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Financial Management Risk Prediction Algorithm of New Energy Enterprises Based on Improved Neural Network

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Abstract: *In order to make new energy enterprises more flexible and stable in development, people must strengthen the control of financial management risks (FMRs for short here) and establish a more strict and standardized financial system. At present, most of the research is based on statistical models, and neural network (NN) has gradually become the research focus of FMRs. However, this method has both advantages and disadvantages and needs continuous improvement. Because there are certain limitations in using traditional methods in risk, this paper attempts to use Back Propagation (BP) NN to predict the risk of new energy enterprises, in order to provide a better FMRs assessment plan for managers and investors. In order to improve the accuracy of prediction, this paper used Particle Swarm Optimization (PSO) to optimize the BP NN. The experimental results showed that the prediction accuracy of BP and PSO-BP was 68.3% and 84.5% respectively under 300 training samples. Under 300 test samples, the prediction accuracy of BP and PSO-BP was 58.3% and 89.5% respectively. It can be found that the prediction accuracy of PSO-BP was higher than that of BP NN whether in training samples or test samples.*

Keywords: *New Energy Enterprises, Particle Swarm Optimization, Back Propagation Neural Network, Financial Management Risk, Improved Neural Network*

1. Introduction

New energy enterprises have established a certain foundation in the society after years of efforts, but with the rapid development of new energy enterprises, there are still many imperfections in the internal management of enterprises. Some enterprises have poor awareness of FMRs, especially in the new energy field. Once serious financial loopholes occur, they would lead to major risks. In order to establish a scientific internal management model, new energy enterprises must pay attention to internal control and FMRs prediction. Prediction can effectively reduce the risks of new energy enterprises, reduce their potential losses, and improve the operational efficiency of enterprises. It can enhance the profits of enterprises and promote the healthy and sustainable development of new energy enterprises. In the market economy, the FMRs of new energy enterprises is an objective phenomenon, which runs through the entire production and operation of enterprises. It is unrealistic to completely eliminate these risks and their consequences. It must conduct a comprehensive analysis of the FMRs, find out the factors that may cause the deterioration of the financial situation as soon as possible, control the problems that affect the enterprise's profits and even survival within a controllable range, and timely predict all kinds of phenomena that may lead to the crisis. Therefore, it is necessary to find effective risk prediction methods. In theory, the relevant theoretical system of FMRs prediction of new energy enterprises should be further improved to enrich its research ideas and methods.

2. Related Work

In the current competitive market economy environment, every new energy enterprise faces various FMRs at different stages of its enterprise life cycle. Valaskova, Katarina found that FMRs was usually

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considered as the risk that enterprises may default on their debts. He regarded the debt and default of enterprises as a way of risk management, and prediction was an inseparable element of risk management. The results showed that the most important prediction factors were the return on net capital, cash ratio, current ratio, etc. [1]. Yang, Weige aimed to explore the optimization of enterprise financial management under the background of big data and provide sustainable financial strategy for enterprise development. He analyzed the shortcomings of the traditional financial management model in the context of big data analysis. Considering the predictability of enterprise FMRs, he applied deep learning to realize the enterprise financial prediction model to predict the potential risks in enterprise finance [2]. Lundqvist, Sara A. believed that enterprise FMRs has become a more comprehensive and comprehensive risk management framework, focusing on how to strengthen the governance of the risk management system. In theory, the FMRs of enterprises should reduce the volatility of cash flow, agency risk and information risk, and ultimately reduce the default risk of enterprises [3]. The scholars found that although new energy enterprises have developed rapidly, there are more and more FMRs.

Effective forecasting methods can provide financial analysis and evaluation tools for investors and creditors of new energy enterprises. It can predict FMRs to a certain extent and make correct judgments to avoid major losses. Kim, Alisa explored the potential of deep learning in supporting FMRs decision-making. He developed a NN model to predict whether individuals would gain profits from future transactions. The result of using NN for operational risk prediction confirmed the feature learning ability of deep learning, and he proved that NN is superior to machine learning prediction method [4]. Devie, Devie aimed to emphasize the research on the correlation between corporate social responsibility, corporate financial performance and FMRs. He also examined the indirect impact of corporate FMRs on social and economic development [5]. Lechner, Philipp found that in recent years, enterprise risk management has become increasingly important, especially due to the increasingly complex risk and the further development of regulatory framework [6]. The scholars believed that establishing a sound risk prediction mechanism can effectively reduce the risk of new energy enterprises. It reduced its potential losses, thus improving its operational efficiency, and thus promoting the healthy and sustainable development of new energy companies.

New energy enterprises play an important role in the national economy and the macro economy. Due to the limitations of its environment and conditions, it has great FMRs in its operation [7]. In order to prevent FMRs from financial crisis, it is necessary to establish a prediction mechanism to predict the potential crisis, so as to ensure the healthy and normal operation of enterprises.

3. Financial Management Risk Prediction Based on PSO-BP NN

3.1 Financial Management Risk

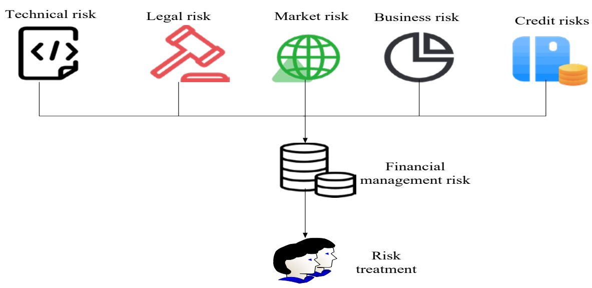

Figure 1 Financial management risk

The new energy industry has received a lot of policy support and also made a lot of profits, but with the number of new energy enterprises increasing. The technological innovation ability, management ability and capital scale of enterprises have been greatly improved. The normal operation of new energy enterprises depends on a variety of factors, among which the overall financial status of enterprises is an important indicator to measure the operation of enterprises. Its good financial performance and business performance can not only ensure the current business decision-making and operation of the enterprise, but also promote the long-term stable and healthy development of the enterprise. Today’s world economic situation is changing rapidly. In order to ensure the sustainable and healthy development of enterprises, enterprises put more energy on the prediction and analysis of enterprise FMRs [8-9]. Financial management risks are shown in Figure 1.

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As shown in Figure 1, FMRs include market risk, legal risk, credit risk, business risk and technical risk. Effective FMRs prediction can make timely adjustment to the FMRs of enterprises. This can play an important guiding role in the operation, management and decision-making of enterprises, and has important guiding significance for the development of enterprises [10-11]. On the whole, the prediction of FMRs has the following important functions:

(1) Help enterprises improve their overall management level

The international economic situation is changing rapidly. The production and operation of new energy enterprises would be affected by external factors, which would have a certain impact on the financial situation of enterprises. In the final analysis, it is due to the confusion of internal management, the lack of scientific decision-making and the inadaptability to the external economic environment that lead to the financial risks of the enterprise [12]. At present, China's economic environment is very complex, and new energy enterprises are facing more and more serious problems, especially financial problems. By effectively predicting the FMRs of new energy enterprises, it can make them better understand the current FMRs and their own shortcomings. This can make correct decisions and provide scientific reference for the development of enterprises [13-14].

(2) It is conducive to protecting the rights and interests of stakeholders

The assets of new energy enterprises include the equity and debt of shareholders. The owner is the investor of the enterprise, while the debt is the creditor of the enterprise. Enterprises should be responsible for all investors and creditors. By effectively predicting the FMRs of new energy enterprises, investors and creditors can have a comprehensive understanding of the financial, operation and development trend of new energy enterprises. This would enable investors and creditors to make investment decisions more rationally [15]. Among creditors, there are not only new energy enterprises, individuals, but also banks. Their debt ratio is very high. Once there is a financial crisis, their economic losses would be greater. Therefore, it is very necessary to predict the risk of financial management.

3.2 BP NN

The development and application of NN has reached a new level, its algorithm and model research has also made considerable progress, and its application range has also been greatly improved. The development of NN is largely due to its ability to imitate some functions of human brain. BP NN is the most widely used and accepted one. Traditional FMRs prediction has its own shortcomings, so a new method is urgently needed. It can not only overcome the limitations of traditional statistical methods, but also achieve better fault-tolerance. At the same time, it would not put forward higher requirements for the internal connection of the original data. The basic framework of BP NN is shown in Figure 2:

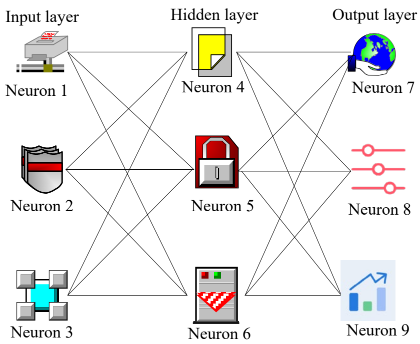

Figure 2 Basic framework of BP NN

As shown in Figure 2, BP NN consists of input layer, hidden layer and output layer. The principle of BP NN is to conduct forward propagation of the input information and form learning of the reverse propagation of errors. Forward propagation is to iterate the sampled data at the input layer through the hidden layer, and then propagate at the output layer if the output result is not consistent with the expected output.

The production functions of BP NN include hyperbolic tangent function and logarithmic function:

$$f(a) = \frac{2}{1+e^{-2n}} - 1 \tag{1}$$

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$$f\left(a^{'}\right)=\frac{2}{1+e^{-a}} \tag{2}$$

The number of nodes in the hidden layer in the BP NN is the key factor affecting the whole BP NN. In order to further improve the accuracy of the network, the following formula can be used to calculate:

$$l=\sqrt{n+m}+a \tag{3}$$

l is the number of hidden layers, and n is the number of input nodes. m is the number of output nodes, and a is a constant.

The advantage of BP NN is that it has fault-tolerance and dynamic tracking and prediction ability. It can continuously adjust its own parameters and find the optimal combination of parameters in complex and changing environments, so as to obtain more accurate prediction results.

BP NN is built to predict the financial situation of enterprises, so as to provide reliable decision-making basis for managers and provide decision-making support for investors. Compared with the previous FMRs prediction model, BP NN has the following advantages:

(1) The parameters of the model are adjusted by learning the data of the target, so as to achieve lower errors, avoid the impact of non-subjective factors such as artificial weighting, and improve the accuracy and scientificity of the prediction.

(2) High accuracy: The biggest advantage of BP NN is that it can reduce the system error to the desired range.

(3) Dynamic prediction can be carried out. When necessary, comparisons can be increased or decreased at any time. This model can carry out more deep learning and dynamic tracking

The basis of BP NN is composed of the forward transmission of signals and the reverse transmission of errors. That is to say, in the actual output process, the operation is carried out in the direction from input to output, and the weight and threshold are adjusted in the direction of input. Output b_i of the ith node of the hidden layer:

$$b_i=\phi\left(net_i\right)=\phi\left(\sum_{j=1}^{M} w_{ij}a_j+\theta_i\right) \tag{4}$$

θ_i represents the threshold value of the ith node of the hidden layer. Output o_k of the k-th node of the output layer:

$$o_k=\psi\left(net_k\right)=\psi\left(\sum_{i=1}^{q} w_{ki}b_i+a_k\right) \tag{5}$$

w_{ki} represents the weight value between the k-th node of the output layer and the i-th node of the hidden layer, so that a new cycle and accurate calculation can be performed. The weight correction $w_{ki}\left(t+1\right)$ of the output layer is:

$$w_{ki}\left(t+1\right)=w_{ki}\left(t\right)+\Delta w_{ki} \tag{6}$$

BP NN shows good nonlinear mapping and fault tolerance in practical applications, but it also has some problems. Because the prediction of FMRs involves many factors, information volume and inconsistency between units, it must be pre-processed. When people conduct empirical analysis of a thing, the increase of the comprehensive consideration index would increase its complexity. In order to solve the problems, researchers should not only ensure to minimize variables, but also try to obtain more information when studying multiple index problems.

3.3 PSO-BP NN

BP NN has been widely used in all walks of life, but its own shortcomings are increasingly

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prominent, which has a certain impact on its scope of application. Many scholars have made some improvements to traditional BP, but the results are not consistent. Among them, the most popular is to combine PSO with BP NN, and use PSO to optimize BP NN when BP NN can not meet expectations. This paper uses PSO-BP NN model to predict the FMRs of new energy enterprises

Due to the slow convergence speed of BP NN, it is easy to fall into local minimum, and the initial parameters are difficult to select. Therefore, PSO can be used to optimize the network, thus improving the convergence speed of the network and improving the overall performance of the network. The FMRs prediction based on PSO-BP NN is shown in Figure 3:

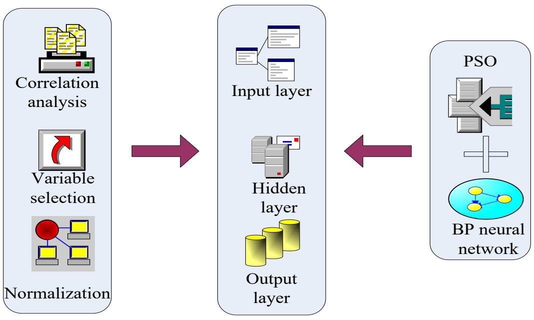

Figure 3 Financial management risk prediction based on PSO-BP NN

Figure 3 shows how the prediction using PSO-BP NN first performs correlation analysis, variable selection and input variable normalization. PSO is easy to use and has good global optimization capability. The current theoretical development is also quite mature, which has obvious advantages for BP NN optimization.

In order to improve and evaluate the traditional BP NN, this paper selects PSO. Figure 4 shows the schematic diagram of PSO:

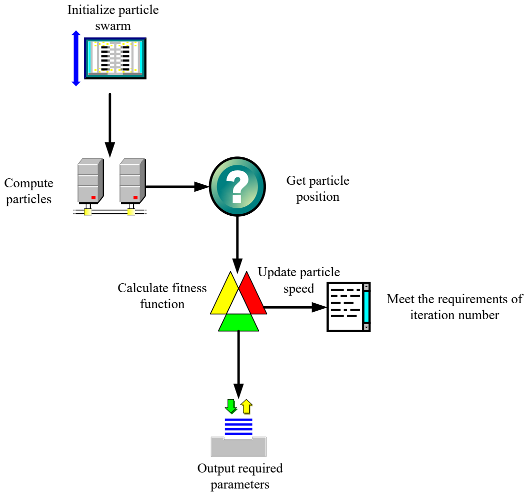

Figure 4 PSO schematic diagram

As shown in Figure 4: PSO first initializes the particle swarm and then calculates the particles, so as to obtain the particle position to calculate the fitness function, update the particle speed to meet the requirements of the number of iterations, and finally output the required parameters. The PSO algorithm assigns the optimal value to the BP NN, and then uses the PSO-BP NN to predict the FMRs of new energy enterprises, and uses the error function to evaluate the prediction results. Based on BP NN, the output node is FMRs degree, and the search space is dimension D:

$$D=(M+1)\times(N+1) \tag{7}$$

The weight and threshold of BP NN correspond to the speed of particle swarm. The weight and threshold of BP NN are usually initialized by the value of [0,1].

The size of particle swarm is determined for practical problems, and the position and speed of particles are initialized and adaptive. The mean square error function is used here:

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$$fitness = \frac{1}{N}\sum_{i=1}^{N}\left(b_{real} - b_i\right)^2 \tag{8}$$

N is the number of training samples, b_{real} is the expected output of the sample, b_i is the actual prediction output of the ith sample, and finally the iteration is completed from the optimized particle. In each iteration, the particle updates its own velocity V_{id}^{k+1} by using individual extremum and global extremum, and its expression is as follows:

$$V_{id}^{k+1} = wV_{id}^{k} + c_1 r_1\left(P_{id}^{k+1} - A_{id}^{k}\right) + c_2 r_2\left(P_{id}^{k} - A_{id}^{k}\right) \tag{9}$$

In the formula, w is the connection weight, c_1 and c_2 are the acceleration factors, and r_1 and r_2 are random numbers distributed between [0,1]. On this basis, this paper modifies the traditional BP NN and adopts the NN error calculation based on the average variance function.

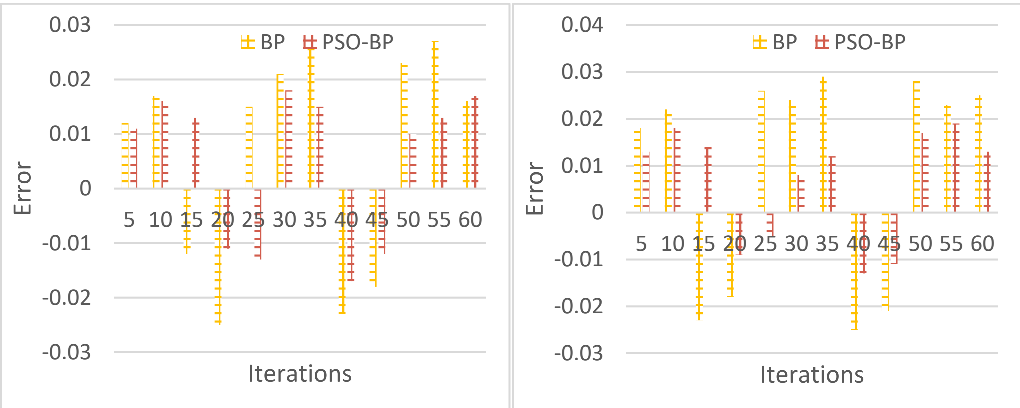
The individual fitness of the current particle swarm can be compared with that of the individual before the iteration. If the current number of particles is good, then the individual fitness of the current particle is the maximum value of the individual of the particle. Under the global optimum condition, if the current fitness of a particle in the existing population is higher than the global optimum, then its current fitness is the global optimum fitness of the population, and its current state is taken as the global extreme value of the population.

4. Prediction effect of PSO-BP NN

4.1 Prediction Error and Speed of Different Algorithms

This paper takes the sample data of financial information risk management of 20 enterprises (a total of 80) with healthy, good, general and serious financial conditions from 2020 to 2021 as the research object. This paper selects 350 groups of data as training samples, 350 groups of data as test samples, and the number of iterations is 60. In this paper, the method of comparative study is used to study the difference of prediction results between BP and PSO-BP NN algorithm.

Parameter setting is very important in BP NN. Instead of relying solely on experience and theory, it is necessary to carry out repeated experiments through BP NN, keep trying, and keep feedback until the error of the model is reduced to the minimum, so as to get the best results.



(a) Prediction error of different algorithms under training samples
(b) Prediction error of different algorithms under test samples

Figure 5 Prediction error of different algorithms under training samples and test samples

The training sample is used to train BP NN to find the optimal parameter combination. Through the training of the sample, the optimal parameter combination can be obtained to predict the financial situation of new energy enterprises. Then, the MATLAB 2012 software is used to input 60 times of iteration to make it reach the convergence state. The prediction error of different algorithms under training samples and test samples is shown in Figure 5.

As shown in Figure 5, it can be seen from (a) that the prediction errors of BP and PSO-BP are 0.012 and 0.011 respectively when the number of iterations is 5 under the training sample.

Through (b), it is found that the prediction errors of BP and PSO-BP are 0.018 and 0.013 respectively when the number of iterations is 5 under the test sample. When the number of iterations is 15, the prediction errors of BP and PSO-BP are -0.023 and 0.014 respectively. When the number of iterations is 30, the prediction errors of BP and PSO-BP are 0.024 and 0.008 respectively. When the number of iterations is 45, the prediction errors of BP and PSO-BP are -0.021 and -0.011 respectively. When the number of iterations is 60, the prediction errors of BP and PSO-BP are 0.025 and 0.013 respectively.

The training speed of different algorithms under training samples and test samples is shown in Figure 6:

(a) Training speed of different algorithms under training samples
(b) Training speed of different algorithms under test samples

Figure 6 Training speed of different algorithms under training samples and test samples

As shown in Figure 6: Through (a) observation, when the training sample is 50, the training speed of BP and PSO-BP is 57.2% and 80.5% respectively. When the training sample is 150, the training speed of BP and PSO-BP is 56.6% and 81.8% respectively. When the training sample is 300, the training speed of BP and PSO-BP is 57.1% and 81.3% respectively. When the training sample is 350, the training speed of BP and PSO-BP is 57.2% and 81.7% respectively.

According to (b), when the test sample is 50, the training speed of BP and PSO-BP is 63.1% and 84.3% respectively. When the test sample is 150, the training speed of BP and PSO-BP is 64.3% and 85.2% respectively. When the test sample is 300, the training speed of BP and PSO-BP is 72.5% and 86.7% respectively. When the test sample is 350, the training speed of BP and PSO-BP is 71.4% and 87.3% respectively.

4.2 Prediction Error Rate of Different Prediction Algorithms

BP NN and PSO-BP NN were used to train 20 enterprises with healthy, good, general, moderate and severe financial status, and the prediction results were statistically analyzed. The error rate of BP NN is shown in Table 1:

Table 1 Error rate of BP NN

Financial situation	Actual quantity	Wrong judgment quantity	Misjudgment rate
Healthy	20	3	15%
Good	20	2	10%
Commonly	20	1	5%
Moderate hazard	20	4	20%
Severe hazard	20	0	0%

As shown in Table 1, this paper conducts experiments on 20 enterprises with healthy, good, general, moderate and severe financial conditions. It was found that in 20 enterprises with healthy financial conditions, the number of miscarriages of BP was 3, and the miscarriage rate was 15%. Among the 20 enterprises with good financial conditions, the number of miscarriages of BP is 2, and the miscarriage rate is 10%. Among the 20 enterprises with average financial status, the number of miscarriages of BP is 1, and the miscarriage rate is 5%. Among the 20 enterprises with moderately dangerous financial conditions, the number of miscarriages of BP is 4, and the miscarriage rate is 20%. Among the 20 enterprises with serious financial risks, the number of miscarriages of BP is 0, and the miscarriage rate is 0%.

The error rate of PSO-BP NN is shown in Table 2:

Table 2 PSO-BP NN error rate

Financial situation	Actual quantity	Wrong judgment quantity	Misjudgment rate
Healthy	20	0	0%
Good	20	0	0%
Commonly	20	0	0%
Moderate hazard	20	1	5%
Severe hazard	20	0	0%

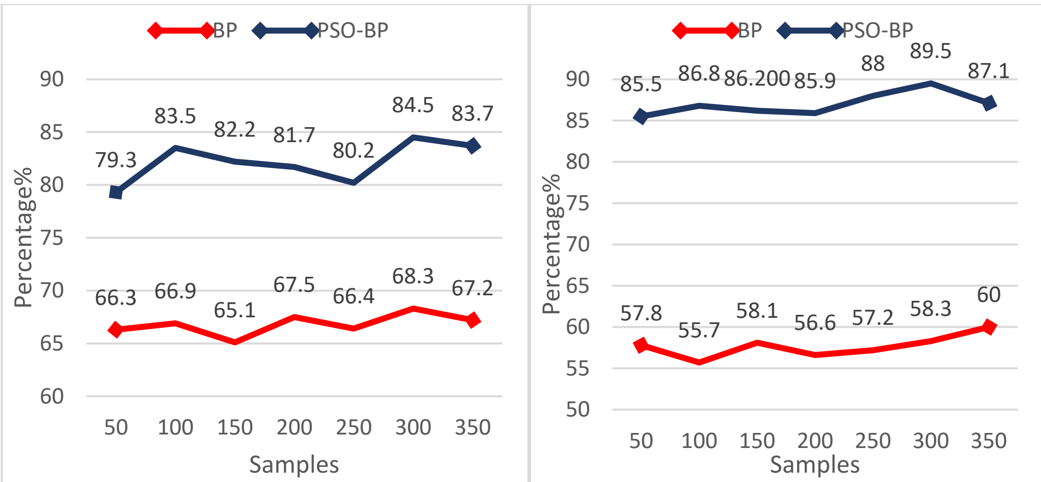
As shown in Table 2, the number of PSO-BP misjudgments is 0 and the misjudgment rate is 0% among 20 enterprises with healthy, good, general and serious financial conditions. Among the 20 enterprises with moderately dangerous financial conditions, the number of PSO-BP misjudgments is 1, and the misjudgment rate is 5%.

PSO-BP NN has good generalization and strong ability of induction and summary, and has good prediction effect for input variables of the same nature.

Compared with BP NN, PSO-BP NN has better operability, scientificity and objectivity. It can timely reflect the financial situation of the enterprise, thus avoiding major financial problems. In this paper, PSO is used to enhance the convergence, thus enhancing the robustness of risk identification. This paper uses PSO to analyze the adaptability of each operation step to reduce the errors of BP NN in risk identification and effectively predict and control the financial information of enterprises.

4.3 Prediction Accuracy of Different Prediction Algorithms

In order to quantitatively analyze the PSO-BP NN, this paper tests the prediction accuracy of the PSO-BP NN. During continuous learning, their prediction ability was improved through repeated practice of samples. Comparative experiments were carried out on the accuracy of different algorithms under training samples and test samples, as shown in Figure 7.



(a) Prediction accuracy of different algorithms under training samples
(b) Prediction accuracy of different algorithms under test samples

Figure 7 Accuracy of different algorithms under training samples and test samples

As shown in Figure 7, it can be seen in (a) that the prediction accuracy of BP and PSO-BP is 66.9% and 83.5% respectively when the number of training samples is 100. When the number of training samples is 200, the prediction accuracy of BP and PSO-BP is 67.5% and 81.7% respectively. When the number of training samples is 300, the prediction accuracy of BP and PSO-BP is 68.3% and 84.5% respectively.

From (b), when the number of test samples is 100, the prediction accuracy of BP and PSO-BP is

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55.7% and 86.8% respectively. When the number of test samples is 200, the prediction accuracy of BP and PSO-BP is 56.6% and 85.9% respectively. When the number of test samples is 300, the prediction accuracy of BP and PSO-BP is 58.3% and 89.5% respectively.

The PSO-BP algorithm proposed in this paper has higher accuracy, which proves that the method proposed in this paper has great potential in financial forecasting. In view of the problem that there are many input variables and large parameters in the enterprise financial forecast, this paper uses BP NN to improve it, and on this basis introduces PSO and BP NN to optimize the parameters.

4.4 Financial Management Risk Response of New Energy Enterprises

(1) Improve enterprise risk control system

The internal risk control system of new energy enterprises involves the whole process of enterprise development, production and sales. Therefore, the modification and improvement of the internal control system of the enterprise must be made by all employees, starting from the comprehensive, scientific and effective principles, and starting from the overall management situation of the enterprise. This paper comprehensively modifies and updates the existing internal control system, and improves and expands the areas not covered by the original system, highlighting the systematic and integrity of the system. Risk management is a top-down transmission process. Managers have a certain understanding of risk control ability and determined the purpose of sustainable development. This can incorporate the corresponding behaviors into the subsequent implementation of the plan and gradually pass them down.

Within a certain period of time, the risk management resources owned by enterprises are limited. How to allocate the limited resources reasonably to achieve the maximum benefits is a problem that every new energy enterprise should consider. The effective allocation of resources depends on the strategic direction of the enterprise, so whether the strategic objectives can be reasonably formulated is the premise to achieve the efficient allocation of resources. At the same time, enterprises must also take the construction of internal control system as a routine work. This would enable all employees and managers to better strengthen the management of risks and make it a good code of conduct. Influenced by its own characteristics, the risk control mechanism of new energy enterprises must keep pace with the times, and must constantly absorb advanced risk control technology and eliminate the previously unscientific methods.

(2) Improve the risk prediction mechanism of financial management

To further improve the FMRs prediction mechanism, it must strengthen the management of the risk process to ensure that it plays its due role in the implementation process. At the same time, real-time monitoring should be carried out. When establishing the FMRs prediction system, it is necessary to clarify the purpose of FMRs control. It determines the current business situation of the enterprise, and carries out targeted design for its existing risks, so as to determine its risk prediction indicators. Financial management risk prediction is a system that runs through the whole business activities and is complementary to the financial evaluation system. The effective prevention of FMRs in the business process has played a positive role in the development of enterprises.

Reducing FMRs is beneficial to create a relatively safe and stable enterprise operation environment. In fact, FMRs in the operation activities of new energy enterprises should be an overall activity involving all departments. A good risk management method is to avoid losses, and the enterprise risk prediction mechanism is an important means for enterprises to carry out FMRs. A monitoring indicator system can be established and relevant indicators can be summarized regularly. The scientific financial forecasting model can be used to evaluate and forecast it and report it to the enterprise management and relevant departments. The financial department should clarify the responsibilities of various risks, not only the responsibilities, but also the subject of responsibility. If risks are found, corresponding measures can be taken.

5. Conclusions

Today, with the rapid development of technology and information, new energy enterprises want to achieve better development. It is necessary to establish a scientific, reasonable and standardized FMRs prediction system to avoid and reduce the losses caused by the FMRs of enterprises, which is conducive to the further improvement of the economic benefits of enterprises. Financial information is

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an indispensable resource for enterprises in the future market competition. There are large errors in the traditional risk prediction methods in financial information management, and it is difficult to meet the requirements of enterprise financial management. In this paper, the PSO-BP NN method was established by combining PSO with BP NN, which reduced the input dimension of BP NN. This paper has carried out experiments on it. The experiments showed that the PSO-BP NN designed in this paper had higher risk prediction accuracy and better application effect.

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