Economic dispatching Optimization of power grid based on IGWO Algorithm

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Abstract. An improved grey Wolf optimization algorithm (IGWO) is proposed to solve economic dispatch (ED) of power systems is proposed in this paper. The column vector composed of the active power of each generator in the power grid system is taken as the decision variable, and the total power generation cost of the power grid is taken as the objective function. The improved grey Wolf optimization algorithm is used to search for the optimal value by introducing the inertial characteristic constant and Gaussian mutation operator, and is compared with particle swarm optimization (PSO). The simulation results show that the proposed method has the characteristics of fast convergence speed, high solution accuracy and easy to jump out of the local optimal solution, and can be used as an effective means to solve ED problems.

1. Introduction

Economic dispatch of power grid is a classical optimization problem in power system. By properly dispatching the power of generators in the power grid system, the generation cost is reduced, so as to reduce the waste of electric energy and improve the generation efficiency, which can also bring considerable economic benefits in large power grid. In the past, Lagrangian method and dynamic programming method were usually used to solve the economic dispatching problem of power grid. With the development of artificial intelligence, many researchers began to use artificial intelligence algorithms or swarm intelligence algorithms such as chaos algorithm [1], particle swarm optimization [2], genetic algorithm [3] and other artificial intelligence algorithms to solve the economic dispatching problem of power system. The difference between these methods and traditional methods is that they do not require high precision of mathematical model, and allow nonlinear constraints and discontinuity factors. Therefore, the use of artificial intelligence algorithm to solve the problem of economic dispatching of power grid can consider such factors as the output active power limit of power grid units, valve point effect and network loss of power grid.

The improved Grey Wolf optimization algorithm (IGWO) [4] is derived from the social hierarchy of wolves. In order to avoid falling into the local optimal solution and improve the search performance of the algorithm in the initial generation, dynamic inertia constant and Gaussian operator variation are introduced in this paper to overcome the problem that the algorithm is prone to falling into the local optimal solution. IGWO has the characteristics of fast convergence speed, high solving precision, and not easy to fall into local optimal.

2. A mathematical model of the Grid Economic Dispatch problem (ED)

The economic dispatch problem of power grid studies the optimization of power resource dispatch in power grid. Under the premise that the power grid satisfies its own physical characteristics, the load constraints of the power grid and guarantees safety and stability, the output power of each unit can be
reasonably allocated to reduce loss and fuel consumption, so as to minimize the power generation cost and maximize the power generation efficiency of the power grid. In order to transform the practical problem into a mathematical problem and simplify it reasonably, the output power of each unit can be allocated to minimize the total cost of the power network only under multiple constraints such as grid dispatching loss, power supply and demand constraints, and working power range of units.

2.1. Basic mathematical model
In mathematics, ED problem can be simplified as a nonlinear programming problem with multiple equality and inequality constraints, and its objective function can be considered as

\[ C = \min \sum_{i=1}^{N} F_i(P_i) \]  

(1)

C is the objective function, N is the total number of generators in the grid system, \( P_i \) is the active power of the \( i \)th generator in the system, and \( F_i(P_i) \) is the energy consumption required when the active power of the \( i \)th generator is \( P_i \).

\[ P_{\text{min}} \leq P_i \leq P_{\text{max}}, \quad i=1,2,\cdots, N \]  

(2)

\( P_{\text{min}} \) is the minimum value of the active power of the \( i \)th generator in the system, \( P_{\text{max}} \) is the maximum value of the active power of the \( i \)th generator in the system.

Since the generator power in the system is equal to the sum of load and network loss, there is a constraint condition

\[ \sum_{i=1}^{N} P_i = P_D + P_C \]  

(3)

where \( P_D \) is the total load of the power grid system, \( P_C \) is the total network loss of the power grid system.

The consumption characteristic curve of the generator can be approximately considered as the quadratic function of the active power of the generator

\[ F_i(P_i) = \alpha_i P_i^2 + \beta_i P_i + \epsilon_i, \quad i=1,2,\cdots, N \]  

(4)

where \( \alpha_i, \beta_i, \epsilon_i \) are constants.

2.2. Consider the valve point effect and network loss
In practice, when the steam turbine inlet valve is opened suddenly, wiredrawing will occur, which will lead to a pulsation effect superimposed on the unit's consumption characteristic curve, namely the valve point effect. Ignoring the valve point effect is bound to affect the model accuracy, which can usually be simplified as the following form

\[ E_i = a_i \sin \left( b_i \left( P_i - P_{\text{min}} \right) \right), \quad i=1,2,\cdots, N \]  

(5)

where \( a_i, b_i \) are constants.

Network loss is a function of generator power, transmission network parameters and network topology, which can be ignored in the calculation of small or micro grid, but cannot be ignored if the network covers a large area. The exact network loss value is usually calculated by power flow. In the experiment, the network loss is usually calculated by B coefficient, and the specific expression is as follows

\[ P_C = P^T B P + P^T B_1 + B_0 \]  

(6)
Where, $P$ is the column vector composed of $N$ active power generators, $B$ is the n-order matrix, $B_1$ is the column vector, and $B_0$ is the constant.

3. Improved grey Wolf optimization algorithm

3.1. GWO algorithm
Grey Wolf Optimizer (GWO) is a population intelligent optimization algorithm proposed by Mirjalili et al., Griffith University, Australia in 2014. [5] Inspired by the gray Wolf's predation activities, this algorithm is an optimization search method, which has strong convergence performance, few parameters and easy implementation. Compared with PSO, gray Wolf optimization can obtain more accurate results with strong convergence. GWO algorithm solves the optimal strategy as follows.

3.1.1. Initialize the gray Wolf. The grey Wolf population is divided into $\alpha$, $\beta$, $\delta$ and $\omega$ by a very strict hierarchy. $\alpha$ is considered as the most appropriate solution, $\beta$, $\delta$ as the suboptimal solution, and the remaining solution is $\omega$. In the GWO algorithm, the first three types of wolves guide the predation, namely the optimization process. First, we initialize the population, and then initially set the length $A$, $C$ of the coefficient vector and the convergence factor $a$.

3.1.2. Surrounded by hunting. The encircling behavior of gray wolves to their prey is expressed as:

$$\text{D} = |C \cdot X_p(t) - X(t)|,$$

$$X(t+1) = X_p(t) - A \cdot D.$$

Where, $t$ is the current iteration number, $A$ and $C$ are coefficient vectors, $X_p$ is the position vector of prey, and $X$ is the position vector of gray Wolf. The calculation formulas of $A$ and $C$ are as follows.

$$A = 2a \cdot r_1 - a,$$

$$C = 2 \cdot r_2.$$

Where, the component of $A$ linearly decreases from 2 to 0 during the iteration, and $r_1$ and $r_2$ are the random vectors between $[0, 1]$.

3.1.3. Hunting and attacking. Save the first three optimal solutions obtained from the current location, namely $\alpha$, $\beta$, $\delta$, and force other gray wolves in the population to update their positions according to the location of the best search agent, gradually approaching the prey. The formula of tracking prey position of individuals in wolves is expressed as follows

$$\begin{align*}
D_\alpha &= |C_1 \cdot X_\alpha - X|, \\
D_\beta &= |C_2 \cdot X_\beta - X|, \\
D_\delta &= |C_3 \cdot X_\delta - X|. 
\end{align*}$$

Where D stands for the distance between $\alpha$ and the other individuals. $\alpha$, $\beta$, $\delta$ represent the current position of $\alpha$, respectively; $C$ is the random vector, and $X$ is the current position of the Wolf.
3.1.4. Search for prey. The gray Wolf searches for prey based on position α, β, δ. Gray wolves separate from each other in search of prey and then gather together to attack it. Based on the divergence of mathematical modeling, the random value of λ greater than or less than 1 can be used to force the gray Wolf to separate from the prey, which enables the GWO algorithm to search for the optimal solution globally. The randomness of C also plays a very important role in avoiding local optimality, especially in the iteration that needs to obtain the global optimal solution finally.

3.2. I-GWO algorithm

Due to the fact that the original Grey Wolf optimization algorithm is prone to local optimality, Improved Grey Wolf Optimization introduces inertial constant strategy and Gauss operator variation to improve the robustness and accuracy of the algorithm [6], which ensures both high accuracy and faster convergence rate when solving problems.

3.2.1. Dynamic inertial strategy. When GWO algorithm is used for predation, the introduction of dynamic inertial strategy can control the ability of search population to find the optimal solution, reduce the possibility of falling into the local optimal solution, and balance the weight of global search and local search. The correlation expression is as follows

$$ C = 2 \cdot \lambda \cdot r_2 $$

The inertia constant λ improves the search ability of gray wolves and decreases with time. In the early stage of the solution, the larger inertia constant λ can make the search step size larger and the search speed faster; in the later stage of the solution, the smaller λ can make the search step size smaller and improve the search precision in a small range.

3.2.2. Gauss operator variation. In the iteration of the algorithm, if a part of the gray Wolf appears serious aggregation in a part of the extreme value points, gaussian operator mutation is carried out on its state to avoid falling into the local optimal. In the program, when the results are unchanged and less than the maximum number of iterations in three consecutive iterations, a corresponding mutation operator is given to the gray Wolf, so as to jump out of the original local optimal and carry out search again. Gaussian operator mutation is to add a random variable obeying Gaussian distribution to the original state of the gray Wolf, and the expression is as follows

$$ X(t) = X(t) \times \left[1 + k \times N(0,1)\right] $$

Where, X(t) is the position of gray Wolf in the t generation, k is the decreasing variable between [0,1], and N (0,1) is the random variable subject to a Gaussian distribution with a mean of 0 and a variance of 1.

4. I-GWO algorithm optimizes economic dispatching of power grid

4.1. Determine the decision variables and objective functions

The N-dimensional column vector composed of the active power of each generator in the grid system is taken as the decision variable, that is, the valve point effect and network loss are considered simultaneously. The objective function is as follows

$$ \left\{x_1, x_2, \ldots, x_N\right\} = \left\{P_1, P_2, \ldots, P_N\right\} $$

$$ C = \sum_{i=1}^{N} F_i(P_i) + \sum_{i=1}^{N} E_i + \lambda \left| \sum_{i=1}^{N} P_i - P_D - P_c \right| $$

$$ (7) $$

$$ (8) $$
Where $l$ is the penalty factor, the constraint condition (2) can realize the constraint on the search range by adjusting the parameters of I-GWO.

4.2. The simulation example

In this paper, Matlab2020A was used to simulate the model, and the number of grey Wolf populations in i-GWO algorithm was set as 10, with 100 iterations. $a=2$, $A=2$, and $C=1.8$. Taking the 3-machine and 6-bus power system of Wen [4] as the simulation object, the total load of the generator of the power grid system is set as $P_D=550$MW. The consumption characteristic curve and active power range of each generator are shown in Table 1.

| Unit | $\alpha_i$ | $\beta_i$ | $\varepsilon_i$ | $a_i$ | $b_i$ | $P_{\min}$ | $P_{\max}$ |
|------|-------------|-----------|----------------|-------|-------|------------|------------|
| 1    | 0.00156     | 7.92      | 561            | 300   | 0.0315 | 100.0      | 600.0      |
| 2    | 0.00194     | 7.85      | 310            | 200   | 0.0420 | 100.0      | 400.0      |
| 3    | 0.00482     | 7.97      | 78             | 150   | 0.0630 | 50.0       | 200.0      |

Tab.1 The coefficients of input-output curves and generation limits of generators

| Solution | $P_1$/MW | $P_2$/MW | $P_3$/MW | $C$    |
|----------|----------|----------|----------|--------|
| 1        | 173.23   | 305.37   | 71.40    | 5749.41|
| 2        | 276.01   | 132.05   | 142.15   | 5839.62|
| 3        | 189.79   | 283.05   | 77.16    | 5721.56|
| 4        | 241.43   | 153.58   | 155.00   | 5754.85|
| 5        | 232.46   | 203.19   | 114.38   | 5710.56|
| Best solution | 310.32 | 180.61   | 59.07    | 5703.74|

It can be seen from Figure 1 that IGWO algorithm has better convergence than particle swarm optimization (PSO) in solving this problem, which converges about 30 generations earlier, and can search for better results within the same time. Table 3 shows the results of 50 iterations of the two algorithms.

| Search agents | Max_iteration | Algorithm | min       | ave       | max       |
|---------------|---------------|-----------|-----------|-----------|-----------|
| 10            | 50            | PSO       | 5813.46   | 5822.61   | 5830.73   |
|               |               | IGWO      | 5780.23   | 5802.83   | 5812.37   |
| 50            | 100           | PSO       | 5723.36   | 5723.41   | 5723.58   |
|               |               | IGWO      | 5703.74   | 5703.74   | 5703.74   |
4.3. Comparison with PSO algorithm
Both IGWO algorithm and PSO algorithm are swarm intelligence algorithms in essence, and gray Wolf optimization algorithm is derived from particle swarm optimization. Therefore, they have many common features. For example, they search for solutions by group, have a set of algorithms that can search and retain the optimal solution and eliminate the unsatisfactory solution, and have the advantage of parallel operation.

4.3.1. IGWO algorithm introduces inertia characteristic constant, which has a high step length in the initial stage of search and a low step length in the final stage, which improves the convergence speed and calculation accuracy of the algorithm. In the example, it can be seen that IGWO algorithm converges 30 generations earlier than PSO algorithm, and the solution obtained by the same calculation time is better.

4.3.2. Because IGWO algorithm adds Gaussian operator variation when searching for the optimal solution, it is easier to jump out of the local optimal solution than PSO, and its searching process can traverse the whole solution space according to the steps of the algorithm, while PSO algorithm eliminates the poor solution according to probability to jump out of the regional optimal solution.

5. Conclusion and application prospect of the algorithm
In this paper, the IGWO algorithm is used to solve the ED problem, and a mathematical model for economic dispatching of power grid is established with both valve point effect and network loss considered. The simulation results show that the IGWO algorithm is accurate and reliable, converges quickly and runs fast, which provides a new solution to the economic dispatching problem of power grid. In the future, this new algorithm is expected to be applied to other optimization problems in power system, such as power flow calculation, discriminant system, process control and so on.

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