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Research Article

An Evaluation Model of Green Coal Supplier for Thermal Power Supply Chain Based on PCA-SVM

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A thermal power supply chain differs from other supply chains in terms of supplier selection, materials transportation, products marketing, and so on. Therefore, the green coal supplier evaluation model has its own characteristics. Although many methods have been developed to solve the green supplier evaluation problem, little is known about how to evaluate the green coal supplier in the thermal power supply chain. To overcome this drawback, an evaluation index system for the green coal supplier is established, and new indexes such as price based on calorific value, quality indexes based on the designed coal type, and transportation indexes such as transportation carbon footprint and environment indexes are created according to the characteristic of the thermal power supply chain. Then, principal component analysis (PCA) is used to create the main evaluation indexes, and the support vector machine (SVM) is adopted for the evaluation model. Finally, a practical example is applied to show that the model established in this paper outperforms others in evaluation accuracy.

1. Introduction

Green supply chain, also known as "Environmentally Conscious Supply chain," was first presented by Michigan State University Manufacturing Research Society in 1996 [1]. As a modern management method taking the environment and comprehensive resource utilization into consideration, its purpose is to guarantee sustainable development of enterprises and society. Therefore, an ecological design is required for the whole supply chain, from purchasing, production, and consumption to waste recycling, in order to ensure harmonization of environmental and supply chain management [2, 3]. With the increasing pressures of climate change and sustainable development of global energy, green supply chain management for the thermal power industry is receiving significant attention at the moment. For example, as the largest carbon emission country in the world, the Chinese government has announced that carbon emissions in China would reach its peak by 2030, and carbon emissions per unit of GDP would be reduced by 60%–65% compared with 2005. Due to its high energy consumption characteristics, coal and power industries are the key areas for emission reduction and environment protection, and building green power supply chains is a key method to solve this problem.

The thermal power supply chain consists of coal companies, power plants, electric power transmission and distribution enterprises, and end-users of various types. Unlike other industries, the thermal power supply chain has its own distinguishing feature. Firstly, thermal power plants account for a large proportion of China's electricity industry. According to the National Bureau of Statistics of China, 69.6% of electric power is generated by thermal power plants in 2019, and more than 50% of total coal output is consumed by thermal power plants. Coal cost accounts for almost 60% to 70% of the total cost of power. Secondly, each plant is designed for a particular type of coal. Power plants select suppliers who can supply coal with specifications close to the type the plants are designed for. Thirdly, since electricity cannot be stored, the electricity generated must be used immediately in real time; otherwise, it will cause grid problems. Fourthly, as the final product cannot be stored, production strictly depends on demand. Therefore, the supply chain must be a demand-pull type, which is the most significant feature of a power supply chain. If generation is more than the demand, there will be a waste of electricity. Conversely, shortage of electric power will affect downstream production and consumers' consumption. Moreover, electricity demand varies with area, time, season, climate, and other aspects of people's lives. Due to the difficulty of storage and rapidly changing demand, precise control is required for timely adjustments, to ensure stability of the entire power supply chain operation. Finally, changes in the supply chain could affect the entire community significantly [4, 5].

As mentioned above, the coal supplier is the core link of the thermal power supply chain, and the green level of the coal supplier is of key importance to the whole supply chain. Environmental pollution of coal mines in China has the following characteristics: (l) emissions of waste water, waste gas, and waste residue are huge and have a wide range of environmental impacts; (2) some of the pollutants in waste water, waste gas, and waste residue have serious effects on human health and environment; (3) coal mine production not only gives rise to direct pollution by emissions, but may also cause indirect pollution; (4) sources of pollution factors are complicated and are difficult to control; (5) coal-based industries are resource intensive industries that involve long construction periods; therefore, their environmental impact is cyclical and continuity [6, 7].

For green supply chain management, green supplier evaluation is of great importance since it affects enterprise comprehensive competitiveness as well as green supply chain's operations. During green supplier evaluation, enterprises need to consider a group of feasible alternatives based on certain criteria. Therefore, green supplier evaluation is a complex and typical multiple criteria decision-making (MCDM) problem [8]. Many methods have been developed to solve the green supplier evaluation problem [9–11]. Lu et al. [12] presented a fuzzy analytic hierarchy process (FAHP) approach for green supplier evaluation. Tsai and Hung [13] constructed a fuzzy multilevel and multi-objective programming model to evaluate green supplier in the mobile phone industry. Hsu and Hu [14] determined the best green supplier in hazardous substance management by using the analytic network process (ANP). Awasthi et al. [15] proposed a fuzzy TOPSIS method to evaluate the environmental performance of green suppliers in the fuzzy environment. Yeh and Chuang [16] determined the ranking of green suppliers in production and transportation by using the multiobjective genetic algorithm. Combined with artificial neural network (ANN) and two Mada Methods (DEA and ANP), Kuo et al. [17] proposed a green supplier evaluation model. By considering economic and environmental indicators, Chen et al. [18] integrated ANP and TOPSIS methods to solve green supplier evaluation and selection in brightening film industry. Hashemi et al. [19] utilized ANP and improved gray relational analysis to determine the best green supplier. Cao et al. [20] proposed an intuitionistic fuzzy MCDM method to evaluate the green supplier in which attribute values take the form of intuitionistic fuzzy numbers and attribute weights are completely unknown in advance. Sang and Liu [21] put forward an new distance computing method for interval type-2 fuzzy sets (IT2 FSs) and then constructed a IT2 FSs-based TODIM approach to determine the ranking of green suppliers.

Although researchers have made some achievements in green supplier evaluation, little is known about how to evaluate the green coal supplier in thermal power supply chains. Only a few research studies investigate this problem by using fuzzy satisfaction methods and only consider economic factors (e.g., quality, price, and delivery time) as criteria for supplier evaluation [22, 23]. Therefore, none of these methods consider the special characteristics of thermal power supply chains, as mentioned above. To address this research gap, in this paper, an evaluation index system for the green coal supplier is established according to the characteristics of the thermal power supply chain. Then, the principal component analysis (PCA) is used to search the main evaluation indexes, and the support vector machine (SVM) [24] is adopted for evaluation of the green coal supplier. Finally, the practical examples show that the model established in this paper outperforms others in evaluation accuracy. The rest of this paper is organized as follows. In Section 2, we establish the index system. In Section 3, we give the evaluation model based on SVM. Section 4 is the example application and analysis. Section 5 concludes the whole paper.

2. Establish the Index System

2.1. Original Indexes. In his seminal paper of green supply chain management, Handfield [1] pointed out that environmental indexes and information should be considered in supplier evaluation, besides the traditional indexes such as price, quality, and delivery. With an eye on the special characteristics of the thermal power supply chain, the evaluation index system for the green coal supplier is created as follows.

2.1.1. Price Index. The first group includes indexes of price: as the price varies with the calorific value of coal, X_1 is used to denote the price, as follows:

$$X_1 = \frac{(p_c + p_t)}{c * 1000}, \tag{1}$$

where p_c is the coal price for a power plant (RMB/t), p_t is the transportation cost, and c is the coal calorific value (MJ/kg). As coal price varies with the type of coal and the transportation cost varies with the distance between the coal mine and the power plant, they cannot tell the competitiveness of the supplier. Therefore, we use the relationship between the price and calorific value as the price index, which can describe the actual cost of the supplier.

2.1.2. Quality Indexes. The second group includes all indexes of coal quality. Usually, there is a designed coal type for each thermal power plant. For a given plant, good quality of coal means it is similar to the designed coal type. Therefore, the ratio between coal quality indexes and the designed coal index is used as the quality index which includes the following:

Calorific index X_2:

$$X_2 = \frac{c_i}{c_d}, \tag{2}$$

where c_i is the coal calorific value of coal from the i^{th} supplier and c_d is the designed value for the plant.

Moisture index X_3:

$$X_3 = \frac{m_i}{m_d}, \tag{3}$$

where m_i is the coal moisture content from the i^{th} supplier and m_d is the designed value.

Volatility index X_4:

$$X_4 = \frac{v_i}{v_d}, \tag{4}$$

where v_i is the coal volatility from the i^{th} supplier and v_d is the designed value. Coal volatility refers to the escaped material (gas or liquid) after subtracting the water content when it is remained at a certain temperature and isolated from air. It is an important indicator for coal classification.

Ash index X_5:

$$X_5 = \frac{a_i}{a_d}, \tag{5}$$

where a_i is the ash content of coal from the i^{th} supplier and a_d is the designed value.

The closer the values of X_2, X_3, X_4, and X_5 are to 1, the better the coal quality is for the given plant because it means all coal quality indexes are close to the designed technical standard of the plant. This would enable the power unit to operate at high efficiency.

2.1.3. Transportation Indexes. The third group includes all indexes of delivery, including X_6 and X_7. X_6 is the transportation carbon footprint and X_7 is the delivery time.

The transportation carbon footprint is calculated using

$$X_6 = c_t + l_t, \tag{6}$$

where c_t is the CO_2 emission value per km (kg/km) and l_t is coal lost per km; the coal value is transformed into its carbon dioxide equivalent (kg/km).

Carbon footprint is presented as the basis of the ecological footprint [25, 26], to measure the amount of CO_2 emissions caused by an activity (or the aggregate amount in the life cycle of a product) [27]. Modes of coal transportation include railways, waterways, and roads. According to different origins of coal, transport mode, and distance, it is possible to calculate specific energy consumption, and then, c_t can be worked out according to rail, water, or road transportation of coal.

2.1.4. Environment Indexes. Mining is a labor-intensive industry. In addition to coal mining and processing, its associated resources are often developed and processed. There are also some small machinery industries, chemicals production, textile processing industry, and agriculture and forestry production surrounding the mine. Although coal suppliers are of different sizes and economic ownership, the main pollution factors in coal are similar. There are only some small differences in secondary pollution as mineral resource development projects are associated with different factors.

The first major concern is air pollution. Mining areas are affected by coal burning which causes air pollution; main air pollutants are harmful gases, and dust generated in the process of underground mining. In China, most coal contains gas. Gas and gas outbursts in mines account for 40% of the total number of mines; the underground mining process generates a large amount of mineral dust, CO_2, H_2S, CO, SO_2, and other harmful gases. Underground mine explosives, use of power machinery, fuel and coal combustion, etc., also produce SO_2, NOx, and other harmful gases. These gases are emitted into the atmosphere through the mine ventilation system and become major pollutants. The gangue in the stacking process also produces a large amount of harmful gases and dust. Coal gangue shale is of a low calorific value, and its stacking process generates and emits large quantities of suspended dust particles into the atmosphere. Due to bad ventilation and heating conditions, spontaneous combustion occurs and produces SO_2, CO_2, H_2S, NOx, and other harmful gases. According to statistics, spontaneous combustion has happened to 121 waste gangue dumps in China's key coal mines, which implies serious threat to mining.

The second main pollution is waste water. Coal mine waste water includes infiltrated surface water, pore water, mine water, underground aquifers, and water drained out of underground mines, besides water used in the production process for dust control, filling, and coal selection. According to statistics, China's coal mines' waste water discharge is 2.2 billion m^3, coal selection waste water is 0.0128 billion m^3, other industrial waste is 0.013 billion m^3, and sewage 0.4 billion m^3. Among them, waste water from coal preparation and related industrial processes contains phenol, cresol, naphthol, and other harmful organisms, especially flotation pharmacy and ammonia polypropylene toxic agents generated in the coal preparation process, which can induce a variety of diseases. Mine water contains large amounts of suspended solids, which are less harmful to humans, but coal mine water constitutes the largest mass of waste water. Coupled with decomposed plant and manure, mineral oil, and emulsions leakage, mine water acquires color and stench. Direct emissions seriously pollute water bodies. In addition, leaching and erosion occur to the gangue pile because of rains result in a number of harmful and toxic coal wastes getting dissolved, to form a polluting runoff, and eventually flow into the mine water system, causing water pollution.

The third main type of pollution is soil pollution. Mine gangue dump is the primary cause of soil pollution. According to statistics, total gangue dumping is about 3.0 billion tons covering an area of 550,000 m^2. Firstly, these gangue dumps directly take up a lot of farmland, and secondly, due to the sun, wind, precipitation, and other forces of nature, a large number of harmful toxic substances such as mercury, chromium, cadmium, copper, and arsenic penetrate into the soil through direct penetration, airborne dust deposition, and rainfall. The radioactive material contained in coal gangue results in radioactive contamination of soil. The dust generated from coal production and transportation is also an important reason for soil pollution.

The fourth is noise pollution. Due to the strong vibration of equipment, such as air compressors, fans, rock drills, picks, and miner, there are various types of noises on the surface and under the ground in coal mining areas. Some coal mines in North China, according to a survey, use equipments that cause noise in excess of 90 dB account for 70% of all equipments, those making noise of 90–100 dB account for 45%, and 25% of equipments generate noise of 100–130 dB. Thus, mechanical noise is considered the primary cause of noise pollution. With the continuous development of coal mines, the increasing traffic and tonnage of trucks traffic noise, noise pollution has become another main pollution.

Based on the analysis above, the fourth group includes all indexes of environment protection and energy saving, including X_8, X_9, X_{10}, and X_{11}. X_8 represents the environment protection level which should consider all pollution factors as mentioned above. The value is calculated as follows:

$$X_8 = a_p + w_p + s_p + n_p, \quad (7)$$

where a_p denotes air pollution, w_p is water pollution, s_p represents soil pollution, and n_p is for noise. As these are qualitative indexes, the method of questionnaire is used to calculate the values. For example, in case of a_p, informants were asked to select "good," "fine," "fair," or "poor" mentioned in the questionnaire. On the basis of the selection frequency and the weight, a final mark is calculated using

$$a_p = \begin{pmatrix} v_1 & v_2 & v_3 & v_4 \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{pmatrix}, \quad (8)$$

where a_p is the final mark for i^{th} supplier, v is the selection frequency, and w is the mark for each grade; "good" is 4, "fine" is 3, "fair" is 2, and "poor" is 0.

As mentioned above, mine water, gas, and gangue are byproducts of the coal production process. Although they cause a great deal of pollution to the mining area and nearby regions, they can also be beneficial to mankind if they are recycled properly. In the past, some mining areas in China have made some achievements in this area, but the degree of "three wastes" recycling is still quite low. The future of "three wastes" recycling is very broad and offers important economic, environmental, and social benefits.

Mine water is a good water source, but our utilization of mine water is very low. Water availability in some mine areas is very tight; people get water at a fixed time only, in rationed amounts. On the contrary, a great amount of mine water is discharged directly, without being recycled. Therefore, mine waste water purification is imperative. As mine water is from different sources, water quality also varies. The principle of "separating clean water from effluents, separating different effluents from each other, and treating them separately" can be followed.

Mine gases contain high concentrations of CH_4, which is a valuable natural resource that can be used not only as high-quality fuel but also as chemical raw materials. If it can be recycled into usable resources, environmental, economic, and social benefits will be significant. The main problems in China's mine gas recycling are low drainage and utilization rates. To improve the drainage effect, funds should be invested to enhance and further improve the drainage system at the same time.

Gangue generation is about 150 million tons per year. So far, the total gangue in China has reached more than 30 million tons. This solid waste has become a major source of pollution for coal mines. Comprehensive utilization of gangue can help save resources, reduce area waste, and improve the environment, besides optimizing industrial structure and promoting sustainable development. They can be comprehensively utilized as follows:

(1) Power generation: usually, gangue contains a certain amount of fuel. Fixed carbon content is generally 10%–30%, and the heat value is sometimes more than 12000 kJ/kg. It can either be directly used or blended with a small amount of coal for power generation. Its economic and environmental benefits can be very significant.

(2) Brick-making and cement manufacture: gangue with a low heat value can be used for production of brick stone and cement.

(3) Fertilizer production: humid acid-rich gangue can be used in fertilizer production by adding the right amount of biological bacteria, phosphorus iron, starch, and other materials.

(4) Filling collapsed area, land reclamation, or road building.

Usages of gangue are wide ranging. In addition to the abovementioned purposes, it can also produce aluminum chloride, a purifying agent PAC, and can be used for recovery of sulfuric acid from pyrite for production of raw materials used to make pottery. Therefore, utilization gangue should be encouraged to increase the green level of the supply chain.

Based on the analysis above, we construct X_9 as the index to evaluate the "three waste" comprehensive utilization rate, which can be calculated as follows:

$$X_9 = s_1 \times w_1 + s_2 \times w_2 + s_3 \times w_3, \quad (9)$$

where s_1 is the gas utilization rate, s_2 denotes the mine water utilization rate, s_3 is the coal gangue utilization rate, and $w_1 = w_2 = w_3 = 1/3$ is the weight.

X_{10} is the local environmental carrying capacity. Experts are invited to give marks for this qualitative index by using Table 1.

Table 1: Mark of the local environmental carrying capacity.

Situation	Cannot load	Maintain	Sustainable
X_{10}	(0–2)	(3–6)	(6–10)

X_{11} is the coal sulfur content, which has great impact on waste emissions of power plants.

2.2. Index Selection by PCA. As some of the original indexes are co-related to a high degree, information repetition is hard to avoid. On the contrary, direct calculation is difficult because the number of indexes is very large. Therefore, principal component analysis (PCA) is used to screen the main indexes. The main idea of PCA is to use dimensionality to reduce the number of indicators by deriving composite indicators. In empirical studies, in order to comprehensively and systematically analyze problems, we must consider a number of factors. These factors, commonly referred to as indicators, are involved in multivariate statistical analysis and are also known as variables. As each variable reflects a certain characteristic of the research questions and they have some correlations among each other, information from such statistics sometimes overlaps to some extent. When we study the multivariables problems by statistical methods, too many variables increase the amount of computation and increase the complexity of the problem. For quantitative analysis, it is good to get more information from fewer variables.

The purpose of PCA is to use fewer variables to explain most of the variation of the original data by turning the large number of related variables into a group of highly independent or relevant variables. Usually, some new variables called principal components are chosen from the original ones. Thus, principal component analysis is actually a dimension reduction method. The basis mathematic model is as follows [28, 29]:

Step 1. All the data are normalized. Suppose $x_1, x_2, x_3, \ldots, x_k$ are index variables; after standardization, we get standard variables $X_1, X_2, X_3, \cdots, X_k$, and

$$X_j = \frac{x_j - \overline{x}_j}{s_j}. \tag{10}$$

Here, $\overline{x}_j$ is the mean of samples and s_j is the standard deviation of samples.

Step 2. The characteristic value of the correlation matrix and the corresponding characteristic vector calculation: if there is a certain linear transform, then

$$\begin{cases} Y_1 = w_{11}X_1 + w_{12}X_2 + \ldots + w_{1K}X_K \\ Y_2 = w_{21}X_1 + w_{22}X_2 + \ldots + w_{2K}X_K \\ \qquad \cdots\cdots \\ Y_K = w_{K1}X_1 + w_{K2}X_2 + \ldots + w_{KK}X_K \end{cases} \tag{11}$$

Formula (11) transforms standard variables X_j ($j = 1,2, \ldots, k$) into Y_i, ($i = 1,2, \ldots, k$), and this linear transform meets three properties, as follows:

(1) Y_i and Y_j are independent of each other, $i \neq j$, $i, j = 1,2, \ldots, k$

(2) $\operatorname{var}(Y_1) \geq \operatorname{var}(Y_2) \geq \ldots \geq \operatorname{var}(Y_k)$

(3) $w_{i1}^2 + w_{i2}^2 + \ldots + w_{ik}^2 = 1$, $j = 1,2, \ldots, k$

$Y_1, Y_2, \cdots, Y_k$ are called the principal components of $X_1, X_2, \cdots, X_k$.

Step 3. List the indexes according to their contribution rate from the largest to the lowest and calculate the cumulative contribution rate. When the cumulative rate meets the requirement of information accuracy (usually above a certain threshold, such as 95 percent), the corresponding top indexes are selected as the main indexes for the green coal supplier evaluation in the next step.

2.3. Experts' Original Evaluation. The selected supplier samples are divided into four categories: "good," "fine," "fair," and "poor." Supply chain management experts in the field of thermal power industry were invited to evaluate each supplier, and their comments were treated by the Delphi method. Finally, the category of each project was confirmed and used to train the SVM evaluation model in the next step.

3. Evaluation Model Based on SVM

Support vector machine (SVM) is a popular method for classification proposed by Vapnik [24]. This approach is systematic and properly motivated by the statistical learning theory. Unlike most traditional neural network models that implement the empirical risk minimization principle, the SVM implements the structural risk minimization principle, which seeks to minimize the training error and a confidence interval term. This eventually results in better generalization abilities.

Due to its good properties such as automatic selection of models (parameters and locations of basic functions), being trained with quadratic programming (globally optimal solution existed) and good learning ability for small samples, the SVM has been widely used by academia and industry in recent years [30].

3.1. Principle of SVM Classification. Let $\{(Y_i, z_i)\}_{i=1}^n$ be a given set of training data of two separate classes, where Y_i is the i^{th} input vector and $z_i \in \{-1, +1\}$ indicates the corresponding desired output, the class label. The objective of SVM is to determine optimal weight w_0 and optimal bias b_0 such that the corresponding hyperplane separates the positive and the negative training data with maximum margin, and this produces the best generation performance. As the actual problems in life are usually nonlinear in nature, it is assumed that the two classes can be separated by a nonlinear classification method. The nonlinear SVM classification method can be introduced such that the original training data Y_i in input space Y is projected into a high-dimensional feature space F via a Mercer kernel operator K, followed by construction of the optimal separating hyperplane in the feature space. In a word, the whole process is to confirm the decision function:

$$f(y) = \operatorname{sign}\left[\sum_{SV} a_i z_i K(y_i, y) + b_0\right], \quad (12)$$

where a_i is the Lagrange multiplier and K is a symmetric positive definite function that satisfies Mercer conditions as follows:

$$\begin{gathered} K(y,z) = \sum_{m=1}^{\infty} a_m \phi(y) \cdot \phi(z), \quad a_m \geq 0, \\ \iint K(y,z) g(y) g(z) d_y d_z > 0, \int g^2(y) d_y < \infty, \end{gathered} \quad (13)$$

in which the kernel represents legitimate inner products in input space:

$$K(y,z) = \phi(y) \cdot \phi(z). \quad (14)$$

In the high-dimensional feature space, the dual Lagrange multiplier is

$$\begin{gathered} L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j z_i z_j K(y_i, y_j), \\ \sum_{i=1}^{n} \alpha_i z_i = 0, \quad \alpha_i \geq 0. \end{gathered} \quad (15)$$

Many kernel functions can be used in the SVM, such as the polynomial $K(y,z) = (1+yz)^d$ and the Gaussian $K(y,z) = \exp(-|y-z|^2/2\sigma^2)$. The training of SVM is a process to solve function (15), which is also a quadratic programming problem.

3.2. The Multiclassification SVM. The basic support vector machine (SVM) is for pair-class problems. Since green coal supplier evaluation in this paper is of four categories, a multiclassification SVM should be established accordingly. Here the method of SVM decision tree [31] is adopted, and its structure is shown in Figure 1.

3.3. The SVM Evaluation Model. On the basis of data treatment and index selection, the samples can be described as $\{(Y_i, y_i)\}_{i=1}^{n}$, where Y_i is the i^{th} input vector (index value of the i^{th} project sample); $y_i \in \{-1, +1\}$ indicates the corresponding desired output and the class label (evaluation result from thermal power supply chain experts). By training the SVM Classifier, a map between the index values and experts' evaluation result is set up, which can be used to judge the green coal supplier level of a given thermal power plant.

4. Example Application and Analysis

In this section, 20 coal suppliers who have performance of 10 years were selected for the model. Their evaluation results for each year are given by the methods mentioned in Section 2.3. In order to enlarge the sample set for SVM, we first regard the annual performance of each supplier as one sample, and then, we have $20 \subseteq 10 = 200$ samples. Secondly, we triple the total samples, and 510 (85%) of them are used to train the SVM model, and the rest is used to test model accuracy.

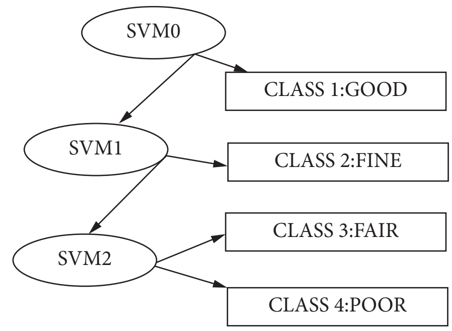

Figure 1: The SVM decision tree.

4.1. Index Selection by PCA. The PCA method is used to screen the main index, and the result is shown in Table 2.

It can be learned from Table 2 that the cumulative contribution rate of the top four indexes is above 98%. That is to say the top four indexes can be chosen as indexes for evaluation in the next step. Since the cumulative contribution rate of the first 4 principal components is above 98 percent, they serve as the new variables. The conversion coefficient between principal components and former indices is shown in Table 3.

4.2. The Training of SVM. The results and discussion may be presented separately or in one combined section, and may optionally be divided into headed sections.

Index values (Y_1, Y_2, Y_3, Y_4) of samples mentioned above are used as the input for the SVM, while experts' evaluation is the output. The Gauss function is selected as the kernel function:

$$K\left(\widetilde{Y}_i, \widetilde{Y}_j\right) = \exp\left(-\frac{\left\|\widetilde{Y}_i - \widetilde{Y}_j\right\|^2}{\sigma}\right), \quad (16)$$

where σ is the width parameter of Gauss kernel.

Usually, the value of parameters σ is selected according to experience; here, we let $\sigma = 0.25, 0.50$, and 1.00 separately to find the best value of σ.

4.3. Results Analysis. The applications results for each σ are listed in Table 4. The same samples and process are also used in a traditional artificial neural network, and the result of testing accuracy is 84.44%.

From the above results in Table 4, it can be learned that the testing accuracy of the SVM model in this paper is well up to the requirement. The maximum testing accuracy is 95.6%, and the minimum value is 90.0%, which are all better than the ANN model. Therefore, the proposed model has strong advantages in solving the green coal supplier evaluation problem.

Table 2: Eigenvalues of the correlation matrix.

Principal	Eigenvalue	Difference	Proportion	Cumulative
Y_1	0.082587	0.074371	0.799420	0.79942
Y_2	0.008216	0.001279	0.079530	0.87895
Y_3	0.006937	0.002532	0.067150	0.94610
Y_4	0.004405	0.003241	0.042637	0.98874
Y_5	0.001164	0.001164	0.011263	1.00000
Others	0	0	0	1

Table 3: Conversion coefficient between principal components and former indices.

w	Y_1	Y_2	Y_3	Y_4
w_1	0.229299	−0.377764	−0.0226	−0.228459
w_2	0.437627	−0.399997	0.108737	0.708044
w_3	0.506059	0.653155	−0.502446	0.071268
w_4	−0.020572	0.304611	0.50429	0.228768
w_5	0.238812	0.026326	0.204594	−0.019878
w_6	0.47413	−0.124861	0.20296	−0.533662
w_7	−0.067721	0.281129	0.423715	−0.025488
w_8	0.087994	0.170734	0.253487	0.02404
w_9	0.283744	0.028826	0.031745	0.19407
w_{10}	0.352939	−0.047015	0.199512	−0.254922
w_{11}	0.012226	0.224477	0.336529	0.000217

Table 4: Application result.

ANN model	SVM model		
Testing accuracy (%)	Parameter (σ)	Training accuracy (%)	Testing accuracy (%)
	0.25	99.99	92.2%
86.37	0.50	99.99	95.6%
	1.00	99.99	90.0%

5. Conclusions

An evaluation model for the green coal supplier in the thermal power supply chain is established, based on principal component analysis and support vector machine, in this paper. Firstly, an evaluation index system for the green coal supplier is established according to characteristics of the thermal power supply chain. Then, principal component analysis is used to select the main indexes, and the SVM is adopted to classify the evaluation results. Finally, a comparison is made between SVM and ANN. The results from this study demonstrate that the AHP-SVM evaluation model gives consistently better classification results as compared with other methods. It can be widely used in green coal supplier evaluation as well as other related practical fields.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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