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Retraction

Retracted: Data Optimization Analysis of Integrated Energy System Based on *K*-Means Algorithm

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] H. Guo, J. Li, Z. Sun, Z. Du, and X. Cheng, "Data Optimization Analysis of Integrated Energy System Based on *K*-Means Algorithm," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1211515, 8 pages, 2022.

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Research Article

Data Optimization Analysis of Integrated Energy System Based on K-Means Algorithm

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To learn about the practical application of K-environment algorithms in electronic data analysis. To increase the thermal efficiency of boiler combustion and reduce nitrogen oxide emissions, the paper uses a 300 MW circulating liquid bed boiler for a thermal power plant as a research product. The studied and improved optimization methods have been successfully used to optimize the combustion of circulating liquefied boilers. Based on the advantages and disadvantages of biogeographic optimization algorithm and K-means clustering algorithm, this paper combines the two algorithms into a new improved clustering algorithm k-bbo-cluster. According to the operation mode of circulating fluidized bed boiler, the calculation method of boiler combustion thermal efficiency and the generation mechanism of nitrogen oxides, the boiler thermal efficiency model, nitrogen oxide emission concentration model and its comprehensive model are established by using the least square support vector machine method based on Bayesian structure framework. The learning outcomes of the vector machines that support the minimum squares of the Bayesian structure are less than 0.05 by the difference between MSE, MAE, and MAPE. The study of optimizing the combustion of circulating liquefied bed furnaces in this article can effectively improve the thermal efficiency of circulating liquefied bed furnaces and reduce nitrogen oxide emissions. Protection is important.

1. Introduction

Data mining, also known as database retrieval, has become a widely used tool in recent years. It is based on information technology and retrieval of confidential information, effective, and accessible from a variety of nonisolated information, obtains time trends and connections, and provides researchers with decision support ability at the level of problem solving. Cluster analysis is a method to classify clustering objects by studying the characteristics of things themselves. Cluster analysis is a very important module in data mining research [1, 2]. What is called a cluster is the division of a source of information into several clusters or classes. The data characteristics of objects in each cluster tend to be similar, and the data characteristics of objects belonging to different clusters are relatively different. The fundamental purpose of cluster analysis is how to successfully classify the data according to the requirements without prior knowledge. The measure of similarity between data is usually described by the distance between objects. Selecting a group of abstract or actual data objects and dividing the data objects into several classes according to the distance between a single data object and each data object is the clustering process. In many practical applications, in the clustered data set, the data in the same category can usually be treated as one data. Numerical cluster analysis is a rapidly developing subject. In machine learning, cluster analysis is different from expert supervised learning such as classification learning. It is a kind of unsupervised learning without expert supervision. It does not rely on the prior confirmation of data categories. Therefore, cluster analysis is another method of learning through observation [3, 4].

Cluster analysis is a very potential field. When applying it to deal with data, there are high requirements for some of its abilities, such as the scalability of the algorithm, the generalization ability of the algorithm, the ability to deal with noisy data, and the ability to deal with high-dimensional data. Therefore, in the research of cluster analysis, we should pay attention to meeting these requirements. This paper applies the combustion optimization of

circulating fluidized bed boiler to the actual production. The main idea of clustering algorithm based on partition method is when the objective function is differentiable, based on the preliminary division of data sources and taking this as the starting point, the clustering results are updated repeatedly until the clustering results do not change (i.e., the objective function converges), and the final clustering results are regarded as the optimal clustering results. Figure 1 shows the data optimization analysis of integrated energy system.

2. Literature Review

In view of the phenomenon that economic development runs counter to environmental protection, we need to pay close attention to environmental governance, emphasize the implementation of the scientific outlook on development, strictly implement the strategic policies of sustainable development, and create a suitable living environment for the people. Among them, the treatment of environmental pollution has become the top priority. Nature is an important resource for human survival. The pollution of natural environment has seriously affected human travel and all outdoor activities and brought serious harm to people's health [5, 6]. The pollution of air pollutants is particularly serious. NOx will form acid rain, chemical smoke, nitrous oxide, and other substances, which are highly toxic pollutants that endanger human health and damage the atmospheric environment. Therefore, how to reduce the combustion emission of thermal power generation has become the primary problem of environmental pollution control [7]. At the same time, the power generation of thermal power station brings another problem: energy consumption. Energy refers to all substances that can provide energy transformation to nature. It is the material basis of human activities. China is rich in energy reserves and carries the energy production and consumption in the forefront of the world [8]. On the other hand, China's geographical environment, climate factors, and mining technology determine the energy distribution of "less oil, more coal and less gas." Coal plays a dominant role in China's energy production and utilization, accounting for more than 90% of the total primary energy. China is vast in territory, abundant in resources, but the per capita share and consumption of resources are far lower than the international average. The country's dependence on energy is becoming more and more serious. Due to science and technology, economy, and other reasons, the degree of energy development and utilization is low, resulting in low energy utilization efficiency and severe energy consumption situation in China [9]. Therefore, due to the importance of energy in economic and environmental development, it is imperative to improve energy efficiency and develop new energy technologies.

Abundant coal resources determine the main mode of power production in China. At present, the State advocates and vigorously develops the utilization of other energy sources. However, by the end of August 2014, the installed capacity of power plants with 6000 kW and above in China was 1.26 billion kw, ranking the second in the world, including 883 million KW thermal power, 71% of the total installed capacity of heat, water, wind, and nuclear. The combustion fuel of thermal power plants is mainly coal, and a large number of air pollutants are often produced in the process of coal combustion. In addition, under the new market situation that China's power generation enterprises implement the separation of plant and network and price competition on the Internet, it is imperative to vigorously develop combustion optimization technology in order to obtain higher economic benefits and enhance their market competitiveness [10]. The boiler combustion optimization guidance system developed in China monitors the changes of boiler combustion efficiency online by monitoring important parameters such as wind speed and pulverized coal concentration, so as to guide the operation of boiler operators [11]. In addition, the neural network model and nonlinear optimization technology are adopted to guide the boiler combustion adjustment, and the model self-correction technology is adopted to realize the long-term effectiveness of the boiler combustion system. After adopting the system, the boiler combustion thermal efficiency can be increased by 0.5-2.5%, and the NOx emission concentration can be reduced by 10-50% [12]. In the aspect of artificial intelligence optimization algorithm, the improved artificial intelligence technology is integrated into the combustion optimization process of utility boiler; in order to optimize the NOx emission process of the boiler, a particle optimization algorithm is used, which effectively reduces the NOx emission concentration of the boiler; optimal MV decision-making model is used to optimize the combustion process of power plant boilers; immunity A cell herd algorithm is proposed to create a multipurpose model. Through the fuzzy mining algorithm, the optimal parameters of boiler operation under various loads are mined [13, 14].

Because the dynamic characteristics of coal-fired boilers in power plants are very complex, it is very difficult to improve the combustion control system. We should use very efficient control methods to improve the role of the system as a whole. Therefore, for the complex system of boiler, combined with hierarchical control theory, on the basis of comprehensive coordination and global optimization, in order to realize intelligent comprehensive control, it has become an important development trend to adopt different control theories under different circumstances [15].

3. Research Methods

3.1. K-Means Clustering Algorithm. The K-means cluster algorithm is a clustering algorithm based on the 1967 division method proposed. It is the most mature classical algorithm in data mining. Because of its fast clustering speed, simple calculation, and high applicability, the algorithm has been widely used in scientific research and industrial application [16]. The basic idea of K-means clustering algorithm is to set K as the input parameter and divide the data source into K clusters according to the distance relationship between data, so as to maximize the data spacing between clusters and minimize the data spacing in each cluster. Then calculate the average values of each cluster and reassemble these averages into a new center point. The center point does
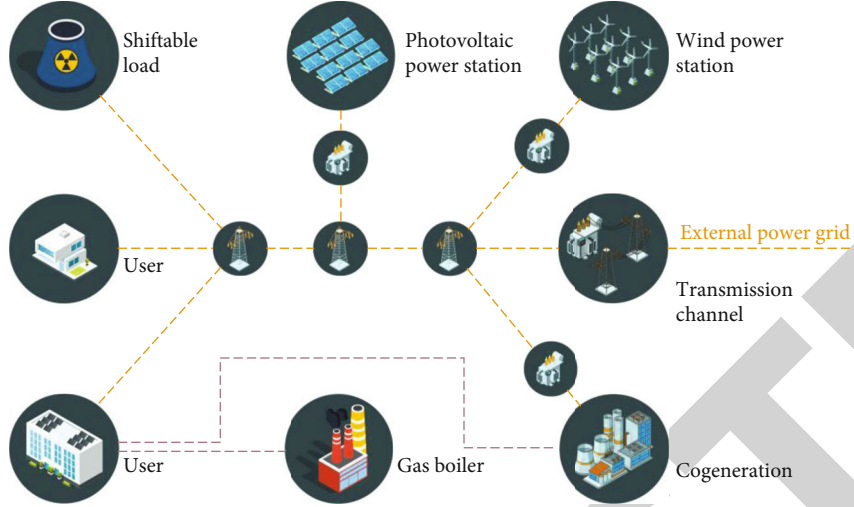
FIGURE 1: Data optimization analysis of integrated energy system.

not change (i.e., the criteria function merge), and then this process is repeated continuously until the cluster is complete. The K-means cluster algorithm uses the Euclidean distance formula to determine the distance between data, as shown in the following equation:

$$d(i, j) = \sqrt{\left(x_{i1} - x_{j1}\right)^2 + \left(x_{i2} - x_{j2}\right)^2 + \cdots + \left(x_{in} - x_{jn}\right)^2}. \quad (1)$$

Among them, $i = (x_{i1}, x_{i2}, \cdots, x_{in})$ and $j = (x_{j1}, x_{j2}, \cdots, x_{jn})$ are two n-dimensional data objects.

Therefore, the criterion function used in the algorithm can be expressed as follows:

$$E = \sum_{i=1}^{k} \sum_{p \in c_i} |p - c_i|^2. \quad (2)$$

The specific steps in the operation of a K-means cluster algorithm are as follows:
Input: number of initial clusters K.
Output: K final cluster centers and K final cluster sets.

Step 1. Set any k data points in the data source as the initial clustering center.

Step 2. Calculate the distance from other data in the data to the selected K cluster centers according to the distance formula, divide each data into the cluster where the corresponding cluster center with the smallest distance is located, and calculate the value of the criterion function.

Step 3. Repeat steps 2 and 3 until the aggregation result does not change, and the agglomeration is complete.

Step 4. Output K clustering results.

Because the noise data will have a great impact on the average value of clustering, k-medoids clustering algorithm
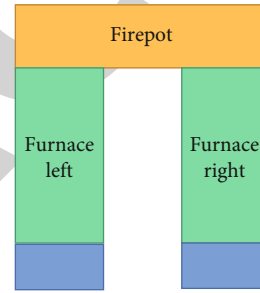

FIGURE 2: Furnace structure of circulating fluidized bed boiler.

changes the selection method of clustering center, so as to eliminate the impact of noise data to a great extent. The basic idea of the K-means cluster algorithm is approximately the same as the K-means cluster algorithm. The biggest difference is the selection of clustering center. K-medoids clustering algorithm takes a point named medoids as the clustering center rather than the average value [17, 18]. Biogeographic optimization algorithms are mainly based on the survival characteristics of biological groups in practical engineering [19]. The biogeographic optimization algorithm has the advantages of simple operation, easy understanding, and strong applicability. It is a global intelligent optimization algorithm, which is very suitable for the optimization of practical projects.

3.2. Combustion Process Model of Circulating Fluidized Bed Boiler.
The combustion system of a circulating liquid boiler is a complex system with many inputs and outputs, and there is a strong connection between the system inputs(coal fee, primary air, secondary air, etc.) and the system outputs (boiler heat efficiency, nitrogen oxide emissions, etc.). Different combustion conditions have different input parameter ratios and lead to different output results. Based on the requirements for the modeling of circulating fluidized bed boiler combustion system, and considering the shortcomings of neural network modeling method, such as long modeling time and
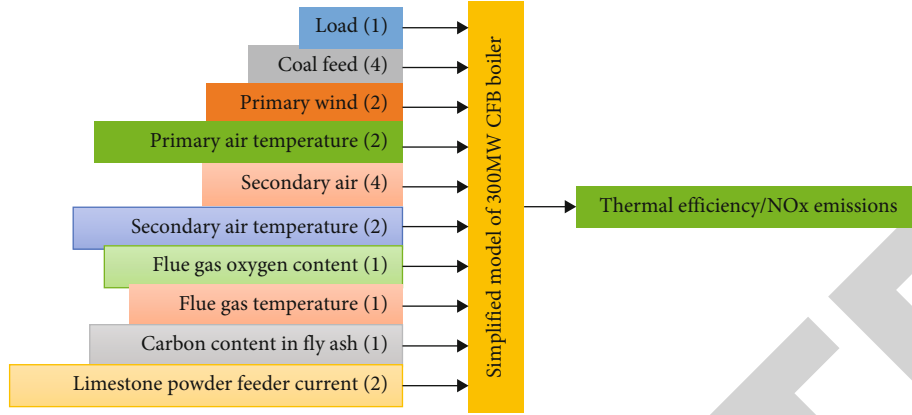
FIGURE 3: Simplified model of thermal efficiency and NOx emission of 300 MW circulating fluidized bed boiler.
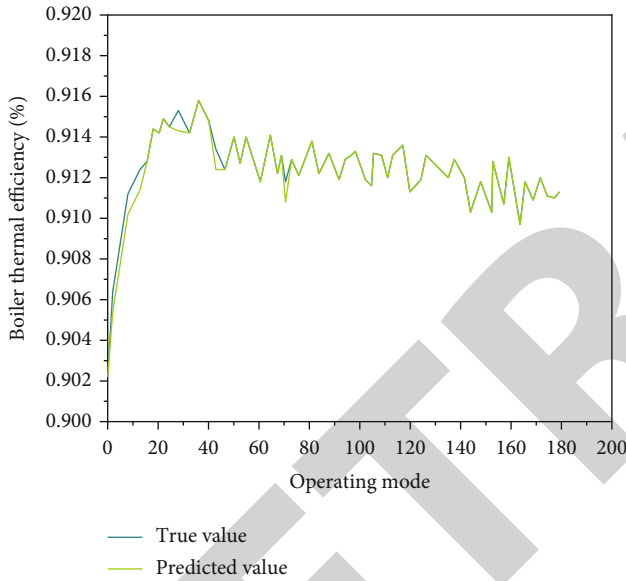

FIGURE 4: Thermal efficiency prediction model of 300 MW circulating fluidized bed boiler.

easy to fall into overfitting [20], a least squares support vector machine modeling method based on Bayesian structure framework is finally used to model and predict the circulating fluidized bed boiler combustion system.

The theory of machine learning in the 1960s is a small sample theory. The support vector machine is a new general training method based on statistical training theory and structural risk reduction principles. The vector machine for supporting minimum squares (LS-SVM) is an improved support vector machine. A vector machine that supports the smallest squares uses the sum of the empirical loss errors of the squares in the data sample as a loss function and improves the inequality constraint in the support vector machine to the equality constraint [21–23]. The least squares support vector machine regression equation is shown in the following formula:

$$y(x_i) = \sum_{i=1}^{l} \alpha_i \cdot K(x_i, x_j) + b. \tag{3}$$

According to the above description, compared with support vector machine, least squares support vector machine simplifies the calculation process of modeling method and improves the modeling speed without affecting the mapping relationship of kernel function and global optimal performance. This is mainly reflected in the number of parameters that need to be optimized during modeling: the parameters that need to be optimized during modeling of the supporting vector machine are C and δ, while the smallest squares are only needed to optimize the vector machine in sum. However, a vector machine that supports the smallest squares has many disadvantages, the most important of which is that it loses the sparse nature of the support vector. A vector machine that supports the smallest squares cannot intersect as freely as a vector machine that supports unsupported vectors without affecting the accuracy of the algorithm. In order to further optimize the support vector machine modeling method, a Bayesian structure framework is proposed. The basic idea of Bayesian structure framework is to maximize the posterior of parameter distribution, so as to obtain the best parameter value and the best model [24, 25].

4. Result Analysis

4.1. Experimental Data Sources. As part of this study, a 300 MW thermal liquid circulating boiler was selected as the study object, and information on the actual work situation was used as research information. For the boiler structure, see Figure 2.

The circulating fluidized bed boiler is a left-right symmetrical natural circulation single drum boiler. There are four coal feeders in the power station site, which are symmetrically distributed on the feeders. Two motors are equipped to transport limestone. The furnace adopts full membrane water wall structure. A cyclone separator is set at the tail of the boiler to separate the unburned coal particles from the flue gas, and a heat exchanger is equipped to adjust the air temperature and bed
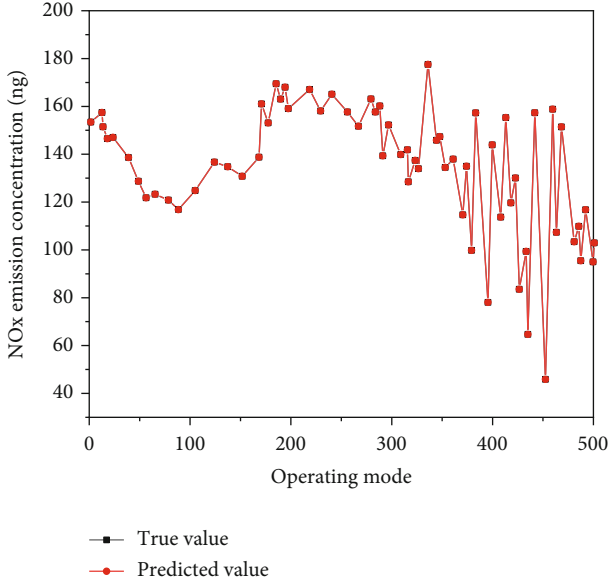
FIGURE 5: Training model of NOx emission concentration of 300 MW circulating fluidized bed boiler.
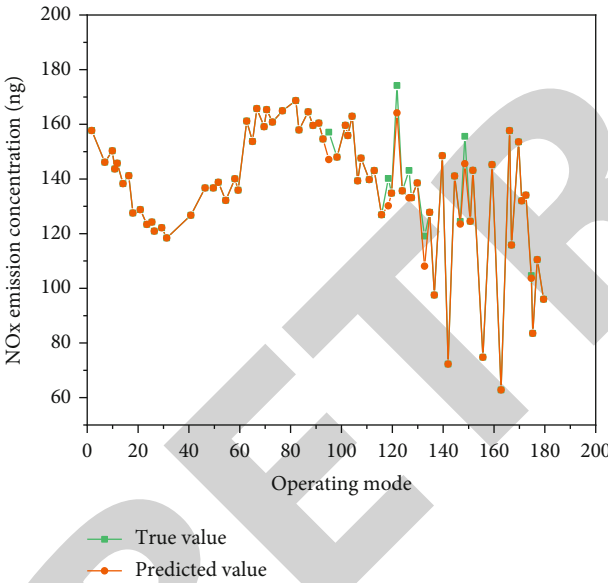

FIGURE 6: NOx emission concentration prediction model of 300 MW circulating fluidized bed boiler.

temperature. The data selected in this document are not information on all combustion conditions of the circulating liquid bed furnace, but the reflected condition parameters are sufficient to reflect the reality of the furnace operation to some extent. Being used to train and creating models for boiler thermal efficiency and nitrogen oxide emissions will not be so different from reality.

4.2. Kernel Function Selection. The accuracy and generality of modeling a vector machine to support the smallest squares are closely related not only to the experimental data but also to the choice of the core function. The control

parameter y and the kernel function parameter δ greatly determine the quality of the model. The following four kernel functions are more widely used to study vector machines that support the smallest squares:

(1) Radial basis function (RBF) kernel function is expressed as follows:

$$K(x, y) = \exp\left(-\|x - \frac{y\|^2}{2\delta^2}\right). \tag{4}$$

(2) Linear Kernel Function. In the case of linear separability, the kernel function can be expressed as the inner product of two parameters, as shown in the following formula:

$$K(x, y) = x \cdot y. \tag{5}$$

(3) Sigmoid kernel function is expressed as follows:

$$K(x, y) = \tan\left(\kappa(x \cdot y) + v\right) \kappa < 0, v < 0. \tag{6}$$

(4) Polynomial kernel function is expressed as follows:

$$K(x, y) = (x \cdot y + c)^d c \geq 0. \tag{7}$$

Among them, because the radial basis function has the advantages of few parameters, simple calculation, and nonlinear mapping, it is particularly commonly used in the four kinds of kernel functions.

4.3. Modeling of Circulating Fluidized Bed Boiler. After analyzing the operation principle of the circulating fluidized bed boiler, the characteristics of NOx emission concentration, the selection of the modeling method, and the influence of parameters on the establishment of the model, we can know that in the multicoupled complex combustion mechanism of the circulating fluidized bed boiler, many parameters such as parameters such as coal amount, primary air, secondary air, carbon content in fly ash, and oxygen content in flue gas have great influence on boiler thermal efficiency and NOx emission concentration. The modeling of CFB boiler thermal efficiency and NOx emissions can be simplified as shown in Figure 3.

(1) Modeling of combustion thermal efficiency of circulating fluidized bed boiler. The working conditions are randomly selected as the model training data, and the rest are used as predictive data to check the overall condition of the model. When training the

Table 1: Evaluation indexes of CFBB thermal efficiency models.

Model	MSE		MAE		MAPE	
	Train	Test	Train	Test	Train	Test
LSSVM	5.543e-004	0.065	0.0028	0.241	1.754-003	0.0028
BP	0.0358	0.046	0.2154	0.256	0.1764	0.0035
Bayesian-LSSVM	2.265e-005	0.0064	3.510e-006	0.0345	3.834e-004	4.425e-006

Table 2: Evaluation indexes of CFBB NOx emission models.

Model	MSE		MAE		MAPE	
	Train	Test	Train	Test	Train	Test
LSSVM	46.256	67.6589	5.1254	5.6542	0.0468	0.0521
BP	51.5689	88.1298	5.3568	6.7985	0.0458	0.0598
Bayesian-LSSVM	0.0198	53.5480	0.0986	4.9865	5.834e-006	0.0684

model, take the boiler load (1, MW) and the coal feeding amount of coal feeder (4, th) under working conditions. Primary air volume (2, knm/h), primary air temperature (2,), secondary air volume (4, knm2/h), secondary air temperature (2,), oxygen content (1,%), powder feeding motor current (2, a), flue gas temperature (1,%), and carbon content of fly ash (1,%) are input parameters, and boiler thermal efficiency (1,%) is output parameters. For the prediction results of the model, see Figure 4

It can be seen from the above figure that in the prediction process, the simulated value curve can well follow the real value curve, indicating that the Bayesian structure framework least squares support vector machine used in this paper shows good following and generalization in the modeling process of combustion thermal efficiency of circulating fluidized bed boiler, which meets the requirements of model verification.

    (2) Modeling of NOx emission concentration of circulating fluidized bed boiler

Like the modeling of combustion thermal efficiency of circulating fluidized bed boiler, the same data and input parameters are used in the modeling process of NOx emission, except that the output parameters are changed from boiler thermal efficiency (1, %) to NOx emission concentration (1, mg/M). The least squares support vector machine training based on Bayesian structure framework is used to establish the model. The training and prediction results of the finally optimized model are shown in Figures 5 and 6, respectively.

The results of the model training and hypothesis show that the vector machine, which supports the smallest squares of the Bayesian structure, adheres well to the NOx emission modeling of circulating liquefied boilers and has a general understanding. Although the performance of the predicted model is not good enough under individual operating conditions, the error results are within the allowable error range, and the NOx emission concentration prediction study does not have a significant adverse effect.

4.4. Modeling Comparison. To evaluate the above model, this paper used three performance indicators to measure the quality of the model: mean square error (MSE), average relative error (MAPE), and average absolute error (MAE).

In order to test the structural accuracy and advantages of the Bayesian structure, the minimum squares support vector machine used in this paper to model the combustion heat efficiency and NOx emission concentration of circulating liquid boilers introduces the minimum squares support vector machine and the BP nervous system. Based on the network, the same training data, and forecast data, the CFB furnace combustion heat efficiency and NOx emission concentrations were compared, and the mean square error, mean relative error, and mean absolute error of the models constructed by each modeling method were calculated. The results are shown in Tables 1 and 2.

From Tables 1 and 2, it can be concluded that this article compares the results of the Bayesian structure minimum squares support vector machine training with the least squares support vector machines and BP neural network training results for MSE. MAE and MAPE values are low. Therefore, the results of the vector machine training to support the smallest squares of the Bayesian structural range show better adherence and generalization.

5. Conclusion

The combustion process of a circulating liquid boiler is a complex, multivariable, powerful combination, with a large amount of delay. The topic of optimizing the combustion of circulating boilers is a topic of great attention around the world today. In this paper, the studied and improved optimization methods have been successfully used to optimize the combustion of circulating liquefied boilers. The main idea of the optimal method is to study all the operating modes of the circulating liquefied boiler, the method of calculating the thermal efficiency of the combustion boiler, and the mechanism of nitrogen oxide formation, according to the respective principles, advantages, and disadvantages of biogeographic optimization algorithm and K-means

clustering algorithm, a new algorithm is formed. Finally, this algorithm is used to cluster the working condition data collected on site and optimize the combustion thermal efficiency and NOx emission concentration of circulating fluidized bed boiler by adjusting the adjustable parameters such as coal feed, primary air volume, and secondary air volume. The specific work and research results are as follows:

(1) Based on the advantages and disadvantages of the biogeographic optimization algorithm and the K-means cluster algorithm, the two algorithms were combined to form the new improved cluster algorithm K-BBO-CLUSTER. This algorithm compensates for the shortcomings of the K-means cluster algorithm, which is highly dependent on the original cluster center, sensitive to noise data, and easily accessible to local optimization solutions. Finally, experimental comparisons of other cluster algorithms have shown that an improved cluster algorithm is a fast, simple, and efficient clustering algorithm

(2) According to the operation mode of circulating fluidized bed boiler, the calculation method of boiler combustion thermal efficiency and the generation mechanism of nitrogen oxides, after analyzing the influence of regularization parameters and kernel function parameters on support vector machine modeling, the boiler thermal efficiency model, nitrogen oxide emission concentration model, and its comprehensive model are established by using the least square support vector machine method based on Bayesian structure framework

In conclusion, the study on optimizing the combustion of circulating liquefied bed furnaces in this article can effectively improve the thermal efficiency of circulating liquefied bed furnaces and reduce nitrogen oxide emissions, which is very consistent with our current "energy saving and emission reduction" policy. Effective use and protection of the environment is very important.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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