Calculation of Pressure Set-point for Coordinated Control System Based on Multi-objective Optimization

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Abstract. In this paper, the calculation and optimization of pressure set-points for large scale ultra- (super-) critical unit coordinated control system are studied, which adopts a multi-objective optimization method based on particle swarm optimization to adjust the pre-machine pressure set-point for the different external load requirements.

1. Introduction
Thermal power generation is still the most important source of electricity in China. According to the “13th Five-Year Plan for Power Development”, it is estimated that the installed capacity of coal-fired power will account for 55% by 2020, and the average coal consumption of the existing coal-fired generating units after transformation is less than 310 g (standard coal)/kWh. Therefore, achieving the optimal operation of thermal power units, improving their power generation efficiency, and reducing coal consumption for power generation are the top priorities for energy conservation and emission reduction in the thermal power industry[1].

In the past few decades, the control and optimization of the thermal process of the large scale unit coordinated control system has been extensively studied. For example, Ning Wang introduced a method of controlling the main steam pressure based on fuzzy self-tuning to make the pressure value of the coordinated control system is well controlled[2]. Liyang Wang introduced a method of controlling the steam temperature of the thermal power unit by the feedforward dynamic compensation method to optimize the control[3]. However, for the coordinated control system, its operation is affected by many factors, so it is difficult to meet multiple optimization requirements by using only one control index at the same time. Therefore, relying only on the adjustment control strategy can hardly achieve optimization of all control objectives, in addition, the increase the optimization of the control system must be considered.

In the coordinated control system, the idea of optimizing the pressure setting value has been embodied in engineering practice. The sliding pressure operation mode of thermal power unit under variable load conditions is one method for optimizing the pressure set-point. At present, a large part of the sliding curve of large scale operation is obtained through field test. Large randomness of the test process, complicated process, all these shortcomings can be overcome by the multi-objective optimization.
The optimization of pressure setting of large-unit thermal power units has gradually become a hot topic in the research field of coordinated control systems recently. Domestic and oversea scholars have applied various multi-objective optimization algorithms to the parameter optimization of coordinated control systems, and have made great progresses: Honghua Hu et al established the objective function for some main parameters and determined the calculation method according to the target value of thermal power unit operation, which was applied in large scale unit sets[4]. Na Yang adopted particle swarm optimization to analyze the coordinated control system and obtained the optimization result[5]. Jiaxing Wang used fuzzy predictive control to make unit set’s load tracking more rapidly[6]. Jiang Chang uses genetic algorithms to realize the multi-objective optimization calculations on the pressure set-points of coordinated control systems[7-9].

In this paper, the pre-machine pressure set-point of coordinated control system is optimized under various load conditions. According to the changed external load, a multi-objective optimization method based on particle swarm optimization is adopted to solve the pressure set-point. Compared with the existing methods, the proposed method can deal with the nonlinear, strong coupling and the large difference of the response speed of the furnace and some other problems, realizing the optimized results of multi-objectives such as reducing coal consumption and reducing throttling loss.

2. Particle Swarm Optimization

2.1 Introduction to Particle Swarm Optimization

The particle swarm optimization algorithm, which is proposed by Dr. Kennedy and Eberhart in the United States in 1995, is a random and parallel optimization algorithm. Besides, the algorithm is simple and easy to implement, does not require the optimized function to be derivable and continuous, and converges faster[10]. Therefore, once proposed, the particle swarm optimization algorithm has been widely favored, and has been deeply developed in various multi-objective optimization problems such as communication networks, pattern classification, and control, etc.

The central idea of particle swarm optimization is to use the cooperation and information sharing among individuals in the group to achieve the optimal solution[11], in which the main parameters are the dimension D of the target, i.e. the number of targets for multi-objective optimization, the velocity v and the position x of the particle, and the learning factor c1 and c2. In this paper, a particle swarm optimization algorithm with shrinkage factor is adopted to ensure its convergence[9], so there is a contraction factor K.

The particle swarm optimization algorithm can search in parallel with high-efficiency clusters, and the results can be obtained in a very short time. It can also search for space according to the optimal solution in the particle tracking group, thereby improving the calculation efficiency and execution speed. In addition, the algorithm can also use real number coding without converting the target to binary code, so it is very convenient to solve the multi-objective optimization problem.

2.2 Particle Swarm Optimization Algorithm

The basic flow of completing the particle swarm algorithm is as follows:

(1) Determine the dimension D (the number of targets) of the search space, determine the objective function, initialize the velocity v and position x of the particle, set the current optimal position of each particle as initial position, and set the global optimal solution as initial optimal solution;
(2) Calculate the objective function value of the particle, store the optimal position of the particle, and calculate the optimal fitness function value as the optimal position of the population;
(3) Update the velocity v and position x of the particle according to the formula, and add the contraction factor based on the formula proposed by Kennedy and Eberhart as shown in Equations 1 to 3:

\[
v_{ij}(t+1) = K \{v_{ij}(t) + c_1 r_1 [p_{ij} - x_{ij}(t)] + c_2 r_2 [p_{ij} - x_{ij}(t)] \}
\]

\[
x_{ij}(t+1) = x_{ij} + v_{ij}(t+1)
\]
The fitness function value of the updated particle, compare the value with the previous optimal value and retain the optimal solution;

(5) Compare the fitness function value of each particle with the optimal position of the entire particle, and retain the optimal solution;

(6) When the set number of cycles is reached or the optimal solution no longer changes, the calculation is terminated and output the optimal solution. If the expected condition is not reached, return to (3);

The algorithm flow chart is as follows:

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**Figure 1. Flow Chart of Multi-objective Optimization Based on Particle Swarm Optimization**

According to the operation flow of the particle swarm optimization algorithm, select the learning factor $c_1 = 2.1, c_2 = 2$ and find $K = 1.2082$, choose the number of evolutions $\text{max}_g = 200$, and the
size of the population $\text{sizepop} = 400$. Use Matlab to realize Multi-objective optimization of particle swarm optimization:

First select $D = 2$, search the optimal value of the test function, test the availability of the program. The test function is:

$$\min f(x) = 0.5 + \frac{\sin \sqrt{x_1^2 + x_2^2} - 0.5}{[1 + 0.01(x_1^2 + x_2^2)]^2}$$

$$\text{s.t.} \quad -100 < x_i < 100, \quad i = 1, 2$$

The optimal result after running is $f(0.0003,0.0032) = 3.25 \times 10^{-3}$, and the fitness function curve is as follows:

![Fitness Function Optimization Result](image)

Figure 2. Result of Fitness Function Optimization

It can be seen from Figure 2 that the algorithm has good adaptability to the test function. In the following, the algorithm will directly be adopted to optimize the pressure set-point parameters of the coordinated control system, and only the basic parameters need to be modified during the operation.

3. The Calculation of Pressure Set-point

The ultra-supercritical unit has different coordination control characteristics from the conventional sub-critical unit: non-linear, strong coupling and large difference in response speed of the furnace while load changing, etc. These features increase the difficulty of coordinated control of ultra-supercritical units. In order to achieve multi-objective optimization in the coordinated control system of large scale units, a nonlinear mapping of the turbine-boiler system is required, which refers to the mapping from varying unit load commands to coordinated control system settings and can realize good control performance. Based on this mapping, the process of finding the optimal feasible solution for coordinating the pre-machine pressure of the control system can be described as follows:

Firstly, establish a mathematical description and model of the coordinated control system in order to rewrite the desired target into an equation and determine the objective function. In this paper, a multi-objective optimization model for ultra- (super) critical thermal power units is selected. Take the output power of the control system, the coal consumption and the throttling loss of the steam turbine valve as optimal objective, adjust the pre-machine pressure setting value to realize the optimization and determine the corresponding objective function.

Secondly, determine the variation range of control domain of each optimization target under different working conditions; the different working conditions in this paper refer to the change of external load command. 10 different operating points are selected at the external load command level between 330MW and 600MW.

Then, after the select of the objective function and determining the control domain, find the optimal solution of the control variable within the feasible range with the help of particle swarm optimization algorithm.

Finally, after obtaining the optimal solution of the control variables, the established coordinated control system model can be used to solve the pre-machine pressure set value.
For a multi-objective minimization model optimization problem, the commonly used optimization methods are stratified sequencing method, constraint method, goal programming method and evaluation function method. The evaluation function method is a convenient and flexible method, the basic idea of which is to use an evaluation function to reflect the importance degree of each target in a concentrated way, and minimize the evaluation function to get the optimal solution of the problem\textsuperscript{[10]}. Common solutions in the evaluation function method are: Linear weighting method, min-max method, ideal point method and so on. Linear weighting as a basic and effective method often has a good effect in practical engineering applications. Its basic principle is that an inertia weight value is given according to the importance of the objective function \( w_i > 0(\sum_1^m w_i = 1) \), then add objective functions with these inertia weights to form a new objective function. By evaluating this new objective function, one solution to the multi-objective optimization problem can be found. In this paper, the evaluation function method is adopted to solve the multi-objective optimization model of the coordinated control system, and the evaluation function is minimized by the linear weighting method to obtain the optimal solution for multiple optimization targets.

3.1 Model and Solution of Multi-objective Optimization

Before calculating the solution with Matlab, it is necessary to determine the optimization model of the ultra- (super) critical unit coordinated control system. In this paper, the unit coordinated control system load control must ensure that the output power meets the change of the unit's external load command, i.e. \( f_1(x_1,\cdots,x_n) = \min | E_0 - E |, x \in R \), among them \( E_0 \) is the theoretical calculation of the unit power, \( E \) is the unit load demand. In addition, under the premise of meeting the external load demand, the coordinated control system should also reduce the coal consumption as much as possible to achieve the purpose of energy saving. Suppose \( x_r \) to be the amount of fuel, there is \( f_2(x_1,\cdots,x_n) = \min x_r, x_r \in R \). Under a fixed unit load level, the smaller the turbine valve opens, the greater the throttling loss will be, which will cause the turbine efficiency to decrease. Considering the turbine efficiency, suppose \( x_s \) to be opening of steam turbine valve, there is \( f_3(x_1,\cdots,x_n) = \max x_s, x_s \in R \).

According to the above analysis, the multi-objective optimization model can be transformed into a multi-objective minimization model:

\[
f_1(x_1,\cdots,x_n) = \min | E_0 - E |, x \in R \tag{5}
\]

\[
f_2(x_1,\cdots,x_n) = \min x_r, x_r \in R \tag{6}
\]

\[
f_3(x_1,\cdots,x_n) = \max x_s, x_s \in R \tag{7}
\]

According to the unit model, the steam turbine fuel quantity \( B \), the valve opening degree \( \mu_r \), and the feed water flow rate \( W \) can be respectively set as \( x_1, x_2, x_3 \), and the final multi-objective optimization model is:

\[
f_1(x_1, x_2, x_3) = \min | E_0 - E |, x_1 \in R \tag{8}
\]

\[
f_2(x_1, x_2, x_3) = \min x_r, x_r \in R \tag{9}
\]

\[
f_3(x_1, x_2, x_3) = \min -x_2, x_2 \in R \tag{10}
\]

\[
E_0 = K_1(P_b - K_2E^{1.5})x_2 \tag{11}
\]

\[
P_b = \frac{2k_1k_2x_1 + 2k_1k_3h_1x_1 + k_1^2h_1x_3 - k_2^2x_2^2}{2k_1k_2h_2x_2} \tag{12}
\]

\[
P_t = P_b - K_2E^{1.5} \tag{13}
\]
Where $P_b$ is the boiler pressure and $P_f$ is the turbine pressure, i.e. the pre-machine pressure setting. According to the formula and data proposed in the literature\cite{12}\cite{13}, the specific parameters of a supercritical coal-fired unit are $k_1 = 3.77, k_2 = 61.74, k_3 = 3.77$, $k_4 = 718955.20, t_f = 284, K_1 = 0.000135, h_s = 2538.90, h_f = 1244.78$.

After the establishment of model, the objective function can be constructed. In this paper, the linear weighting method of evaluation function method is adopted. Therefore, three weighting factors need to be set. When setting the weighting factor, the most important task of the coordinated control system must be considered, that is to ensure that the unit can meet the external load command, on this basis, to take the goal of reducing coal consumption and reducing throttling loss into account is also necessary. So select $w_1 = 0.7, w_2 = 0.1, w_3 = 0.1$, the objective function is:

$$
\Phi[f(x)] = w_1 f_1 + w_2 f_2 + w_3 f_3 \quad (14)
$$

Taking the data calculated from the reference above into Equation 14 gives:

$$
\Phi[f(x)] = 0.7 | E - 47.31(P_b - 0.000135E^{1.5})x_2 | + 0.2x_1 - 0.1x_2 \quad (15)
$$

Where $P_b$ is the boiler pressure, see in Equation 12.

After determining the fitness function, we can calculate the feasible domain of the target model. According to the literature, the feasible parameters of the target parameters under different load commands can be calculated, where E is the unit load demand (MW), $x_1$ is the turbine fuel quantity; $x_2$ is the valve opening; $x_3$ is the feed water flow, $x_1, x_2, x_3$ are all in percentage, the table of feasible field is as follows:

| $E$  | $x_1$ Min | $x_1$ Max | $x_2$ Min | $x_2$ Max | $x_3$ Min | $x_3$ Max |
|------|-----------|-----------|-----------|-----------|-----------|-----------|
| 600  | 0.7099    | 0.9034    | 0.7837    | 0.9995    | 0.7043    | 0.8867    |
| 570  | 0.6938    | 0.8860    | 0.7418    | 0.9996    | 0.7106    | 0.8540    |
| 540  | 0.6729    | 0.8622    | 0.7048    | 0.9992    | 0.6805    | 0.8206    |
| 510  | 0.6473    | 0.8329    | 0.6719    | 1.0000    | 0.6497    | 0.7868    |
| 480  | 0.6179    | 0.7988    | 0.6427    | 0.9994    | 0.6185    | 0.7525    |
| 450  | 0.5850    | 0.7605    | 0.6166    | 0.9992    | 0.5868    | 0.7180    |
| 420  | 0.5488    | 0.7187    | 0.5934    | 0.9994    | 0.5543    | 0.6832    |
| 390  | 0.5281    | 0.6817    | 0.5729    | 0.9166    | 0.5334    | 0.6480    |
| 360  | 0.5053    | 0.6444    | 0.5549    | 0.8363    | 0.5104    | 0.6125    |
| 330  | 0.4804    | 0.6065    | 0.5395    | 0.7581    | 0.4852    | 0.5765    |

After obtaining the feasible domain, use the Matlab program in Section 3.2 to obtain the optimal value of $x_1, x_2, x_3$ under different conditions. The parameters are set as $c_1 = 2.1, c_2 = 2, K=1.2082$, number of evolutions $maxg = 200$, population size $sizepop = 400$, dimension $D = 3$, randomly selected population initial position and velocity, then run the program.

According to the program, the optimal values under different conditions are as shown in the following table, where $E$ is the unit load demand (MW), $x_1$ is the turbine fuel quantity; $x_2$ is the valve opening; $x_3$ is the feed water flow, $x_1, x_2, x_3$ are all in percentage.
Table 2. The results of Matlab optimization

| $E$ | $x_1$ | $x_2$ | $x_3$ |
|-----|-------|-------|-------|
| 600 | 0.7528 | 0.7898 | 0.7415 |
| 570 | 0.7256 | 0.7652 | 0.7230 |
| 540 | 0.6854 | 0.7421 | 0.6957 |
| 510 | 0.6798 | 0.7209 | 0.6541 |
| 480 | 0.6417 | 0.7033 | 0.6359 |
| 450 | 0.6149 | 0.6784 | 0.6146 |
| 420 | 0.5871 | 0.6614 | 0.5811 |
| 390 | 0.5502 | 0.6359 | 0.5521 |
| 360 | 0.5310 | 0.6017 | 0.5338 |
| 330 | 0.4999 | 0.5742 | 0.4855 |

3.2 Analysis of Pressure Set-point Optimization’s Result

Calculate the turbine pressure according to Equations 11, 12, and 13, we can conclude the optimum value of the turbine pressure set-point under different external load commands, as shown in the table below, where $E$ is the unit load demand in MW, which is the theoretical calculation of the unit power. $P_b$ is the boiler pressure, $P_t$ is the turbine pressure, all in Mpa.

Table 3. The result of pressure set-point calculation

| $E$ | $P_t$   | $P_b$   | $E_o$   |
|-----|---------|---------|---------|
| 600 | 18.18809| 16.20400| 597.8036|
| 570 | 17.58139| 15.74423| 569.9666|
| 540 | 16.90189| 15.20785| 533.9286|
| 510 | 16.46973| 14.91488| 508.6836|
| 480 | 15.81644| 14.39674| 479.0246|
| 450 | 15.25073| 13.96203| 448.1128|
| 420 | 14.62954| 13.46754| 421.4104|
| 390 | 13.93429| 12.89454| 387.9248|
| 360 | 13.54557| 12.62345| 359.3444|
| 330 | 12.95372| 12.14443| 329.9082|
As above table and figure show, according to the calculation results of this paper, with the help of the multi-objective optimization based on particle swarm optimization in solving the pressure set-point the unit can meet the power load demand very well. Even if there are some changes in external load commands, the unit can still achieve the required output power. Compared with the test-based method, the multi-objective optimization solving process is simpler and faster, and saves a lot of time and effort for physical test.

It can be seen from Figure 4 that after multi-objective optimization calculation, the coal consumption obtained in the coordinated control system is closer to the lower limit of the control domain of coal consumption, indicating that to some extent the coal consumption is reduced by optimization, that is, in the objective function \( f_2 \) got optimized. Compared with the results obtained from the experimental results of the sliding pressure curve, the particle swarm optimization algorithm can reduce the coal consumption based on tracking load change so that it can ultimately reduce the overall power generation energy consumption.
According to the calculation results of Matlab, the graph of the turbine pressure set-point at different powers obtained by multi-objective optimization is plotted and compared with the curve of the sliding pressure operation as shown in Figure 5. It can be analyzed from the calculation results and the graph that the pressure set-point obtained by the particle swarm optimization algorithm is lower than the original theoretical pressure set-point. Under various load conditions, the valve opening will change with the load, which causes steam to create a throttling effect in the valve, reducing the pressure. A lower turbine pressure setting reduces the throttling loss of the turbine valve, which is $f_3$ in the objective function of this chapter. Compared with the traditional test-based method, this method takes into account the influence of the coordinated control system on the equipment, and can extend the service life of the equipment to some extent.

From the above analysis that the multi-objective optimization of the pre-computer pressure set-point achieves the expected goal of tracking external load changes, reducing coal consumption and throttling losses. Compared with the traditional test-based method to obtain the sliding pressure curve, the multi-objective optimization can not only track the external command changes but optimize the system in terms of reducing coal consumption and reducing throttling loss, and overall improves the power generation efficiency. Since the goal with the highest weight conforms to the change of external working conditions, it can be concluded from the table that the calculated output power is very close to the external requirement while the weights of coal consumption and throttling loss are small, of which the optimization effect of these parts is therefore less than the optimization effect on the load.

4. Conclusion
In this paper, a multi-objective optimization method based on particle swarm optimization (PSO) is proposed for the optimization of pressure set-points in coordinated control systems. This method is adopted to optimize the output power of the optimized unit, and to reduce the coal consumption and the throttling loss as much as possible. Compared with the traditional physical test-based method, this method in this paper is more convenient, simple, and less random, of which the optimized effect also meets the expected performance index, providing a new idea for the unit to achieve high-efficiency and energy-saving power generation.

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