Application of Economic Load Distribution of Power System Based on BAS-PSO

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Abstract. Beetle Antennae Search (BAS) is a heuristic algorithm proposed in 2017. BAS is the bionic optimization algorithm. The principle comes from the fact that Tianniu finds food by sensing the direction of flight by sensing the strength of the smell emitted by the left and right. The BAS algorithm has better optimization speed and precision when solving low-dimensional problems. However, it is easy to fall into local optimum when solving high-dimensional problems. For the purpose of the better search ability of BAS, we have combined particle swarm optimization (PSO) algorithm and proposed a new hybrid BAS and PSO algorithm (BAS-PSO). In BAS-PSO, First use the standard PSO for particle position update and velocity update. Particle learning ontology information and group optimal individual information for evolution, then the particles are seen as individual beetles to use BAS. Each beetle individual performs a local search and continues to cycle until it finds the optimal value. In this paper, the design simulation experiment is applied to the problem of economic load dispatching (ELD) allocation. By comparing the optimization results of BAS-PSO with the three types of algorithms, the results suggest that the BAS-PSO algorithm is better in the ELD optimization problem.

1. Introduction

BAS [¹] is a new intelligent algorithm proposed by the Shuai Li etc in 2017 for multi-objective function optimization. In BAS, the beetle position is defined as the solution to the problem to be solved, and the food represents the optimal solution to the problem. When the beetle preys, the two antennae of the beetle can sense the intensity of the odor emitted by the food. According to the different smell of antennae, the beetle updates the direction of flight and eventually finds the food. The standard BAS only defines one individual beetle. It updates flight directions by learning its own local information. Therefore, this algorithm has the characteristics of small amount of calculation, fast optimization speed and good local optimization performance. The algorithm has achieved good results in BP neural network optimization and realized the storm surge disaster loss prediction function [²]. However, the algorithm is mainly suitable for the optimization of single-objective problems. In order to expand the application range of BAS, Shuai Li etc [³] improved the standard BAS algorithm and successfully applied it to multiobjective optimization problems. However, when this algorithm is applied to multidimensional and multimodal problems, the algorithm is very easy to stagnate and falls into a local optimum.
PSO [4] is an intelligent optimization algorithm proposed by J. Kennedy and R.C. Eberhart in 1995. In PSO, there is a group of particles with the same properties, which can be used to optimize the calculation of the problems. Each particle in the swarm determines the speed of evolution and direction by learning its own experience and group experience. The basic PSO has the characteristics of simple optimization, fast convergence, and so on, so it has been widely used.

Based on the research results mentioned above, this paper will mix standard BAS and standard PSO, and a new intelligent optimization method called BAS-PSO is proposed. The algorithm mixes BAS and PSO at the population level. Firstly, the PSO algorithm is used to update the speed and position of each particle in the particle swarm. Then apply the BAS algorithm. Each particle in the particle swarm is viewed as an individual beetle individual. Search based on the beetle antenna's perceptual information, and then continue to circulate, prompting optimization calculations to evolve toward better solutions. Finally, the simulation experiment is designed, and the BAS-PSO is applied to the economic load distribution of the example. The simulation results are compared with the optimization results of genetic algorithm and chaos algorithm, and the advantages of BAS-PSO algorithm in dealing with ELD problem are analyzed.

2. Another Days cattle algorithm and standard particle swarm algorithm

2.1 Basic principles of BAS.

(1) The directions of the beetle antennas are random vectors, which are first normalized. Where random() is a random function and K is the dimension of the optimization problem.

\[ \vec{b}_r = \frac{\text{rands}(k,1)}{\|\text{rands}(k,1)\|} \quad (1) \]

The beetle's left and right antenna positions are calculated according to the following formula.

\[ \begin{align*}
    x_{r_t} &= x' + d \cdot \vec{b}_r / 2 \\
    x_{l_t} &= x' - d \cdot \vec{b}_r / 2
\end{align*} \quad (2) \]

Where \( x \) represents the individual position of the beetle, \( x_{r_t}, x_{l_t} \) represent the position of the left and right antennas respectively, and \( d \) represents the distance between the antennas.

According to the problem to be optimized, the fitness values of the left and right antennas are obtained. That is \( f(x_{r_t}) \) and \( f(x_{l_t}) \).

The beetle position update is performed according to the following formula.

\[ x = x - \delta \cdot \vec{b} \cdot \text{sign}(f(x_{r_t}) - f(x_{l_t})) \quad (3) \]

Where: \( \delta \) is the step size factor and sign() is the sign function.

The step size is used to control the search ability. Therefore, the initial step size should be as large as possible so that it can cover the search area and avoid falling into a local optimal solution. This article uses a linear decrement method to ensure the precision of the search.

\[ \delta^{k+1} = \delta^k \cdot \text{eta} \quad (4) \]

In the formula, \( k \) is the algebra of evolution and \( \text{eta} \in [0,1] \) is the attenuation coefficient.

2.2 Page Principles of standard particle swarm optimization algorithm

First, in the D-dimensional problem space, \( N \) particles are randomly generated as a population. Each particle has a velocity information and position information. The velocity information represents the solution to the problem. The velocity information represents the amount of change in the solution. The speed information of the i-th particle is recorded as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \), position information is marked as \( X_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \). In the flight process (algorithm evolutionary process), each particle has its own optimal location information \( p_i = (p_{i1}, p_{i2}, \ldots, p_{iD}) \) as well as its own neighborhood or global optimal location information \( p_g = (p_{g1}, p_{g2}, \ldots, p_{gD}) \). During the flight of a particle, its velocity information and position information are calculated according to the following formula.
3. BAS-PSO hybrid optimization algorithm

The learning modes of the two standard algorithms are different. Standard BAS focuses on local exploration, and standard PSO focuses on global search. First, the standard PSO algorithm is used to update the position and velocity information of each particle in the particle swarm. Ensure each particle learns its own best search experience and the best individual’s search experience in the group, and then treats the particles in the group as individual beetles. Apply the standard BAS algorithm to ensure that beetle individuals learn their own surrounding information independently for local search. In this continuous cycle, the entire population is moving in the direction of the optimal solution to the problem.

4. Mathematical model of ELD

4.1 Objective function

The ELD problem can be described mathematically as a nonlinear programming problem that satisfies several equality and inequality constraints. The aim of the solution is to minimize the value function. The value function is as follows.

\[
C(P) = \sum_{i=1}^{n} F_i(P_i)
\]

(7)

Where: \(C\) is the value function; \(n\) is the total number of generators in the system; \(P_i\) is the active power of the \(i\)-th generator; and \(F_i(P_i)\) is the energy consumption required per unit time when the \(i\)-th generator generates the active power \(P_i\), so \(F_i(P_i)\) is called the consumption characteristic. The generator consumption characteristic curve is similarly expressed by the quadratic function of the generator active power, as follows.

\[
F_i(P_i) = a_i P_i^2 + b_i P_i + c_i
\]

(8)

In the formula, \(a_i\), \(b_i\), and \(c_i\) are constants.

4.2 Restrictions

The constraints of economic load distribution mainly consider the operating constraints and power balance constraints of the generator.

1) The operating constraints of the generator are as follows:

\[
P_i^{\text{min}} \leq P_i \leq P_i^{\text{max}}
\]

(9)

In the formula, \(P_i^{\text{min}}\) and \(P_i^{\text{max}}\) are the minimum and maximum values of the active power of the \(i\)-th generator, respectively.

2) The power balance constraints are as follows:

\[
\sum_{i=1}^{n} P_j = P_L + P_s
\]

(10)

Where \(P_L\) is the total load within the system; \(P_s\) is the total network loss of the system.

4.3 The valve point effect of the generator consumption curve.

The valve point effect can be expressed as follows:

\[
E_i = \left| g_i \sin(h_i (P_i - P_i^{\text{min}})) \right|
\]

(11)
In the formula, \( g_i \) and \( h_i \) are constants.

5. Economic Distribution of Power System Loads Using Improved Particle Swarm Optimization Algorithm

5.1 Case study

The example to be analyzed in this paper uses the calculation example of the 3-machine 6-bus system in Literature [6]. The valve point effect is considered during the analysis and the network loss of the system is not considered. The generator consumption characteristics and active power limit values are shown in the table below.

| Table 1. Consumption characteristics and active power limitation |
|---------------------------------------------------------------|
| unit | \( a_i \) | \( b_i \) | \( c_i \) |
| 1    | 0.001 56  | 7.92   | 561   |
| 2    | 0.001 94  | 7.85   | 310   |
| 3    | 0.004 82  | 7.97   | 78    |

| unit | \( h_i \) | \( P_i^{\text{max}} \) | \( P_i^{\text{min}} \) |
| 1    | 0.031 5   | 100.0   | 600.0  |
| 2    | 0.042 0   | 100.0   | 400.0  |
| 3    | 0.063 0   | 50.0    | 200.0  |

The values of each parameter are: number of particles \( N=10 \), step size=20, number of iterations \( D=100 \), inertia weight \( \omega=0.729 \), \( c_1=c_2=2 \), \( r_1, r_2 \) is a random number between 0 and 1.

Two cases are considered in each analysis process:
- **Case1**: The total load assumed by the generator is \( P_L = 500 \) MW;
- **Case2**: The total load assumed by the generator is \( P_L = 850 \) MW.

5.2 Case analysis

After Matlab programming simulation, the trend of the total cost as a Iterative function is shown in Figures 1 and Figures 2. Comparing the two cases, it can be concluded that the total system consumption increases due to the valve point effect. At the same time, its increase is nonlinear, which causes a large change in the load power distribution between the units. Therefore, if the optimization process does not consider the influence of the valve point effect, the result will be very inaccurate.

| Figures 1 | Figures 2 |

The simulation results of Case 1 and the simulation results using the chaotic algorithm to solve the same problem in Literature [6] are shown in Table 3 below. The simulation results of Case 2 are compared with the simulation results of the same problem solved by the genetic algorithm in Literature [6], as shown in Table 4 below.

| Table 2. Comparison of case 1 optimization results |
|---------------------------------------------------|
| Algorithm          | \( P_1 \)/ MW | \( P_2 \)/ MW | \( P_3 \)/ MW | \( P_4 \)/ MW | \( \text{Cost}_1 \)/ $ | Time/ S |
|-------------------|--------------|--------------|--------------|--------------|----------------|--------|
| BAS-PSO            | 199.9        | 200.2        | 99.9         | 500          | 5132.6         | 0.106  |
| Chaotic            | 199.2        | 100.5        | 99.3         | 500          | 5192.1         | 0.115  |
| GA                 | 199.7        | 100.4        | 99.7         | 500          | 5195.2         | 0.049  |
| PSO                | 199.9        | 200.2        | 99.9         | 500          | 5265.1         | 0.057  |
Table 3. Comparison of situation 2 optimization results

| Algorithm | $P_1$/MW | $P_2$/MW | $P_3$/MW | $P_\sum$/MW | Cost$/$/ | Time/$s$ |
|-----------|----------|----------|----------|-------------|---------|--------|
| BAS-PSO   | 499      | 250.6    | 100.4    | 850         | 8230.4  | 0.102  |
| Chaotic   | 299.8    | 390.5    | 159.7    | 850         | 8238.5  | 0.118  |
| GA        | 300      | 400      | 150      | 850         | 8233.8  | 0.051  |
| PSO       | 499      | 250.6    | 100.4    | 850         | 8241.4  | 0.057  |

Comparing the data in the above two tables, we can find that the results obtained by using the BAS-PSO algorithm are better than the total cost obtained by the particle swarm algorithm, the genetic algorithm and the chaotic algorithm respectively. Total cost of the BAS-PSO algorithm is lower than that of the other three algorithms, and the effect is better; in terms of time-consuming performance, although the average time-consuming and shortest time-consuming of the BAS-PSO algorithm are slightly higher than the results of the two algorithms, it is obvious that the optimization results of the three algorithms are locally optimal and do not reach the global optimum; in addition, the optimal value obtained by the BAS-PSO algorithm is lower than that obtained by the Chaotic algorithm, and the time consumption is significantly reduced. The BAS-PSO algorithm is easier to obtain the global optimal solution under high dimensional conditions than other algorithms. The above example shows that BAS-PSO algorithm is an excellent method to solve ELD problem of power system.

6. Conclusion

This paper proposes to apply a BAS-PSO algorithm to the ELD problem of power systems. This algorithm can be used to optimize non-convex, high-dimensional, nonlinear constraints. Compared with the traditional particle swarm optimization algorithm, the algorithm overcomes a "premature" shortcoming of the common particle swarm optimization algorithm which is easy to fall into a local optimal extremum. In principle, the global optimal problem can be solved with a large probability. The algorithm improves calculation accuracy and efficiency and is easy to implement. The algorithm is used to simulate the power system economic load optimization problem, and another three algorithms are designed to compare the simulation experiments. The test results prove the feasibility and effectiveness of the BAS-PSO algorithm.

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