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A Multi-Strategy Improved Moth-Flame Algorithm and Its Application to Power System Stabilizer Tuning

Lyuyang Ye

Guangzhou College of Commerce, Guangzhou, Guangdong, 511363, China

ABSTRACT

To address the issues that the Moth-Flame Optimization (MFO) algorithm tends to fall into local optima and suffers from insufficient convergence accuracy, a multi-strategy improved Moth-Flame Optimization algorithm (MMFO) is proposed. First, the Sine-Tent-Cosine chaotic map is employed to initialize the population, enhancing population diversity. Second, the oscillation mechanism of the Sine Cosine Algorithm (SCA) is integrated to balance global exploration and local exploitation. Finally, the somersault foraging strategy is introduced to strengthen the algorithm's ability to escape local optima. The proposed MMFO is applied to optimize the parameters of two types of Power System Stabilizers (PSS), namely Lead-Lag and PID controllers. Simulations are conducted on a Single-Machine Infinite-Bus (SMIB) system under four error criteria: IAE, ISE, ITAE, and ITSE. Comparative analyses with MFO, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Flower Pollination Algorithm (FPA), and Jaya algorithm demonstrate that the PSS optimized by MMFO achieves the best comprehensive performance in suppressing low-frequency oscillations, reducing overshoot, and shortening settling time, thereby verifying its effectiveness and superiority.

KEYWORDS

Moth-flame optimization; Chaotic map; Sine cosine algorithm; Somersault foraging; Power system stabilizer

1 Introduction

Power System Stabilizers (PSS) are critical devices for enhancing the dynamic stability of power systems by providing additional damping to suppress low-frequency oscillations [1-2]. The performance of PSS highly depends on parameter tuning, and traditional methods such as pole placement have limitations when dealing with nonlinear problems . Swarm intelligence algorithms, owing to their strong global search capability, have been widely applied to PSS optimization, including Particle Swarm Optimization (PSO) [3] and Genetic Algorithms (GA) [4].

The Moth-Flame Optimization (MFO) algorithm, proposed by Mirjalili, is a novel meta-heuristic algorithm whose spiral search mechanism effectively balances exploration and exploitation [5]. However, the standard MFO suffers from randomly distributed initial populations and a tendency to fall into local optima in later stages, which affects its optimization accuracy. To address these limitations, this paper proposes a Multi-Strategy Improved Moth-Flame Optimization algorithm (MMFO). The proposed algorithm first employs the Sine-Tent-Cosine chaotic map[6] to optimize population initialization. Second, it incorporates the oscillation mechanism of the Sine Cosine Algorithm (SCA) [7] to balance global exploration and local exploitation. Third, it integrates the somersault foraging strategy[8] to enhance the ability to escape local optima. The MMFO is then applied to optimize the parameters of both Lead-Lag PSS and PID PSS. Simulations are conducted on a Single-Machine Infinite-Bus (SMIB) system under multiple criteria to validate its performance.

2 Brief Introduction to Moth-Flame OptimizationAlgorithm

The Moth-Flame Optimization (MFO) algorithm simulates the spiral flight behavior of moths around flames [5]. In this algorithm, the position of a moth represents a candidate solution, while the flame represents the current optimal solution. The position update is performed using a logarithmic spiral function:

$$S\left(M_i,F_j\right)=D_i\cdot e^{bt}\cdot\cos(2\pi t)+F_j \tag{1}$$

$$D_i=\left|F_j-M_i\right| \tag{2}$$

where D_i denotes the distance between the moth and the flame, b is a constant defining the shape of the logarithmic spiral, and $t\in[-1,1]$ is a random number controlling the convergence speed. The algorithm balances exploration and exploitation by adaptively reducing the number of flames during the iteration process:

$$flame\ \text{No.}=round\left(N-i*\frac{N-1}{L}\right) \tag{3}$$

Where N is the maximum number of flames, i is the current iteration number, and L is the maximum number of iterations.

The time complexity of MFO is O($tnd + tn^2$), and its space complexity is O(nd), wherenis the population size, d is the dimension of the search space, and t is the number of iterations [5]. However, the standard MFO algorithm has two main limitations: random initialization leads to uneven population distribution, and the single spiral strategy makes it prone to

* **Corresponding Author:** Lyuyang Ye, endless_data@163.com

falling into local optima in the later stages of optimization.

3 Multi-Strategy Improved Moth-Flame Optimization Algorithm (MMFO)

3.1 Chaotic Initialization

The Sine-Tent-Cosine composite chaotic map[6] is employed to generate the initial population [7]. Its mathematical description is as follows:

$$x(i+1)=\begin{cases}\cos(\pi(r\sin(\pi x(i))+2(1-r)x(i)-0.5)), \text{if } x(i)<0.5\\ \cos(\pi(r\sin(\pi x(i))+2(1-r)(1-x(i))-0.5)), \text{else}\end{cases}, r\in[0,1] \tag{4}$$

This strategy enhances the diversity of the initial population, laying a foundation for subsequent optimization.

3.2 Integration of Sine-Cosine Operator

The oscillation mechanism of the Sine Cosine Algorithm (SCA) is introduced into the position update [7], with equal probability of selecting either sine or cosine operation. The improved spiral function is defined as:

$$S\left(M_i,F_j\right)=\begin{cases}r_1\cdot\sin(r_2)\cdot\left|r_3\cdot F_{\text{best}}-F_j\right|+D_i\cdot e^{bt}\cdot\cos(2\pi t), \text{if } r<0.5\\ r_1\cdot\cos(r_2)\cdot\left|r_3\cdot F_{\text{best}}-F_j\right|+D_i\cdot e^{bt}\cdot\cos(2\pi t), \text{else}\end{cases} \tag{5}$$

where r_1 is a control parameter that adaptively decreases with iterations, defined as:

$$r_1=k\cdot\left(1-\frac{\text{Iteration}}{\text{Max iteration}}\right) \tag{6}$$

In Equation (5), r_2 and r_3 are random numbers, and F_{best} represents the best flame found so far. This mechanism allows some moths to expand their exploration range while others converge quickly, balancing global exploration and local exploitation.

3.3 Introduction of Somersault Foraging Strategy

Inspired by manta ray foraging [8], the somersault foraging strategy is introduced during the iteration stages where the number of moths exceeds the number of flames:

$$S\left(M_i,F_j\right)=\begin{cases}r_1\cdot\sin(r_2)\cdot\left|r_3\cdot F_{\text{best}}-F_j\right|+O\cdot(r_4\cdot F_{\text{best}}-r_5F_j)+D_i\cdot e^{bt}\cdot\cos(2\pi t), \text{if } r<0.5\\ r_1\cdot\cos(r_2)\cdot\left|r_3\cdot F_{\text{best}}-F_j\right|+O\cdot(r_4\cdot F_{\text{best}}-r_5F_j)+D_i\cdot e^{bt}\cdot\cos(2\pi t), \text{else}\end{cases} \tag{7}$$

Where $O=2$ is the somersault factor, and $r_4,r_5\in[0,1]$.

3.4 Algorithm Flow and Complexity Analysis

The flowchart of MMFO is shown in Figure 1. The improvements only add conditional checks and random number generation without introducing additional loops. Therefore, the complexity remains the same as MFO, i.e., $O(tnd+\text{tn}^2)$.

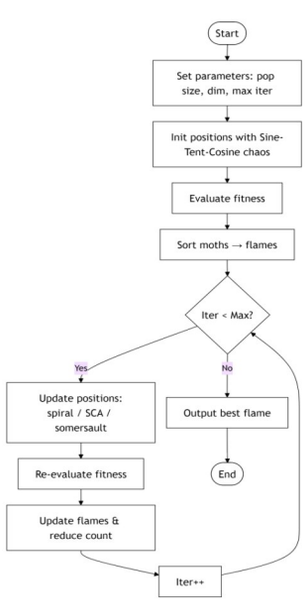

Figure 1 Flowchart of the MMFO algorithm.

4 Optimal Design of Power System Stabilizers Using MMFO

4.1 Power System Model

The single-machine infinite-bus (SMIB) system is adopted for stability analysis [9]. The system consists of a synchronous

generator connected to an infinite bus through a transmission line, equipped with an automatic voltage regulator (AVR). The system is modeled in Matlab/Simulink using the 1.1 generator model, which includes a main excitation winding and an equivalent damping winding on the q-axis. After linearization, the Heffron-Phillips constants (K_1 *to* K_6) are obtained, and the linearized state-space model is expressed as:

$$\Delta\dot{x} = A\Delta x + B\Delta u \tag{8}$$

$$y = C\Delta x \tag{9}$$

where *A*, *B*, and *C* are the system, input, and output matrices, respectively.

4.2 Structure of Power System Stabilizers

Two types of power system stabilizers (PSS) are considered.

4.2.1 Lead-Lag PSS

The structure of a Lead-Lag PSS consists of a gain block (K_{PSS}), a washout filter with time constant T_w=10.0 s, and a lead-lag phase compensator with time constants T_1 and T_2. The input signal is the speed deviation Δω. The transfer function is:

$$U(s) = K_{PSS}\left(\frac{1+sT_1}{1+sT_2}\right)\Delta\omega(s) \tag{10}$$

The search ranges for the parameters are:

$$\begin{gathered} 0.001 \leqslant K_{PSS} \leqslant 15^{[10]} \\ 0.001 \leqslant T_1 \leqslant 10^{[10]} \\ 0.001 \leqslant T_2 \leqslant 10^{[10]} \end{gathered} \tag{11}$$

4.2.2 PID PSS

The transfer function of a PID PSS is:

$$U(s) = \left[K_P + \frac{K_i}{s} + K_d s\right]\Delta\omega(s) \tag{12}$$

$$\begin{gathered} 0.001 \leqslant K_P \leqslant 15^{[10]} \\ 0.001 \leqslant K_i \leqslant 10^{[10]} \\ 0.001 \leqslant K_d \leqslant 10^{[10]} \end{gathered} \tag{13}$$

4.3 Objective Functions

Four error integral criteria are used as fitness functions to minimize the error signal, which is equivalent to reducing the overshoot and settling time of power system oscillations. The criteria are defined as follows:

$$IAE = \int_0^{ts} |e(t)|dt \tag{14}$$

$$ISE = \int_0^{ts} e(t)^2 dt \tag{15}$$

$$ITAE = \int_0^{ts} t \times |e(t)|dt \tag{16}$$

$$ITSE = \int_0^{ts} t \times e(t)^2 dt \tag{17}$$

where $e(t)$ is the deviation between the actual output and the desired output, and t_s is the total simulation time.

5 Simulation Results and Analysis

5.1 Simulation Setup

All simulations are carried out in MATLAB R2018a on a laptop with an Intel Core i5-11400H processor (4.5 GHz) and 64 GB RAM. The population size of each swarm intelligence algorithm is set to 10, and the maximum number of iterations is 20. A step disturbance of 0.01 p.u. is applied, and the rotor speed deviation is recorded.

5.2 Results for Lead-Lag PSS

The optimal parameters of the Lead-Lag PSS obtained by MMFO under different objective functions are listed in Table 1. Table 2 compares the performance values of MMFO with those of MFO, FPA, GWO, PSO, and Jaya [11].

Table 1 Optimized Lead-Lag PSS parameters using MMFO

Lead-Lag PSS	K_{PSS}	T_1	T_2
IAE	15	0.814844	0.001415
ISE	14.8947704	5.238267575	0.002020426
ITAE	8.577109624	0.642403866	0.642403866
ITSE	3.158418956	3.586654266	0.001

Table 2 Performance comparison for Lead-Lag PSS

Lead-Lag PSS	Performance Indicator			
	IAE	ISE	ITAE	ITSE
MFO	3.83E-05	2.08736E-09	1.84917E-05	8.17E-10
MMFO	4.92E-10	1.75426E-09	8.03909E-06	4.53E-10
FPA	5.63E-10	1.96962E-09	2.81755E-05	2.82E-08
GWO	5.07822E-05	1.7593E-09	8.87922E-06	7.75E-10
PSO	0.000429812	2.09831E-09	0.000163152	7.97E-10
Jaya[11]	3.47E-05	1.76E-09	8.24E-06	4.80E-10

As shown in Table 2, the MMFO algorithm achieves the smallest IAE value of 4.92E-10, which is nearly two orders of magnitude lower than that of the standard MFO (3.83E-05). This remarkable improvement demonstrates the effectiveness of the proposed multi-strategy approach in reducing the integral absolute error. Under the ISE criterion, MMFO also outperforms all other algorithms except for a negligible difference from GWO. For ITAE and ITSE, MMFO ranks either first or second among all six algorithms. Specifically, MMFO achieves an ITAE of 8.03909E-06, which is lower than MFO (1.84917E-05) and GWO (8.87922E-06), and an ITSE of 4.53E-10, the lowest among all methods. The consistently superior performance across four different error criteria indicates that MMFO is robust and not sensitive to the choice of objective function. Moreover, the improvements are particularly significant for the IAE and ITSE criteria, where MMFO outperforms the second-best method by a substantial margin. These results confirm that the three enhancement strategies—chaotic initialization, sine-cosine operator, and somersault foraging—collectively enable MMFO to achieve better convergence accuracy and faster search speed.

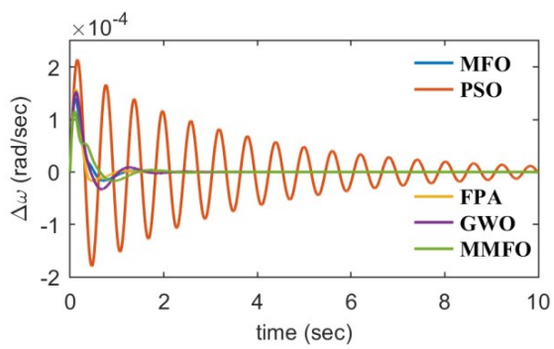

Figure 2 IAE criterion (Lead-Lag PSS)

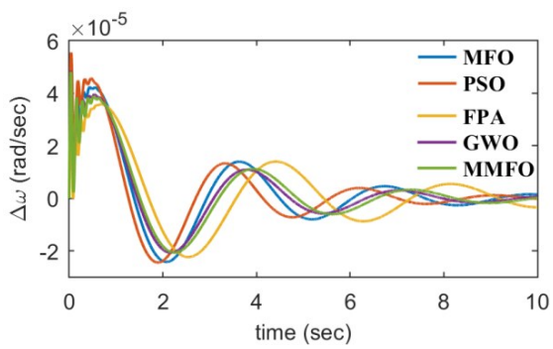

Figure 3 ISE criterion (Lead-Lag PSS)

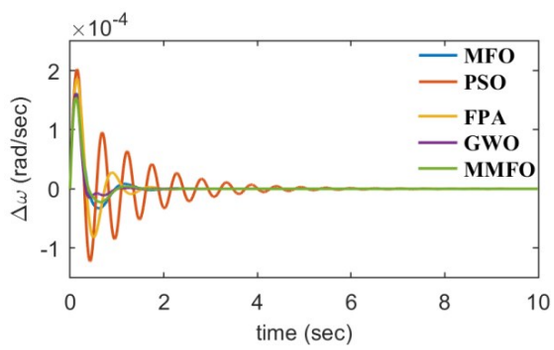

Figure 4 ITAE criterion (Lead-Lag PSS)

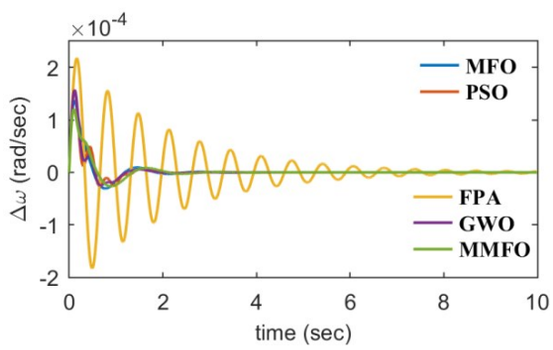

Figure 5 ITSE criterion (Lead-Lag PSS)

Figures 2–5 show the rotor speed deviation responses under the IAE, ISE, ITAE, and ITSE criteria, respectively. Under the IAE criterion (Figure 2), the system with MMFO-optimized Lead-Lag PSS reaches steady state fastest and exhibits the smallest overshoot. Under the ISE criterion (Figure 3), MMFO achieves the smallest overshoot and the shortest settling time. Under the ITAE criterion (Figure 4), MMFO gives the smallest overshoot, and its response speed is second only to GWO but with fewer oscillations. Under the ITSE criterion (Figure 5), MMFO again shows the smallest overshoot. These results demonstrate that MMFO provides the best comprehensive performance for Lead-Lag PSS optimization.

5.3 Results for PID PSS

Table 3 lists the optimal PID PSS parameters obtained by MMFO. Table 4 shows that MMFO achieves the best performance indices under the IAE, ITAE, and ITSE criteria, and is slightly inferior to FPA but better than other algorithms under the ISE criterion.

Table 3 Optimized PID PSS parameters using MMFO

PID PSS	K_P	K_I	K_D
IAE	15	0.828280145	5.881230246
ISE	15	15	15
ITAE	15	1.520523331	5.295717478
ITSE	15	15	8.674844052

Table 4 Performance comparison for PID PSS

PID PSS	Performance Indicator			
	IAE	ISE	ITAE	ITSE
MFO	3.54745E-05	2.23404E-09	8.59496E-06	4.46605E-10
MMFO	3.48199E-05	2.22759E-09	8.54988E-06	4.45163E-10
FPA	3.52453E-05	2.25124E-09	8.91552E-06	4.4943E-10
GWO	3.52796E-05	2.23404E-09	8.56646E-06	4.49576E-10
PSO	3.52652E-05	2.23404E-09	8.57796E-06	4.46915E-10
Jaya[11]	3.50E-05	2.23E-09	8.55E-06	4.46E-10

For the PID PSS case, the improvements brought by MMFO are less dramatic than those for the Lead-Lag PSS, but still evident and consistent. Under the IAE criterion, MMFO achieves a value of 3.48199E-05, which is better than MFO (3.54745E-05) and all other algorithms except Jaya (which gives nearly the same value of 3.50E-05). Under the ISE criterion, MMFO obtains 2.22759E-09, slightly better than MFO (2.23404E-09) and second only to FPA (2.25124E-09). However, the difference is marginal, and all algorithms perform similarly in terms of ISE. Under the ITAE criterion, MMFO achieves the best value of 8.54988E-06, outperforming MFO, FPA, GWO, and PSO. Under the ITSE criterion, MMFO again gives the smallest value of 4.45163E-10, which is better than MFO (4.46605E-10) and other algorithms. These results indicate that MMFO is at least as effective as other state-of-the-art algorithms for PID PSS optimization, and in most criteria it performs best. The fact that MMFO works well for both types of PSS suggests that it is a general-purpose optimizer suitable for different controller structures.

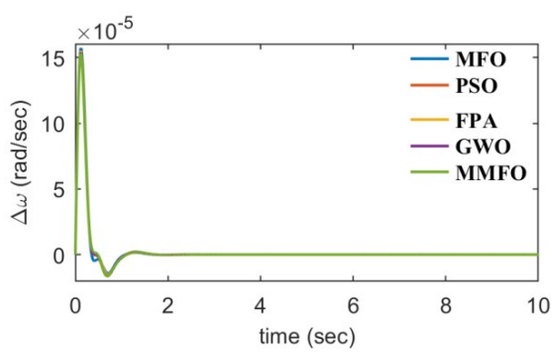

Figure 6 IAE criterion (PID PSS)

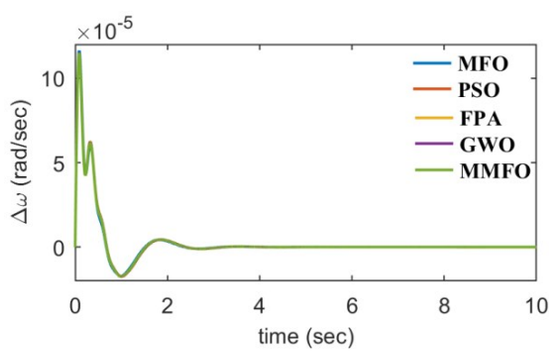

Figure 7 ISE criterion (PID PSS)

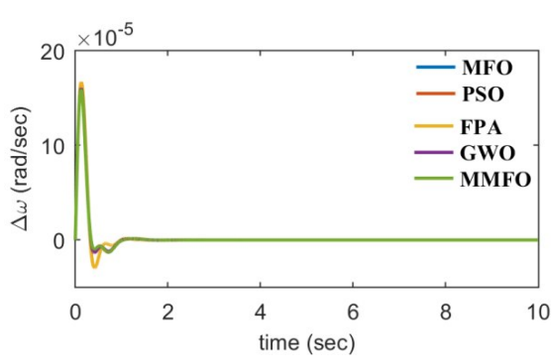

Figure 8 ITAE criterion (PID PSS)

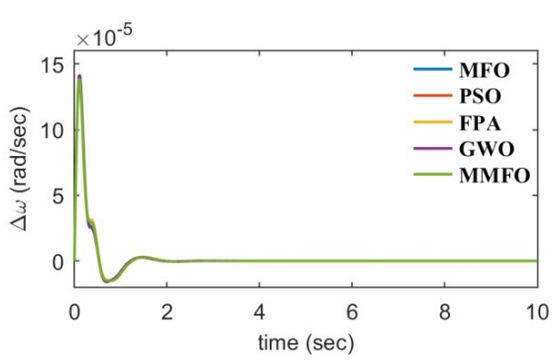

Figure 9 ITSE criterion (PID PSS)

Figures 6~9 present the rotor speed deviation responses for PID PSS under the four criteria. Under IAE (Figure 6), MMFO gives a relatively small overshoot. Under ISE (Figure 7), all algorithms perform similarly, with MMFO being slightly better. Under ITAE (Figure 8), MMFO achieves the smallest overshoot. Under ITSE (Figure 9), MMFO again shows the smallest overshoot. These results verify that MMFO is at least as effective as other algorithms for PID PSS optimization, demonstrating its feasibility and good performance.

6 Conclusions

This paper proposes a multi-strategy improved moth-flame optimization algorithm (MMFO) to address the limitations of the standard MFO algorithm, namely uneven initial population distribution and susceptibility to local optima. The MMFO incorporates three improvement strategies: Sine-Tent-Cosine chaotic map for population initialization, the sine-cosine algorithm for balancing global exploration and local exploitation, and the somersault foraging strategy for enhancing the ability to escape local optima.

The algorithm is applied to optimize the parameters of two types of power system stabilizers (Lead-Lag PSS and PID PSS) on a single-machine infinite-bus system. Simulation results under four error integral criteria (IAE, ISE, ITAE, ITSE) demonstrate that the MMFO-optimized PSS outperforms the MFO, PSO, GWO, FPA, and Jaya algorithms in terms of suppressing low-frequency oscillations, reducing overshoot, and shortening settling time. The proposed MMFO provides an effective and robust solution for the optimal design of power system stabilizers.

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