A Manta-Ray Forging Algorithm Solution for Practical Reactive Power Optimization Problem

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Abstract. This paper proposes a solution to the power grid system's reactive power optimization scheduling problem (RPSP) based on a novel Manta ray forging algorithm (MRFO) evolutionary algorithm. By applying the penalty function for the reactive power optimization model, the management of the constraints of the RPSP optimization formula is counting on for calculation. The experimental results of the proposed MRFO scheme are contrasted with other approaches for the IEEE 30 bus system, such as Particle swarm optimization (PSO), Grey wolf optimizer (GWO), Moth-flame optimization algorithm (MFO), and Whale optimization algorithm (WOA). Comparative results show that the MRFO algorithm can generate stable, strong convergence, high reliability effectively, and a feasible figuration needed space in solving optimization problems with reactive power optimization.

Keywords: Power system; Manta ray foraging algorithm; Reactive power optimization

1 Introduction

In the age of exponential growth of science and technology, the conventional methods of optimization are increasingly suffering the computational complicated time whenever facing large scaling problems[1], such as the combinatorial problem of the reactive power optimization scheduling problem (RPSP)[2]. The traditional methods of optimization would be replaced by modern approaches[3]. The rise of the evolutionary algorithm[4] has significantly changed industrial development, including industrial production, improvement of medical equipment, advancement in transportation, etc. [5].

The advantages of an evolutionary algorithm compared with the traditional algorithm are the affirmation of the evolutionary algorithm[6], e.g., genetic algorithm (GA)[7] from the proposed to the rapid development of various industries[5]. Due to the high efficacy of the evolutionary algorithm, in recent years, more and more researchers are beginning to study evolutionary algorithms, for example, for animal predation-inspired evolutionary algorithms[8], such as the Grey Wolf algorithm (GWO)[9], the Bat algorithm (BA)[10], the Whale optimization algorithm (WOA)[11]. Inspired by species' living habits, there are several suggested algorithms, and a firm representative is a Moth-flame algorithm (MFO)[12]. The evolutionary algorithms are inspired by species, but also by human beings and physical phenomena. Typical representations inspired by nature are the multi-verse algorithm (MVO)[13] and the gravitational search algorithm (GSA)[14]. The Brainstorm optimization algorithm (BSO)[15] is typical human-inspired representatives of the teaching-learning-based optimization algorithm. One of the lifeblood's of the growth of a nation is electric power; the power system is becoming more and more involved with the rising demand for it [2]. A long-term problem of scholars is how to hold the power system in a healthy and stable state for a long time. Reactive power has a significant effect on the power system's safe and regular service[16]. Therefore, the optimization of reactive power dispatch has been given more importance. The efficient delivery and management of reactive power are the issues we need to deal with in time.

The optimal reactive power dispatch for the RPSP of the power system is to monitor the reactive power flow of the power system. The changing generator reactive power output, transformer tap location, and reactive power compensation device output (such as synchronous phase modifier and static var., a compensator) change the power system's reactive power flow to allow the entire system to work in a safe setting. The reactive power distribution is closely related to the efficiency of the system's voltage. The problems with reactive power optimization scheduling have been dealt with by applying through the advancement of artificial intelligence algorithms, e.g., PSO[16], WOA[17], GWO[18], and MFO[19] algorithms. In the power grid, excess reactive power can contribute to an increase in grid voltage. The power equipment will lose insulation efficiency when the voltage increases above a certain level, which will affect the protection and reliability of the device operation; the absence of reactive power will cause the grid voltage to decrease. It is easy to cause voltage collapse, system disconnection, and devastating incidents when the system appears to be a significant disruption. The algorithm would easily fall into the pit of local optimization by using an intelligent optimization algorithm for reactive power optimization when the device size becomes more comprehensive. Therefore, searching for a more efficient algorithm to solve the problem of reactive power optimization scheduling will ensure the reliability and security of the operation of the system more effectively.

The Manta ray forging algorithm (MRFO)[20] is a recently novel evolutionary algorithm with robust, stability, convergence, high reliability, and efficient implementation. This paper suggests a solution to the functional reactive power optimization problem (RPSP), e.g., for the IEEE30 bus power system based on the MRFO. The objective function of optimization is to minimize the system's active power loss. The penalty technique is used to deal with the figuration control variables out of the optimization constraints. For contrast, four algorithms include the PSO, GWO, MFO, and WOA schemes for the RPSP system, are used to compare with the proposed method to evaluate its effect performance. The experimental findings suggest that MRFO's effect is more potent than other algorithms.

2 Related Work

2.1 Manta ray foraging algorithm

The Manta ray foraging algorithm is a new algorithm inspired by manta ray foraging characteristics. Manta ray is a kind of marine organism that feeds on plankton [20]. It gathers plankton by controlling the flow, swallow food and water together, and then releases water back to the ocean through its special filter. Because the plankton in the ocean is not evenly distributed or concentrated, manta rays need to use their unique foraging methods to obtain food. When manta rays are foraging, they usually go out in groups, and their foraging ways are generally divided into chain foraging, cyclone foraging, and somersault foraging.

(1) Chain foraging: The manta ray colony moves towards the direction with a high concentration of plankton and continuously seeks a better food source. At this time, the manta ray colony forms a feeding chain. After the formation of the feeding chain, in addition to the first manta ray moving forward, the last manta rays not only move to the current food but also to the best food [20]. The mathematical model is expressed as follows:

$$s_i^d(t+1) = \begin{cases} s_i^d(t) + r \cdot \left(s_g^d(t) - s_i^d(t)\right) + \alpha \cdot \left(s_g^d(t) - s_i^d(t)\right) i = 1 \\ s_i^d(t) + r \cdot \left(s_{i-1}^d(t) - s_i^d(t)\right) + \alpha \cdot \left(s_g^d(t) - s_i^d(t)\right)\ i \neq 1 \end{cases} \tag{1}$$

$$\alpha = 2 \cdot \mathrm{r} \cdot \sqrt{|\log(r)|} \tag{2}$$

where, $s_i^d(t)$ is the position of iteration t in the d dimension, r is the random vector in the range of [0,1], α is the weight coefficient， $s_g^d(t)$ is the plankton with high concentration. The position of the i^{th} individual is determined by the current position $s_{i-1}(t)$ of the $(i-1)^{th}$ and the position $s_i(t)$ of the food.

(2) Cyclone foraging: the second foraging mode of manta ray population, manta rays swarm forward in a spiral path to find better food. Combined with chain foraging, manta rays swarm continuously move to food in the form of a helical line [20]. The special foraging mode is conducive to the development of the optimal solution found at present. While it is beneficial to growth, rotary foraging can also be used for exploration. If satisfied $\mathrm{T} / \mathrm{Tmax} < \mathrm{Rand}$ (T is the current number of iterations and Tmax is the maximum number of iterations.), manta rays are exploited. Its mathematical model is shown in the formula (3).

$$s_i^d(t+1) = \begin{cases} s_g^d(t) + r \cdot \left(s_g^d(t) - s_i^d(t)\right) + \beta \cdot \left(s_g^d(t) - s_i^d(t)\right)\ i = 1 \\ s_g^d(t) + r \cdot \left(s_{i-1}^d(t) - s_i^d(t)\right) + \beta \cdot \left(s_g^d(t) - s_i^d(t)\right)\ i \neq 1 \end{cases} \tag{3}$$

$$\beta = 2e^{r_1\frac{T-t+1}{T}}\sin(2\pi r_1) \tag{4}$$

When $T / Tmax \geq Rand$, manta ray colony will carry out exploration, and its mathematical model is as follows as shown in formula (5) and (6)

$$s_i^d(t+1) = Lb^d + r \cdot (Ub^d - Lb^d) \tag{5}$$

$$s_i^d(t+1) = \begin{cases} s_r^d(t) + r \cdot \left(s_r^d(t) - s_i^d(t)\right) + \beta \cdot \left(s_r^d(t) - s_i^d(t)\right) i = 1 \\ s_r^d(t) + r \cdot \left(s_{i-1}^d(t) - s_i^d(t)\right) + \beta \cdot \left(s_r^d(t) - s_i^d(t)\right) i \neq 1 \end{cases} \tag{6}$$

(3) Somersault foraging: the last foraging method of manta rays, in which the position of food is regarded as a central point around which each manta rays turn. Flipping each manta ray makes it possible to move to any location in a new search field, which is located between its current position and its symmetrical position[20]. As the number of iterations decreases adaptively, the disturbance to the current situation decreases, and the manta ray population gets closer to the food and the best food. The mathematical expression of this foraging mode is as follows, as shown in formula (7).

$$s_i^d(t+1) = s_i^d(t) + S \cdot \left(r_2 \cdot s_g^d - r_3 \cdot s_i^d(t)\right), i = 1, \dots, N \tag{7}$$

where S is the tumbling coefficient of manta rays, $S = 2$, r_2 and r_3 are two random numbers in $[0, 1]$. The effective combination of the three foraging methods can effectively improve the efficiency of the algorithm. When $\gamma < 0.5$, the manta ray swarm uses a cyclone foraging scheme, and select switch is used for exploration or exploitation in cyclone foraging. When $\gamma \geq 0.5$, chain feeding was used. After the first two methods, the flipping foraging strategy is used to obtain the final optimal solution.

2.2 Mathematical model of reactive power optimal dispatch

Reactive power optimal dispatch is an essential part of optimal power flow in the power system. The purpose of reactive power optimal dispatch is to reduce operating cost, improving the voltage quality of each node in the power system, and reduce network loss with as little reactive power input as possible. Specifically, when the system's operation mode and control variables are determined, the appropriate value of control variables can be selected to make the system operation meet all constraints, and all performance indicators of the system can be optimized. The reactive power optimal dispatch model is generally composed of the objective function, power constraints, and variable constraints. On the premise of ensuring the voltage quality, the terminal voltage of the generator, the system's reactive power compensation capacity, and the tap of the transformer should be adjusted appropriately to reduce the active power loss of the system network.

2.2.1 Objective function

The objective function reflects that one or more indicators are optimal, so there are usually many choices. In this paper, from an economic point of view, a mathematical model is established to minimize the system's active power loss. The objective function expression is as follows:

$$\min(p_{loss}) = \sum_{i=1}^{N}\sum_{j=1}^{N} G_{ij}\,(V_i^2 + V_j^2 - 2V_iV_j\,cos\delta_{ij}) \tag{8}$$

Where: N is the number of system branches participating in the calculation of network active power loss; G_{ij} is the branch conductance between two nodes, V_i、V_j is the voltage of node i and node j, respectively. δ_{ij} is the phase angle difference between two nodes.

2.2.2 Constraints

The function of constraints is to ensure that the system is in a normal operation state when the reactive power optimization dispatching is carried out. The constraints are divided into the following two kinds of constraints.

(1) Equality constraint conditions: The essence of the equality constraint of optimal reactive power dispatch is the power balance equation of nodes in the system.

$$\begin{cases} P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N} V_j(G_{ij}\,cos\delta_{ij} + B_{ij}\,sin\delta_{ij}) = 0 \\ Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N} V_j(G_{ij}\,sin\delta_{ij} - B_{ij}\,cos\delta_{ij}) = 0 \end{cases} \tag{9}$$

Where V_i，V_j is the voltage amplitude of node i and j, respectively; P_{Gi}、Q_{Gi} is the active output and reactive power output of the i[th] generator, respectively; P_{Di}、Q_{Di} is the active load and reactive load of node i respectively G_{ij}、B_{ij} is the real part and imaginary part of the elements in row i and column j of the system admittance.

(2) Inequality constraints: there are two variables in power system reactive power optimization, namely control variable and a state variable. The inequality constraints of control variables are as follows.

$$\begin{cases} T_t^{min} \le T_t \le T_t^{max}\,, k \in NT \\ V_g^{min} \le V_g \le V_g^{max}\,, k \in NG \\ Q_c^{min} \le Q_c \le Q_c^{max}\,, k \in NC \end{cases} \tag{10}$$

Among them: T_t is the tap position with transformer, T_t^{min} and T_t^{max} are the upper and lower limits of the transformer tap position. NT is the number of transformers, V_g is the voltage amplitude of generator terminal. V_g^{max} and V_g^{min} are the maximum and minimum value of generator terminal voltage, NG is the number of transformers. Q_c is the reactive power compensation capacity, Q_c^{max} and Q_c^{min} are the maximum and minimum value of reactive power compensation capacity, NC is the number of transformers.

The constraints of state variables are as follows:

$$\begin{cases} V_i^{min} \le V_i \le V_i^{max} \\ Q_g^{min} \le Q_g \le Q_g^{max} \end{cases} \tag{11}$$

Where: V_i is the voltage amplitude of each load node, V_i^{max} and V_i^{min} are the maximum and minimum value of voltage amplitude of each load node, Q_g is the reactive power injected into each generator; Q_g^{max} and Q_g^{min} are the maximum and minimum value of reactive power injected by each generator.

3 Application of MRFO in optimal reactive power dispatch

In this paper, the system's electricity and the security of the system are considered when the optimal dispatching of reactive power is carried out. Therefore, the objective function is to minimize the network's active power loss of the system. Simultaneously, the node voltage overrun and generator reactive power output overrun are treated as penalty functions. Therefore, the objective process of reactive power optimization is changed from formula (1) to:

$$min\,F = P_{loss} + \lambda_1 \sum_{k=1}^{N_G} (\Delta Q_{Gi})^2 + \lambda_2 \sum_{j=1}^{N_{notG}} (\Delta V_i)^2 \tag{12}$$

Among them are:

$$\Delta Q_{Gi} = \begin{cases} Q_{Gimin} - Q_{Gi}, & Q_{Gi} < Q_{Gimin} \\ 0, & Q_{Gimin} < Q_{Gi} < Q_{Gimax} \\ Q_{Gi} - Q_{Gimax}, & Q_{Gi} > Q_{Gimax} \end{cases} \tag{13}$$

$$\Delta V_i = \begin{cases} V_{imin} - V_i, & V_i < V_{imin} \\ 0, & V_{imin} < V_i < V_{imax} \\ V_i - V_{imin}, & V_i > V_{imax} \end{cases} \tag{14}$$

In the formula, P_{loss} is the active power loss of system network obtained from power flow calculation, λ_1 is the penalty factor of generator reactive power output exceeding the limit, λ_2 is the penalty factor of voltage amplitude exceeding the limit. N_{notG} is the number of all nodes except generator; N_G is the number of generator nodes; Q_{Gimin} and V_{imin} are the lower limit values of state variables; Q_{Gimax} and V_{imax} are the upper limit values of state variables.

In this paper, the MRFO algorithm is used to solve the optimal reactive power dispatch problem. The purpose is to find the minimum value of active power loss in the system network. In the MRFO algorithm, the position of manta rays in the search space corresponds to the control variables of reactive power optimization, including generator terminal voltage, adjustable transformer tap, reactive power compensation capacity. The search space (dimension) of each manta ray is the number of control variables

$$S_i = [V_{G1}, \ldots, V_{GN}, T_{t1}, \ldots, T_{tN}, Q_{t1}, \ldots, Q_{tN}] \tag{15}$$

Where V_{Gi} is the generator terminal voltage, and GN is the number of generators in the system. Where T_{ti} is the transformer ratio, and tN is the number of transformers in the system. Where Q_{ti} is the reactive power provided by the reactive power compensator, GN is the number of generators in the system.

4 Experimental results

In this section, the IEEE30 bus system is selected to calculate the optimal reactive power dispatch. The topology of the selected system is shown in Figure 1. The generator is installed at nodes 1, 2, 5, 8, 11, and 13, and the generator terminal voltage regulation range is 0.9-1.1. Four voltage regulating transformers are located at 6-9, 6-10, 4-12, and 27-28 of the line, and the regulating range of the transformers is 0.85-1.15.

Eight parallel reactive power compensation devices are located at nodes 12, 15, 17, 20, 21, 23, 24, and 29. The range of each reactive power compensation device is 0-10Mvar. The power output of each node generator, the tap position of the transformer and the capacity of the parallel compensator are all within the range of constraints.

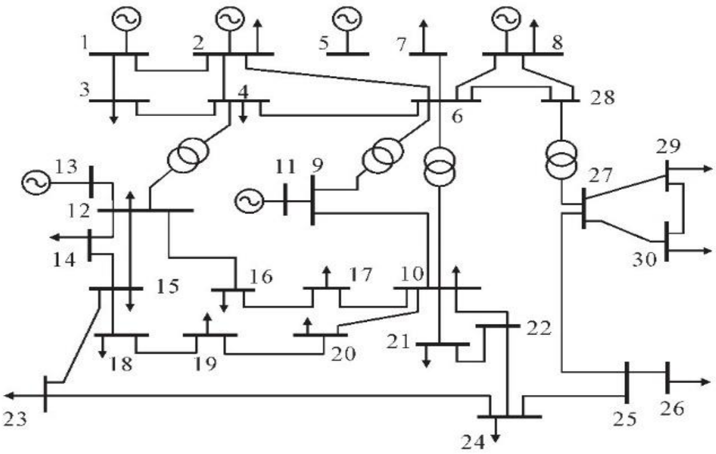

Fig. 1. An IEEE 30 nodes system

In order to verify the feasibility of MRFO in reactive power optimization, PSO[16], GWO[18], MFO[19], and WOA [17] are used to compare with it. For all the algorithms involved in this paper, the number of iterations is set to 200, and the search agent is set to 20. The master power flow calculation package is used for power flow calculation. The basic parameters of all algorithms are shown in Table 1.

Table 1. The initial parameter of all algorithms

Algorithm	Parameter
PSO[16]	$c_1 = c_2 = 2, w = 0.7298, v_{max} = 5, v_{min} = -5$
GWO[18]	$a = [2,0]$
MFO[19]	$b = 1, t = [-1,1], a \in [-1,-2]$
WOA[17]	$a = [2,0], b = 1$
MRFO	$S = 2$

The initial setting of the system is as follows: the generator terminal voltage is 1.0, the transformer transformation ratio is 1.0, and the reactive power compensation switching value is set to 0. Through the calculation of power flow, the active power loss of the system network obtained in this initial case is: $P_{loss} = 21.0188$MW. Each algorithm runs independently 30 times, and the results of network active power loss obtained by various algorithms are recorded in Table 2. Table 2 contains the best value, average value, and standard deviation obtained by different algorithms under 30 independent operation conditions.

Table 2. Experimental results of all algorithms (Unit: MW)

Algorithm	Best	Mean	Std.
PSO[16]	16.0643	16.6271	0.2919
GWO[18]	15.9991	16.0859	0.0660
MFO[19]	15.9328	15.9529	0.0359
WOA[17]	15.9772	16.3127	0.2173
MRFO	15.8871	15.8878	0.0007

By analyzing the data in Table 2, we can know that the network active power loss obtained by using MRFO for reactive power optimization is the minimum. For the 'Best' value obtained by various algorithms for 30 times, the MRFO wins by 15.8871MW, and the 'Mean' MRFO wins by 15.8871MW. The two indexes of 'Best' and 'Mean' show that the optimization accuracy of MRFO is higher than other algorithms, which shows the feasibility of MRFO in reactive power optimization. The parameter 'Std.' indicates that MRFO has better stability than different algorithms. The average value of network active power loss obtained by all algorithms is compared with that of the original network functional power loss. The PSO algorithm is used for optimization; the network's operating power loss decreases by 20.8942% compared with the initial value. The GWO algorithm is used for optimization. The active power loss of the structure reduces by 23.4690% compared with the initial value. When the MFO algorithm is used for reactive power, the network's dynamic power loss decreases by 24.1018% compared with the initial value. When the WOA algorithm is used for reactive power, the network's active power loss decreases by 22.3900% compared with the initial value. The MRFO is used for optimization, the network's active power loss reduces by 24.4115% compared with the initial value. When MRFO is used for reactive power optimization, the system's network active power loss is minimum. Fig. 2 is the convergence curve of reactive power optimization under the IEEE30 node.

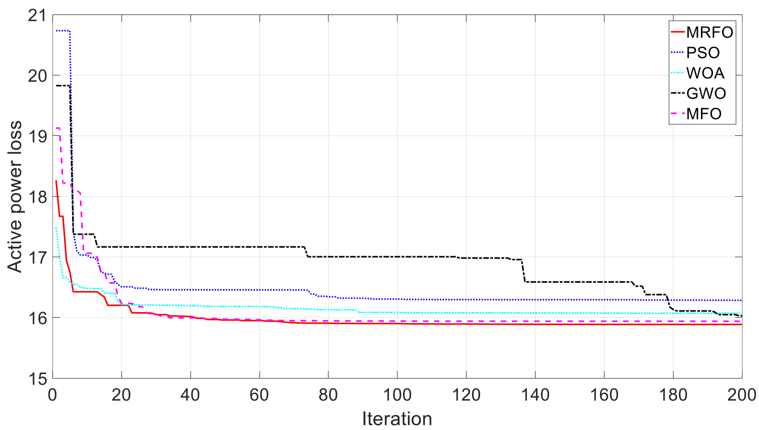

Fig. 2. A comparison of the proposed scheme's performance diagram with algorithms, e.g., the PSO, GWO, MFO, and WOA schemes for the IEEE 30 node system.

As can be seen from Fig.2, the compared results of the proposed scheme with the PSO, GWO, WOA, and MFO schemes, the convergence rate of the MRFO is obviously better than that of the PSO, GWO, WOA, and MFO. The MRFO can find the minimum network loss faster, which is an advantage of MRFO in reactive power optimization.

Fig.2 shows that when the MRFO algorithm is used for reactive power optimization, the minimum loss obtained is better than the other four algorithms, consistent with the data shown in Table 2. It shows that when the MRFO algorithm is used for reactive power optimization, this algorithm's optimization accuracy is the best.

5 Conclusion

In this paper, we suggested a solution to the reactive power optimization problem (RPSP), e.g., the IEEE30 bus power system based on a new evolutionary algorithm of the Manta Ray Foraging Optimization (MRFO). The objective function of optimization was to minimize the system's active power loss. The penalty technique has been used to deal with the figuration control variables out of the optimization constraints. Experimental results of the proposed MRFO scheme were compared with the other methods, e.g., the Particle swarm optimization(PSO), Grey wolf optimizer (GWO), Moth-flame optimization algorithm(MFO), and Whale optimization algorithm(WOA) for the RPSP, such as the IEEE 30 bus system. Compared results show that the MRFO algorithm can effectively produce stable, good convergence, and high reliability, which is feasible in solving reactive power optimization problems.

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