J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 5511--5536

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on corporate profitability prediction model integrating fuzzy logic and financial ratios

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ABSTRACT

This study integrates fuzzy logic with DuPont ratio analysis reflecting financial ratios to construct enterprise profitability prediction model. The main indicators of DuPont analysis system are processed by principal component analysis (PCA) algorithm to obtain the calculation method of the mean value of enterprise comprehensive profitability indicators. The BP neural network is used to construct the enterprise profitability index model, and the momentum term is introduced into the model to improve the convergence speed of the BP neural network. The Takagi-Sugeno type fuzzy neural network is utilized to construct the enterprise development ability index model, and the enterprise profitability prediction model is constructed by combining the output structure of BP neural network. The relevant data of 792 listed enterprises in a certain industry in China's A-share market are selected as the research objects of this paper, and the data are inputted into BP neural network and Takagi-Sugeno fuzzy neural network to obtain the output results of the model, and the output results are used as the input data of the final profitability prediction model to forecast the profitability of the enterprise in the next five years. The experimental results show that the model in this paper can effectively realize the prediction of corporate profitability, which is significantly conducive to the sustainable development of enterprises and the adjustment and improvement of strategic policies.

Keywords: fuzzy logic, DuPont financial ratio analysis, BP neural network, PCA algorithm, profitability

1. Introduction

As we all know, profitability is one of the important indicators of enterprise operation, which is directly related to the survival and development of the enterprise, so the prediction of enterprise profitability is of great significance [1-2]. Enterprise profitability prediction is a complex task, which needs to be considered in many aspects to get accurate prediction results, and the methods and applications of profitability prediction are various, and the common methods include fuzzy logic and financial ratios,

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Received 10 January 2024; Revised 25 February 2024; Accepted 15 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-305

etc., which need to be selected in combination with the actual situation, so as to get the most effective prediction results [3-6].

Fuzzy logic is to establish a set of logical framework for those things with fuzzy concepts. In the prediction of corporate profitability, although some economic indicators are clear and easy to predict, more indicators have certain uncertainties [7-10]. Fuzzy logic can effectively deal with these uncertainties, providing a more refined and flexible analytical framework for corporate profitability prediction [11-12]. Financial ratios, on the other hand, are a kind of indicators derived from the calculation of financial indicators in the financial statements of enterprises, which are used to measure the profitability, solvency and operational capacity of enterprises [13-15]. Financial ratios include profitability ratios, solvency ratios and operational capacity ratios [16]. Profitability ratios are indicators for assessing the profitability and efficiency of an enterprise, mainly including gross profit margin, net profit margin and return on investment, etc., of which gross profit margin reflects the difference between the sales price of a product or service and the cost of production [17-19]. The net interest rate reflects the relationship between the sales revenue and net profit of the enterprise, while the return on investment indicates the rate of return obtained by the enterprise utilizing capital [20-21]. It should be noted that accurate prediction of profitability requires comprehensive consideration of various factors and the use of scientific analytical methods, and at the same time, the prediction results may be affected by uncertainty, so careful assessment and risk management are needed when using the prediction results [22-25].

Literature [26] examined corporate profitability forecasting based on an ergodic model, which reveals a parsimonious diffusion process of corporate profitability that accounts for all the characteristics of the data and the method achieves better sample forecasting performance over different time horizons, which contributes to corporate valuation. Literature [27] examines the use of life-cycle information by market participants in forming expectations, noting that the use of life-cycle information is inefficient in analyst forecasts and absent in management forecasts, and that there is a correlation between life-cycle forecasts and anomalous stock returns before the year. Literature [28] analyzes corporate earnings forecast accuracy in the digital era and examines the relationship between regional digital finance and corporate earnings forecast accuracy, emphasizing that increasing regional digital finance can effectively improve corporate forecast accuracy. Literature [29] emphasizes the importance of improving the performance of public enterprises and argues that a mathematical model that helps to predict the profitability of future contracts will be of great significance to the development of enterprises large and can be used as a tool to avoid political interference. Literature [30] assesses the trends in the development of family businesses, the level of revenues and profits, and proposes and tests a methodology for econometric analysis and forecasting based on econometric time series methods. Literature [31] describes the use of fuzzy logic models to quantify the relationship between the level of corporate profitability performance and the factors affecting profitability, verifies the effectiveness of fuzzy logic in modeling the relationship between profitability and its influencing factors, and provides the possibility of profitability modeling research. Literature [32] proposes a methodology for assessing the creditworthiness of enterprises based on fuzzy logic, which is revealed to serve as a basis for establishing a decision support system for lending to enterprises by analyzing the indicators of industry and regional characteristics, the indicators of small business activity, and the typical financial and economic indicators of services and trade. Literature [33] explores profitability forecasting of financial statements, specifies that research on financial statement analysis has been slow to develop and has received limited attention, and emphasizes that there is a great opportunity for influential research on fundamental analysis and market inefficiencies.

Based on DuPont financial analysis system, this paper explores the main financial ratio indicators reflecting the profitability of enterprises and their calculation methods. The principal component analysis is utilized to process six indicators, including return on total assets, and to construct the integrated indicators of corporate profitability. BP neural network is selected to construct the enterprise profitability index model, and the momentum term α is introduced to improve the BP neural network and solve the problems such as slow convergence speed during training. Based on Takagi-Sugeno type fuzzy neural network to construct the enterprise development ability index model, and use the result value of it and BP neural network as the input value to construct the final enterprise profitability prediction model. Through the sample enterprise data set selection, sample data processing and network model simulation training, the effectiveness of this paper's profitability prediction model is verified, which provides decision support for enterprises to deploy corresponding strategies according to the results of profitability prediction.

2. Enterprise profitability analysis system

2.1. DuPont Financial Ratio Analysis System Framework

The ideal effect of enterprise analysis of the level of profitability is to be able to have an overall perception of the business situation and financial capacity, but most analytical data in the analysis of enterprise profitability has a certain one-sidedness, and can not be evaluated comprehensively and objectively. DuPont financial ratio analysis system is a very classic method of analyzing corporate finance [34], commonly used in finance-related research, can reflect the level of the ability of the enterprise as a shareholder to obtain profits from investment. The advantage of this system lies in its ability to comprehensively consider various factors, which in turn can objectively evaluate the company's operating conditions and financial capabilities, Figure 1 shows the framework of DuPont's financial ratio analysis system. As can be seen from the figure, in order to analyze the operation status and profitability of the company, the analysis system takes the return on net assets as the core of the analysis. Through layer by layer decomposition, all the indicators affecting finance are integrated to form a system, thus providing reference materials for operators.

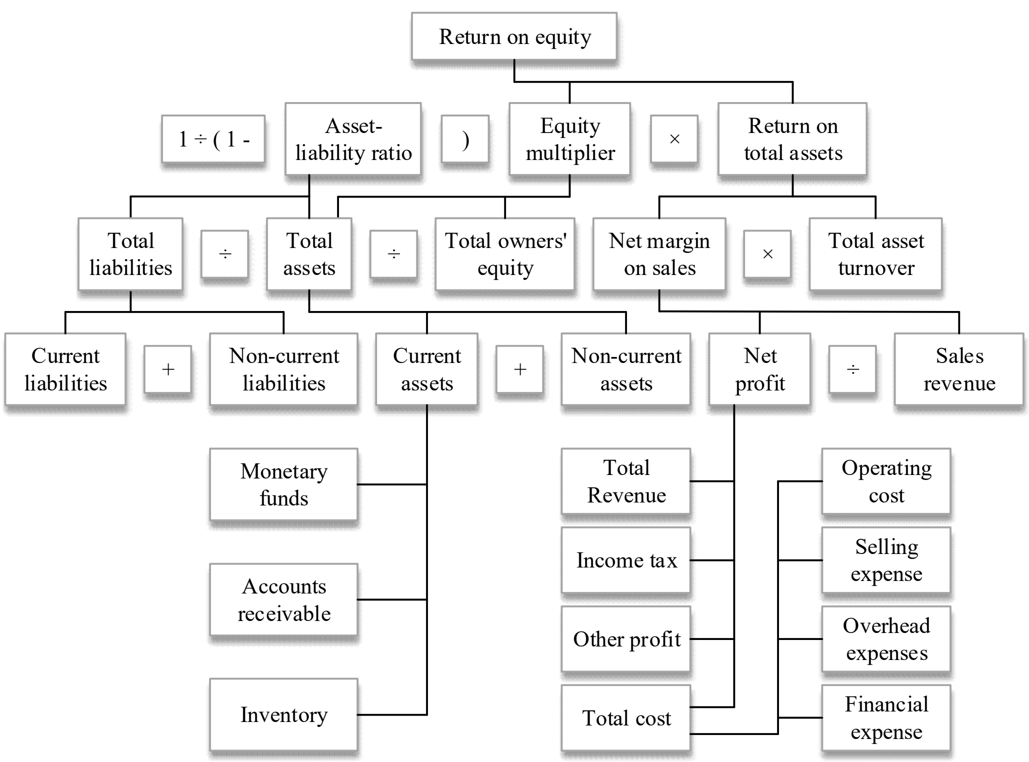


Fig. 1. DuPont financial analysis system framework

The analysis of the model shows that the return on total assets has the most significant impact on the return on net assets, which can be divided into two indicators: net sales margin and total asset turnover. The total asset turnover ratio can reflect the speed of the company's working capital, which can reflect the business results. The net sales margin shows the liquidity of the goods sold. The net sales margin rises when the sales department of a company achieves more sales and at the same time reduces its costs. Equity multiplier is an indicator of the debt position of the business. The higher the value of the equity multiplier, the higher the debt level of the business and the higher the risk index. Conversely, it indicates that the business has a low level of debt and is taking less risk.

For enterprises that have been listed, only based on the above mentioned profitability indicators can not make an objective analysis of the enterprise, the company's profitability is also related to the stock trend, so it is necessary to supplement the corresponding indicators to carry out a more objective analysis. Earnings per share is an indicator that reflects the profitability of each common share for the company. In profitability per share, the two key indicators obtained from the decomposition reflect the net assets per share as well as the return on shareholders' equity, respectively. The net assets of the company corresponding to each share, i.e., net assets per share, is composed of three main components: the financial leverage utilization, the ratio of liabilities to cash flow, and the value of operating cash flow corresponding to each share. In this case, the return on equity is also divided into operating and financial components, and specific factors are subdivided when performing different activities. When analyzing the profitability of a company, the constant addition of new indicators is conducive to a more comprehensive and objective consideration, and to the current situation of the enterprise to explore the sources of deep-seated problems and think about the path to a solution.

2.2. DuPont Analysis System Key Indicators

When analyzing a company's profitability, six factors are typically considered: return on total assets, return on net assets, operating profit margin, net cost-expense margin, surplus cash cover multiple, and return on capital.

2.2.1. Return on total assets. The total return on assets is used to analyze the profitability of the enterprise with the help of the data on the return on investment. For the evaluation of the return on investment of the enterprise, it is necessary to use the rate of return on investment, which is the ratio of two indicators: the profit of the enterprise and the average total assets. The rate of return on total assets is used to analyze and evaluate the efficiency of the enterprise in the use of assets, reflecting how much profit the enterprise can generate with the help of assets, which is a reflection of the level of profitability. Its calculation formula is:

$$\begin{aligned}&\text{Return on total assets}\\&=(\text{total profits}+\text{interest expense})/\ \text{average total assets}\times 100\%\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{Average total assets}\\&=(\text{total assets at the beginning of the year}+\text{total assets at the end})/2\end{aligned} \tag{2}$$

Return on Total Assets (ROA) shows the level of profitability and the inputs and outputs of an enterprise. The return on total assets analyzes the profitability of an enterprise based on the return on investment, and as one of the indicators for evaluating the efficiency of an enterprise's assets, this data reflects how an enterprise uses its assets to create value.

2.2.2. Return on net assets. The net return on assets represents the income situation from the point of view of shareholders and evaluates the extent to which the enterprise creates benefits with the help of free capital, and the data is calculated as the ratio of the net profit of the enterprise to the average shareholders' equity for a given period, and the formula for calculating the indicator is as follows:

$$\begin{aligned}&\text{Roe}=\text{Net profit}\times\text{ total asset turnover}\\&=(\text{after-tax profit/owner's equity})\times 100\%\end{aligned} \tag{3}$$

$$\text{Return on equity} = (\text{Net profit/average net assets}) \times 100\% \tag{4}$$

In the formula, the degree of value creation of assets, the gearing ratio and the tax rate corresponding to the current income tax all have a certain impact on the return on net assets, and the relationship between them is as follows:

This indicator reflects the profitability of its own assets; the higher the value, the greater the ability of the company to obtain net profits, meaning that investors will receive more income.

2.2.3. Operating profit margin. The profitability of the business represents the efficiency of the business operation, which can be subdivided into operating profit and operating income from an internal point of view. Enterprises need to refer to this data when discounting operating costs and examining profitability. The formula is described below:

$$\text{Operating margin} = (\text{Operating profit/operating revenue}) \times 100\% \tag{5}$$

This data is used to consider the extent to which a company's operating profit is related to its profitability level. The higher the value of the indicator, the more profitable the company is, the more competitive it is in the marketplace, and the more opportunities it has in its operations, which translates into operating income. On the opposite side of the spectrum, a lower value indicates that the company still has a lot of room to grow in terms of profitability.

2.2.4. Net cost-expense margin. The net cost-expense margin captures the link between a business's expenses and revenues. The formula is as follows:

$$\text{Cost expense margin} = (\text{Net profit/total cost expense}) \times 100\% \tag{6}$$

This indicator shows both the profitability of the enterprise and the standard of its cost management. The higher the value, the more profitable the company is in this area. On the other hand, it means that the company has to enhance its profitability by strengthening its cost management.

2.2.5. Surplus cash cover multiple. Surplus cash security multiplier is the ratio of operating income and net profit of the enterprise in a certain period of time, reflecting the degree of guarantee of cash income in the net profit of the enterprise in the current period, which truly reflects the quality of the enterprise's profitability. The formula is:

$$\text{Surplus cash cover ratio} = (\text{net operating cash flow/net profit}) \times 100\% \tag{7}$$

This indicator evaluates the quality of the enterprise's income from the point of view of changes in cash dynamics. The larger the indicator, the more reliable the enterprise's earnings are and the more contribution to cash that net profit can provide. However, changes in the value of the indicator are affected by changes in the denominator, which is why this indicator needs to be emphasized.

2.2.6. Rate of return on capital. The rate of return on capital considers the ability of an enterprise to generate income with the help of capital, and the data is calculated as the ratio of the average capital of the enterprise to its net profit. The formula is as follows:

$$\text{Return on capital} = (\text{Net profit/paid-in capital}) \times 100\% \tag{8}$$

As an indicator for investors to consider, superior numerical performance can attract investors to participate, and the investment risk of the enterprise is low. For operators, when the value of the return on capital is greater than the cost of debt capital rate, proper debt asset operation is beneficial to the business. On the contrary, overly indebted operations can reduce profitability and income for investors.

3. Analysis and construction of profitability indicators

According to the study of DuPont financial ratio analysis system, this paper initially clarifies the selection of evaluation indexes for enterprise profitability. This section will combine with the principal component analysis (PCA) algorithm enterprise profitability integration index construction, for the next step in the prediction of enterprise profitability to lay the data foundation.

3.1. PCA algorithm

Principal Component Analysis is a widely used algorithm for data dimensionality reduction [35]. Its core idea is to map the n-dimensional features of the original data onto a brand new k-dimensional coordinate system and reconstruct the k orthogonal features, also known as principal components. The PCA algorithm is to find a set of mutually orthogonal axes sequentially from the original data, so as to obtain the new axes, and the specific calculation steps are as follows:

Step 1: Centering data. The original data will be composed of n rows m columns matrix X by columns, centering the original data, i.e., subtracting the mean value of each feature, so that the mean value of each feature is zero.

Step 2: Calculate the covariance matrix. The centered data is subjected to matrix multiplication to obtain a covariance matrix C, which represents the correlation between each feature:

$$C = \frac{1}{m} X X^{\mathrm{T}} \tag{9}$$

where: X is the original data matrix. m is the dimension of the data.

Step 3: Calculate the eigenvalues and eigenvectors. Eigenvalue decomposition is performed on the covariance matrix to obtain the eigenvalues $\lambda_1, \lambda_2, \lambda_3, \cdots, \lambda_n$ and the corresponding eigenvectors $v_1, v_2, v_3, \cdots, v_n$. If vector v is the eigenvector of matrix C, it satisfies the equation (10) shown in which λ is the eigenvalue corresponding to the eigenvector v, and the eigenvector denotes the projection direction of each feature in the new eigenspace, and the principal component influence factor is calculated based on the calculated eigenvalue, defining the cumulative contribution rate greater than or equal to 85% as the screened out $b(b < m)$ principal component factor:

$$Cv = \lambda v \tag{10}$$

Step 4: Select principal components. Sorting the eigenvalues in order from largest to smallest, the top K eigenvectors are selected as the principal component matrix P, K is the dimension of the new feature space, i.e., the number of dimensions after dimensionality reduction.

Step 5: Data dimensionality reduction. Multiply the original data matrix X and the transformation matrix P to get the matrix Y after dimensionality reduction:

$$Y = PX \tag{11}$$

3.2. Construction of profitability indicators

3.2.1. Selection and construction of individual indicators of profitability. On the basis of existing research and analysis of DuPont's financial ratio system, this paper selects single indicators reflecting corporate profitability from six perspectives: return on assets (X1), return on shareholders' return, sales profitability, cost control efficiency, earnings quality and capital utilization efficiency: return on total assets (X1), return on net assets (X2), operating profitability (X3), net cost/expense ratio (X4), surplus cash security multiple (X5) and return on capital (X6).), surplus cash cover multiple (X5) and return on capital (X6). The main meanings and calculation methods of these indicators have been given in the previous section and will not be repeated in this section.

According to the Guidelines on Industry Classification of Listed Companies formulated by the China Securities Regulatory Commission (CSRC), this paper selects listed companies in a certain industry in China's A-share market from 2010 to 2024 as a sample, and statistically analyzes their profitability individual indicators, and the results are shown in Table 1. Analyzing the data in the table shows that:

1) When profitability is measured in terms of return on assets, the overall profitability of the sample companies changes less from 2010 to 2024.

2) When return on net assets, surplus cash security multiple and return on capital are used as representative indicators of profitability, the overall profitability of the sample companies fluctuates more. The mean value of return on net assets bottomed out in 2015 (-0.149), climbed to a peak in 2018 (0.699), and has since fallen back rapidly. The mean return on capital reached its lowest point in 2016 (-0.083), while a maximum occurred in 2018 (0.324).

3) When profitability is measured in terms of operating profit margin and net cost-expense margin, the profitability of the sample companies generally shows an upward trend over the 14-year period.

Table 1. The mean of the individual index of enterprise profitability

Year	X1	X2	X3	XX4	X5	X6	Number
2010	0.044	0.104	0.268	0.230	0.088	0.071	40
2011	0.051	0.088	0.267	0.220	0.068	0.061	41
2012	0.033	0.107	0.309	0.274	0.052	0.063	43
2013	0.027	0.098	0.261	0.196	0.042	0.034	43
2014	0.026	0.014	0.256	0.141	0.002	-0.007	47
2015	0.026	-0.149	0.346	0.282	0.017	0.031	48
2016	0.042	0.182	0.448	0.323	-0.090	-0.083	51
2017	0.054	0.144	0.484	0.359	-0.048	0.046	55
2018	0.060	0.699	0.597	0.464	-0.068	0.324	57
2019	0.069	0.155	0.632	0.500	0.086	0.099	59
2020	0.049	0.137	0.681	0.487	0.083	0.089	59
2021	0.049	0.099	0.550	0.541	0.072	0.083	61
2022	0.033	0.094	0.530	0.529	0.054	0.075	62
2023	0.047	0.080	0.518	0.521	0.065	0.073	63
2024	0.035	0.088	0.531	0.522	0.074	0.078	63

It can be seen that when examining the profitability of listed companies from different perspectives, different individual indicators show different trends, and it is difficult to make an overall judgment on profitability based on individual indicators. In order to reasonably, objectively and comprehensively reflect the profitability of Chinese listed companies in this industry, it is necessary to construct an integrated indicator.

3.2.2. Construction of integrated profitability indicators. To construct profitability integration indexes using principal component analysis, firstly, the individual indexes must be standardized, and the eigenvalues of the factors and their variance contribution ratios must be calculated. Second, the principal component factors are determined based on the variance contribution rate. Then, the eigenvectors are calculated based on the component matrix and eigenvalues, and the principal component factors are determined by combining the standardized data of individual indicators. Finally, the variance contribution rate is used as the coefficient to linearly combine the principal component factors to obtain the integrated indicators.

In this paper, we combine the data from 2010-2024 (a total of 792 samples) of listed companies in a certain industry in China's A-share market, standardize the data by using SPSS statistical analysis software, and use the processed data to conduct a factor analysis to obtain the factor $Y_i(i=1,2,\cdots,6)$ which contains all the information of the original indicators. The eigenvalues and variance contributions of each factor are shown in Figure 2. The corresponding principal component matrix of each factor is shown in Figure 3. As can be seen from Figure 2, the cumulative variance contribution rate of the first three factors $Y1,Y2,Y3$ reaches 93.41%, which satisfies the principle that the cumulative variance contribution rate is more than 85%, and it can be taken as the principal component factors. Combined with the component matrix in Figure 3, the component vectors of $Y1,Y2,Y3$ are selected, and the principal component eigenvectors are calculated by using the formula $\overline{Y}_i^* = \frac{\overline{Y}_i}{\sqrt{\delta_i}}$. Where $\overline{Y}_i^*$ denotes the eigenvector of the $i(i=1,2,3)$ th principal component. $\overline{Y}_i$ is the component vector of the ith principal component (see Figure 3). δ_i is the eigenvalue of the ith principal component (see Figure 2).

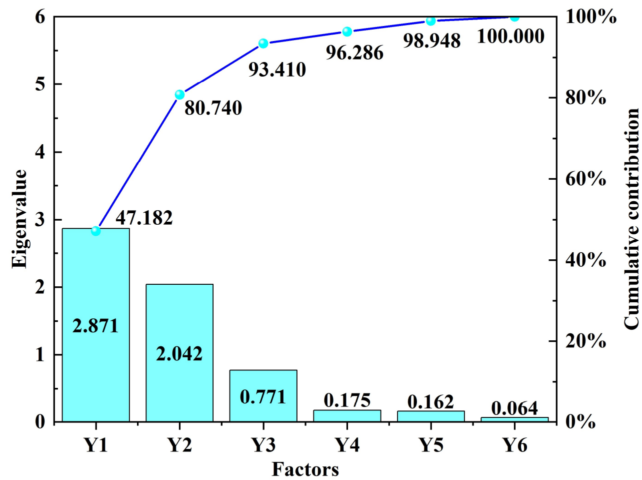


Fig. 2. Eigenvalue and cumulative contribution rate of main component factors

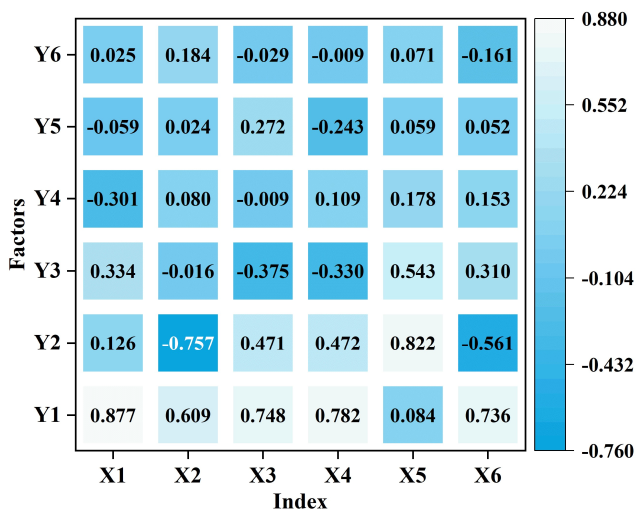


Fig. 3. Component matrix

ZX$ denotes the standardized data of a single indicator:

The eigenvectors of the principal components $Y1,Y2,Y3$ can be calculated according to the formula, and the results are shown in Fig. 4. According to the principal component eigenvectors in the figure, each principal component can be expressed as a linear function of the original indicator (standardized data), and the results are shown in Eqs. (12) to (14), where ZX denotes the standardized data of a single indicator:

$$Y1 = 0.521ZX1 + 0.383ZX2 + 0.436ZX3 + 0.447ZX4 + 0.040ZX5 + 0.417ZX6 \quad (12)$$

$$Y2 = 0.101ZX1 - 0.529ZX2 + 0.334ZX3 + 0.320ZX4 + 0.578ZX5 - 0.412ZX6 \quad (13)$$

$$Y3 = 0.382ZX1 - 0.013ZX2 - 0.451ZX3 - 0.362ZX4 + 0.627ZX5 + 0.311ZX6 \quad (14)$$

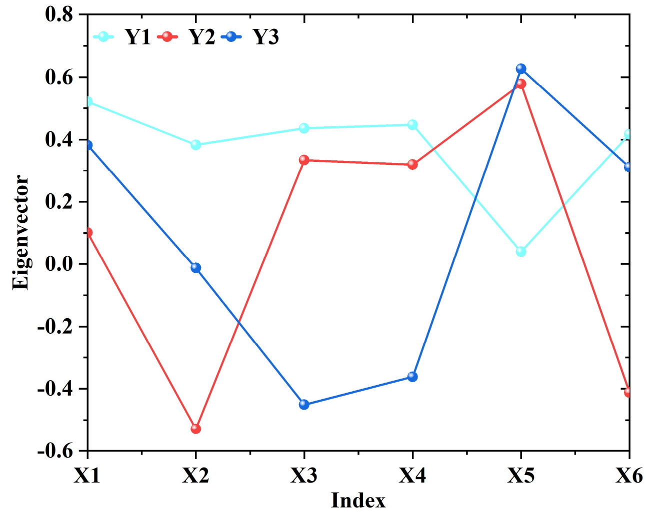


Fig. 4. Principal component eigenvector

Combined with the variance contributions in Figure 2, an integrated indicator reflecting profitability can be constructed P:

$$P = 0.472Y1 + 0.336Y2 + 0.127Y3 \quad (15)$$

Using the data of the sample companies from 2010-2024, the average value of the integrated profitability indicator of the listed companies in the industry can be calculated for each year, and the results are shown in Figure 5, where the different sizes of the round balls indicate the different values of the integrated indicator P, and the different background colors indicate the different stages of the changes in the profitability of the listed companies. As can be seen from the figure, the average value of the integrated profitability indicator P of the sample enterprises in 2010-2018 is generally in an upward trend, reaching a peak value of 0.41 in 2014 and 0.38 by 2018. While in the second stage of 2019-2022, due to the impact of the external objective factors of the enterprises, the average value of the integrated profitability indicator P of the enterprises in 2019-2022 is in an upward trend, and the average value of the integrated profitability indicator P of the enterprises in 2019-2022 is in an upward trend. 2020 showed a sharp decline, falling to the lowest value of 0.13 in the last 15 years by 2020, although in 2020-2022, the profitability of the enterprise rose back, but the overall level is still at a low level.2023-2024 is the third stage of the change in the profitability of the enterprise. In this stage, due to the gradual improvement of the external environment, the average value of the enterprise's comprehensive profitability index P shows an upward trend again, and reaches 0.39 in 2024.The above results show that the comprehensive profitability of the sample enterprises selected in this paper has a large ups and downs, and the enterprise's profitability is very susceptible to the influence of the external environment. Therefore, selecting an appropriate method to forecast the profitability of enterprises is crucial for the sustainable development of enterprises and effective external shocks.

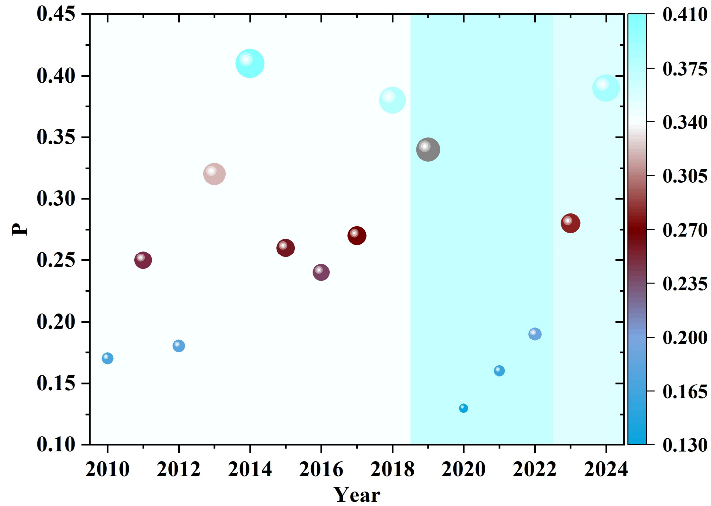


Fig. 5. The mean of the integration index of profitability

4. Enterprise profitability forecasting model

From the data and analysis in the previous section, this paper concludes that the prediction of enterprise profitability is crucial to the development of enterprises, which can assist enterprises to clarify their future development trends and make timely adjustments and improvements to their development strategies, and has significant application value. Therefore, this section mainly explores the fuzzy logic and financial ratios (i.e., DuPont financial analysis indexes) integration of corporate profitability prediction model to predict the profitability of enterprises.

4.1. Basis for modeling

4.1.1. BP Neural Networks. With the advent of the big data era, artificial neural networks have been rapidly promoted as a statistical model that can be quickly computed, gradually penetrating into various fields of economic life, and BP neural network is one of the most widely used models. The construction of BP neural network model [36] includes an input layer, which consists of the input vectors $X = (x_1, x_2, cdots, x_m)$ represents the information of each variable of the target to be predicted, while the output layer consists of the output vector $Y = (y_1, y_2, \cdots, y_n)$, which is the prediction result of the target to be predicted, and the hidden layer is like a "black box". The hidden layer acts as a "black box", connecting the two with invisible weight changes. When the neural network is trained with large enough samples, the error between the estimated value and the expected value of the input layer, which is reflected in each training, is adjusted to the error between the expected value and the estimated value of the output layer, and the error of the implicit layer is adjusted through feed-forward behaviors, and so on, the error of the three layers is adjusted continuously and iteratively until the error of each layer is within the first set threshold range. At this point, the current option coefficient value W_{ij} and the threshold value (when $i = 0$, W_{ij} represents the threshold value) held by the neural network are the results obtained through the neural network's self-learning and self-adaptation process. It can be proved by Kosmogorov's theorem that the hidden layer of a 3-layer BP neural network containing Sigmoid neurons can theoretically approximate all continuous functions arbitrarily if enough nodes are present. In spite of this powerful advantage, the iterative method of BP neural network adopts the fastest descent method, which is based on the negative gradient of the error function in the network when adjusting the weights of each layer, and this method will lead to a decrease in the speed of the neural network, and it may even be confined to a certain localized smallest region and fail to produce the results.

On this basis, adding the momentum term α to the model can effectively improve the convergence speed of the BP neural network and effectively improve the problem of slow learning speed of the BP neural network. In the process of training neural networks, the gradient descent method used in the error function is very strict on the requirements of the error interval, usually each error interval is infinitely small, at this time to change the weights of a certain layer of neural network learning speed will become very slow. Generally, the learning rate η is set as a constant, and the larger η is, the larger the fluctuation of weights in the network. Here if you wish to control the weight fluctuation in the neural network, you should be very careful about the setting of the learning rate, but no matter how it is set, a constant value of the learning rate often fails to get the desired results, and by introducing the momentum term, the learning rate of the model can be finely adjusted by each error adjustment in each learning rate, i.e., the learning rate η is no longer a constant. The weighted adjustment formula for the algorithm containing the momentum term is:

$$\ddot{A}w(t+1) = \eta E / \partial w + \alpha \ddot{A}w(t) \tag{16}$$

where α is the momentum term factor in the neural network, generally taken as 0.9.

Through the introduction of the momentum term can be adjusted each time the error function of the weights through the momentum term factor α to transfer, in this process the learning rate η of the value of the learning rate will be adjusted each time to change, no longer a fixed constant, at the same time, adding the momentum term can be adjusted to the various layers of weights towards the bottom of the average direction of the approach, to control the amplitude of its fluctuations within a reasonable range. The role of the momentum term here is mainly to smooth the error of each layer and control the fluctuation of the weights of each layer.

If the system enters the flat region of the error function, the change of the error at this time will be very small, i.e., $\ddot{A}w(t+1)$ is approximately equal to $\tilde{A}w(t)$, and $\tilde{A}w(t)$ after being averaged will become:

$$\ddot{A}w(t) = (-\eta / (1-\alpha)) \quad (E / w) \tag{17}$$

At this point, the effectiveness of $\dfrac{-\eta}{1-\alpha}$ is strengthened by the ability to regulate this weight to move it out of the saturation zone as quickly as possible.

In fact, for a weight W_{ij}, there are:

$$\ddot{A}w(t+1) = \ddot{A}w_{ij}(t+1) + \alpha \ddot{A}w_{ij}(t) \tag{18}$$

$\ddot{A}w_{ij}(t+1) = -\eta \partial E / \partial w_{ij}$ denotes the current direction of convergence, and if $\ddot{A}w_{ij}(t+1)$ is of the same sign as $\ddot{A}w_{ij}(t)$, then in the case of an error super surface, if convergence from the w_{ij} axis in that direction reduces the error within a certain range, so here $\ddot{A}w_{ij}(t+1)$ can be appropriately modified by increasing the magnitude of the modification, utilizing $\ddot{A}w_{ij}(t+1)$ with $\ddot{A}w_{ij}(t)$ can be achieved with a small number of iterative math operations. If $ddotAw_{ij}(t1)$ is opposite to $ddotAw_{ij}(t)$, then on the w_{ij} axis, from $ddotAw_{ij}(t1)$ to $ddotAw_{ij}(t)$ has passed a local minimum point, in order to avoid large fluctuations, at this time, $ddotAw_{ij}(t1)$ should appropriately reduce the range of its weight modification, but at this time, a large number of iterations and mathematical operations of $ddotAw_{ij}(t)$ and $ddotAw_{ij}(t)$ can also be used to meet the algorithm requirements.

In summary, it can be seen that the BP neural network in dealing with the error of each layer, in order to prevent the error from producing large fluctuations in the setting of the error interval is generally set to smaller intervals, but at this time the convergence speed of the neural network is significantly reduced. The introduction of the momentum term can adjust the learning rate according to the weight change each time, and thus a larger error interval can be used, while controlling the fluctuation of the weights of each layer. In general, larger values of α and η are preferred because a larger momentum factor and learning rate can increase the learning rate of the neural network more quickly, and although lowering the values of the two can also yield basically the same results, the speed, efficiency and accuracy of the operation is slightly inferior to that of a larger value.

4.1.2. Fuzzy logic systems. In general, fuzzy generator, fuzzy rule base, fuzzy inference machine, and fuzzifier make up the fuzzy logic relations, while fuzzy logic system [37] refers to those systems that are directly related to fuzzy concepts and fuzzy logic, and its structure is shown in Fig. 6.

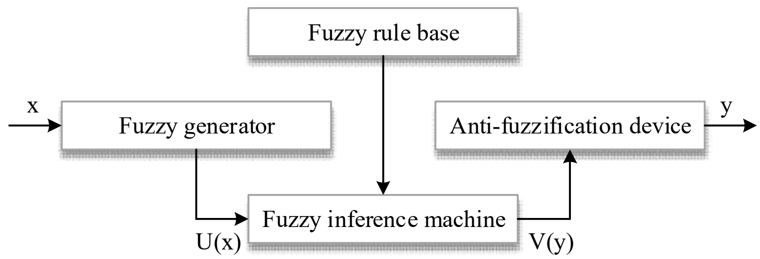


Fig. 6. Fuzzy logic system

1) Fuzzy generator. A fuzzy generator is a mapping of a definite point $x=(x_1,x_2,\cdots,x_n)^T$ on $U\in R^n$ to a fuzzy set A. There are two ways of mapping:

(1) Single-valued fuzzy generator. If the fuzzy set A is fuzzy single-valued with respect to the support set x, then for a point $x^{'}=x$, there is $\mu_A(x^{'})=1$, and for all the rest of the $x^{'}\neq x$, there is $\mu_A(x^{'})=0$.

(2) Non-single-valued fuzzy generator. When $x^{'}=x$, $\mu_A(x^{'})=1$, but as $x^{'}$ moves progressively away from x, $\mu_A(x^{'})$ starts to decay from 1 all the way up to 0$.

In most cases, the first method, i.e., single-valued fuzzy generator, is generally adopted.

2) Fuzzy rule base. A fuzzy rule base is composed of several fuzzy inference rules. The fuzzy inference rules are of the form:

$$R^{(l)}: if\ x_1\ is\ F_1^l, x_2\ is\ F_2^l, \ldots, x_n\ is\ F_n^l, theny\ is\ G^{'} \tag{19}$$

where F_i^l and G^l are fuzzy sets on $U_i\subset R$ and $V\subset R$, respectively, and $x=(x_1,\cdots,x_n)\in U_1\times\cdots\times U_n$ and $y\in V$ are linguistic variables, $i=1,2,\cdots,n, l=1,2,\cdots,m$, and m is the total number of fuzzy rules. x and y are the inputs and outputs of the fuzzy logic system, respectively.

3) Fuzzy Inference Machine. The function of a fuzzy inference machine is to map fuzzy sets on $U_1\times\cdots\times U_n\subset R^n$ into fuzzy sets on V. The fuzzy inference machine is a system of fuzzy logic that uses fuzzy logic as its input and output. Fuzzy rules:

$$R^{(l)}: if\ x_1\ is\ F_i^l, x_2\ is\ F_2^l, \cdots, x_n\ is\ F_n^l, theny\ is\ G^l \tag{20}$$

can be represented as a fuzzy implication $F_1^l\times F_2^l\times\cdots\times F_n^l\times F_n^l\rightarrow G^l$ on a product space U×V. Assuming that the fuzzy set $A^{'}$ on U is the input to the fuzzy inference machine, if the synthetic operation is utilized, then the fuzzy set $B^{'}$ on V derived from each fuzzy inference rule is:

$$\mu_{B^l}(y)=\underset{x\in U}{\vee}(\mu_{F_1^l\times\cdots F_n^l}\rightarrow G^l(x,y)\wedge\mu_{A^l}(x)) \tag{21}$$

4) Defuzzifier. The role of an defuzzifier is to map a fuzzy set G on $V \subset R$ to a definite point $y \in V$. The following three types of defuzzifiers are common:

(1) Maximum value defuzzifier:

$$y = \arg \vee_{y \in V} [\mu_B(y)] \tag{22}$$

(2) Center-averaged inverse fuzzifier:

$$y = \sum_{y=1}^{m} \bar{y}(\mu_B(\bar{y})) \Big/ \sum_{l=1}^{m} \mu_B(\bar{y}) \tag{23}$$

where $\bar{y}$ is the center of the fuzzy set G, i.e., $\mu_G(y)$ achieves its maximum value at the point $\bar{y}$ on V.

(3) Improved center-averaged defuzzifier:

$$y = \sum_{l=1}^{m} \overline{y^l}(\mu_B(\overline{y^l}) / \delta^l) \Big/ \sum_{l=1}^{m} (\mu_B(\overline{y^l}) / \delta^l) \tag{24}$$

where δ is a characteristic parameter that determines the shape of $\mu_c(y)$, such as the width of the curve.

4.2. Profitability prediction model based on fuzzy neural network

In this paper, in order to simplify the network structure and improve the network training speed and accuracy, a combined model based on fuzzy neural network is proposed, which firstly constructs the enterprise profitability index model by using BP neural network, and then constructs the enterprise development ability index model by using Takagi-Sugeno type fuzzy neural network, and finally, constructs the enterprise development ability index model based on Takagi-Sugeno type fuzzy neural network by using the learning results of the above two models again. -Sugeno type fuzzy neural network for enterprise profitability prediction model.

4.2.1. BP Neural Networks to Build Profitability Indicator Models. In this paper, BP neural network is used to process the data of enterprise profitability index, and the profitability index model with three-layer network structure is constructed. In the model, p_{xi} is used to denote the value of the i th profitability evaluation index of the p th sample, which is denoted as $X_p = (x_{p1}, x_{p2}, \cdots, x_{pn})$. $wij(i = 1, 2, \cdots n; j = 1, 2, \cdots, m)$ denotes the connection weight coefficients from the i neuron in the input layer to the j neuron in the hidden layer, $w_j(j = 1, 2, \cdots, m)$ denotes the connection weight coefficients from the j neuron in the hidden layer to the neurons in the output layer, o_p is the prediction result value of sample p.

4.2.2. Based on Takagi-Sugeno type fuzzy neural network models:

1) Network structure. The structure of the Takagi-Sugeno based network model is shown in Figure 7. The model consists of two sub-networks i.e., the antecedent network and the posterior network. The final output of the network is equal to the weighted sum of all rule posteriors and the weighting factor is the applicability of each fuzzy rule output by the antecedent network.

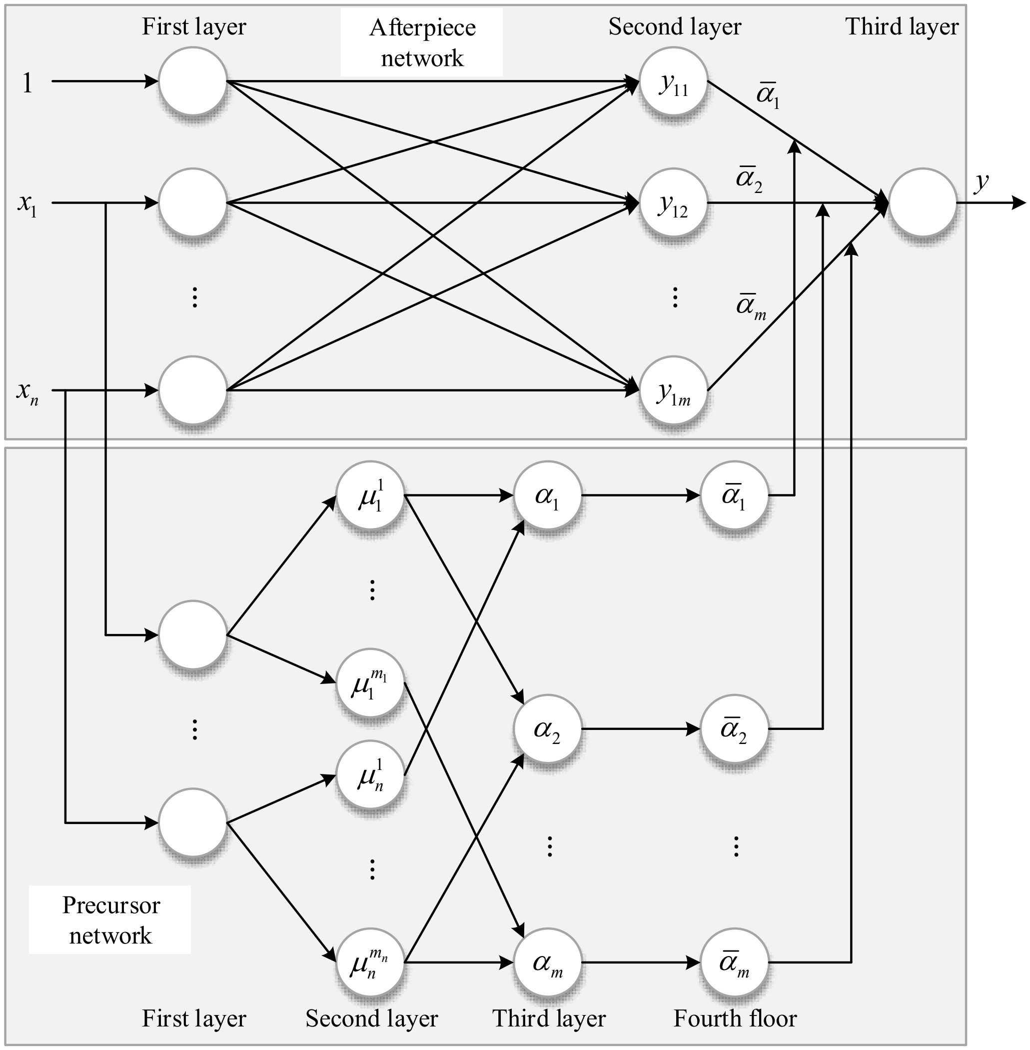


Fig. 7. Structure of Takagi-Sugeno-based fuzzy neural network

(1) Prefactor network. The antecedent network consists of 4 layers. The first layer is the input layer. Each of its nodes is directly connected to each component of the input vector x_i, which plays the role of directly transmitting the input values $x=(x_1,x_2,\cdots,x_n)^T$ to the next layer. The number of nodes in this layer is $N_I=n$.

The second layer is the fuzzification layer. Each node represents a linguistic variable value, and in this paper, four linguistic variables (excellent, good, medium and poor) are chosen. The role of this layer is to calculate the affiliation degree μ_i^j of each input component belonging to the fuzzy set of each linguistic value, where:

$$\mu_i^j=\mu_{A_i^j}(x_i), i=1,2,\ldots,n, j=1,2,\ldots,m_i, m_i=4 \tag{25}$$

n is the dimension of the input and the fuzzy partition number of x_i is 4. In this paper, the Gaussian function is used for the affiliation function:

$$\mu_i^j=e^{-(x_i-c_{ij})^2/\sigma_{ij}^2} \tag{26}$$

In equation (26), c_{ij} and σ_{ij} denote the center and width of the affiliation function, respectively. The total number of nodes in the layer is:

$$N_2 = 4n \tag{27}$$

The third layer is the rule inference layer. Each node in this layer represents a fuzzy rule, which is used to match the antecedents of the fuzzy rules and calculate the applicability of each rule. Namely:

$$\alpha_j = \mu_1^{i_1} \mu_2^{i_2} \dots \mu_n^{i_n} \tag{28}$$

where $i_1 \in \{1, 2, \dots, 4\}, \dots, i_n \in \{1, 2, \dots, 4\}$, $j = 1, 2, \dots, m, m = 4^n$.

The fourth layer is the normalization layer. This layer has the same number of nodes as the third layer, i.e., $N_4 = N_3 = m$, and it implements the normalization computation. Namely:

$$\overline{\alpha_j} = \alpha_j / \sum_{i=1}^{m} \alpha_i, j = 1, 2, \dots m \tag{29}$$

where $i_1 \in \{1, 2, \dots, 4\}, \dots, i_n \in \{1, 2, \dots, 4\}$, $j = 1, 2, \dots, m, m = 4^n$.

The fourth layer is the normalization layer. This layer has the same number of nodes as the third layer, i.e., $N_4 = N_3 = m$, and it implements the normalization computation. Namely:

$$y_{1j} = p_{j0}^1 + p_{j1}^1 x_1 + p_{j2}^1 x_2 + \dots + p_{jn}^1 x_n, j = 1, 2, \dots m \tag{30}$$

The third layer is the output layer and the output values are the predicted result values:

$$y_1 = \sum_{j=1}^{m} y_{1j} \overline{\alpha_j} \tag{31}$$

y_1 is the weighted sum of the posteriors of each rule, and the weighting coefficients are the applicability of each fuzzy rule after normalization $\bar{\alpha}_j$, i.e., the outputs of the antecedent network are used as the connectivity weights of the third layer of the posterior network.

2) Learning Algorithm. The Takagi-Sugeno based self-organizing fuzzy inference system (ANFIS) provides a hybrid learning algorithm for fuzzy modeling capable of extracting the corresponding fuzzy rules from the dataset, which adjusts the parameters as follows:

(1) Tuning the antecedent parameters. Assume that the network has L layers and the number of nodes in the k th layer is #(k). (k, i) denotes the i th node in the k th layer, whose node function or node output is denoted as O_i^k, and is a function of the input signal ensemble parameter set, which can be denoted as:

$$O_i^k = O_i^k (O_1^{k-1}, \cdots, O_{\#(k-1)}^{k-1}, a, b, c, \dots) \tag{32}$$

where a, b, c etc. are the parameters of the node.

Given a training dataset with N groups, define the error measure function for the $p(1 \le p \le N)$ group of sample data as:

$$E_p = \sum_{m=1}^{\#(L)} (T_{m,p} - O_{m,p}^L)^2 \tag{33}$$

where $T_{m,p}$ denotes the target output value of the m th element of the p th group of samples; and $O_{m.p}^L$ denotes the actual output value of the m th element of the p th group of samples. The total error of the network is:

$$E = \sum_{p=1}^{N} E_p \tag{34}$$

Using the gradient descent method, the error change rate of the p th group of sample data for each output node is first calculated as: $\partial E_p /_{\partial O}$, and the error change rate of the ith node (L,i) of the output layer is denoted as:

$$\partial E_p / \partial O_{i,p}^L = -2(T_{i,p} - O_{i,p}^L) \tag{35}$$

The internal node (k,i), whose error rate of change is derived from the chain rule:

$$\frac{\partial E_p}{\partial O_{i,p}^k} = \sum_{m=1}^{\#(k+1)} \frac{\partial E_p}{\partial O_{m,p}^{k+1}} \frac{\partial O_{m,p}^{k+1}}{\partial O_{i,p}^k} 1 \le k \le L-1 \tag{36}$$

Assuming that α is a parameter given by the network, the rate of change of the error of the $p(1 \le p \le N)$ th set of sample data on the parameter α is:

$$\frac{\partial E_p}{\partial \alpha} = \sum_{o^*} \frac{\partial E_p}{\partial O^*} \frac{\partial O^*}{\partial \alpha} \tag{37}$$

where O^* is all nodes whose outputs depend on α. Therefore, the rate of change of the overall network error for α is:

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{N} \frac{\partial E_p}{\partial \alpha} \tag{38}$$

The amount of error variation in α is:

$$\Delta \alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{39}$$

where η is the learning rate:

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} (\frac{\partial E}{\partial \alpha})^2}} \tag{40}$$

k is the length of the gradient change in the parameter space i.e. the step size. Then the correction formula for α is:

$$\alpha = \alpha + \Delta \alpha = \alpha - \eta \frac{\partial E}{\partial \alpha} \tag{41}$$

(2) Adjustment of posterior parameters. Assuming that the unknown linear parameters form a vector of θ, the matrix equation can be obtained from the known P set of sample data:

$$A\theta = y \tag{42}$$

Then the optimal solution that minimizes θ for $\| A\theta - y \|^2$ is the least squares estimator (LSE) θ^*:

$$\theta^* = (A^T A)^{-1} A^T y \tag{43}$$

where A^T is the transpose of A and $(A^T A)^{-1} A^T$ is the pseudo-inverse of A if $A^T A$ is nonsingular. Let the ith row vector of matrix A be α_i^T and the ith row vector of y be y_i^T, then θ can be computed iteratively as follows:

$$\begin{cases} \theta_{i+1} = \theta_i + P_{i+1}\alpha_{i+1}(y_{i+1}^T - \alpha_{i+1}^T\theta_i) \\ P_{i+1} = P_i - \dfrac{P_i\alpha_{i+1}\alpha_{i+1}^T P_i}{1+\alpha_{i+1}^T P_i \alpha_{i+1}}, i = 0,1,\cdots,N-1 \end{cases} \tag{44}$$

where the minimum estimator θ^* is equal to θ_N, and the initial conditions required to compute the above equation are $\theta_0 = 0, P_0 = \gamma I$, with γ a large positive number, and I the unit matrix.

5. Analysis of projected enterprise profitability

The data used for the analysis in this section are the relevant data of 792 sample enterprises selected in the previous section from 2010 to 2024, which are divided into the training set and the test set according to the ratio of 8:2, in which the training set contains the relevant data of 634 sample enterprises and the test set contains the relevant data of 158 sample enterprises.

5.1. Profitability indicator model training

The structure of the enterprise profitability indicator model based on BP neural network model constructed in the study is three-layered, with a total of three nodes in the input layer, that is, three new indicator data extracted by principal component features in Section III, and the number of neurons in the output layer is 1 (the output result is the enterprise's comprehensive profitability indicator P). The determination of the number of hidden layer nodes is a difficult point in the study, where you can refer to the empirical formula $k = \sqrt{n+m} + \varepsilon$ (where k is the number of neurons in the hidden layer, n is the number of neurons in the input layer, m denotes the number of neurons in the output layer, and ε is the random number between 1 to 10). On this basis, training starts with a smaller value, and stops if the number of training times exceeds the specified number of times or if the model does not converge within the predetermined error range within the specified number of training times. The number of neuron nodes in the hidden layer is incremented sequentially, and under the premise of meeting the predetermined error range, the network structure is taken to be as simple as possible, that is, the number of nodes in the hidden layer is taken to be as few as possible. In the process of training the number of neurons in the hidden layer of the enterprise profitability index model, the number of neurons in the hidden layer can be derived from the empirical formula by substituting the numerical values into the empirical formula, and the number of neurons in the hidden layer is approximately between 5 and 15. The pre-set learning rate is 0.001, the target accuracy value of the training error is 0.00001, and the maximum number of training times is stipulated to be 500. Then the selection of the number of neurons in the hidden layer training is shown in Figure 8. The left vertical axis of the figure indicates the number of iterations for the model to reach the target error of 0.00001, which corresponds to the bar graph. The right vertical axis indicates the mean square error (MSE) between the network output and the desired output, corresponding to the blue circle. As can be seen from the figure, sequentially incrementing the number of neuron nodes in the hidden layer, the number of iterations for the network model to reach the target error of 0.0001 varies, and the mean square error between the network output and the desired output also varies. Among the 11 network models, when the number of neurons in the hidden layer is 9, the mean square error between the network output and the desired output is the smallest, with a value of 0.09087, and the number of iterations at this time is 328. In order to simplify the complexity of the network structure and to save the time of the network evaluation, the structure of BP neural network with the number of neurons in the hidden layer of 9 is finally determined.

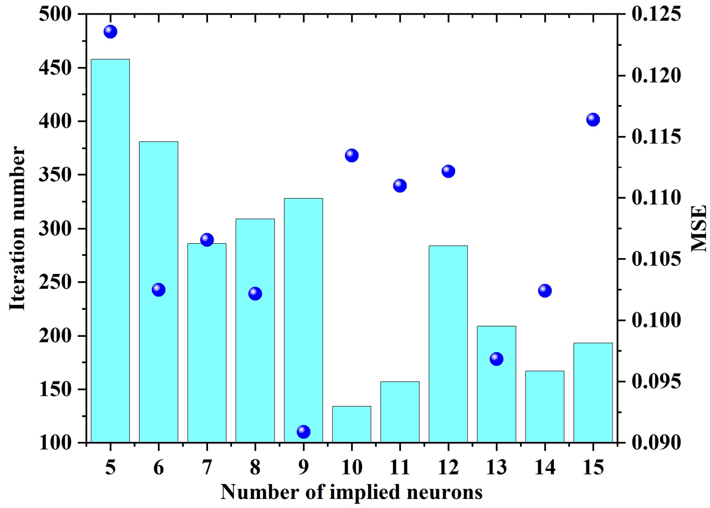


Fig. 8. Number selection of neurons in hidden layer

The error of the corporate profitability indicator model training is shown in Figure 9. From the figure, it can be seen that with the increasing number of iterations of the model, the training mean square error gradually approaches the optimal mean square error. After 92 iterations, the training mean square error of the model reaches and stays at the optimal mean square error level.

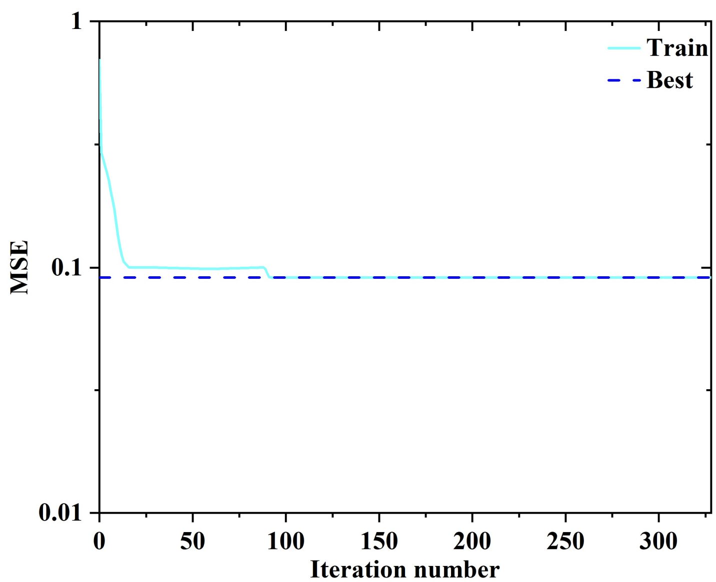
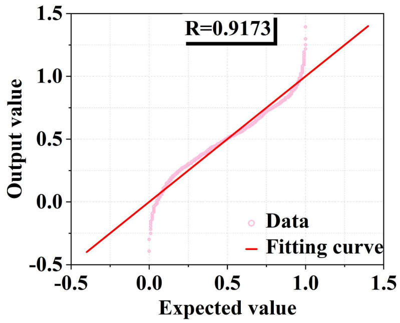
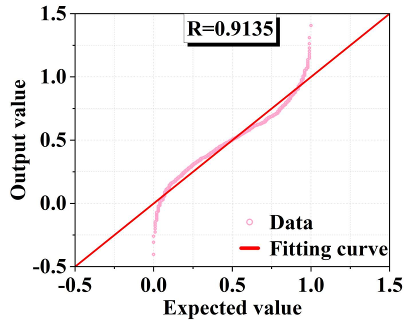


Fig. 9. Training error curve of BP neural network

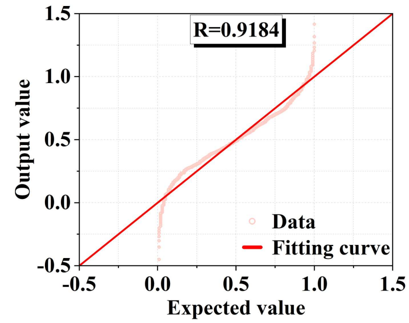
In addition, in order to further test the fit of the actual output of the model to the desired output, this study also used regression analysis to regress the results of the testing experiments of the network model, and the regression curves are shown in Fig. 10, with (a)-(o) denoting the fitting results of the 634 samples of the training set from 2010 to 2024, respectively. The horizontal coordinate represents the expected output, i.e., the actual value of the enterprise's comprehensive profitability index P, and the vertical coordinate represents the output of the results of the BP neural network model training, and R in the graph represents the correlation coefficient between the output of the model test results and the expected output, and the closer the value of R is to 1, the closer it is between the model output and the expected output, and the better the model's predictive performance is. As can be seen from the graph, the R values of the model's fitting results for the sample enterprises from 2010 to 2024 are all above 0.9, which indicates that the model has a good fit.



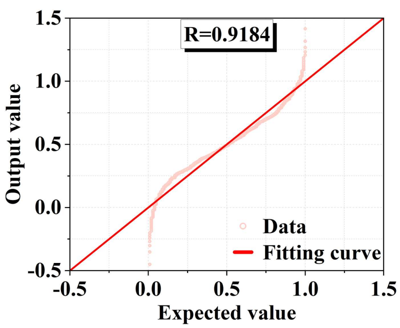
(a) 2010



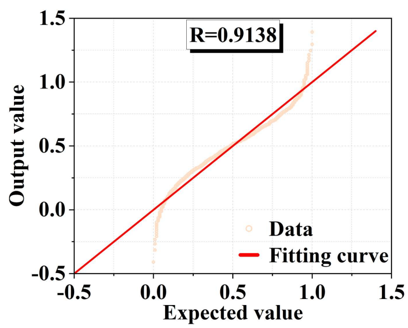
(b) 2011



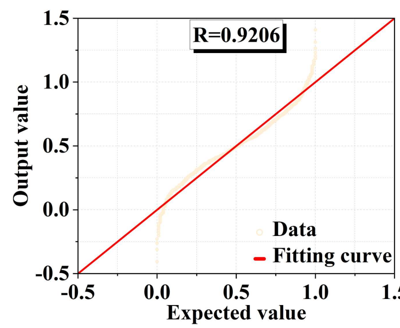
(c) 2012



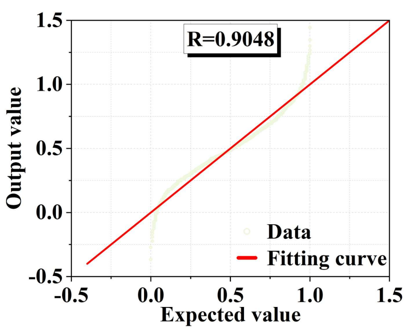
(d) 2013



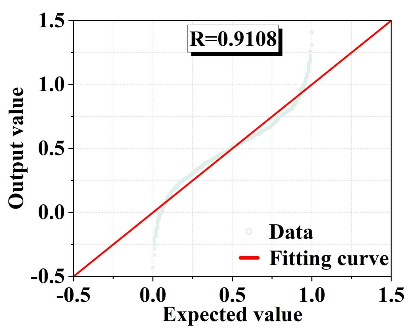
(e) 2014



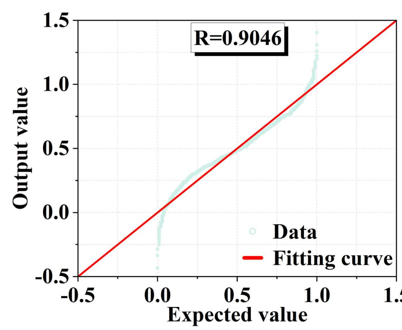
(f) 2015



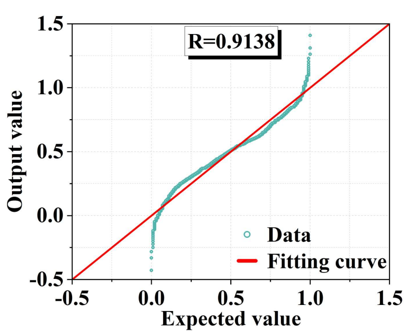
(g) 2016



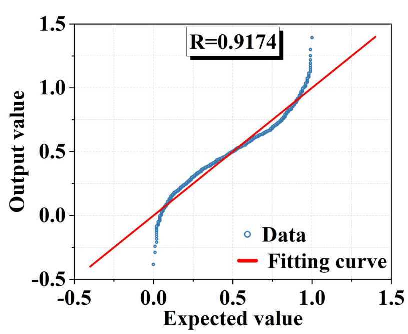
(h) 2017



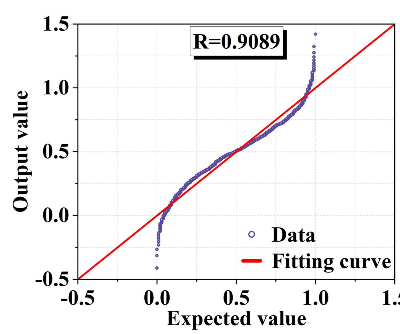
(i) 2018



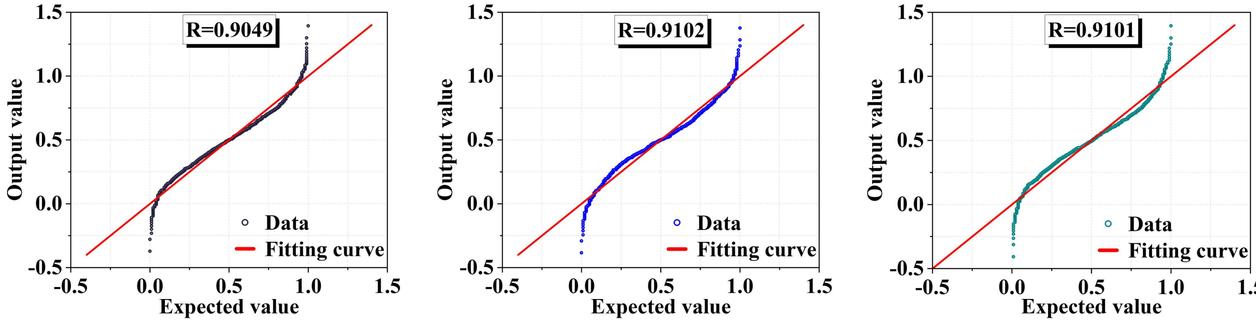
(j) 2019



(k) 2020



(l) 2021



(m) 2022 (n) 2023 (o) 2024

Fig. 10. BP neural network training regression analysis

After the corporate profitability indicator model has been trained, the input layer to hidden layer weight matrix is a 3×9 matrix W, where w_{ij} corresponds to each element in the matrix W, indicating the connection weights of the i neuron in the input layer to the j neuron in the hidden layer, and the specific values are shown in Table 2.

Table 2. Input layer to hidden layer weight

	1	2	3
1	-3.2674	-3.4038	-4.0178
2	3.1807	12.6172	1.6984
3	-0.1024	0.7983	-2.2857
4	-4.5638	-0.8842	7.7647
5	3.6974	-1.3645	-5.8892
6	1.5849	-2.6074	6.7066
7	1.2048	-5.2831	5.2332
8	1.2136	-4.7764	-3.0287
9	-0.0947	-1.3096	-1.4096

The weights from the hidden layer to the output layer are obtained after model training:

$$w_{ij} = (-33.9748, 34.5039, 31.5213) \tag{45}$$

The input layer to the hidden layer is thresholded:

$$b_j = (3.7841, -3.2683, 2.9476) \tag{46}$$

The threshold from the hidden layer to the output layer is:

$$b_k = -8.6742 \tag{47}$$

Finally. The trained BP neural network model is validated and analyzed using the data related to 158 enterprises in the test set, and the results obtained are shown in Figure 11. From the figure, it can be seen that the difference between the actual output results of the model for the 158 enterprise samples and the expected output results is relatively small, and the output results of 9 out of the 15 years from 2010-2024 are completely consistent with the expected results, which fully proves that the model of this paper has a good fitting effect.

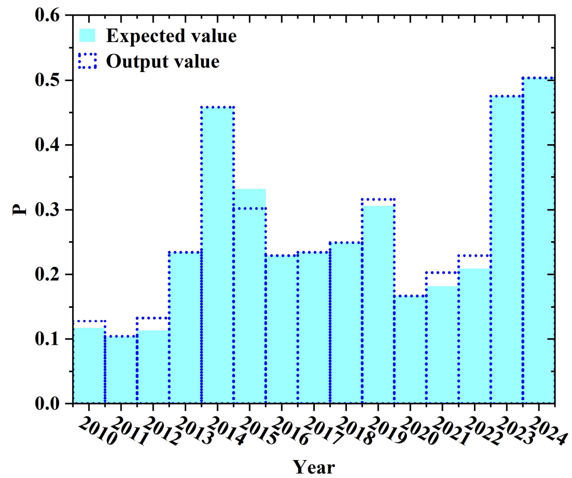


Fig. 11. Test sample results

5.2. Development capacity model training

There are a total of four nodes in the input layer of the development capability network model, i.e., the indicators of enterprise development capability category selected in this paper, including four indicators of enterprise management level, development and innovation capability, human quality status and customer satisfaction. The output layer of the model consists of only one node (enterprise development capability indicator). Each indicator is scored by experts according to their experience, and each indicator is divided into 3 fuzzy subsets ("low", "medium" and "high") on their respective domains. Therefore, the structure of this assessment model is 4-12-81-81-1 structure.

In order to simplify the training steps of the model and save the training time, the training set sample data are brought into the fuzzy neural network model for training through MATLAB programming, and the fuzzy neural network training error diagram is shown in Fig. 12. The model reaches MSE of 0.000792, which is less than 0.001, after 500 training cycles.

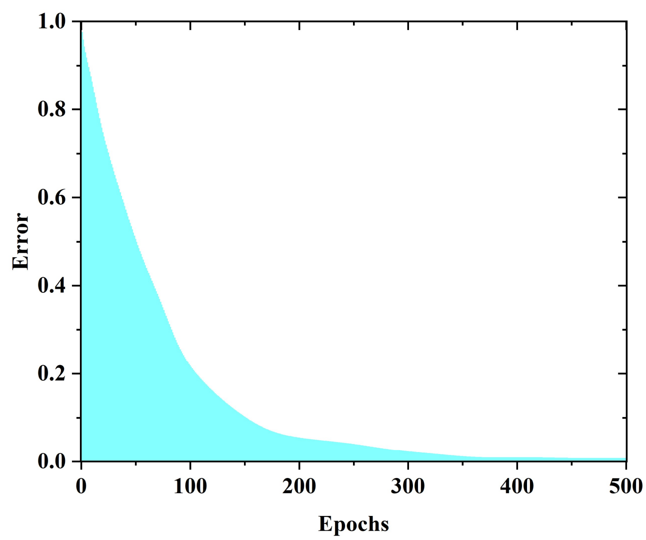


Fig. 12. Training error of Takagi-Sugeno fuzzy neural network

The trained Takagi-Sugeno fuzzy neural network is analyzed for predictive performance validation using the test set of 158 samples of enterprise development capacity index data.The comparison of the mean value of the expected output development capacity of the 158 samples from 2010 to 2024 and the actual output data of the model is shown in Figure 13. From the figure, it can be seen that the prediction effect of the model is better, and the model output results in 11 out of 15 years are completely consistent with the expected results, and the training effect of the network is better.

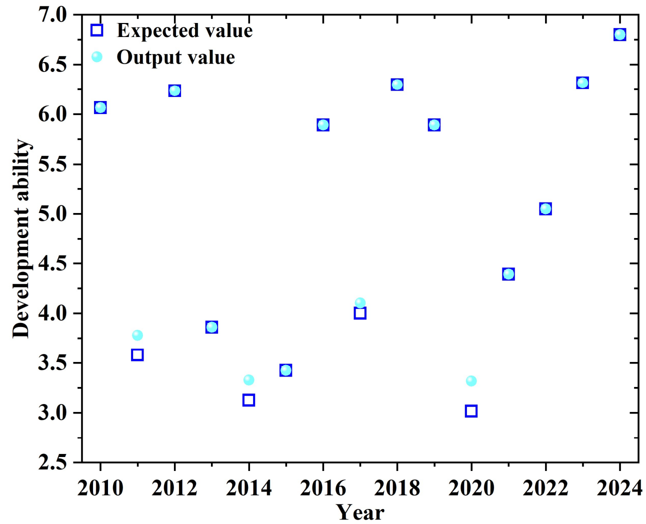


Fig. 13. Comparison between expected value and output value

5.3. *Training in corporate profitability prediction modeling*

The enterprise profitability prediction model constructed in this paper consists of input layer, fuzzification layer, output layer and fuzzy rule base. After the training of the enterprise profitability indicator model as well as the development ability indicator model, the output results of the two models can be obtained. Taking the output result values of the above two models as the input of the prediction model, the number of input nodes of the enterprise profitability prediction model is 2. The output layer represents the predicted enterprise profitability, and the number of nodes in the output layer is 1. Dividing the fuzzy subset of the indicators in the input layer into 4, the model The number of nodes in the fuzzy layer is 8, and the number of fuzzy rules is $4^2 = 16$.

The network model parameters as well as the affiliation function are learned and trained, and Figure 14 shows the model training error results. The model reaches the predefined accuracy of 0.00001 for the mean square error after 200 training cycles, with an instrumental value of 7.28E-6.

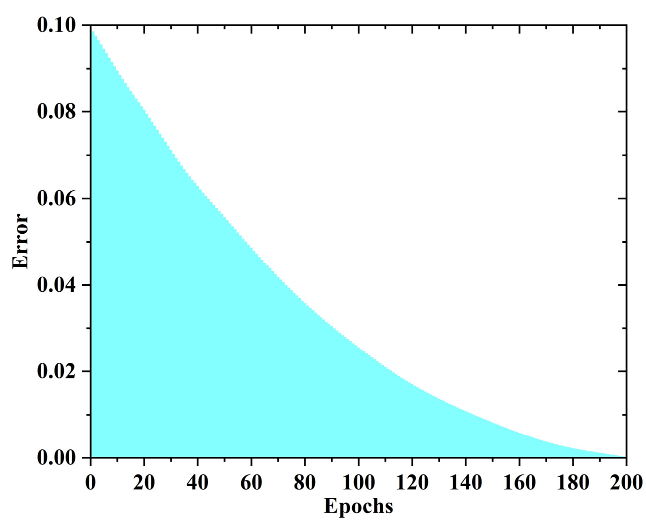


Fig. 14. Training error of combined model

The data of 158 sample enterprises used to test the performance of the model are inputted into the trained enterprise profitability prediction model, and the output results are statistically analyzed and the profitability of the enterprises in the next five years (2025-2029) is predicted, and the prediction results of five sample enterprises (denoted as A, B, C, D and E) are selected for visualization as shown in Figure 15. The box in the figure indicates the expected output from 2010 to 2024, the circle indicates the actual output of the model from 2010 to 2024, and the ball indicates the predicted output of the model from 2025 to 2029. From the figure, it can be seen that after combining the BP neural network and fuzzy neural network, the gap between the actual output of the combined model and the desired output is further reduced. The actual output of the model in the lowest 12 out of the 15 years from 2010 to 2024 is in perfect agreement with the desired output. It shows the effectiveness of combining BP neural network and fuzzy neural network in this paper. And in the predicted output of the model from 2025 to 2029, it can be seen that the profitability of enterprise A is on a downward trend as a whole, except for the increase in profitability from 2025 to 2026, which may be due to enterprise A's own management problems resulting in a low score of its development ability index, which in turn affects the overall profitability of the enterprise. The profitability of the remaining four enterprises has small ups and downs, but the overall trend is up. The experimental results significantly demonstrate the effectiveness of this paper's prediction model for enterprise profitability prediction.

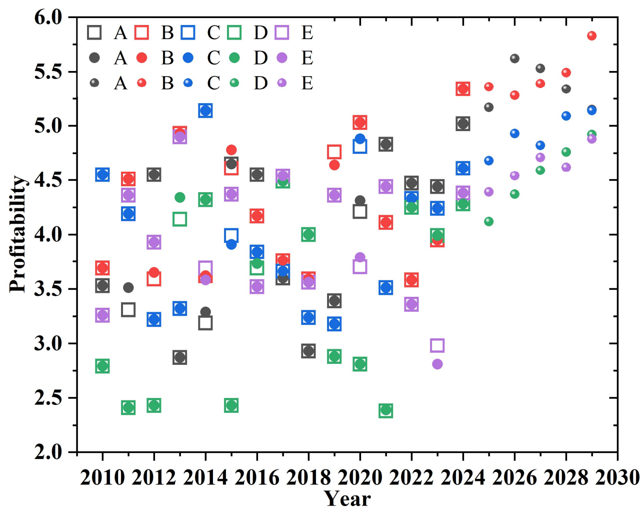


Fig. 15. Profitability forecasting results

6. Conclusion

This paper constructs a predictive model of corporate profitability based on DuPont financial ratio analysis system and fuzzy neural network. A sample of 762 Chinese A-share companies listed in a certain industry is selected to verify the practicality of the model. The results show that the model is able to output results that are close to the expected value based on the selected data, and is able to predict the profitability of enterprises in the next five years. It provides a new idea for the research in the field of corporate profitability prediction. Future research can further improve the evaluation index of enterprise profitability, fully reflecting the era and flexibility of the evaluation index. At the same time, it can further expand the sample data fusion and field scope, collect more data related to different types of enterprise profitability in different fields as much as possible, and enhance the generalization ability of the enterprise profitability prediction model in this paper.

Acknowledgements

This work was supported by Tianjin Philosophy and Social Science Planning project "Research on Tianjin Investment and Financing System under the background of Supply-side Structural Reform" (TJGL18-28), phased research results.

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