Construction of Economic Management Performance Model of Mining Enterprises under the Background of Supply-side Reform

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Abstract: - The proposal of supply-side structural reform measures has ushered in new development opportunities for mining enterprises in the bottleneck period. As a result, a model for evaluating the economic management performance of mining firms at the new performance level must be established. This paper suggests an assessment model for the economic management of mining firms against the backdrop of supply-side reform in light of this. This study reasonably incorporated financial and non-financial performance indicators, constructed the Economic Management Performance (EMP) evaluation index system of mining enterprises, and created an economic management performance evaluation model of mining enterprises based on the BP neural network and analytic hierarchy process. The study selected the relevant data of five mining companies A, B, C, D, and E from 2017 to 2022 as the research object, verified the effectiveness of the model, and analyzed the performance evaluation results of the companies. The research results show that the model constructed in this study can evaluate the economic management performance level of enterprises within a reasonable range (the mean relative error is 1.98%). Since 2017, the comprehensive performance level of these five mining companies has gradually declined. But thanks to the supply-side reform, the comprehensive performance has gradually recovered after 2022 and among the five mining companies, company A has always been at the performance level way ahead. Overall, the model developed in this research has strong operability and practicability and can be utilized more effectively to forecast the mining industry's potential for future growth.

Key-Words: - Supply-side reform; Mining enterprises; Performance evaluation; BP neural network; Analytic hierarchy process

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1 Introduction

For the development of China's social economy, mineral resources are an important material basis, and the mining industry is also in a relatively front-end position in the social industrial chain. It is one of China's most significant basic industries, [1]. Since the founding of New China, China has been one of the greatest mineral resource nations in the world because of its fast-growth mining sector, making outstanding contributions to the sustained and stable development of China's national economy, [2]. In recent years, due to the impact of the soft landing on China's economy, mining enterprises have encountered development bottlenecks. After the supply-side structural reform measures were put forward, mining companies actively responded to the call and began to remove outdated production capacity and reduce inventory. The mining market gradually restored the balance between supply and demand, [3], [4]. In today's era where challenges and opportunities coexist, it is particularly important to establish a new economic management performance evaluation model after major mining companies have passed a series of tests such as industrial upgrading and resource integration, [4], [5]. In view of this, this study constructs the economic management performance model of mining enterprises under the background of supply-side reform. It is hoped that the model constructed in this study can effectively comprehensively assess the degree of mining businesses' EMP, to determine their future prospects. It also provides some reference value for the policy formulation of relevant government departments.

2 Related Work

Regarding the construction of the economic management performance model, there are already many scholars doing research on it. Researchers such as Hall studied the foundation for performance management focusing on policy results, and they employed structural equation modeling to quantify the effect of municipal tax policies on economic development performance. The experiment measured the impact on the economy by the underlying structure of growth in property values and new home construction. The final experimental results showed that the choice of taxation could have an important impact on economic development, [6]. Researchers began their studies with the connection between national public health spending, the logistics performance index, renewable energy, and ecological sustainability. They also used the structural equation model to examine how the four factors affected the performance of economic development. The final experimental results showed that utilizing renewable energy responsibly would enhance environmental and economic development outcomes. At the same time, the increase in National spending on public health and poor environmental performance would cause damage to the healthy growth of the economy, [7]. Researchers investigated the function of blockchain technology in circular economy practice and its influence on ecological and environmental performance and used the least squares structural equation for modeling this topic. The experiment selected the data of 404 companies operating in cross-border supply chains located in China and Pakistan for empirical research. The final experimental results showed that blockchain technology and circular economy can stimulate the environmental performance and financial performance of multiple companies, which verified the validity of the model, [8]. Several studies integrated machine learning into the discussion of enterprise performance management. The experiments measured the accuracy and interpretability of machine learning algorithms by discussing machine learning usage in the enterprise. Afterward, the article discussed three enterprise cases that used machine learning algorithms. The experiment finally provided an overall summary of the challenges and opportunities that machine learning algorithms needed to face when deploying them in the enterprise, [9]. Researchers proposed MOPSO to balance the factors of economy, energy, ecology, coal ore economic benefits, and social benefits in green coal production. The model was verified on the DTLZ function, and its effectiveness was contrasted with that of a number of other well-known multi-objective algorithms in experiments, which verified the validity of the model. This method provided a reference value for the economic performance management of coal enterprises, [10].

This article chooses to introduce machine learning algorithms into the enterprise economic benefit evaluation model. Machine learning algorithms have also been favored by scholars from all walks of life in research. To improve the quality of corporate social responsibility performance evaluation, researchers such as Li suggested an enhanced AHP-BP algorithm and included the algorithm in the CSR performance evaluation model. The experiment used the model for CSR performance evaluation in the BP neural network training stage after introducing expert scoring in the AHP stage. The final experimental results showed that the upgraded AHP-BP model performed better than the traditional BP model, and it could be used as a good factor for CSR performance evaluation, [11]. To evaluate the performance of enterprise personnel, scholars proposed a spatially distributed data mining algorithm based on the BP network. The algorithm first constructed spatial network data in cloud computing and then used the BP network to classify and identify the mined data features. Experimental results showed that this method had higher accuracy in predicting the performance of enterprise personnel and had better efficiency in big data processing, [12]. Scholars started from the development of real estate and developed a CSR performance assessment methodology that took into account aspects including financial success, corporate morality, environmental stewardship, and social responsibility. The model was realized based on AHP and fuzzy comprehensive evaluation method, and it was improved on this basis. The final experimental results showed that the proposed AHP-FCE model could provide a good reference value for CSR performance evaluation, [13]. Researchers compiled with the influence of national policies and macroeconomics and proposed a performance evaluation method for enterprise innovation capabilities that combined deep learning fuzzy systems and convolutional neural networks. This method drew on the traditional performance evaluation method, and at the same time introduced an intelligent deep learning algorithm, which was a relatively innovative enterprise performance evaluation method. Simulation findings demonstrated this method's considerable applicability and importance to firms' resource optimization strategies, [14]. Researchers constructed an assessment model based on AHP-DEMATEL beginning with the variables that cause coal mine occupational illnesses. The experiment used the model to construct the coal mine occupational hazard evaluation system and combined the case analysis. The experimental results showed that the evaluation's findings and the management of coal mining firms' current circumstances accord rather well. And this index had strong versatility and adaptability, and it also had certain enlightening significance for the evaluation model of enterprise EMP, [15].

To sum up, the performance model of enterprise economic management and machine learning algorithm are recent research hotspots. Although some researchers have combined the two to conduct relevant discussions, research on constructing an enterprise economic management performance model based on neural networks and other machine learning methods is still rare. Therefore, this study incorporated financial and non-financial performance indicators reasonably, constructed a mining enterprise EMP evaluation index system, and built a mining enterprise EMP evaluation model based on BP neural network and analytic hierarchy process.

3 Construction of Economic Management Performance Model of Mining Enterprises under the Background of Supply-side Reform

3.1 Construction of Mining Enterprise Performance Evaluation Index System under the Background of Supply-Side Reform

Many academics have created a technique for evaluating the general-sense economic management performance with an eye on the uniqueness of coal mining companies. In the past, financial indicators were often utilized as the basis for the indicators used to assess economic management success. In the context of supply-side reform, only using financial indicators to evaluate the EMP of enterprises can no longer continue to meet the information needs of stakeholders. Therefore, it is necessary to use a new perspective to look at the EMP evaluation of mining enterprises under the background of supply-side reform, and then formulate a sustainable, multi-angle, and all-round economic management performance evaluation system, [16], [17]. The concepts of objectivity, science, and systematicity serve as the foundation for this research, referring to the "Blue Book of Corporate Social Responsibility Report". Meanwhile, based on financial performance indicators and combined with the characteristics of the mining industry, some non-financial evaluation indicators have been appropriately included. The experiment ultimately constructed the EMP evaluation index system for mining enterprises, as shown in Table 1.

Table 1. Economic management performance evaluation index system of mining enterprises

Secondary Indicators of Financial Performance	Level 3 Indicators of Financial Performance	Non-financial performance secondary indicators	Level 3 Indicators of non-financial Performance
Solvency (U1)	Asset-liability ratio (U11)	Social Contribution (U5)	Commodity mine output (million tons) (U51)
	Asset Current Ratio (U12)		Social contribution value per share (yuan/share) (U52)
	Net Operating Cash Flow Debt Ratio (U13)	Energy saving and environmental protection (U6)	Average recovery rate of mining area (U61)
Developing Capabilities (U2)	Net profit growth rate (U21)		Comprehensive energy consumption per 10,000 yuan output value (ton of standard ore/10,000 yuan) (U62)
	Growth rate of total assets (U22)		Comprehensive utilization rate of wastewater (U63)
Operational Capability (U3)	Inventory turnover (U31)	Safe Production (U7)	Investment in safety production (100 million yuan) (U71)
	Accounts receivable turnover ratio (U32)		Mortality rate of workers mining millions of tons of mines (U72)
	Total asset turnover ratio (U33)	Technology Research and Development (U8)	Number of patents obtained in the year (U81)
Profitability (U4)	equity (U41)		Proportion of R&D investment in operating income (U82)
	Basic earnings per share (U42)		\
	Cost Expense Profit Margin (U43)		

As can be seen from Table 1, this study thoroughly assesses the economic management performance of mining firms while taking into account a number of variables, including technological advancement and employee safety. Moreover, each evaluation index in the table is a quantitative index, which neutralizes the subjectivity of the weight assignment of the index. Therefore, it is reliable and objective and can avoid affecting the evaluation results.

3.2 Construction of Mining Industry Performance Evaluation Model based on BP Neural Network and Analytic Hierarchy Process

The topology of a BP neural network consists of one input layer, one output layer, and one or more hidden layers, [18]. The role of the input layer is to incorporate the external information data into the neural network; The hidden layer connects the input and output layers; The output layer can transmit information from the hidden layer, which can also backpropagate the error. A multilayer perceptron utilizing the BP algorithm is the core of a BP neural network. BP neural network is a typical forward network (that is, the input of the previous level is accepted by the neuron and then output to the next level, and the information is processed by a simple nonlinear function). The model structure of the BP neural network is seen in Figure 1.

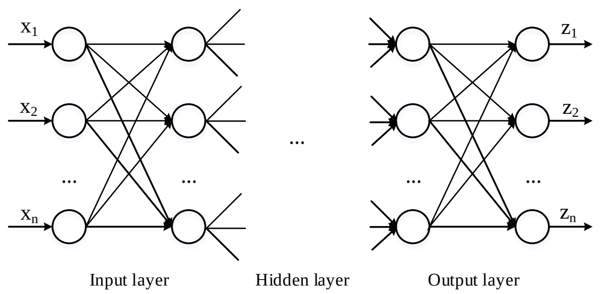

Fig. 1: BP neural network model

Figure 1 demonstrates that the basic principle of the BP neural network model is actually that a group of input vectors is activated after being stimulated by neurons after entering the network; Then transferred to the output layer through the hidden layer; Finally, the corresponding output is achieved through the output layer, and a positive propagation is completed immediately. To complete a backpropagation from the output layer to the input layer, the threshold value and weight value are altered in the opposite direction by assessing the error between the predicted output and the actual output. Finally, after constant adjustment, the error reaches an acceptable range. Then stop the learning process of the model to realize the mapping between input and output data. Assuming that the input, hidden layer, and output nodes in Figure 1 are respectively x_i , y_i and z_i , and the activation functions are both f , the output of the hidden layer node is:

$$y_i = f\left(\sum w_{ji}x_i - \theta_j\right) = f\left(net_j\right) \tag{1}$$

In Formula (1), w_{ji} is the connection weight, which connects the input node and the hidden layer node; θ_j is the hidden layer neuron threshold. The output of the output layer node is:

$$z_i = f\left(\sum v_{ij}y_j - \theta_l\right) = f\left(net_l\right) \tag{2}$$

In Formula (2), v_{ij} is the connection weight, which connects the output node and the hidden layer node; θ_l is the neuron threshold of the output layer. The mean square error function between the expected and actual output is then:

$$\begin{aligned} E &= \frac{1}{2}\sum_l \left(t_l - z_l\right)^2 \\ &= \frac{1}{2}\sum_l \left(t_l - f\left(\sum_j v_{lj} f\left(\sum_i w_{ji}x_i - \theta_i\right) - \theta_i\right)\right)^2 \end{aligned} \tag{3}$$

In Formula (3), t_l is the desired output. The connection weights are derived by this error function v_{ij} :

$$\frac{\partial E}{\partial v_{lj}} = \sum_{k=1}^{n} \frac{\partial E}{\partial z_k} \times \frac{\partial z_k}{\partial v_{lj}} = \frac{\partial E}{\partial z_l} \times \frac{\partial z_l}{\partial v_{lj}} \tag{4}$$

In Formula (4), E is a function of $z_k\left(1 \le k \le n\right)$, and only z_l is related to v_{lj} , then:

$$\frac{\partial E}{\partial v_{lj}} = -\left(t_l - z_l\right) \times f'\left(net_l\right) \times y_j = -\delta_l y_j \tag{5}$$

In the Formula (5), let δ_l (output node error) be $\delta_l = \left(t_l - z_l\right) \times f'\left(net_l\right)$. Derive the connection weight w_{ji} through the error function of Formula (3):

$$\frac{\partial E}{\partial w_{ji}} = \sum_i \sum_j \frac{\partial E}{\partial z_l} \times \frac{\partial z_l}{\partial y_j} \times \frac{\partial y_j}{\partial w_{ji}} \tag{6}$$

In Formula (6), (A) E is a function of (A) $z_l\left(1 \le l \le n\right)$, one (A) w_{ji} corresponds to one (A) y_j, and is related to (A) $z_l\left(1 \le l \le n\right)$. Trial and error are the technique employed in this study to calculate the number of hidden layer nodes. To do this, the model is first trained using the fewest possible nodes, followed by a progressive increase in the number of training samples as the training proceeds. By comprehensively considering the time of model learning and the number of iterations, etc., the number of hidden layer nodes finally determined in this study is 8. The constructed economic management performance evaluation model of mining enterprises constructed is shown in Figure 2.

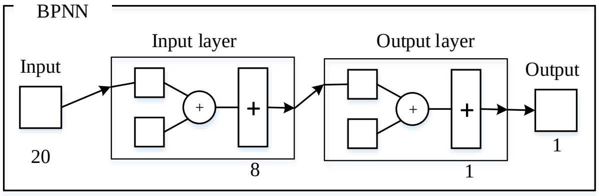

Fig. 2: Economic management performance evaluation model of mining enterprises

Figure 2 shows the 20 input samples, 8 hidden layer nodes, and 1 output layer node of the BP neural network-based mining enterprise economic management performance assessment model developed in this research. The expected output of the model is determined by the analytic hierarchy process. The analytic Hierarchy Process (AHP) is an evaluation method that can take a complex multi-objective decision-making problem as a whole and model the research problem hierarchically. It is characterized by multi-level decomposition of objectives, then dividing each level into levels with multiple indicators, and calculating the priority weight of indicators at each level through the discriminant matrix, [19], [20]. The EMP evaluation index system of mining enterprises built in this study has various levels and covers a wide range, so it needs to be sorted and summarized using the analytic hierarchy process, [21]. In this study, the EMP evaluation index system of mining enterprises is divided into two first-level indicators, namely financial performance indicators and non-financial performance indicators. There are four secondary indicators under each primary indicator, and the secondary indicators also include the tertiary evaluation indicators of the economic management performance of mining enterprises. Taking the secondary indicator U2 as an example, the indicator weight is calculated by constructing a discrimination matrix. The discriminant matrix is shown in Formula (7).

$$A = \begin{vmatrix} B_{11} & B_{12} & \cdots & B_{1n} \\ B_{21} & B_{22} & \cdots & B_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ B_{m1} & B_{m2} & \cdots & B_{mn} \end{vmatrix} \tag{7}$$

Refer to matrix A to calculate the weight vector, use the product Mi of each row of the matrix to solve the n square root, and obtain the normalized vector. Based on this $\sum_{i=1}^{n} W_i = 1$, the weight coefficient of each index can be obtained. After obtaining the weight coefficient, the key point is to maintain the consistency of the final judgment. Use the formula $CR = \frac{CI}{RI}$ (CI is the consistency index of the judgment matrix, RI is the random consistency index of the paired comparison matrix) to judge by taking its ratio. The judgment matrix passes the consistency test and eventually determines the weight of each index if CR is less than 0.1. The overall analysis flow chart of the AHP is shown in Figure 3.

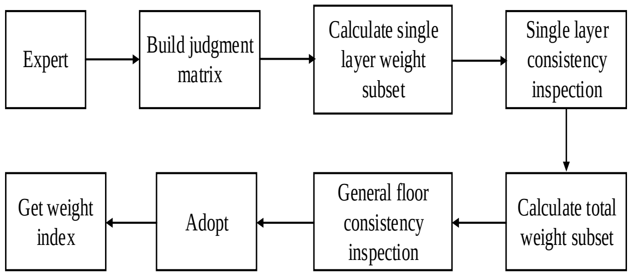

Fig. 3: Overall flow chart of analytic hierarchy process

According to the logical relationship among various indicators in the economic management performance evaluation index system of mining enterprises constructed in Table 1, the judgment matrix that needs to be constructed in this study can be calculated. The quantity and significance of the judgment matrix are shown in Table 2.

Table 2. Number table of judgment matrix

Judgment matrix	Serial number
Overall performance	A
Financial Performance	B1
non-financial performance	B2
Profitability Level 3 Indicators	C1
Level 3 indicators of solvency	C2
Three-level indicator of operating capability	C3
Level 3 Indicators of Development Ability	C4
Three-level indicator of safety production	C5
Three-level indicators of technology research and development	C6
Three-level indicators of energy conservation and environmental protection	C7
Level 3 Index of Social Contribution	C8

Table 2 demonstrates that 11 judgment matrices must be built for this investigation. Taking the financial performance index as an example, the judgment matrix of each evaluation index is constructed. The judgment matrix of financial performance indicators is shown in Table 3.

Table 3. Judgment matrix of financial performance indicators

Financial Performance Indicators B1	Profitability C1	Solvency C2	Operating Capability C3	Development Ability C4	Weights
Profitability C1	1	2	3	2	0.4256
Solvency C2	1/2	1	2	1	0.2293
Operating Capability C3	1/3	1/2	1	2/3	0.1323
Development Ability C4	1/2	1	3/2	1	0.2128

From the expert scoring results in Table 3, the judgment matrix of financial performance indicators can be constructed, as follows:

$$B1=\begin{bmatrix} 1 & 2 & 3 & 2 \\ 1/2 & 1 & 2 & 1 \\ 1/3 & 1/2 & 1 & 2/3 \\ 1/2 & 1 & 3/2 & 1 \end{bmatrix} \tag{8}$$

Take the judgment matrix B1 of Formula (8) as an example, use ATLAB R20214a software to calculate its maximum eigenvalue and eigenvector. The consistency ratio of the calculated results is 0.0038. See Table 4 for the weights of each indicator. The judgment matrices A, B2, and C1-C8 are constructed in turn according to the way of constructing judgment matrix B1. The consistency test is carried out for each interpretation matrix, and the consistency ratio CR is less than 0.1. Therefore, the index weight distribution in the following table is obtained through a consistency test.

Table 4. Comprehensive weight of indicators for economic management performance evaluation of mining enterprises

First level standard layer (a)	Weights	Secondary indicator layer (b)	Weights	Three-level indicator layer (c)	Weights
Financial performance indicators	0.67	Solvency	0.23	Assets and liabilities	0.26
				Asset current ratio	0.41
				Net operating cash flow debt ratio	0.33
		Development ability	0.21	Net profit growth rate	0.75
				Growth rate of total assets	0.25
		Operating capacity	0.13	Inventory turnover	0.44
				Accounts receivable turnover ratio	0.39
				Total asset turnover	0.17
		Profitability	0.43	Net interest rate	0.39
				Basic earnings per share	0.17
				Cost profit margin	0.44
Non-financial performance indicators	0.33	Social contributions	0.16	Commodity mine output (million tons)	0.33
				Social contribution value per share (yuan/share)	0.67
		Energy saving and environmental protection	0.33	Average recovery rate of mining area	0.37
				Comprehensive energy consumption per 10, 000 yuan output value (ton of standard ore/10,000 yuan)	0.49 _
				Comprehensive utilization rate of wastewater	0.14
		Safe production	0.15	Safety production investment (100 million yuan)	0.67
				Mortality rate of workers mining a million tons of mines	0.33
		Technology r & d	0.36	Number of patents obtained in the year	0.67
				R&d investment as a percentage of revenue	0.33

The weights of each index in Table 4 have passed the consistency test, so they have a certain degree of objectivity. The weights of each index will be used in the calculation of the evaluation results.

4 Model Verification and Analysis of Evaluation Results

Five mining companies are chosen for this research, and the social responsibility report serves as the foundation to assure the accuracy and completeness of the data. Among them, Enterprise A is the largest worldwide mining enterprise, a massive, all-encompassing energy company with coal as its primary fuel source, as well as a land, sea, and chemical industrial company. Coal mining, washing, smelting, geological research, and CBM development make up the bulk of Enterprise B's activities. Enterprise B is more focused on coal than Enterprise-A. Leading coal export company Enterprise C is primarily involved in the production of raw coal, mining, operations, manufacture of equipment, and other enterprises. Currently focusing on finance and logistics, Enterprise D is primarily involved in the coal chemical industry, coal mining, coal processing, and coal-related equipment. Corporation E is primarily involved in the mining and trading of coal. It is also a huge, multifaceted enterprise that also operates in the construction materials, coal chemical, and power supply industries.

After collecting certain information on the official website of enterprises and the online information publicity platform designated by the CSRC, 30 data from five mining enterprises A, B, C, D, and E in 2017-2022 were selected as analysis samples. 1-6 belong to A mining enterprise sample, 7-12 belong to B mining enterprise sample, and so on. Set the learning samples of the BP model as 1-5, 7-11, 13-17, 19-23, and 25-29, and conduct training and testing on the model. The following Figure 4 displays the findings.

Figure 4 demonstrates that the BP model's mean square error was less than the target error after 169 steps, demonstrating that the model has a strong simulation impact. The final actual output value of the model is shown in the figure to be extremely near to the predicted actual output value after training, demonstrating the model's excellent accuracy and suitability for performance assessment. After saving the trained model, input samples numbered 6, 12, 18, 24, and 30, and Table 5 displays the test results.

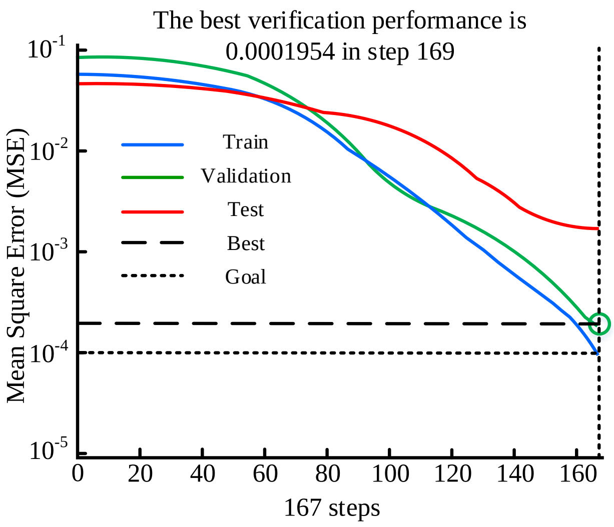

Fig. 4: Training results of BP neural network

Table 5 shows that the final real output of the BP is remarkably similar to the predicted output after five prediction samples have been inputted. The absolute error is almost less than 0.01, the minimum value of the relative error is only 0.23%, and the maximum is only 3.11%, which is acceptable for the EMP evaluation of mining enterprises. It is clear that the BP model's assessment results are excellent, having a low error rate and high efficiency. As a result, it may be extensively used in the evaluation of mining businesses' economic management performance in the future. Based on the model constructed, the following research evaluates the economic management performance of mining enterprises A, B, C, D, and E from three aspects: comprehensive performance, financial performance, and non-financial performance. Figure 5 shows the results of the comprehensive performance evaluation.

Table 5. Comparison results of expected output and the actual output of the BP neural network

Forecast sample	Expected output	Actual output	Relative error	Absolute error	Mean relative error	Mean absolute error
6	0.4523	0.4586	1.32%	0.0062	1.98%	0.00517
12	0.3321	0.3323	0.23%	0.0007		
18	0.2137	0.2133	0.24%	0.0005		
24	0.2857	0.2721	5.67%	0.0137		
30	0.1473	0.1531	3.11%	0.0045		

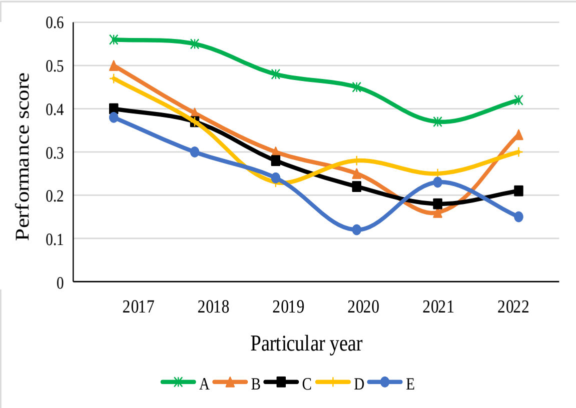

Fig. 5: Comprehensive performance evaluation results of five mining enterprises from 2017 to 2022

Figure 5 shows that the overall performance levels of the mining firms A, B, C, D, and E are quite different from one another. Since 2017, the comprehensive performance scores of the five mining enterprises have declined year by year, and the decline is obvious. On the whole, they are at a low level. However, the comprehensive performance of mining enterprises D and E began to show a small upward trend in 2019 and 2022, respectively. It can be seen that there is still room for the development of mining enterprises, and it is inevitable that the performance will decline for several consecutive years. At the same time, the comprehensive performance of mining enterprise A has always been far ahead of the other four enterprises in 2017-2022. It can also be seen from the figure that in 2022 the comprehensive performance scores of mining enterprises A, B, C and D showed a rising trend. This is mainly due to the supply side structural reform of mining enterprises promoted the balance of supply and demand in the mineral market, which has promoted the sales volume of mineral products. Therefore, the operating conditions of the enterprise have gradually improved. The results of the financial performance assessment are shown in Figure 6.

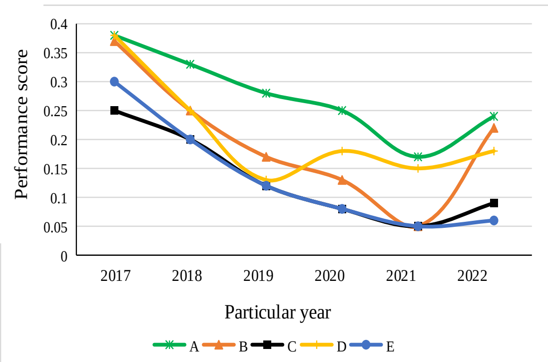

Fig. 6: Financial performance evaluation results of five mining enterprises in 2017-2022

The financial performance of mining enterprises A, B, and D in 2017 can be seen in Figure 6, but the comprehensive performance scores in Figure 5 are quite different. This shows that the non-financial performance scores are the main factors affecting the EMP of these three mining enterprises in 2017, as shown by the close financial performance of these three mining enterprises in 2017. In 2017-2019, the comprehensive performance score of mining enterprise C is much higher than that of mining enterprise E, but the financial performance score shown in Figure 6 is very close to or even lower than that of mining enterprise E. It is clear that the comprehensive performance score of a C mining enterprise depends on its good non-financial performance, so C mining enterprises should pay greater attention to financial management in the future. The outcomes of the non-financial performance assessment are shown in Figure 7.

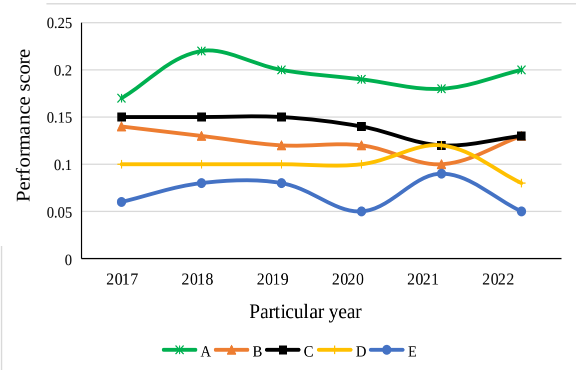

Fig. 7: Non-financial performance evaluation results of five mining enterprises A, B, C, D, and E from 2017 to 2022

As observed in Figure 7, there is no discernible increase or decreasing trend in the non-financial performance level of mining firms A, B, C, D, and E. The reason is that the market cyclical fluctuation has little impact on the score of non-financial performance indicators. In addition, the overall business policies of different mining enterprises in terms of technology research and development, safety products, and other aspects have changed little. Mining enterprise A also has outstanding performance in non-financial performance, ahead of mining enterprises B, C, D, and E, followed by mining enterprises C, B, D, and E. However, from the perspective of the law of economic and social development, the non-financial performance of enterprises should show an upward trend with the economic development, while the non-financial performance of enterprises A, B, C, D, and E did not improve as expected with the economic development, and even showed a downward trend.

The above situation indirectly shows that in the face of survival pressure, mining enterprises cannot take into account the overall development, thus ignoring the input in non-financial performance, resulting in a decline rather than a rise in performance scores.

5 Conclusions and Recommendations

This study creatively built the EMP evaluation index system of mining enterprises and the EMP evaluation model of mining enterprises based on BP neural network and analytic hierarchy process to assess the EMP of mining enterprises against the backdrop of supply-side reform. The study conducted training and validation of the model by analyzing relevant data such as the social responsibility reports of five mining companies A, B, C, D, and E from 2017 to 2022. The research results show that the model constructed in this study has a small relative error (1.98%), and the absolute difference between the actual and predicted output is always controlled below 0.01, indicating that the model has certain practicability. In addition, the study also analyzed the evaluation results of the five mining companies. The evaluation results show that mining company A is always ahead of the other four companies in terms of performance, and the economic management performance scores of mining companies A, B, and D mainly depend on non-financial performance scores, while Company C should pay greater attention to its financial management performance. Although this study has achieved certain results, due to the relatively small sample data, the accuracy of the model may be low. It is hoped that it can be improved in future research.

Despite the fact that China's mining companies are currently on the decline as a whole, this trend also presents opportunities for mining company mergers and reorganizations, which accelerates the process of industrial structure adjustment and boosts the core competitiveness of Chinese mining companies. According to the design idea of the EMP evaluation index system of mining enterprises proposed in this study, and in light of the difficulties existing in the comprehensive performance of mining enterprises, the following proposals are made. First, in terms of financial performance, enterprises should correctly control the dynamics of the macro market, minerals, and related industries; And learn to be good at capturing policies applicable to themselves, seize the opportunity of reform, and explore new development paths. Secondly, when it comes to technology research, development, and invention, enterprises need to be oriented towards reform and innovation, and meet customer orientation; Meanwhile, it applies cutting-edge technologies such as big data and the Internet of Things to comprehensively upgrade core technologies and operational models. Thirdly, to effectively prevent and regulate the pollution of noise, wastewater, and waste gas, as well as to recycle the slag, it is important to make sure that businesses have pollution prevention equipment and processes in the manufacturing process.

The method in this paper uses the trained neural network to set the weight on a given threshold so that it can evaluate the comprehensive performance of any coal mining company, which is more operable in practical applications. The model constructed in this paper can be applied to evaluate the comprehensive performance level of coal enterprises and predict their future development potential. Meanwhile, it can also provide some reference for government departments to formulate public policies, so it has great application potential. This article innovatively combines BP neural network and analytic hierarchy process to effectively allocate and quantify the weight of each indicator. The model transforms subjective and artificial judgments into objective statistical data, thereby enhancing the rationality, intuition, and credibility of the analysis conclusions. This research provides an important reference value for future researchers to apply intelligent algorithms to the estimation of enterprise economic benefits.

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