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Corporate Financial Forecasting Models Supported by Differential Evolutionary Algorithms in the New Era Economy

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ABSTRACT

The enterprise financial risk under the new era economy exists in all aspects of enterprise operation, thus this paper screens the enterprise financial risk early warning indicators from the four aspects of enterprise profitability, operation ability, development ability, and debt repayment ability. The logistic Steele model is introduced to optimize the population size function of differential evolution algorithm to achieve the dynamic adaptive population size. Then the adaptive differential evolution algorithm is used to optimize the threshold value of BP neural network, and the neural network prediction model based on the improved differential evolution algorithm is derived. Analyze the operation steps of the improved differential neural network algorithm model in enterprise financial security detection to realize the optimal solution of the enterprise financial risk warning model. Compare and analyze the predicted value of the improved differential neural network algorithm model with the real value of the enterprise financial development, and analyze the use of differential evolutionary algorithm in the prediction of enterprise financial risk.The prediction error of the net asset growth rate of enterprise Q in the 1st quarter and the 3rd quarter of the year 2024 is 0.0119 and -0.05309, respectively, with a smaller absolute value of the error, and the improved differential neural network algorithm is able to effectively predict the corporate financial risk.

Keywords: differential evolutionary algorithm, BP neural network, financial prediction model, financial risk

1. Introduction

In the modern economy, it is crucial to accurately forecast and manage the financial position of a company. Financial forecasting is a process of estimating a company's future financial position and helping to make decisions to achieve financial goals, and financial forecasting is important for business management and decision-making [1-4]. First, financial forecasting can help companies plan and

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manage resources. Through the prediction of existing and future capital needs, enterprises can timely adjust investment plans, financing programs and financial strategies to meet the capital needs of enterprises at different stages [5-8]. Secondly, financial forecasting can provide a basis for enterprise decision-making. By forecasting and analyzing different decision-making scenarios, enterprises can choose the best decision-making scheme and optimize the business results. In addition, financial forecasting can help enterprises assess risks and opportunities [9-12]. By analyzing financial data and market trends, enterprises can identify risks and opportunities in a timely manner and take appropriate measures to reduce risks or exploit opportunities [13-14].

Differential evolution (DE) is a kind of heuristic optimization algorithm, which is a heuristic stochastic search algorithm based on group differences, and the algorithm has the characteristics of simple principle, few controlled parameters, and strong robustness [15-17]. In recent years, DE has been widely used in constrained optimization computation, clustering optimization computation, nonlinear optimal control, neural network optimization, array antenna directional map synthesis and other aspects [18-20]. The DE-supported enterprise financial forecasting model is a modeling method that can be used to predict the future financial situation, and based on the current enterprise financial situation forecast, it can help the enterprise to do the budget planning, capital management and so on [21-23].

Literature [24] assists in risk management and investment decision-making based on artificial intelligence (AI) deep learning algorithms by using ARIMA regression models to predict corporate financial anomalies and development trends in order to cope with financial risks and capitalize on investment opportunities. Literature [25] describes the application of AI-driven predictive analytics models in financial forecasting, and by assessing the capabilities of AI predictive analytics, it points out that it has had a positive impact in refining risk assessment and supporting decision-making, but it also faces barriers to AI financial forecasting, such as data security and model interpretability. Literature [26] introduces the drivers of enterprise value and mainstream value assessment methods from both financial and non-financial aspects based on the literature review of financial analysis, points out the problems of the current mainstream valuation methods through comparison, and puts forward coping strategies. Literature [27] examines the application of four models, namely, LSTM, Z-score, Logistic and BP neural network, in financial forecasting, and discusses the feasibility of recurrent neural network in the early warning of corporate financial risk, showing that BP model is superior to other models in corporate financial forecasting and has an impact on corporate financial forecasting. Literature [28] utilizes time series forecasting and BP neural network algorithm for financial early warning, and compares the prediction error values of the two methods, and applies them to the combination forecasting method, which reveals that the BP method is the best in forecasting, and that the combination forecasting method is superior to any other method. Literature [29] explored the problem of financial crisis prevention of enterprise system, proposed the early warning and crisis prevention mechanism of enterprise system, constructed the estimation model of crisis threat of enterprise system by utilizing neural network and other methods in order to predict the threat of financial crisis of the enterprise, including the current and the future, and verified its effectiveness. Literature [30] introduces the early warning method of enterprise financial risk based on the evidence theory-random forest (DS-RF) model, and the comparison of early warning results by other methods reveals that the DS-RF model has higher early warning accuracy, improves the efficiency of enterprise financial risk early warning, and is conducive to the enterprises to make response decisions. Literature [31] analyzes the intelligent prediction model of enterprise financial risk from the perspective of budget constraints, and describes the composition of the model and constructs a quantitative financial indicator system, which is conducive to improving the governance efficiency of enterprises. The above study examines the effective application of enterprise financial forecasting models using ARIMA regression model, BP neural network model, DS-RF model, etc., and describes that the application of these models in financial forecasting helps enterprises to make corresponding countermeasures for financial problems.

This paper puts forward the process of differential evolution algorithm and points out the deficiencies of the algorithm, and carries out adaptive optimization of the differential evolution algorithm. The BP neural network is used as the enterprise financial prediction model in this paper, and the weights and thresholds of the neural network are optimized by the adaptive differential evolution algorithm, so as to improve the accuracy of the BP neural network in the prediction of enterprise financial risk. Build the adaptive differential evolutionary algorithm to optimize the BP neural network process framework, and propose the improved differential neural network algorithm model. Analyze the characteristics of financial risk in the new era, screen out the early warning indicators of corporate financial risk in the new era, and use the improved differential neural network algorithm to find the optimal solution of corporate financial prediction. Compare the predicted and real values of the model with the four dimensions of profitability, operation capability, development capability and debt repayment capability of the enterprise.

2. Improvements in adaptive differential evolutionary algorithms

2.1. Differential Evolutionary Algorithm

Differential evolutionary algorithm (DE) is simple to implement and has a short operation process, which mainly includes four basic operations: initialization, mutation, crossover and selection of the population. The basic idea of the algorithm is that the initial population vector $x_{ij}=\left[x_{i1},x_{i2},\cdots,x_{ij}\right],i=1,2,\cdots,NP,j=1,2,\cdots,D$ consists of NP individuals with D -dimensional decision variables, and a new individual vector is formed by superimposing a random individual vector of the population with two other difference vectors different from this individual vector with certain weights, which is the mutation operation. Then this individual vector and the target vector are exchanged and mixed by a certain method with corresponding dimensional positions to form a new individual vector, this process is called crossover. Compare the crossover individual with the parent, if the crossover individual has better fitness value than the parent, then the crossover individual will successfully participate in the next generation and replace the parent, on the contrary, the parent will replace the crossover individual to enter the next generation, which is called the selection operation. After each generation of iteration, the optimal individual vector is selected as the final vector, which is called the global optimal solution [32].

Population initialization is the generation of NP D -dimensional individual $x_{i,j}$ within a specified feasible domain according to a certain equation, which generates individuals as shown in equation (1):

$$x_{i,j}^{(0)}=L_j+rand(0,1)\cdot(U_j-L_j) \tag{1}$$

where L_j,U_j is the lower and upper bounds of the decision variable, respectively. $x_{i,j}^{(0)}$ is the j th component of the initial individual vector $x_{i,j}^{(0)}=\left[x_{i,1}^{(0)},x_{i,2}^{(0)},\cdots,x_{i,p}^{(0)}\right](i=1,2,\cdots,NP)$ at iteration number $t=0$, D denotes the decision space dimension, NP denotes the initial population size, and $rand(0,1)$ denotes a random number within 0 to 1.

The mutation operation is the core of the DE algorithm, and at generation G, the individuals are mutated to produce a new vector $v_i^{(G+1)}=\left\{v_{i,1}^{(G+1)}\,v_{i,2}^{(G+1)}\cdots v_{i,D}^{(G+1)}\right\}$. The mutation operation mainly consists of a difference vector and a basis vector, and the basic form is shown in equation (2):

$$v_i^{(G+1)}=x_{r1}^G+F\times(x_{r2}^G-x_{r3}^G) \tag{2}$$

where $v_i^{(G+1)}$ denotes the vector of variant individuals for the G-generation individual $x_{i,j}^{(G)}$. x_{r1}^G is the base vector, and $(x_{r2}^G - x_{r3}^G)$ is the differential individual vector. F is the learning factor, also known as the scaling factor, which controls the learning speed of the difference vector to approach the base vector, and is generally in the range [0, 1]. $r1, r2, r3$ represents the subscripts of individuals randomly selected from the population, and $r1 \neq r2 \neq r3$, $r1, r2, r3 \in [1, NP]$, The above variation strategy is the "DE/rand/1" strategy, and other commonly used variation strategies are as follows:

"DE/rand/2":

$$v_i^{(G+1)} = x_{r1}^G + F \times (x_{r2}^G - x_{r3}^G) + F \times (x_{r4}^G - x_{r5}^G) \tag{3}$$

"DE/best/1":

$$v_i^{(G+1)} = x_{best}^G + F \times (x_{r1}^G - x_{r2}^G) \tag{4}$$

"DE/best/2":

$$v_i^{(G+1)} = x_{best}^G + F \times (x_{r2}^G - x_{r3}^G) + F \times (x_{r4}^G - x_{r5}^G) \tag{5}$$

"DE/current to best/1":

$$v_i^{(G+1)} = x_i^G + F \times (x_{best}^G - x_i^G) + F \times (x_{r1}^G - x_{r2}^G) \tag{6}$$

where x_{best}^G represents the individual with the lowest adaptation value in the G nd generation population. The DE algorithm is based on the base vectors, which are merged with the difference vectors to obtain new vectors of variant individuals, the difference vectors perturb the base vectors, and the learning factor *F* added to the difference vectors controls the rate at which the difference vectors learn from the base vectors, and likewise the balance between diversity and convergence within the population.

A crossover probability parameter *CR* is introduced in the crossover operation to control the probability of selection of two individual paralogous genes. Commonly used crossover operations are binomial crossover and exponential crossover, where binomial crossover usually deals with problems where there is no obvious relationship between the variables, and exponential crossover usually solves problems where there is a link between the variables.

Two crosses:

$$u_{i,j}^{(G+1)} = \begin{cases} v_{i,j}^{(G+1)} & rand(0,1) \leq CR \text{ or } j = jrand \\ x_{i,j}^{(G)} & \text{Or else} \end{cases} \tag{7}$$

$jrand$ denotes a random value within $[1, 2, \cdots, D]$, and $rand$ denotes a [0, 1] random value. $x_{i,j}^{(G)}$ denotes the j th component in the ith individual of the parent, and $v_{i,j}^{(G+1)}$ is the j th component in the i th individual of the variant individuals. Where $i = 1, 2, \cdots, NP, j = 1, 2, \cdots, D$. The crossover probability within $CR \in [0,1]$, indicates the proportion of experimental vectors in the variant individuals, and $j = jrand$ indicates that at least one of the variables comes from the variant individual vector.

The selection strategy of the differential evolutionary algorithm first calculates the fitness values of all generated individuals and then compares them one by one with the target vector fitness values. For the minimization problem, if the adaptation value is lower, then it means that the vector is better, and the individual vector corresponding to this adaptation value is retained into the next generation, otherwise the target vector is retained into the next generation of individuals to continue iterating, as follows:

$$x_i^{(G+1)} = \begin{cases} u_i^{(G+1)} & f(u_i^{(G+1)}) < f(x_i^{(G)}) \\ x_i^{(G)} & \text{Or else} \end{cases} \tag{8}$$

$f(\cdot)$ represents acclimatization values, and $x_i^{(G+1)}$ represents individuals that successfully entered the $G+1$rd generation.

2.2. BP Neural Network Model

BP neural network is the model for corporate financial forecasting in this paper, and it is chosen because of its good fitting ability. And, unlike deep learning, the three-layer BP neural network does not require a particularly large amount of data to produce a good fit, so it is used as a financial forecasting model in this paper.

BP neural network is a shallow neural network with an input layer, a hidden layer and an output layer. It is important to design the network structure of BP neural network properly.

Forward propagation of BP neural network. Each layer of neurons is connected to the lower layer of neurons by connecting the weights to perform the corresponding operations. For a neuron in a non-input layer, the input can be expressed as follows:

$$\sum_{i}^{n} w_i x_i \tag{9}$$

where x_i represents neurons, w_i represents connection weights, and n is the number of neurons in this layer.

Take a neural network with a single hidden layer as an example to describe its derivation process. Suppose the set of input samples is X. For a single sample $x \in X, x = (x_1, x_2, ..., x_n)$, each sample can be regarded as a n-dimensional vector. In Eq. (10), w_{ih} is the connection weight from the input layer to the hidden layer, b is the bias of the hidden layer neuron, and the hidden layer neuron h_i can be expressed by Eq. (10):

$$h_i = \sum_{i=1}^{n} w_{ih} x_i + b \tag{10}$$

The output vector of the hidden layer is $h_{outi} = f(h_i)$, where function f is the activation function. The neurons in the output layer can be represented by equation (11):

$$y_i = \sum_{i=1}^{n} w_{hy} h_{outi} + b \tag{11}$$

where w_{hy} is the hidden layer to output layer connection weights and b is the bias of the neurons in the output layer.

The output vector of the output layer is $y_{out} = f(y_i)$. It can be seen that the dimensions of the inputs and outputs of each layer are the same, and that the dimensions of the last output layer are the same as the final desired result $d = (d_1, d_2, ..., d_m)$. Therefore, if the root mean square error is used to define the loss, the error function can be defined in the form of the following equation, where L is the error value:

$$L = \frac{1}{2} \sum_{i=1}^{m} (d_i - y_{out})^2 \tag{12}$$

The partial derivative of the error function with respect to the connection weights w_{hy} of the hidden and output layers can be expressed in the following equation:

$$\frac{\partial L}{\partial w_{hy}} = \frac{\partial L}{\partial h_{out}} \cdot \frac{\partial h_{out}}{\partial w_{hy}} \tag{13}$$

And one of them, can be further written in the form of the following equation:

$$\frac{\partial h_{out}}{\partial w_{hy}} = \frac{\partial f\left(\sum_{i}^{m} w_{hy} h_{outi} + b\right)}{\partial w_{hy}} \tag{14}$$

Then, one can proceed to calculate the partial derivatives of the error function with respect to the hidden layer neurons with the formula shown below:

$$\frac{\partial L}{\partial h_i} = \frac{\partial\left(\frac{1}{2}\sum_{i=1}^{m}(d_i - f(w_{ho}h_{outi} + b))^2\right)}{\partial h_{outi}} \cdot \frac{\partial h_{outi}}{\partial h_i} \tag{15}$$

And, the global error can be expressed by the following equation:

$$E = \frac{1}{2n}\sum_{i=1}^{n}\sum_{j=1}^{m}(d_j - y_i)^2 \tag{16}$$

BP neural networks have weak global search capability and may fall into “local optimization”. Although neural networks are a good fit, there are some problems. For example, the neural network solves for the optimum using a gradient descent algorithm, but the gradient descent algorithm may fall into a “local optimum”. BP neural networks are generally more complex due to the error function that is searched as a result of optimization by “step size”. When the function is relatively "flat", the step size may be small, the optimization speed may be slow, and the step size of each iteration is too large and may "cross" the optimal solution, while the use of "dynamic step size" requires the formulation of iterative rules in advance, which will increase the time complexity. Therefore, a function that can quickly find the neighborhood of the global optimal solution is needed, and the differential evolution algorithm can be a good solution to the above problem.

2.3. Improved model of differential neural network algorithm

2.3.1. Defects and Improvements in Differential Algorithms. In this paper, on the basis of classical differential algorithm, the law of change of biological population size is introduced, so that the population size, deflation factor and crossover rate of differential evolution algorithm can adaptively change, and the standard differential evolution algorithm can be improved to achieve the purpose of optimizing the differential evolution algorithm.

Logistic Steele model is a famous model of the change law of biological populations. It exposes the law of the change of the number of members of the population in the process of dynamic evolution of biological populations. Therefore, in this paper, it is used in the change function of population size in differential evolutionary algorithm using the logistic Stee model as in order to achieve the dynamic adaptive of population size. The adaptive population size formula is as follows:

$$POP(t) = \frac{POP_{min}e^{at} - POP_{max}e^{-at}}{e^{at} + \left(\frac{POP_{min}}{POP_{max}} - 2\right)e^{-at}} \tag{17}$$

where t is the number of current population iterations and a is the regulation parameter. $POP(t)$ is rounded to the nearest whole number in the algorithm. The other two important parameters of the differential evolution algorithm are the crossover rate CR and the scaling factor F . In the algorithm's mutation operation, in order to be able to quickly grasp the global situation and improve the global optimization ability, it is necessary to make the scaling factor F larger. But not the larger the better, F but after reaching a certain level the convergence speed of the algorithm will be affected. Therefore, a dynamic change process is needed to make the search ability and convergence speed of the algorithm reach a relative balance.

In order to be able to take into account the search ability, its value should be increased appropriately. In this paper, the adaptive parameter formulas for F and CR are designed as follows:

$$F(t) = \frac{F_{min} e^{\omega t} - F_{max} e^{-\omega t}}{e^{\omega t} + \left(\frac{F_{min}}{F_{max}} - 2 \right) e^{-\omega t}} \tag{18}$$

$$CR(t) = \frac{CR_{\max} e^{at} - CR_{\min} e^{-at}}{e^{at} + \left(\frac{CR_{\max}}{CR_{\min}} - 2 \right) e^{-at}} \tag{19}$$

where t is the number of current population iterations and a is the regulation parameter.

The variation strategy also has a certain impact on the global contraction and convergence speed of the differential evolutionary algorithm. The newly adopted variation strategies in this paper are as follows:

$$V_{i,G} = \lambda X_{r1,G} + F * (X_{r1,G} - X_{r2,G} + \lambda (X_{r3,G} - X_{r4,G})) \tag{20}$$

where $\lambda = (T - t) / T$, T is the total number of iterations, the new mutation strategy introduces the addition of momentum factor λ, which enables the mutation strategy to dynamically adapt to the evolutionary demands as the number of iterations increases. So that the algorithm has a strong global contraction ability at the beginning of the evolution, convergence speed is faster, and at the later stage of the accuracy has improved accuracy.

2.3.2. Adaptive Differential Evolutionary Algorithm to Optimize BP Neural Networks. This paper is based on differential evolutionary algorithm and BP neural network, proposed based on adaptive differential evolutionary algorithm optimization of the neural network algorithm, and in the enterprise financial risk detection application.

In the process of the improved differential evolutionary algorithm to optimize the BP neural network, the object of optimization is the BP neural network weights and thresholds. In this way, the BP neural network can play its performance better, and at the same time avoid the defects of the BP algorithm. In this way, the BP neural network will have a better performance and improve the accuracy in the enterprise financial risk detection.

Adaptive Differential Evolutionary Algorithm Optimization BP neural network optimization process is shown in Figure 1. The improvement of BP network in this paper is to make the improved differential evolutionary algorithm combined with it. The error function of the network is taken as the middle indicator of the differential algorithm in the selection process, and the weight and threshold parameters of the neural network are taken as the population of the improved differential evolutionary algorithm. In this way, the improved differential algorithm is combined with the BP neural network, the BP neural network selects the population for the differential algorithm, and the differential algorithm helps the BP neural network to select the best initial weight parameters. Ultimately, the purpose of optimization is achieved.

The optimization process is described as:

Step 1: Start to select the training samples, initialize the neural network parameters, initialize the differential evolution algorithm population and parameters. The neural network parameters are used as the differential evolution algorithm parameters.

Step 2: Calculate the population fitness (using the neural network error as the fitness).

Step 3: Judge whether the fitness value meets the error termination condition, meet the termination condition jump to step eight, do not meet for step four.

Step 4: Perform the mutation operation of the new strategy on the population composed of the weight threshold.

Step 5: Perform the new strategy crossover operation on the population composed of weight thresholds.

Step 6: Selection operation is performed on the population consisting of weight value thresholds to obtain a new population.

Step 7: The number of iterations t=t+1 and the population size is adaptive according to the iterations. Then, return to step two.

Step 8: Assign the population that meets the conditions to the neural network and start training the neural network until the termination conditions are met.

After the above process, the theoretically optimized algorithm will absorb the advantages of the original differential algorithm, and at the same time get rid of its own fall into the local optimum problem, speeding up the speed of the algorithm. Let the BP neural network in the original contradiction has been balanced, the formation of a virtuous cycle.

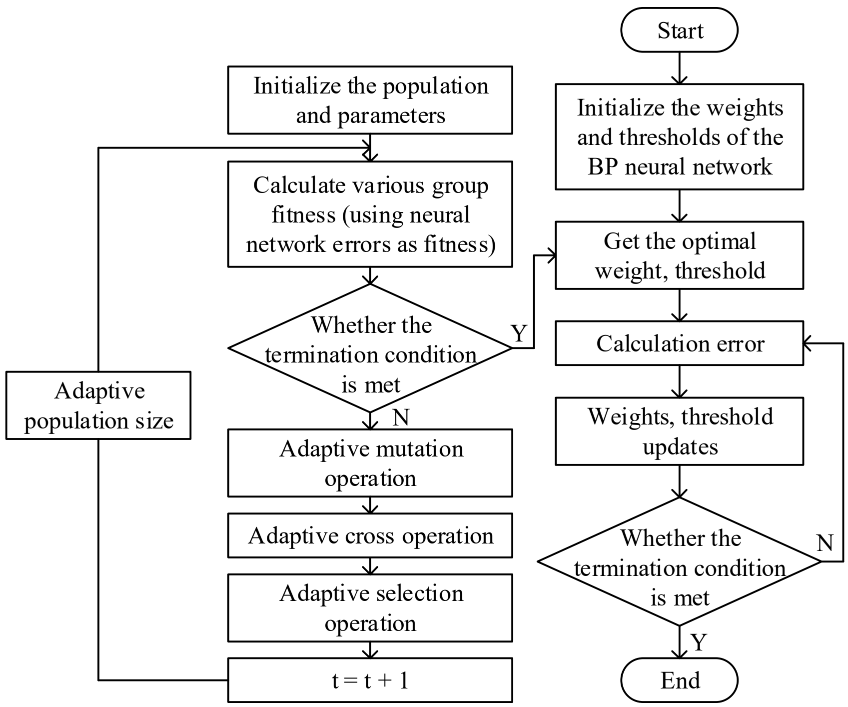

Fig. 1. The difference evolution algorithm optimises the bp neural network process

3. Enterprise financial forecasting model construction and application

3.1. Enterprise financial risk management in the new era

Under the economic system of the new era, the national economy is growing and developing steadily, and the overall development direction and pattern has been gradually improved and formed. At this moment it brings an opportunity for enterprises to grow and develop, and it is also a challenge for the enterprises themselves, which can not only improve the comprehensive competitiveness of the enterprises, but also promote the innovative development of the enterprises, so it is vital for the enterprises to continuously strengthen the internal management. In an enterprise, risk and management are inseparable, financial management is the key to the internal management of the enterprise, which is also the core content of the work of the enterprise, can to a certain extent to avoid the occurrence of risk, is conducive to avoiding the generation of financial risk, financial management and financial risk is closely related to the work, throughout the development of the enterprise [33-34].

Enterprises want to do a good job in the management of financial risk, we must first understand the characteristics of financial risk:

1) The source of enterprise financial risk factors, will be affected by various aspects. For the outside of the enterprise, it will be affected by the market economic environment, the relevant national legal policy and the current currency circulation policy and other factors. For the internal enterprise, will be subject to risk management system, internal control system restrictions.

2) Enterprise financial risk exists in all aspects of enterprise operation, including financing, investment, capital recovery and income distribution. Enterprise financial risk has complexity, financial risk is related to all aspects of production, operation and management of the enterprise, in the implementation of the management of financial risk, according to the actual situation of the enterprise's operation and development, need to be flexible and appropriate adjustments.

3.2. Establishment of an indicator system

The selection of the financial sample set must consider the accuracy of the empirical results and select reasonable and reliable sample data. This paper defines ST companies of listed enterprises as financial crisis enterprises and non-ST companies as financial health enterprises.

According to the annual report disclosure system of listed enterprises, the listed company is made special treatment year positioning T year that is the year of financial crisis, then a listed company in T year whether special treatment by the company in the previous year that is the financial report published in the year T-1, and the two almost at the same time. Therefore, if the early warning model is built only on the basis of the financial data of year T-1, the predictive ability of the early warning model will be overestimated, and its application will not be reflected in the actual prediction.

Listed companies on the disclosure of non-financial information on the relevant report pointed out that 99% of listed companies to provide non-financial information disclosure is not qualified, and because the financial indicator information can indirectly reflect the non-financial indicator information, so this paper from the enterprise reimbursement capacity, profitability, operational capacity, development capacity of the four aspects of the selection of the relevant financial indicators to establish early warning indicator system. Enterprise financial crisis early warning indicators are shown in Table 1.

Profitability includes: total asset margin, cost and expense margin, net sales margin, return on net assets, cash ratio.

Repayment ability includes: current ratio, earnings per share, gearing ratio, operating cash debt ratio, cash flow ratio.

Development capability includes: growth rate of main business income, growth rate of total assets.

Operating capacity includes: inventory turnover ratio, total asset turnover ratio, current asset turnover ratio.

Table 1. Enterprise financial crisis warning index

	Index type	Index name
Enterprise financial crisis warning index system	Profitability	Gross margin
		Cost margin
		Net profit
		Return on equity
		Cash ratio
	Solvency	Mobility ratio
		Earnings per share
		Asset ratio
		Cash liability
		Cash flow ratio
	Development ability	Main business revenue growth

		Total asset growth rate
	Operational capacity	Inventory turnover
		Total asset turnover
		Turnover of current assets

3.3. Predictive Model Realization

The principle of the multi-indicator financial risk prediction model based on the improved adaptive difference algorithm optimized BP neural network is as follows:

Let the input data be $X=[x_1,x_2,\ldots,x_n]$ and the data dimension be m. The execution steps of the comprehensive evaluation method of corporate financial risk based on adaptive differential evolutionary algorithm are as follows:

Firstly, the input data are standardized using equation (21):

$$x' = \frac{x-\overline{x}}{S_j} \tag{21}$$

where $\overline{x}$, S_j are the mean and standard deviation of the input data x, respectively, and the formulas are shown in Eqs. (22) and (23), respectively:

$$\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{22}$$

$$S_j = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\overline{x})^2}{n-1}} \tag{23}$$

Complex correlation coefficient method, mean value method and so on are used to calculate the index weights.

Since the problem solved at this time is a constrained nonlinear optimization problem, the improved differential neural network algorithm model is used to find the optimal solution of this optimization model:

1) Set the experimental parameters of the adaptive differential evolutionary algorithm: population size, iteration number, variance factor F, crossover factor CR.

2) Initialize the population with initial population $X(0)$ and current number of generations $t=0$.

3) Calculate the value of the fitness function of the individuals of the population $J(X(t))$.

4) Execute the mutation operation, use DE/rand/1 mutation method to generate mutated individuals $V_i(t)$, as shown in the following equation:

$$V_i(t) = X_a(t) + F\times(X_b(t)-X_c(t)) \tag{24}$$

where $X_a(t), X_b(t)$ and $X_c(t)$ are three distinct individuals in the trd generation population.

5) Perform the crossover operation using binomial crossover for the population individuals and the variant individuals to obtain the experimental individuals. The binomial crossover formula is shown in the following equation:

$$u_i(t) = \begin{cases} v_i(t), \text{if } rand_j(0,1) \le CRor(j=Ir) \\ x_i(t), \text{otherwise} \end{cases} \tag{25}$$

6) Perform a selection operation to select individuals with better adaptation values as offspring into the new population by the following equation:

$$x_i(t+1)=\begin{cases}u_i(t),\text{if } f(u_i(t))\le f(x_i(t))\\ x_i(t),\text{if } f(u_i(t))> f(x_i(t))\end{cases} \tag{26}$$

7) Algorithm termination test. When the number of iterations reaches the preset maximum number of iterations or the objective function reaches the preset accuracy, the algorithm terminates and outputs the optimal solution X_{best} and the value of the optimal fitness function $f(X_{best})$. Otherwise, it returns to (3) to continue the process of sending generations.

The optimal solution obtained is used as the integrated weight of the indicator, and the integrated weight vector W is obtained, as shown in the following equation:

$$W=\left[w_1,w_2,\dots,w_m\right]^T=\left[x_1,x_2,\dots,x_m\right] \tag{27}$$

A comprehensive risk evaluation of the corporate financial security forecast data using the indicator composite weight vector W yields a comprehensive corporate financial security risk evaluation value Y, as shown in the following equation:

$$Y=\begin{bmatrix}y_1\\y_2\\\cdots\\y_n\end{bmatrix}=X\cdot W=\begin{bmatrix}x_{11}&x_{12}&\cdots&x_{1m}\\x_{21}&x_{22}&\cdots&x_{2m}\\\cdots&\cdots&\cdots&\cdots\\x_{n1}&x_{n2}&\cdots&x_{nm}\end{bmatrix}\begin{bmatrix}w_1\\w_2\\\cdots\\w_n\end{bmatrix} \tag{28}$$

Usually the acquired sample data will have some ambiguities due to the existence of the financial statement itself, etc. In order to avoid interfering with the training process, it is necessary to screen the selected data and eliminate the data that have a large difference with the other data levels. And because the meaning of the financial indicator data is not the same, therefore, this paper adopts the proportion of compression method to normalize all the data before the BP network training. After normalization, the sample data will fall within [-1~1].

Since the number of nodes in the input and output layers of the BP neural network will be swayed by the actual problem, according to the financial indicators such as cost-expense margin, total asset turnover, total asset growth rate, liquidity ratio and operating cash debt ratio, it can be seen that the number of neural units in the input layer is 15. The output case is classified into two cases of 1 and 0 based on whether or not it is processed by the ST, i.e., there is only one output. Through many experiments and analysis, the number of neural units in the implied layer is finally selected as 18.

The corporate financial warning model is implemented using C++ as the development language and VC6.0 as the development tool, and is trained by importing the financial warning sample.txt document data, followed by the prediction.

4. Results and analysis of enterprise financial projections

4.1. Data sources and sample selection

The quantitative data in this paper mainly come from CSMAR database and WIND database, while the text-based data of company annual reports are mainly obtained from Oriental Fortune and Juchao. Since data from different industries are not sufficient for horizontal comparison, this paper constructs a financial risk prediction model based on the quantitative data and text-based data of listed companies in the industry of manufacturing.

Listed companies in the manufacturing industry that were first ST during the five-year period from January 1, 2019, to January 1, 2024, were selected, and companies that had been ST many times and had extremely unstable financial conditions were excluded to prevent them from affecting the accuracy of the model. At the same time, companies with too much missing data or text are excluded, and finally listed manufacturing companies that were ST for the first time are selected. Non-ST listed manufacturing companies with similar listing time and smaller difference in asset size are randomly selected as paired samples in the ratio of 1:1 to prevent the extreme imbalance of sample data from affecting the accuracy of the model.

4.2. Model analysis

Financial data indicators can reflect the earnings, costs and losses as well as future development trends of listed companies in the process of production, operation, sales and other aspects, etc. Extracting important financial indicators for modeling and analysis can predict certain risks in advance.

For the study of financial risk prediction based on quantitative data, this paper takes quantitative financial and non-financial indicators as model inputs, and utilizes machine learning models SVM, Random Forest, XGBoost, and the improved differential neural network algorithm model proposed in this paper to predict the financial risk of listed companies.

In this paper, a total of 300 samples are selected, in which the ratio of ST listed companies to non-ST listed companies is 1:1, 20% of all sample companies, i.e., 60 listed companies, are randomly selected as the test set, and the remaining 240 listed companies are used as the training set of the model.

In the training set and test set, the ratio of ST-listed companies to non-ST-listed companies is still 1:1. For model output, according to the relevant library package for machine learning models in python, it can output whether a sample company is ST or not, and also the probability of whether a sample company is an ST company (p_1, p_2). p_1 denotes the probability that the sample firm is an ST firm, and p_2 denotes the probability that the model predicts that the sample firm is a non-ST firm. In addition, the threshold value selected in this paper is 0.5, i.e., when the test set samples are substituted into the prediction value derived from the model trained using the training set. If it is greater than the threshold value of 0.5, the model is judged to be a listed company in the ST manufacturing industry, and if it is less than the threshold value of 0.5, the model is judged to be a listed company in the non-ST manufacturing industry.

For the same training set and test set, this paper uses different models to carry out the corresponding training and testing, in order to effectively verify the improved differential neural network algorithm model prediction performance. The specific parameter values of each model are shown in Table 2. Where the parameter C represents the penalty coefficient of SVM model, the larger the value of the model is more likely to overfitting, in order to maintain the generalization ability of the model, this paper sets the value of C to 0.720.

Table 2. The specific parameters of the models

Model	SVM	Random forest	XGboost	Improved differential neural network algorithm model
Parameter	/	n_estimators=120	num_round=231	/
	$C = 0.720$	criterion=‘entropy’	subsample=0.99	F(0.5, 0.3)
	kernel=‘rbf’	max_depth=6	eta=0.03	Number of nerve units=18
	gamma=0.0075	max_features=22	gamma=0.6	Sample size[-1,1]

In this paper, 240 listed companies in the manufacturing industry were randomly selected as the training set for training, and the trained model was used to predict whether the remaining 60 listed companies in the manufacturing industry in the test set had financial risks, and the final model prediction results were shown in Table 3.

The accuracy of the four models, SVM, Random Forest, XGboost, and Improved Differential Neural Network Algorithm model, all reach 80% and above. The accuracy rate of the improved differential neural network algorithm model is better than the remaining three models. In predicting financial risk, the percentage of all listed companies that were predicted to be ST was higher than those that were actually ST as well. Its specificity is also significantly better than SVM and XGboost models. If manufacturing listed companies need to go as far as possible to identify all financially normal companies accurately in real situations, the improved differential neural network algorithm model can be chosen.

Table 3. Different model prediction results

Model	Accuracy rate	Precision rate	Recall rate	F1score	Specificity	AUC
SVM	0.8231	0.7556	0.8235	0.8178	0.7595	0.8657
Random forest	0.8569	0.8295	0.7963	0.8062	0.8614	0.8773
XGboots	0.8611	0.7519	0.8984	0.8279	0.7793	0.9124
Ours	0.8704	0.8493	0.9021	0.8281	0.8802	0.9356

4.3. Evaluation of the effectiveness of enterprise financial forecasting

In this paper, firm Q is selected for financial risk prediction. Q Enterprises, as a manufacturing company, has the core competitiveness consisting of brand quality, advocating green and healthy lifestyle, excellent production location and unique process advantages. The company has weathered the storm, against the current, has a strong anti-risk ability. Q Enterprises upholds the quality concept of integrity and trust, and has a loyal customer base.

Optimization of BP neural network using differential evolutionary algorithm to build improved differential neural network prediction model is based on the financial data between 2019 and 2023, and the prediction results obtained are the profitability, operating capacity, development ratio, solvency and cash flow financial data for three quarters of 2024.

Comparing the real 2024 financial data with the data obtained from the prediction, it can be proved that the accuracy of the prediction data of the prediction model based on the improved differential neural network used for financial prediction is worthwhile.

4.3.1. Profitability. The accuracy of the improved differential neural network prediction model is judged to be qualified by comparing the absolute error between the predicted value and the true value.

The predicted value of profitability, the real value is shown in Figure 2. It reflects the absolute error between the predicted value and the real value of profitability. According to the improved differential neural network prediction model fitting data, the average absolute error absolute value of the model is 0.0451, which also means that the absolute error absolute value is less than or about 0.0451 is trustworthy.

According to the data in the figure, it is obvious that the acceptability of the absolute error of the forecast value and the real value is high, indicating that the forecast of the model is accurate. It also shows that the profitability in the three quarters of 2024 is maintained at a normal level without major adjustments. Summarizing the data in the figure, it can be concluded that the improved differential neural network prediction model is accurate for the prediction of profitability indicators.

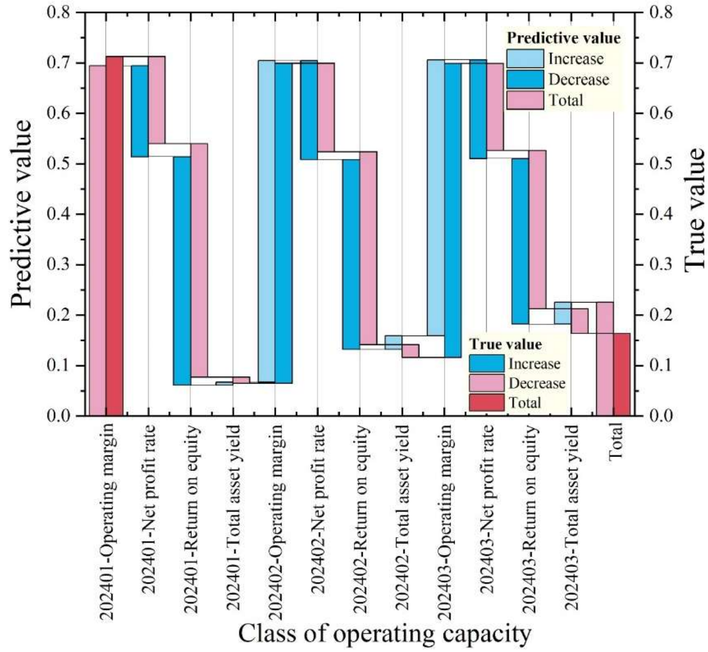

Fig. 2. Predictive value and real value of profitability

4.3.2. Operational capacity. The predicted value, true value and absolute error of operational capacity are shown in Table 4, which demonstrates the predicted and true values of accounts receivable turnover, inventory turnover, current asset turnover, fixed asset turnover, and total asset turnover of enterprise Q in three quarters in 2024.

It can be known that the predicted values and the real values have a good fit, that is, the improved differential neural network prediction model almost accurately predicts each index, and the error is controlled within the range of [-4,0.3].

However, looking closely at the predicted and true values, it is easy to see that the turnover of accounts receivable is significantly lower than the conventional value, indicating that the true situation is as predicted, and the turnover of accounts receivable is a noteworthy problem.

Firm Q has maintained good profitability despite the setbacks in the industry as a whole, however, the lower turnover of accounts receivable shows that perhaps the firm has adopted a relaxed credit policy. When a firm relaxes credit terms and credit periods, it stimulates sales growth. However, it can also increase the amount of accounts receivable and thus reduce the rate of accounts receivable around. As far as the current data is concerned, there should be increased vigilance on this indicator.Q Companies should determine a reasonable credit policy based on the actual situation and strengthen the collection of goods to increase the rate of accounts receivable around as much as possible.

Table 4. Operational ability predictive value, real value and absolute error

Year	Operational capacity category	Predictive value	True value	Error
202401	Receivable turnover	0	3.05127	-3.05127
	Inventory turnover	0.46362	0.55108	-0.08746
	Turnover of current assets	0.20231	0.18924	0.01307
	Fixed asset turnover	0.51326	0.46362	0.04964
	Total asset turnover	0.13889	0.13362	0.00527
202402	Receivable turnover	0	3.99005	-3.99005
	Inventory turnover	0.81793	0.97031	-0.15238
	Turnover of current assets	0.40369	0.31425	0.08944
	Fixed asset turnover	1.09063	0.82664	0.26399
	Total asset turnover	0.31006	0.21364	0.09642
202403	Receivable turnover	0	2.89543	-2.89543
	Inventory turnover	1.24436	1.41223	-0.16787
	Turnover of current assets	0.55639	0.42458	0.13181
	Fixed asset turnover	1.40397	1.14266	0.26131
	Total asset turnover	0.40124	0.32117	0.08007

4.3.3. Developing capacity. The predicted, true and absolute errors of growth capacity are shown in Figure 3. It can be clearly observed that the error between the predicted value and the true value of the indicators responding to the growth ratio is much larger relative to the profitability indicators, operation indicators and solvency indicators.

The predicted and true values of net asset growth rate of enterprise Q in the first quarter of 2024 are 0.9836 and 0.08646 respectively, and the prediction error is 0.0119, which is less than 0.02. The predicted and true values of net asset growth rate of enterprise Q in the third quarter of 2024 are -0.00155 and 0.05154 respectively, and the error is -0.05309.

This may be because, the management of Enterprise Q anticipated the crisis and took remedial measures accordingly, so the true result is more optimistic than the predicted value. Nonetheless, the true values still reflect the same message as the predicted values, i.e., the growth rate of the firm has slowed down.

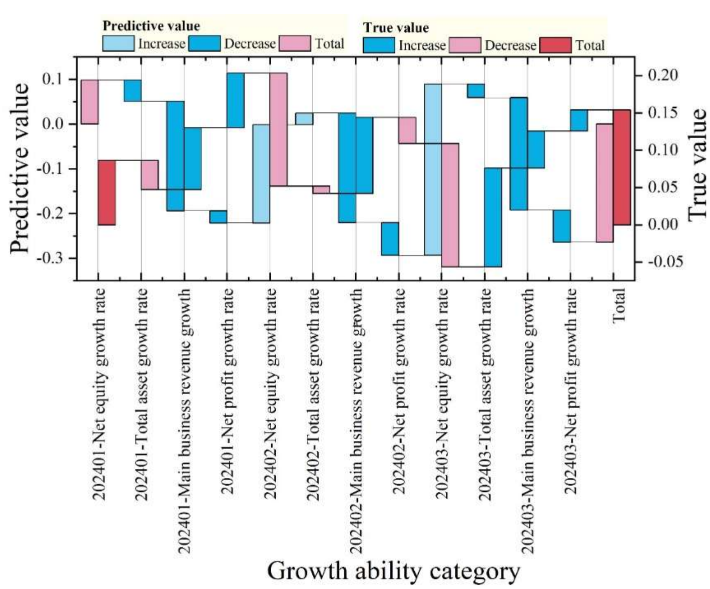

Fig. 3. Growth ability predictive value, real value and absolute error

4.3.4. Solvency. The predicted, true and absolute errors of solvency are shown in Figure 4. The predicted values of the improved differential neural network prediction model for the cash ratios for the three quarters are 3.03654, 2.88694, and 2.96841, and the true values are 3.51241, 3.30258, and 2.55687, respectively. The forecast errors for the three quarters were -0.47587, -0.41564, and 0.41154, respectively. It can be seen that the readiness of the forecasts for the third quarter of 2024 is extremely high. Combining the data, it can be concluded that the readiness of the improved differential neural network forecasting model for forecasting results is high.

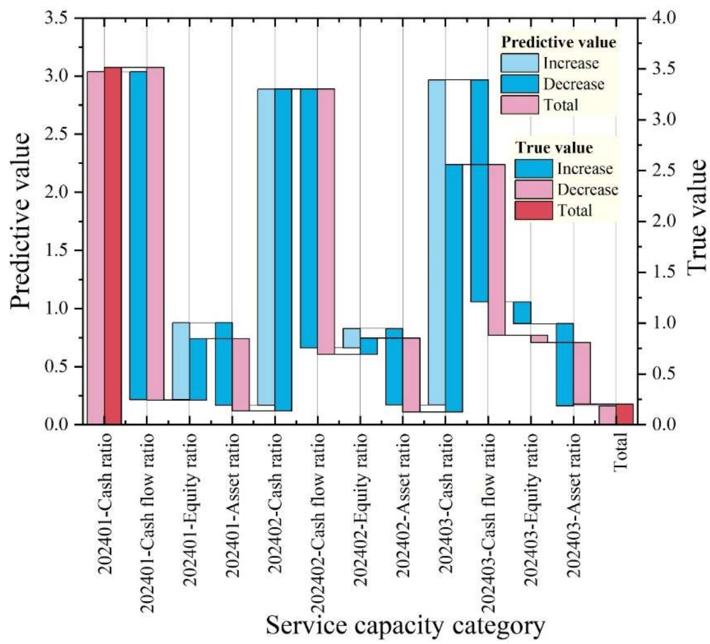

Fig. 4. The solvency prediction, the real value and the absolute error

5. Conclusion

In this paper, adaptive differential evolutionary algorithm is used to optimize the BP neural network and form an improved differential neural network algorithm model. Bringing in the financial data of the enterprise from 2019 to 2023, the simulation sets the number of neural network layers to 18, and carries out the prediction of the enterprise's finance in the third quarter of 2024. Compare the gap between the real value and the predicted value, and analyze the role of the improved differential evolution algorithm in the enterprise financial prediction.

Combining the test set data, SVM, Random Forest, XGBoost, and the improved differential neural network algorithm models are used to predict the financial risk of listed companies, and all four models achieve good results. However, the improved differential neural network algorithm model has an AUC of 0.9356, which is more in line with the needs of enterprise financial risk prediction. Bringing in the financial development data of enterprise Q during the five-year period from 2019-2023, the improved differential neural network prediction model is utilized to derive the financial data of the first three quarters of 2024. Based on the enterprise financial risk early warning indicator system, the comparison between the predicted and real values of the enterprise profitability, operational capacity, development capacity and debt service capacity is carried out respectively. In the dimension of enterprise operating ability, the improved differential neural network algorithm model has a prediction error [-4,0.3] and high prediction accuracy. In this case, the turnover of accounts receivable is lower than the constant value, and the decrease in the turnover of accounts receivable of Q Enterprises shows that there is a change in the credit policy of the company. As far as the model predicted value and the real value are concerned, enterprise Q should pay attention to the development of accounts receivable turnover index, and enterprise Q should determine a reasonable credit policy according to the actual situation to maintain the steady development of the enterprise.

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