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Optimal load distribution in plant-level based on equipment status

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In TW the method of a load optimization model based on equipment state is proposed. MSET state evaluation method is used to evaluate the induced draft fan, and optimization algorithm is used to optimize the distribution model to improve the power system economy.

TW purpose – the stability and economy of the power grid and the stability of the unit are improved by the state monitoring patrol algorithm.

TW contains: According to the results of the condition diagnosis of the induced draft fan, the optimization algorithm based on the state of the equipment finds that the optimization results based on the state of the equipment are safer, more stable and less economical than the direct optimization results.

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ABSTRACT

With the continuous reform of the electric power industry, the operation mode of the electric power industry has been changed from the original national unified pricing to "separation of power plant and power grid, bidding for power grid". Therefore, thermal power units are faced with the problem of bidding for power grid. Thermal power plants need to improve the competitiveness of thermal power plants, the safety and stability of unit operation and auxiliary equipment by reducing the operation cost and the safety and stability of thermal power units Relevant, the reliability of equipment is an important factor affecting the load stability of the unit. The instability of load not only brings economic loss to the power plant, but also destroys the stability of the power grid. Therefore, the stability of the load can be improved by considering the operation status of equipment in the optimal load distribution. Unit operation will produce polluting gas, which will damage the environment. Therefore, in the optimal load distribution, we should not only pursue the lowest economic cost, but also consider the pollutant emissions. As the cost of energy consumption is very small, the multi-objective load optimization algorithm is used in this paper.

In this paper, multiple state estimation (MSET) is used to evaluate the equipment state. In this paper, the orthogonal local preserving projection (OLPP) algorithm is introduced to reduce the dimension of parameters in the model, and the accuracy of OLPP feature extraction and classification is high. The OLPP-MSET state evaluation model is established.

Based on the analysis of the type and function of the auxiliary equipment of the thermal power unit, combined with the principle of equipment selection, this paper selects the main auxiliary equipment that affects the load, and selects the state evaluation parameters according to the type and cause of the failure of the auxiliary equipment. Because of the interference of the complex and bad selection data in the operation environment of the thermal power unit, there may be deviation between the real data and the data, the wavelet transform theory is used to reduce the noise of the data. Then take the induced draft fan as an example to verify the validity of olpp-mset model. It is found that the model can reduce the false alarm rate of state evaluation and discover the development process of equipment.

According to the load capacity of the computer group based on the equipment status, when the equipment fault status or fault development process is detected and it is considered that the equipment cannot carry load, the maximum load value of each kind of equipment is calculated according to the importance and redundancy of the equipment, then the minimum value of the maximum load value of each equipment is taken as the load capacity of the unit, and the load capacity of the unit is taken as the approximate value of the load optimal distribution Beam condition. The optimization of load distribution is based on economic cost and environmental cost. The improved multi-objective particle swarm optimization (MOPSO) algorithm is applied to optimize the load distribution. The results show that the optimization ability of the improved MOPSO algorithm is stronger than that of MOPSO. Considering that the load optimization

distribution of equipment status is not affected by the equipment status when the load is in, the load optimization distribution can reduce the power plant loss when the load is in high load section, and the load distribution loss considering the equipment status in a short time is very small compared with the equipment and equipment parts. The optimal load distribution considering the equipment status can not only improve the safety of the unit, reduce the economic loss of the power plant, but also improve the stability of the power grid and increase the competitiveness of the power plant.

1 INTRODUCTION

1.1 Research Background and Significance

With the implementation of the bidding system, reducing the cost of power generation has become the key to the survival and development of enterprises. The basis of economic power generation is the safety and reliability of equipment. The operation reliability of power plant equipment is not only related to the safe and continuous operation of thermal power plants, but also related to the stability of power grid system. Therefore, the reliability of thermal power unit equipment is an important factor affecting the unit safety and power grid reliability [1]. In 2013, China Power Federation investigated the non-stop times and duration of thermal power units of 100MW and above. It was found that 920 unplanned outages occurred to the units, with a total duration of 52443.5h. Among them, the non-stop plan caused by the boiler and its auxiliary equipment has reached 500 times. Frequent failures of thermal power plant equipment will not only bring economic losses to the power plant, but also damage the stability of the power grid. Therefore, in the optimization of load distribution, reliable operation of unit equipment has become an urgent factor to be considered.

The existing detection condition is that the thermal power plant system detects the single point value of the equipment. When the single point value of the equipment reaches the alarm value, the system alarms, which can not realize the evaluation of the operation status of the whole equipment, and can only analyze and solve the problem afterwards when or after the fault occurs. By analyzing the data after the fault, the traditional fault diagnosis method can find the symptom data of the fault and build a database, which can give a warning when the fault occurs. The advantages of traditional fault diagnosis can accurately determine the type of fault, its disadvantage is that it can only give early warning to some faults in the database and has high requirements for data. The thermal power unit equipment is complex, and there are many types of fault. Therefore, this method can not realize the accurate evaluation of equipment status. It is easy to cause power plant loss and damage the stability of power grid if the overall operation of equipment cannot be accurately evaluated.

In the face of the shortcomings of the traditional way and the development of the current operation mode to the direction of intelligence and automation, at the same time, the generation of fault is a gradual development process, the whole process will be accompanied by some abnormal changes of characteristic signals or data trends, using and analyzing data information to find out the abnormal operation status of detection equipment in advance. Based on the mass data of equipment operation, the state detection and evaluation of the three main equipment of the power plant, namely, the machine, the furnace and the electricity, and the important auxiliary equipment are carried out, so as to realize the evaluation of the load capacity of the unit, improve the reliability of the load optimal dispatching of the power plant, and realize the economic and safe load regulation. With the reduction of primary energy and environmental pollution, the state attaches more and more importance to energy conservation and consumption re-

duction. The state puts forward new requirements for the energy consumption and pollutant emission of large-scale coal-fired power units. How to reduce the coal consumption and pollutant emission of thermal power units has become the main method for energy conservation and consumption reduction of thermal power units. This requires us to control the environmental cost when considering the optimal load dispatch of thermal power plants. In recent years, the development and application of on-line monitoring system provides data support for load optimal dispatching operation and planning of thermal power plant. It is of great significance to detect the equipment of thermal power plant by various methods, carry out the research on health status evaluation of auxiliary equipment, and reasonably adjust the operation according to the health status of the unit to improve the safety, economy and reliability of the whole unit.

1.2 Research status at home and abroad

1.2.1 Research status of equipment condition monitoring

In today's society, technology is becoming more and more important. Therefore, it is necessary for us to take the real-time state detection and fault early warning of operating equipment as an important activity of industrial production. At present, EPRI company completes the relevant standard customization of the world's power industry. At the same time, EPRI company has made great achievements in observation and early warning, and also has many applications in thermal power units. The company designed and developed the condition monitoring and fault diagnosis system of power plant in 1981, which is based on artificial intelligence algorithm and applied in thermal power plant in 1984. Electric power REINST, USA Inc [2] designed a kind of monitor that can realize early warning of equipment failure, and obtained patent. Herzog et al. [3] of American real Argonne laboratory developed a set of new algorithm. It is about that when venturi feed water flowmeter is used in nuclear power plant, the real flow can be estimated by using multiple states which reduce the precision of surface corrosion, the data obtained will be analyzed, and then the multiple states will be used to estimate the real flow The state estimation method can well reflect the equipment state by comparing the displayed flow with the real flow. Liu [4] combines Dempster Shafer theory and Bayesian theory, and puts forward a new method of information fusion DSmT (Dezert Smarandache theory) to deal with the problem of state evaluation. Through the research and analysis of state estimation, a state estimation model based on DSmT is proposed, and the generalized basic belief allocation and information fusion rules are established. And compared with DSmT and DST. The results show that DSmT improves the quality of fusion results and the performance of state evaluation by reducing the calculation time. Yang et al. [5] put forward a state classification evaluation model based on matter-element theory, and established a hierarchical state evaluation index system. The state variables are expressed by matter-element, and the evaluation indexes are quantified by differential square transformation. The matter-element of expert effectiveness is introduced to deal with the weight more objectively, and the concept of Euclidean closeness degree is in-

troduced to realize the pattern recognition or classification of states. Raheja et al [6] proposed a composite CBM architecture based on data fusion / data mining. Data fusion is widely used in national defense. It is a process of automatically combining the information of multiple information sources to make decisions on the target state. Data mining searches for unknown patterns and relationships in large data sets; this method is used to support multiple levels of data fusion and model generation. Chen etal [7] proposed a method of condition monitoring and performance evaluation based on the operating condition of the unit. The condition criterion and operation state synchronization method of on-line monitoring system are described in detail. Zheng etal [8] in order to meet the needs of equipment condition based maintenance and overcome the shortcomings of traditional condition evaluation model in data collection method, component classification, performance index and scoring model, a comprehensive multi information condition evaluation model (CCEM) based on condition evaluation model is proposed. Combined with off-line testing, on-line testing, on-line monitoring, and testing operation environment, equipment standards, bad use conditions (USC) and equipment defects are reclassified. In order to improve the reliability of condition evaluation of large-scale equipment and provide reasonable decision-making for condition based maintenance, a new method of transformer condition evaluation based on multi-level extension evaluation is proposed by combining the multi-level extension evaluation method with the influencing factors of equipment condition. The weight of transformer state information is calculated by eahp.

Li Jianlan et al [10] put forward a new theory of correlation degree, and established a grey model for the evaluation of auxiliary equipment shape of power station by applying the grey correlation degree. The quantitative evaluation of equipment can be realized by calculating the grey correlation degree between the observation parameters and rated parameters of the evaluated equipment, and the similarity degree between the actual operation state and rated operation state of the equipment. Dong Yuliang and other teachers proposed to extract the characteristics of the state parameters of the steam feed pump based on the local orthogonal maintenance projection algorithm (olpp), input the data of the steam feed pump in the normal condition to the self-organizing neural network (SOM) to adjust the parameters in the SOM at the same time, that is, to build a model of the data of the steam feed pump in the good operation condition, Then the distance between the real-time feature vector and the trained neural network neuron weight vector is compared to realize the equipment state evaluation [11,12]. Liu Jizhen etal. [13] also have deep views on fault early detection, especially in state estimation technology (Mset). The method to judge whether the fan works normally is to compare the difference between the observation vector and the estimated value, that is, to build a nonparametric model by using Mset, and to determine the fault early warning threshold by using the sliding window method. Through a series of practical applications, this method is proved to be feasible. Zeng Qinghua etal. [14] also mentioned the advance judgment of faults. His method is a little different. He uses neural network and information entropy. He also uses local projection method (LPP) to extract high-dimensional and non-linear characteristic parameters of wind turbine, improve modeling accuracy,

reduce modeling complexity, establish neural network prediction model of target state, and adopt The information entropy method analyzes the residual trend of the target state parameter prediction model to realize the early warning of wind turbine.

1.2.2 Development status of load optimization

The load optimal distribution mainly includes two aspects: one is to set the unit combination of the power plant as the premise, and to coordinate the optimal distribution among the units. The purpose is how to make the reasonable distribution to minimize the power consumption rate, the coal consumption and the economic benefits of the whole thermal power plant. Second, it is used to optimize the load distribution during deep peak load regulation, and determine the start and stop plan of the unit during peak load regulation.

The earliest method of load optimal distribution is base load method, which includes sequential input method and reverse sequence cut-off method [15]. The sequential input method ranks the units according to efficiency, and the units with high efficiency first carry full load, and then the units with low efficiency and so on. The reverse sequence cut-off method starts from the low efficiency unit to cut off the load. Later, researchers found that the most efficient point is not the full load point, so they found the best point load method. These methods are simple and easy to operate, but there is no theoretical basis. Through research, it is found that the optimal allocation of the leading load is the slightly increased energy consumption rate, rather than the energy consumption rate [16]. Li Shushan [17] proposed a load optimal allocation method with output duration constraint by combining equal incremental rate with generation sequence table. In the reform of power market, the optimal load distribution is that the power plant pursues the economic optimization of the whole plant, and the power grid pursues the minimum power purchase cost according to the power plant quotation curve. When the unit participates in peak load regulation, it is difficult to determine the energy consumption function of unit start and stop, and the non convex function appears in the quoted price of power grid, so the method of micro increase rate is no longer applicable. People are actively looking for the optimal load distribution method under complex load conditions. Nonlinear programming method, dynamic programming method, genetic algorithm and particle swarm optimization algorithm are all well applied. The optimal load distribution with generation cost and power supply cost as the objective function can be solved by combining the operation research algorithm. In the bidding mechanism, the power plant quotes and loads according to the unit equipment status and economic cost, and the power grid selects units to generate electricity according to the quotes and loads [18].

The main mathematical optimization algorithms are linear programming, Lagrange relaxation and dynamic programming. The advantages of the linear programming method are simple operation and less calculation. The disadvantages of the linear programming method are that the objective function and constraint conditions are approximately linearly treated. There is a deviation between the linear treated coal consumption char-

acteristic curve and the real coal consumption characteristic curve, and the calculation results are not accurate. In reference [19], the relationship between the coal consumption characteristic curve and the load of the unit is treated linearly, and the optimal load distribution is carried out by using the linear programming method. Lagrange relaxation algorithm is a dual optimization algorithm, which adds constraints to the objective function. The advantage of Lagrange relaxation algorithm is that it can get better results when dealing with more unit commitment problems. The disadvantage is that the objective function of Lagrange relaxation algorithm must be convex function, and the optimal solution of non convex function may not be the optimal solution. In reference [20-23], the Lagrangian algorithm is used to calculate the optimal load distribution and good results are obtained. The dynamic programming method has the advantages of fast calculation speed and high precision, and the units with more calculation shortcomings are easy to fall into dimension disaster. In reference [24-25], the dynamic programming method is applied to realize the combination of units in power system, including the start and stop of units and the load distribution of units.

The modern intelligent optimization algorithm can find the global optimum more quickly and accurately. The intelligent optimization algorithm mainly includes particle swarm optimization algorithm, genetic algorithm, cosine algorithm and so on. Particle swarm optimization was proposed by Kennedy and Eberhart in 1995. Particle swarm optimization (PSO) realizes information sharing by simulating the migration and aggregation behavior in the predatory behavior of bird swarm, and information transfer between individuals and populations, so as to update the particle position and speed and find the global optimum. Reference [26] shows that particle swarm optimization algorithm is better than the traditional algorithm in load optimization. Particle swarm optimization (PSO) is easy to fall into local optimum and slow in global convergence. Li Shaojin et al. [27] used the fuzzy mechanism to establish the particle adaptive membership function, modified the weight through the current particle fitness, so that the weight is updated in the cycle, the same generation of particles have the same weight, so as to avoid falling into the local optimum. Zhao Jianwei [28] put forward the strategy of quadratic term improvement and the strategy of self-adaptive adjustment of weight and acceleration coefficient improvement to balance the global optimum and the local optimum, in which the weighting method is more complicated, and also put forward the virtual ideal particle swarm optimization algorithm. Some scholars [29] limit the scope of particle search in order to overcome the particle falling into local optimum. There are many references [30,33] that combine PSO with other algorithms. In order to improve the efficiency of particle swarm optimization (PSO), it is proposed in [31,32] to dynamically change the spatial dimension of PSO. With the development of wind energy, when large-scale wind energy is connected to the grid, the stability of the power system becomes poor due to the randomness of wind power output. For the power system with wind farms, the combined scheduling of units becomes an urgent problem to be solved. Tengbaian [33] applies the method of combining multi-objective particle swarm optimization and ant colony algorithm to solve the problem of power generation cost and envi-

ronmental pollution cost The multi-objective optimal scheduling problem of power system with wind farm is the objective.

The development of load optimization algorithm on the constraint conditions: the load optimization distribution in reference [34-36] is mainly to pursue the optimal economy of the whole plant on the premise of meeting the total load requirements. With the strengthening of environmental protection requirements, the literature [37,38] takes environmental factors or emission price factors into account, mainly limits and emissions. Wang Zhiguo [39] will be fast.

1.3 Research content

With the development of renewable energy in recent years, the stability of power system is threatened. In order to maintain the stability of the power grid, thermal power plants need to reduce load fluctuations. Therefore, the reliability and load capacity of the unit need to be considered in the optimal load distribution of the plant level. The whole process of the thermal power unit is completed by the main and auxiliary equipment, so the reliability and load capacity of the unit are related to the auxiliary equipment of the unit. According to the basic process of thermal power plant, this paper determines the auxiliary equipment that mainly affects the unit status and load capacity, and introduces the evaluation method of auxiliary equipment operation status in detail, then determines the unit load capacity according to the auxiliary equipment status, finally takes the unit load capacity as the constraint condition, and then carries on the load optimization distribution model with the goal of coal consumption cost and environmental cost Solution. The main work of this paper is as follows:

The first chapter: introduce the research significance, main content, domestic and foreign research status of this topic, and determine the application method of the research topic.

In Chapter 2, multi state estimation method (Mset) is used to evaluate the state of equipment. Because characteristic parameters are needed in the process of equipment state evaluation, and there is coupling between characteristic parameters, this paper introduces the method of dimension reduction of characteristic parameters, applies olpp algorithm to dimension reduction of characteristic parameters, and establishes Mset state estimation model based on olpp algorithm. The kernel smoothing density estimation method is used to determine the early warning threshold.

Chapter three: according to the process and equipment selection principle of thermal power unit, select the auxiliary equipment which mainly affects the reliability and load capacity of the unit to evaluate the equipment status. In this paper, the selection and processing of state evaluation parameters are introduced, and wavelet transform is used to denoise the original data. Taking the induced draft fan as an example, the equipment status evaluation model based on olpp-mset is applied to evaluate the equipment and verify the validity and accuracy of the model.

Chapter four: according to the status of auxiliary equipment of thermal power unit, the degree of influence on load and the capacity of computer group with or without standby equipment, determine the constraints of optimal load distribution. The least square method is used to fit the relationship between coal consumption cost and load, and the relationship between pollutant emission and load. Then, a load optimal distribution model is established with energy consumption cost and environmental cost as the objectives, and the unit load capacity, power balance and pollutant emission limit as the constraints based on the equipment status.

Chapter five: the multi-objective particle swarm optimization (MOPSO) algorithm is easy to fall into the local optimum, so the MOPSO algorithm is improved. The improved MOPSO algorithm is applied to optimize the load distribution of thermal power units, and the optimization ability of the improved algorithm is verified. Finally, the optimal load distribution considering the equipment state is compared with that without considering the equipment state.

2 ESTABLISHMENT OF OLPP-MSET STATE EVALUATION MODEL

2.1 Feature dimension reduction

2.1.1 Local preserving projection algorithm

LPP is a linear dimensionality reduction method. LPP can well aggregate the same kind and classify the different kinds. It not only overcomes the defect that the projection matrix of the Laplacian feature mapping algorithm (LE) can't be displayed, but also solves the problem that the PCA method can't keep the original data nonlinear. LPP algorithm constructs projection matrix by adjacent graph, multiplies the original data by projection matrix to get the dimension reduction data after projection, and tries to keep the local structure of the original data as much as possible after dimension reduction. In order to improve the local retention ability of projection and the recognition ability of classification, a new distance definition method based on Euclidean distance can effectively use the known category information and keep the local geometry The distance formula is improved to improve the polymerization ability of the same kind and the separation ability of the different kind.

Assuming that there is a high-dimensional space R^m, it represents a training sample $X=[x_1,x_2,x_3,\cdots,x_n]$. $x_i \in \mathrm{R}^m (i=1,2,\cdots,m)$ The sample is projected into a low-dimensional space through a projection matrix. The low-dimensional space keeps the local structure of the original data $A=[a_1,a_2,\cdots,a_l]$ $a_i \in \mathrm{R}^n$, and the low-dimensional feature subspace is $Y=[y_1,y_2,\cdots,y_n]$, $y_i \in \mathrm{R}^l$ ($l<m$), then there is $y_i = A^{\mathrm{T}} x_i$. The linear transformation is obtained by minimizing the objective function (2.1):

$$\min \sum \left\| y_i - y_j \right\|^2 w_{ij} \tag{2.1}$$

where w_{ij} – similarity between adjacent samples;

W – symmetric similarity matrix.

Thermonuclear calculation (2.2):

$$w_{ij} = \begin{cases} \exp\left(-\dfrac{\left\| x_i - x_j \right\|^2}{\beta} \right), \beta \in R & i, j, near \\ 0 & i, j, not \end{cases} \tag{2.2}$$

Formula:

Simple binary assignment calculation $\beta > 0$:

Simple binary assignment calculation (2.3):

$$w_{ij} = \begin{cases} 1 & i, j, near \\ 0 & i, j, not \end{cases} \tag{2.3}$$

There are two methods to construct adjacency graph:

1. k Neighbor, if $x_j \in d_k(x_i)$, then x_j and x_i neighbor, otherwise non neighbor, where $d_k(x_i)$ is the x_i of nearest points k.

2. Near neighbor δ, if $\|x_j - x_i\| \le \varepsilon$ so x_j is a near neighbor x_j, otherwise it is not a near neighbor.

The distance formula redefined in the case of neighbor and non neighbor is as follows (2.4):

$$d \begin{cases} \dfrac{\|x_i - x_j\|^2}{\delta} & x_i, x_j, near \\ \delta \|x_i - x_j\|^2 & x_i, x_j, not \end{cases} \tag{2.4}$$

After dimension reduction, the distance between new sample points is determined by the size, and the selection method is as follows (2.5):

$$\delta = \alpha \frac{\max\limits_{i,j \in d_k} \|x_i - x_j\|^2}{\min\limits_{i,j \notin d_k} \|x_i - x_j\|^2} \tag{2.5}$$

In the formula $\max\limits_{i,j \in d_k} \|x_i - x_j\|^2$, it represents the farthest distance of i, j, $\min\limits_{i,j \notin d_k} \|x_i - x_j\|^2$ the nearest neighbor and the nearest distance of the non nearest neighbor. It is the user's reference data $\alpha \ge 1$. In this way, it can ensure that any sample point does not contain any non nearest neighbor

When the minimization objective function (2.1) is taken into account, the following formula is obtained (2.6):

$$\min \sum \|y_i - y_j\|^2 w_{ij} = \min \sum A^{\mathrm{T}} XLX^{\mathrm{T}} A \tag{2.6}$$

The diagonal matrix D is the sum of the columns W. Laplace matrix is defined as $L = D - W$. In order to eliminate the arbitrariness of scaling and translation of the minimum problem, the following constraints are made (2.7):

$$A^{\mathrm{T}} XDX^{\mathrm{T}} A = 1 \tag{2.7}$$

Transform the objective function of (2.3) into (2.2) into (2.8):

$$\arg\min A^{\mathrm{T}} XLX^{\mathrm{T}} A \tag{2.8}$$

That is to say, the generalized eigenvalue of solution (2.6) in a formula (2.9):

$$XLX^{\mathrm{T}} A = \lambda XLX^{\mathrm{T}} A \tag{2.9}$$

The projection matrix is composed of the eigenvectors corresponding to the smallest non-zero eigenvalues in the (2.9) formula, and the final result is reduced to the result.

2.1.2 Orthogonal local preserving projection algorithm

The steps of olpp algorithm are as follows:

Input: high dimensional dataset $X = [x_1, x_2, x_3, \cdots, x_n]\ x_i \in \mathrm{R}^m$, cumulative contribution rate, nearest neighbor parameter k and α

Output: low dimension embedded coordinates $Y = [y_1, y_2, \cdots, y_n]\ y_i \in \mathrm{R}^l\ (l < m)$

1. First, PCA algorithm is used for initial projection, the initial reduced dimension projection matrix is $\mathrm{A}_{\mathrm{PCA}}$, and the initial training set after projection is $\bar{X}$;
2. Construct the adjacent undirected graph. When one point is one of the nearest k points of another point, the two points are connected by edges;
3. Construct the weight vector W, and calculate the weight matrix by the hot kernel method or simple method;
4. Calculate the orthogonal basis function and solve the orthogonal basis vector $A_{\mathrm{OLPP}} = [a_1, a_2, \cdots, a_m]$;
5. Olpp embedding, the low-dimensional embedding coordinate is $Y = A^{\mathrm{T}} X$, where $A = A_{\mathrm{PCA}} A_{\mathrm{OLPP}}$.

2.2 Multivariate state estimation model

2.2.1 Principle of multivariate state estimation

MSET is an anomaly detection method adopted by Argonne National Laboratory in the United States [3]. MSET is a multivariable estimation technology. By comparing the real-time data with the historical data, the real state of the equipment is obtained. In essence, the state evaluation model is established by learning the relationship between the parameters of the normal operation of the training equipment. The health state evaluation model should include all the health states. Calculate the orthogonal basis function and solve the orthogonal basis vector. Each real-time state vector corresponds to an

estimation vector in the state estimation model, and the deviation between the real-time state vector and the estimation vector is used as the indicator to judge the state evaluation. When the equipment fails, there is no corresponding state parameter in the multivariate state estimation model, and the deviation will exceed the warning threshold. At the same time, MSET model can also realize the prediction of equipment state detection parameters to achieve the classification of fault types. At present, multivariate state estimation technology has been applied to sensor fault detection [47], electronic product life prediction [48] and state detection of various industrial equipment [49].

Multivariate state estimation is a non-linear and non parametric model, which does not need to specify additional parameters. There is a correlation and coupling between parameters, and the non-linear relationship of parameters is established by mining. The key of Mset model to accurately diagnose equipment status is to establish a proper process model, which must cover all operating conditions of the equipment, and the detection parameters of the model can truly and effectively express the equipment status., and the non-linear relationship of parameters is established by mining. Multivariate state estimation is a non-linear and non parametric model, which does not need to specify additional parameters.

Each column of the process memory matrix represents a state observation vector D , and each row represents all normal state values of a detection variable. Assuming that the state detection variables n are needed for equipment state diagnosis, the state detection variables n constitute the state observation vector. That is $X(i)=[x_1,x_2,\cdots x_n]^{\mathrm{T}}$. When the normal operation state of the equipment includes historical observation vectors, the process memory matrix D is constructed as follows(2.10).

$$\mathrm{D}=[\mathrm{X}(1),\mathrm{X}(2),\cdots,\mathrm{X}(\mathrm{m})]=\begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(m) \\ x_2(1) & x_2(2) & \cdots & x_2(m) \\ \cdots & \cdots & & \cdots \\ x_n(1) & x_n(2) & \cdots & x_n(m) \end{bmatrix}_{n\times m} = \begin{bmatrix} \mathrm{D}_{11} & \mathrm{D}_{12} & \cdots & D_{1m} \\ \mathrm{D}_{21} & D_{22} & \cdots & D_{2m} \\ \cdots & \cdots & & \cdots \\ \mathrm{D}_{n1} & D_{n2} & \cdots & D_{nm} \end{bmatrix}_{n\times m} \tag{2.10}$$

The essence of the process memory matrix is to learn and memorize the normal operation characteristics of the equipment. The normal operation characteristics of the equipment are represented by the historical observation characteristic state parameters. The input of MSET model is the new observation vector $\mathrm{X}_{\mathrm{obs}}$ of the equipment, and the output is the estimation vector X_{est} of the state in MSET model. The estimation vector is obtained by weighting the vectors in the memory matrix, namely:

The estimated vector is X_{est} (2.11).

$$X_{\text{est}} = \mathrm{D} \bullet W = \left[\mathrm{X}(1), \mathrm{X}(2), \cdots, \mathrm{X}(\mathrm{m})\right] \bullet [w_1, w_2, \cdots, w_m] \tag{2.11}$$

The weight vector W represents the similarity between this state and the state in the process memory matrix. The residual between the estimated vector and the new observation vector is (2.12)

$$\varepsilon = \mathrm{X}_{\text{obs}} - X_{\text{est}} \tag{2.12}$$

In order to obtain accurate diagnosis results of equipment status, the residual error should be minimized. The corresponding weight vector solution company is (2.13):

$$\min \varepsilon = \left|\mathrm{X}_{\text{obs}} - X_{\text{est}}\right| = \left|\mathrm{X}_{\text{obs}} - \mathrm{D} \cdot W\right| \tag{2.13}$$

The sum of the squares of the residuals is (2.14)

$$\varepsilon^2 = \sum_{i=1}^{n} \left(\mathrm{Xobs}(i) - \sum_{j=1}^{m} wj\mathrm{D}ij \right)^2 \tag{2.14}$$

In order to get the minimum value of the residual, we need to find the extreme value of the sum of the squares of the residual. The process of extreme value calculation is the process of residual square sum and partial derivation of each value in the weight vector (2.15).

$$\frac{\partial \varepsilon^2}{\partial w_k} = -2\sum_{i=1}^{n} \left(\mathrm{X}_{\text{obs}(i)} - \sum_{j=1}^{m} w_j \mathrm{D}_{ij} \right) \mathrm{D}_{ik} = 0 \tag{2.15}$$

That is to say, the weight vector W is (2.16)

$$W = \left(\mathrm{D}^{\mathrm{T}} \cdot \mathrm{D}\right)^{-1} \cdot \left(\mathrm{D}^{\mathrm{T}} \cdot \mathrm{X}_{\text{obs}}\right) \tag{2.16}$$

To sum up, the estimation vector of this state is (2.17):

$$X_{\text{est}} = \mathrm{D} \cdot W = \mathrm{D} \cdot \left(\mathrm{D}^{\mathrm{T}} \cdot \mathrm{D}\right)^{-1} \cdot \left(D^{\mathrm{T}} \cdot \mathrm{X}_{\text{obs}}\right) \tag{2.17}$$

In the calculation of the weight vector, $\mathrm{D}^{\mathrm{T}} \cdot \mathrm{D}$ is the point multiplication relationship between the state vectors in the memory matrix, $\mathrm{D}^{\mathrm{T}} \cdot \mathrm{X}_{\text{obs}}$ represents the point multiplication relationship between the state vectors in the memory matrix and the new state quatities. When there is a linear relationship between the state vectors. In order to get the minimum value of the residual, we need to find the extreme value of the sum othe

squares of the residual. When the equipment is in normal state, the observation vector is located in the memory matrix,

matrix is replaced by nonlinearity, and the expression after change is as follows (2.18):

$$X_{\text{est}} = \mathrm{D} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathrm{D}\right)^{-1} \cdot \left(\mathrm{D}^{\mathrm{T}} \otimes \mathrm{X}_{\text{obs}}\right) \tag{2.18}$$

When the equipment is in normal state, the observation vector is located in the memory matrix, so the residual between the estimation vector fitted by the state vector in the memory matrix D and the new observation vector is very small. When the equipment is in an abnormal state, it is difficult for the memory matrix D to fit the estimation vector of the fault to match the state, so the residual between the estimation vector and the observation vector increases. The residual between the estimation vector and the observation vector implies the fault information of the equipment.

2.2.2 Similarity function

Mset model mainly reflects whether the equipment is in normal or fault state by the residual between the observed value and the estimated value. Different faults of equipment are manifested in different parameters. Obviously, it is impossible to accurately determine the state of equipment only through the residual of some parameters of equipment. Therefore, this paper uses the degree of difference between observation vector and estimation vector to diagnose the state of equipment, which can comprehensively utilize the characteristics of parameter changes.

Similarity measure theory is the most commonly used data mining method. It is one of the similarity measures used to mine vectors and samples. In the process of data analysis and data mining, we need to express the degree of difference between vectors and samples, and classify samples according to the degree of difference between samples. The common methods are similarity function and distance function.

In this paper, the Euclidean distance in distance function is used to express the similarity between two vectors, and the Euclidean distance is used to express the absolute distance of space vector. The larger the distance is, the lower the similarity between the two vectors is, which is very inconsistent with people's understanding of the concept of similarity. Therefore, the similarity function in this paper is (2.19):

$$\mathrm{S}\left(X,Y\right) = 1\text{-}\sqrt{\sum_{\mathrm{i}=1}^{n} (x_i - y_i)^2} \tag{2.19}$$

2.3 State evaluation model based on OLPP-MSET

MSET The key of the model is to construct the memory matrix D. Peng Jian [57] uses the spatial equidistant sampling method to construct the memory matrix. This method has the disadvantage that it is easy to miss the representative observation sam-

ples and the historical memory matrix is not representative. The dynamic method is used to construct the memory matrix. This method updates the memory matrix in real time according to the distance between the input observation vector and the memory matrix vector, although it can improve the phase of the memory matrix However, similarity increases the amount of calculation and takes a long time; when using the two norm probability density to construct the history matrix, multiple parameters need to be specified, and the construction effect of the history matrix is affected by subjective factors. In this paper, an OLPP-MSET device state diagnosis method is proposed. The studied device extracts multi feature parameters, uses OLPP to reduce the dimension of feature data and find the internal structure of the data. Then, the multi-component state estimation model (MSET) is established with the projection data of the normal state of the device. Then, the multi-component state estimation model (MSET) is established with the projection data of the normal state of the device. Dong Yuliang et al [11-12] prove that the OLPP clustering effect is better than other clustering methods. The equipment state is diagnosed by measuring the distance between the observed data and the estimated data. The equipment status diagnosis model of OLPP-MSET is as follows figure 2.1.

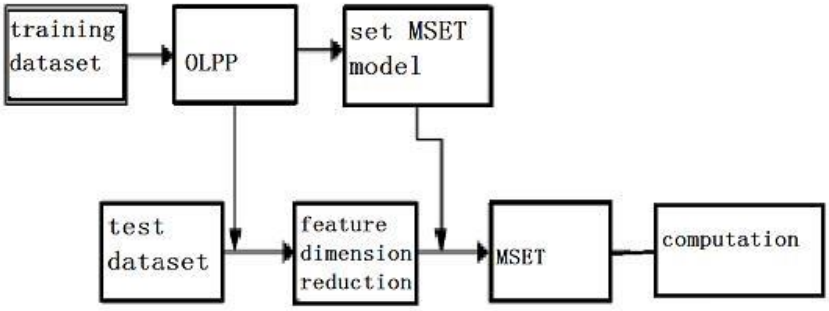

Figure 2.1 – Flow chart based on OLPP-MSET model

Method steps:

1 Data acquisition;

2 OLPP algorithm is used to reduce the dimension of the original data and find the internal structure of the data;

3 Select the normal state data to establish MSET model and determine the size of each parameter;

2.4 Summary of this chapter

This chapter introduces the olpp algorithm in detail, which can effectively classify and cluster the data. At the same time, the principle of multi-element state estimation model and similarity theory are introduced, and the method and process of equipment state evaluation based on olpp-mset model are summarized. Calculate the similaritybetween observation vector and estimation vector. In order to evaluate the state of olpp-mset model, we need to determine the early warning threshold.

3 STATE EVALUATION BASED ON OLPP-MSET MODEL

3.1 Overview of auxiliary equipment of power station

3.1.1 Selection of equipment

The main system of thermal power unit includes: fuel supply system, water supply system, air and smoke system, steam system, cooling system, electrical system and its auxiliary equipment. The types of equipment can be classified as follows: fluid mechanical equipment and heat exchange equipment, in which fluid mechanical equipment mainly includes various pumps, fans and their driving motors, steam turbines, etc.; heat exchange equipment includes: water wall, superheater, reheater, etc. Compared with the fluid equipment, the pipeline and heat exchanger can not only transport the fluid energy or exchange the energy between the fluids. From the above many equipment, select some equipment that affects the load for equipment status evaluation and unit load capacity calculation. The selection principle of equipment:

3.1.1.1 Objective principle

Compliance with purpose is the premise of equipment selection. The purpose of equipment scope and parameters selection is to diagnose the operation status of thermal power unit and the generating capacity of the unit. Therefore, it is necessary to comprehensively consider which equipment and systems have an impact on the generating capacity of the unit and which equipment failure may cause the unit to reduce load or not stop.

3.1.1.2 Completeness principle

The completeness of the equipment range is that the selected range should be able to comprehensively and objectively reflect and measure the generating capacity of the unit, and the existence and function of some equipment cannot be ignored.

3.1.1.3 Principle of independence

It should satisfy the principle of completeness and the independence between equipment and parameters. If there is redundancy between equipment and parameters, not only workload will be increased, but also information will be strengthened, leading to inaccurate evaluation results.

In the coal-fired unit, the internal equipment of each system coordinates with each other to complete the whole process of power generation, and the classification is more about the functional structure of the equipment. In the unit state evaluation, the influence of parameters on the system function should also be considered, such as furnace negative pressure, which is mainly affected by the air volume of induced draft fan,

forced draft fan and primary fan. Therefore, furnace negative pressure should be classified as air and flue gas system rather than boiler body. According to the level of equipment and the influence degree of equipment operation state on the overall state, further build the evaluation index system of thermal power unit equipment state, analyze the influence of equipment on the unit operation state, and lay the foundation for the unit load capacity. Various systems of the unit need auxiliary machines to complete, so the state of auxiliary machines is very important to the load capacity of the unit.

The pulverizer plays an important role in the pulverizing system. The state of the pulverizing system in operation is directly determined by the pulverizer. Six blower is an important equipment of the air and smoke system of the boiler. The induced draft fan maintains the negative pressure of the furnace, the forced draft fan provides the air volume of the furnace, and the primary fan provides the air volume of the pulverizer. The main function of the forced draft fan is to maintain the oxygen content in the furnace. The induced draft fan delivers the flue gas generated by combustion to the chimney while maintaining the negative pressure in the furnace. The primary fan mainly dries and transports the pulverized coal to the furnace. The feed water pump is the core equipment of the water supply system. The feed water pump will deliver the feed water in the deaerator through thermal deaeration to the boiler feed water pipeline after boosting. After the steam turbine has finished its work, the exhaust steam is discharged to the condenser, condensed into condensate in the condenser, and then transmitted to the deaerator by the condensate pump to complete the steam water circulation. The air preheater will preheat the flue gas in the tail flue of the boiler through the internal heat sink to the air before entering the boiler to a fixed temperature.

3.1.2 Selection and treatment of parameters

After the equipment selection and scope determination, it is necessary to study how to select the evaluation indexes of each equipment, that is, which parameters are used as the evaluation indexes of the equipment, the main basis and thinking of the equipment parameter selection: refer to the technical specifications of the equipment manufacturer, the operation regulations of the power plant and the equipment faults in the actual operation, and analyze the common faults of the equipment and the causes of the faults to reflect the equipment faults On the index, the parameters of equipment condition evaluation are selected synthetically.

The important state parameters of a coal-fired unit are very large. Many parameters represent the same state characteristics or the same fault type of the equipment. Many parameters represent the same state characteristics or the same fault type of the equipment. If all parameters and state evaluation, parameter redundancy may lead to inaccurate state evaluation. The number of measuring points of the same parameters is different, and different selection methods are adopted for different measuring points:

Multiple measuring points: for many measuring points, it is impossible to select all measuring points for state evaluation, three measuring points: for important parameters, Three measuring points: for important parameters, such as fan bearing temperature

and motor bearing temperature, the method of three out of three is adopted.

Two measuring points: only two measuring points are left after the configuration of two measuring points or data screening, and the larger one is generally used.

3.2 Fault analysis of induced draft fan

According to the occurrence time of fan fault, fan fault can be divided into three categories: chronic fault, instantaneous fault and intermittent fault. Chronic fault is the potential cause that accumulates with time and the degree of fault increases gradually, which will not affect the normal operation of the equipment at the beginning of the fault; transient fault is that the occurrence of the fault has nothing to do with time; intermittent fault is that the fault changes periodically with time. The main fault of the fan is chronic fault. Through the diagnosis of the chronic fault state, the early warning can be provided for the equipment operators. The operators can adjust the operation strategy according to the equipment state to improve the economic benefits and safety of the thermal power plant. At the same time, the operation and maintenance personnel can maintain the fault early to reduce the loss.

3.2.1 Common faults and causes

The induced draft fan exhausts the flue gas of the boiler, maintains the stability of the negative pressure of the boiler and the balance of the oxygen content in the boiler. The operation of the induced draft fan directly affects the safe operation of the boiler and the stability of the unit load. The induced draft fan exhausts the flue gas of the boiler, maintains the stability of the negative pressure of the boiler and the balance of the oxygen content in the boiler. The operation of the induced draft fan directly affects the safe operation of the boiler and the stability of the unit load. However, the operation environment of induced draft fan is always in a bad state, which leads to a high failure rate in the operation of induced draft fan. The common faults of induced draft fan in actual operation are: fan vibration, mechanical friction, blade wear and fracture, air rush, impeller dust accumulation. Once there is a fault, even if there is no major mechanical fault, the unit can continue to operate, but it may cause problems such as abnormal increase of motor power supply, increase of static blade opening, decrease of outlet oxygen content, and decrease of induced draft fan output. The unit operation plan of the power plant will be affected, which will lead to the unit shutdown in case of serious load reduction operation.

The possible causes of induced draft fan failure are as follows:

1 Flue resistance rise

The air resistance of the flue is positively related to the ash accumulation in the flue gas. When the flue gas flows through the heating surface, the ash carried in the flue gas will deposit on the surface of the heating surface to form ash accumulation. A large amount of ash accumulation will cause the flue gas to block and hinder the normal flow of the flue gas.

2 Air leakage of air preheater and electrostatic precipitator

Due to the structural characteristics of the equipment, the air preheater and other equipment in the power plant have sealing devices, but the sealing condition cannot be fully guaranteed, so there is air leakage rate. However, with the increase of air leakage rate of air preheater, a large number of cold air will leak out and mix with flue gas and enter the flue directly and be pumped out by induced draft fan. In order to maintain the amount of oxygen required for normal combustion of boiler, the load of induced draft fan must be increased, resulting in the increase of static blade opening and power of induced draft fan. A kind of

3 Change in mechanical properties

When the induced draft fan operates continuously for a long time, there is a continuous accumulation of impurities on the blade, the uneven accumulation of impurities, the corrosion of the impeller and blade by the acid substances in the flue gas, and the continuous change of the impact angle when the substances in the flue gas scour the back of the blade and the windward end of the blade, resulting in the unbalance of the weight of the blade and the bearing vibration. When the induced draft fan operates continuously for a long time, there is a continuous accumulation of impurities on the blade, the uneven accumulation of impurities, the corrosion of the impeller and blade by the acid substances in the flue gas, and the continuous change of the impact angle when the substances in the flue gas scour the back of the blade and the windward end of the blade, resulting in the unbalance of the weight of the blade and the bearing vibration.When the induced draft fan is rotating at high speed, when the positive impact angle is formed between the air flow and the blade, the positive impact angle exceeds a certain critical value, the flow condition at the back of the blade deteriorates, eddy current is generated in the mainstream direction, and the internal stable flow field is destroyed, resulting in stall. Insufficient lubricating oil in the bearing of induced draft fan, insufficient cooling water in the cooler, dirt adhering to the cooler, impurities in the bearing, and damage to the bearing will cause the bearing temperature to be too high. The rotor blade support bearing is short of oil, the operation machinery is jammed, the internal adjusting and cutting mechanism of the hub is damaged, which leads to the rotor blade stuck, the wrong operation of the equipment management personnel leads to the pipeline disturbance, which makes the fan enter the unstable working area, and the current, voltage and air volume of the induced draft fan fluctuate. Due to other reasons, the blade of the fan may be worn, and the angle of the stationary blade may also be deflected to change the characteristics of the stationary blade induced draft fan.

3.2.2 Selection of induced draft fan parameters

The status detection signal of induced draft fan contains the information reflecting the operation status of the fan equipment, which is the basis of realizing the status diagnosis of the fan. According to the cause analysis of the failure of the induced draft fan and combined with the current real-time monitoring information system of the power

plant, the health status evaluation parameters of the induced draft fan are determined and input to the status model of the induced draft fan equipment as table 3.1.

Table 3.1 – Modeling parameters of induced draft fan

Serial number	Parameter name	dimension
1	2	3
1	Inlet flue gas pressure	p_a
2	Motor bearing temperature	℃
3	Motor current	A
5	Motor stator winding temperature	℃
6	Motor front bearing temperature	℃
7	Vibration of front bearing of induced draft fan (horizontal and vertical)	*mm*
8	Motor out of vibration (horizontal, vertical)	*mm*
9	Temperature of front bearing of induced draft fan	℃
10	Temperature of rear bearing of induced draft fan	℃
11	Vibration of rear bearing of induced draft fan (horizontal and vertical)	*mm*
12	Outlet flue gas pressure	p_a
13	Outlet flue gas temperature	℃
14	Lubricating oil pressure of induced draft fan	p_a
15	Lubricating oil supply temperature of induced draft fan	℃
16	Flue gas temperature at the inlet of induced draft fan	℃
17	Adjustable static blade mechanism valve position of induced draft fan	%
18	Differential pressure of lubricating oil filter screen	p_a
19	Oil level of lubricating oil tank	mm
20	Temperature of lubricating oil tank	℃
21	Hydraulic oil screen differential pressure	p_a

3.3 Data processing of induced draft fan

The historical operation data and real-time operation data of auxiliary equipment in the power plant can truly reflect the operation status of the equipment at all historical and current times. These data can provide reliable basis for judging the fault type after

the fault, guiding the maintenance and state evaluation of equipment operation. The power plant equipment is complex and the operation environment is bad. In the actual operation, the sensor may have measurement errors and the sensor is subject to external interference, resulting in abnormal points of the data taken, and the displayed data deviates from the real value [50]. The authenticity of the data affects the accuracy and reliability of the calculation results. The authenticity of the data affects the accuracy and reliability of the calculation results. Through the processing of the data, the noise of data interference is eliminated, and the accuracy of the data is improved [51].

3.3.1 Wavelet transform theory

Wavelet transform is the evolution of Fourier transform. Fourier transform decomposes the signal function $f(t)$ and decomposes the original function into harmonic functions of different frequencies, but the Fourier function $f(t)$ ignores the local changes of the signal, that is, the whole spectrum changes when the signal function changes, while the local frequency band cannot determine the signal function $f(t)$. In most practical engineering problems, we will find that the signal is basically time-varying and non-stationary, so we need to pay attention to the characteristics of the signal in the local range [52].

Wavelet analysis is used to analyze the signal in time and frequency domain. The signal with complex wave characteristics can be decomposed into real signal and noise signal. It can accurately study the wave part of the signal, identify the mutation of noise signal, and its filtering effect is better than Fourier transform. The wavelet transform decomposes the original signal into different scale characteristic signals by scaling and translation, and obtains the wavelet sequence $\psi_{a,b}(t)$. The formula is as follows (3.1).

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \cdot a \neq 0 \tag{3.1}$$

a – expansion factor; b – translation factor.

3.3.2 Wavelet transform decomposition process

The signal applied in this paper is one-dimensional signal, which can be expressed as follows (3.2).

$$s_{(i)} = d_{(i)} + z_{(i)} \tag{3.2}$$

$s_{(i)}$ – original wave containing noise signal; $d_{(i)}$ – real wave; $z_{(i)}$ – noise signal wave; In practice, the common original wave is composed of real signal and noise signal, the real

signal is low frequency wave, and the noise signal is high frequency wave. There is useful information in the low-frequency signal, so wavelet transform is used to remove the high-frequency noise signal and retain the useful low-frequency signal. Wavelet transform noising is based on the local analysis of the signal and the singularity of the noise. The singularity represents the irregularity of the signal, and the positive definiteness represents the smoothness of the signal [53]. Wavelet transform can gradually remove the noise signal, leaving the low-frequency signal that can meet the needs of analysis, that is to say, the noise can be removed again after decomposite $d_{(i)}$, and so on to get the original signal that is not affected by the noise.

3.3.3 Data processing of induced draft fan by wavelet transform decomposition

According to the selection principle of historical data, the modeling parameters are selected, and the data of equipment operation period is selected. According to the selection principle of historical data, the modeling parameters are selected. The operation environment of thermal power plant is bad, and the sensor is easy to be interfered by the outside world, which makes the measurement data deviate from the normal value. These are not normal changes of the data itself, which deviate from the normal trend due to external interference. These points will have a serious impact on the results of data analysis and the selection of thresholds. Data cleaning is to process the data deviating from the normal trend. These points will have a serious impact on the results of data analysis and the selection of thresholds. Data cleaning is to process the data deviating from the normal trend.

Some parameters of the equipment fluctuate greatly, so it is difficult to judge whether the data is normal fluctuation or abnormal fluctuation by naked eyes. Some parameters of the equipment fluctuate greatly, so it is difficult to judge whether the data is normal fluctuation or abnormal fluctuation by naked eyes.

The wavelet analysis tool in MATLAB is used to describe the wavelet analysis process with 1152 sets of data in July 2018 of horizontal vibration of induced draft fan bearing as an example. The wavelet base is chosen as db1. When the data is decomposed three times, the fluctuation amplitude of the data is obviously reduced, and the decomposition layer is determined as three times, figure 3.1.

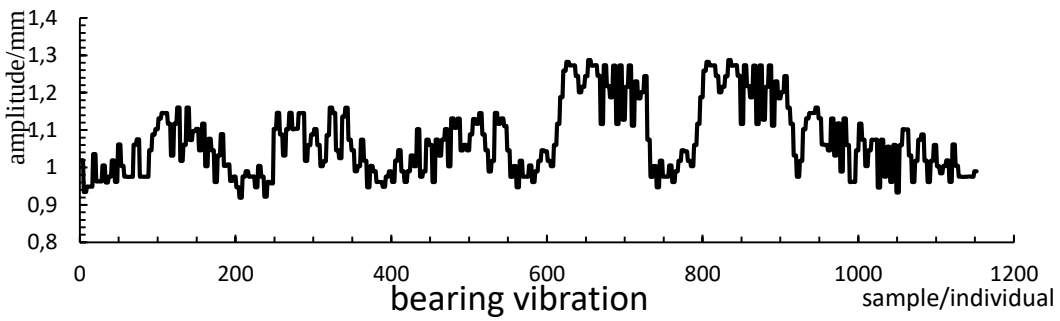

Figure 3.1– Data after secondary wavelet transform

3.4 Evaluation example of induced draft fan state based on OLPP-MSET model

3.4.1 Determination of model parameters and induced draft fan data

According to the maintenance records of unit 3 of a power plant in Shanxi Province, it is known that the A-induced draft fan failed at 3:35 on July 22, 2018, and 1152 sets of data were analyzed from 3:45 on July 14, 2018 to 3:35 on July 22, 2018 every 10 minutes eight days before the failure. The data with strong correlation in this period is shown in Figure 3-2. It can be seen from the data that there is no mutation in the data before the fault, indicating that the fault is a gradual development process. The data includes normal state data and fault development process data. The fault development usually shows symptoms a few hours before the fault occurs. Therefore, this paper selects 1008 groups of data in the first 7 days as normal state data, 864 groups of data are used to establish the historical memory matrix in the OLPP-MSET model, the remaining 144 groups of normal data are used to test the accuracy of the model, and 144 groups of fault development process data are checked on the last day Verify the validity of the model.

The selection of dimensionality reduction dimension is based on the cumulative contribution rate of the principal component, which will lead to data redundancy if the cumulative contribution rate is too high, and the principal component which is too low can not fully represent the original data matrix. Generally, the cumulative contribution rate is more than 85%. Based on the cumulative contribution rate of OLPP state feature extraction $\alpha=6$、$k=7$, the false alarm rate of fault early warning threshold is 0.1%.

3.4.2 Effectiveness of the model

144 sets of normal data from 3:45 on July 20, 2018 to 3:35 on July 21, 2018 were used to test the accuracy of the model as figure 3.2.

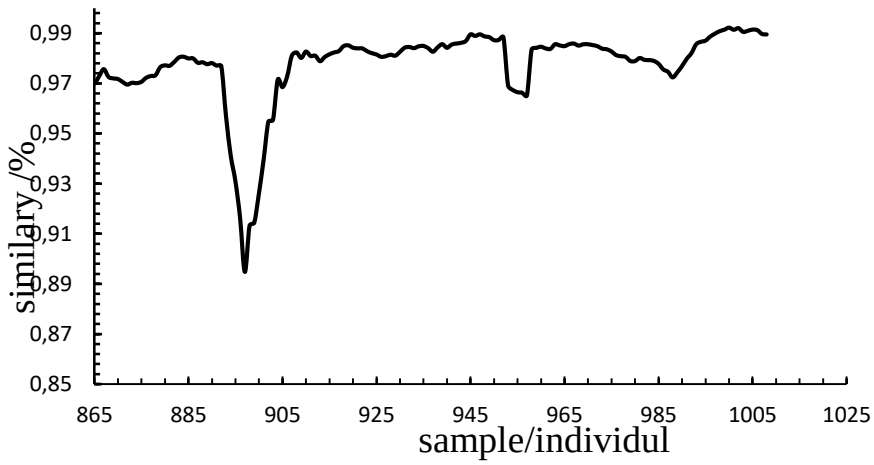

Figure 3.2 – MSET model estimation relative error

The figure shows the validation of the standard MSET model. First, the original data is processed and then the data is normalized. The processed data is brought into the original MSET model for training validation. he selection of dimensionality reduction dimension is based on the cumulative contribution rate of the principal component, which will lead to data redundancy if the cumulative contribution rate is too high, and the principal component which is too low can not fully represent the original data matrix. He selection of dimensionality reduction dimension is based on the cumulative contribution rate of the principal component, which will lead to data redundancy if the cumulative contribution rate is too high, and the principal component which is too low can not fully represent the original data matrix. Taking bearing water vibration as an example, the model validation can be seen from the figure above that the relative majority is within 0.5%, only a few are more than 0.5%, but the relative error is within 1.5%. It can be proved that MSET model has a good estimation effect, It can be proved that MSET model has a good estimation effect, It can be proved that MSET model has a good estimation effect, and MSET model can be used to evaluate the state of equipment. It can be proved that MSET model has a good estimation effect, and MSET model can be used to evaluate the state of equipment .

3.4.3 Evaluation example of induced draft fan status

The induced draft fan failed at 3:35 on July 22, 2018. In order to find the development process of the failure, the data of the day before the failure was taken, and the observation data of the induced draft fan was calculated and estimated using the established induced draft fan state evaluation model. In this paper, the fault early warning threshold in the equipment state evaluation was determined as 0.6811 by the kernel smoothing density estimation method. The results are as figure 3.3.

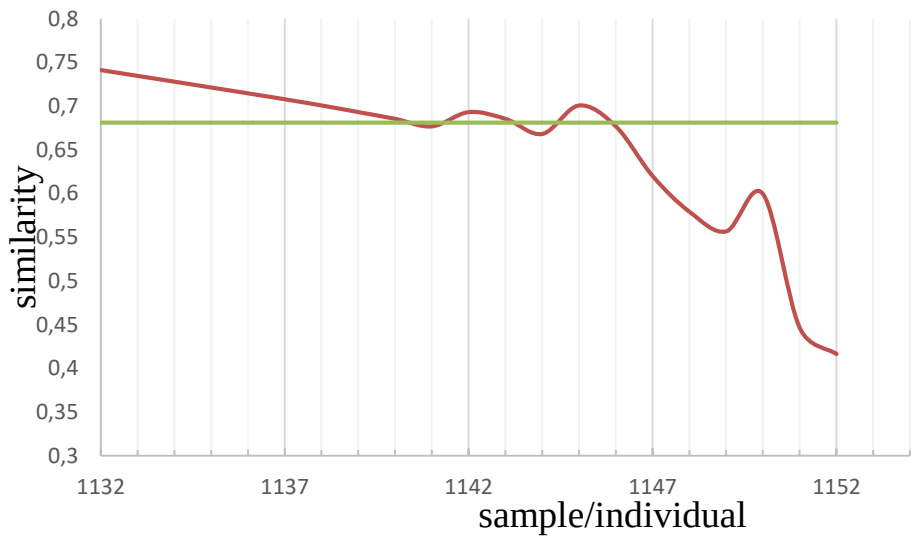

Figure 3.3 – Similarity sequence

From the figure below, it can be seen that the similarity between 1138-1139 data points reaches the alarm threshold, and the status of the equipment can be accurately understood. The equipment fault can be found 130-140 minutes in advance, and the operator on duty can adjust the load in advance, which can not only improve the reliability of the thermal power unit, but also meet the stability of the power grid. At the same time, the economic benefits of the thermal power plant can be improved in today's competitive power grid.

3.5 Summary of this chapter

This chapter gives a brief introduction to the principle and scope of the selection of auxiliary equipment in the power station. The selection of equipment should conform to the objective, that is, the principle of having influence on the machine load, completeness and independence, as well as the selection method of parameters and the treatment method of multiple measuring points of parameters. There may be deviation between the read data and the real data in the bad operating environment of power plant, so wavelet transform theory is used to noise the data. The advantages of OLPP-MSET model compared with standard MSET model are analyzed. OLPP-MSET model has higher similarity and can realize the diagnosis of equipment status more accurately.

4 OPTIMAL LOAD DISTRIBUTION MODEL BASED ON EQUIPMENT STATUS

At present, the power grid uses the single machine scheduling method to directly send the load instruction to the unit unit according to the real-time electricity quantity. This scheduling method requires the unit to fluctuate frequently with the load instruction of the power grid, resulting in the unit life loss. At the same time, the power grid is prone to fall into the disaster of dimensionality, poor calculation of real-time performance, and the power grid is unable to master the energy consumption and state of the unit. Therefore, the unit cannot be optimized for scheduling There is a certain lack of flexibility [55]. With the improvement of the automatic control technology, the control system of the unit can monitor the running state of the equipment, the energy consumption of the unit and the emission of pollutants in real time, which provides conditions for the economic and stable dispatching of the power grid. In this chapter, based on the operation state of the unit, the load capacity of the computer group is taken as the constraint, and the optimal load distribution model at the plant level is established with energy consumption cost and environmental cost as the objective.

4.1 Unit load capacity based on equipment status

The main task of load optimal distribution is to maximize the economic benefits of the power plant, while maintaining the balance of load supply and demand to ensure the safe and reliable operation of the power grid. The basis of ensuring the economic benefits of the unit is the reliability of the unit. The reliability of the unit is reflected in the stabilityof load and the ability of changing load. By calculating or evaluating the unit load capacity value, the reference value is provided for the optimal load distribution at the plant level. The load of thermal power unit is mainly determined by each system, in which the working medium circulation of air and smoke system, steam water system and oil system is mainly completed by auxiliary machine. Therefore, the status of auxiliary equipment is closely related to the unit load.

4.1.1 Influence of equipment on load capacity of unit

The evaluation method of thermal power unit load capacity based on auxiliary machine state: the observation vector is estimated according to olpp-mset model, and the estimation vector and real-time observation vector are compared to calculate the operation state of reaction equipment. When all auxiliary machines are in normal operation state, the unit can operate under full load. When the auxiliary equipment of the unit fails or there is a trend of failure, according to the unit equipment performance, parameter configuration and control logic, the current maximum load capacity of the computer group.

Different auxiliary machines have different effects on the load of the unit. When the auxiliary equipment fails or trips, the load of the unit will be greatly reduced. When the

auxiliary equipment fails seriously or is not handled properly, the unit may be shut down. This kind of auxiliary equipment mainly includes water pump, fan, coal feeder, pulverizer, heater, etc. If the auxiliary equipment in the system is redundant configuration, the unit load stability and load capacity of the unit are high, and the unit is relatively stable. For the auxiliary equipment without redundancy configuration, the unit can meet the unit requirements through load reduction. The load capacity of different auxiliary equipment is different. Generally, the maximum load of single side air and flue gas system is 60% of the rated load; the steam feed pump is 50% of the maximum rated load; the electric feed pump is 30% of the rated load. The auxiliary equipment of the unit is analyzed as table 4.1 shows .

Table 4.1 – Basic analysis of auxiliary equipment

Analysis of name	Degree of importance	Redundancy	situation analysis
Condensate pump	high	Ready to use	Fast start-up speed and short time tolerance during tripping and pump switching
Vacuum pump	high	Two ready to use and Ready to use	Fast start-up speed and short time tolerance during tripping and pump switching
Lubricating oil pump	high	One uses two reserves.	Fast start-up speed and short time tolerance during tripping and pump switching
EH oil pump	high	One uses two reserves.	Fast start-up speed and short time tolerance during tripping and pump switching
Stator cooling water pump	high	One uses two reserves.	Fast start-up speed and short time tolerance during tripping and pump switching
Induced draft fan	high	none	When tripping, equipment output is less than load request, Rb acts
Air blower	high	none	When tripping, equipment output is less than load request, Rb acts
Primary fan	high	none	When tripping, equipment output is less than load request, Rb acts
Feed water pump	high	two uses one reserves.	When tripping, equipment output is less than load request, Rb acts
Air preheater	high	none	When tripping, equipment output is less than load request, Rb acts
Coal mill	high	six	When tripping, equipment output is less than load request, Rb acts

reduced by a certain amount of load if the combined start is successful; if the combined start fails, the unit load will be reduced or the unit will trip. Because the load influence value cannot be calculated accurately when the above auxiliary machine fails, the main scope of auxiliary equipment for load capacity calculation of thermal power unit is RB logic associated equipment. Taking a 660 MW unit of a power plant in Shanxi as an example, its auxiliary equipment with RB function includes: coal pulverizer, forced draft fan, induced draft fan, primary fan, feed pump and air preheater.

4.1.2 Unit load capacity calculation based on equipment status

Based on the assessment of the load capacity of the auxiliary machine, the assessment steps are as follows:

1 The current observation vector of the equipment is compared with the estimated vector of OLPP-MSET model to diagnose the equipment;

2 If the equipment is in fault development state, determine the fault type;

3 According to the influence value of auxiliary equipment on load, the load capacity of the computer group is set.

The influence value of equipment load is corrected according to the original design value of the unit and the operation failure rule of the equipment. The following is the influence value of auxiliary equipment load of a power plant in Shanxi Province,Table 4.2 shows the load limit calculation of main auxiliary equipment.

Table 4.2 – Load limit calculation of main auxiliary equipment

Name of auxiliary equipment	Final load limit
Coal mill	70t / h × number of pulverizers in available state (related to coal quality)
Primary fan	396mw × number of primary fans in available state
Induced draft fan	396mw × number of induced draft fans in available state
Air blower	396mw × number of forced draft fans in available state
Feed water pump	Steam driven 330MW × number of available feed pumps + electric 198mw
Air preheater	396mw × number of air preheaters available

4.2 Economic cost

The standard coal consumption rate of unit power supply is one of the important economic indicators. The lower the coal consumption rate, the better the unit economy. The coal consumption rate is related to boiler efficiency, pipeline efficiency, turbine

thermal efficiency, unit load rate and other factors. The standard power supply coal consumption rate of the unit decreases with the increase of load. In actual operation, the power supply coal consumption rate is the lowest when the unit is under 80% load, and increases rapidly with the decrease of load when the unit is under low load. Calculation formula of unit power supply coal consumption rate as formula (4.1).

$$b_s = \frac{H_r}{29.271 \times \eta_{gl} \times \eta_{gd}(1-\xi)} \tag{4.1}$$

where b_s – Standard coal consumption of unit power supply $g/(kW \bullet h)$; H_r – Heat consumption rate of steam turbine $KJ/(KW \bullet h)$; η_{gl} – Boiler efficiency $\%$; η_{gd} – Pipe insulation efficiency $\%$; $\%$ – Auxiliary power consumption rate of unit, $\%$;

Take the logarithm of the two ends of the above formula and derive of formula (4.2).

$$\Delta b_s = b_s \frac{dH_r}{H_r} - b_s \frac{d\eta_{gl}}{\eta_{gl}} - b_s \frac{d\eta_{gd}}{\eta_{gd}} + b_s \frac{d\xi}{1-\xi} \tag{4.2}$$

It can be seen from the above formula that the change of coal consumption rate and relevant parameters of each parameter causes the change of coal consumption rate. In the actual operation, the change of parameters first causes the change of auxiliary power consumption rate, boiler efficiency, steam turbine thermal efficiency, pipeline efficiency, etc., while the boiler pipeline is complex and the insulation measures are good, so the pipeline efficiency is considered as the fixed value. The changes of boiler efficiency, steam turbine heat rate and auxiliary power rate are mainly considered in the coal consumption rate of power supply of computer group.

4.2.1 Economic indicators

There are positive balance method and reverse balance method in the calculation of boiler efficiency. The calculation amount of positive balance method is complex, so the reverse balance method is generally used in the actual calculation. The reverse balance method is to use the total energy of the boiler minus the loss energy. The calculation formula of the anti balance method is as follows:

4.2.2 Energy efficiency characteristic curve fitting

In actual operation, each load corresponds to a standard coal consumption rate of power supply. In order to find out the relationship between the standard coal consumption rate of power supply and the load, several discrete points from the load and the standard coal consumption rate of power supply are fitted. The energy consumption characteristic equation of thermal power unit can be quasi synthesized (4.3)

$$C_k(P_i) = a_k P_i^2 + b_k P_i + c_k \tag{4.3}$$

where $C_k(P_i)$ – coal consumption of each unit under different loads $g/kW \cdot h$; P_i – current power of each unit MW; a_k、b_k、c_k – coal consumption characteristic coefficient.

Steps of least square curve fitting:

1 Filter out the calculated raw data. Select several groups of data for each operating point, and screen the unreasonable data.

2 Calculate the arithmetic mean of each group of data. The arithmetic average calculation of the effective data selected for each operating point can effectively reflect the coal consumption characteristics of the unit. Arithmetic average calculation formula (4.4).

$$X = \frac{\sum_{i=1}^{n} X_i}{n} \tag{4.4}$$

3 The least square method is used for fitting. In this paper, the relationship between the standard coal consumption rate of power supply and the load is simplified as the relationship under steady state. The load and the standard coal consumption rate of power supply are a group of discrete points. The load and the standard coal consumption rate of power supply are a group of discrete points. In order to express the relationship between the two, the least square method is used for fitting. The principle of fitting is that the mean square error of the distance between data points and curve points is the smallest, and the mean square error is formula (4.5).

$$f(p_i) = \sum_{i=1}^{n} \left(a p_i^2 + b p_i + c - B_i \right)^2 \tag{4.5}$$

there are coal consumption data points $(p_i \quad B_i)$, $i = 1, 2 \cdots n$

The energy consumption characteristic curve coefficients $a \ b \ c$ of each unit can be obtained by combining the equations of 4.18 to 4.20. In this paper, a power plant operating 2 × 660 units in Shanxi Province is taken as the research object, and the data under stable conditions are collected for fitting analysis. The number of these two units and the fitted energy consumption characteristic curve and coefficient are as follows. Table 4.3 shows the energy consumption characteristic coefficient of unit.

Table 4.3 – Energy consumption characteristic coefficient of unit

Unit	*a*	*b*	*c*
3	0.000084878	-0.1217	352.0714
4	0.000292	-0.347	406.24

Characteristic curve of coal consumption as figure 4.1.

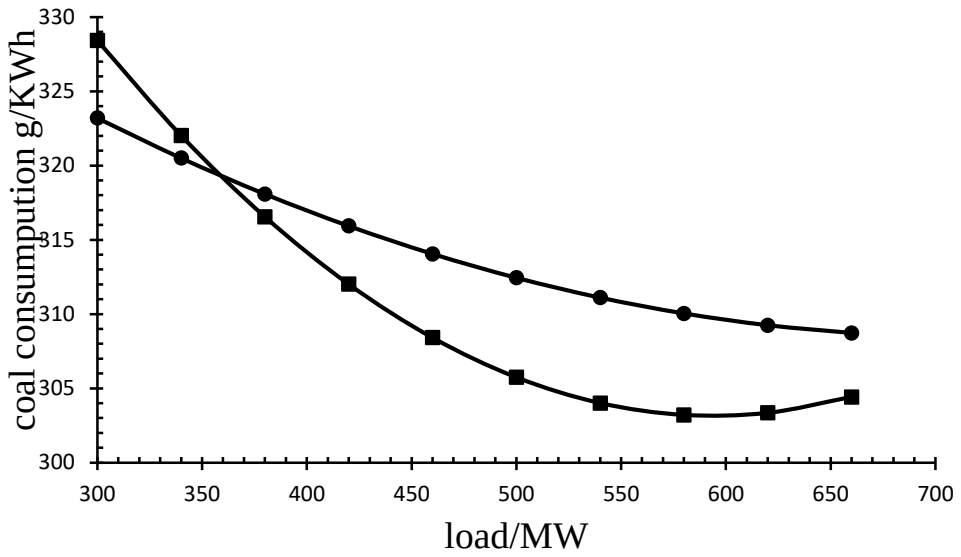

Figure 4.1 – Coal consumption curve fitting of 660MW Unit

4.3 Environmental cost

4.3.1 Calculation of SO2 environmental cost

1 Concentration of raw flue gas SO2 (4.6):

$$C_{SO2} = \frac{32}{16Q_{indry}} K_{SO2} S_{ar} b \tag{4.6}$$

1 Emissions (4.7):

$$G_{SO2} = C_{SO2} Q_{indry} (1 - \eta_{SO2}) \tag{4.7}$$

where G_{SO2} – discharge amount g/h ; η_{SO2} – desulfurization efficiency of desulfurization unit,%;

The energy consumption characteristic curve coefficients a b c of each unit can be obtained by combining the equations of 4.18 to 4.20. In this paper, a power plant operating 2 × 660 units in Shanxi Province is taken as the research object, and the data under stable conditions are collected for fitting analysis. The number of these two units and the fitted energy consumption characteristic curve and coefficient are as follows. The number of these two units and the fitted energy consumption characteristic curve and coefficient are as follows.

The unit conversion of pollutant emissions of thermal power plant under different loads is carried out, and the least square method is used to fit the corresponding pollu-

tant emissions under different loads, and the pollutant emissions emissions are simulated into as formula (4.8):

$$f_k(P_i) = A_k p_i^{\ 3} + B_k p_i^{\ 2} + C_k p_i + D_k \tag{4.8}$$

The result as table 4.4 shows the SO2 emission concentration model coefficient

Table 4.4 – SO2 emission concentration model coefficient

unit	*A*	*B*	*C*	*D*
3	3.55×10-8	-3.95×10-5	1.114×10-2	0.1098
4	9.27×10-9	-1.22×10-5	4.32×10-2	0.216553

4.3.2 Calculation of NOx environmental cost

During the operation of the unit, it is mainly composed of and, of which no accounts for about 95%. It can be divided into fuel type, thermal type and fast type. 60-80% of the fuel type is formed when the coal contains a lot of n elements in combustion, 20-30% of the thermal type is generated by air neutralization reaction.

1 NOx production

The formula for calculating the content of no and NO2 in the flue gas at the furnace outlet is as follows (4.9):

$$C_{\mathrm{NO}} = \frac{C_{\mathrm{NOx}}}{2.05} \times 0.95 \times 1.34 \tag{4.9}$$

C_{NOx} – NOx concentration in flue gas (generally 300 for dry flue gas under standard state and actual oxygen content) $\mathrm{mg/Nm^3}$;

The concentration as formula (4.10):

$$C_{\mathrm{NO_X}} = \frac{30.8}{14 Q_{\mathrm{in\,dry}}} K_{\mathrm{NOX}} N_{\mathrm{ar}} b \tag{4.10}$$

NOx emission (4.11):

$$G_{\mathrm{NOx}} = \frac{30.8}{14} b \cdot N_{\mathrm{ar}} \cdot \frac{K_{\mathrm{NOx}}}{m} \left(1\text{-}\eta_{\mathrm{NOx}}\right) \tag{4.11}$$

The quantity of NOx discharged from the boiler is calculated based on the mass concentration of NO2. NOx concentration in flue gas (generally 300 for dry flue gas under

standard state and actual oxygen content) $^{mg/Nm^3}$ The unit conversion of pollutant emissions of thermal power plant under different loads is carried out, and the least square method is used to fit the corresponding pollutant emissions under different loads, and the pollutant emissions are simulated into(4.12):

$$g_k(P_i) = \alpha_k p_i^3 + \beta_k p_i^2 + \gamma_k p_i + \lambda_k \tag{4.12}$$

Through the analysis of the above formula, it is found that NOx emission is related to unit load, denitration efficiency, NOx concentration at the inlet, etc. When the load of the unit changes, the coal consumption and flue gas quantity of the unit change. The NOx emission and load are fitted below. Table 4.5 shows the NOx emission concentration model coefficient

Table 4.5 – NOx emission concentration model coefficient

unit	α	β	γ	λ
3	1.58×10-8	-2.23×10-5	9.114×10-3	3.089×10-2
4	3.28×10-8	-3.92×10-5	1.314×10-2	5.073×10-2

At present, China adopts a certain charging standard for pollutant discharge [56], ^{NO_x} discharging charging standard is 630 yuan / T; ^{SO_2} discharging charging standard is 630 yuan / T [57].

4.4 Mathematical model of load optimization

4.4.1 Objective function

There are many operation schemes in the actual operation, which is more economical and more in line with the actual needs. Need a measure index, measure index can use a function to calculate, then the function is the objective function. Thermal power plants pursue the lowest generation cost, which is related to the coal consumption rate. There are many operation schemes in the actual operation, which is more economical and more in line with the actual needs. Need a measure index, measure index can use a function to calculate, then the function is the objective function. Thermal power plants pursue the lowest generation cost, which is related to the coal consumption rate. There are many operation schemes in the actual operation, which is more economical and more in line with the actual needs.There are many operation schemes in the actual operation, which is more economical and more in line with the actual needs. Need a measure index, measure index can use a function to calculate, then the function is the objective

function. Thermal power plants pursue the lowest generation cost, which is related to the coal consumption rate.Therefore, the coal consumption rate of power supply is taken as the objective function. Therefore, the coal consumption rate of power supply is taken as the objective function. At the same time, the emission of pollutants should be minimized according to the requirements of environmental protection. These two objective functions constitute the load optimal distribution model (4.13):

$$\min\begin{cases}\sum_{i=1}^{n} C_i(P_i)=\sum_{k=1}^{2}(a_k p_i^{\,2}+b_k p_i+c_k)\\ \sum_{i=1}^{n} g_i(P_i)=\sum_{k=1}^{2}\begin{bmatrix}\xi_1\left(A_k p_i^{\,3}+B_k p_i^{\,2}+C_k p_i+D_k\right)\\ +\xi_2\left(\alpha_k p_i^{\,3}+\beta_k p_i^{\,2}+\gamma_k p_i+\lambda_k\right)\end{bmatrix}\end{cases} \tag{4.13}$$

4.4.2 Constraints

In the process of function optimization, decision variables and state variables should be limited or the relationship between them should be limited. There are two kinds of constraints: equality constraints and inequality constraints. If there is no constraint, the model will lose its practical significance. If the constraint is wrong, it will produce wrong results, and the optimization will lose its original significance. The load optimization constraints in this paper are: power balance constraints, unit output constraints, pollutant emission constraints.

1Power balance (4.14):

$$\sum_{i=1}^{n} P_i = P_Z \tag{4.14}$$

P_Z – total load of the current power plant, MW .

2 Upper and lower limits of unit output (4.15):

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{4.15}$$

$P_{i,\min}$ – minimum output of i unit MW ; $P_{i,\max}$ – maximum output of the first unit, MW .

Restriction of pollutant emission: the environmental protection requirements of thermal power plants in different regions are different. In this paper, the emission requirements of Shanxi Province are taken as the restriction.

4.5 Summary of this chapter

This chapter mainly studies the relationship between equipment and load, through analyzing the influence of equipment on the unit load capacity, the calculation method of unit load capacity based on equipment status is obtained. Then the load optimization

problem is analyzed to determine the objective function and constraints of the load optimization problem. Due to the different equipment status, the upper and lower limits of the constraints are readjusted to get new constraints. The new constraints can ensure the safety and economy of the unit, and improve the stability of the power grid. The objective function of the load optimization problem mainly considers the economic cost and environmental cost. The economic cost obtains the coal consumption of power supply from the above analysis and calculation formula, and uses the least square method to fit the discrete points into a quadratic function to obtain the coefficients. The environmental cost mainly considers SO2 and NOx. The least square method is used to fit the coefficients of the cubic function. According to the above analysis, the mathematical model of optimal load distribution is determined.

5 APPLICATION OF IMPROVED MULTI-OBJECTIVE PARTICLE SWARM OPTIMIZATION IN LOAD DISTRIBUTION

5.1 Multi-objective particle swarm optimization algorithm

Pareto dominant mechanism is to store the optimal solution of a single particle's historical data into a non inferior solution. The combination of the global attraction mechanism and the previous individual non inferior solution can guide the particle to converge to the global optimal solution and get the optimal solution set. The steps of multi-objective particle swarm optimization algorithm are as follows:

1 Initialize the whole population, randomly generate the initial position and initial velocity of each particle,

2 Evaluate the fitness of each particle in the population;

3 The local and global solutions are selected;

4 The location of non inferior solution particles is stored in an external file;

5 The multi-dimensional search space is formed, and each particle is located in the space according to the corresponding objective function value;

6 The initial memory of each particle is used to guide the flight of search space;

7 When the number of cycles is less than the maximum number of cycles, turn to step 2 until the algorithm reaches the set iteration termination condition.

Particle's speed and position update formula (5.1) and (5.2):

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot rand()(p_i(t) - x_i(t)) + c_2 rand()(\mathrm{REP}(h) - x_i(t)) \tag{5.1}$$

$$x_i(t+1) = x_i(t) + v_i(t) \tag{5.2}$$

where w – inertia weight; $rand()$ – random number within the range $[0,1]$; p_i – iterate to the historical optimal position of the current particle i; $\mathrm{REP}(h)$ – stored value in the external archive.

At least one particle space is allocated with an fitness, which is equal to or greater than 1 in numerical value divided by the total number of particles in this multidimensional space. This method can reduce the fitness of the space with many particles. The multi-dimensional space and the number of particles are selected according to the fitness of each space. After space is selected, the algorithm selects particles from this space to calculate the current target value of particles.

The evolution process of population is in the target space. When a particle exceeds the boundary of flight space in the evolution process, the decision variable value of the particle beyond the boundary is taken as the boundary value or the speed of the decision variable is reversed to make it return to the target space. After iteration, the particles compare and select all particles in the population, store the non dominated solution in the external file, and delete the dominated solution in the external file. When the exter-

nal file is full, delete the particles in the external file, delete the most crowded area or delete the individuals who violate the constraints.

5.2 Improved multi-objective particle swarm optimization algorithm

5.2.1 Improvement of multi-objective particle swarm optimization algorithm

In the particle swarm optimization algorithm, the particle speed is too large, and the particle search is not fine and easy to miss the optimal solution in the process of particle optimization; the particle with too small speed moves slowly, which easily leads to the particle falling into the local optimal. In this paper, the particle speed is improved to improve the accuracy of the multi-objective particle swarm optimization algorithm, and the inertia weight of the speed of the multi-objective particle swarm optimization algorithm is changed.

It is an important parameter of particle swarm optimization algorithm. The value affects the accuracy and calculation speed of calculation results. The larger the value is, the faster the population convergence speed is. When the inertia weight is small, the higher the population convergence accuracy is. The accuracy and speed of the algorithm will be improved by selecting appropriate values. Experiment [61] shows that the larger one can speed up the convergence at the beginning, and the smaller one can improve the convergence accuracy, so the fixed value is changed to the value varying with the number of iterations as formula (5.3):

$$w = 0.9 - 0.4 \times \left(2 \times \frac{t+1}{Maxgen} - \left(\frac{t+1}{Maxgen}\right)^2 \right) \tag{5.3}$$

5.2.2 Steps of improved multi-objective particle swarm optimization algorithm

Set the maximum number of particle swarm iterations T, number of particle swarm N, external file size K, self-study and sociological coefficients of particles c_1、c_2, and coefficient of disturbance term c_3.

1 The initial population randomly generates particle position and velocity in the search space, and iterates the pedometer $t = 0$;

2 The fitness values of m objective functions corresponding to N particles are calculated;

3 The local optimal solution and the global optimal solution are selected;

4 The global optimal solution is searched in variable neighborhood;

5 Update external files;

6 Change the inertia weight according to formula (5.3);

7 In the external file, a particle is randomly selected as the disturbance term, and the Gaussian mutation disturbance operation is performed on the particle;

8 Update particle velocity and position according to (5.1) and (5.2);

9 If the current number of iterations meets the stop condition, the iteration stops, otherwise, turn to step 2.

The speed and position updating formula of the improved multi-objective particle swarm optimization algorithm is as follows (5.4):

$$v_i(t+1) = wv_i(t) + c_1 rand()(p_i(t) - x_i(t)) + c_2 rand()(p_g(t) - x_i(t)) + c_3 rand()(p_d(t) - x_i(t)) \quad (5.4)$$

5.3 Optimization results based on improved MOPSO algorithm

In order to verify the rationality of the model of the improved multi-objective particle swarm optimization algorithm and the effectiveness of the optimization ability of the optimization algorithm, the load optimization and distribution program of the improved MOPSO algorithm is compiled with MATLAB, in which the parameters are set as: population size $N = 150$, maximum number of iterations $T = 500$, size of external files k = 300 The maximum and minimum inertia weights are particle self-learning coefficient $W\max = 0.9, W\min = 0.5$, social learning coefficient $c_1 = 1.5$、$c_2 = 1.5$ and disturbance term coefficient $c_3 = 1.2$.

Table 5.1 – Upper and lower limits of unit output power

Unit	3	4
Lifting load rate (MW/min)	12	12
Upper limit of unit output MW	660	660
Unit output offline MW	264	264
Upper limit of unit instantaneous output MW	727.369	727.369

The results of the improved MOPSO algorithm are compared with those of the MOPSO algorithm and improved multi-objective particle swarm optimization algorithm are compared with AGC instruction.The result shown in table 5.2.

Table 5.2 – Comparison between two algorithms and AGC instruction results

Method	Unit3/ MW	Unit 4/ MW	Coal consumption	Energy cost	Environmental
AGC instructions	439.299	502.800	312.988	22.7047	0.258
MOPSO	422.9	519.199	310.9038	22.5915	0.25792
Article method	431	511.099	310.2628	22.5069	0.25776

Average standard coal consumption of power supply in three methods as figure 5.1.

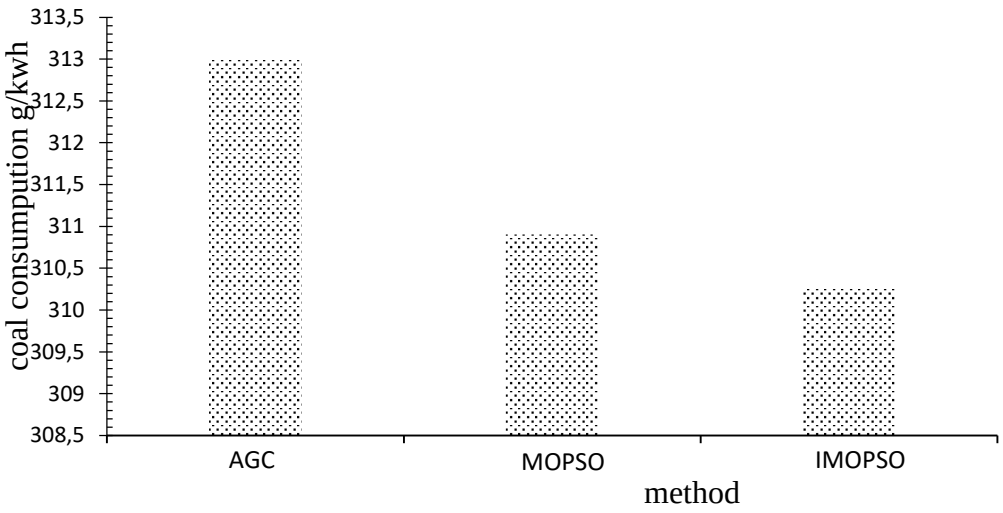

Figure 5.1 – Average standard coal consumption of power supply in three methods

From table 5.2 It can be seen that the energy consumption cost of this method is 22.5069 under the operation condition of total load of 942.099, which is 0.1978 lower than the result of power grid dispatching AGC instruction, and 0.0846 lower than that of multi-objective particle swarm optimization algorithm. The improve multi-objective pariticle swarm optimization algorithm has good optimical result. The results of AGC scheduling are compared with the results of load optimization considering the equipment status. Result as tables 5.3.

Table 5.3 – Comparison between the results of equipment state optimization allocation and the results of AGC command under different loads

AGC scheduling results						Optimal load distribution in case of induced draft fan failure			
Serial number	Total load	Unit 3	Unit 4	Energy cost	environmental costs	Unit 3	Unit 4	Energy cost	environmental costs
1	679.6	345.3	334.2	16.82	0.217	330.1	349.53	16.702	0.216
2	722.3	379.3	343.0	17.79	0.222	353.2	369.17	17.643	0.221
3	773.6	399.3	374.2	18.89	0.226	360.5	413.12	18.782	0.225
4	819.6	403.1	416.4	19.91	0.233	378.1	441.50	19.8	0.231
5	865.3	417.9	447.3	20.97	0.240	371.5	493.80	21.143	0.249
6	880.8	440.7	440.0	21.31	0.243	383.6	497.25	21.457	0.247
7	942.0	439.2	502.8	22.70	0.258	396	546.09	22.742	0.261

It can be seen from the above figure that in the process of optimization, the low load section is not affected by the status of the fan, and the environmental cost can play an optimization role and reduce the environmental cost. However, in the higher load section, the environmental cost increases because the unit load is affected by the state of the fan. The increase of the environmental cost is very small. In the optimal load distribution considering the equipment status, the maximum load of the unit is 1056MW as figure 5.2.

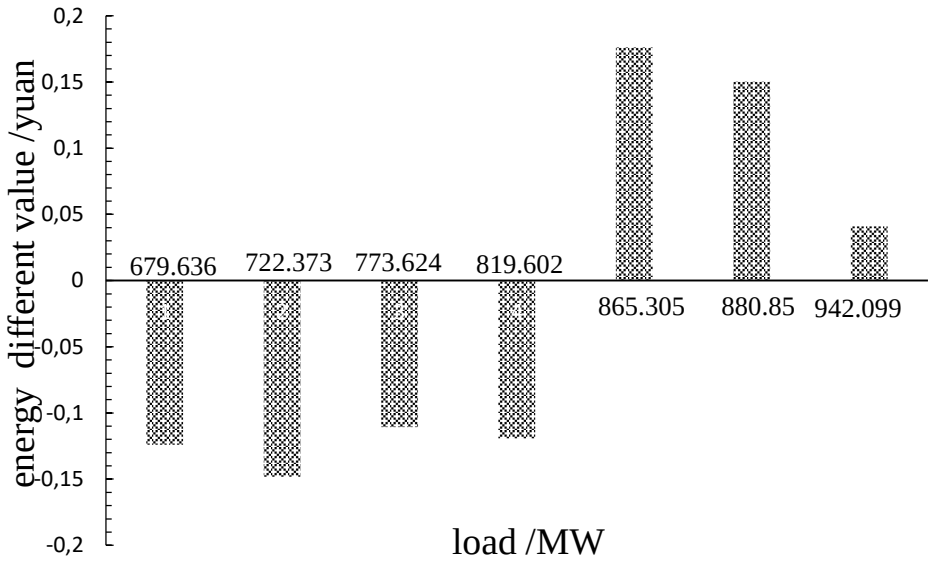

Figure 5.2 – Energy consumption cost difference between the two methods

Therefore, consider the optimal load distribution of the equipment state as table 5.5.

Table 5.4 – Optimization results of load considering equipment status and not considering equipment status

	Optimization results of unit under normal state					Optimization results after induced draft fan failure			
	total Load	Unit 3	Unit 4	energy cost	Environmental cost	Unit 3	Unit 4	energy cost	Environmental cost
1	679	330.1	349.536	16.702	0.218	330.1	349	16.702	0.216
2	722	353.2	369.173	17.643	0.224	353.2	369	17.643	0.221
3	773	360.5	413.124	18.782	0.229	360.5	413	18.782	0.225
4	819	378.1	441.502	19.8	0.231	378.1	441.	19.8	0.231
5	865	416.2	449.105	20.903	0.236	371.5	493	21.143	0.249
6	880	433.5	447.35	21.213	0.246	383.6	497	21.457	0.247
7	942	431	511.099	22.506	0.257	396	546	22.742	0.261

It can be seen from the above figure that the optimization result considering the equipment status before 865.305mw is the same as that without considering the equipment status, that is, the equipment status can increase the reliability and safety of the equipment without any economic loss. When the load is high, the energy consumption and environmental cost will increase because of the load constraints as figure 5.11.

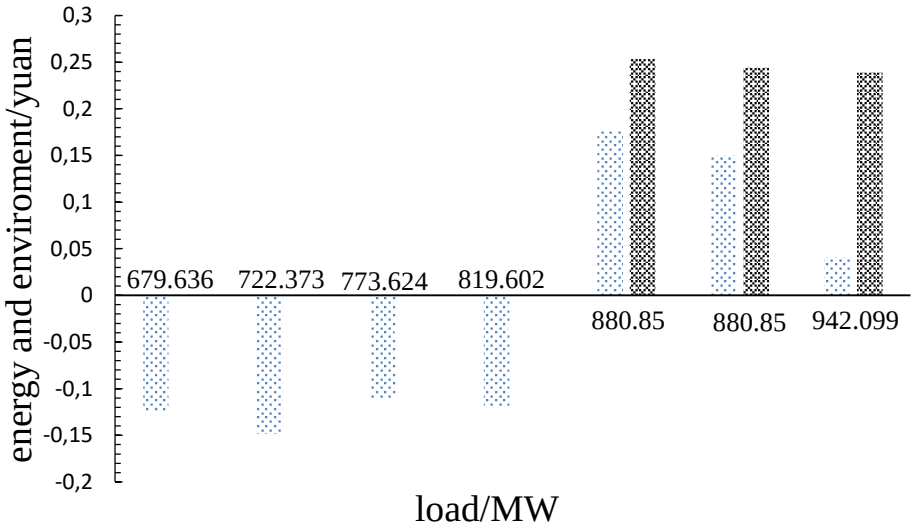

Figure 5.11 – Comparison of total difference between energy consumption environment and AGC considering and not considering equipment status

This paper compares the total difference of energy consumption and environmental cost between AGC power grid dispatching allocation and the improved multi-objective particle swarm optimization algorithm considering the equipment status, and the total difference of energy consumption and environmental cost between the improved multi-objective particle swarm optimization algorithm considering the equipment status and not considering the equipment status. It organically combines the company's strategy with its internal resources and external environment. The greater the difference of the latter indicates that the improved multi-objective particle swarm optimization algorithm has the ability of optimization Ability.

5.4 The analysis strengths and weaknesses of technology, opportunities and threats of its application

SWOT is an abbreviation for Strengths, Weaknesses, Opportunities and Threats. SWOT analysis is actually a method to synthesize and summarize all aspects of internal and external conditions of the enterprise, and then analyze the advantages and disadvantages of the organization, opportunities and threats. It organically combines the company's strategy with its internal resources and external environment.

1. Strengths (S) refers to the ability of an enterprise to surpass its competitors, or refers to something unique to the enterprise that can improve competitiveness. The

strengths can be in the following aspects: technical skills, tangible assets, intangible assets, etc.

2. Weaknesses (W) refers to something that a certain enterprise lacks or does not do well, or refers to a condition that will put the enterprise at a disadvantage. The factors that may lead to weakness are: lack of competitive skills and technologies, lack of competitive assets, and the loss of competitiveness in key areas.

3. Opportunities (O). Enterprise managers should identify each opportunity, evaluate the growth and profit prospects of each opportunity, and select the best opportunities that can match their own financial and organizational resources to maximize the potential of the company's competitive advantage.

4. Threats (T). In the external environment of an enterprise, there are always certain factors that pose a threat to profitability and market position. Managers should promptly identify threats that threaten the future interests of the enterprise, make evaluations and take corresponding strategic actions to offset or mitigate their impact.

The steps of SWOT analysis:

1. List the strengths and weaknesses, opportunities and threats of the enterprise.

2. Combine the advantages and disadvantages of the enterprise with the opportunities and threats of the external environment to form SO, ST, WO, and WT strategies.

3. Choose SO, ST, WO, and WT strategies and determine the specific strategies that the enterprise should adopt.

The promotion of electric vehicles helps to alleviate energy shortages and environmental pollution problems. The promotion of electric vehicles helps to alleviate energy shortages and environmental pollution problems. The promotion of electric vehicles helps to alleviate energy shortages and environmental pollution problems. The promotion of electric vehicles helps to alleviate energy shortages and environmental pollution problems. The charging behavior of electric vehicles is characterized by randomness, which may bring many effects to the power grid [1]. With the development of the competitive charging market, accurately understanding user charging behavior patterns has become a valuable asset for power service providers [2]. This chapter first introduces the basic multi-objective particle swarm optimization (MOPSO), according to the shortcomings of the multi-objective particle swarm optimization algorithm to improve the multi-objective particle swarm optimization algorithm, the improved particle swarm optimization algorithm convergence speed fast optimization results more accurate. The improved multi-objective particle swarm optimization algorithm is applied to optimize the load optimization model considering the equipment status.The optimization results show that the load optimization allocation result considering the equipment status in the high load section is slightly less than that in the AGC power grid dispatching. The key to the industrialization of electric vehicles is to optimize the planning of charging facilities and improve their related theories, The key to the industrialization of electric vehicles is to optimize the planning of charging facilities and improve their related theories, which can provide technical and theoretical support for the actual planning work and contribute to the development of electric vehicles.The SWOT matrix analysis combined with the techniques of this paper is shown in table 5.6.

Table 5.6 – SWOT matrix analysis of technology in this paper

Internal factor / External factor	Strength	Weaknes
	1. Energy saving, environmental protection and clean energy. 2. Improve the reliability and economy of power grid operation. 3. Lay the foundation for charge and discharge scheduling of electric vehicles. 4. Protect user privacy of electric vehicles. 5. Improve the economic benefits of charging facilities. 6. Promote the formation of the electric vehicle ecosystem.	1. The amount of data is insufficient. 2. The charging facility planning scheme is not perfect.
Opportunities	SO	WO
1. Electric vehicles are valued by countries all over the world. 2. China has introduced many preferential policies related to electric vehicles. 3. The number of electric vehicles in China is increasing, and the scale of charging facilities is also expanding.	1. Promote the popularity of electric vehicles. 2. Provide users with personalized services, and increase satisfaction. 3. Guide charging behavior, and maintain the safety and stability of the power grid. 4. Alleviate the tension of data leakage and protect user privacy.	1. With the popularity of electric vehicles and the improvement of charging facilities, more data can be used for analysis. 2. Speed up the construction of supporting facilities.
Threats	ST	WT
1. Electric vehicles are in the initial stage of development. 2. The application of automotive electronic technology needs further research and development 3. Imperfect supporting facilities. 4. The market recognition of electric vehicles is not high.	1. Accelerate the research of related technologies. 2. Provide convenient charging methods to drive potential users' purchase enthusiasm. 3. Innovate business operation models and build reasonable charging facilities.	1. Establish an electric vehicle technology platform. 2. Increase the research and development of electric vehicles.

Electric vehicles are now in the initial stage of development, and electric vehicles are very important for achieving energy transformation in the transportation field. At the same time, China has introduced many preferential policies related to electric vehicles, which has greatly promoted the share of electric vehicles. Moreover, the number of electric vehicles and charging facilities is increasing. The application of research and development informatization and intelligent automotive electronic technology, the improvement of the construction of charging facilities, and the provision of convenient services to users can promote the formation of an electric vehicle ecosystem and help alleviate energy shortages and environmental pollution.

5.5 Gantt's schedule of actions for implementation of technology based on the operating and collaborating model of virtual power plant based on blockchain technology in power industry

In this section, I draw a Gantt chart for the entire article. Gantt chart shows the whole process of my thesis. Project determination, model design, model analysis, algorithm selection, calculation, calculation result analysis, PPT preparation. Unit load optimal distribution is an important part of operation optimization measures for thermal power plants, and also a typical optimization problem in power system [1]. The traditional load optimal distribution considers that the thermal power unit is fully adjustable, but in the actual power generation process, there are many uncontrollable factors in the thermal power unit, so it is not easy to think that the unit is fully adjustable. It is necessary to take the operation state of the thermal power unit equipment into account in the load optimal distribution model [2]. Firstly, the sensitive parameters of the equipment status evaluation are determined according to the common faults and causes of the equipment. The selected parameters are used as the input parameters of the equipment status evaluation, and the equipment status evaluation model is established. [3] Judge the equipment available status and determine the unit load capacity. Judge the equipment available status and determine the unit load capacity. Judge the equipment available status and determine the unit load capacity. The adjustable range of load is determined according to the load capacity of the unit. In order to optimize load distribution, a model of load optimization distribution should be established. The objective function of load optimization distribution is economic cost and environmental cost. The constraints are power balance constraint, unit load constraint and pollutant emission constraint [4,5]. The traditional load optimal distribution considers that the thermal power unit is fully adjustable, but in the actual power generation process, there are many uncontrollable factors in the thermal power unit, so it is not easy to think that the unit is fully adjustable. It is necessary to take the operation state of the thermal power unit equipment into account in the load optimal distribution model. Select the calculation method for the calculation of load optimal distribution model, and analyze the calculation results. Combined with distributed, It can be seen in table 5.7

Table 5.7 – Gantt's schedule of actions for plant level load optimal distribution based on equipment status

Research and Project stages	Performers	Period of implementation of the project 2019 - 2020, month								
		9	10	11	12	1	2	3	4	5
1	2	3								
1. Development of introduction.	X.Wei R. Alabugina									
2.Search for references	X.Wei									
3.Project to determine	X.Wei R. Alabugina									
4.Model design	X.Wei									
5.The analysis model	X.Wei									
6.Algorithm selection	X.Wei									
7. Algorithm	X.Wei									
8.Analysing results of algorithm	X.Wei									
9. Preparing PPT	X.Wei R. Alabugina									
10.Finishing Final Paper	X.Wei R. Alabugina									

5.6 Summary of this chapter

This chapter first introduces the basic multi-objective particle swarm optimization (MOPSO), according to the shortcomings of the multi-objective particle swarm optimization algorithm to improve the multi-objective particle swarm optimization algorithm, the improved particle swarm optimization algorithm convergence speed fast optimization results more accurate. The improved multi-objective particle swarm optimization algorithm is applied to optimize the load optimization model considering the equipment status.The optimization results show that the load optimization allocation result considering the equipment status in the high load section is slightly less than that in the AGC power grid dispatching.

6 CONCLUSION AND PROSPECT

6.1 Conclusion

Firstly, this paper analyzes the thermal power unit and obtains the main auxiliary equipment that affects the unit load. Analyze the types and causes of equipment faults and extract the characteristic parameters needed for equipment state evaluation. The extracted data may have deviation due to the environmental impact. Use wavelet transform theory to denoise the data. In this paper, multivariate state estimation method is used to evaluate the equipment status. When there are too many parameters, the calculation time will be increased and the redundancy of the parameters will be increased. If there are too few parameters, the evaluation results will not be comprehensive. Therefore, olpp algorithm is introduced to reduce the dimension of the data. This paper takes the induced draft fan as an example to evaluate the equipment status. According to the state of equipment and the redundancy of equipment, the load capacity of the computer group is used as the load constraint condition of the optimal load distribution among thermal power units, and the improved multi-objective particle swarm optimization algorithm is applied to the load distribution among units. The main conclusions are as follows:

1 Different auxiliary equipment has different influence on the unit load. In this paper, according to the importance and selection principle of auxiliary equipment, the auxiliary equipment with great influence on the load is selected for evaluation. The evaluation parameters are selected according to the equipment fault classification and the fault reason, and the parameter set of the equipment state evaluation model is constructed.

2 Due to the bad operating environment of thermal power units, the selected data may have deviation. In this paper, wavelet transform is used to denoise the data, and the processed data is used as the input vector of the model. In this paper, the orthogonal local preserving projection algorithm is introduced to reduce the dimension of data.

3 In this paper, the state evaluation model based on olpp-mset is established, and the program code is compiled by MATLAB. The state of induced draft fan is evaluated by taking induced draft fan as an example. The fault information is hidden in the deviation between the output estimation vector and the actual observation vector of the state evaluation model. According to the deviation, the similarity is defined between 0-1. The greater the similarity is, the closer the state is to the normal state in the model. The results show that the similarity between observation vector and estimation vector is higher in normal state based on olpp-mset model, and the similarity between observation vector and estimation vector in fault state is very small, which can reduce the false alarm rate. At the same time, the similarity calculated by the model is smoothed by the average filtering method, so as to reduce the influence of uncertain factors and random interference. According to the kernel smoothing density estimation method, the fault early warning threshold is determined.

4 According to the importance of thermal power unit equipment and equipment redundancy, the load capacity of the unit is calculated, and the availability of equipment is

determined according to the evaluation equipment status. In case of equipment failure, this paper assumes that the equipment is not available and needs to be maintained, and determines the maximum load value of each equipment according to the status of all auxiliary equipment. The minimum value of the maximum load value of the equipment is the maximum load value of the unit.

5 According to the data relationship between power supply coal consumption rate load and air pollutant emission load, the characteristic curve and function relationship of power supply standard coal consumption rate and air pollutant emission are established by using the theory of least square method, and the optimal distribution model of negative load is established with the objective of minimum energy consumption cost and environmental cost.

6 The improved multi-objective particle swarm optimization algorithm is used to simulate the model. The results show that the improved MOPSO algorithm has stronger optimization ability and can find a better operation scheme. In the process of optimization, the energy consumption cost is mainly reduced, and the environmental cost changes little. In the low load section, the equipment state has no effect on the load distribution of the unit. In the high load section, the energy consumption cost and environmental cost of power grid dispatching AGC considering the equipment status are higher than those of power grid dispatching AGC without considering the equipment status, but the optimization can reduce some losses. Considering the condition of the equipment, the increase of the loss of load optimal distribution is between 1700-1800 yuan per hour, which is much smaller than that of the equipment and its components in a short time. Therefore, the optimal load distribution considering the equipment status can reduce the loss of the thermal power plant, and improve the safety of the thermal power unit and the stability of the power grid.

6.2 Outlook

1 Based on the olpp-mset model, only one set of data is used to verify the validity of the model, and there is no research on whether it is applicable to other equipment or other types of faults.

2 Due to the limitation of fault type and fault data, the influence of different fault types on load is not taken into account. Some faults of equipment will not cause fault expansion or trip for a period of time, and can be kept under the limit of load operation for a period of time under fault condition.

3 In the optimization of load distribution, the start and stop of equipment and the change direction of load current state (load increase and decrease or constant load) are not considered. It is necessary to avoid the reverse load change of the unit in a short time, resulting in the fatigue loss of the unit load change. In the actual optimization of load distribution, the real-time change of coal consumption rate, the shorter the time of load optimization distribution, the better and other issues are not considered in the optimization of load distribution In the matching model.

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