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Combining Artificial Intelligence Algorithm to Study the Application of Power Plant Boiler in Thermal Power

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Abstract: Thermal power generation has been widely used in many development fields, and its application in power plant boilers has received the attention of many research teams in recent years. Artificial intelligence algorithms have been applied to the prediction and optimisation of complex variables in various industrial sites, and many results have been achieved with promising development, of which the particle swarm algorithm is a common intelligent optimisation algorithm. Therefore, this paper uses the particle swarm optimisation algorithm to establish a support vector machine prediction model to analyse and predict the operating state of a boiler when it is in online operation. This paper uses the support vector machine to search for the global optimal solution to obtain the optimal output variables in the boiler combustion process. These output variables can include boiler efficiency, NOx emission concentration, etc. Through the optimisation of these target variables, the boiler combustion in power plants can achieve the goal of energy saving and emission reduction.

1. Introduction

Boiler occupies an important position in the field of electric power production and is an important part of power station operation [1]. In order to meet the demand of society for electric power, the structure of electric power industry is constantly being adjusted and upgraded, and the internal structure of power plant boilers is more complicated and the internal parameters are more diversified, which poses a higher challenge to the boiler combustion system [2-3]. The explosive growth of artificial intelligence theory provides theoretical support and application foundation for the modeling method based on artificial intelligence algorithm [4]. For the combustion optimization of power plant boilers, we can improve the thermal efficiency of power plant boilers and reduce the emission of acidic oxides based on particle swarm optimization algorithm, complete the design of objective function and solve the optimal solution of objective function [5-6].

With the continuous development and progress of artificial intelligence algorithm technology, many scholars apply this method to the analysis, processing and research of boiler operation data in power plants [7]. For example, experts such as Bezzina G made a comprehensive analysis of the risk factors in the process of limited space maintenance of power plant boilers, put forward the limited space operation procedures, and worked out detailed release and construction process conditions. The results showed that the boiler drum was successfully repaired in a safe construction environment [8]. Raj A and other researchers have developed a boiler thermal performance change influence model, which can calculate the oxygen content of exhaust gas. Using this model, the goal of minimizing net carbon consumption is achieved, and the optimal exhaust oxygen content of boiler under different loads is determined through model analysis [9]. Artificial intelligent algorithm is beneficial to the improvement of thermal energy combustion efficiency of power plant boilers.

In this paper, the combustion optimization of power plant boiler is studied with artificial intelligence algorithm. Therefore, the main research content of this paper is divided into three parts. The first part is a basic overview of power plant boilers through boiler combustion system and combustion optimization requirements. The second part is the optimization of boiler combustion, including data collection, data processing and simulation of reference working conditions. The third part is the analysis of vector machine prediction model, mainly including particle swarm optimization support vector machine and boiler combustion optimization based on multi-objective particle swarm optimization.

2. Basic Overview

2.1. Boiler Combustion System

All boiler systems are combined with each other and rely on each other to accomplish the task of main steam generation, which is obviously systematic. The systems are closely related and influence each other. Once an abnormal situation occurs in a certain system or equipment, it may affect the normal operation of other systems and equipment, resulting in the normal work of some or even the whole system being affected. Therefore, the research of advanced fault diagnosis technology, timely diagnosis of boiler faults and early warning to staff can effectively improve the safety of system operation and avoid more serious faults.

Among all subsystems of the boiler, the combustion system is the most important. It is the system that generates superheated steam in all systems of the boiler, and it is also the foundation of all subsequent subsystems. Once the combustion system fails, the boiler system will run abnormally. Through years of boiler operation in power plants and expert research and summary, the combustion system generally has the following main faults: boiler fire extinguishing, boiler coking, reburning in tail flue and abnormal main steam temperature.

2.2. Combustion Optimization Requirements

Through the research on the generation principle of acid oxides (SO2 and NOx) and the thermal efficiency of the boiler, we can draw the following conclusions: if chemical fuels are volatilized in large quantities under the condition of insufficient oxygen, the emissions of acid oxides can be effectively reduced. There are two specific methods in boiler control: one is to reduce the excess air index; The second is to prolong the reduction zone and slow down the total contact time between pulverized coal fuel and primary and secondary air. In order to achieve the goal of high efficiency and low pollutant emission of power plant boiler, this paper chooses artificial intelligence algorithm and modeling optimization method to optimize the boiler combustion control system. When the optimization is completed, the boiler in the power plant can run stably and safely, while giving consideration to economy and environmental protection.

3. Boiler Combustion Optimization

3.1. Data Collection

In this paper, data is collected from the boiler combustion system, and the workflow of data collection is shown in Figure 1. In Figure 1, the optimization strategy can be selected according to the actual optimization requirements, and given the range of fixed parameters and adjustable parameters, this part is related to the parameter adjustment range of the subsequent optimization part, and some irrational optimization results can also be avoided. Finally, the operation of reading database files. This part mainly completes the preparatory work of combustion optimization, so as to prevent negative or unreasonable values from appearing in the combustion optimization results, which will affect the overall optimization effect.

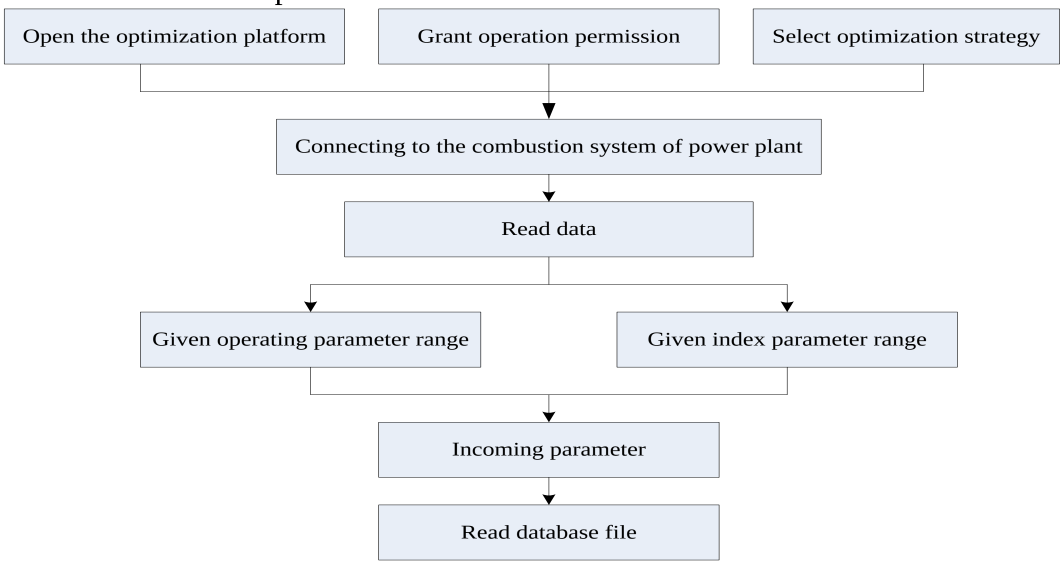

Figure 1. Flow chart of data collection

The calculation stage includes prediction part, optimization part, optimization result display and parameter callback part. The prediction part mainly includes the selection of internal parameters of the algorithm, and the evaluation of parameters including mean square deviation and square correlation coefficient after regression calculation. Then, it is judged whether the working condition to be optimized has reached the optimal working condition parameter, which is the optimal historical data combination, mainly the ideal index parameter combination, and if not, the optimization part is started. In the optimization part, the particle swarm optimization algorithm is used to optimize and adjust the parameters. After the parameters are set, the optimization calculation is carried out. At the same time, the iterative convergence curve can be drawn. When the set convergence condition is reached after the calculation, the result of optimization will be displayed. Finally, whether to call back the optimized operating parameters or not can be selected, and the data visualization stage can be started.

3.2. Data Processing

In order to build a convincing model, we need to get the real-time data of boiler operation, which will make the model built by machine learning convincing. During the actual operation of the power plant boiler, most of the required operation data of the boiler will be kept in the control system of the power plant, which will help us to randomly select the sample data. Normalize the data, and the normalization formula is Formula (1) and the inverse normalization formula is Formula (2). The formula expression is as follows.

$$Y^* = \left[Y - \frac{\max(Y) + \min(Y)}{2} \right] / \frac{\max(Y) - \min(Y)}{2} \tag{1}$$

$$Y = \min(Y) + Y^* (\max(Y) - \min(Y)) \tag{2}$$

3.3. Simulation of Benchmark Working Conditions

According to the actual situation of the power plant, this section mainly analyzes the flow field distribution, temperature distribution and distribution characteristics of each component in the combustion chamber. Under the reference condition, the equivalent ratio in the combustion chamber is 0.516, the total natural gas volume is 1.52kg/s, the total air volume is 40.35kg/s, and the cooling air volume is 5.78kg/s, in which the inlet air temperature is 715k, the inlet fuel temperature is 513k, and the inlet pressure is 2.1MPa Under ISO condition, it is fully premixed combustion, so the ratio of D5 fuel is 0, and the other ratios of PM1, PM2 and PM3 are 13.67%, 33.46% and 52.43% respectively. The comparison between the simulation results of the combustion chamber outlet under the benchmark condition and the actual data of the power plant is shown in Table 1. The simulation results show that the outlet temperature of the combustion chamber is 2146k, the NOx emission is 21.38ppm, the maximum amplitude of pressure pulsation is 6.54kPa, and the average velocity at the outlet section is 134.2 m/s. The measured outlet temperature of the combustion chamber in the power plant is 2155k, the NOx emission is 22.07ppm, the maximum amplitude of pressure pulsation is 6.79k, and the average flow velocity at the outlet section is 139.4m/s, with an error of less than 4%. The simulation results are satisfactory and meet the requirements of subsequent analysis and optimization.

Table 1. Comparison between simulation results and actual data of benchmark working conditions

Project	Analog result	Actual data of power plant	Error(%)
Combustion chamber outlet temperature (k)	2146	2155	0.42
Average NOx at combustor outlet (ppm)	21.38	22.07	3.13
Maximum amplitude of pressure pulsation (kPa)	6.54	6.79	3.68
Average outlet velocity (m/s)	134.2	139.4	3.72
Average value of COmbustion chamber outlet co (ppm)	5.33	5.49	2.91

4. Analysis of Vector Machine Prediction Model

4.1. Particle Swarm Optimization Optimization Support Vector Machine

Using particle swarm optimization, a support vector machine prediction model under 550MW load is established. The optimized support vector machine model NOx emission prediction results are shown in Figure 2, and the relative error results of NOx emission prediction before and after algorithm optimization are shown in Figure 3. The training set is Sample 1 to Sample 10, and the test set is Sample 11 to Sample 15. By observing Figure 2, the following conclusions can be drawn. On the whole, the deviation between the predicted result of the training set model and the real value is small, which indicates that the model fits well on the training set and has high accuracy. The deviation between the predicted results of test set data and the actual values is also small, which indicates that the model has good prediction ability. It can be seen from Figure 3 that the maximum relative average relative error of the prediction results in the training set is 2.69%, the minimum relative average error is 1.18%, and the average relative error is 1.947% before the parameters of the support vector machine are optimized; The maximum relative error is 2.54% and the average relative error is 1.642%. After optimization, the maximum relative average relative error of prediction results in training set is 2.33%, the minimum relative average error is 1.09%, and the average relative error is 1.718%. The maximum relative error of the test is 2.30%, and the average relative error is 1.404%, which indicates that the optimized support vector machine has higher accuracy in NOx emission prediction.

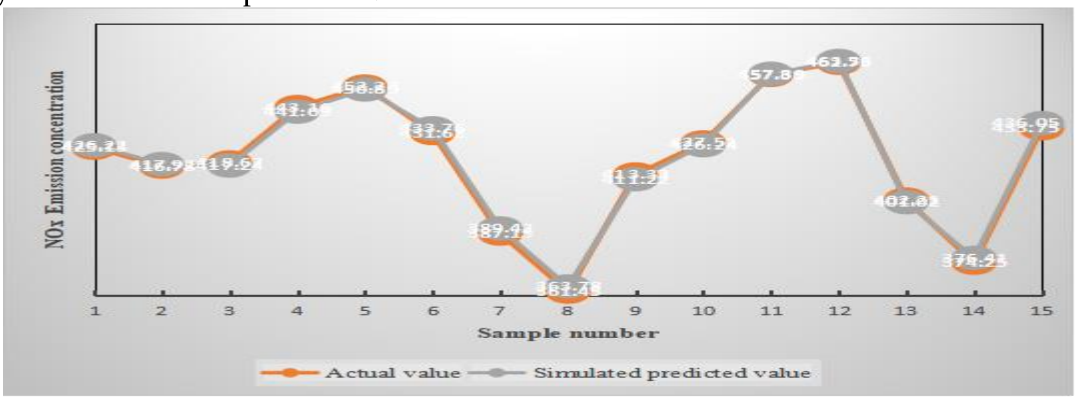

Figure 2. Optimized support vector machine NOx emission prediction results

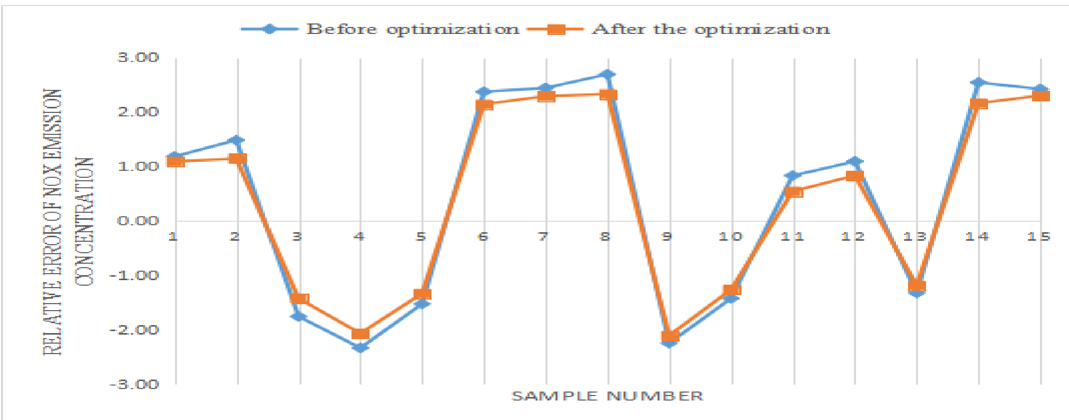

Figure 3. Relative error results of NOx emission prediction before and after optimization

4.2. Boiler Combustion Optimization Based on Multi-Objective Particle Swarm Optimization Algorithm

Multi-objective optimization of boiler combustion is based on a model that can predict boiler indexes well. Considering the actual situation and the advantages and disadvantages of the model, the support vector machine model is adopted as the prediction model, and then the multi-objective particle swarm optimization algorithm is used to optimize and adjust the boiler operation parameters with low-concentration NOx emission and high-efficiency boiler combustion as the objective functions.

Under the same 550MW load, the operating parameters are optimized in case 3, where the NOx emission is high and the combustion thermal efficiency of the boiler is low. It is hoped that the optimization of this case can ensure the thermal efficiency of the boiler while reducing the NOx emission, and the optimization results are shown in Figure 4, which is a pareto solution set with multiple optimization solutions. The results in Figure 4 show that after the optimization algorithm is adopted, the NOx emission concentration of the boiler is obviously reduced, and the lowest emission concentration is 318 mg/m3 compared with that before the optimization, but the thermal efficiency of the boiler is also obviously reduced compared with that before the optimization of 92.4%. At this time, we need to pay attention to the fact that we should not excessively damage the economy of the boiler by aiming at low NOx emission. There are feasible solutions in pareto solution set that meet the requirements of NOx emission reduction and thermal efficiency increase at the same time. Therefore, for the optimized pareto feasible solution set, operators need to select appropriate feasible solutions according to actual engineering experience to adjust the operating parameters.

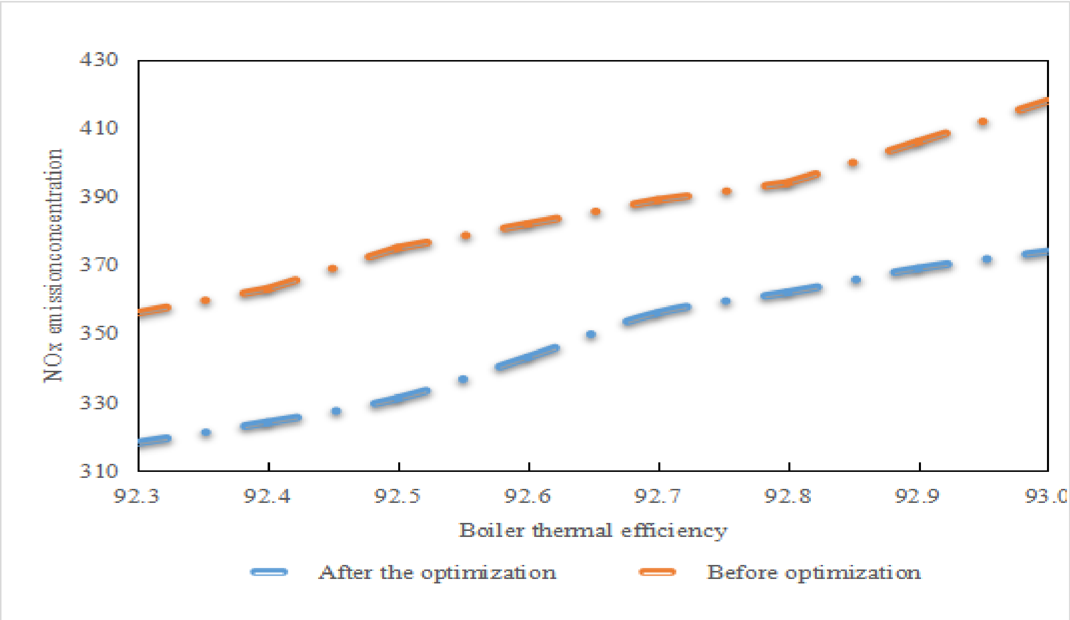

Figure 4. Pareto solution set before and after optimization in case 3

5. Conclusion

Thermal power generation plays an important role in China's power structure. In this paper, particle swarm optimization (PSO) is used to analyze the NOx emission concentration of power plant boilers. Through analysis, it is found that the optimized support vector machine is more accurate in predicting NOx emission. Through the analysis of boiler combustion optimization based on multi-objective particle swarm optimization algorithm, it is found that after the optimization algorithm is adopted, the NOx emission concentration of the boiler shows a decreasing trend. Artificial algorithm modeling has advantages and disadvantages. The method has the advantages that the real-time optimization guidance of operating parameters can be realized according to the actual operating conditions; The disadvantage is that it is difficult for the algorithm to reflect the change rules of flow field, temperature field and pollutant generation caused by the change of operating parameters. At the same time, its accuracy depends on the integrity and diversity of data samples.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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