Pelican Optimization Algorithm Based on Hybrid Strategy for Optimizing Power Flow in Power Systems

Xun Liu, Jie-Sheng Wang*, Song-Bo Zhang, Yuan-Zheng Gao, Jia-Hui Zhao

Abstract—**To comply with the criteria of the optimum power flow issue in power systems, this research offers a multi-strategy enhanced POA (MPOA). In response to the problems of delayed convergence and easy trapping in local optima in the original pelican optimization algorithm during the solution process, this paper introduces four improvement strategies: using the Logistic chaotic sequence to get started the sample to increase the variety of the original population. By adopting an inertia weight component to strike an equilibrium between global exploration along with local exploitation, as well as using a periodic mutation method to improve the algorithm's capacity to avoid local optima. And designing a fitness-driven evolutionary direction decision making mechanism to accelerate convergence and improve the quality of the solution. The performance of the improved algorithm was verified on the CEC2022 test function set. The findings showed that MPOA beat the original method in terms of solution correctness and convergence efficiency. Furthermore, this paper applies MPOA to the IEEE 30-bus system, with fuel cost, system loss, and bus voltage deviation as the optimization objectives for single-objective solution, and compares it with other algorithms. The simulation results show that MPOA has good optimization performance and engineering application value in solving the OPF problem**

Index Terms—**Optimal power flow, POA, Periodic mutation, Inertia factor, Evolution mechanism**

I. Introduction

Optimal Power Flow (OPF) is one of the most significant issues for power system planners and operators. The fundamental goal of OPF is to discover the optimal configuration for a particular power system network [1], maximize specified objective functions, and meet power flow equations, system security, and equipment operating restrictions [2].

The traditional solutions for optimal power flow include nonlinear programming and linear programming. Nonlinear programming can be further divided into simplified gradient method [3], Newton method [4-5], quadratic programming [6] and interior point method [7]. However, traditional optimization methods rely on derivative operations, making it difficult to guarantee the acquisition of the global optimal solution. They also require the assumption that the objective function is convex and differentiable to simplify the solution process. Nevertheless, the OPF is inherently non-convex, non-smooth, and non-differentiable, with highly nonlinear characteristics and the possibility of multiple local optimal solutions, which makes it difficult for traditional methods to solve effectively. Therefore, there is an urgent need for optimization methods that can overcome these limitations. In recent years, artificial intelligence optimization algorithms have developed rapidly and have been widely applied in various fields. Compared with traditional methods, these algorithms have a simple concept, do not require the construction of strict mathematical models, can effectively solve non-convex optimization problems, avoid local optimal traps, and have played a vital part in the research field of electrical system optimization, especially in the solution of optimal power flow, demonstrating significant advantages and promising development prospects.

Layth et al. employed an augmented differential evolution approach to handle the optimal flow of electricity issue in an IEEE 30 bus network. The goal function sought to reduce producing unit fuel costs, pollution, and power losses in transmission lines, among other factors [8]. Khunkitti et al. introduced a multi-objective power flow issue based on the SMA algorithm, which included cost, emissions, and transmission line losses as objective functions in the power system, and utilized the IEEE 30, 57, and 118-bus systems to validate the performance [9]. Alanazi proposed a new adaptive teaching-learning-based optimization algorithm (AGTLBO), and used test systems conforming to the IEEE standards of 30-bus, 57-bus and 118-bus to verify the performance of the proposed algorithm. A total of 12 different scenarios were introduced to evaluate the algorithm, collectively verifying that the proposed AGTLBO is more efficient [10]. Mohamed provided an improved particle swarm optimization method to solve the OPF problem, minimizing the fuel cost of power generation for public utility and industrial companies while satisfying a set of system constraints, and compared

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the obtained results with those from the PSO algorithm and other algorithms [11]. Nadimi et al. suggested an effective WOA (EWOA-OPF) for tackling the OPF problem, and employed standard IEEE 6,14,30,118-bus platforms to assess the EWOA-OPF for overcoming OPF difficulties in systems of various sizes [12].

Pelican Optimization Algorithm [13] optimizes problems by simulating the behavior and strategies of pelicans. Scholars have widely used it to a variety of sectors. Alamir et al. applied the POA to optimize the energy management system of microgrids, aiming to enhance the economic benefits of microgrid operators and reduce overall operational costs [14]. Tuerxun et al. employed an upgraded POA to optimize parameters including the amount of feature nodes, enhanced nodes, and mapping layers of features in a generalized learning system, and then applied it to diagnose the defect kinds of wind turbine units [15]. Khaleel suggested two optimization methods, the POA and PSO, to offer the ideal route for mobile wheeled robots to avoid collisions in the presence of impediments [16].

This research provides a multi-strategy enhanced POA (MPOA) and applies it to the solution of the optimal power flow problem. The second portion offers mathematical modeling of the system and the optimization objective function. The third part elaborates on the basic framework of POA and the improvement strategies, including: using the Logistic chaotic sequence to initialize the population, introducing the inertia weight factor, adopting the periodic mutation strategy, and introducing the fitness-driven evolutionary direction decision mechanism to enhance the convergence efficiency. The fourth part evaluates the performance of MPOA on the CEC2022 test functions and compares it with other optimization algorithms, verifying its advantages in solution accuracy and convergence speed. The fifth part applies MPOA to the IEEE 30-node system, optimizing and solving with fuel cost, system loss, and bus voltage deviation as single objectives respectively, further demonstrating its effectiveness. The sixth part summarizes the entire paper.

II. Mathematical Modeling of the System and Objective Function

A. System Mathematical Modeling

The optimal power flow problem in power systems is to determine the setting parameters of system control variables under the given network structure parameters and power system load, so as to satisfy the operating constraints of system equipment and improve the desired variables such as system fuel cost, active power loss, and bus voltage deviation. It is a core issue in energy safety, grid arranging, and reliability analysis, as well as a nonlinear constrained issue. It can be briefly expressed by the following mathematical model:

$$\text{Minmize} \quad f(x,y) \tag{1}$$

$$s.t. \quad g(x,y) \tag{2}$$

$$h(x,y) \le 0 \tag{3}$$

In Eq. (1)-(3), $f(x,y)$ represents the objective function of the OPF problem, $g(x,y)$ implements the equality restrictions, the inequality constraints are $h(x,y)$. x,y respectively represent the control variables and state variables. The $g(x,y)$ and $h(x,y)$ of this paper are detailed in Ref. [17].

This study's test environment is the IEEE 30-bus. Fig. 1 illustrates the particular structure.The detailed topology of this system can be found in Ref. [18], which consists of 6 generators, 4 transformers and 2 sets of reactive power compensation capacitors. The system uses 100 MVA as a base, with a rated active power demand of 283.4 MW and a reactive energy requirement of 126.2 MVAR. The generator's power bus has a voltage range of 0.95-1.10 p.u., whereas the load bus's voltage range is limited to 0.95-1.05 p.u. Among them, bus 1 is set as the slack bus.

B. Function 1: Fuel Cost

Generally speaking, the operating cost function relationship of each generator can be expressed as a quadratic function relationship:

$$F_{cost} = \sum_{i=1}^{NG} a_i + b_i P_{G_i} + c_i P_{G_i}^2 \tag{4}$$

where, a_i, b_i, c_i are the generator's expense coefficients for producing output power. In the formula, NG represents the number of generating units, and P_{Gi} represents the active power output of unit i. The cost coefficients of the entire power generation system can be found in Ref. [17].

C. Objective Function 2: Active Power Loss of the System

Due to the inherent resistance in the transmission lines, the active power generated by the generator is inevitably subject to losses.

$$F_{Ploss} = \sum_{i=1}^{Nl} \sum_{j \ne i}^{Nl} G_{ij}[V_i^2 + V_j^2 - 2V_i V_j cos(\delta_i - \delta_j)] \tag{5}$$

Let Nl represent the set of all branches, V is the absolute value of the node voltage, δ is the angle of the voltage, and G is the line conductance.

D. Objective Function 3: Bus Voltage Deviation

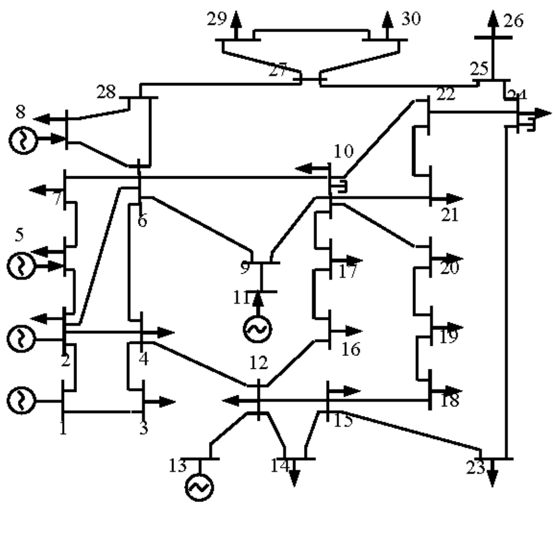


Fig. 1 IEEE 30-node structure diagram.

The change in the operation mode of the power supply and distribution system and the slow variation of the load will cause the voltage at each point in the power supply and distribution system to change accordingly. At this time, the difference between the actual voltage at each point and the nominal voltage of the system is called voltage deviation, which is expressed by the following formula:

$$F_V = \sum_{m=1}^{Nl} | V_{RN} - 1.0 | \tag{6}$$

where, V_{RN} is the ratio of the actual voltage to the nominal voltage of the power grid.

III. Improving the POA Using Multiple Strategies

In this section, the basic principle of the POA and various improvement strategies for this algorithm are introduced. Specifically, the improvement measures mainly include the following four aspects: First, the Logistic chaotic sequence is adopted to initialize the pelican population to generate a more uniformly distributed initial population, thereby its global search capabilities and speed of convergence. Second, an inertia weight factor is introduced to dynamically adjust the correlation between the new position of the pelican and the current position information of the pelican, enhancing the balance of the algorithm in different search stages. Third, a periodic mutation strategy is used, by perturbing individuals within specific iteration cycles, to increase the diversity of the population and prevent the algorithm from getting trapped in local optima. Finally, a fitness-determined evolution direction mechanism is introduced, which dynamically adjusts the search direction based on the fitness value of individuals, ensuring the dominant role of superior individuals in population evolution and further improving the quality of the solution and convergence efficiency. These improvement measures work together to significantly enhance the global search ability, local search accuracy, and population diversity of the POA, and strengthen the algorithm's adaptability and robustness in solving complex optimization problems.

A. Model of Pelican Optimization Algorithm

POA is a new meta-heuristic algorithm, which has the advantages of fast convergence speed, few parameters and strong robustness. Its inspiration mainly comes from two hunting stages of pelicans: the stage of approaching prey and the stage of capturing prey. The initial population position is randomly generated by Eq. (7):

$$x_{i,j} = lb_j + rand \cdot ub_j - lb_j \tag{7}$$

where, $x_{i,j}$ indicates the location of the i-th pelican in the j-th dimensional space, lb_j and ub_j denote the bottom and top limits of the j-th dimensional solution space, and rand provides an arbitrary number between 0 and 1.

(1) The Stage of Approaching the Prey

At this stage, the pelican locates its prey and travels in that direction. The specific mathematical model is as follows:

$$x_{ij}^{P_1} = \begin{cases} x_{ij} + R \cdot \left(P_j - I \cdot x_{ij} \right) & , F_p < F_i \\ x_{ij} + R \cdot \left(x_{ij} - P_j \right) & , else \end{cases} \tag{8}$$

$$x_i = \begin{cases} x_i^p & , F_i^p < F_i \\ x_i & , else \end{cases} \tag{9}$$

Let $x_{i,j}$ denote the position of individual i in the j-th dimension, R represent a random number within the range of [0,1], and P_j indicate the location of the target in the j-th dimension. F_p and Fi respectively stand for the fitness values of the prey and individual i. I is a random number of either 1 or 2. $x_{ij}^{p_1}$ represents the new position of $x_{i,j}$ after the first stage. F_p is the fitness value of the prey. F_i^p is the fitness value of $x_{ij}^{p_1}$ after the position update of the pelican individual. After the pelican individual moves towards the prey, if the function value improves, it updates its position through Eq. (9), otherwise, no position update is made.

(2) The stage of capturing prey

After the pelican reaches the water surface near its prey, it will skim the water to collect the prey. The main purpose of this stage is to enhance the development capability of POA.

$$x_{ij}^{P_2} = x_{ij} + R \cdot (1 - t / T) \cdot (2 \cdot R - 1) \cdot x_{ij} \tag{10}$$

$$x_i = \begin{cases} x_i^p & , F_i^p < F_i \\ x_i & , else \end{cases} \tag{11}$$

where, $x_{ij}^{p_2}$ represents the updated position of the current stage, R is a random number with a range of [0,1], I is an integer at random with a range of [1, 2], t is the present iteration , and T is the maximum number of repetitions. and F_i^p is the fitness value of the updated position $x_{ij}^{p_2}$ of the pelican individual. After the pelican individual skims the water surface, if the fitness value is improved, it updates its position through Eq. (11), otherwise, it does not update its position.

B. Improving the Pelican Optimization Algorithm with Multiple Strategies

(1) Initialization Based on Logistic Chaotic Sequence

The initialization of the pelican population affects the convergence speed and search ability of POA. The original POA uses the random method to generate the initial pelican population position, but the individuals it generates have poor traversal in the search space and are prone to local aggregation, thereby limiting the global exploration capability. Therefore, we choose the Logistic chaotic mapping with strong randomness and traversal to perform initialization, to improve the stability of the mapping, generate a more uniform initial population to expand the search range.

$$x_{i+1} = a x_i (1 - x_i) \tag{12}$$

where, a is a control parameter, taking values in the range (0,4]. The larger the value of a, the higher the degree of chaos. When a=4, it is in a state of complete chaos. The range of chaotic orbit state values is (0,1). In this paper, the value of a is set to 3.

(2) Improve the Correlation between the New Place of the Individual and the Current Individual.

In the optimization process of meta-heuristic algorithms, the coordination of local and global search capacity is a critical component determining the algorithm's correctness and convergence speed. Because the position update in the first stage is heavily reliant on the current individual's position, the original POA algorithm is prone to being stuck in local optima. As a result, this study provides an inertia weight factor w to alter the correlation degree between the pelican's new and present positions, as demonstrated in Eq. (13).

$$w = -0.5 * \left(cos\left(pi * \ t / T \right) - 1 \right) \tag{13}$$

During the beginning stage of the algorithm iteration, the inertia weight factor w is quite small. At this point, the optimizing individual's position update is less impacted by the current pelican location, which contributes to the expansion of the search space and so improves the algorithm's global exploration capabilities. As the iteration progresses, the value of w steadily increases, making the optimizing individual's position update more dependent on the current pelican location, reducing the search range and accelerating the algorithm's convergence to the optimal solution. This method not only increases the algorithm's capacity to leverage local resources, but it also speeds convergence. The modified formula for pelican position is given below:

$$x_{ij}^{p_1} = \begin{cases} w \cdot x_{ij} + R \cdot \left(P_j - I \cdot x_{ij} \right) & , F_p < F_i \\ w \cdot x_{ij} + R \cdot \left(x_{ij} - P_j \right) & , else \end{cases} \tag{14}$$

(3) Increase Population Diversity by Using Periodic Mutations

In the second stage of the Pelican Algorithm, periodic mutations are introduced to the first half of the population to promote species variety and facilitate escaping from local optima. A pelican's fitness value is lower than the population's average fitness value, indicating that it is in an aggregated condition. Currently, to boost pelican variety, periodic mutations are carried out every ten generations until the pelican's fitness value exceeds the population's average. Then, the original pelican position updating mechanism is used.

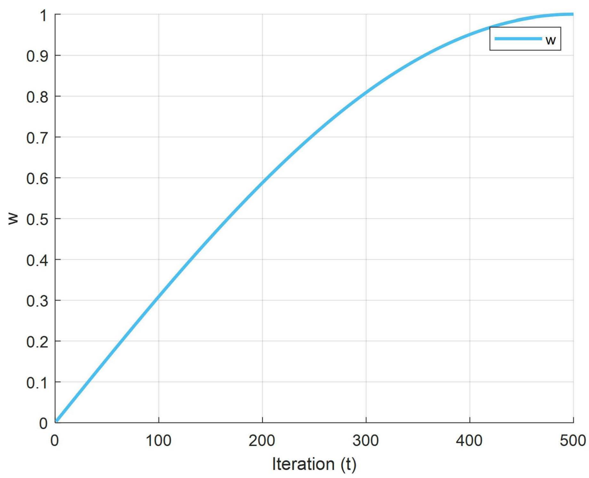


Fig. 2 The graph of w.

$$x_{ij}^{p_2} = \begin{cases} x \cdot \left(1 + A \cdot \left(0.5 - rand\left(1, dim\right) \right) \right) & F_i^{p_2} < F_{AVG} \\ & and mod\left(iter, AT \right) == 0 \\ x_{ij} + R \cdot (1 - t / T) \cdot (2 \cdot R - 1) \cdot x_{ij} & else \end{cases} \tag{15}$$

F_{AVG} represents the average fitness value, A is the mutation amplitude, AT is the mutation interval, which is set to 10 in this paper, and the value taken in this paper is 1. dim is the dimension of the independent variable for the problem to be solved.

(4) Introduce the Mechanism Where Fitness Determines the Direction of Evolution.

In this paper, fg represents the global best fitness value and fw represents the global worst fitness value. When $fi > fg$, the pelican is on the edge of the population and is extremely vulnerable to predator attacks. When $fi = fg$, it indicates that pelicans in the middle of the population are likewise in danger and should approach other pelicans to lessen their chances of being preyed upon. Inspired by SSA, we introduces a fitness-determined evolution direction mechanism for the second half of the pelican population in the second stage, and its formula is as follows:

$$X_{i,j}^{t+1} = \begin{cases} X_{best}^t + \beta \mid X_{i,j}^t - X_{best}^t \mid & if\ fi > fg \\ X_{i,j}^t + K \cdot \left(\dfrac{\mid X_{i,j}^t - X_{worst}^t \mid}{(fi - fw) + \varepsilon} \right) & if\ fi = fg \end{cases} \tag{16}$$

where, X_{best} stands for the present global optimal status, β is a random number from the standard normal distribution that is used as the step size regulate parameter, K is a random quantity between -1 and 1, fi is the current pelican individual's fitness score, fg is the global best wellness value, fw is the global worst wellness value, and ε remains the constant that keeps the equation from dividing by zero.

IV. Simulation Experiments and Result Analysis of Test Functions

The CEC2022 Optimization Function Test Suite is a set of widely applied benchmark test sets, including 12 single-objective functions. Among them, F1 is a classic uni-modal function, while F2-F5 are multi-modal functions with multiple local extreme points, aiming to evaluate the global search ability of algorithms in complex solution spaces. F6-F8 are hybrid functions, which combine different types of optimization problems to test the adaptability and robustness of algorithms in various different environments. F9-F12 are composition functions, consisting of multiple sub-functions, each with different weights and bias values. This further increases the complexity of the optimization problem, requiring algorithms to be capable of handling multi-level and multi-dimensional optimization tasks.

To verify the effectiveness of the improved algorithm, the CEC2022 optimization function test set was selected for this experiment. In the experiment, 500 iterations were set for each function's test, the population size was 30, and the average value was taken after 30 independent experiments. The improved Pelican Optimization Algorithm (MPOA) was compared with the original POA, BOA [19], RSA [20], SCSO [21] and WOA. The experimental results fully demonstrated the advantages of the proposed improved algorithm in terms of solution efficiency and accuracy, showing strong global search capabilities and faster convergence speed. This validates the efficiency and adaptability of MPOA in handling complicated optimization issues. Through comprehensive evaluation of the performance of each comparison algorithm and comparison with existing optimization methods, the improvement effect of MPOA was further verified. The specific algorithm parameter settings are given in Table I.

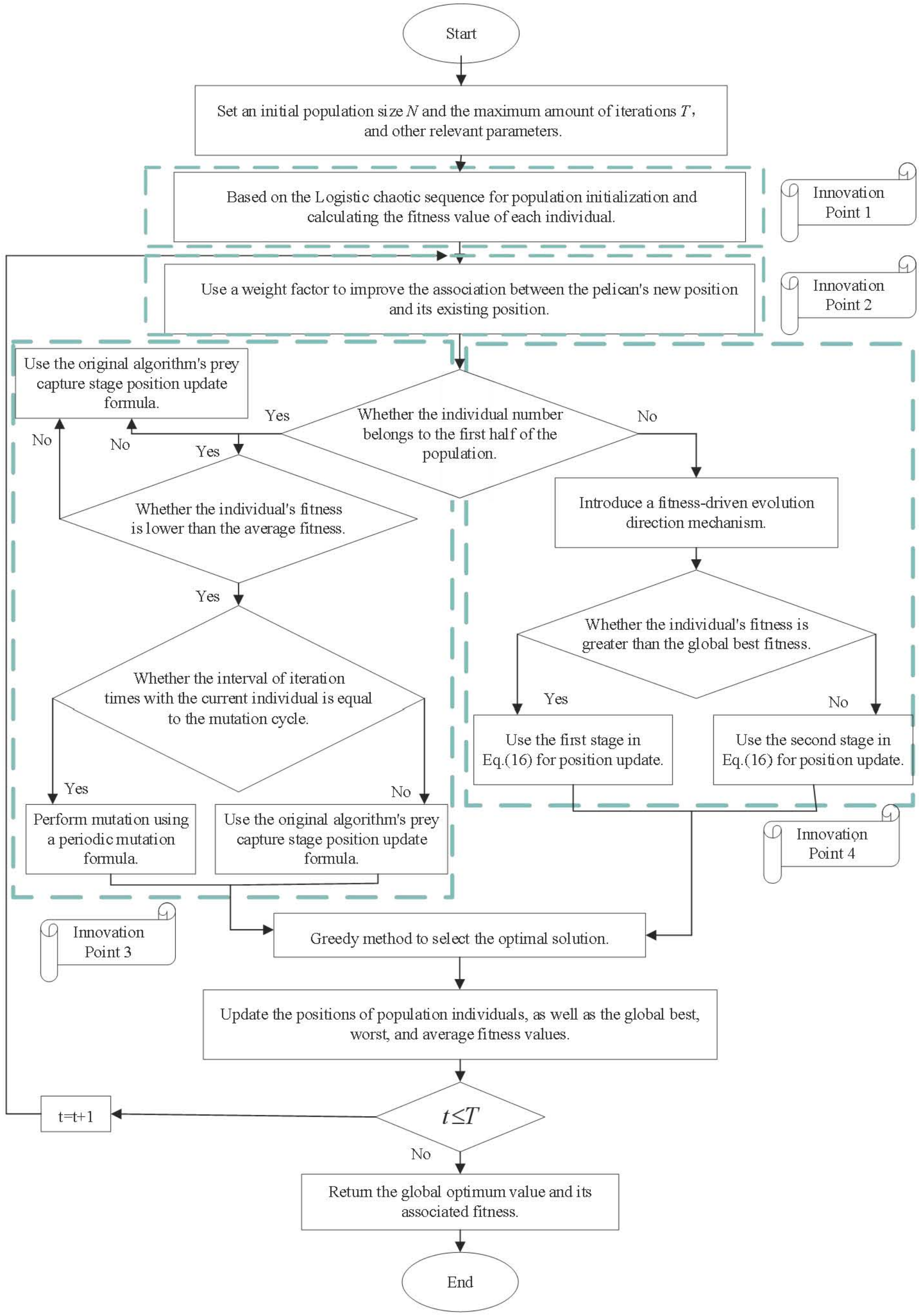


Fig. 3 Flowchart of the improved pelican optimization algorithm.

Based on the experimental findings, as indicated in Table II and Fig. 4, MPOA achieved the best average values in all the tested functions F1 to F12, demonstrating its outstanding stability and optimization ability when dealing with various optimization problems, and effectively avoiding getting trapped in local optimal solutions. It obtained the optimal average value, minimum value and optimal standard deviation in F1, F2, F8 and F9, indicating the effectiveness of optimization. In the tests of F3 to F7, MPOA still showed strong competitiveness, and the overall stability (lower standard deviation) indicated that MPOA had better robustness in multiple runs. In the tests of F3, F4 and F7, the average value of MPOA was significantly better than other algorithms, and the standard deviation was lower, indicating that its result convergence was stronger. In the test of F6, the average value and standard deviation of MPOA were much lower than those of other algorithms, indicating that its search ability in high-dimensional complex functions was more advantageous. In the tests of F10 to F12, MPOA still maintained the best average value, and obtained the minimum standard deviation in F11 and F12, indicating that its solution stability was the highest.

In conclusion, compared with other optimization algorithms, MPOA demonstrated the best performance on multiple tested functions, especially in terms of convergence stability and search accuracy, outperforming other algorithms significantly. This indicates that MPOA can provide stronger solving capabilities in different types of optimization problems and is suitable for complex optimization scenarios.

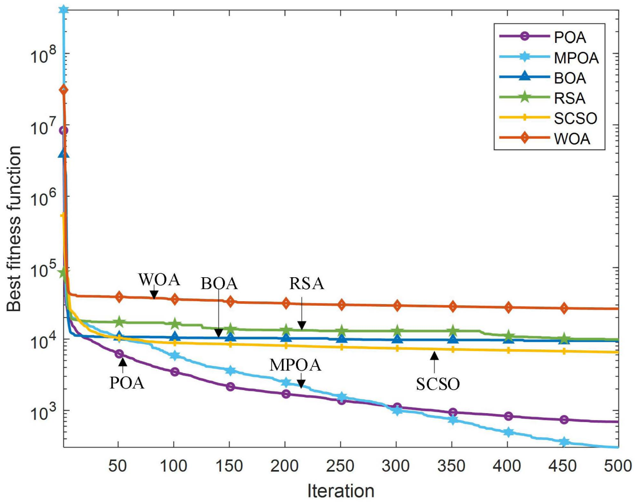
TABLE I. THE CORRESPONDING PARAMETERS FOR EACH ALGORITHM

Number	Algorithm	Parameter settings
1	POA and its variants	R=rand，I=1or 2
2	BOA	p=0.8，a=0.1，c=0.01
3	RSA	$Alpha$=0.1，$Beta$=0.005
4	SCSO	s_M=2，r_G=s_M-((2*s_M*it)/(2*T))
5	WOA	a=2*(1-(it/T))，A=2*a*rand-a，C=2*rand(1,dim)

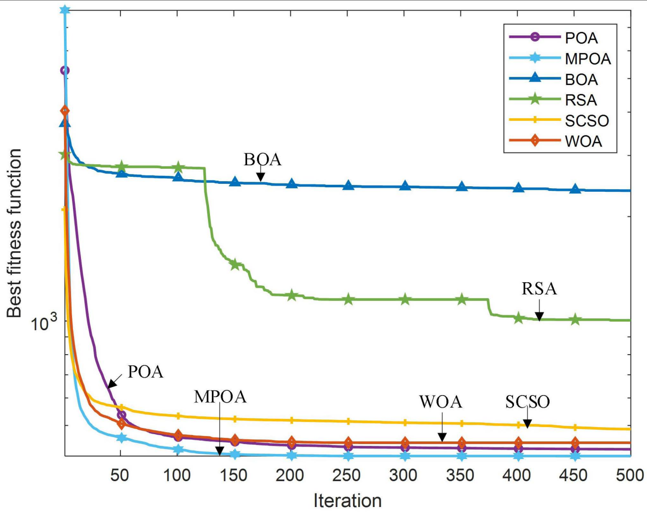
TABLE II. COMPARISON RESULTS WITH OTHER ALGORITHMS

Function	Meteic	POA	MPOA	BOA	RSA	SCSO	WOA
F1	Ave	6.928E+02	**3.042E+02**	9.453E+03	9.875E+03	6.543E+03	2.654E+04
	Std	7.104E+02	**9.328E+00**	3.746E+03	3.437E+03	3.375E+03	1.130E+04
	Best	3.301E+02	**3.000E+02**	3.882E+03	4.536E+03	9.109E+02	6.507E+03
F2	Ave	4.269E+02	**4.080E+02**	2.376E+03	1.005E+03	4.879E+02	4.457E+02
	Std	2.804E+01	**1.248E+01**	1.154E+03	4.762E+02	9.113E+01	3.325E+01
	Best	4.003E+02	**4.000E+02**	8.517E+02	5.423E+02	4.006E+02	4.062E+02
F3	Ave	6.234E+02	**6.070E+02**	6.484E+02	6.500E+02	6.288E+02	6.414E+02
	Std	1.067E+01	7.778E+00	9.573E+00	**7.571E+00**	1.192E+01	1.274E+01
	Best	6.052E+02	**6.000E+02**	6.313E+02	6.319E+02	6.072E+02	6.162E+02
F4	Ave	8.241E+02	**8.228E+02**	8.531E+02	8.505E+02	8.291E+02	8.458E+02
	Std	6.132E+00	**5.328E+00**	7.802E+00	8.590E+00	7.793E+00	2.193E+01
	Best	8.101E+02	8.129E+02	8.321E+02	8.323E+02	8.187E+02	**8.099E+02**
F5	Ave	1.118E+03	**1.075E+03**	1.362E+03	1.531E+03	1.222E+03	1.584E+03
	Std	**1.292E+02**	2.394E+02	1.532E+02	1.556E+02	1.926E+02	3.418E+02
	Best	9.076E+02	**9.001E+02**	1.085E+03	1.136E+03	9.461E+02	1.014E+03
F6	Ave	3.697E+03	**2.258E+03**	1.323E+08	8.233E+07	5.833E+03	5.700E+03
	Std	2.258E+03	**5.093E+02**	1.918E+08	7.238E+07	4.417E+03	3.937E+03
	Best	**1.842E+03**	1.847E+03	1.001E+04	4.896E+06	1.988E+03	2.085E+03
F7	Ave	2.039E+03	**2.030E+03**	2.102E+03	2.140E+03	2.058E+03	2.077E+03
	Std	**1.205E+01**	1.777E+01	1.840E+01	2.831E+01	2.144E+01	2.773E+01
	Best	2.014E+03	**2.008E+03**	2.073E+03	2.080E+03	2.026E+03	2.037E+03
F8	Ave	2.228E+03	**2.221E+03**	2.356E+03	2.269E+03	2.236E+03	2.238E+03
	Std	3.008E+01	**6.042E+00**	1.243E+02	4.848E+01	2.314E+01	1.210E+01
	Best	2.204E+03	**2.204E+03**	2.238E+03	2.235E+03	2.223E+03	2.226E+03
F9	Ave	2.549E+03	**2.529E+03**	2.831E+03	2.744E+03	2.584E+03	2.611E+03
	Std	3.180E+01	**1.410E-01**	9.693E+01	5.922E+01	3.015E+01	4.457E+01
	Best	2.529E+03	**2.529E+03**	2.678E+03	2.644E+03	2.530E+03	2.530E+03

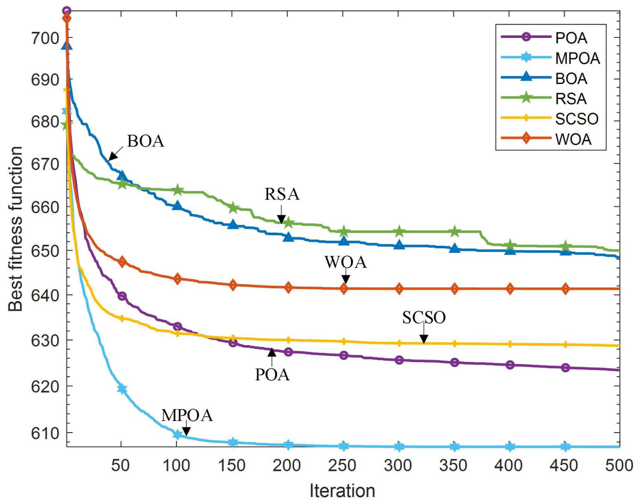
	Ave	2.551E+03	**2.536E+03**	2.575E+03	2.659E+03	2.712E+03	2.624E+03
F10	Std	6.280E+01	**6.009E+01**	7.958E+01	9.616E+01	3.106E+02	2.031E+02
	Best	**2.500E+03**	2.500E+03	2.502E+03	2.514E+03	2.500E+03	2.500E+03
	Ave	2.801E+03	**2.783E+03**	3.360E+03	3.232E+03	2.870E+03	2.853E+03
F11	Std	1.822E+02	**1.238E+02**	5.429E+02	4.086E+02	2.031E+02	1.544E+02
	Best	2.602E+03	**2.600E+03**	2.769E+03	2.846E+03	2.622E+03	2.673E+03
	Ave	2.871E+03	**2.868E+03**	2.954E+03	2.967E+03	2.916E+03	2.916E+03
F12	Std	1.440E+01	**5.589E+00**	5.754E+01	7.203E+01	2.831E+01	4.697E+01
	Best	2.862E+03	**2.861E+03**	2.870E+03	2.884E+03	2.868E+03	2.868E+03



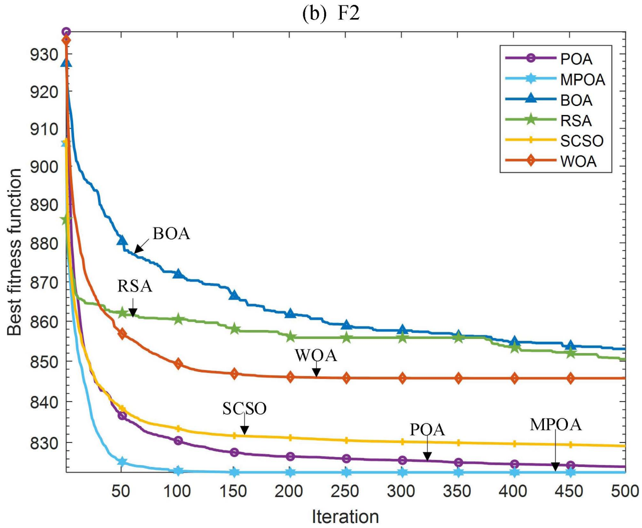
(a) F1



(b) F2



(c) F3



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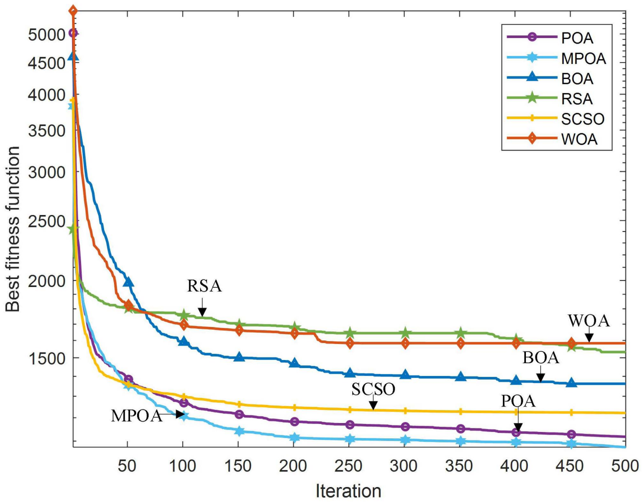

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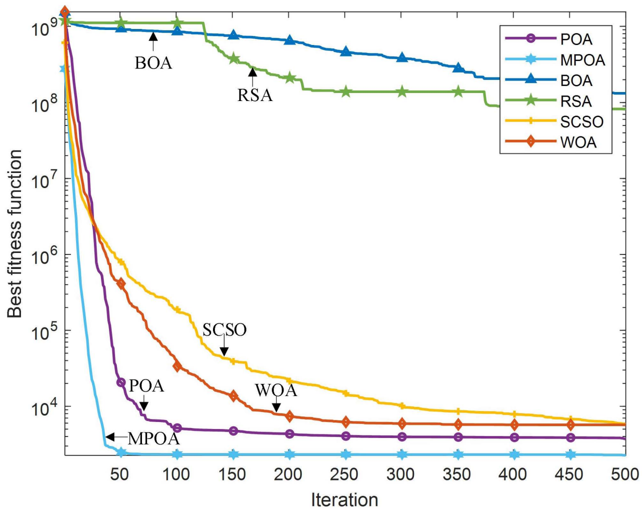

(f) F6

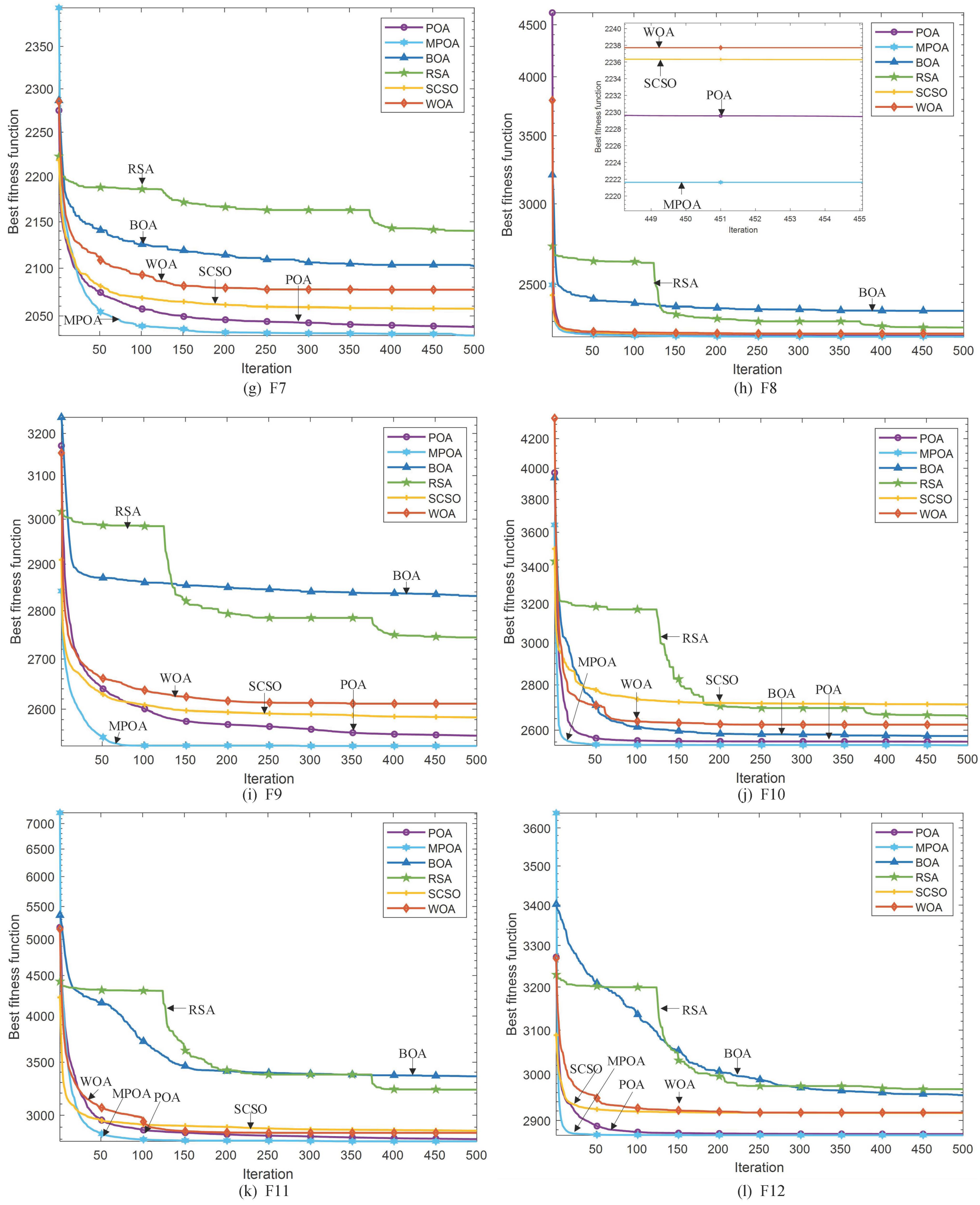

Fig. 4 Simulation results of test functions for each algorithm.

V. Results and Analysis of the Optimal Power Flow Case Study

To verify the effectiveness of the improved Pelican Optimization Algorithm (MPOA), in this section, the results are validated using the IEEE 30-bus system. In this experiment, three single-objective functions are used, namely fuel cost, active power loss, and bus voltage deviation. Each algorithm's population count is established at 50, with a maximum of 100 iterations. They are independently run 30 times for each case, and the average values are plotted.

A. *Results of the Fuel Cost Case Study*

Fig. 5 shows the iterative convergence curves of each algorithm, and the Table III respectively presents the minimum value, maximum value and average value of each algorithm, and lists the active power loss (Ploss) and bus voltage deviation (VD) of the system corresponding to the minimum fuel cost of each algorithm, so as to conduct a more comprehensive and objective evaluation of the algorithm performance.

Among all the algorithms, MPOA performed the best in fuel cost optimization, achieving the optimal average value of 800.4818 \$/h and the minimum value of 799.1879 \$/h. Compared with the original POA, the average fuel cost was reduced by 0.17%, demonstrating better economic efficiency. Additionally, the maximum fuel cost of MPOA was 801.9365 \$/h, which was 0.50% lower than that of POA at 805.9783 \$/h. This indicates that MPOA can maintain a lower fuel consumption in multiple experiments, showing stronger stability and global search capability, and effectively avoiding local optimal solutions. Overall, MPOA outperforms other algorithms in terms of fuel cost, effectively reducing the generation cost while ensuring search accuracy, and demonstrating stronger stability and robustness under different operating conditions. It provides an efficient and reliable solution for economic dispatch in power systems.

We use the radar chart Fig. 6 to visually represent the ranking of the average fuel cost of each algorithm. And we use the radar chart Fig. 7 to show the ranking of the results of other objective functions when the fuel cost is optimal. The results indicate that MPOA demonstrates balanced and stable comprehensive performance, especially excelling in minimizing fuel cost. In terms of fuel cost, MPOA achieved the lowest value of 799.1879 among all algorithms, ranking first, significantly outperforming the others. This indicates that MPOA can effectively reduce the economic cost of power generation when optimizing the power generation dispatch plan. In terms of Ploss, MPOA ranked third with a result of 8.6893, only behind BOA and POA, still at an excellent level. Considering that active power loss directly affects energy utilization efficiency, MPOA maintaining a low value in this aspect indicates its strong adaptability in improving system efficiency. In the radar chart, although the overall contour of MPOA is slightly weaker in the VD direction, it is significantly better than other algorithms in the Fuel cost and Ploss directions, which can be intuitively reflected in its core advantages from the graph.

Overall, MPOA has an absolute advantage in fuel cost, maintains an excellent level in active power loss, and is at a controllable level in voltage deviation, demonstrating good trade-off capabilities.

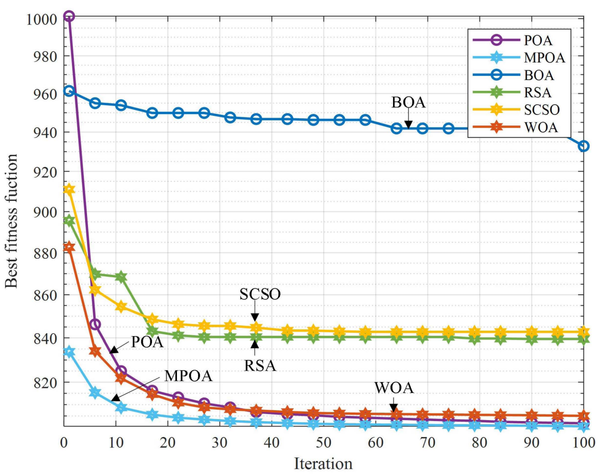

Fig. 5 Results of fuel cost for each algorithm.

TABLE III. FUEL COST RESULTS OF EACH ALGORITHM

Algorithm	Min	Max	Mean	Rank
POA	799.4926	805.9783	801.8120	2
MPOA	799.1879	801.9365	800.4818	1
BOA	839.6819	1070.7650	932.8447	4
RSA	819.3466	853.3661	839.4743	5
SCSO	816.8220	879.2313	842.7588	6
WOA	799.4692	812.3927	805.0487	3

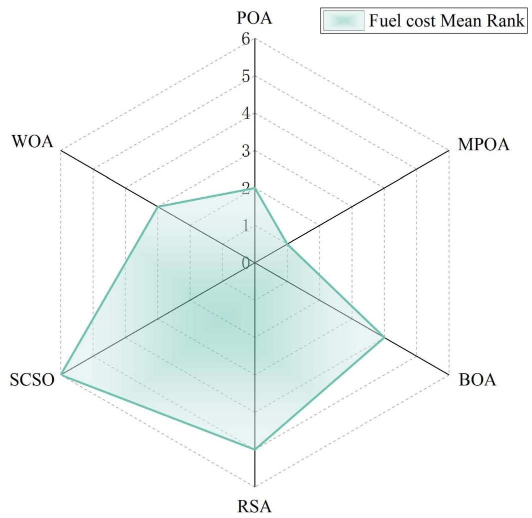

Fig. 6 The average ranking of fuel cost.

TABLE IV. COMPARISON OF THE OPTIMAL SOLUTIONS OF EACH ALGORITHM IN THE FUEL COST CASE

Algorithm	Fuel cost	Rank	Ploss	Rank	VD	Rank
POA	799.9619	3	8.5886	2	2.2250	5
MPOA	799.1879	1	8.6893	3	2.4973	6
BOA	838.6819	6	7.4317	1	0.7824	2
RSA	818.3466	5	11.7882	6	1.8275	3
SCSO	816.8220	4	11.7826	5	0.6966	1
WOA	799.4692	2	8.8010	4	2.2152	4

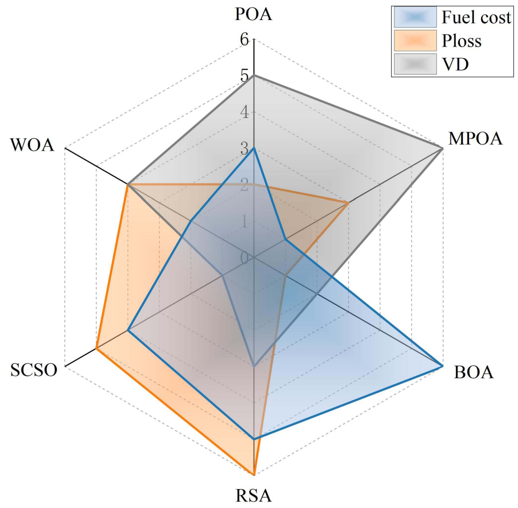

Fig. 7 Ranking of objective function results at fuel cost optimum.

B. *Active Power Loss Case Results*

The smaller the active power loss is, the more active power can reach each load, thereby improving the transmission efficiency of the power system.Fig. 6 shows the iterative convergence curves of each algorithm, and the Table V presents the minimum, maximum and average values of each algorithm under this objective. The fuel cost and bus voltage deviation corresponding to the minimum active power loss of each algorithm, to comprehensively evaluate the performance of the algorithms in the power system.

Among all the algorithms, MPOA performs the best in terms of active power loss, achieving the minimum average value of 1.2033 MW and the minimum value of 1.1503 MW. Compared with the original POA with 1.4395 MW and 1.1840 MW, it has decreased by 16.41% and 2.85% respectively, effectively reducing the power loss of the power system, indicating that it has stronger local search ability and better solution accuracy. At the same time, the maximum value of active power loss of MPOA is also significantly reduced, only 1.6058 MW, far lower than 2.1505 MW of POA, further demonstrating the stability and robustness of this algorithm in multiple experiments.

Compared with other algorithms, MPOA also demonstrates significant advantages in active power loss. Compared with the third-ranked WOA, the average active power loss of MPOA is reduced by 30.10%, indicating that it is more efficient in reducing power transmission loss and can achieve better energy transmission in complex power systems.At the same time, MPOA also outperforms WOA in the minimum active power loss index, reducing it by 10.91%, further verifying its effectiveness and robustness in power loss optimization. Overall, when the active power loss is the optimization objective, MPOA can effectively reduce the loss during power transmission and maintain a lower average value and a better minimum value in multiple experiments, highlighting its outstanding performance in power system dispatching.

We use the radar chart Fig. 8 to visually rank the active power loss results of each algorithm. And we use the radar chart Fig. 9 to express the ranking of other objective function results when the active power loss is the smallest. The results show that MPOA performs most prominently in terms of active power loss, ranking first with the minimum value of 1.1503, indicating its significant advantage in reducing system energy loss and making it the preferred algorithm for this optimization objective. Although MPOA does not have an advantage in fuel cost and voltage deviation, its absolute lead in the main objective function makes it the overall best-performing solution.

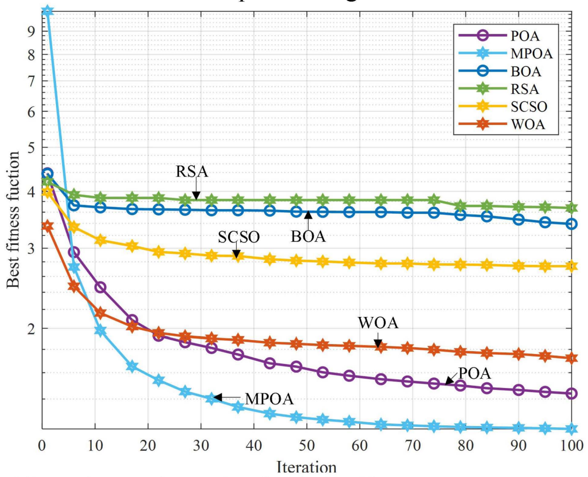

Fig. 6 Power loss results graphs of each algorithm.

TABLE V. THE ACTIVE POWER LOSS RESULTS OF EACH ALGORITHM

Algorithm	Min	Max	Mean	Rank
POA	1.1840	2.1505	1.4395	2
MPOA	1.1503	1.6058	1.2033	1
BOA	1.9393	4.8280	3.3923	5
RSA	2.0746	5.3021	3.6772	6
SCSO	1.3733	4.8271	2.7385	4
WOA	1.2913	3.1013	1.7215	3

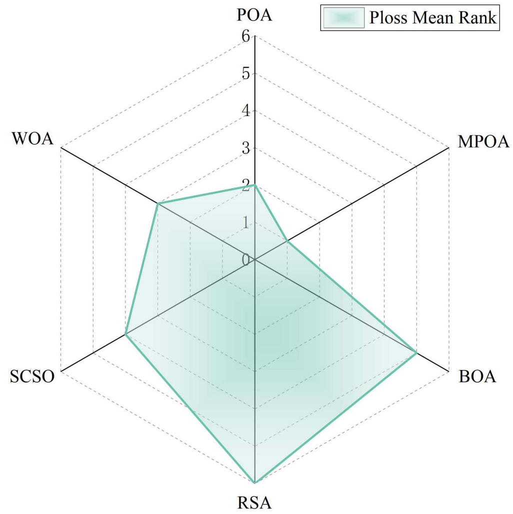

Fig. 8 The average ranking of Ploss.

TABLE VI. COMPARISON OF THE OPTIMAL SOLUTIONS OF EACH ALGORITHM IN THE ACTIVE POWER LOSS CASE

Algorithm	Fuel cost	Rank	Ploss	Rank	VD	Rank
POA	1480.4550	4	1.1840	2	2.6072	4
MPOA	1486.3485	5	1.1503	1	2.6954	6
BOA	1416.1191	2	1.9393	5	2.1051	1
RSA	1210.3307	1	2.0746	6	2.4578	3
SCSO	1467.5702	3	1.3733	4	2.3639	2
WOA	1496.9215	6	1.2913	3	2.6692	5

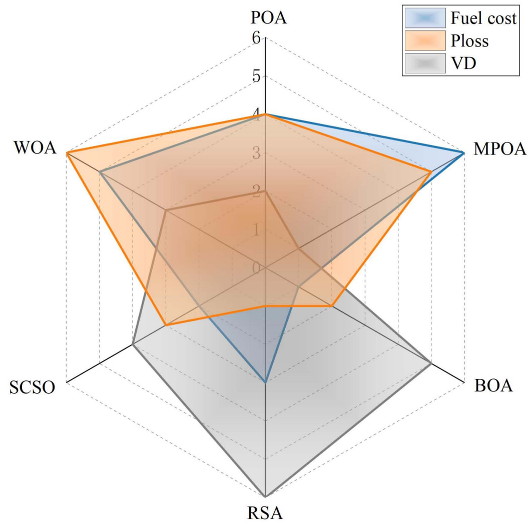

Fig. 9 Ranking of objective function results at Ploss optimum.

C. *Case Results of Bus Voltage Deviation*

When the voltage deviation (VD) is taken as the optimization objective, a lower target value indicates a higher voltage quality, with the voltage being closer to the rated value. Fig. 7 shows the iterative convergence curves of each algorithm, and the Table VII provides the minimum, maximum, and average values of each algorithm. Furthermore, it lists the corresponding fuel cost and active power loss of the system when the voltage deviation is at its minimum for each algorithm, to comprehensively evaluate the optimization effect of each algorithm.

We use the radar chart Fig. 10 to visually represent the ranking of bus voltage deviation for each algorithm. And we use the radar chart Fig. 11 to show the ranking of other objective functions when the bus voltage deviation is the smallest. From the perspective of bus voltage deviation, MPOA ranks first with the minimum value of 0.1557, performing the best among all algorithms, effectively maintaining voltage stability and contributing to improving the power quality of the power system. Besides, MPOA also ranks high in the other two indicators. The fuel cost is 1129.6343 dollars, ranking second, only behind RSA, demonstrating good economic performance; the active power loss ranks second, only behind POA, indicating a high level of control over system losses. Overall, MPOA ranks first, second, and second in the three objective functions respectively, with an extremely high overall ranking and no obvious weaknesses, making it the algorithm with the best comprehensive performance among all. In conclusion, MPOA not only achieves the best result in bus voltage deviation but also ranks second in fuel cost and active power loss, demonstrating extremely strong comprehensive optimization capabilities. Its balanced, stable, and energy-saving characteristics make it stand out in multiple performance dimensions, making it the best algorithm choice in this optimization.

Among all the algorithms, MPOA performs the best in terms of voltage deviation, achieving the minimum average value of 0.1823 p.u. and the minimum value of 0.1557 p.u., which are 7.83% and 5.86% lower than the 0.1978 p.u. and 0.1654 p.u. of the original Pelican Optimization Algorithm, respectively. This indicates that MPOA has a significant advantage in improving voltage quality. Compared with other algorithms, MPOA also demonstrates outstanding performance and stronger adaptability. The average value of voltage deviation of MPOA is 34.10% lower than that of the third-ranked WOA (0.2766 p.u.), and the minimum value is 17.63% lower, indicating that it is more effective in enhancing the voltage quality of the system.

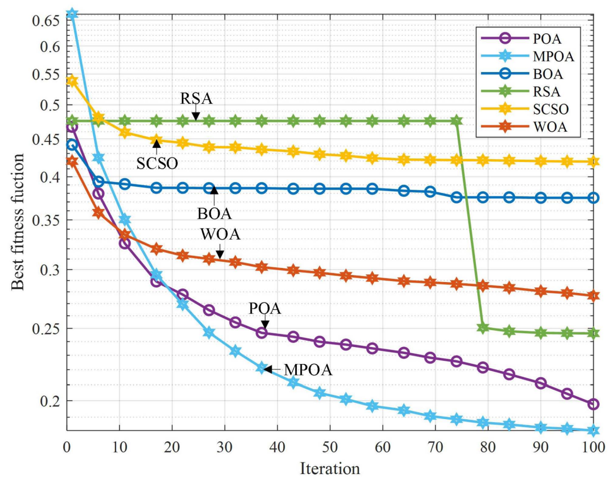

Fig. 7 The results graphs of bus voltage deviation for each algorithm.

TABLE VII. THE RESULTS OF BUS VOLTAGE DEVIATION FOR EACH ALGORITHM

Algorithm	Min	Max	Mean	Rank
POA	0.1654	0.2606	0.1978	2
MPOA	0.1557	0.2654	0.1823	1
BOA	0.2345	0.4362	0.3748	5
RSA	0.2279	0.2608	0.2462	3
SCSO	0.2627	0.5323	0.4193	6
WOA	0.1890	0.3778	0.2766	4

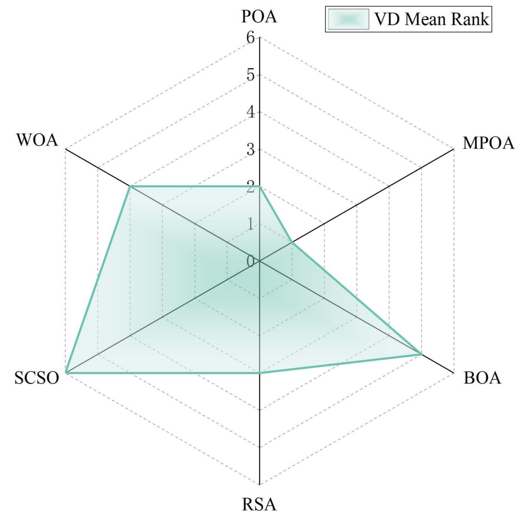

Fig. 10 The average ranking of bus voltage deviation.

TABLE VIII. COMPARISON OF THE OPTIMAL SOLUTIONS OF EACH ALGORITHM IN THE BUS VOLTAGE DEVIATION CASE

Algorithm	Fuel cost	Rank	Ploss	Rank	VD	Rank
POA	1559.7245	4	3.4052	1	0.1654	2
MPOA	1129.6343	2	3.4627	2	0.1557	1
BOA	1785.4560	5	5.5655	4	0.2345	5
RSA	915.4837	1	21.1181	6	0.2279	4
SCSO	1533.6098	3	5.3854	3	0.2627	6
WOA	1983.2572	6	8.7395	5	0.1890	3

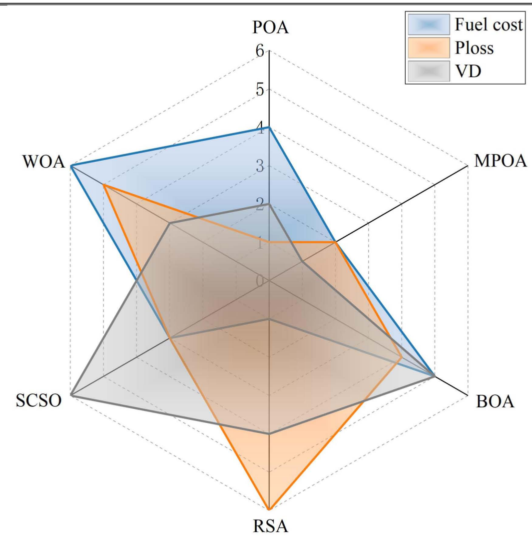

Fig. 11 Ranking of objective function results at VD optimum.

In summary, MPOA excels in the optimization targeting bus voltage deviation, demonstrating stronger global search capability and optimization stability. Compared with other algorithms, MPOA can maintain high voltage quality while reducing fuel consumption and power loss, providing a more efficient, economical and reliable solution for power system dispatching.

VI. Conclusion

This research provides a multi-strategy enhanced POA (MPOA), which integrates four innovative strategies to enhance its optimization performance. Specifically, the proposed strategies include the following four points. (1) Utilize Logistic chaotic sequences for initialization to increase the diversity of the initial solutions. (2) Introduce an inertia weight factor to balance both local and global search potential and speed up resolution. (3) Use a periodic mutation method to improve the algorithm's capacity to escape from local optima. 4) Implement a fitness-based evolutionary direction mechanism to adaptively adjust the search direction during the process and improve the global search capability.

To verify the effectiveness of the improved algorithm, this paper conducts performance tests on the CEC2022 test function set and compares it to other optimization strategies. The outcomes suggest that MPOA performs well on multiple standard test functions, demonstrating its stronger global optimization ability and faster convergence speed. This paper also applies MPOA to the IEEE 30-node power system and optimizes three single-objective functions: fuel cost, active power loss, and bus voltage deviation. Comparisons are made with POA, BOA, RSA, SCSO, and WOA. The experimental results indicate that MPOA can achieve the optimal solutions in all three objectives, further verifying its effectiveness and wide applicability in power system optimization.

References

[1] M. R. Adaryani, and A. Karami. “Artificial Bee Colony Algorithm for Solving Multi-objective Optimal Power Flow Problem”, *International Journal of Electrical Power & Energy Systems*, vol.53, pp. 219-230, 2013.

[2] M. R. AlRashidi, and M. E. El-Hawary, “Applications of Computational Intelligence Techniques for Solving Revived Optimal Power Flow Problem”, *Electric Power Systems Research*, vol. 79, no. 4, pp. 694-702, 2009.

[3] H. W. Dommel, and W. F. Tinney, “Optimal Power Flow Solutions”, *IEEE Transactions on Power Apparatus and Systems*, vol. 87, no. 10, pp. 1866-1876, 1968.

[4] G. R. M. Da-Costa, K. Langona, and D. A. Alves, “A New Approach to the Solution of the Optimal Power Flow Problem Based on the Modified Newton's Method Associated to an Augmented Lagrangian Function”, *International Conference on Power System Technology*, vol. 2, pp. 909-913, 1998.

[5] D. I. Sun, B. Ashley, and B. Brewer, “Optimal Power Flow by Newton Approach”, *Power Engineering Review*, vol. 4, no. 10, pp. 39, 1984.

[6] G. F. Reid, P. Johnson, and L. Hasdorff, “Economic Dispatch Using Quadratic Programming”, *IEEE Transactions on Power Apparatus and Systems*, vol. 6, pp. 2015-2023, 1973.

[7] K. A. Clements, P. W. Davis, and K. D. Frey, “An Interior Point Algorithm for Weighted Least Absolute Value State Estimation”, *IEEE Power Engineering Society Winter Meeting*, pp. 3-7, 1991.

[8] A. L. B. Layth, A. L. K. Murtadha, and A. L. Jaleel, “Solving Optimal Power Flow Problem Using Improved Differential Evolution Algorithm”, *International Journal of Electrical and Electronic Engineering & Telecommunications*, vol. 11, no. 2, pp. 146-155, 2022.

[9] S. Khunkitti, A. Siritaratiwat, and S. Premrudeepreechacharn, “Multi-objective Optimal Power Flow Problems Based on Slime Mould Algorithm”, *Sustainability*, vol. 13, no. 13, pp. 7448, 2021.

[10] A. Alanazi, M. Alanazi, and Z. A. Memon, “Determining Optimal Power Flow Solutions Using New Adaptive Gaussian TLBO Method”, *Applied Sciences*, vol. 12, no. 16, pp. 7959, 2022.

[11] S. A. Mohamed, N. Anwer, and M. M. Mahmoud, “Solving Optimal Power Flow Problem for IEEE-30 Bus System Using a Developed Particle Swarm Optimization Method: towards Fuel Cost Minimization”, *International Journal of Modelling and Simulation*, vol. 45, no. 1, pp. 307-320, 2025.

[12] M. H. Nadimi-Shahraki, S. Taghian, and S. Mirjalili, “EWOA-OPF: Effective Whale Optimization Algorithm to Solve Optimal Power Flow Problem”, *Electronics*, vol. 10, no. 23, pp. 2975, 2021.

[13] P. Trojovský, and M. Dehghani, “Pelican Optimization Algorithm: A Novel Nature-inspired Algorithm for Engineering Applications”, *Sensors*, vol. 22, no. 3, pp. 855, 2022.

[14] N. Alamir, S. Kamel, and T. F. Megahed, “Developing Hybrid Demand Response Technique for Energy Management in Microgrid Based on Pelican Optimization Algorithm”, *Electric Power Systems Research*, vol. 214, pp. 108905, 2023.

[15] W. Tuerxun. Li, C. Xu, and M. Haderbieke, “A Wind Turbine Fault Classification Model Using Broad Learning System Optimized by Improved Pelican Optimization Algorithm”, *Machines*, vol. 10, no. 5, pp. 407, 2022.

[16] R. Z. Khaleel, H. Z. Khaleel and A. H. Abdullah, “Improved Trajectory Planning of Mobile Robot Based on Pelican Optimization Algorithm”, *Journal Européen des Systèmes Automatisés*, vol. 57, no. 4, pp. 1005, 2024.

[17] J. H. Zhu, J. S. Wang and X. Y. Zhang, “Mathematical Distribution Coyote Optimization Algorithm with Crossover Operators to Solve Optimal Power Flow Problem of Power System”, *Alexandria Engineering Journal*, vol. 69, pp. 585-612, 2023.

[18] X. L, J. H. Zhu, and J. S. Wang, “Nutcracker Optimization Algorithm to Address Power System's Optimal Power Flow Issue”, *Engineering Letters*, vol. 32, no. 8, pp. 1644-1658, 2024.

[19] S. Arora, and S. Singh, “Butterfly Optimization Algorithm: A Novel Approach for Global Optimization”, *Soft Computing*, vol. 23, pp. 715-734, 2019.

[20] A. Nichol, and J. Schulman, “Reptile: A Scalable Metalearning Algorithm”, *DOI:10.48550/arXiv.1803.02999,* 2018.

[21] A. Seyyedabbasi, and F. Kiani, “Sand Cat Swarm Optimization: A Nature-inspired Algorithm to Solve Global Optimization Problems”, *Engineering with Computers*, vol. 39, no. 4, pp. 2627-2651, 2023.