Energy saving optimization scheduling of intelligent energy station based on beetle antennae searching-particle swarm optimization algorithm

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Abstract—New energy and distributed power generation system of smart energy station need to cooperate with energy storage device to carry out peak cutting and valley filling, so as to meet the requirements of grid connection. Rational distribution of power suppression tasks of batteries and other energy storage components will reduce the generation cost of smart energy stations, protect energy storage devices and prolong their life. In this paper, variational modal decomposition algorithm is used to decompose the difference between the original power and the target power and distribute it to each energy storage unit. In addition to considering the decomposition mode number of VMD algorithm, the size of the secondary penalty factor and the power boundary frequency of the energy storage system, the grid-connected target power is also taken as the quantity to be optimized, which further reduces the requirements on the maximum instantaneous power and capacity of the energy storage system. Simulation results show that the proposed method is effective.

1. Introduction

New energy and distributed power generation equipment are the basis for intelligent energy stations to improve regional energy efficiency, save energy and reduce costs. Energy storage is an important support for balance adjustment between supply side and consumption side of comprehensive intelligent energy in multi-energy complementary parks [1]. Energy storage equipment can eliminate the adverse effects of intermittent fluctuations of the new energy itself.

However, improper allocation of power tasks can lead to a sharp increase in payment costs and even damage storage devices. At present, when new energy and distributed power generation equipment are connected to the power grid, energy storage equipment is used to reduce peak load and fill valley, so that the target power meets the requirements of the power grid [2]. At present, the common method is to determine the target power first and then determine the power distribution of energy storage devices by EMD, VMD, empirical wavelet transform and other methods [3,4]. Liu C used window test method to determine the target power [5]. The specific method is to gradually increase the length of the moving average filter window until it reaches the requirements of grid-connection, and then take the filtering results obtained at this time as the target power of grid-connection. The basic idea is: the longer the filter window, the higher the requirements for the maximum instantaneous power and capacity of the energy storage equipment. This paper proves that this view is wrong. In fact, properly improving the stability of the power grid can reduce the demand for energy storage equipment, while a reasonable target power
can improve the stability of the power grid and save costs. The research purpose of this paper is to include the length of the moving average filter window and the boundary frequency of energy storage equipment as variables to be optimized into the optimization system. The main research content is the improvement of optimization algorithm and the selection of reasonable signal decomposition method.

2. Construction and Geometrical Dimensions of Specimens
The research on standard particle swarm optimization and related literature have been very rich, this paper will not describe the source and core algorithm formula of standard particle swarm optimization, but focus on beetle antennae search algorithm and how to integrate it with particle swarm optimization as an improved strategy.

2.1. Beetle antennae search algorithm
BAS is an algorithm developed according to the principle of long copper foraging. This algorithm has the characteristics of fast global search speed and high solving accuracy. Longhorns have two long antennae. When a cow searches for food based on the smell of food, if the intensity of the smell received by the right antenna is higher than that received by the left, it searches for food to the right, and vice versa. The model of longicorn beetle is obtained as shown in figure 1.

![Fig. 1 Simplified model of longicorn beetle](image)

A longhorn consists of a centre of mass and two whiskers. The distance between the left whisker and the right whisker $d_{0i}$, the relative position between the two whiskers and the centroid of Longicorn beetle did not change. Longicorn beetles move in the solution space of d-dimensional optimization problem, and the initial centroid position is $x_0 = [x_1, x_2, ..., x_d]$. Define the direction vector $\vec{r}$ orientation as the right whisker of beetle and the left whisker.

The equations for the location of the Beetles are:

$$x^{k+1}_{i} = x^k_{i} - \vec{r} \cdot L \cdot \text{sign} \left( f(x^k_{\text{right}}) - f(x^k_{\text{left}}) \right)$$

In this equation, $f(x)$ is the fitness function of point $x$, $L$ is the step size, and sign is the function to judge positive and negative signs. The direction in which the Beetles move is that of the fittest of the two tentacles. The direction vectors are completely random as the Beetles move to a new location.

2.2. Combination strategy of Longicorn whisker and particle swarm optimization
The standard particle swarm optimization algorithm has many disadvantages, such as poor local search ability, easy to fall into local extremum and low search accuracy. In order to solve these problems, it is necessary to enlarge the population and increase the number of iterations of the population, which sacrifices the computational speed and convergence speed. In addition, the standard particle swarm algorithm has oscillation phenomenon, because all the particles in the population have to be updated, and the fitness of the next position of the particle may be backward.
In view of this phenomenon, longicorn is used to replace the standard particle. On the basis of maintaining the optimum of group optimization search learning population and individual, the ability of individual to independently learn surrounding information is increased. Another improvement is to ensure that the population does not degenerate by ranking the fitness of each generation in an ascending order so that the top individual is not renewed. The steps of longicorn – particle swarm optimization are as follows:

1. Set population parameters and initialize
2. Calculate the fitness of all particles
3. Select the location corresponding to the optimal fitness of the current individual and population
4. Updates the velocity and position of each particle in the population.
5. Calculate the position of the left whisker and right whisker of longhorn particles
6. Update the location of longicorn particles
7. Judge whether convergence conditions are met, if not, return to step 4. If the convergence condition is satisfied, the best individual of the population is returned as the solution of the problem.

3. Simulation case

3.1. Variables to be optimized and fitness function

In this paper, the variational modal decomposition method is used to divide the power task between battery pack and supercapacitor. Variational modal decomposition is a signal decomposition estimation method. In the process of obtaining the decomposed components, the frequency centre and bandwidth of each component are determined by iteratively searching the optimal solution of the variational model, so the subdivision of frequency domain and the effective separation of each component are realized adaptively.

Variational modal decomposition can prespecify the number of decomposition modes and the quadratic penalty factor, and different modal number and quadratic penalty factor will significantly affect the decomposition result. Therefore, the decomposition modal number $K$ and the quadratic penalty factor $\alpha$ are taken as the variables to be optimized.

The distribution principle of ultracapacitors and batteries can be summarized as follows: the component below the cut-off frequency is allocated to the battery, and the component above the cut-off frequency is allocated to the ultracapacitor. There is no hard and fast limit to the amount of power that supercapacitors and batteries can carry, and a frequency between 1 and 10 minutes is acceptable. Therefore, the bounding frequency can be used as a variable to be optimized.

The sliding filtering window is also used as a variable to be optimized. The moving average filter window must reach a certain length to meet the requirements of network connection. The wind power capacity of the smart energy station is 30MW. China’s regulation on grid-connected power of 30MW wind farms is that the fluctuation in 10min shall not exceed 10MW, and the fluctuation in 1 minute shall not exceed 3MW. For the combination of parameters that cannot meet this standard, a penalty term is added to the fitness. For the combination of parameters that meet this requirement, the penalty term is zero.

On the basis of meeting the national standard of wind farm grid connection, there are the following optimization indexes, which are used as the calculation function of population fitness:

3. Reduce the capacity demand of energy storage system. Make the instantaneous power change of the energy storage system as small as possible to reduce the maximum instantaneous current of the supercapacitor and battery. Fitness indicators are defined as:

$$F_1 = |P_{bat}|_{\text{max}} + |P_{sc}|_{\text{max}}$$

(2)

2. The closer the average charging and discharging power of the energy storage system is to 0 within 300min, the lower the SOC requirement of the energy storage system is. The fitness index is defined as:

$$F_2 = \frac{1}{T} \int_0^T P_{bat} dt + \frac{1}{T} \int_0^T P_{sc} dt$$

(3)
(3) For the parameter combination that does not meet the standard of grid-connected power fluctuation, it will be punished according to formula (4)

\[ F_{\text{punish}} = p \times 10^6 \]

\[ p = \begin{cases} 0 & \text{Meet the standard} \\ 1 & \text{Failure to meet standards} \end{cases} \]  

(4)

There are differences in the order of magnitude among the three fitness indicators, and the same value reflects different advantages and disadvantages in different indicators, so the three indicators need to be normalized. The fitness component after normalization is defined as:

\[ \text{Fitness} = \sum_{i=1}^{3} F_i + F_{\text{punish}} \]  

(5)

3.2. Evolution of populations

The standard particle swarm optimization algorithm and BAS-particle swarm optimization algorithm were used. Figure 2 compares the evolution process of longicorn whisker particle swarm optimization algorithm and standard particle swarm optimization algorithm. The initial population corresponding to the two algorithms is consistent, so the fitness of the initial population is the same, so the comparative results of the evolutionary process of the two algorithms are more convincing.

![Fig. 2 Change process of fitness of Longhorn beetles](image)

Through studying the evolution process, it is not found that the shorter the window of moving average filtering, the smaller the burden of energy storage system. In the existing literature, the filter window length is set to a value just enough to meet the requirements of grid-connection by default, which not only reduces the smoothness of grid-connection, but also increases the demand for the capacity of energy storage system. Figure 3 shows the relationship between filtering window length and fitness. When the moving average filter window reaches \( N = 228 \), the target power of grid-connected can meet the requirements. Therefore, starting from \( N = 228 \), the change of fitness as the window length gradually increases under different decomposition modes was counted.
Fig. 3 The relationship between the length of moving average filtering window and fitness

3.3. Energy storage system power

Figure 4 shows the original power and two target power of the smart energy station's wind power generation within 18,000 seconds. The length of the moving average filtering window corresponding to the two target powers is 228 and the optimal result is 541.

When N=228, the 10-minute maximum wave momentum of the grid-connected target power is 9.96MW, and the 1-minute maximum wave momentum is 2.84MW. When N=541, the 10-minute maximum wave momentum of the grid-connected target power is 7.11MW, and the 1-minute maximum wave momentum is 2.49MW. Figure 5 shows the respective power of the two energy storage devices. The power of the battery varies greatly and the frequency is low. The power of an ultracapacitor varies in a smaller range and faster frequency. It can be seen that the power frequency band of the energy storage system has been separated, and the smoothness of grid-connection has been improved as much as possible.
4. Conclusion
In this paper, by improving the particle swarm optimization algorithm, a more reasonable task of power distribution between the target power of wind power grid-connected smart energy station and the energy storage device is obtained more quickly, and the following conclusions are drawn:

(1) The capacity and maximum instantaneous power requirements of the energy storage system do not increase with the length of the moving average filtering window. Appropriately increasing the filtering window length can reduce the requirements of the energy storage system.

(2) The improved Longicorn whisker-particle swarm optimization algorithm has a faster optimization speed and does not backslide. In the case of high real-time requirement, if it is necessary to return a solution which is not necessarily optimal but within the acceptable range within a short time, the advantages of Longicorn whisker-particle swarm optimization algorithm are more obvious.

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