International Journal for Housing Science and Its Applications
Publish August 3, 2025. Volume 46, Issue 3 Pages 229-242

https://doi.org/10.70517/ijhsa46316

Research on optimization of corporate innovation strategy and financial performance in the context of digital economy based on fuzzy logic and neural network

Qingqing Chang[1,2,*], Ying Wang[3] and Xiuyun Yang[2]
[1] Business School of Xi'an International Studies University, Xi'an, Shaanxi, 710128, China
[2] School of Economics and Finance of Xi'an Jiaotong University, Xi'an, Shaanxi, 710049, China
[3] School of Computer Science and Technology of Xidian University, Xi'an, Shaanxi, 710071, China
Corresponding authors: (e-mail: changqingqing@xisu.edu.cn).

Abstract With the arrival of the digital era, how enterprises can promote their financial performance through the implementation of digital transformation has become a hot issue. This paper establishes an enterprise financial performance evaluation system based on fuzzy theory and BP neural network. First, a reasonable neural network structure including the number of network layers, the number of nodes in the hidden layer, the training method and other related parameters are set, and then the adaptive step maximum gradient descent method is applied to train and test the BP neural network, and the constructed fuzzy system, which is combined with the BP neural network, is applied to the evaluation of corporate financial performance. Finally, taking Company Q in the traditional Chinese medicine industry as the research object, the construction of the financial performance evaluation index system is completed, and the four common factors representing 85.692% of the information of the original variables are extracted by using the factor analysis method to complete the scientific description of the enterprise's financial performance management level. The evaluation model based on fuzzy logic and BP neural network achieves an average prediction accuracy of more than 95% for the test samples, realizes excellent financial performance optimization and innovation, and puts forward comprehensive measures such as setting up internal enterprise financial performance management values, exerting the performance appraisal mechanism and guiding the systematization of performance evaluation, which to a certain extent improves the enterprise performance management system.

Index Terms Fuzzy theory, BP neural network, Factor analysis method, Financial performance evaluation system

I. Introduction

With the rise of big data, the Internet of Things, artificial intelligence, blockchain and other digital technologies, the digital economy is developing at an unprecedented rate, based on big data analysis, and has become the "new engine" of national economic growth [1]. The development of the digital economy further enhances the transmission of information between market entities, implying a further shift in the economic paradigm at a deeper level. Entrepreneurs of all kinds are striving to be the pioneers of the digital economy by leading the digital transformation and upgrading of enterprises. Large enterprises in all fields are riding on the express train of the digital economy to carry out bold digital changes, and innovation, as the backbone of enterprise change, takes the enterprise's own internal innovation as the main output, and absorbs external resources for integration and innovation as the secondary output point, which promotes the emergence of new business models and economic activities, and opens up a new way for enterprises to realize broad value [2]-[5]. At the same time, from the financial point of view, the application of digital technology has accelerated the improvement of the efficiency of corporate finance to collect, analyze and utilize data, such as more accurately predicting market trends through big data analysis, formulating accurate marketing strategies to improve sales and market share or reducing operating costs with the help of digital technology, improving productivity and enhancing overall profitability [6]-[9]. The significant changes in financial data profoundly reflect the multidimensional and intricate interaction between the digital economy and corporate financial performance [10]. However, in the era of digital economy, there are still a number of challenges in corporate innovation strategy decision-making and financial performance optimization. In innovative strategic decision-making, the cycle of digital technology updating is gradually shortened, and the effectiveness cycle of strategic decision-making is shortened. The development of the digital economy may lead to the disappearance of some traditional industries and jobs, exacerbating social inequality, and the market presents dynamic ambiguity. The deepening of enterprise digitization and the expansion of structured and unstructured data increase the difficulty of quantitative decision support [11]-[13]. In financial performance optimization, some investments and returns show long-tail effects and increase risk linkages due to the business environment of digital supply chains [14], [15].

Fuzzy logic has a unique advantage in dealing with uncertainty and ambiguity, which can be applied in the fields of control systems and optimization. While neural networks are composed of a large number of neurons interconnected with each other, they are used for data processing and pattern recognition by learning and adjusting the connection weights between neurons, which gradually evolves from a simple linear model to a complex multilayer nonlinear structure. Literature [16] introduced fuzzy control algorithms and Q-learning for adaptive learning and fuzziness processing of enterprise data, so as to optimize enterprise innovation decisions. Literature [17] combines artificial neural networks and particle swarm optimization algorithms to evaluate enterprise innovation and formulate enterprise innovation strategy strategies through the evaluation results. Literature [18] constructed a fuzzy system model and convolutional neural network-supported enterprise innovation performance evaluation model, which not only understands the problems of enterprise innovation, but also optimizes enterprise resource scheduling. Literature [19] established a financial system and financial risk assessment for enterprise supply chain through blockchain technology and fuzzy neural network algorithm, respectively, which strengthened the supply chain risk processing capability. Literature [20] uses genetic algorithm to improve back propagation neural network, plus fuzzy logic supported hierarchical decision-making model to process fuzzy data in enterprise finance, and jointly participate in enterprise financial management prediction and optimization decision-making. Literature [21] used self-organizing mapping and convolutional neural network to predict the financial performance of enterprises, the correct rate is up to more than 95%, which provides a reference for enterprise operation strategy. These examples provide support for fuzzy logic and neural networks for enterprise innovation strategy and financial performance optimization.

In this paper, an innovative enterprise financial performance evaluation model is designed by effectively combining fuzzy system theory and BP neural network in artificial neural network theory. The model includes a 5-layer structure of input layer, fuzzification layer, fuzzy inference layer, defuzzification layer and output layer, which is a multi-input and single-output model. The training and testing of the model network was then completed on MATLAB. Through data research, we collected relevant indicators on enterprise financial performance evaluation in various ways, and took Company Q as the research object, and constructed a systematic enterprise financial performance evaluation index system from the four aspects of profitability, solvency, operating ability and development ability. Several modeling experiments are used to verify the innovation and feasibility of the enterprise financial performance evaluation system in this paper.

II. Financial performance optimization based on fuzzy logic and neural network

II. A. Theory of fuzzy systems

Fuzzy theory is a science that imitates human cognition of the objective world. The connection between things can be explained by fuzzy theory, people's cognition of the world is fuzzy, it is difficult to accurately locate through some descriptions, and the affiliation between them and the set is vague and unclear.

II. A. 1) Fuzzy sets and fuzzy relationships

Fuzzy set: a set of elements that belong to it in some way. The transition from affiliation to disaffiliation is not regular as in the case of ordinary sets, but exists randomly. Similarly, the objects of fuzzy sets are unambiguous truths, and fuzzy conjunctions and inference rules are antithetical to classical two-valued logic. Let X be a discrete or continuous set, X is called the domain of the argument, and set the mapping $A(X): X \to [0,1]$ to determine a fuzzy subset A on X, $A(X)$ is called the affiliation function of A.

$A(X)$ is used to state the degree to which an element x in the domain X belongs to its fuzzy subset A. The closer the value of $A(X)$ is to 1, the greater the degree to which x is subordinate to A. The closer the value of $A(X)$ is to 0, the smaller the degree to which x is subordinate to A. Therefore, when the value domain of $A(X)$ is {0, 1}, the subordination function $A(X)$ becomes the characteristic function of the classical set, and the fuzzy set A also becomes a classical set, it can be said that the fuzzy set is the conceptual broadening of the classical set, and the subordination function is the broadening of the characteristic function. The classical set is a special form of the fuzzy set, and the characteristic function is also a special expression of the affiliation function. For $\forall x \in X, A(X) \in [0,1]$ is called the degree of affiliation of x.

Fuzzy sets are expressed in the following ways:

(1) The ordinal pair representation, as in the following equation:

$$A = \{(x, A(x)) \mid x \in U\} \tag{1}$$

(2) The domain x is a finite domain and is represented by a vector as follows:

$$A = \sum \frac{A(x_i)}{x_i} \tag{2}$$

(3) The argument domain C is an infinite domain, which can be is expressed by the following equation:

$$A = \int_U \frac{x_A(x)}{x} \tag{3}$$

A fuzzy relation is a mathematical model that describes the degree of correlation between fuzzy elements and is an important part of the composition of fuzzy mathematics [22]. A fuzzy relation on the direct product space $X \times Y = \{(x,y) \mid x \in X, y \in Y\}$ is a fuzzy subset R of $X \times Y$, and the affiliation function $R(x,y)$ of R denotes the degree of correlation between an element x in X and an element y in Y. It is called a binary fuzzy relationship and its characterization is described by the affiliation function of equation (4):

$$\mu_R : X \times Y \to [0,1] \tag{4}$$

When the argument domain $X = Y$, call R a fuzzy relation from X to Y. When the domain is n sets, the fuzzy relation R corresponding to the direct product $X_1 \times X_2 \times \cdots \times X_n$ is called n fuzzy relation.

The essence of fuzzy relation is fuzzy set, so the operation law of fuzzy relation is similar to that of fuzzy set, and the fuzzy relations on different product spaces can be synthesized by composite operation, and the most typical composite operation is the composite operation of “taking the big - taking the small”, and the affiliation function is shown as follows:

$$\mu_{Q \cdot R}(u,w) = \vee(x_Q(u,v) \wedge x_R(v,w)) \tag{5}$$

where: u,v,w are the elements of the domain U,V,W respectively. Q,R are the fuzzy relations from U to V and from V to W respectively. $\vee$ means to take the large value and $\wedge$ means to take the small value.

II. A. 2) Subsidiary functions

The key to solving practical problems by fuzzy set theory lies in choosing the appropriate affiliation function [23], and constructing the affiliation function that can truly reflect the law, scientificity and objectivity is an indispensable step in establishing a fuzzy evaluation model for the evaluation of effects.

Commonly used methods to determine the affiliation function include: Delphi method [24], fuzzy statistical method, expert scoring method and fuzzy measurement method, etc., which need to be analyzed in the context of the actual situation. The types of affiliation function distribution are as follows:

(1) Rectangular distribution or semi-rectangular distribution (applicable to clear concepts)

1) Skewed small:

$$A(x) = \begin{cases} 1, x \le a \\ 0, x > a \end{cases} \tag{6}$$

2) On the large side:

$$A(x) = \begin{cases} 1, x \ge a \\ 0, x < a \end{cases} \tag{7}$$

3) Intermediate:

$$A(x) = \begin{cases} 0, x < a \\ 1, a \le x \le b \\ 0, x > b \end{cases} \tag{8}$$

(2) Normal distribution

1)Skewed small:

$$A(x) = \begin{cases} 1, x \le a \\ e^{-(\frac{x-a}{\sigma})^2}, x > a \end{cases} \tag{9}$$

2) On the large side:

$$A(x)=\begin{cases}0, x\le a\\ 1-e^{-(\frac{x-a}{\sigma})^2}, x<a\end{cases} \tag{10}$$

3) Intermediate:

$$A(x)=\begin{cases}e^{-(\frac{x-a}{\sigma})^2}, x<a\\ 1, a\le x\le b\\ e^{-(\frac{x-b}{\sigma})^2}, x>b\end{cases} \tag{11}$$

Plotting several common affiliation functions through Python, currently there is no standardization for the determination of affiliation functions, the commonly used affiliation functions are as follows:

(1) Gaussian-type affiliation function (Gaussmf function), the function expression is:

$$f=(x,\sigma,c)=\exp(-\frac{(x-c)^2}{2\sigma^2}) \tag{12}$$

(2) The trapezoidal subordination function (trapmf function), which has the mathematical expression:

$$f(x,a,b,c,d)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ 1 & b\le x\le c\\ \dfrac{d-x}{d-c} & c\le x\le d\\ 0 & x\ge d\end{cases} \tag{13}$$

(3) The trigonometric affiliation function (trimf function), which has the mathematical expression:

$$f(x,a,b,c)=\begin{cases}0 & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ \dfrac{c-x}{c-b} & b\le x\le c\\ 0 & x\ge c\end{cases} \tag{14}$$

II. A. 3) Fuzzy logic systems

Fuzzy logic systems [25], are dynamic models with fuzzy information processing capabilities based on fuzzy rules. Fuzzy systems can be classified into pure fuzzy logic systems, T-S fuzzy logic systems and other fuzzy logic systems. Pure fuzzy logic systems consist only of a knowledge base and fuzzy inference machine, whose outputs and inputs are fuzzy sets.The T-S fuzzy system consists of four parts: fuzzy generator, fuzzy rule base, fuzzy inference machine, and inverse fuzzifier, whose structure is shown in Fig. 1:

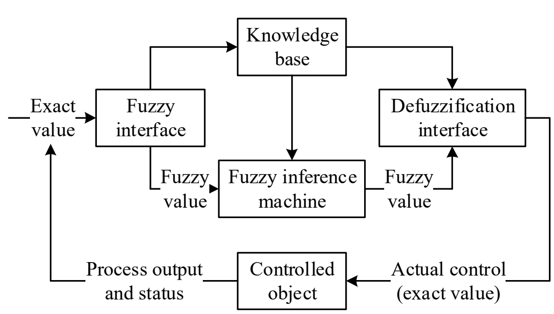

Figure 1: T-S fuzzy logic system

II. B.Artificial Neural Network Theory

II. B. 1) Artificial Neuron Model

Neurons are the most basic units that make up an artificial neural network, artificial neurons mimic the structure of biological neurons is a model of distributed processing information that mimics the behavioral characteristics of biological neural networks.

Similar to biological neurons, artificial neurons consist of inputs, weights, thresholds, activation functions, and outputs, similar to the structure of the brain's synaptic connections to process information. The input $x_i (i = 1, 2, \ldots, n)$ represents signals coming from other neurons or is directly the starting point of the signal. The weights w_{ij} denote the connection weights between two connected neurons, which are adjusted for training according to the different weights of the input signals in the layer. The threshold value θ_j is the set of inputs to the neuron based on the inputs and weights. The values are then fed into the activation function, which is also called the activation function, and different types of neurons correspond to different activation functions, e.g., the sigmoid function. The output of the neuron is processed by the activation function, which indicates that the output signal of this neuron is passed to the next neuron, and finally the whole process of the input to the output of a single neuron is completed.

II. B. 2) Artificial neural network structure

Artificial neural network is a model for parallel distributed processing of information, early human research on its structure was established to mimic biological neural networks, artificial neurons can be seen as similar to biological nerve cells.

BP neural network, also called feed-forward neural network, is characterized by a layered arrangement of neurons, consisting of three parts: the input layer, the intermediate layer (also called the hidden layer), and the input layer, with a feedback mechanism to correct existing problems in a timely manner.

Feedback-type neural network structure () is a fully connected artificial neural network structure, different from the layer-to-layer connection of BP neural network, this neural network has a binary system structure, each neuron is connected to each other, and it can realize the neural network's storage memory function to store the training samples. When using the feedback neural network, due to its ability to ensure that the network converges to a local minimum point, in a way, the Hopfield neural network's stability exceeds the BP neural network, which allows for associative memory and optimization calculations.

II. C.Fuzzy neural network modeling

Neural networks have powerful nonlinear mapping capabilities such as learning and adaptive ability, and are often applied to the study of non-deterministic problems with complex causal relationships. The basic topology is as follows: the output result is compared with the reference value, the error is fed back to the input of the network and the weights are automatically corrected, and the actual output of the system is gradually approximated to the desired output.

The neural network used to realize the above fuzzy rules has three layers, and the first layer is used to judge the matching of the input fuzzy variables with the rule antecedents.

Among them:

$$\begin{cases} f = f(net) \\ net = \overline{A}(x_i)^* A^*(x_i) \end{cases} \tag{15}$$

In the above equation, if $net \geq 1$, it indicates that "$x\ is\ A$" does not hold and this neural network node is suppressed. If $net < 0$, it indicates that "$x\ is\ A$" holds and that neural network node is fully fired. Thus the output of this layer of neural network is the extent to which the input fuzzy variables match the rule antecedents.

The second layer of the neural network takes into account the rule weight w and the degree of rule ignition u, the values of these two variables are obtained during the learning process of the neural network.

$$\begin{cases} g = g[1 - \min(1, net)] \\ net = wPoss[\overline{A} / A^*] + uPoss[\overline{B} / B^*] \end{cases} \tag{16}$$

In the above equation, if $net \geq 1$, the node is fully suppressed, if $net = 0$, the node is fully ignited, and if $0\square net\square$, the node is ignited to a degree of g.

The activation function for the third layer of the neural network is of the same form as the second layer, assuming that the input to this layer is g', the output of this layer is:

$$H(z) = 1 - g'\overline{C} = 1 - g + gC \tag{17}$$

Similarly, if there are N rules in total, then each rule has an output $H_j(z)$ for "u is C", then the total output of this set of neural networks is:

$$H(z) = \min|H_j(z)| \quad j = 0,1,\ldots,P \tag{18}$$

This neural network has a total of three layers of structure which are input, hidden and output layers. The first layer serves to fuzzify the exact quantity. The number of neurons in the second layer can largely affect the overall network performance.

The number of neurons in the hidden layer in the model of this paper is calculated. The fuzzy logic data is first normalized when it enters the input layer to avoid the error in the results caused by the differences in the metrics in terms of magnitude and type. The normalization process is calculated according to the following function:

$$b = \frac{(b_{\max} - b_{\min}) \times (a - a_{\min})}{a_{\max} - a_{\min}} + b_{\min} \tag{19}$$

where a is the variable before normalization, $a_{\min}, a_{\max}, b_{\min}, b_{\max}$ are the minimum and maximum values of the sample data, and b is the variable after normalization. The size of the weights and the size of the threshold are automatically adjusted during the autonomous learning process of the fuzzy neural network, so as to satisfy the output fuzzy results within a reasonable range.

II. D.Implementation of model construction

II. D. 1) Neural network structure of the model

The fuzzy neural network model is shown in Fig. 2, which is a multi-input single-output system including 5 layers: input layer, fuzzification layer, fuzzy inference layer, defuzzification layer and output layer. The network input is: $X = (x_1, x_2, \cdots, x_m)$, i.e., there are m inputs, n variable languages, and a single output.

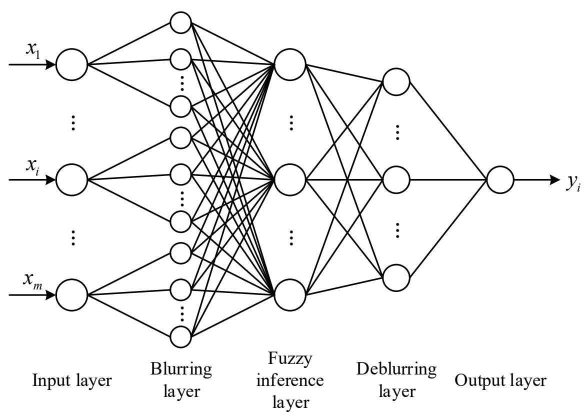

Figure 2: Fuzzy neural network model

The elements in the input layer are the original values of the performance evaluation indexes of patented technology transformation of each research institute, and the indexes are processed to be benefit type, i.e., the larger the value, the better.

There are a total of m neurons in the input layer, and the input and output of the neurons in the input layer are:

$$I_j^1 = x_j \quad j = 1,2,\cdots,m \tag{20}$$

$$O_i^1 = x_j \quad i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{21}$$

In this paper, the input of the input layer is the evaluation value of the performance evaluation index of patent technology transformation of scientific research institutes, and the output of the input layer is the un-normalized enterprise financial performance evaluation data.

The defuzzification layer is to defuzzify the inputs, i.e. to find out the value of each input fuzzy variable according to the affiliation function. In this paper, we use the affiliation function for fuzzification, where the domain is A, $A_{ij} = \{A_1, A_2, A_3, A_4\}$, n=4, then there are four fuzzy subsets, corresponding to "poor", "Medium", 'Good' and 'Excellent'. The output of the fuzzification layer is the affiliation value of each index.

The input and output formulas of the fuzzification layer are as follows:

$$I_{ij}^2 = O_{ij}^{'} \quad i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{22}$$

$$O_{ij}^2 = A_{ij}(x_j) \quad i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{23}$$

The fuzzy inference layer accomplishes the comprehensive fuzzy evaluation of a certain input vector X. From the evaluation linguistic domain, the corresponding fuzzy evaluation vector is obtained, and its input and output formulas are as follows:

$$I_{ij}^3 = O_{ij}^2 \quad i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{24}$$

$$O_i^3 = \sum_{j=1}^{m} w_j I_{ij}^3 \quad i = 1,2,\cdots,n; j = 1,2,\cdots,m \tag{25}$$

The defuzzification layer judges the inputs based on certain fuzzy rules and algorithms, and obtains the affiliation vector of the input evaluation, which is the result of the fuzzy evaluation. The maximum value defuzzifier is used in this layer.

The input and output formulas of this layer are as follows:

$$I_i^4 = O_i^3 \tag{26}$$

$$O_4 = U(I_1^4, I_2^4, \cdots, I_m^4) \tag{27}$$

The output layer outputs the final result of the fuzzy evaluation, i.e., the final evaluation result of the financial performance of the firm.

II. D. 2) Setting of model-related parameters

The parameters to be set include the following: number of network layers, transfer function, number of nodes in the hidden layer, learning rate, training method, initialization weights, training samples, error range, and training target value.

1. Number of network layers

The fuzzy neural network in this paper is designed as 5 layers, which are input layer, fuzzification layer, implicit layer, defuzzification layer, and output layer.The input layer, implicit layer and output layer of BP neural network correspond to the fuzzification layer, implicit layer and defuzzification layer in this paper, respectively.

2. Transmission function

Since the affiliation degree of the evaluation result is between 0-l, the transfer function is a Sigmoid function, i.e., $f(x) = \frac{1}{1+e^{-x}}$, while the transfer function between the fuzzification layer and the fuzzy inference layer is a Tansig function.

3. The number of hidden layer nodes

Generally use the trial-and-error method to determine the number of hidden layer nodes, mainly using the same set of sample data, by constantly increasing the number of hidden layer nodes to find the number of hidden layer nodes that minimize the network error.

4. Learning rate

The learning rate determines the amount of change in the weights produced by each cycle. Smaller and more appropriate learning rate can ensure the stability of the system, but usually use the adaptive learning rate, because this learning rate can be adjusted according to the need to adjust the size of their own.

5. Training method

In this paper, the adaptive step-speed gradient descent method is used to train the network, i.e., traingdx. Because, the use of the network in this paper belongs to the pattern recognition class of problems, and it is necessary to establish a small and medium-sized fuzzy neural network for the evaluation of the performance of the transformation of patented technology in research institutes.

6. Selection of initialization weights

The selection of the initial value has a great relationship with the length of training time, whether the learning can reach the maximum and whether it can converge. In order to make the learning speed of the network faster, it is necessary to make the initial net input of each node in the vicinity of the zero point, because this position is the most sensitive region of the transfer function change.

7. Selection of training samples

The number of training samples is the training sample size, theoretically, the larger the training sample size, the more reliable the evaluation results of the model, but in practice, the sample size is too large to ensure the homogeneity of the sample set. Generally, the size of the training sample is chosen to be more than 10, preferably greater than or close to the number of input nodes.

8. Selection of error range

A smaller error expectation can be obtained by increasing the number of nodes in the hidden layer and the training time, or the expected error can be determined by increasing the number of iterations.

In this paper, 10° is chosen as the desired error.

9. Setting the training target value

The training target value can be obtained by using other evaluation methods, such as gray multilevel evaluation method, fuzzy comprehensive evaluation method, etc., and can also be obtained based on previous relevant historical data. The target value obtained by these methods can be applied to the neural network model, which can play a good role in the learning ability of the neural network and reduce the impact of especially subjective factors on the evaluation results.

II. D. 3) Network training and testing of models

The network training and testing of the model in this paper is realized by using MATLAB, and the version of MATLAB is 7.10.0 (R2010a).

In this paper, the network is trained by the adaptive step-maximum gradient descent method, which is an algorithm that introduces the momentum factor a and continuously adjusts the learning rate based on the gradient descent method of the BP algorithm. According to the aforementioned network structure, there are learning samples $(x_{1p}, x_{2p}, \cdots, x_{mp}; t_p)$, and randomly given the network connection weight vector W, which yields the output value of the network to be y_p for the sample P. The output error of the network is then:

$$d_p = t_p - y_p \tag{28}$$

The error function is:

$$e_p = \frac{1}{2}(t_p - y_p)^2 \tag{29}$$

The network learning process is the process of continuously adjusting the value of the connection weight vector W, with the error d_p gradually decreasing, thus improving the computational accuracy of the network.

The process of model testing is the process of inputting the test sample data into the already trained model to get the test results.

III. Evaluation of corporate financial performance based on fuzzy neural network modeling

III. A. Sample Selection and Data Sources

Q Company belongs to the Traditional Chinese Medicine industry, which is part of the Pharmaceuticals industry, as classified by the Shenyin Wanguo Industry Classification Standard (2014 Edition). As of the end of 2023, there are 70 listed companies in this sector. To ensure the comparability and validity of the performance assessment results, the following criteria were adopted to screen the 70 samples. First, all Chinese medicine companies listed on China's A-share market were selected for this study. Given that in previous studies, listed companies generally engage in surplus management in the year before, the year of, and the year of IPO. Therefore, firms listed after 2021 were excluded. Based on this, 60 listed enterprises in the traditional Chinese medicine industry were selected for the establishment of corporate financial performance evaluation methods.

III. B. Selection of indicators

In this paper, 12 financial indicators that can better reflect the company's financial performance ability are selected from four aspects: profitability, operating ability, solvency and development ability. The selected profitability indicators are: return on net assets (A1), return on assets (A2), net asset margin (A3). The solvency indicators are: current ratio (A4), quick ratio (A5), and gearing ratio (A6). Development capacity indicators are: earnings per share growth rate (A7), operating profit growth rate (A8), net assets growth rate (A9). Operating capacity indicators are: inventory turnover ratio (A10), current assets turnover ratio (A11), total assets turnover ratio (A12).

III. C. Enterprise financial performance evaluation system

The applicability of factor analysis needs to be verified by Bartlett sphericity test and KMO test method. By observing the results of KMO and Bartlett sphericity test, it is found that the KMO test result is 0.685 > 0.5 and the Bartlett sphericity test significance is 0.000 < 0.05, which indicates that there is a relatively strong correlation between the indicators, and also indicates that the selected variables are suitable for factor analysis.

Table 1 shows the total variance interpretation results, the cumulative variance contribution rate of the first four principal components reaches 85.692% of the variance contribution rate of all principal components, which shows that the first four principal components can represent 85.692% of the information of the original variables, which is sufficient to describe the level of financial performance of the traditional Chinese medicine industry, and therefore these four common factors are extracted.

Table 1: Total variance interpretation

Constituent	Initial eigenvalue			Extracting the load of the load		
	Total	Percentage of variance	cumulative/%	Total	Percentage of variance	cumulative/%
1	4.532	37.797	37.797	4.532	37.797	37.797
2	3.241	27.021	64.818	3.241	27.021	64.818
3	1.392	11.576	76.394	1.392	11.576	76.394
4	1.117	9.298	85.692	1.117	9.298	85.692
5	0.565	4.779	90.471			
6	0.499	4.113	94.584			
7	0.354	2.966	97.550			
8	0.138	1.115	98.665			
9	0.082	0.696	99.361			
10	0.046	0.408	99.769			
11	0.021	0.186	99.955			
12	0.016	0.021	99.976			

Table 2: The component matrix after rotation

	Constituent			
	1	2	3	4
Return on equity (average)	0.940	0.022	0.149	0.202
Asset returns	0.930	0.083	0.207	0.173
Net profit rate	0.923	0.137	0.214	0.174
Mobility ratio	0.098	0.946	-0.089	-0.064
Speed ratio	0.091	0.949	-0.110	0.014
Asset ratio	-0.080	-0.840	-0.065	0.058
Earnings per share	0.226	-0.038	0.948	0.067
Rate of operating profit	0.321	-0.104	0.909	0.084
Net equity growth rate	0.729	0.012	0.159	-0.142
Inventory turnover	-0.030	0.090	0.101	0.875
Turnover of current assets	0.244	-0.601	0.095	0.574
Total asset turnover	0.420	-0.393	0.023	0.722

The maximum variance method is chosen to rotate the factor component matrix to make the factors have naming interpretability, and the rotated component matrix is obtained as shown in Table 2. According to the load size of the factor on each variable, the economic significance represented by the factor is clear to name the factor, as follows: the public factor F1 in the net asset interest rate, return on assets, return on net assets variables on the load is larger, the load is 0.923, 0.930 and 0.940, respectively, the three variables are reflecting the enterprise's profitability, so the F1 will be named as the profitability factor. The loadings of public factor F2 on current ratio, quick ratio and gearing ratio variables are larger, respectively 0.946, 0.949 and -0.840, and all three variables are related to the solvency of the enterprise, so F2 is named as the solvency factor public factor.F3 has a larger loading on operating profit growth rate and earnings per share growth rate, and both operating profit growth rate and earnings per share growth rate represent the development ability of the enterprise, so F3 is named as the development ability factor. F3 has a larger loading on operating profit growth rate and earnings per share growth rate, and both operating profit growth rate and earnings per share growth rate represent the development capability of the enterprise, so F3 is named as development capability factor.

IV. Evaluation system modeling based on fuzzy logic and neural network

IV. A. Normalized input data

A total of 120 groups of samples were collected in this round of test, excluding the samples with large asymmetry of data distribution, 100 groups of valid samples were screened out, and the collected data were processed by using the MATLAB software function tool to count the data of the six selected feature parameters and get the adjusted scores according to the scoring processing method mentioned above. The input data were divided into training and testing groups, 90 groups in the training group and 10 groups in the testing group. The two groups of data were normalized separately, and the normalization was done using the mapminmax function in the MATLAB function toolbox.

IV. B. Initial modeling

In the actual modeling, in order to improve the training speed and training accuracy, we compared the results of several rounds of tests and found that by first modeling the model in one round, and then through the design of the relevant parameters for the second round of modeling, the final result of the model prediction effect is better. Type anfisedit in MATLAB to start the tool, import the training data in dat format, select the structural parameters of the proposed fuzzy system, switch the training algorithm between BP and hybrid algorithms, set the number of training times to 50, and start the initial training.

Figure 3 shows the initial training results, after selecting the BP algorithm, with the increase in the number of training times, the training error in the gradual reduction, but still did not reach the desired error range, the later still need to switch the algorithm to continue training, after the end of the training can be obtained by testing the training samples to the results of the model training output comparisons, comparative results shown in Figure 4. Save the trained model as fismat, as the initial training model for subsequent processing.

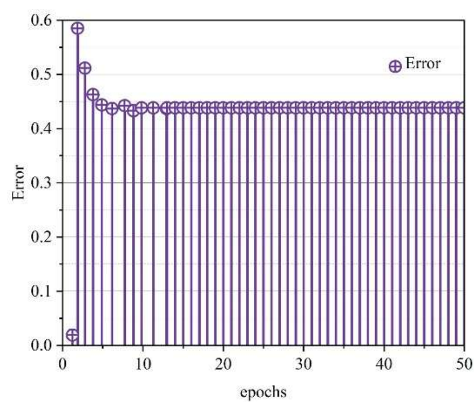

Figure 3: Initial training results

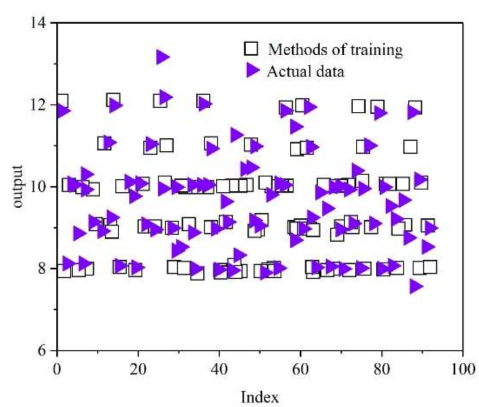

Figure 4: Comparison of training results

IV. C. Training models

After cross-training this initial model with BP algorithm and fuzzy logic algorithm for 6000 times, the training accuracy reaches 0.0006. After the training is over and the results are observed, the comparison of the training results and the training error are shown in Fig. 5 and Fig. 6, respectively, which shows that the training scores and the input adjusted scores basically overlap in the graphs, and the interval of the training error is [8.1*10^{-3},12.2*10^{-3}].

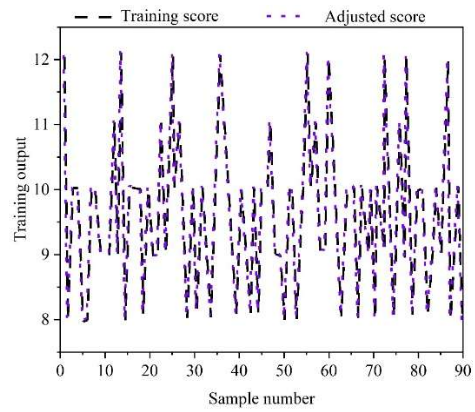

Figure 5: Training Results Comparison

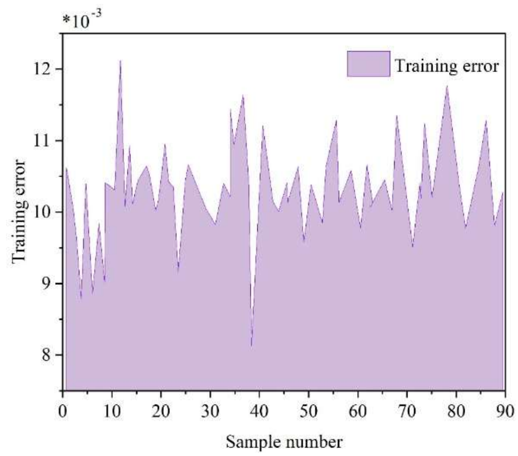

Figure 6: Training error

IV. D. Forecast results and analysis

The ultimate purpose of building the model is to achieve the prediction function well, and evaluating the goodness of the built model needs to test its generalizability, i.e., to test whether the model is overfitting or underfitting in the learning process. The ten sets of data of the test group are substituted into the model for scoring prediction, and the prediction scores are rounded up and rounded down to the nearest whole number, and then the relevant statistics are carried out, and the calculation results are shown in Table 3.

Table 3: Statistical error rate

Sample number	1	2	3	4	5	6	7	8	9	10
Actual grade	12	8	12	11	11	12	9	11	10	10
grade	4	3	4	4	4	4	3	4	4	4
Prediction score	11	8	11	10	11	11	9	10	10	10
grade	4	3	4	4	4	4	3	4	4	4
Difference value	1	1	0	0	1	1	0	1	1	1
Error rate	8.33	0	8.33	9.09	0	8.33	0	9.09	0	0
Average error rate	4.317									

It can be seen that the average error rate of the model prediction is 4.317%, there are five samples of the predicted value is consistent with the actual results, and the other differences are all 1, indicating that the model's prediction effect on the financial performance of the enterprise is more satisfactory, i.e., the evaluation system based on adaptive neural network fuzzy system established by the local area characteristics is able to realize the rating prediction of the enterprise's financial performance.

V. Corporate innovation and financial performance management optimization strategies

V. A. Establishing corporate financial performance management values

First, determine the strategic objectives of enterprise development. Financial performance management needs to be closely integrated with the development goals of the enterprise, for different stages of the strategic objectives of the enterprise, set the corresponding financial indicators to support the overall development of the enterprise. Second, the development of a scientific performance appraisal mechanism. Performance assessment should take into account the overall strategic planning of the enterprise, clarify the importance of each task and the actual completion of the situation, and use data analysis and other scientific methods for assessment to ensure that the assessment results are reliable, fair and scientific. Third, strengthen the performance data analysis capability. Establish a perfect data collection, analysis and feedback mechanism, through data analysis to identify urgent problems, discover potential risks to the business, and promote process optimization or other necessary changes to the implementation of measures. Fifth four, promote digital transformation. Achieve digital transformation in financial performance management, use advanced information technology to create automated data collection, analysis and feedback systems, and establish risk early warning mechanisms to more quickly and accurately understand and predict changes in financial performance.

V. B. Effectiveness of appraisal results

First, strengthening goal management. Enterprise financial performance management needs to strictly abide by the rules of formulating, implementing, supervising and improving the goal management year by year, clarifying the completion standards and time schedule of each task, and tying it to the subsequent performance evaluation, so that the goal is truly transformed into action. Second, ensure the accuracy of the assessment data. For the data required for performance appraisal, it is necessary to establish a scientific collection and recording mechanism to ensure the validity and accuracy of the data. At the same time, focus on the use of data analysis methods and techniques to ensure that the results based on data are more convincing and stable, and to improve the recognition of the results of the performance appraisal of employees. Third, establish a transcendental incentive model. The use of incentives to induce all employees and teams to take the initiative to participate in the new performance is a very important part of financial performance management. For different professional areas of work and business characteristics, you can set up different bonuses or benefits to motivate employees to actively participate in the work.

V. C. Lead to systematization of performance evaluation

First, establish reasonable performance evaluation indicators. Enterprises should establish scientific and quantitative performance evaluation indexes for different departments and business characteristics, and pay attention to the interconnectedness of different links and forward and backward interspersability in the implementation process, so that the performance management program can better take into account the interests of all parties. Second, promote the idea of performance management. Strengthen the performance awareness of all employees, promote the construction of performance management culture, and implement performance management into the company's strategic planning, business process optimization, talent management and other aspects. Increase employees' understanding and awareness of target independence and the implementation of autonomous decision-making power. Third, improve the enterprise financial accounting system, strengthen the construction of internal control system. Several accounting methods and through the integration of data as an important basis for internal audit, so as to be able to timely identify and start to solve potential problems, improve the accuracy, authenticity and completeness of accounting.

VI. Conclusion

Based on fuzzy logic and BP neural network, this paper explores the optimization method of enterprise innovation and financial performance, and designs the innovation evaluation method of enterprise financial performance based on fuzzy neural network model.

Taking Company Q in the pharmaceutical industry as the research object, a total of 12 indicators, such as return on net assets, current ratio, operating profit growth rate, etc., are selected from four aspects, namely profitability, solvency, operating ability and development ability, and four common factors that can represent 85.692% of the information of the original variables are synthesized and extracted by using the factor analysis method, with which to describe the level of the enterprise's financial performance management.

The established evaluation model based on fuzzy logic and BP neural network has an average error rate of 4.317% for the prediction of test samples, which realizes a more excellent prediction of the innovation rating of the enterprise's financial performance management level, and side by side verifies the feasibility of this method to improve the evaluation level of the enterprise's financial performance management.

The paper concludes with the design of enterprise innovation and financial performance management optimization strategy, which will greatly promote the research process of enterprise innovation strategy and financial performance optimization under the background of digital economy by establishing the values of enterprise financial performance management, exerting the effectiveness of appraisal results and guiding the systematization of performance evaluation.

Funding

This work was supported by General Special Scientific Research Project of Shaanxi Provincial Department of Education(23JK0192); 2024 Annual Project of Shaanxi Provincial 14th Five-Year Plan for Education Science Research (SGH24Q443).

About the Authors

Qingqing Chang born in Qingyang, Gansu, China, in 1990. She obtained her Master's degree at the University of Sydney in Australia and is currently pursuing a Doctor of Philosophy (Ph.D.) degree at Xi’an Jiaotong University. She currently working at the Business School of Xi'an International Studies University. Her main research direction is Corporate innovation, corporate strategy, performance management.

Ying Wang was born in Xi’an, Shaanxi, China, in 1990. He obtained a master's degree at Xidian University in China. He currently studying at the School of Computer Science and Technology of Xidian University. His main research direction is Data mining and application.

Xiuyun Yang was born in Chengcheng, Shaanxi, China, in 1968. She obtained a Ph.D. at Xi’an Jiaotong University in China. She currently working as a Professor and Doctoral Supervisor at School of Economics and Finance of Xi'an Jiaotong University. Her main research direction is Digital economy, industrial efficiency.

References

[1] Jurayevich, M. B., & Bulturbayevich, M. B. (2020). The impact of the digital economy on economic growth. International Journal on Integrated Education, 3(6), 16-18.

[2] Li, R., Rao, J., & Wan, L. (2022). The digital economy, enterprise digital transformation, and enterprise innovation. Managerial and Decision Economics, 43(7), 2875-2886.

[3] Yu, W., Zhang, L., & Yang, C. (2023). The impact of the digital economy on enterprise innovation behavior: Based on CiteSpace knowledge graph analysis. Frontiers in Psychology, 14, 1031294.

[4] Zhiyong, Z., Yongbin, X., & Jiaying, C. (2024). Digital economy, industrial structure upgrading and green innovation efficiency of family enterprises. International Entrepreneurship and Management Journal, 20(1), 479-503.

[5] Ding, C., Liu, C., Zheng, C., & Li, F. (2021). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. Sustainability, 14(1), 216.

[6] Liu, J., Zhou, K., Zhang, Y., & Tang, F. (2023). The effect of financial digital transformation on financial performance: the intermediary effect of information symmetry and operating costs. Sustainability, 15(6), 5059.

[7] Chen, Y., & Zhang, Y. (2024). The impact of digital transformation on firm's financial performance: evidence from China. Industrial Management & Data Systems, 124(5), 2021-2041.

[8] Deku, W. A., Wang, J., & Preko, A. K. (2024). Digital marketing and small and medium-sized enterprises’ business performance in emerging markets. Asia Pacific Journal of Innovation and Entrepreneurship, 18(3), 251-269.

[9] Yang, Y., & Wu, Y. (2023). The digital economy, entry mode strategies, and the profitability of foreign subsidiaries: A global view. Economic Modelling, 127, 106480.

[10] Осадча, О. О., Ляшенко, О. М., Павелко, О. В., Марков, Р. В., & Юрків, Н. Я. (2020). Methodology of financial and economic analysis of innovative activities of enterprises in the conditions of the digital economy. Financial and credit activity problems of theory and practice, 4(35), 202-211.

[11] Markova, O. V., Listopad, E. Y., Shelygov, A. V., Fedorov, A. G., & Kiselevich, I. V. (2021). Economic and legal aspects of the innovative activity of enterprises in the context of the digital economy. Nexo Scientific Journal, 34(02), 964-972.

[12] He, Z., Lu, W., Hua, G., & Wang, J. (2021). Factors Affecting Enterprise Level Green Innovation Efficiency in the Digital Economy Era–Evidence from Listed Paper Enterprises in China. BioResources, 16(4).

[13] Shi, Y., & Wei, F. (2024). Comparative analysis of digital economy-driven innovation development in China: An international perspective. Journal of the Knowledge Economy, 1-43.

[14] Peng, H. U. O., & Luxin, W. A. N. G. (2022). Digital economy and business investment efficiency: Inhibiting or facilitating?. Research in International Business and Finance, 63, 101797.

[15] Zhao, N., Hong, J., & Lau, K. H. (2023). Impact of supply chain digitalization on supply chain resilience and performance: A multi-mediation model. International Journal of Production Economics, 259, 108817.

[16] Jia, Y., & Wang, Z. (2024). Application of artificial intelligence based on the fuzzy control algorithm in enterprise innovation. Heliyon, 10(6).

[17] Zhang, Q., Zeng, X., Lo, W., & Fan, B. (2023). Enterprise innovation evaluation method based on swarm optimization algorithm and artificial neural network. Neural Computing and Applications, 35(36), 25143-25156.

[18] Abudureheman, A., Nilupaer, A., & He, Y. (2020). Performance evaluation of enterprises' innovation capacity based on fuzzy system model and convolutional neural network. Journal of Intelligent & Fuzzy Systems, 39(2), 1563-1571.

[19] Wang, Y. (2021). Research on supply chain financial risk assessment based on blockchain and fuzzy neural networks. Wireless Communications and Mobile Computing, 2021(1), 5565980.

[20] Wang, S., & Mansoor, M. (2025). Optimization model for enterprise financial management utilizing genetic algorithms and fuzzy logic. PeerJ Computer Science, 11, e2812.

[21] Zhou, M., Liu, H., & Hu, Y. (2022). Research on corporate financial performance prediction based on self‐organizing and convolutional neural networks. Expert Systems, 39(9), e13042.

[22] Hong Ding,Guangcai Wen,Qingming Long,Jiaokun Wu & Yong Chen. (2025). Research on Grading Evaluation of Coal and Gas Dynamic Disasters Based on Fuzzy Mathematics. Applied Sciences,15(6),2990-2990.

[23] Juan Fernando Lima,Andrés Patiño León,Marcos Orellana & Jorge Luis Zambrano Martinez. (2025). Evaluating the Impact of Membership Functions and Defuzzification Methods in a Fuzzy System: Case of Air Quality Levels. Applied Sciences,15(4),1934-1934..

[24] Lenhoff, T. (2024). Energy-Preserving Optimal Control of Multibody Systems via Advanced Direct Transcription Methods[J], *TK Techforum Journal (ThyssenKrupp Techforum)*, 2024 (2). 15-24.

[25] Marwa Abdellah Osman Ahmed,Ghada Saed Abdel Azim & Yasser Elsayed. (2024). Prediction of COVID-19 based on neurological manifestations using a fuzzy logic system. The Egyptian Journal of Neurology, Psychiatry and Neurosurgery,60(1),141-141.