1.4, showing a significant improvement compared to its performance on previous unimodal and multimodal functions. Meanwhile, IRTH, which previously dominated in F1–F13, actually ranked last in this category with a sum rank of 14 and a mean rank of 1.6, giving it a Total Rank of 3. This indicates that although IRTH is very strong in simple to moderate problems, it struggles in handling high complexity fixed-multimodal functions, where RTH and MPA show better exploration capabilities and exploration-exploitation balance. Thus, the superiority of an algorithm depends heavily on the characteristics of the problem at hand, and in the context of these complex functions, RTH proves to be the most robust.

Table 3. Rank comparison of algorithms on unimodal benchmark functions (F1-F7)

Function	IRTH	MPA	RTH
Sum Rank	8	18	10
Mean Rank	1.14	2.57	1.43
Total Rank	1	3	2

Table 4. Rank comparison of algorithms on multimodal benchmark functions (F8-F13)

Function	IRTH	MPA	RTH
Sum Rank	6	15	9
Mean Rank	1	2.5	1.5
Total Rank	1	3	2

Table 5. Rank comparison on fixed-dimension multimodal functions (F14-F23)

Function	IRTH	MPA	RTH
Sum Rank	14	10	12
Mean Rank	1.6	1.4	1.2
Total Rank	3	2	1

The superior performance of IRTH on most benchmark functions can be attributed to the improved balance between exploration and exploitation introduced through the modified search equations. In the original Red-Tailed Hawk (RTH) algorithm, the search behavior primarily relies on hunting phases, including high soaring, low soaring, and diving. Although these mechanisms provide a reasonable search capability, the exploration performance may become limited when the population starts to converge prematurely. To address this limitation, the proposed IRTH incorporates adaptive components based on the iteration number and the average position of the population. These components dynamically guide the search process toward more promising regions of the solution space while maintaining sufficient population diversity. As a result, the search process becomes more adaptive and capable of adjusting its exploration–exploitation balance during the optimization process.

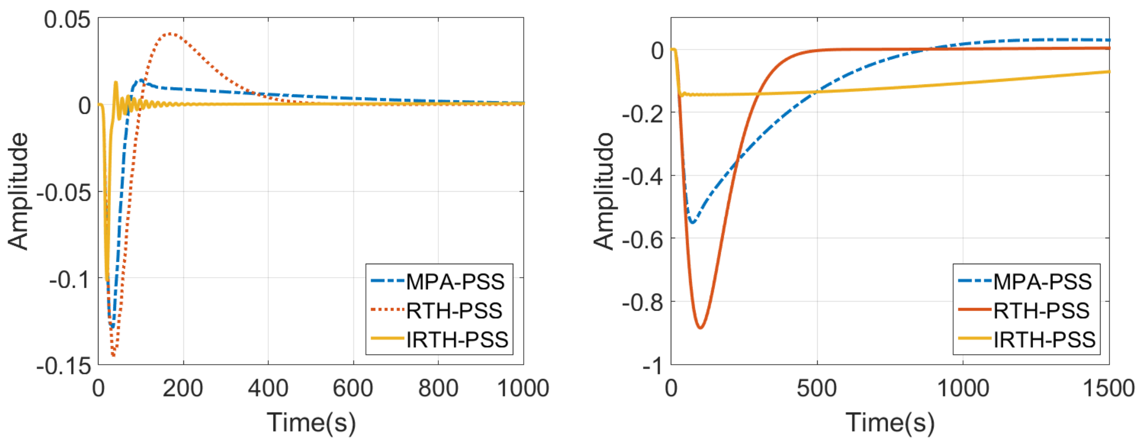
From an optimization perspective, this modification enhances global exploration during the early iterations, allowing the algorithm to explore a broader search space and reducing the probability of being trapped in local optima. As the iterations progress, the influence of the population mean gradually strengthens the exploitation phase, enabling more precise convergence toward the best candidate solution. This adaptive mechanism explains why IRTH performs particularly well on unimodal functions (F1–F7) and multimodal functions (F8–F13). For unimodal functions, the adaptive convergence mechanism accelerates the movement toward the single global optimum, resulting in faster convergence and higher solution accuracy. For multimodal functions, the increased diversity introduced by population-based guidance helps the algorithm escape local minima and maintain a more stable search trajectory. However, the performance degradation observed in fixed-dimension multimodal functions (F14–F23) indicates that the current IRTH strategy may still face challenges when the search landscape contains extremely complex structures characterized by dense local optima and strong variable interactions. In such cases, algorithms equipped with stronger diversification mechanisms may demonstrate better robustness. To further evaluate the optimization performance, the convergence curves are analyzed not only in terms of solution accuracy but also with respect to convergence speed. The convergence curve illustrates how rapidly each algorithm approaches the optimal solution throughout the iterations. The results indicate that IRTH exhibits a faster convergence trend compared with the comparison algorithms, demonstrating its ability to identify promising regions of the search space more efficiently.

3.2. Implementing to PSS

The Power System Stabilizer (PSS) design was implemented using the Heffron–Phillips single-machine infinite bus (SMIB) model as the test system. The IRTH algorithm was used to optimize the PSS control parameters with the objective of minimizing system oscillations and improving damping performance. To evaluate the robustness of the designed PSS, the system was subjected to disturbance scenarios representing large-signal operating conditions, including 100% load disturbance applied to the generator system. The performance of the proposed IRTH-PSS was compared with RTH-PSS and MPA-PSS using key transient performance indicators such as overshoot, undershoot, and settling time of rotor speed and rotor angle responses. This configuration ensures that the simulation framework provides a consistent and fair comparison among the optimization algorithms while accurately capturing the dynamic behavior of the power system under disturbance conditions. Performance verification is obtained by comparing with other algorithms, as shown in Fig. 3. Transient response tests are given in Table 6.

Table 6. Transient response

Algorithm	Rotor Angle Output			Speed Output		
	Overshoot	Undershoot	Settling Time (s)	Overshoot	Undershoot	Settling Time (s)
MPA-PSS	0.03	-0.55	1600	0.0139	-0.1286	1102
RTH-PSS	No Overshoot	-0.885	500	0.04	-0.146	586
IRTH-PSS	No Overshoot	-0.146	2200	0.0136	-0.1	293



(a) (b)

Fig. 3. Dynamic responses of PSS controllers under disturbance: (a) Speed response; (b) rotor angle response

Fig. 3(a) shows the speed response of three Power System Stabilizer (PSS) methods under an initial disturbance over a simulation period of 1000 seconds. The results indicate that IRTH-PSS provides the most stable response, characterized by minimal overshoot and fast convergence to a steady state. MPA-PSS demonstrates acceptable performance but exhibits moderate oscillations before stabilizing. In contrast, RTH-PSS experiences larger deviations and longer oscillation periods, indicating weaker damping capability. Overall, the results demonstrate that IRTH-PSS achieves superior dynamic stability compared with the other approaches.

Fig. 3(b) shows the rotor angle response of the three Power System Stabilizer (PSS) methods under disturbance conditions over a simulation period of 1500 seconds. The results indicate that IRTH-PSS produces the smoothest dynamic response with minimal oscillations and no significant overshoot, demonstrating effective damping capability. MPA-PSS shows a relatively faster recovery but exhibits a larger initial deviation before approaching a stable condition. In contrast, RTH-PSS experiences the largest initial undershoot and requires a longer time to stabilize. Overall, these results suggest that IRTH-PSS provides a better balance between stability and oscillation damping compared with the other methods.

In addition, robustness was evaluated by applying disturbance scenarios to the power system model and observing the dynamic responses of rotor speed and rotor angle. The comparison of overshoot, undershoot, and settling time among IRTH-PSS, RTH-PSS, and MPA-PSS demonstrates the consistency and stability of the proposed method in damping system oscillations. This repeated evaluation framework ensures that the reported results reflect the algorithm's true optimization capability rather than outcomes from isolated simulation runs.

4. Conclusion

This research successfully developed and implemented the Improved Red-Tailed Hawk Algorithm (IRTH) for optimal Power System Stabilizer (PSS) design in electric power systems. The proposed IRTH enhances the original Red-Tailed Hawk (RTH) algorithm by improving global exploration capability, convergence speed, and robustness against premature convergence. The benchmark evaluation demonstrates that IRTH achieves strong optimization performance on unimodal (F1–F7) and multimodal (F8–F13) functions, obtaining a total rank of 6 and a mean rank of 1.0, which indicates high accuracy and consistency in finding optimal solutions. However, the algorithm shows reduced performance on complex fixed-multimodal functions (F14–F23), particularly F15, where it ranks last compared with other algorithms. In contrast, the standard RTH algorithm shows better robustness on these highly complex landscapes with a mean rank of 1.2. This limitation suggests that although IRTH is effective for problems requiring strong global exploration and rapid convergence, its performance can degrade when facing highly irregular search spaces containing many local optima. In the PSS tuning application using the Heffron–Phillips power system model, the IRTH-based PSS demonstrates the best dynamic performance among the tested methods. The system speed response achieves a settling time of 293 seconds with minimal overshoot (0.0136), while the rotor angle response shows no overshoot, indicating effective oscillation damping and improved system stability. In comparison, RTH-PSS exhibits significant undershoot (–0.885) and requires approximately 500 seconds to stabilize, whereas MPA-PSS shows much slower dynamic responses with settling times ranging from 1102 to 1600 seconds. Overall, these results confirm that IRTH provides competitive and reliable optimization performance for PSS parameter tuning and demonstrates strong potential for practical engineering applications. From an implementation perspective, the algorithm is computationally feasible and can be integrated into power system controller design frameworks for damping oscillations in single-machine systems. Nevertheless, further research is needed to enhance its robustness for highly complex optimization landscapes and to validate its effectiveness in larger-scale power systems, such as multi-machine networks and renewable energy-integrated grids.

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