Optimal Dispatching of Microgrid Based on Improved Particle Swarm Optimization

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Abstract. In order to enable the microgrid to meet the system load demand while performing economically optimal operation scheduling, this paper establishes an island-type microgrid model, which is optimized by using an improved immune particle swarm algorithm, and the inertia weight and learning the two parameters of the factor are improved. On the basis of the immune particle swarm algorithm, a power exponential function operator is added to the inertia weight to improve the search ability of the algorithm, in order to reduce the computing time, the dynamically adjusted learning factor is introduced to optimize the immune particle swarm algorithm the local search ability is stronger. Two examples are selected to verify the algorithm, the results prove that the method has better global convergence and local search capabilities and the convergence speed has been improved.

1. Introduction

As the energy structure changes, distributed power generation has been used more and more because of its advantages such as low loss and environmental protection \cite{1}. Microgrids have been widely used due to their flexibility and intelligence. With the continuous popularization and development of microgrid technology, how to optimize the economic and environmental benefits of microgrid has become a very important research topic \cite{2}.

This paper establishes a multi-objective optimization dispatching model for island microgrid including photovoltaic array (PV), wind turbine (WT), micro gas turbine (MT) and battery (BA). On the basis of satisfying the constraints of power balance, micro source output and battery operation, the improved immune particle swarm optimization algorithm was used to optimize the scheduling, and the optimal output of each micro source was obtained. The inertia weight and learning factor were considered to change according to the number of iterations to further improve the optimization effect. The typical load, light intensity, wind speed and other data of a certain region in summer and winter were analyzed for example to verify the effectiveness of the model.
2. Microgrid model

2.1. Mathematical Model of Microgrid
In this paper, we study a typical island microgrid structure, in which the distributed power supply includes photovoltaic array, wind turbine, micro gas turbine and battery energy storage system, in a coordinated and stable power supply for local load.

2.1.1. Photovoltaic array model
The output power of the photovoltaic array has nonlinear characteristics and is greatly affected by environmental factors, mainly related to factors such as light intensity and temperature. The mathematical expression of the output power of the photovoltaic array is shown in formula (1):

$$P_{PV} = P_{STC} \frac{G_n}{G_{STC}} \left[1 + k(T_r - T_{ref})\right] \quad (1)$$

Among them, $G_{STC}$ is the irradiation intensity under standard test conditions (solar irradiance 1000, battery surface temperature 25 degrees Celsius), $G_n$ is the irradiation intensity at the working point, $k$ is the power temperature coefficient (the power decreases by 0.3% for each degree of temperature rise), $T_r$ is the surface temperature of the photovoltaic cell, $T_{ref}$ is the reference temperature, $P_{STC}$ is the rated output power (kW) under standard test conditions.

2.1.2. Wind turbine model
The output power of the fan is mainly determined by the wind speed at the hub of the fan. The mathematical expression of the output power of the fan is as shown in formula (2):

$$P_{WT} = \begin{cases} 
0, & 0 \leq v \leq v_{ci} \\
\frac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} P_r, & v_{ci} \leq v \leq v_r \\
P_r, & v_r \leq v \leq v_{co} \\
0, & v \geq v_{co} 
\end{cases} \quad (2)$$

Among them, $v_{ci}$ is the cut-in wind speed, $v_r$ is the rated wind speed, $v_{co}$ is the cut-out wind speed, $P_r$ is the rated power.

2.1.3. Micro gas turbine model
Micro gas turbines use natural gas and other fuels as energy sources to generate electricity, and play an important role in coordinated operation as a supplementary energy source in the micro grid. The expression between the fuel cost of the gas turbine and the actual output power is as shown in formula (3):

$$C_{MT} = \frac{P_{MT} C_{ng}}{Q\eta} \quad (3)$$

Among them, $C_{MT}$ is the fuel cost consumed at the current power, $P_{MT}$ is the actual power generated by the gas turbine in a certain period of time, $C_{ng}$ is the price of one cubic meter of natural gas, $Q$ is the heat generated by the complete combustion of one cubic meter of natural gas, $\eta$ is the energy conversion efficiency of the micro gas turbine.

2.1.4. Energy storage device model
The energy storage system has the dual characteristics of load and power supply. In the period of low load, the energy storage system can be used as the load to store the electric energy. In the period of
high load, the energy storage system can release the previously stored electric energy to supply power for the power system and reduce the power supply pressure of the power system. During the working process of the battery, the actual capacity is different from the rated capacity, and its capacity is affected by the use temperature. The mathematical expression of the actual capacity of the battery is shown in Equation (4):

\[ C = C_r \left[ 1 + k \left( T_T - T_{STC} \right) \right] \] (4)

Among them, \( C_r \) is the rated capacity under standard test conditions, \( k \) is the temperature coefficient of capacity, which represents the effect of temperature on the actual battery capacity, generally \( 6 \times 10^{-3} \), \( T_T \) is the battery operating temperature, \( T_{STC} \) is the temperature under standard test conditions, generally 25°C.

2.2. Objective function
Taking the minimum value of the integrated operating cost of the island microgrid as the objective function of the optimization model, the optimal solution is obtained through the algorithm to achieve the purpose of improving the economic operation of the microgrid. The objective function is as formula (5):

\[ \min C = C_{PV} + C_{WT} + C_{BAC} + C_{MF} \] (5)

Among them, \( C \) is the total cost of microgrid, \( C_{PV} \) is the cost of photovoltaic array power generation, \( C_{WT} \) is the cost of power generation of wind turbines, \( C_{BAC} \) is the total cost of battery charging and discharging, \( C_{MF} \) is the cost of gas turbine power generation and the required fuel cost.

2.3. Restrictions
In order to enable the normal and stable operation of the microgrid, the following constraints need to be satisfied:

2.3.1. System power balance constraint

\[ P_{load}(t) = P_{PV}(t) + P_{WT}(t) + P_{BAC}(t) + P_{DE}(t) + P_{MF}(t) \] (6)

Among them, \( P_{load}(t) \) is the current load demand power of the microgrid at the current moment.

2.3.2. System power balance constraint

\[ P_{min} \leq P_i(t) \leq P_{max} \] (7)

Among them, \( P_i(t) \) is the actual output power of the third micro power supply, and \( P_{min} \) and \( P_{max} \) are the lower and upper limits of the output power of the third micro power supply, respectively.

2.3.3. System power balance constraint

\[ P_{BACmin} \leq P_{BAC} \leq P_{BACmax} \] (8)

Among them, \( P_{BACmax} \) is the maximum charge and discharge power of the battery, \( P_{BACmin} \) is the minimum charge and discharge power of the battery.

3. Improved particle swarm algorithm

3.1. Particle swarm algorithm
Particle Swarm Optimization (PSO) is an algorithm inspired by the swarm aggregation model and
applied to solve optimization problems. It was proposed by Kennedy and Eberhat in 1995\(^4\). The principle is to first generate a group of randomly distributed particles, and each particle has its own speed and position, and then continuously pursue individual extreme points (Pbest) and global extreme points (Gbest) in each subsequent iteration to update the parameters of the particles themselves\(^5\)\(^6\). The update formula of position and speed is as formula (9)(10):

\[
\begin{align*}
    v_i^{k+1} &= \omega v_i^k + c_1 r_1 (P_{best_i}^k - x_i^k) + c_2 r_2 (G_{best_i}^k - x_i^k) \\
    x_i^{k+1} &= x_i^k + v_i^{k+1}
\end{align*}
\]

Among them, \(x_i^k\) and \(v_i^k\) are the position and velocity of the particle before the update, \(x_i^{k+1}\) and \(v_i^{k+1}\) are the position and velocity after the update, \(P_{best_i}^k\) and \(G_{best_i}^k\) are the positions of the individual extreme points and global extreme points of the current population, respectively, \(\omega\) is the inertia weight coefficients, generally 0.8–1.2, \(r_1\) and \(r_2\) are random numbers between \([0,1]\), \(c_1\) and \(c_2\) are the self-learning factors and social learning factors.

3.2. Immune particle swarm algorithm

For the particle swarm optimization algorithm, since the adjustment of the speed and position of each particle depends on the individual optimal particle and the global optimal particle, the characteristics of all particles tend to be the same after multiple iterations, resulting in The diversity of the population has dropped sharply, and once it falls into a local optimum, it is difficult to jump out\(^7\)~\(^11\). In order to avoid falling into the local optimum, Immune Particle Swarm Optimization (IA-PSO) introduces the immune mechanism into the particle swarm optimization.

In the immune mechanism, antibodies and antigens are the set of optimal solutions and candidate solutions respectively, and their affinity describes the degree of similarity between the candidate solution and the optimal solution. Antibodies with high affinity to the antigen and low concentration can be promoted, and vice versa can be inhibited, ensuring the diversity of antibodies\(^12\). At the same time, the antibodies stimulated by the antigen are retained as memory cells. When they are stimulated by the same antigen again, the memory cells will produce a large amount of antibodies to avoid premature convergence\(^13\)~\(^15\).

The affinity between antigen and antibody is usually calculated by its Euclidean distance as shown in formula (11):

\[
aff(x_i) = \frac{1}{\sqrt{\sum_{i=1}^{L} (x_i - y_i)^2} + 1}
\]

3.3. Improved immune particle swarm algorithm

In order to further improve the optimization effect, this paper proposes an improved immune particle swarm optimization algorithm (IA-PSO-A). Based on the immune particle swarm optimization algorithm, the two parameters of inertia weight and learning factor are improved, and the inertia weight is increased. A power exponential function operator can expand the search space of each particle during search, thereby increasing the diversity of the population, improving the search ability of the algorithm, and reducing the computing time. The calculation formula of inertia weight using power exponential function operator is as formula (12):

\[
\omega = \alpha + (\alpha - \beta) D_i^\delta / D_{max}^\delta
\]

Among them, \(D_i\) is the current iteration number, \(D_{max}\) is the maximum iteration number, \(\alpha\), \(\beta\), and \(\delta\) are parameters.
The learning factor is also an important parameter of the immune particle swarm algorithm. The learning factor can adjust the ratio of one's own experience and social experience. The learning factor set in this article takes a larger value for $c_1$ in the early stage of the iteration, and a smaller value for $c_2$, which increases the proportion of own experience and enhances the overall situation. Search ability. In the later stage of the iteration, $c_1$ takes a smaller value and $c_2$ takes a larger value to increase the proportion of the particle’s social experience and enhance the local search ability. The value formula of the dynamic learning factor used in this paper is as formula (13) (14):

$$c_1 = c_{1,\text{start}} + \frac{(c_{1,\text{end}} - c_{1,\text{start}})}{D_{\text{max}}} \cdot D_t$$

(13)

$$c_2(t) = c_{2,\text{start}} + \frac{(c_{2,\text{end}} - c_{2,\text{start}})}{D_{\text{max}}} \cdot D_t$$

(14)

Among them, $D_{\text{max}}$ is the maximum number of iterations, $D_t$ is the current number of iterations, and the learning factor takes $c_{1,\text{end}} = 2.5$, $c_{1,\text{start}} = c_{2,\text{end}} = 0.5$, $c_{2,\text{start}} = 2.5$.

4. Case analysis

4.1. Model parameters and output analysis

In order to verify the optimization ability of the algorithm in solving the optimization scheduling of the microgrid, a microgrid in a certain place was selected for testing. The distributed power supply in this microgrid includes photovoltaic arrays, wind turbines, micro gas turbines and energy storage systems. Figure 1, Figure 2, and Figure 3 respectively select the 24 hours of photovoltaic, wind turbine power generation and user load data for a certain day in summer and winter in this area. Other distributed power parameters are shown in Table 1.

| DG | Power upper limit (kW) | Power lower limit (kW) | Operation and maintenance cost (yuan/kW) |
|----|------------------------|------------------------|----------------------------------------|
| PV | 150                    | 0                      | 0.010                                  |
| WT | 60                     | 0                      | 0.045                                  |
| BA | 150                    | -100                   | 0.045                                  |
| MT | 60                     | 0                      | 0.048                                  |

Figure 1. Photovoltaic power generation
Figure 2. Wind turbine power generation
4.2. Analysis of optimization results

Using Matlab 2016a software as the development environment, particle swarm, immune particle swarm and improved immune particle swarm optimization algorithm are used to solve the economic dispatch problem of small island microgrid system respectively. This simulation will independently run the same program 10 times, and select the average of the 10 results as the final simulation result. Initialize the particle swarm algorithm parameters as follows: take $c_1$ as 2.5, $c_2$ as 0.5, $N$ as 100, $w$ as 0.8, and $D_{\text{max}}$ as 500. Three algorithms are used to optimize the simulation and get the operating cost of the microgrid. The cost comparison before and after optimization is shown in Table 2:

| Algorithm  | Summer | Winter |
|-----------|--------|--------|
|           | Cost (yuan) | Time (s) | Cost (yuan) | Time (s) |
| PSO       | 12862  | 9.083  | 14392  | 10.281  |
| IA-PSO    | 10552  | 10.427 | 11983  | 11.935  |
| IA-PSO-A  | 10373  | 10.058 | 11503  | 11.426  |

It can be seen from Table 2 that compared with the PSO algorithm, the IA-PSO algorithm can effectively improve the optimization effect. After the IA-PSO-A algorithm adds the adjustable inertia weight and learning factor on the basis of the IA-PSO algorithm, the optimization effect is achieved. Further improvement, while the convergence speed has been improved to a certain extent. Compared with the PSO algorithm, the IA-PSO-A algorithm can effectively save about 19.35% of the cost. Compared with the IA-PSO algorithm, the IA-PSO-A algorithm can effectively save about 3.54% of the time, indicating that the algorithm is effective Reduce costs and improve economy, while also shortening computing time. The overall operation of the microgrid is shown in Figure 4. The convergence curve of the iterative process of the improved immune particle swarm algorithm is shown in Figure 5.

5. Conclusion

This paper discusses the principle of the improved immune particle swarm algorithm and its application in the optimization of microgrid economic operation. By establishing a microgrid model that includes photovoltaic arrays, wind turbines, micro gas turbines, and batteries, the optimal operating strategy of each unit and the economic cost of the overall economy are obtained. The
comparison with the other two particle swarm optimization algorithms fully proves the feasibility and effectiveness of this algorithm are verified. This article provides a new solution for the optimization of economic and stable operation of microgrid.

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