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Research Article

Intelligent Optimization Model of Enterprise Financial Account Receivable Management

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As a key component of enterprise assets, accounts receivable play an important role in enterprise financial management and determine the long-term development of enterprises in the later period. In order to minimize the financial risk brought by the credit sales of enterprises, this subject studies the intelligent optimization of enterprise financial account receivable management. BP neural network and K-means clustering algorithm are used to evaluate the risk of account receivable and the owner's credit, respectively. The account balance accounts for 45.20% of the total amount, and the risk rating of accounts receivable is 4. The training result of BP neural network algorithm has high accuracy. With K-means clustering algorithm, accurate evaluation of owner's credit can be achieved, which can provide reference for optimization of enterprise account receivable management mode.

1. Introduction

Commercial competition is becoming increasingly fierce. In order to improve business performance and market share, enterprises usually carry out credit sales business, which means that they need to recover the corresponding accounts within a certain period of time, or write off bad debts [1]. The scientific management method adopted for accounts receivable is the enterprise's account receivable management. Its main purpose is to timely recover the receivable accounts and effectively avoid the risk of economic loss [2]. The traditional economic performance research and account receivable management methods of mining enterprises mainly rely on manual analysis and empirical judgment. This method has drawbacks such as slow manual analysis speed, difficulty in processing large amounts of data, and inability to make real-time decisions. BP neural network can approximate any nonlinear function with arbitrary accuracy, which gives it great advantages in dealing with complex nonlinear problems [3]. The K-means algorithm can be applied to various types of data, including continuous and discrete data. Therefore, in response to the shortcomings of traditional methods, this study adopts BP neural network and K-means clustering algorithm to study the economic performance of mining enterprises and intelligent optimization of financial account receivable management. The main purpose of the study is to analyze and learn historical data through machine learning algorithms, in order to more accurately evaluate the economic performance of mining enterprises and predict future development trends. At the same time, we study the use of intelligent algorithms to manage financial receivables, aiming at automatic classification, early warning, and optimization, and greatly improve management efficiency.

2. Related Works

Due to the complex operating environment, ever-changing market demand, and long industrial chain of mining enterprises, the management of accounts receivable is difficult and the risk of bad debts is high. Therefore, how to improve the management efficiency and risk control ability of financial accounts receivable in mining enterprises has become an urgent problem to be solved [4]. At present, accounts receivable and related accounting factors are widely concerned by researchers in various countries. Based on support vector machine, Guo and Zhao established a financial crisis early warning model of listed companies by taking return on net assets, account receivable turnover, and quick ratio as input variables and defining "default" as output variable. Through empirical analysis, the prediction accuracy of this model was 97.7% [5]. Liu designed a financial index analysis system based on data mining technology and found through experimental research that the application of this system improved the efficiency of enterprise management decision-making and saved cost for the enterprise [6]. Taking the accounts receivable of enterprises as the starting point, they studied the game strategies, possible optimal decisions, and corresponding profits among suppliers, manufacturers, and banks. Finally, they proved that the initial capital of suppliers, bank interest rates, and other factors have a significant impact on the financing of such enterprises through case analysis. Frankel et al. led his research team to analyze the factors affecting the quality of enterprise accounts receivable and deeply studied the impact of aging-report loan contingents on the quality of accounts receivable [7]. Once the financial risks accumulate to a certain extent, if the enterprise fails to take timely measures, it will certainly lead to greater financial crisis. For this reason, Wang established an enterprise financial crisis early warning model based on the RBF neural network algorithm to avoid the enterprise financial crisis. The research results show that the established model has a high accuracy [8].

After sorting out the research related to accounts receivable in recent years, most of the researches in this field focus on the treatment of accounts receivable and its impact on the overall financial situation of the enterprise, but there are few studies that focus on the management of enterprise accounts receivable and combine computer modeling technology with it. Therefore, this research establishes an optimization model of enterprise account receivable management and optimizes account receivable health situation with the help of computer algorithms.

3. Construction of an Intelligent Management Model for Accounts Receivable Based on BP Neural Network and K-Means Algorithm

3.1. Optimization of Intelligent Risk Assessment Method for Accounts Receivable Based on BP-K-Means Algorithm. Effective intelligent assessment of account receivable risk can help mining enterprises reduce bad debt losses, reduce capital occupation, improve asset quality and operational efficiency, and thus enhance the overall competitiveness and market position of enterprises. To ensure the good operation and capital security of enterprises, it is necessary to strengthen the risk management of accounts receivable. BP (backpropagation) network algorithm is a supervised learning algorithm, which is used to adjust the weight of the neural network according to the input data and corresponding target output data, so that the network can make correct predictions on the input data. BP algorithm can continuously adjust the weight and threshold of the network through backpropagation to minimize the sum of squared errors of the network and has strong nonlinear mapping ability, so that it can better process and analyze complex account receivable data. Therefore, the BP neural network algorithm is used in the intelligent assessment of enterprise account receivable risk. The model of BP neural network algorithm is shown in Figure 1 [9].

According to Figure 1, when designing and initializing parameters, it is necessary to determine the number of neurons in each layer of the BP network, including the input layer and the output layer. Forward propagation means that under the activation of the transfer function, the neuron value in the hidden layer is obtained by linear transformation between the set weight value and the data in the input layer, and the neuron value in the output layer is obtained by multiple calculations [10, 11]. Then, the error between the fitting value and the output value is compared, and the error gradient is calculated, so as to continuously adjust the weight value and finally output.

The construction of enterprise account receivable risk evaluation model with BP neural network can give full play to the nonlinear mapping ability and fault tolerance ability of BP network and ensure the accuracy of training evaluation results [12]. First, let the input, output, and hidden layer contain c, d, and e nodes, respectively. The weight between input layer and hidden layer is V_{iw}, and the weight between the output layer and hidden layer is V_{jw}. The functions of hidden layer and output layer are f_1 and f_2, respectively. The output value of the hidden layer can be obtained as follows:

$$Z_k = f_1\left(\sum_{i=1}^{n} V_{ik}X_i\right), \quad k = 1, 2, \cdots, q. \tag{1}$$

The node output of the output layer is obtained as

$$y_m = f_2\left(\sum_{m=0}^{d} W_{dm}Z_m\right), \quad m = 1, 2, \cdots, d. \tag{2}$$

The number of learning samples input into the model is c, and the samples are represented as $x_1, x_2, \ldots, x_c$. When the number of input samples reaches P, its output can be expressed as $y_j^c (j = 1, 2, \cdots, c)$. The error value of the Pth sample as shown in Equation (3) can be obtained through the square error function.

$$E_p = 0.5 \sum_{j=1}^{c} \left(t_j^p - y_j^p\right)^2. \tag{3}$$

In Equation (3), t_j^p represents the expected output value. The overall error value of P sample size can be expressed as

$$E = \frac{1}{2} \sum_{P=1}^{P} \sum_{j=1}^{m} \left(t_j^P - y_j^P\right)^2. \tag{4}$$

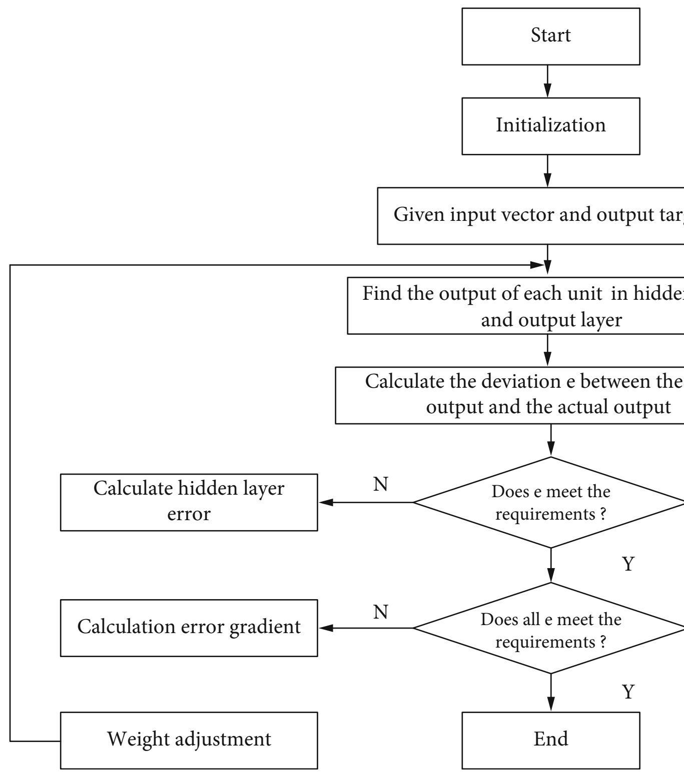

FIGURE 1: Structure diagram of BP neural network algorithm model.

Then, the cumulative error algorithm can adjust W_{jw}, which can reduce the value of E, as shown in

$$\Delta W_{jw} = -\gamma \frac{\beta E}{\beta W_{jw}} = -\gamma \frac{\beta}{\beta W_{jw}} \left(\sum E_p \right) = \sum_{p=1}^{p} -\gamma \frac{\beta E_p}{\beta W_{jk}}. \quad (5)$$

In Equation (5), γ represents the learning rate. Through the analysis of the trend and structure of enterprise account receivable, the analysis of the liquidity of account receivable is completed.

In the risk assessment of accounts receivable, the intelligent credit evaluation of enterprise credit sales object is of great significance. Through intelligent credit evaluation, enterprises can conduct comprehensive and objective analysis and evaluation of customers' credit status, so as to reduce credit risk, reduce bad debt losses, optimize sales strategies, and improve the overall competitiveness. As a commonly used clustering analysis algorithm, K-means clustering algorithm can classify and aggregate these feature variables through cluster analysis, thus reducing the dimension of data and extracting key feature variables, which helps enterprises to identify customers' credit risk more quickly and accurately. Therefore, the paper introduces K-means clustering algorithm on the basis of BP network algorithm to conduct intelligent analysis of the credit status of enterprise sales objects [13]. The flow of K-means algorithm is shown in Figure 2.

The K-means algorithm first initializes the data, selects the number of clusters K, and randomly initializes K cluster center points. Then, allocate samples, and for each sample, calculate its distance from each cluster center point, and assign the samples to the cluster corresponding to the nearest cluster center point. Next, update the cluster center points, and repeat the allocation of samples and update the cluster center points until the stop condition is met. Output the clustering results to obtain the final clustering results [14, 15]. The objective function commonly used in K-means algorithm is the square error criterion function.

$$\sum = \sum_{i=1}^{k} \sum_{p \in c_i} \|p - c_i\|^2. \quad (6)$$

In Equation (6), p is the data object, c_i represents the center of mass of cluster C_i, and E represents the sum of square errors of all experimental objects in the data set. In the experiment, Ω is a known sample set containing n data, as shown in

$$\Omega = \{x_i | x_i = (x_{i1}, x_{i2}, \cdots, x_{id})\}. \quad (7)$$

In Equation (7), $i = 1, 2, \cdots, n$. $x_i = (x_{i1}, x_{i2}, \cdots x_{id})$ is a d-dimensional vector, which means that data i has d different attributes. The size of the experimental samples is expressed as n. The cluster center of the cluster can be expressed as

$$C = \{c_j | c_j = (c_{j1}, c_{j2}, \cdots, c_{jd}), j = 1, 2, \cdots K\}. \quad (8)$$

In the j cluster class, $c_j = (c_{j1}, c_{j2}, \cdots c_{jd})$ is the center point. Each center point c_j contains d different attributes. K is the number of cluster classes. $D(x_i, c_j)$ represents the Euclidean distance between x_i and c_i, and its expression is shown in

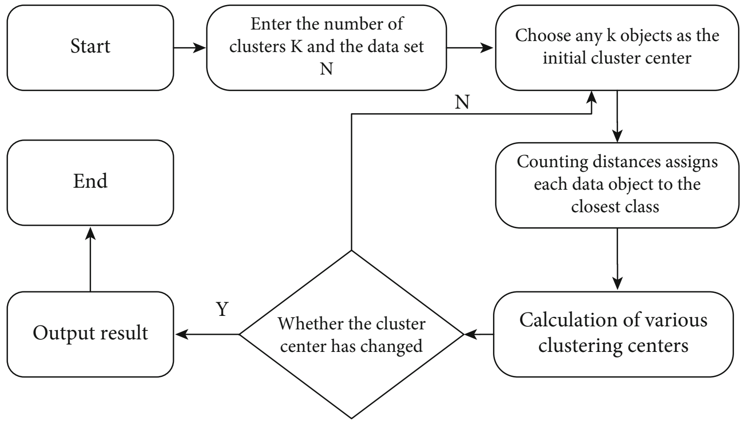

Figure 2: The flow of K-means algorithm.

$$D(x_i, c_j) = \sqrt{\sum_{i=1}^{d} (x_{i1} - c_{j1})^2}, \quad (9)$$

where $x_i = (x_{i1}, x_{i2}, \cdots, x_{id})$ and $c_j = (c_{j1}, c_{j2}, \cdots c_{jd})$. K is the number of cluster classes. c_j is the center point of the same cluster, as shown in

$$c_{jl} = \frac{1}{N(\phi_j)}. \quad (10)$$

In the same cluster ϕ_j, $N(\phi_j)$ represents the amount of data. $x_i = (x_{i1}, x_{i2}, \cdots, x_{id})$. $l = 1, 2, \cdots, n$. K is the number of cluster classes [16]. The criterion function is the sum of squares within the class, as shown in

$$\mathrm{SSE} = \sum_{j=1}^{K} \sum_{x_i \in \phi_j} \mathrm{dis}(x_i, c_j). \quad (11)$$

In Equation (11), $x_i = (x_{i1}, x_{i2}, \cdots, x_{id})$, and $c_j = (c_{j1}, c_{j2}, \cdots c_{jd})$. To sum up, the study combines BP neural network and K-means algorithm to evaluate enterprise receivable risk and credit, aiming to help mining enterprises improve assessment efficiency, timely discover potential risk points, and optimize sales strategies and risk management measures.

3.2. Construction of Intelligent Account Receivable Management Model of Mining Enterprises Based on BP-K-Means Algorithm. The main function of enterprise account receivable management is to strengthen financial control, optimize financial management process, avoid financial risks, and ultimately improve the efficiency of financial management [17]. In terms of the financial management of general enterprises, it is crucial to optimize the management of accounts receivable [18]. It is usually optimized from the following aspects; first of all, the person in charge of the industry, sales personnel, and financial personnel need to fully understand the financial risk and understand the risk and harm of receivables. Then, the enterprise should convene a regular account receivable meeting to urge the recovery of goods and timely coordinate to deal with the relevant problems existing in accounts receivable. Finally, by improving its credit evaluation system, it conducts strict credit evaluation for customers who place orders and understands their credit history, assets, and other information, so as to control the risks of enterprises through good credit management measures. Besides, the design of the overall management status of enterprise financial account receivable requirements mainly focuses on three aspects, namely, account receivable risk management, automatic prompt of account receivable term, and automatic cross system retrieval [19, 20]. The framework of enterprise account receivable management is shown in Figure 3.

Figure 3 shows the enterprise's intelligent account receivable management framework, which includes three departments, financial sharing center, subsidiary company, and capital settlement center, which manage projects such as owners, contracts, management, and collection. The management process forms a closed loop with high integrity and standardization. The intelligent management model for enterprise financial accounts receivable based on BP neural network and K-means algorithm is shown in Figure 4.

In the intelligent management model of financial accounts receivable for mining enterprises based on the BP-K-means algorithm, data integration and processing are first carried out. Account receivable-related data is integrated from different sources such as the financial system and sales system of the mining enterprise, and cleaned, integrated, and standardized processing is carried out. Then, the K-means algorithm is used to segment the customers of mining enterprises, dividing them into different groups based on their financial status, credit history, and other information. This helps companies better understand customer needs, behavioral patterns, and risk situations, thereby formulating more precise financial management strategies. Evaluate and predict the account receivable risk of each customer based on BP neural network. By training neural networks, the model can automatically learn and identify key factors that affect account receivable risk and predict the possibility of bad debts in the future based on historical data. Then, optimize the sales strategy and automatically generate various account receivable-related reports, such as overdue account receivable detail table and bad debt analysis table.

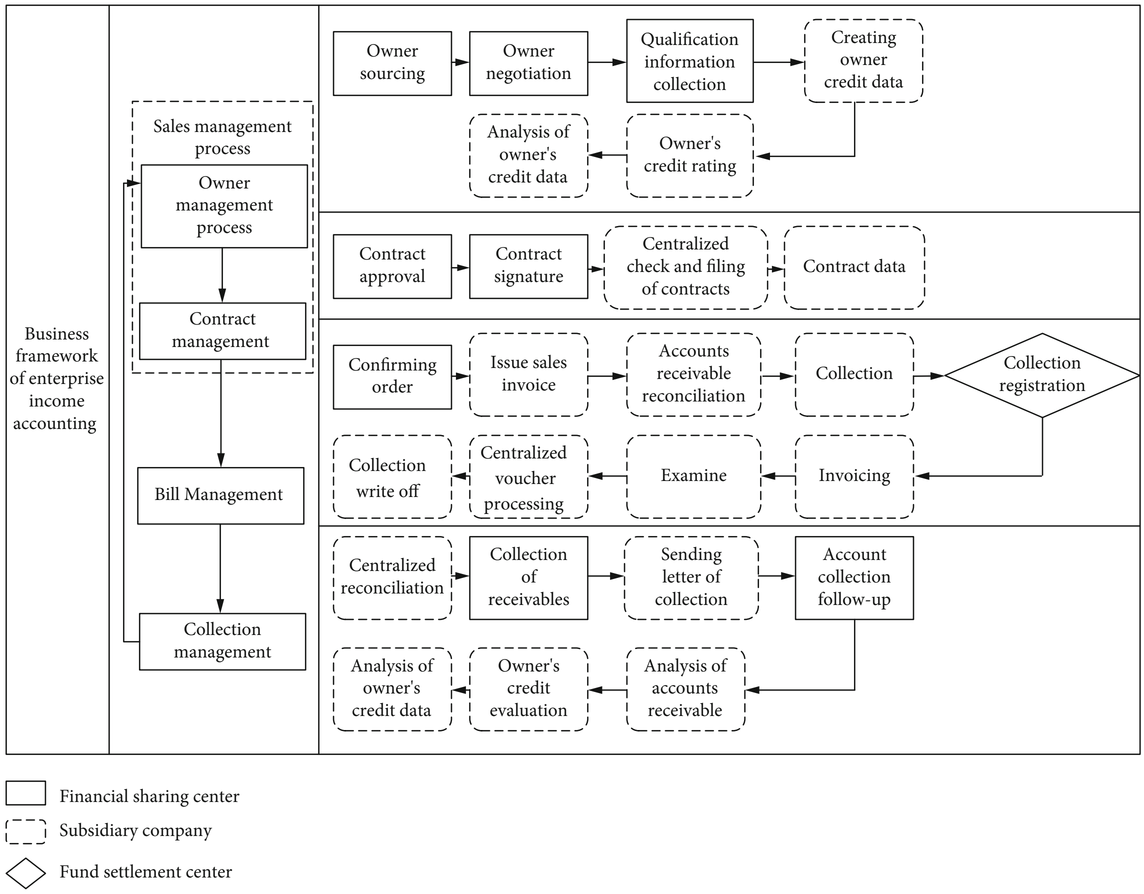

Figure 3: Business framework of enterprise account receivable management.

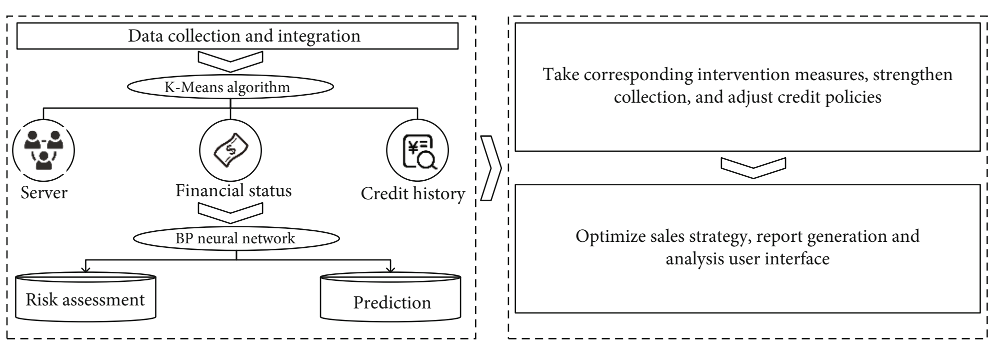

Figure 4: An intelligent management model for enterprise financial accounts receivable based on BP-K-means algorithm.

Finally, provide an intuitive and user-friendly user interface for mining enterprise users to operate and manage.

4. Intelligent Optimization Results of Enterprise Financial Account Receivable Management

4.1. Intelligent Credit Evaluation of Enterprise Credit Sales Objects. Before forecasting the risk of accounts receivable of enterprise A, the relevant financial indicators should be analyzed in advance, and the relationship between account receivable data and capital flow should be excavated. Figure 5 shows the financial indicators of accounts receivable of enterprise A in recent years.

According to Figure 5, from 2014 to 2015, the net profit and product revenue of enterprise A decreased by 30.23% and 16.13%, respectively, while its accounts receivable increased by 43.92%. In 2016, the net profit and product revenue decreased by 11.47% and 29.05%, respectively, and the amount of accounts receivable decreased slightly, only 8.20%. In 2017, enterprise A performed well in three indicators. In 2018, the net profit and product revenue increased by 44.88% and 36.93%, respectively, but the amount of

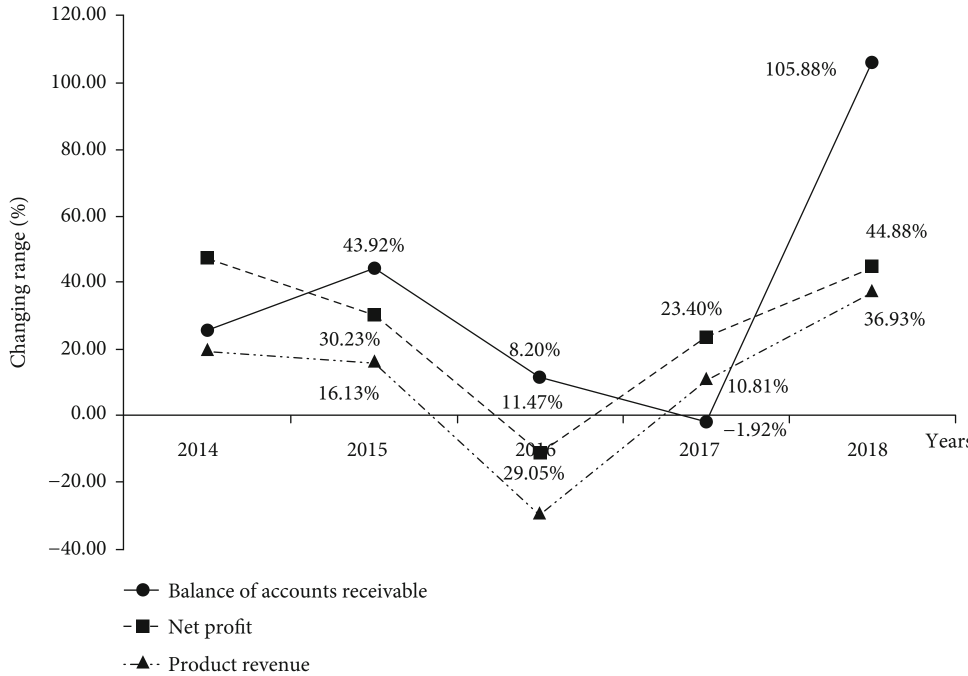

Figure 5: Relevant financial indicators of accounts receivable of enterprise A from 2014 to 2018.

accounts receivable increased significantly, with a growth rate of 105.88%. In recent years, the amount of accounts receivable of enterprise A has shown a high and growing trend, which is not conducive to its capital operation and industrial investment and restricts the improvement of profits and the long-term development of the enterprise. If the accounts receivable continue to rise, enterprise A will face greater operational risks. This subject experiment first constructs the risk prediction model of accounts receivable based on BP neural network and conducts training and testing in a single cycle. Then, repeat it for many cycles, round up the output fitting value after each cycle, compare it with the target output value, and then calculate the accuracy of the cycle output value. Let the number of nodes in the maximum hidden layer act as the maximum number of cycles. When all cycles are completed, the optimal value of the number of hidden layer nodes and the accuracy of the cycle output value can be filtered. Different types of enterprises including enterprise A are selected for multiple trainings, including special treatment (ST) companies and non-ST companies. The results are shown in Figure 6.

Figure 6 shows that the higher the proportion of enterprise account receivable balance in total accounts receivable, the higher the bad debt risk prediction level and account receivable risk rating, and the lower the turnover rate of accounts receivable. Take enterprise 1 (enterprise A) as an example. When the balance of accounts receivable accounts for 45.20% of the total amount, the enterprise's bad debt risk prediction rating is high, reaching 3.98, while the risk rating of accounts receivable is 4, which is at a high-risk level. At this time, the turnover rate of accounts receivable is only 3%. Then, all the data are input into the risk prediction model to test the accuracy of the prediction (see Figure 7 for detail).

Figure 7 shows that the risk prediction of accounts receivable based on BP neural network is highly practical and accurate and can predict the risk of all selected ST companies and non-ST companies to determine whether there will be a major economic crisis in the near future. Among them, the risk prediction accuracy of ST company is 90%, and the risk prediction accuracy of non-ST company is 85%. It can be seen that the method based on BP neural network can accurately predict the enterprise's account receivable risk.

4.2. Implementation Results of Owner's Credit Evaluation. According to the business characteristics of enterprise A, this experiment applies K-means clustering algorithm to analyze the financial data of enterprise A and companies in related industries. The results are shown in Figure 8.

It can be seen from Figure 8 that there are significant differences in the operating profit margins of the 25 enterprises, including enterprise A, among which the operating profit margins of enterprise 1 (enterprise A), enterprises 7 to 12, and enterprise 18 are much higher than those of other enterprises. This is mainly because the above enterprises with high operating profit margins have obtained considerable scores in the comprehensive scores of the owner's credit evaluation. In addition, their account receivable management model is also an important reason. In the process of credit sales, enterprise A needs to further optimize its own management mode of accounts receivable, and the most critical point is to strengthen credit management. According to the analysis results of K-means clustering algorithm, it is very important to accurately evaluate the credit status of customers. Customer credit ratings need to be assessed and classified, and corresponding credit policies should be provided for customers or owners with different credit ratings.

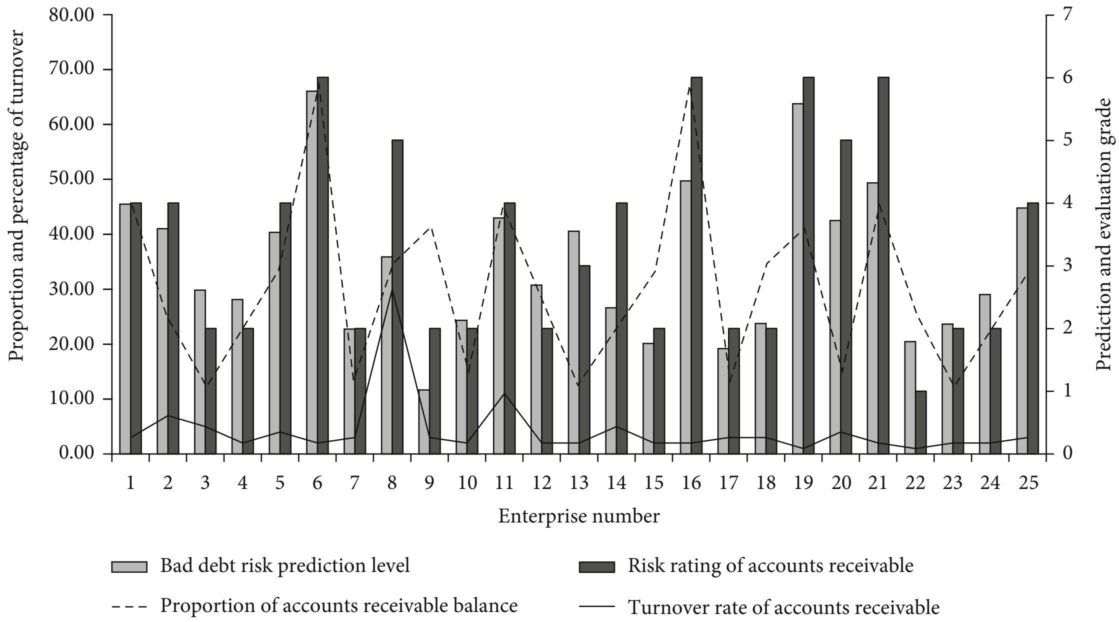

Figure 6: Partial training results of BP neural network algorithm.

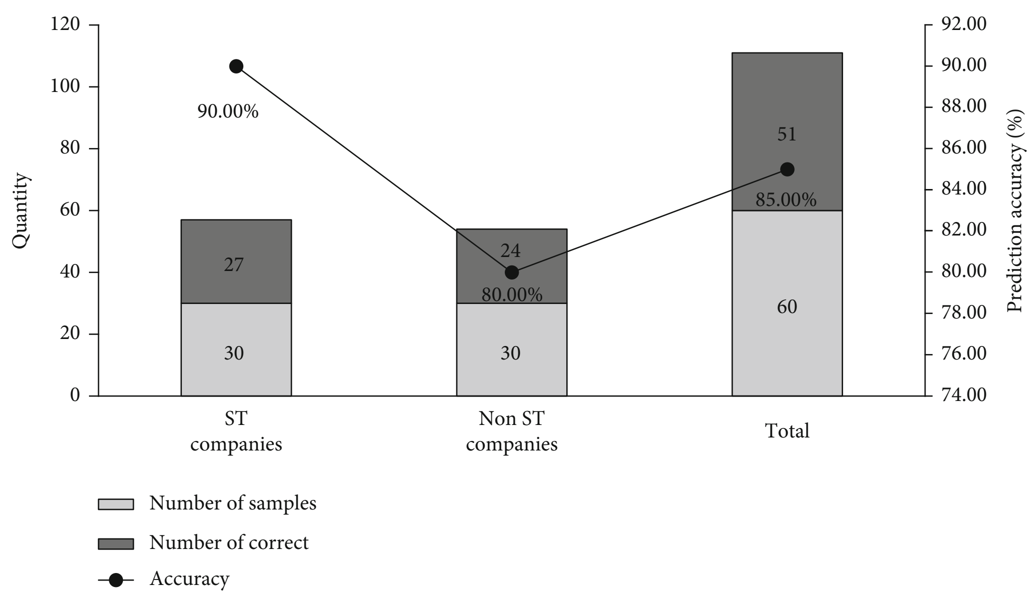

Figure 7: Accuracy of risk prediction model.

5. Discussion

BP neural network is a concept put forward by scientists led by Rumelhart and McClelland in 1986 [21]. It is a multilayer feed-forward neural network trained according to the error backward propagation algorithm. The main application value of BP neural network in financial management is reflected in risk warning, financial prediction, fraud detection, customer segmentation, and credit evaluation. In this experiment, BP neural network was used to predict the risk of all selected ST companies and non-ST companies, and the prediction accuracy reached more than 85%, which was consistent with the research results of Zhang et al. [22]. The K-means algorithm dates back to 1957, when Stuart Lloyd first proposed this standard algorithm and applied it to pulse-code modulation technology. K-means algorithm is widely used in data mining, image processing, pattern recognition, and other fields. Through cluster analysis, K-means algorithms can help enterprises identify outliers or outliers in financial data, thereby finding potential risk points. In this study, the K-means algorithm can process and analyze the financial information of enterprises, accurately analyze the significant difference between the operating profit rate of different enterprises, and predict the risk. This finding is consistent with the findings of Miraftabzadeh et al. [23].

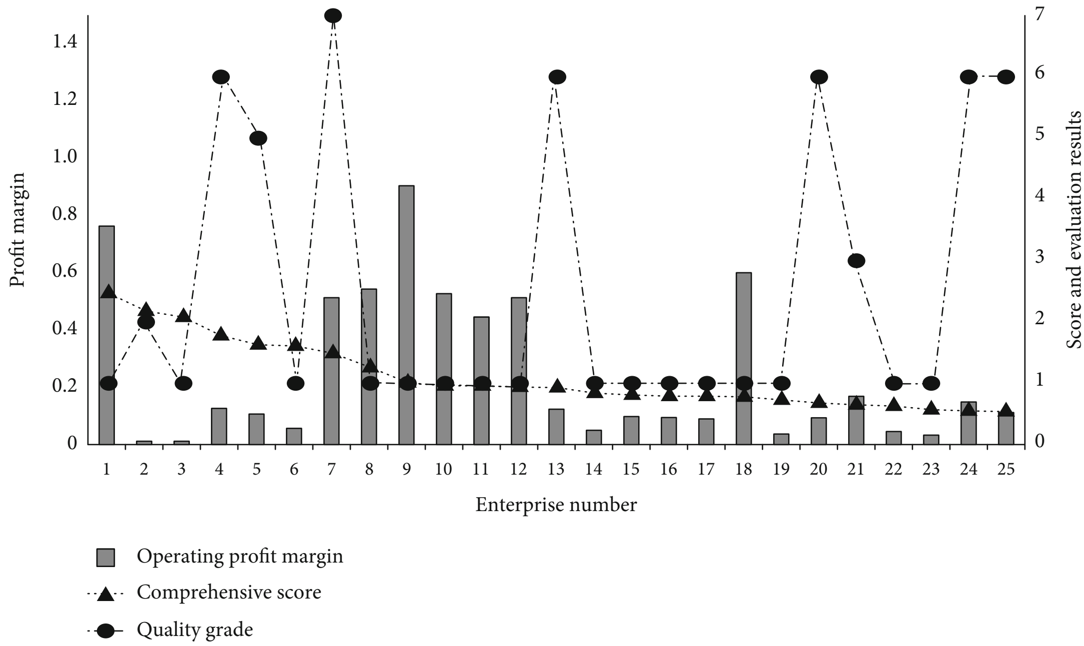

Figure 8: Variable analysis results of enterprise A and its related industries.

In summary, the research of intelligent management model of enterprise financial receivables based on BP neural network and K-means algorithm can provide new ideas and methods for the theoretical framework of financial management. By combining neural network and clustering algorithm, the model can better reveal the internal law and correlation of financial receivable data and provide strong support for the development of financial management theory. In practice, through automated and intelligent data processing and analysis, this model can help enterprises quickly obtain accurate account receivable information and risk assessment results, reduce manual intervention and cumbersome reporting work, reduce management costs, and improve financial management efficiency. At the same time, through the comprehensive analysis of customer segmentation and risk assessment, the model can provide strong support for the sales strategy and customer management of enterprises. On the policy side, the study may facilitate the release of relevant policies that emphasize data privacy and security protection. Policy makers may formulate corresponding laws, regulations, and policies that require companies to comply with relevant regulations on data privacy and security protection when applying AI technology to prevent data leakage and abuse.

6. Conclusion

With the rapid development of the global economy, mining enterprises play an important role in the national economy. However, mining enterprises are faced with many challenges, among which financial management and account receivable management is one of the key issues. Therefore, this paper proposes an enterprise account receivable management model based on BP-K-means algorithm. The design of the model should have good flexibility and extensibility, so as to customize the configuration and function expansion according to the actual needs of the enterprise. For example, the method of customer segmentation, indicators for risk assessment, and warning thresholds can be adjusted at any time. Through experimental analysis, the accuracy of account receivable risk prediction based on BP neural network is more than 85%, which has high practicability and accuracy. According to K-means algorithm, the ratio of account receivable balance to total accounts receivable is positively correlated with bad debt risk forecast grade and account receivable risk rating and negatively correlated with account receivable turnover rate. To sum up, compared with traditional research methods, the risk assessment mechanism based on BP neural network and K-means algorithm can help mining enterprises to give early warning and timely discover high-risk customers and potential bad debt risks. In the future, customer segmentation technology based on K-means algorithm can help enterprises better understand customer needs and behavior patterns. In the following research, this model can further expand its customer segmentation ability and provide more accurate personalized services for enterprises according to customers' financial status, credit history, and purchase behavior. A shortcoming of this study is that the effectiveness of the model largely depends on the quality and quantity of the data. If the enterprise lacks high quality, comprehensive financial receivable data, or the amount of data is insufficient, it may affect the accuracy and reliability of the model. Therefore, it is necessary to strengthen the unstructured data processing capability of this model in future research.

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 declared that they have no competing interests.

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