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A Financial Performance Optimization Model Based on Group Intelligence Algorithm and Its Effectiveness Evaluation

Xiaoyang Meng[1,✉], Yujing He[1]
[1] *School of Accounting, Jiaozuo University, Jizozuo, Henan, 454100, China*

ABSTRACT
Financial performance optimization is an important embodiment of enterprises to improve operational efficiency and optimize management level. The article proposes a method of financial performance optimization and evaluation using group intelligence algorithm in order to optimize the financial performance of enterprises. EVA is introduced to establish the evaluation index of enterprise financial performance. The financial performance prediction model is constructed according to the propagation process of BP neural network, and the IPSO-BP algorithm is utilized to avoid BP from falling into local optimum and improve the prediction accuracy. In the learning ability test, the relative errors of the EVA value, EVA payoff and EVA rate of the IPSO-BP algorithm are controlled within 6%, 8% and 10% respectively, and the average relative error of the model application results is 3.87%. The model in this paper can achieve more accurate financial performance assessment and prediction, which is conducive to the optimization of financial performance management of enterprises.

Keywords: IPSO, BP neural network, EVA, group intelligence algorithm, financial performance

1. Introduction

Financial performance has become one of the basic contents in modern enterprise management. It is a reference to the financial statement data (such as the income statement and balance sheet), to measure the business performance indicators, through the financial indicators to quantitatively analyze the economic efficiency and financial status of enterprises, reflecting the results of business operations, and provide basic data support for subsequent management decisions [1]. Therefore, enterprises should pay close attention to the changes in the economic environment and the capital market, timely adjust the enterprise business strategy, surplus management, financial management, and improve the enterprise financial performance can also improve the competitiveness and influence of the enterprise market [2-4].

Financial performance indicators can be customized according to the needs of different companies, but generally relate to income, assets, investment returns and funds, etc., to help assess whether the

✉ Corresponding author.
E-mail address: hnjzmxy2023@163.com (X. Meng).
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enterprise has made significant progress in meeting its expected earnings and compensation goals [5]. Financial performance reflects the performance of the enterprise as a whole and the performance of each department, which in turn helps managers to find out the space to optimize business performance, so as to adjust their business strategies and achieve business objectives [6]. At the same time, financial performance can also help analysts to evaluate the company's performance, capital flow and asset structure, in order to provide investors with effective investment reference [7]. There are many factors affecting the financial performance of enterprises, which can be categorized into internal and external factors. The internal factors are the enterprise's strategic planning, governance structure, organizational structure, financial management level, human resource management, and innovation ability [8-11]. Among them, strategic planning is the first factor, a clear, reasonable and forward-looking strategic planning can point out the direction of development for the enterprise, clear business objectives, if the enterprise strategic positioning is inaccurate, blind pursuit of diversification or over-expansion, which may lead to the dispersion of resources, the decline in the competitiveness of the core business, thus affecting financial performance. The level of financial management of the enterprise is directly related to the advantages and disadvantages of financial performance. External factors are macroeconomic environment, policy and regulatory changes, market changes, industry development trends, social and cultural environment [12-15]. Economic prosperity and recession, inflation level, high and low interest rates and exchange rate fluctuations will have a direct or indirect impact on the financial performance of enterprises. The adjustment of tax policy is directly related to the level of tax burden of enterprises. The intensity of market competition directly affects the market share and product prices of enterprises.

Enterprise financial performance can directly reflect the business situation of the enterprise, is a good guarantee for the sustainable development of the enterprise, and is also the key to realize the effective governance of an enterprise [16]. In the era of intelligence, the optimization of enterprise financial performance can grasp the health of the enterprise in a timely manner, which is of great significance to improve the operating results of the enterprise and enhance the level of management. In order to solve various optimization problems, academia and industry have cooperated to introduce a variety of algorithms based on group intelligence [17]. Because the algorithms are easy to implement and debug, have good robustness; can deal with multi-objective optimization problems, and can optimize multiple objectives at the same time; have good global search ability, and can find a more excellent solution; and are flexible, and can adjust the model according to the specific problem, and have been widely used in various fields, including finance, healthcare, and energy, transportation and other fields [18-21].

In order to realize the optimization and assessment of financial performance, this paper firstly analyzes the necessity and evaluation principle of using EVA index to evaluate the financial performance of enterprises. Based on the propagation process of BP neural network model, a BP neural network model that can be used for enterprise financial performance prediction is proposed. Aiming at the defect that traditional BP neural network is easy to fall into the local optimum, the standard particle swarm algorithm is used to encode the inter-layer connection weights of the neural network and the thresholds of each node in the implicit and output layers into particles, and the PSO algorithm is used to solve the global optimum. On this basis, the learning factor of asynchronous change is introduced, nonlinear decreasing weights are used to replace inertia weights, and the optimized IPSO algorithm is utilized to avoid premature convergence and improve convergence accuracy. Learning ability and generalization ability analysis are carried out using the new model, and finally the practical application effect of the model is examined.

2. Introduction of EVA's corporate financial performance evaluation system

EVA, or Economic Value Added, is to a certain extent the residual value of shareholders, which is formed by deducting the cost of capital of the enterprise from the net operating profit after tax. With the continuous improvement and development of the EVA theory, the EVA concept can be used as the dominant concept of enterprise management, and the EVA index can be an important tool for enterprise performance evaluation.

2.1. Analysis of the need to introduce EVA

2.1.1. The need to reflect the real business situation of enterprises. Compared with the traditional financial indicators, EVA indicators redefine the enterprise profit, and EVA indicators are based on the economic profit after the adjustment of accounting items to the accounting profit. In addition, the adjustment of accounting profit can, to a certain extent, effectively avoid the influence of the enterprise's inflated profit, low cost and other behaviors, and correct the deviation of the assessment results under the traditional performance evaluation system. Therefore, the EVA index can truly reflect the operation status and value-added ability of enterprises, and a performance evaluation index that can accurately judge the information of enterprise value creation for shareholders is widely needed.

2.1.2. Need to strengthen capital cost management and improve efficiency in the use of funds. The introduction of EVA can effectively prevent enterprises from taking up capital resources by over-investing capital in unimportant businesses in pursuit of short-term benefits. In China, due to the influence of national preferential policies and subsidies, a large number of small and medium-sized enterprises (SMEs) have come into the new energy industry, and enterprises are competing for market share and expanding blindly, which leads to the emergence of problems such as overcapacity, serious product homogenization, and difficulties in the research and development of new products, etc. These problems in the new energy industry are also the problems faced by the company. Because of this, the introduction of the EVA concept can strengthen the management of the enterprise's cost of capital and increase the investment in the research and development of new products, thus improving the competitiveness of products. In addition, it is also very important for reducing short-term blind investment and improving the efficiency of capital utilization.

2.1.3. The need for sustainable enterprise development. The EVA concept helps guide companies to focus on long-term development, incentivize corporate value creation, and focus on shareholder wealth growth. In addition, the EVA concept encourages innovation and new product development, which is in line with the concept of “innovation for all” that China has been advocating in recent years. The sustainable development of enterprises requires them to focus on the improvement of core competitiveness, which can effectively reduce external risks and improve the operational efficiency of enterprises. Therefore, the introduction of EVA financial performance evaluation system is very necessary for the sustainable development of enterprises.

2.2. Principles of financial performance evaluation

2.2.1. Principle of combining importance and comprehensibility. The principle of materiality mainly emphasizes that in the process of calculating EVA, the enterprise's own development situation and the characteristics of the industry in which the enterprise is located should be fully considered, and the accounting items that are more relevant to the core competitiveness of the enterprise and more affected by the fluctuation of the industry should be selected for adjustment, so that the appropriate evaluation indexes can be selected in the end. Understandability requires that the performance evaluation results based on EVA. It is simple and clear, and can be understood and accepted by shareholders, management, employees and so on. Therefore, the evaluation process should combine the importance and comprehensibility, select the appropriate performance evaluation indexes, and derive the calculation results that can be understood by the information users, so as to provide data support for the future investment decisions of the enterprise and make the enterprise develop in the right direction.

2.2.2. Principle of combining objectivity and operability. The specific goal of the evaluation is to make the enterprise resources to be reasonably allocated, the enterprise operation is more robust, so as to promote the enterprise value appreciation, and under this premise, it is necessary to do sufficient research on the enterprise capital structure, organizational structure and the daily operation of the enterprise, and fully grasp the actual situation of the enterprise's profit and loss projects. The principle of operability is that under the direction of the principle of objectivity, the data of financial and non-financial indicators of the enterprise can be obtained in time, and the calculation task can be successfully accomplished through the corresponding calculation model, so that the evaluation method is more feasible.

2.2.3. Principle of combining authenticity and comparability. The principle of authenticity requires that the financial data and non-financial data obtained from the enterprise should be kept as real and effective as possible, and this requirement can be said to be very strict. When acquiring financial data and selecting evaluation indexes, it is also necessary to avoid the influence of human calculation errors and financial fraud data. On the other hand, for the principle of comparability, in the evaluation results based on the EVA evaluation system, the calculated results should be vertically comparable in time and horizontally comparable in the industry. Under the principle of comparability, enterprises will be more comprehensive and objective when making strategic decisions. Therefore, the combination of authenticity and comparability, under the premise of obtaining reliable data, performance data can be compared with each other to calculate, so as to reflect the overall performance status of the enterprise [22].

2.3. Financial performance evaluation indicators

2.3.1. EVA. The EVA value, i.e. Economic Value Added, is the core indicator of the system, which is the difference between the net operating profit after tax and the total cost of capital used by the enterprise in a certain period of time. EVA value can objectively reflect the value created by the enterprise for the shareholders. The EVA value is subject to the E of accounting estimation and accounting policy, which is widely used in the performance evaluation of the enterprise. The formula of the EVA value is as follows: EVA value = Net operating profit after tax - cost of capital.

2.3.2. EVA rate of return. The EVA rate of return is the ratio of economic value added to the cost of capital, which reflects the ability of an enterprise to create wealth for its shareholders. Under quality constraints, the greater the EVA ratio, the more efficient the economic value added generated by invested capital and the greater the value created for the enterprise.

2.3.3. EVA rate. EVA rate can intuitively reflect the profitability and development ability of the enterprise, the larger the EVA rate, the higher the efficiency of the enterprise's utilization of capital, the more wealth it creates for shareholders. EVA rate for the evaluation of the enterprise's financial performance is an important evaluation index, the formula for calculating the EVA rate is: EVA rate = EVA/adjusted capital.

2.3.4. EVA growth rate. EVA growth rate, also known as EVA growth rate, is a dynamic indicator that reflects the degree of change in the EVA value within a certain period of time, and it is also a basic indicator that reflects whether the value creation of an enterprise has vitality. The higher the EVA growth rate, the more wealth a company creates for its shareholders.

3. Based on the IPSO-BP financial performance prediction model

3.1. BP Neural Network Prediction Model Fundamentals

The BP neural network model consists of three modules, the input layer, the hidden layer and the output layer, and the neurons between two neighboring layers correspond to each other two by two, forming a complete connection. And neurons that are inside the same layer do not form direct connections between them. In essence, the process of network learning is an optimization process based on the error generated in the propagation process, and the weights and thresholds in the network are corrected and adjusted, and the results of its learning are reflected in the changes of the weights and thresholds. Therefore, the BP algorithm can be divided into forward propagation and backward propagation, i.e., the two stages of error calculation and parameter adjustment in the practical application of multilayer networks.

3.1.1. BP neural network propagation process. The BP neural network is trained by calculating the model error through forward propagation and backpropagating to each weight threshold for numerical updating through back propagation. During forward propagation, the input data enters the first hidden layer through the input layer and is transmitted to the output layer after layer-by-layer processing in the hidden layer. During this period, each neuron in the layer only affects the state of the next neuron in the propagation path by connecting to each other. If the error between the expected result and the output result of the output layer is larger than the acceptable error, it enters the back-propagation phase of the network propagation, and performs a layer-by-layer original return operation on the model error by connecting the channels between the neurons, and adjusts and modifies the parameter in the direction of the target negative gradient by the gradient descent method, so as to minimize the error signal.

3.1.2. Financial performance prediction model construction based on BP neural network. BP neural network before the prediction work needs to train the network, the key is the determination of the weights and thresholds in it, through training to determine the main parameters, so that the network has the ability to memorize and associate, in order to play its role in prediction. The training process of BP neural network includes the following steps [23]:

1) Structure Determination. Determine the BP neural network topology, i.e., the number of hidden layers and the number of neurons in each layer.

2) Initialization. Initialize all the ownership values and thresholds in the network, and determine the activation function, in this paper, the hidden layer activation function $f(\cdot)$ adopts the tangent S-type transfer function tansig, and the output layer activation function $g(\cdot)$ adopts the linear transfer function purelin, and the model is trained using the L-M optimization algorithm.

3) Data input. Input training set $T=\{(x,y)\}$.

4) Parameter input. Input learning rate η, learning accuracy ε, maximum number of iterations R. In this paper, when constructing the model, the corresponding BP neural network part of the parameters are set to 0.01, 0.001, 5000.

5) Forward propagation. Calculate the input value and output value of each neuron according to Eqs. (1)-(4).

6) Error calculation. Calculate the network output layer error according to equation (5).

7) Back propagation. Calculate the hidden layer and output layer gradient terms δ_j and δ_h according to Eq. (7) (11) Update the network weights and thresholds according to Eq. (8) (9) (12) (13).

8) Return to 5) until the error value is within ε or the iteration reaches a value of R, stop the iteration and output the model.

BP neural network through the back propagation of the error signal, and constantly correct the model parameters, until the error between the model output y_j' and the desired output y_j in the learning accuracy range, and then input new sample data to repeat the learning process, until the N data samples to complete the training or to reach the maximum number of set training times, at this time, $(d+l+1)\times q+l$ to be determined parameters are determined, that is, to complete the training of the model.

3.2. Model Improvement Methods

3.2.1. Particle Swarm Algorithm. The particle swarm algorithm simulates a sociological behavior of a flock of birds interacting with information while foraging for food, and searches for the optimal point on a global scale, the algorithm initializes the resulting random particles, and maps the potential feasible solutions to the required optimization problem through continuous iterative turnover [24]. For S particles in a D-dimensional search space, the position, velocity, individual historical optimal position, and overall optimal position of the particle swarm for the i rd $(1\le i\le S)$ particles at d-dimensional $(1\le d\le D)$ are respectively:

$$x_i=(x_{i1},x_{i2},\dots,x_{iD}) \tag{1}$$

$$v_i=(v_{i1},v_{i2},\dots,v_{iD}) \tag{2}$$

$$p_i=(p_{i1},p_{i2},\dots,p_{iD}) \tag{3}$$

$$p_g=(p_{g1},p_{g2},\dots,p_{gD}) \tag{4}$$

According to the "positional convergence" and "central aggregation" of clusters, the evolutionary formulas for particle velocity and positional update for generation k are:

$$\begin{aligned} v_{id}(k+1)=\omega v_{id}(k)+c_1 rand_{id}(\cdot)\left[p_{id}(k)-x_{id}(k)\right] \\ +c_2 rand_{id}(\cdot)\left[p_{gd}(k)-x_{id}(k)\right] \end{aligned} \tag{5}$$

$$x_i(k+1)=x_i(k)+v_i(k+1) \tag{6}$$

Where, ω represents the particle inertia weight and $\omega\in[0,1]$. c_1 and c_2 represent the acceleration coefficients of the particles, all of which are non-negative constants. The $rand(\cdot)$ function represents the random number generated in the $[0,1]$ interval.

From the evolution formula, it can be seen that the update of the particle position depends on the velocity update, and the update of the velocity depends on the influence of three aspects: first, the current state of the particle, related to the current velocity $v_{id}(k)$ and inertia weights ω. The second is the particle's own experience, related to the distance between the particle's own position $x_{id}(k)$ and its historical optimal position $p_{id}(k)$. The third is the information sharing, and the velocity adjustment by the distance between its own position $x_{id}(k)$ and the current optimal position $p_{gd}(k)$ in the particle swarm.

For the particle individual historical optimal position and the particle swarm optimal position update formula are respectively:

$$p_i(k+1)=\begin{cases} p_i(k) & if\ f\left[x_i(k+1)\right]\ge f\left[p_i(k)\right] \\ x_i(k+1) & if\ f\left[x_i(k+1)\right]< f\left[p_i(k)\right] \end{cases} \tag{7}$$

$$p_g(k+1)=\arg\min_{p_i(k+1)} f\left[p_i(k+1)\right] \tag{8}$$

where, $f(\cdot)$ the fitness function, which in this paper is set to the mean absolute error MAE.

3.2.2. Genetic Algorithms. Genetic algorithm is a kind of heuristic algorithm based on the phenomenon of biological evolution in nature, following the natural selection law of "survival of the fittest" and "survival of the fittest". In practice, the key to the genetic algorithm is to start coding the feasible solutions of the research object to form a chromosome, and then combine multiple chromosomes to form a research population, and the genes on the chromosome represent the factors affecting the feasible solutions or analyzing dimensions. Each iteration in the algorithm is a process of selecting the optimal solution by calculating the fitness of the individual, retaining the chromosomes with high fitness, and then mimicking the crossover interchanges during the meiotic division of organisms, and the genetic variation during the DNA replication period for the generation of new individuals, and conducting a new round of screening based on the fitness. After many iterations, the individuals left behind are more and more adaptive to the external environment, which also represents that the remaining chromosomes are closer and closer to the optimal solution of the problem [25].

3.3. BP neural network model optimized based on improved particle swarm algorithm

3.3.1. Particle Swarm Algorithm to Optimize BP Neural Network Models：

1) Standard particle swarm algorithm. Particle Swarm Algorithm (PSO) is a population-based stochastic optimization technique. The basic principle of particle swarm algorithm is: first assume that the dimension of the solution is S, randomly generate N massless particles, one particle represents a feasible solution, any particle has two attributes-velocity and position, which are denoted by $V_i=\left(V_{i1},V_{i2},\ldots,V_{it}\right)^T\ i=1,2,\ldots,N$ and $X_i=\left(X_{i1},X_{i2},\ldots,X_{iz}\right)^T$, respectively. Each particle moves continuously in the search space, and the velocity of each particle is constrained by the maximum velocity V_m, and when $V_{ij}>V_m$, then $V_{ij}=V_m$, $\left(1\le i\le N,1\le j\le S\right)$. Similarly, X_{ij} is constrained by X_m, and when $X_{ij}>X_m$, then $X_{ij}=X_m$, $\left(1\le i\le N,1\le j\le S\right)$. All particles in the swarm complete the search for the global optimal solution G_{best} based on the currently searched individual extremes P_{best}. The formulas used for updating the velocity and position of the particles are (9) and (10):

$$V_{id}^{k+1}=\omega V_{id}^k+c_1r_1\left(P_{beetid}^k-X_{id}^k\right)+c_2r_2\left(G_{bestid}^k-X_{id}^k\right) \tag{9}$$

$$X_{id}^{k+1}=X_{id}^k+V_{id}^{k+1} \tag{10}$$

In Eq. (10): $d\in[1,S]$ is the number of dimensions, k is the number of current iterations, c_1 and c_2 are the learning factors, c_1 is the step size of the particle moving to the individual optimal position, c_2 is the step size of the particle moving to the global optimal position, and r_1 and r_2 are random numbers between $[0,1]$. ω is the inertia weight.

2) Optimization of BP neural network by particle swarm algorithm. BP neural network according to the method of error back propagation constantly adjust the connection weights between the nodes of each layer and the implied layer, the threshold value of each node of the output layer, in order to minimize the error, but it is easy to fall into the local optimum. The PSO algorithm is used to optimize the BP neural network by encoding the connection weights between the neural network layers and the thresholds of the nodes in the implicit layer and the output layer into particles, and solving for the global optimum using the PSO algorithm described previously. This approach not only avoids the problem that BP neural networks are easy to fall into the local minimum, but also improves the convergence speed of the neural network, and the prediction results will be more accurate.

3.3.2. Optimization of model parameters.

As all the particles in the PSO algorithm constantly converge to the individual optimal and global optimal position, it is easy to make the particle swarm appear fast convergence effect, which will make the particle swarm fall into the local extremes, and even premature convergence or even the phenomenon of the search process stops. In order to avoid the above problems of PSO algorithm and further improve the convergence accuracy, so that the optimization effect reaches the best, the PSO algorithm is improved, that is, the Improved Particle Swarm Algorithm (IPSO) [26].

Firstly, asynchronous learning factors are introduced to replace the original learning factors c_1 and

c_2. In the pre-search phase, the asynchronous learning factors can make the particles in the swarm focus more on self-learning and less on global learning, which enhances the global search function of the swarm. In the late search stage, each particle focuses more on global learning and less on self-learning, which makes it easier for the particle swarm to obtain the global optimal solution. The variation formula of the learning factor is:

$$c_1 = c_{1,ini} + \frac{c_{1,fin} - c_{1,ini}}{t_{\max}} \times t \tag{11}$$

$$c_2 = c_{2,ini} + \frac{c_{2,fin} - c_{2,ini}}{t_{\max}} \times t \tag{12}$$

In the above equation: $c_{1,ini}$ and $c_{2,ini}$ represent the initial values of c_1 and c_2 respectively. $c_{1,fin}$ and $c_{2,fin}$ represent the final value of iteration c_1 and c_2 respectively. t represents the current number of iterations. $t_{\max}$ represents the final number of iterations.

Since the inertia weight ω is throughout the whole search process, it not only plays a role in the local search function of the particles, but also has a certain impact on the search for the global optimal solution of the particle swarm. If the value of ω is large, then the ability of each particle to search for the global optimal solution is stronger. On the contrary, with a relatively small value of ω, the ability of the particles to search for individual extremes P_{best} becomes stronger. Therefore, nonlinear decreasing weights are used to replace the original direct assignment of values to ω:

$$\omega = \left[\left(\omega_0 - \omega_1 \right) \cos\left(t / \pi t_{\max} \right) + \left(\omega_0 + \omega_1 \right) \right] / 2 \tag{13}$$

where ω_0 and ω_1 denote the initial and final values of ω, and $\omega_0 > \omega_1$. ω decreases according to the cosine function, which ensures that the global search for the optimal solution can be fast at the beginning of the iteration and lasts for a long time, so that it does not fall into the local search too early, and also completes the local optimisation at a slower speed in the later search phase.

3.3.3. Basic Steps for Optimising BP Neural Networks with Improved Particle Swarm Algorithm：

1) Set the values of the parameters in the IPSO algorithm, including the number of particles N, the number of loop iteration steps, the particle dimension S, the initial inertia weight ω_0 and the final inertia weight ω_1, the initial value of the learning factor $c_{1,ini}$, $c_{2,ini}$ and the final value of the iteration $c_{1,fin}$, $c_{2,fin}$.

2) The BP neural network is designed as a three-layer network structure, and the number of nodes in each layer is given according to the actual prediction problem. Since the dimension of the particles depends on the connection weights between the input layer and the hidden layer, the hidden layer and the output layer and the node thresholds of the hidden layer and the output layer, the dimension of the particles is calculated as:

$$S = S_{in} S_h + S_h S_{out} + S_{out} \tag{14}$$

In Eq. (14), S_{in}, S_h and S_{out} are the number of nodes in the input layer, hidden layer and output layer, respectively.

3) Initialise the BP neural network, import the sample dataset, calculate the mean square deviation between the expected output and the actual output, and use the mean square deviation as the fitness function of the particle swarm algorithm.

4) According to the speed, position and learning factor of the particle swarm and inertia weights of the improvement of the formula to make each particle to complete the required number of speed and position changes, while the need to ensure that $V_{ij} \in [-V_m, V_m]$, $X_{ij} \in [-X_m, X_m]$.

5) Iterative operation. Determine the fitness value of each particle in the particle swarm f_i, if $f_i < P_{best}$, then $P_{best} = f_i$, if $f_i < G_{best}$, then $G_{best} = f_i$, until the number of iterative steps are completed,

the global optimal solution searched by the particle swarm is the BP neural network of each connection weights and thresholds.

6) Import the training sample data into the identified neural network to achieve the training of the BP neural network, and then import the test sample data to get the prediction results.

4. Validation of IPSO-BP neural network financial performance prediction model

4.1. Analysis of examples

The IPSO optimised BP neural network forecasting model is validated, and the forecasting ability of IPSO optimised BP neural network, standard PSO optimised BP neural network and BP neural network are comparatively analysed and validated. EVA value, EVA payoff ratio and EVA rate are used as evaluation indexes of corporate financial performance, respectively. The financial data of a company for a total of 34 months from March 2021 to December 2024 is selected as the data set, of which 24 months of data are taken as the training set and 10 months of data are taken as the validation set, and the arithmetic analysis is carried out using the method of this paper.

4.1.1. Learning Capability Validation. The prediction results and relative error comparison curves of enterprise EVA value, EVA payoff and EVA rate under 24 sets of training samples are analysed in Figs. 1-3, respectively.In the prediction value fitting results, it can be seen that the prediction value of IPSO-BP is closer to the target value, i.e., in the relative error comparison curves, the training error of IPSO-BP is better than the training errors of PSO-BP and BP. In the learning ability of EVA value, EVA payoff and EVA rate, the PSO-BP algorithm's training samples are controlled within 13%, 12% and 19% of the training error, while the IPSO-BP algorithm's relative errors are controlled within 6%, 8%, and 10% of the learning ability, respectively.

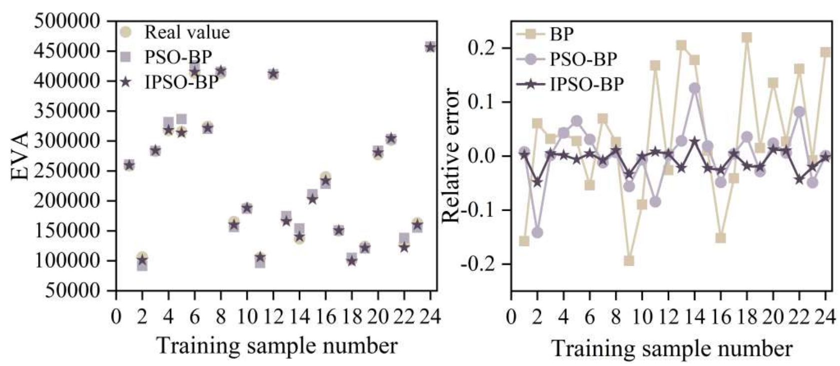

Fig. 1. Comparison of learning ability prediction of EVA value

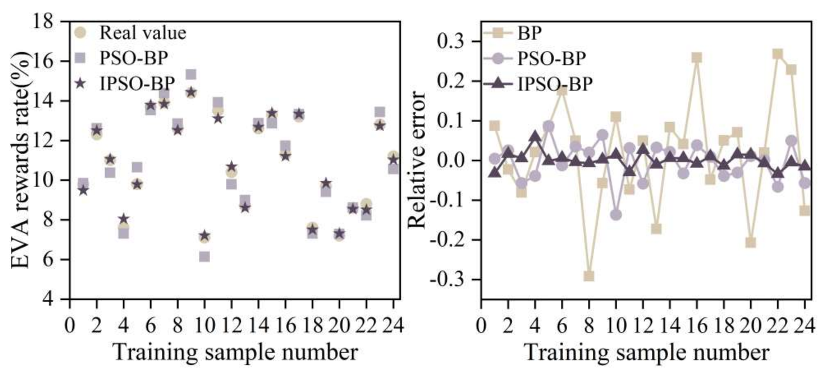

Fig. 2. Comparison of learning ability prediction of EVA reward rate

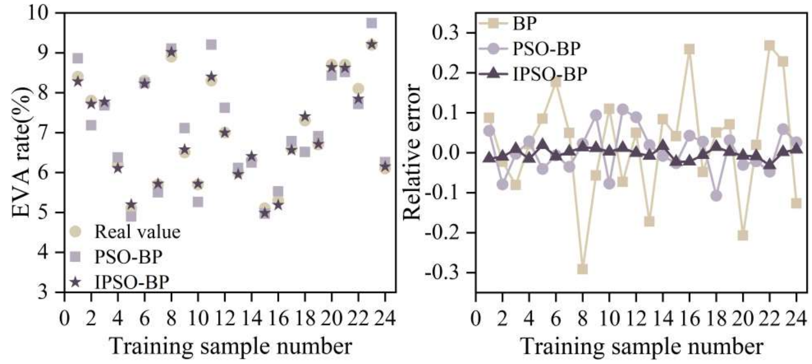

Fig. 3. Comparison of learning ability prediction of EVA rate

4.1.2. Verification of generalisation capabilities. Figures 4 to 6 show the prediction results and relative error comparison curves for EVA, EVA payoff and EVA rate for the 10 groups of test samples, respectively. In the fitting results of the predicted values, it can be seen that the predicted values of IPSO-BP are the closest to the target values, and the prediction accuracy is better than that of BP and PSO-BP.In the relative error comparison curves, it can also be intuitively compared to find that the test error of IPSO-BP is lower than that of PSO-BP and BP.

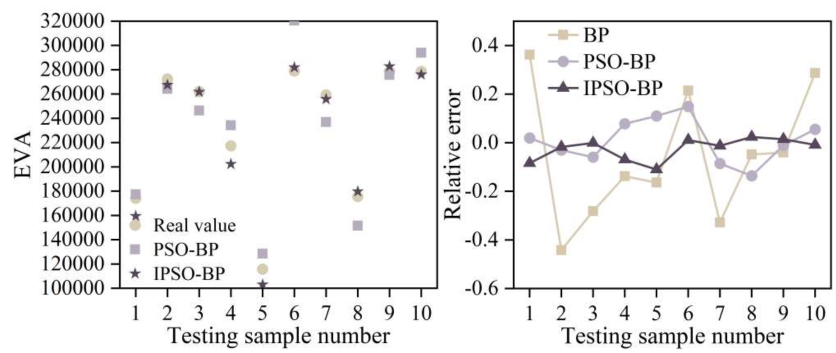

Fig. 4. Comparison of generalization ability prediction of EVA value

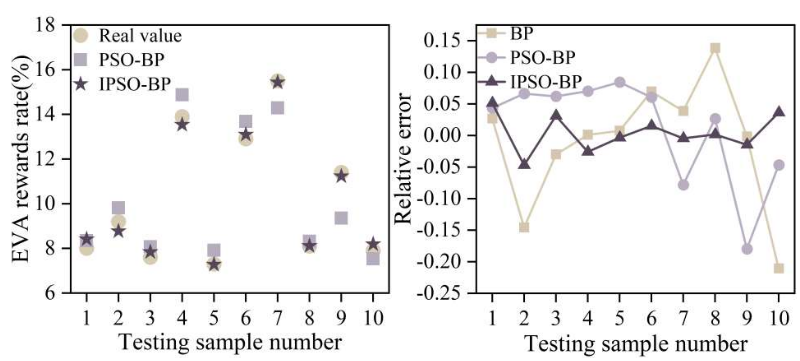

Fig. 5. Comparison of generalization ability prediction of EVA rewards rate

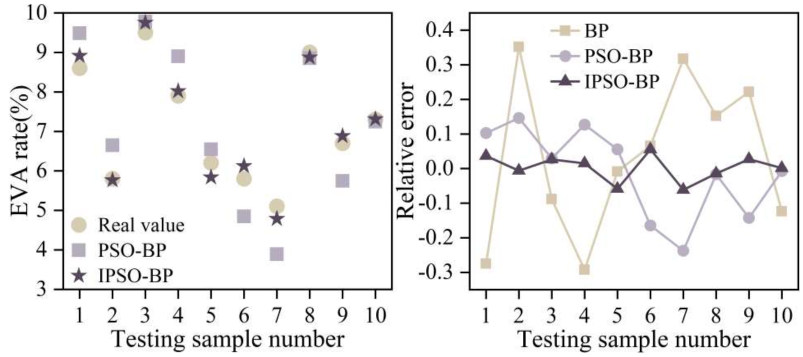

Fig. 6. Comparison of generalization ability prediction of EVA rate

The optimisation and improvement of the BP algorithm based on the learning ability and generalisation ability of the neural network, it can be seen from the sample prediction results and relative error results, the optimisation and improvement of the error reduction, the reduction of the relative error, shows the advantages of the optimisation and improvement of the prediction accuracy of the BP neural network, and the improvement of the prediction results are more accurate and credible.

4.2. Modelling applications

For the enterprise financial performance sample data, the EVA growth rate is selected as the evaluation index, 12 groups of financial data of an enterprise are randomly selected as training samples, and the remaining 12 groups are used as test samples. The BP model, PSO-BP model and IPSO-BP model were established, and the comparison charts of the prediction results and relative errors of the three models are shown in Figures 7 and 8, respectively. It can be seen that the prediction results of IPSO-BP algorithm are more accurate, with smaller errors and stable performance.

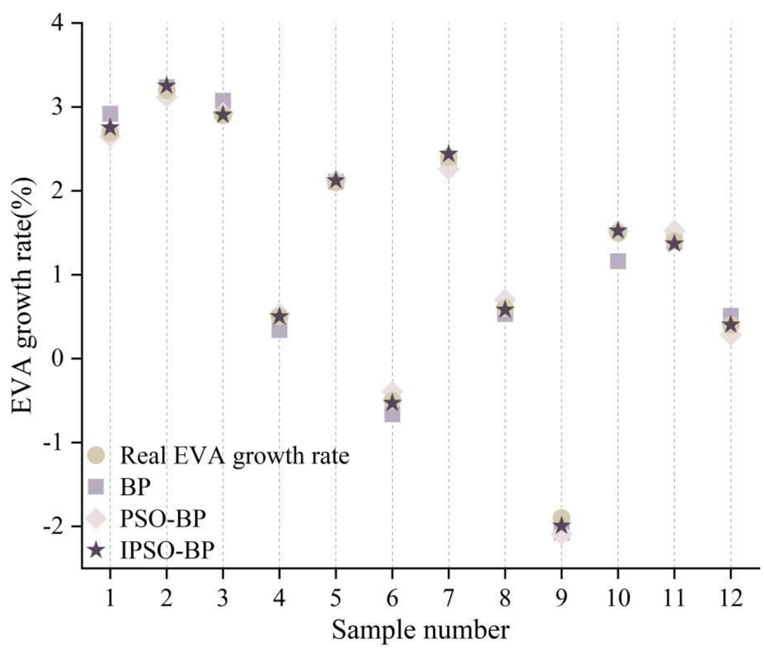

Fig. 7. The EVA prediction of the three models

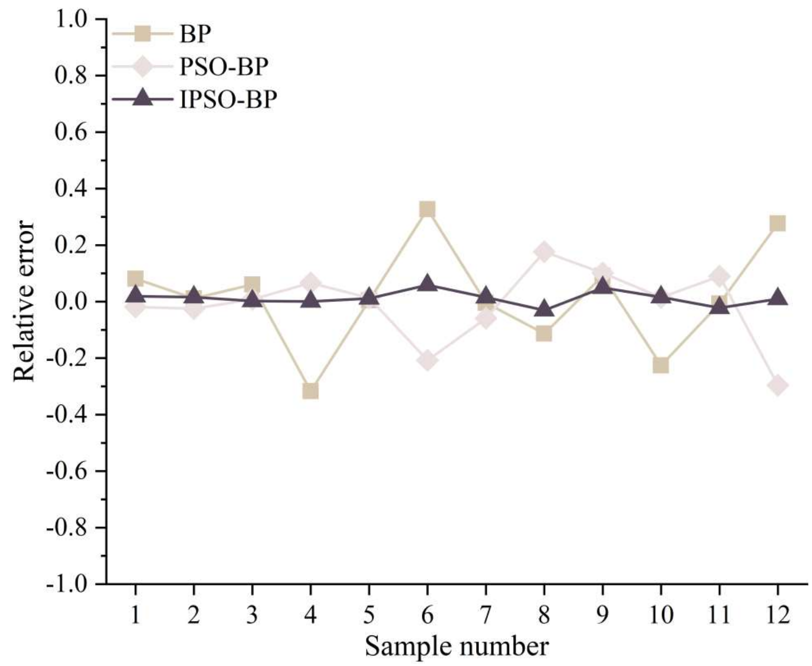

Fig. 8. The comparison of the prediction relative error of the three models

The predicted output values and error analysis results of the three prediction models are shown in Table 1.The prediction effect of the BP model is poorer, the maximum relative error reaches 32.69%, the minimum relative error is only 0.43%, the average relative error is 8.38%, and the root-mean-square error is 1.235.It can be seen that the fluctuation of the BP model is large when it comes to the prediction, and it is not sufficiently stable, and compared with the BP model, the PSO- The prediction accuracy of the BP model has improved substantially, with an average relative error of 4.58% and a root mean square error of 0.813. The maximum relative error of the predicted values of the IPSO-BP prediction model is only 5.86%, the minimum relative error is 0.08%, and the average relative error is 3.87%, with a root mean square error of 0.621, which are lower than that of the PSO-BP and BP prediction models, respectively, showing higher stability and accuracy. They are lower than PSO-BP and BP prediction models, showing high stability and accuracy.

Table 1. The output values and error analysis of each prediction model

No.	Real value (%)	BP		PSO-BP		IPSO-BP	
		P.V (%)	R.E.	P.V (%)	R.E.	P.V (%)	R.E.
1	2.7	2.92	8.07%	2.65	-1.89%	2.75	1.93%
2	3.2	3.24	1.10%	3.12	-2.50%	3.25	1.61%
3	2.9	3.07	6.03%	2.92	0.84%	2.91	0.21%
4	0.5	0.34	-31.70%	0.53	6.60%	0.50	0.08%
5	2.1	2.11	0.43%	2.13	1.28%	2.12	1.13%
6	-0.5	-0.66	32.69%	-0.40	-20.76%	-0.53	5.86%
7	2.4	2.39	-0.47%	2.26	-5.89%	2.44	1.55%
8	0.6	0.53	-11.31%	0.71	17.64%	0.58	-3.06%
9	-1.9	-2.07	9.13%	-2.09	10.13%	-1.99	4.95%
10	1.5	1.16	-22.58%	1.52	1.45%	1.52	1.61%
11	1.4	1.39	-0.67%	1.53	9.01%	1.37	-2.23%
12	0.4	0.51	27.70%	0.28	-29.59%	0.40	0.97%
MAPE		8.38%		4.58%		3.87%	

RMSE	1.235	0.813	0.621

5. Conclusion

The research path of this paper mainly focuses on the prediction of enterprise financial performance through the improved particle swarm and genetic algorithm, combined with the EVA index system, which facilitates the enterprises to optimise their financial management and assess their financial performance based on the prediction results. The financial data of a company is used as a data set for example analysis. The results of the example point out that the IPSO-BP algorithm in this paper is significantly better than the BP algorithm and the PSO-BP algorithm before the improvement in the learning ability test, with the relative errors controlled within 6%, 8%, and 10%, respectively. In unfamiliar samples, this paper's algorithm also has better generalisation ability, and the test error is smaller than the comparison algorithm. In the application analysis, the maximum relative error of IPSO-BP is only 5.86%, the average relative error is 3.87%, and the root mean square error is 0.621 respectively, which has high stability and accuracy. The above analysis shows that the IPSO-BP model is able to achieve a more accurate prediction and assessment of corporate financial performance, providing a feasible path for the optimal assessment of financial performance.

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