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Research on Large-scale Multi-target Units Combination Model Based on IAFSA

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Abstract: Because the advantages of new energy units in the whole life cycle of economy and environmental protection have been gradually highlighted. In the large-scale multi-target unit combination problem, more consideration of the composition of new energy units has become the current hot spot. This paper establishes a large-scale multi-target unit combination model, considering the two goals of economic and environmental protection, as well as the power abandonment rate, rotating reserve, unit output and other constraints of new energy units. The multi-target problem is transformed into a single target problem by adopting a multi-target processing scheme based on linear weighting method. The Improved Artificial Fish Swarm Algorithm (IAFSA) iterative hybrid algorithm is proposed. Comparison with Artificial Fish Swarm Algorithm (AFSA) shows that the proposed algorithm can globally search better, achieves more convergence and faster in large-scale and multi-objective convergence conditions.

1. Background

At present, China's power grid scale ranks the first in the world. It also ranks first in the world in the installed capacity of new energy. While achieving a series of achievements, we also face many challenges. The power supply forms of the power grid are more diversified, and the advantages of the new energy units in the whole life cycle of economy and environmental protection have been gradually highlighted. How to optimize the combination of different types of power generation units has become a hot research issue.

The literature study uses the optimized particle swarm algorithm combined with the general distribution theory to construct the dispatch model of wind-fire power generation system, which can effectively coordinate the dispatch of new energy power generation and reduce the operating cost [1]. Li et al proposes a combined energy efficiency evaluation method that considers the accident frequency constraint and analyzes the importance of each unit for the system risk improvement. Zhang et al propose a multi-stage data-driven robust unit combination model [2,3]. The influence of power network and unit operation parameters, conservatism degree and correlation control parameters are also considered. Cheng et al review the application of robust optimization in the combination decision of power system units, and compares analyzes the characteristics and adaptation scenarios of classical robust optimization and distribution robust optimization methods [4].

Gao [5] focuses on the combination problem of incorporating new energy into the system rotating standby power system unit, so as to obtain the dispatching scheme with better global economy.

Unit combination refers to the formulation of the start-stop and output plan of each unit during the dispatching cycle, generally with the lowest total cost of the system power generation, on the premise of meeting the load demand and various constraints of the power system. With the continuous expansion of the power grid scale, the number of units that need to consider the coordinated control of output is becoming larger and larger [6], and the form of unit power supply has also changed from the traditional thermal power and hydropower to the new energy units with a larger proportion of new energy units [7]. Therefore, it is necessary to consider the unit characteristics of various different forms of power generation when studying the optimal output of the unit combination [8]. At the same time, in order to solve the problem of large-scale multi-target unit combination, this paper introduces artificial fish group algorithm to build economy, carbon indicators and other multi-targets, and adopts linear weighting, segment optimization, applied to the unit start-stop output arrangement [9].

2. Multi-unit Combination Model of Power Grid

For the comprehensive demand response model, a multi-objective optimization method involving economy and carbon emission is proposed [10]. While improving the economy, the dual-carbon target policy implemented by the country is also considered, and the multi-objective function is designed as follows.

2.1. Economic Objectives

The minimum of new energy power is taken as the target function. At the same time, the output of conventional unit and energy storage device are considered.

$$\min F = \sum_{t=1}^{T}[P_L(t) - P_C(t) - P_N(t) + P_S(t)] \tag{1}$$

F is the economy of generating electricity. *T* is the schedule period. P_L(t) is the total system load at time t. P_C(t) is the total output of the conventional unit of the system at time *t*. The main consideration is thermal power and hydropower units. P_N(t) is the total output of the new energy unit of the system at time t. The main consideration is photovoltaic and wind turbine. P_S(t) is the output of the system energy storage device at time t. The energy storage device can run in charging or discharging state according to the needs of the system operation.

2.2. Environmental Protection Goals

The environmental protection target considers that the lowest CO_2 and SO_2 emissions of each unit in the whole life cycle. The whole life cycle includes production, operation and maintenance, residual recycling and treatment and other links.

$$\min E = \sum_{i=1}^{I}[E_M(i) + E_O(i) + E_R(i)] \tag{2}$$

E is the system environmental protection target value. I is the total number of units. $E_M(i)$ is the total emission of CO_2 and SO_2 in the production and manufacturing process. $E_O(i)$ is the total emission of CO_2 and SO_2 during operation. $E_R(i)$ is the total emission of CO_2 and SO_2 in the recycling process. It needs to be emphasized that in the operation satge, according to the different hours of unit operation, the emission gap is large. Formula (3) gives the mathematical model of the operation stage.

$$E_O(i)=\sum_{t=1}^{T}[(a_i p_{it}^2+b_i p_{it}^2+c_i)k_{it}] \tag{3}$$

a_i, b_i, c_i are the emission coefficient of CO_2 and SO_2 of each unit. p_{it} is the output of each period of the unit. k_{it} indicates the start/stop state of the unit. The value is 0 or 1.

3. Constraints

Constraints are an important prerequisite to ensure that the power generation plan has the optimal configuration results. Facing different constraints, the same system may have different optimal results. This paper mainly considers power balance, unit output constraint, unit start-stop time constraint and unit climbing constraint.

3.1. Limit on Power Abandonment Rate of New Energy Units

Considering the energy storage device, the system power stability can be adjusted to a certain extent. In the mathematical model establishment of this paper, the charging and discharging two working states of the energy storage device have been considered. Therefore, in the power balance constraint, the unit is considered to equal the output to the system load. In order to ensure the utilization rate of new energy units, the power abandonment rate constraint of new energy units is considered in the system.

$$Z_N \le Z_{set} \tag{4}$$

Z_N is the power abandonment rate of the new energy unit during operation. Z_{set} is the maximum power abandonment rate allowed by the system.

3.2. Rotate the Standby Constraint

To ensure the reliability of the power supply, the power system requires the generator set to keep the necessary generating capacity. In order to ensure the reliability of the rotating reserve capacity, more conventional generating sets and energy storage devices are generally considered.

$$\sum_{i=1}^{I}k_{it}p_i \ge P_L(t)+R(t) \tag{5}$$

$R(t)$ is the spare capacity of the system at time t.

3.3. Output Constraint

Because of the limitations of installed capacity and operating stability, each type of unit has its output maximum and minimum value. The power of each unit during operation shall not exceed the limit.

$$p_{i,\min} \le p_{it} \le p_{i,\max} \tag{6}$$

$P_{i,min}$ is the minimum output value of unit i. $P_{i,max}$ is the maximum output value of unit i.

3.4. Unit Start and Stop Constraints

All types of units have start and stop time requirements. Frequent start and shutdown will seriously affect the service life of the unit. Because of the large inertia constant of hydropower and thermal power units, the frequent start and stop will affect the service life of the generator set shaft system, and even affect the power flow distribution and stability of the whole system. Photovoltaic and w ind turbine due to sunshine, regular maintenance and other factors, also have the maximum continuous operation requirements, comprehensive consideration as follows.

$$T_{i,\min} \le T_i \le T_{i,\max} \tag{7}$$

T_i is the continuous operation time of unit i. $T_{i,min}$ is the shortest continuous operation time of unit i. $T_{i,max}$ is the longest continuous operation time of unit i.

3.5. Unit Climbing Constraint

The increased or reduced output per unit time is called climbing rate and landslide rate, respectively. In the economic dispatching of the power system, due to the introduction of the unit climbing speed constraint, the dispatching decision of the unit is not only the spatial correlation, but also the temporal correlation in the whole dispatching cycle, so that the system mathematical model is more specific.

$$\begin{cases} p_{it} - p_{i,t-1} \le G_{iu} \\ p_{i,t-1} - p_{it} \le G_{id} \end{cases} \tag{8}$$

G_{iu} is the maximum climbing rate of unit i. G_{id} is the maximum landslide rate of Unit i.

4. Multi-objective Processing Strategy

The model uses a multi-objective processing strategy based on the linear weighting method to normalize each objective function for a uniform dimension.

$$h(x) = \frac{f(x) - f_{\min}}{f_{\max} - f_{\min}} \tag{9}$$

$h(x)$ is the target function after the programming norm. $f(x)$ is the original target function. f_{min} is the minimum of the original target function. f_{max} is the maximum value of the original target function.

The multi-objective problem is transformed into the single objective problem in the same dimension.

$$\min Y = \sum_{i=1}^{n} w_i h_i(x) \tag{10}$$

$$\sum_{i=1}^{n} w_i = 1, w_i > 0 \tag{11}$$

w is the weight value of the objective function after normalized processing.

According to the above steps, the target in the model can get the target function of both economy and environmental protection. Among them, the minimum value and the maximum value of each original target take the target function value of the maximum output and the maximum hourly output of all the units in the operation state, respectively.

$$\min Y = w_1 F^{'} + w_2 E^{'} \tag{12}$$

$$\begin{cases} F^{'} = \dfrac{F - F_{\min}}{F_{\max} - F_{\min}} \\ E^{'} = \dfrac{E - E_{\min}}{E_{\max} - E_{\min}} \end{cases} \tag{13}$$

w_1 and w_2 are the weight value of the objective function after normalized processing.

5. Artificial Fish Swarm Algorithm

The artificial swarm algorithm simulates four biological behaviors of fish: foraging, clustering, rear-end, and random swimming. Parameters such as visual field, step length, crowding factor, and number of population individuals are defined in the algorithm. Through the behavioral selection of the artificial fish after each iteration, the fish was gradually moved to the area of higher food concentration for finding the optimal solution.

Artificial fish group algorithm is an intelligent algorithm, which has the advantages of easy implementation, low sensitivity to the initial value, fast early optimization speed, and strong robustness, and has good results when solving nonlinear optimization problems. In addition, the algorithm also has the characteristics that other intelligent algorithms do not have. For example, AFSA avoids complex processes, and each iteration produces populations much more directional. The algorithm prevents the occurrence of precocious maturity, and the requirements for parameters are more relaxed.

For the shortcomings of artificial fish algorithm, this paper designs an improved algorithm, IAFSA iterative hybrid algorithm. Improve the convergence performance and global search ability of the algorithm in the late optimization stage, and test the improvement algorithm with the test function to test whether the improvement scheme is effective. The core idea of the IAFSA iterative hybrid algorithm is to obtain the appropriate initial value σ with the fast global optimization ability of $AFSA_0$, Put it into the Newton iterative method, so that different iterative initial values can be obtained according to different conditions, effectively solve the problem of convergence is not.

First set the AFSA parameters. In a *p*-dimensional target search space, there are *N* artificial fish forming a colony. The state of each artificial fish can be expressed as $\sigma =(\sigma_1,\sigma_2 ... ,\sigma_p)$, where $\sigma_i(i=1,2... ,p)$ is the variable to be optimized. The fitness value of the current location of the artificial fish is $\rho=f(\sigma_n)$. Artificial fish distance between individual is expressed as $d=||\sigma_i–\sigma_j||$. The perceptual range of artificial fish is expressed as *v*. The moving step of artificial fish is expressed as *s*. The crowding factor is expressed as *δ*. The maximum number of attempts per foraging by the artificial fish is expressed as *t*. The maximum number of board replacements is expressed as N_{max}.

After setting the basic parameters of AFSA, calculate the fitness value *ρ* of each artificial fish in the initial school and compare the value. According to the requirements, take the minimal value artificial fish state *σ* and assign it to the male to board. Each artificial fish simulates foraging behavior, rear-end pursuit behavior, swarm behavior and random behavior respectively, and selects the best behavior by comparing their fitness values.

The optimal solution σ_0 obtained by AFSA was substituted into the Newton iteration formula, and the maximum iteration number N_{max} and iteration accuracy E_{pre} were set. When the result reached the iteration accuracy and the iteration number was less than N_{max}, the final result σ_n was output. Otherwise, the calculation continues. The mixed algorithm process is shown in Figure 1 as below.

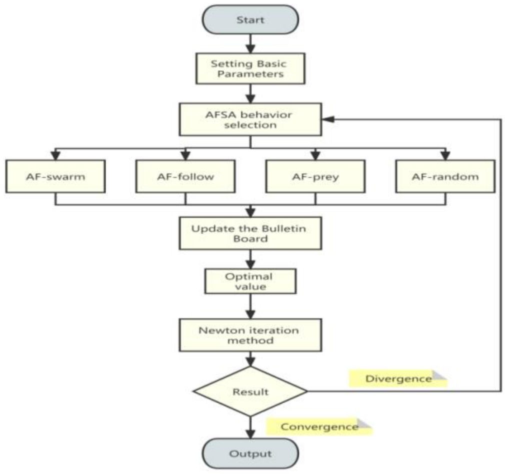

Figure 1: Algorithm flow chart.

6. Example Calculation and Result Analysis

To verify the effectiveness of the algorithm and model in handling multi-objective problems, multi-objective optimization simulation experiments for 100,200,400,800 units are implemented. At the same time, adjust the system load demand equally. For example, if the unit size is expanded to twice the original, then the load demand of each period of the system should also be expanded to twice the original. In order to simulate the gradually increasing development trend of the proportion of new energy units, the proportion of various types of units is shown in Table 1 as below.

Table 1: Unit allocation proportion.

Total number of units	Thermal power units	Hydroelectric units	PV units	Wind units	Energy storage unit s
100	50	15	15	15	5
200	80	30	40	40	10
400	150	70	70	70	40
800	250	120	170	170	90

Then, compare the calculation time of the conventional artificial fish group algorithm and the proposed IAFSA iterative hybrid algorithm in this paper, as shown in Figures 2-5. It can be seen that for the system of 100 units and 200 units, the improved algorithm iteration speed is slightly better than the conventional algorithm, and the two algorithms are basically the same in the iteration target value. The number of iterations required for both algorithms increases as units expand to 400 and 800. At the same time, the improved algorithm faces the increasing number of new energy units, and has higher optimization efficiency and stronger global search ability in complex situations, and the convergence point is also better than the conventional algorithm. This shows that the improvement algorithm iterfaster when solving multi-objective problems.

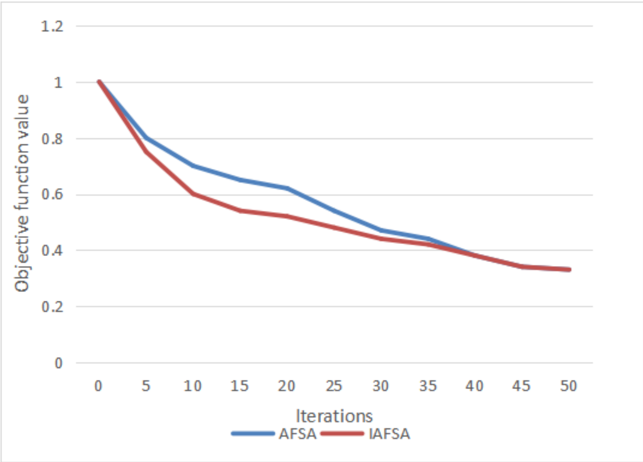

Figure 2: Comparison of algorithms for 100 units.

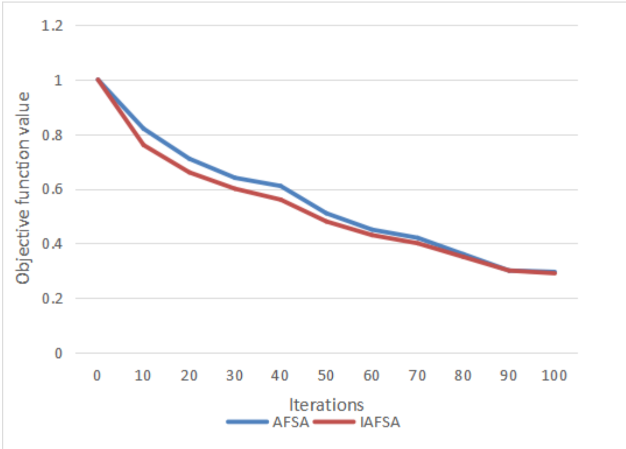

Figure 3: Comparison of algorithms for 200 units.

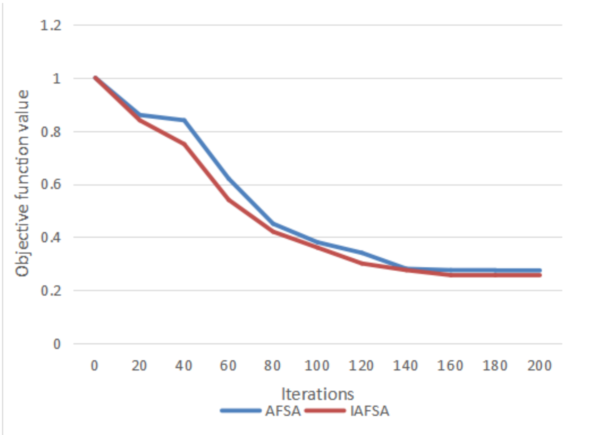

Figure 4: Comparison of algorithms for 400 units.

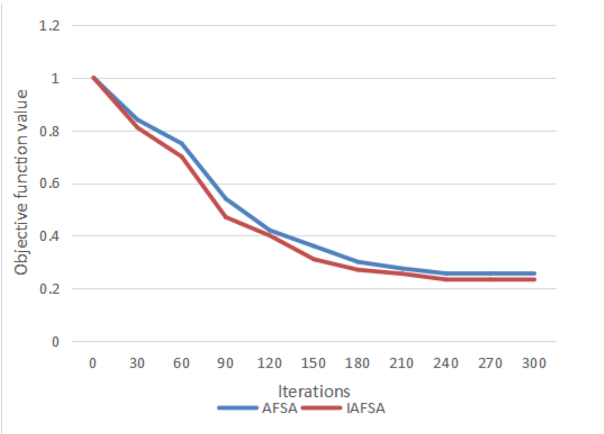

Figure 5: Comparison of algorithms for 800 units.

Then, to verify the effectiveness of the improved algorithm in practical engineering, the computational time required for conventional algorithms and improved algorithms was recorded in 100, 200, 400 and 800 unit systems.

When the improved algorithm is adopted, the artificial fish simultaneously updates the start-stop plan and output of the unit in each iteration, calculates the total economic and environmental cost, and performs the operation by comparing the size of the total cost. As shown in Figure 6, the improved algorithm does not have much advantage over the conventional algorithm when the number of units is small. Because the AFSA algorithm with improved algorithm, the operation steps increased. When the amount of data is small, it does not save time. With the increase of the number of units and the increase of the proportion of new energy units at special times, the advantages of finding advantages under the multi-machine combination are gradually highlighted. The improved algorithm shortens the number of iterations and improves the solution efficiency. Therefore, the proposed algorithm is more suitable for the optimal solution of large-scale unit access systems.

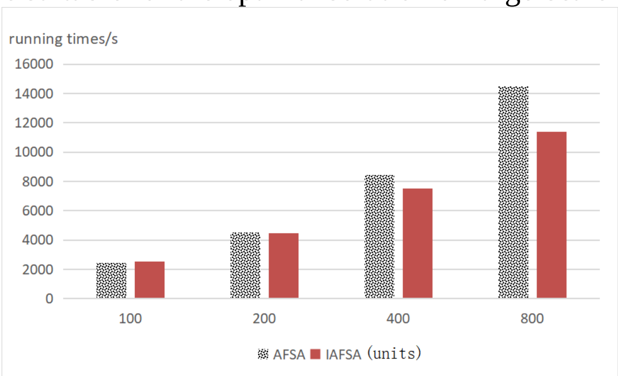

Figure 6: Computation time comparison.

7. Conclusions

In order to solve the problem of large-scale and multi-objective units, this paper constructs a power grid unit combination model and designs a multi-objective processing strategy based on linear weighting method. The model considers the two objectives of economy and environmental protection and a variety of constraints. By adopting the multi-objective processing scheme based on linear weighting method, the multi-objective problem is transformed into a single objective problem. To solve the large-scale multi-objective unit combination problem, the addition of IAFSA better solves the problems that AFSA is easy to fall into local optimization, and the convergence is faster.

Although the IAFSA convergence time is slightly longer, the resulting convergence rate is higher in the large-scale, multi-objective case. In the next step, the research will focus on how to improve the general applicability of the algorithm, and strive for better matching degree and calculation speed advantages in units of various sizes. For the future system online deployment in the unit output scheduling to improve the excellent decision-making mode.

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