Particle Swarm Optimization with Compression Factor for Solving the Power Systems Economic Dispatch Problem

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Abstract. With the rapid development of economy, the demand for electricity is increasing rapidly. Therefore, how to effectively realize power scheduling becomes very important. In this paper, we first introduced the basic principle of particle swarm optimization, then discuss the influence of parameter selection on the efficiency of particle swarm optimization. After that, we use the compression factor method to set the parameters of the particle swarm optimization algorithm. The experimental results show that the parameter selection method based on compression factor is effective and feasible.

1. Introduction

Nowadays, with the rapid development of economy, people have an increasing demand for electricity. As a result, how to make effective use of power resources has become a hot issue in the field of power systems. In this paper, we choose the power system economic scheduling problem as our research object. Specifically, the purpose of power system economic scheduling problem is to realize the minimum cost of power generation under the premise of satisfying the system power balance and a series of constraints\(^1\). For power systems economic scheduling problem, people have made the corresponding research from different angles.

The mathematical essence of power system scheduling problem is optimization problem. Therefore, the traditional mathematical optimization method based on gradient information is employed to solve power system scheduling problem. The most common methods are equal incremental discharge criterion and interior point method. However, we must pay attention to the fact that the traditional scheduling algorithm based on gradient information requires the problem to be convex, continuous and differentiable. The optimal dispatching problem of power system comes from practical engineering, the objective function of power systems optimal dispatching problem is often non-differentiable, for example, the optimal scheduling problem considering the valve point effect. At this point, we can't use traditional mathematical method based on gradient information to deal with power system optimization scheduling problem.

Fortunately, intelligent algorithms have developed rapidly in recent years, such as particle swarm optimization\(^2\), genetic algorithm\(^3\) and simulated annealing algorithm. The biggest advantage of intellectualization is that it does not require the mathematical properties of differentiable, continuous and smooth of objective functions, we only need to know the objective function and constraints of the optimization problem.

In this paper, we use particle swarm optimization (PSO) to solve the economic scheduling problem of power system. The key of the paper is to find the best parameter configuration of PSO to achieve the optimal efficiency.
2. The Mathematical Model of Power Systems Economic Dispatching Problem

The mathematical model of power system economic scheduling problem can be divided into two parts: objective function and constraint conditions.

2.1 Objective Function

In the power system, the value of coal consumed by the generator can be expressed as a quadratic function with the active power generated by the generator as a variable[^1]. For the power system network composed of multiple generator sets, the total generation cost can be expressed as:

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

where \( F_i \) is the consumption cost function of the \( i \)-th generator set, \( P_i \) is the active power output of the \( i \)-th generator set. \( a_i \), \( b_i \) and \( c_i \) are the corresponding coefficients of the quadratic function, and the specific value of \( a_i \), \( b_i \) and \( c_i \) can be determined experimentally.

2.2 Constraint Conditions

The constraint conditions of the economic dispatching model of power system are power balance and the upper and lower limits of generator output.

1) Power balance

\[ \sum_{i=1}^{n} P_i = P_L \]

where \( P_i \) is the active power output of the \( i \)-th generator, \( P_L \) is the total active load of power system.

2) The upper and lower limits of generator active output

\[ P_{i_{min}} \leq P_i \leq P_{i_{max}} \]

where \( P_i \) is the active power output of the \( i \)-th generator, \( P_{i_{max}} \) and \( P_{i_{min}} \) are the upper and lower limits of the \( i \)-th generator active output respectively.

3. Particle Swarm Algorithm

3.1 The Basic Particle Swarm Algorithm

The particle swarm optimization algorithm is proposed by Dr. Eberhart and Kennedy, and is derived from the research on the predatory behavior of birds. In a flock of birds, each bird can remember its former best position. What is more, different birds can communicate with each other to get the best location of the whole flock. As a result, each bird can adjust its flight path according to its historical best position and the historical optimum position of the whole flock. The specific steps of particle swarm optimization can be expressed as follows:

Step 1. Initialization: Initialize the particle swarm, each particle represents a solution in the solution space. The position and speed of the \( i \)-th particle in solution space is given by \( X_i \) and \( V_i \) respectively. The best position in the history of the \( i \)-th particle is recorded as \( P_i \), the historical optimum position of the population is recorded as \( P_g \).

Step 2. Fitness function: Substitute the initial particle value into the target function, calculate the value of the target function, and update \( P_i \) and \( P_g \).
Step3. Update the position and velocity of particles, generate new population, and judge whether the position and velocity of particles are out of bounds, then do the corresponding treatment. The updated formula of particle position and velocity can be expressed as:

\[ V_{i}(t+1) = wV_{i}(t) + c_{1}r_{1}(P_{i} - X_{i}(t)) + c_{2}r_{2}(P_{g} - X_{i}(t)) \]  \hspace{1cm} (4)

\[ X_{i}(t+1) = X_{i}(t) + V_{i}(t+1) \] \hspace{1cm} (5)

where \( w \) is called inertia weight, and \( c_{1} \) and \( c_{2} \) are called learning factor, also known as acceleration factor. Generally, \( r_{1} \) and \( r_{2} \) are random number uniformly distributed within the range of \((0,1)\).

Step4. The newly generated particles are substituted into the target function to calculate the fitness function value and update \( P_{i} \) and \( P_{g} \).

Step5. Check whether the iteration process meets the end condition, if so, the optimization process ends; if not, the number of iterations plus one and go to step 3.

3.2 Particle Swarm Optimization Algorithm with Compression Factor

The value of inertia weight is very important for the convergence of particle swarm optimization algorithm. When the inertia weight is large, it ensures faster search in solution space. However, it may cause the algorithm to easily miss the optimal solution in local search. By contrast, when the inertia weight is small, the advantage is that it is conducive to local search, but the global search cannot be carried out quickly, thus affecting the convergence speed of the algorithm.

The learning factors represent each particle’s ability to summarize its own experience and learn from better experience in the group. When the learning factor is small, it can make the particles have enough time to search the solution space between the current position and the optimal value. Of course, the cost is the low efficiency of the algorithm. When the learning factor goes to a large value, the particle will search in the target area quickly. However, the search interval of the particle in the solution space may be too large and it is easy to directly cross the target area.

Therefore, in order to avoid the above situation and make the algorithm converge to the global optimal value quickly and effectively, Clerc proposed the compression factor method to select inertia weight and learning factor in. The updated formula of particle position and velocity with compression factor can be expressed as:

\[ V_{i}(t+1) = \alpha \{V_{i}(t) + c_{1}r_{1}(P_{i} - X_{i}(t)) + c_{2}r_{2}(P_{g} - X_{i}(t))\} \] \hspace{1cm} (6)

where

\[ \alpha = \frac{2}{2 - c_{1} - \sqrt{c_{1}^2 - 4c_{2}}} \] \hspace{1cm} (7)

For the formula (6), its classical parameter value can be expressed as \( c_{1} = c_{2} = 2.05 \). This is formally equivalent to basic particle swarm algorithm with \( c_{1} = c_{2} = 1.49445 \) and \( w = 0.729 \).

4. Simulated Analysis

In this paper, a power system consisting of 6 generating sets is adopted as a simulation example\(^{[5]}\). The total load of the system is 1263 MW. Parameters of quadratic function representing generator cost, and the upper and lower limits of generator active output are shown in the table 1.
In this paper, in order to verify the influence of particle swarm optimization parameters selection on algorithm convergence and efficiency, we choose different parameters to run the simulation example, the specific parameter settings are shown below:

Case 1: \( c_1 = c_2 = 1.49445 \) and \( w = 0.729 \);
Case 2: \( c_1 = c_2 = 5 \) and \( w = 0.729 \);
Case 3: \( c_1 = c_2 = 0.5 \) and \( w = 0.729 \);
Case 4: \( c_1 = c_2 = 1.49445 \) and \( w = 1.2 \);
Case 5: \( c_1 = c_2 = 1.49445 \) and \( w = 0.2 \).

### Table 1. The data of Generators

| Generator | Pmax | Pmin | \( a \) | \( b \) | \( c \) |
|-----------|------|------|--------|--------|--------|
| 1         | 500  | 100  | 0.007  | 7      | 240    |
| 2         | 200  | 50   | 0.0095 | 20     | 200    |
| 3         | 300  | 80   | 0.009  | 8.5    | 220    |
| 4         | 150  | 50   | 0.009  | 11     | 200    |
| 5         | 200  | 50   | 0.008  | 10.5   | 220    |
| 6         | 120  | 50   | 0.0075 | 12     | 190    |

### Table 2. Simulation results

| Case | P1     | P2     | P3     | P4     | P5     | P6     | Total cost     |
|------|--------|--------|--------|--------|--------|--------|----------------|
| 1    | 445.0275 | 160.1144 | 283.6849 | 122.2466 | 167.3307 | 84.5958 | 1.5281e+04    |
| 2    | 500.0000 | 126.1143 | 300.0000 | 150.0000 | 66.8944  | 120.0000 | 1.5431e+04    |
| 3    | 472.6241 | 165.2154 | 273.6065 | 114.1046 | 152.9537 | 84.4650  | 1.5285e+04    |
| 4    | 435.8268 | 151.8208 | 234.3507 | 121.2413 | 120.0000 | 120.0000 | 1.5308e+04    |
| 5    | 430.1210 | 200.0000 | 248.8343 | 110.2556 | 153.7638 | 120.0000 | 1.5302e+04    |

**Figure 1.** PSO iterative curve with different parameter settings

In order to have a unified judgment standard, we stipulate that the population size of the particle swarm optimization algorithm is 100, and the maximum number of iterations of the particle swarm optimization algorithm is set as 200. In other words, when the number of iterations of the particle swarm optimization algorithm reaches 200, the iteration process stops and outputs the results.

According to the information shown in the figure 1 and table 1, it is clear that particle swarm optimization algorithm achieves the best results when the parameters are evaluated according to case 1.
5. Conclusion
In this paper, we first introduce the mathematical model of power system economic scheduling problem. Then, we introduce the basic particle swarm optimization and discuss the influence of parameter selection on convergence and efficiency of particle swarm optimization. After that, we choose the compression factor method to set the learning factor and weight of the particle swarm optimization algorithm. Finally, the simulation results show that the compression factor method is effective in selecting the parameters of particle swarm optimization.

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7. References
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