Optimization model of power system unit commitment allocation problem considering the value-point effect and its simulation analysis

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Abstract

Based on the studies of the allocation problem of large-scale unit commitment in the power system, a mathematical optimization model is established involving the valve point effect of unit commitment. The optimal solution obtained from the method that the standard artificial fish swarm algorithm (AFSA) is applied to the commitment allocation problem of three-units improves the result recently reported in literature. Considering the visual selection of AFSA affects foraging, huddling and other activities and convergence performance much when increasing the unit size, the proposed improved artificial fish swarm algorithm(IAFSA) in this paper uses the linear decreasing vision function instead of the fixed vision. It can speed up the convergence, jump out of local convergence effectively, and obtain a global optimal solution. Finally, the simulation comparing experiment is conducted for commitment allocation problem of ten-units. The simulation result shows that the IAFSA not only improves the convergence but also enhances the global search capability.

Keywords: unit commitment, valve point effect, linear decreasing

1 Introduction

Large-scale unit combination problem (UC) in the power system is a high-dimensional, discrete, nonlinear engineering optimization problems [1, 2]. It belongs to the category of NP - Hard problem completely. For a long time, these kind of combinatorial optimization problems are widely concerned. As is known to all, when the size of the system is large, it's very difficult to obtain optimum solution accurately in theory. It is very necessary to study the large scale unit combination problem. Because the traditional optimization algorithm in solving the problem of UC all has some defects more or less, it often can not get ideal global optimum solution. The modern intelligent optimization algorithm for handling constraints is convenient and has strong global search ability, so its application in the optimal combination problem has showed strong advantage. Some progress has been made in this field currently. Some modern intelligent algorithms, such as particle swarm optimization (PSO) [3, 4], genetic algorithm (GA) [5], artificial neural network (NN), tabu search (TS), simulated annealing (SA) etc. have been successfully applied to this kind of problem.

However, for the above modern intelligent optimization, the original algorithm also exists some shortage, such as complicated calculation, easy to fall into local optimum and premature convergence. But AFSA applied to solving large scale UC, its research is still rare. AFSA belongs to a class of swarm intelligence optimization algorithm based on animal behaviour [6, 7]. The AFSA's structure is simple, and it is easy to implement, has fast convergence rate and higher computational efficiency. The tracing behaviour inside is easy to find the global optimal solution of the problem, has a strong ability to avoid falling into local extremum and the search space also have certain adaptive ability. AFSA is not sensitive to initial value and parameter selection, has stronger robustness and better convergence performance. At present, AFSA has been successfully applied to solving a large number of nonlinear, non-differentiable, high-dimensional complex optimization problems, such as optimization of forward neural network, signal processing, TSP, and achieved some progress.

In this paper, AFSA is applied to solve UC. Inspired by the idea to UC in literature [8], if its field of vision in AFSA is too big, convergence speed will be slow and if the vision is too small, artificial fish algorithm easy to fall into local optimal solution. Therefore, IAFSA is proposed in this paper, the main improvement is that the algorithm uses the linear decreasing vision function instead of the fixed vision. The advantage of IAFSA is that early vision of artificial fish is larger, the easier it is to find the global optimal value. With the deepening degree of evolution, vision continuously decreased, and the smaller the field of vision, it is more conductive to get local optimal solution. Therefore, to select the appropriate value of vision can balance the global and local search ability of AFSA, get better approximate

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solutions. Finally, the standard of AFSA and IAFSA applied to UC of the same problem, the experimental results showed that IAFSA in solving UC has better accuracy and stronger global search ability.

2 Mathematical model of UC considering valve point effect

UC is also known as short-term planning problem, which arrange the units' on and off reasonably to make the system to minimize the total operation cost while meeting all kinds of unit operation conditions in a certain period.

In the actual situation, the turbine inlet valve produces the valve point effect when it is opened suddenly, which affects obviously the solution for the optimal allocation. So, the aim of this paper is a static UC optimization problem considering the valve-point effect. UC optimization model is established with restraint to load equalization and units' output etc., to obtain minimal generation costs.

2.1. OBJECTIVE FUNCTION

$$\min F = \min \sum_{i=1}^{N} F_i(P_i) , \tag{1}$$

where F is the total electricity costs, N is the total number of generators of the system, P_i is the meritorious power of the i generator and F_i is the electricity cost of the i generator respectively.

Generally, $F_i(P_i)$ can be described as follows:

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i , \tag{2}$$

where a_i , b_i and c_i stand for the i generator running character parameters.

If considering the valve point effect, then

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + E_i , \tag{3}$$

$$E_i = \left| e_i \times \sin(f_i \times (P_{i\min} - P_i)) \right| , \tag{4}$$

where e_i and f_i stand for the valve point effect coefficient of the i generator respectively, and $P_{i\min}$ is the minimum output of the i generator.

Research shows that the valve point effect influences the optimal distribution scheme obviously [9].

2.2. CONSTRAINTS

When the system is running, it subjects to the power balance constraints and the power generation unit operation constraints. The power balance constraint is that the active power generator is equal to the sum of the system total network loss and the system total load.

The power balance constraint

$$\sum_{i=1}^{N} P_i = P_L + P_D , \tag{5}$$

where P_L is the system loading and P_D is the system network loss.

When the electric system network cover is dense we can ignore network loss. According to the thought of the literature [9, 10] and combining with the practical situation, we ignore network loss in this paper. Then, the power balance constraint is simplified as follows:

$$\sum_{i=1}^{N} P_i = P_L . \tag{6}$$

The power generation unit output constraint

$$P_{i\min} \le P_i \le P_{i\max} , \tag{7}$$

where $P_{i\min}$ and $P_{i\max}$ are the output minimum value and the output maximum value of UC respectively.

In summary, the optimization model of UC considering the valve point effect as follows:

$$\min F = \min \sum_{i=1}^{N} F_i(P_i)$$
$$S.T. \begin{cases} F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + E_i \\ E_i = \left| e_i \times \sin(f_i \times (P_{i\min} - P_i)) \right| \\ \sum_{i=1}^{N} P_i = P_L \\ P_{i\min} \le P_i \le P_{i\max} \end{cases} . \tag{8}$$

3 Description of AFSA

In this paper, the artificial fish are defined four basic behaviours, namely foraging, huddling, following and random behaviour [11, 12].We simulate four kinds of activities of fish to let them live in the environment.

3.1 RELATED DEFINITIONS

$X = (x_1, x_2, ..., x_n)$ is the state of artificial individual fish, where x_i $(i = 1, 2, ..., n)$ is the variable. $Y = f(X)$ is the food concentration of artificial fish at its current location, where Y is the objective function value. $d_{ij} = \left\| X_i - X_j \right\|$ is the distance of i and j . *step* is the maximum step size of artificial fish moving. *visual* is the vision of artificial fish. *try_number* is the number of attempts. δ is the congestion factor. N is the total number of artificial fish.

3.2 BEHAVIOUR DESCRIPTION

Foraging. Foraging is a kind of the basic behaviour of artificial fish, which is an activity that tends to food. X_i is the current state of artificial fish i. X_j is a state that selects randomly within the artificial fish's sensing.

$$X_j = X_i + Visual \cdot Rand(), \tag{9}$$

where $Rand()$ is a random number between 0 and 1. If Y_i is bigger than Y_j, make a step forward to this direction.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\| X_j - X_i^t \|} \cdot Step \cdot Rand(). \tag{10}$$

Otherwise, select a new state X_j and judge if it meets the conditions of moving forward.

If it still does not meet the conditions after trying try_number numbers, make a step forward randomly.

$$X_i^{t+1} = X_i^t + Visual \cdot Rand(). \tag{11}$$

Bunching. X_i is the current state of artificial fish i. n_f is the number of partners and X_c is the centre position in the current field ($d_{ij} < Visual$). If $\frac{Y_c}{n_f} > \delta Y_i$, it shows that there are more food around the partner and it's not too crowded. Then move a step forward to the centre position of this partner

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\| X_c - X_i^t \|} \cdot Step \cdot Rand(). \tag{12}$$

Otherwise, perform foraging behaviour.

Tailgating. X_i is the current state of artificial fish i. Y_j is the greatest partner in the current field ($d_{ij} < Visual$).

If $\frac{Y_j}{n_f} > \delta Y_i$, it shows that there are more food around X_j and it's not too crowded. Then move a step forward to the direction of X_j.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\| X_j - X_i^t \|} \cdot Step \cdot Rand(). \tag{13}$$

Otherwise, perform foraging behaviour.

Random. Random behaviour is to select a state in the field of vision, and then move to the direction. In fact, it is a default behaviour of foraging. The next position of X_i is as follows:

$$X_{i|next} = X_i + Visual \cdot Rand(). \tag{14}$$

4 Three-Unit combination experiments

In order to test AFSA has better convergence speed and higher precision. Comparing the improved particle swarm algorithm and AFSA as given in literature [8] and [13], the result is as follows:

TABLE 1 Comparing the results of three-unit combination

	overall load P *(MW)*	*all-in cost* C($)
IPSO[13]	500	5266.48
LIPSO[8]	500	5250.77
AFSA	500	5095.81

where, P is the total load for generators and C is the generating cost. Table 1 shows that solving three-unit UC with AFSA can gain higher accuracy of the approximate optimal solution, which it can balance, the global search ability and local search ability of the algorithm well, and improve the adaptive ability of the algorithm and accuracy.

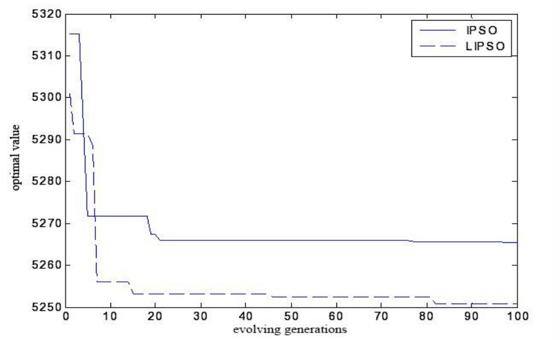

FIGURE 1 Objective function convergence curves of IPSO and LIPSO

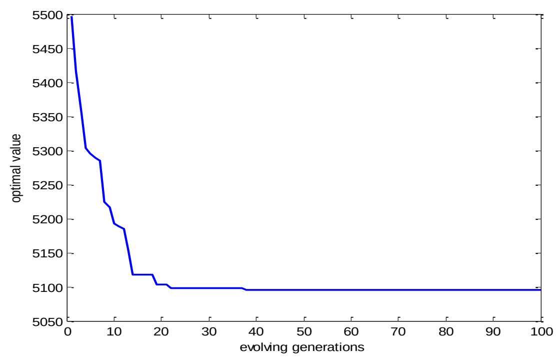

FIGURE 2 Objective function convergence curve of AFSA

Figure 1 and figure 2 shows that AFSA can obtain objective function value with better accuracy, namely the total electricity cost is less, and especially it can jump out of local convergence more effectively and obtain the global approximate optimal value.

5 AFSA based on improved vision

In the foraging behaviour of the standard AFSA, the vision is fixed. Due to the vision has great influence on each behaviour of the algorithm [14, 15, 16], its change affects the convergence performance complicatedly. Generally speaking, when the field of vision is small, the foraging and random behaviour are more frequent. On the opposite, the following and huddling become more frequent. It is not conducive to find the global extreme point for the artificial fish near the position of the global extreme value when the foraging and random behaviour happened in a large range. In general, greater the field of vision is, easier it is to make artificial fish finding global extreme value and converged. So changing the vision of artificial fish is an efficient way to improve the performance of AFSA.

If the field is too large, the convergence speed will be very slow. On the other hand, if the field of view is too small, AFSA may lead to local optimal solution. In order to overcome these disadvantages, we propose the following improvement strategies.

In the initial stages of AFSA, each artificial fish looks for solutions with a large field of vision, which will expand the scope of optimization. With the generation of algorithm increasing, the vision of fish has appropriately reduction to accelerate the rate of convergence. Therefore, in the initial stages of algorithm, to enhance the global search ability and convergence speed, the artificial fish search in the broader vision hastily with a bigger field of vision. As the search progressing, the field of vision gradually decreases and the algorithm gradually evolved into local search. The algorithm locates at the nearby area of the optimal solution and does fine search so as to improve the local search ability and the accuracy of the optimal value.

So, the vision function defined as follows:

$$f(gen) = V_{\max} - \frac{(V_{\max} - V_{\min})}{MAXGEN} \cdot gen\,, \tag{15}$$

where, $V_{\max}$, $V_{\min}$ are the upper and lower horizons respectively, gen is the evolution generation currently, $MAXGEN$ is the maximum evolution generation.

The flow chart of IAFSA as follows:

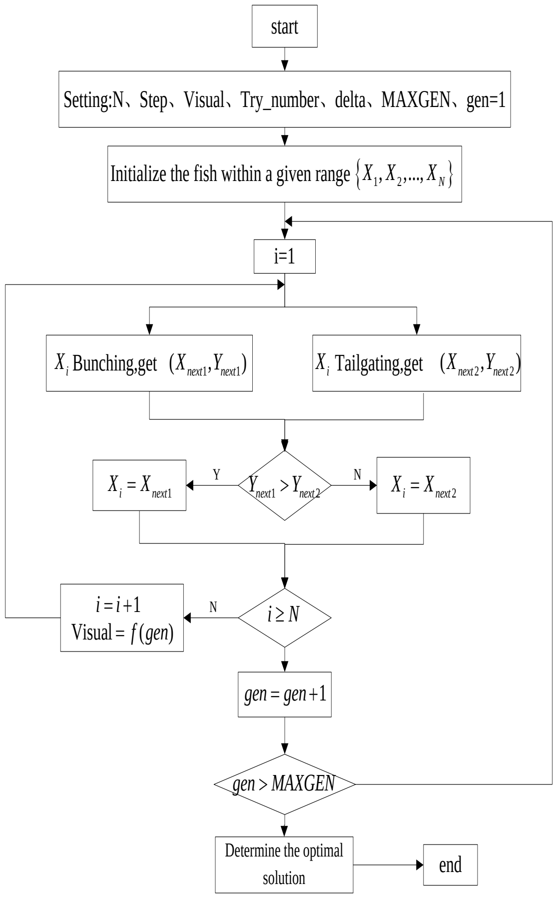

FIGURE 3 The flow chart of IAFSA

Remark 1: After the initialization of the fish, X_i is the current state of artificial fish. When fish simultaneously conduct huddling and following, comparing the objective function values of huddling and following, the algorithm chooses the bigger one.

Remark 2: When the evolution of artificial fish is complete, the algorithm uses the linear decreasing vision function instead of the fixed vision.

6 Simulation experiment

In order to test the effectiveness of the proposed algorithm (IAFSA), the simulation comparing experiment is conducted for the combination experiments of ten-unit. To make the calculation more convenient, this paper ignores system network loss. The characteristic constants of the energy dissipation, the constants of valve point effect, the upper and lower limit of the active power of ten-unit refer to the data of literature 9.

In this experiment, $fishnum$ =100, $MAXGEN$ =300, try_number =100, $delta$ =12, $visual$ =[6,15], $step$ =10, PL =2500MW, where $fishnum$ is the number of artificial fish, $MAXGEN$ is the evolution generation of fish, try_number the maximum number of trying, $visual$ is the scope of perceived distance, and PL is the total load of generators respectively.

Take the best optimization calculation results of 30 times as the value of the objective function. The simulation calculation results are shown in table 2.

TABLE 1 Comparison of simulation results of 10-unit

	overall load *P (MW)*	*all-in cost* C($)
AFSA	2500	6921.91
IAFSA	2500	6844.81

The objective function convergence curve is shown in figure 4.

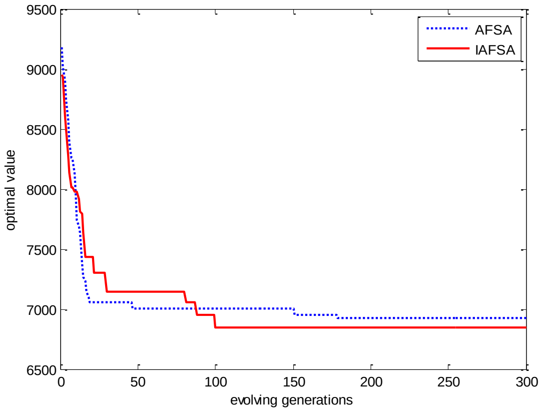

FIGURE 4 Convergence comparison charts of AFSA and IAFSA

The experimental results show that AFSA with a linear decreasing vision is better than the one with a fixed vision, and its iteration speed of IAFSA is faster. It gets the approximate optimal value near the 150th generation, while AFSA gets the approximate optimal value near the 260th generation or so. Compared with AFSA, IAFSA has the better approximate optimal value and faster rate of convergence.

7 Conclusion

This paper reviewed the rules and characteristics of AFSA, IAFSA is proposed, and it was used for solving UC problems. AFSA is a new kind of random search optimization algorithm and this algorithm adopts a bottom-up design pattern. Between the various behaviours there is relative independence and complementarily, so the convergence of the algorithm is stable. The artificial fish's vision function was improved based on AFSA. Through the analysis of the linear decrease vision function, we know that IAFSA can guarantee the algorithm to jump out of local minima areas quickly and speed up the convergence of the algorithm. Finally, the simulation comparison between different scales of UC shows that IAFSA has faster rate of convergence and higher precision while it is applied to solve large-scale UC problems, and the actual effect is satisfactory. It is easy to implement and convenient to be used in electric power systems engineering.

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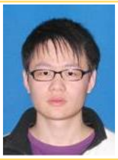

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