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Study on the evaluation mechanism of enterprise performance activities based on fuzzy neural network

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ABSTRACT

Enterprise performance evaluation is an important basis in enterprise management. This paper study on the evaluation mechanism of enterprise performance based on fuzzy neural network. First of all, analyzing the structure and the algorithm of fuzzy neural network model, also constructing the network model including five simplified levels. Then, choosing 100 listed equipment manufacturing enterprises as the object of study for empirical research. The result shows that using a combination model based on fuzzy neural network for firm's performance has higher accuracy. This study utilizes the fuzzy netural network model and the qualitative and quantitative indexes are included in the evaluation index system, which has a certain novelty, also make the results more comprehensive and more convincing.

KEYWORDS

Model of fussy neural network; Enterprise performance; Enterprise management; Evaluation mechanism.

INTRODUCTION

Under the background of the market economy and globalization, the enterprise's survival depends on its performance in the market, also the market will be strict to the enterprise survival of the fittest. Therefore, it's necessary for the manager or the auxiliary person to evaluate the performance of the enterprise. On one hand, it can help enterprise managers to make right decisions, on the other hand it also helps enterprise stakeholders make support or opposition decision through the business performance information. The performance evaluation can be quantitative or qualitative. With the development of modern enterprise management technology, enterprise performance evaluation must treat the qualitative assessment as the basis, otherwise the evaluation result does not reflect the exact situation of enterprises, but also the lack of external persuasiveness. At present, the enterprise managers and scholars have made great effort on the study of the enterprise performance evaluation method. There are a lot of methods have been successfully applied in practice, mainly including the balanced score card, efficacy coefficient method, factor analysis, principal component analysis, comprehensive index method, economic value added method and the fuzzy comprehensive evaluation method etc. However, these methods are limited by many prerequisites in application, such as, the principal component analysis cannot make quantitative analysis on the non financial factors, evaluation of the balanced score card can only evaluate enterprise performance at one point. In fact, enterprises will relate to financial factors and non financial factors in the process of management, at the same time, the business activities of enterprises and the business environment is always changing, so the evaluation of enterprise performance cannot be limited to a certain factors and a certain point, otherwise the authenticity and the guidance of evaluation result will be limited. Some scholars introduce some ideas and methods of artificial intelligence technology into the enterprise performance evaluation, in which the neural network technology is the most common one. In this kind of technology, the enterprise internal and relevant departments and staffs are treated as a nervous system, in which any node stimulate or change will cause stress reaction of other nodes and even the whole system. This kind of technology extends the evaluation factor to financial and non-financial indicators, and these indicators will be subdivided, which in order to facilitate the identification and control. However, some factors are difficult to describe accurately by using existing mathematical knowledge, so these factors like a human brain thinking of abstract graphics, it is difficult to use language to express. In order to analyze these factors, some scholars introduced the concept of fuzzy logic, combining with the technology of neural network, resulting in the fuzzy neural network technology. The technology has wide scope and strong adaptability, which can realize the information acquisition, storage and computation for determining, uncertain, linear and nonlinear problems. Then, this paper will research the mechanism of enterprise performance evaluation based on the fuzzy neural network technology, and use the model to evaluate the enterprise performance.

STRUCTURES AND ALGORITHM OF THE FUZZY NEURAL NETWORK MODEL

Analysis of the structure of the fuzzy neural network

The overall fuzzy neural network model used in this study is divided into two parts after: the back network and front network. The back network consists of three layers, mainly used to implement the fuzzy rules, the front network consists of four layers, mainly used to match the fuzzy rules, as show in Figure1.

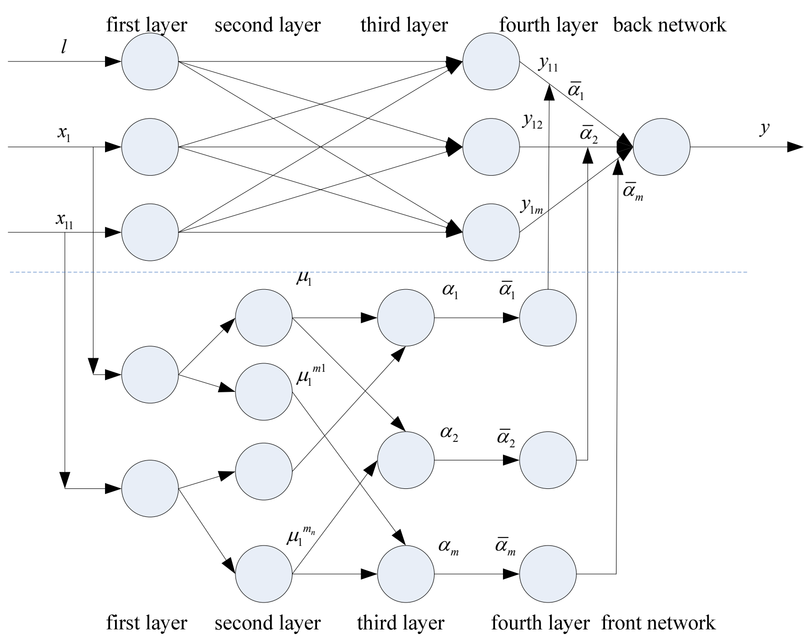

Figure 1: Fuzzy Neural Network Structure Diagram

(1)Analysis of the front network

At the 4 level of the front network, different layer has different functions, which are connection cooperation with each other. The first layer is the input layer, interfacing the fuzzy neural network with external data interface. It can control the input vector and its components. Column vector $x = (x_1 , x_2 ,.. , x_n)^T$ enters the next layer after the regular recognition of the current layer. This layer has N_1 nodes.

The second is the fuzzy layer. This layer needs to blur the input variables from the first layer through the linguistic variables set in advance. The linguistic variables have four levels, which are excellent, good, middle and poor. Subordinate degree of input component is computing by the following formula.

$$\mu_i^j = e\frac{-(x_i - c_{ij}^2)}{\sigma_{ij}^2} i = 1,2\ldots,n; j = 1,2,\ldots,4 \quad \textbf{(1)}$$

Where n is the dimensionality of input variables, x_i is the fuzzy partition (the experimental value is 4), c_{ij} is the center of the subordinate degree function, σ_{ij} is the width of the subordinate degree function. Subordinate degree represents for the possibility of variables being included in linguistic variables. The number of node has an important effect on subordinate degree. In the formula (1), N_2 is computing by the following formula:

$$N_2 = 4n \quad \textbf{(2)}$$

The third layer is used to reason the role. In this layer the fuzzy rule is correlate with the node one-for-one, that is to say, every node represents for one fuzzy rule. The subordinate degree of the node in this layer can be computed by formula (3):

$$\alpha_j = \mu_1^{i_1} \bullet \mu_2^{i_2} \bullet \cdots \bullet \mu_n^{i_n}$$

where $i_1 = 1,2,...,4; i_n = 1,2,...,4; j = 1,2,..., m$. In this layer, $N_3 = m$.

The subordinate degree of linguistic variable is directly related to the distance corresponding to the input point. The distance to input point is closer, and then the value of subordinate degree is greater, otherwise smaller. In some cases, the subordinate degree will closer to or equal to 0. In this paper, the principle is when the subordinate degree is smaller to 0.05, and then the subordinate degree can be treated as 0.

The fourth is normalized layer. The layer will not generate new node, so the number of this layer is same with the third layer, that is $N_4=N_3=m$. The output of normalization is calculated as the following formula:

$$\bar{\alpha}_j = \frac{\alpha_j}{\sum_{i=1}^{m} \alpha_i}, j = 1,2,\ldots,m \quad \textbf{(4)}$$

Where $\bar{\alpha}_j$ represents for the last subordinate degree of input vector.

(2) Analysis of the back network

The first is input layer, which is same with the front network and the input value is $x_0 = 1$. The input layer need to recognize the constant term and transfer the fuzzy rule to the next layer.

The second is computing layer, which should compute the back value and deliver it to the third layer. The second has *m* nodes and the principle of computing the back value as follow:

$$y_{1j} = p_{j0}^1 + p_{j1}^1 x_1 + p_{j2}^1 x_2 + \cdots + p_{jn}^1 x_n \ , j = 1,2,\ldots,m \quad \textbf{(5)}$$

The third layer is responsible to the result output after computing in the second layer. The result will be used to analyze the evaluating object. The formula of output is:

$$y_1 = \sum_{j=1}^{m} y_{1j} \bar{\alpha}_j \quad \textbf{(6)}$$

The final result y_1 is the weighted value of every rule-generalization back piece, in which the weighting coefficient is the application degree of fuzzy rules α_j. α_j is the normalization result of back network.

After the normalization of the third layer in the back network, the result of the fuzzy neural network is simplified. The simplified fuzzy neural network has 5 layers, as show in Figure 2.

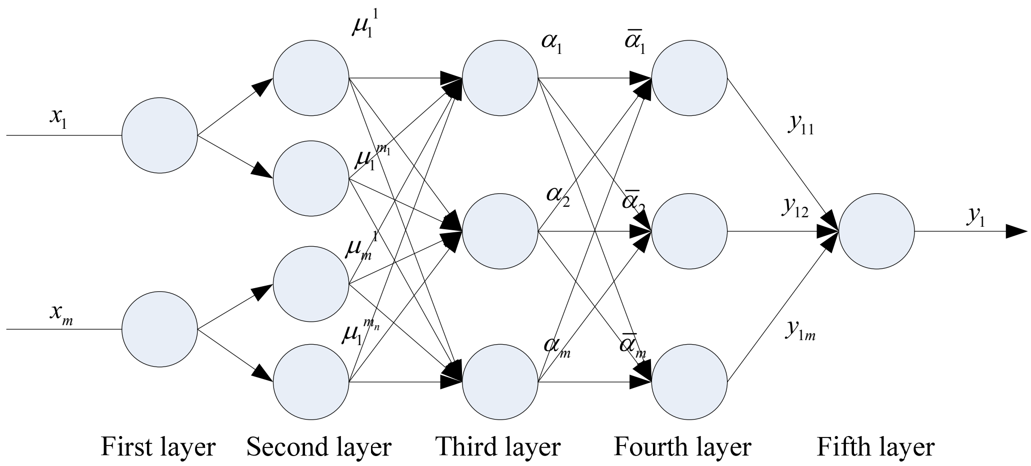

Figure 2 : The Simplified Fuzzy Neural Network Structure Diagram

Algorithm of node function and parameter of the fuzzy neural network

The parameters of the simplified fuzzy neural network need to be adjusted and the adjusted parameters can be used to evaluate the performance of enterprises. Because of the fuzzy neural network has more than one level, and the level of operation depends on the previous one (which is the feed-forward network structure), therefore, the error back propagation algorithm can be used to calculating the parameter. In the next, the error back-propagation algorithm is used to adjust the connection weight of the fifth layer. At the same time, the key value and the width of gradation in the second layer c_{ij} and σ_{ij} *also* need to be adjusted.

Node function

Firstly, assuming the *j*th node of the *q*th layer including n x-variables and n y-variable, the specific form is $f^{(q)}[x_1^{(q-1)}, x_2^{(q-1)}, \ldots, x_n^{(q-1)}; y_{j1}^{(q)}, y_{j2}^{(q)}, \ldots, y_{jn}^{(q)}]$, in addition, the output form is $x_j^q = g^{(q)}[f^{(q)}]$. The node function of each layer is as follow:

The node function of the first layer: $f_i^{(1)} = f_i^{(0)} = x_i$

The node function of the second layer: $f_{ij}^{(2)} = \dfrac{-(x_i^{(1)} - c_{ij})^2}{\sigma_{ij}^2}$, $x_{ij}^{(2)} = \mu_i^j = g_{ij}^{(2)} = e^{f_{ij}^{(2)}} = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}$, $i = 1, 2, ..., n; j = 1, 2, ..., m_i$

The node function of the third layer: $f_j^{(3)} = x_{1i_1}^{(2)} x_{2i_2}^{(2)} \cdots x_{ni_n}^{(2)} = \mu_1^{i_1} \mu_2^{i_2} \cdots \mu_n^{i_n}$, $x_j^{(3)} \alpha_j = g^{(3)}$, $i = 1, 2, ..., n; j = 1, 2, ..., m$; $m = \prod_{i=1}^{n} m_i$

The node function of the fourth layer: $f_j^4 = \dfrac{x_j^{(3)}}{\sum_{i=1}^{m} x_j^{(3)}} = \dfrac{\alpha_j}{\sum_{i=1}^{m} \alpha_j}$, $x_j^4 = \bar{\alpha}_j = g_j^{(4)} = f_j^{(4)}$, $j = 1, 2, \ldots, m$; $m = \prod_{i=1}^{n} m_i$

The node function of the fifth layer: $f_1^{(5)} = \sum_{j=1}^{m} y_{1j} x_j^{(4)} = \sum_{j=1}^{m} y_{1j} \bar{\alpha} j$, $x_1^{(5)} = y_1 = g_1^{(5)} = f_1^{(5)}$

The error is allowed and the error function *E* is: $E = \dfrac{1}{2}(t_1 - y_1)^2$

In the formula (12), t_1 is the expected output, y_1 is the actual output.

The learning algorithm of parameter p_{ji}^1 and σ_{ij}

The back-propagation algorithm is used to adjust the parameter p_{ji}^1 and σ_{ij} Firstly, computing and adjusting the p_{ji}^1 by the formula (13)

$$\frac{\partial E}{\partial p_{ji}^1} = \frac{\partial E}{\partial y_1}\frac{\partial y_1}{\partial y_{1j}}\frac{\partial y_{1j}}{\partial p_{ji}^1} = -(t_1 - y_1)\bar{\alpha}_j x_i$$
$$p_{ji}^1(k+1) = p_{ji}^1(k) - \beta\frac{\partial E}{\partial p_{ji}^1} \quad \textbf{(13)}$$
$$j = 1,2,...,m; i = 0,1,...,n$$

TABLE 1: Enterprise performance evaluation index system

Level 1 index	Level 2 index	No.	Level 3 factor
Financial performance	Profitability	X1	Net profit of capital
		X2	Profit rate of main business
		X3	Profit rate of cost
		X4	Capital appreciation ratio
		X5	Rate of return on total assets
		X6	Rate of return on net assets
	condition of capital operation	X7	Nonperforming assets ratio
		X8	Net asset turnover ratio
		X9	Fixed assets turnover ration
		X10	Accounts receivable turnover ratio
		X11	Inventory turnover ratio
		X12	Current assets turnover ratio
		X13	Total assets turnover ratio
	Debt paying ability	X14	Cash flow and debt ratio
		X15	Current ratio
		X16	Cash ratio
		X17	Quick ratio
		X18	Interest coverage ratio
		X19	asset-liability ratio
	Development ability	X20	The growth rate of net profit
		X21	The growth rate of main business income
		X22	The growth rate of total assets
		X23	The rate of capital accumulation
	Non-financial index	X24	Social contribution
		X25	Customer satisfaction
		X26	Employee satisfaction
		X27	Staff quality status
		X28	Ability of development and innovative
		X29	Management Level of operator
		X30	Basic quality of operators

Formula (14) is used to adjust the parameter σ_{ij} :

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - \beta\frac{\partial E}{\partial \sigma_{ij}} \quad \textbf{(14)}$$
$$i = 1,2,...,n; j = 1,2,...,m_i$$

The β is the learning ratio of index corresponding to parameter σ.

EMPIRICAL RESEARCH ON ENTERPRISE PERFORMANCE EVALUATION

Construction of the evaluation index system

The evaluation index is divided into two categories in accordance with the financial and non-financial indicators. The whole evaluation index system contains 5 second level indexes and 30 third level factors. The second level indexes have one non-financial index and 4 financial index, including profitability, capital operation, solvency and development ability. The reliability and comprehensiveness of this index system is based on the evaluation index system of the Ministry of finance of state-owned capital performance, which including the quantitative and qualitative indexes.

Sample selection

Financial indexes in this study are from A stock market of Shanghai and Shenzhen, which are all the manufacturing industry, the data by the end of 2013. Non-financial indexes are soured from survey and expert interview. The experiment selects 100 groups of effective sample data and divides them into 60 groups of experimental (training) data and 40 groups of test data.

Simulation training on data using fuzzy neural network

In the simulation training on data using fuzzy neural network, increasing the dimension of input will lead to an increase of the number of fuzzy rules into exponential. If this model of operation applies to all the data, it may lead to the complexity of the research model in the structure and time. It is necessary to construct a fuzzy neural network model of enterprise performance evaluation which is after the structure transformation. BP neural network is used to deal with quantitative indexes, fuzzy neural network is used to deal with qualitative non-financial indicators, construction of the two models as input of the combination model of enterprise performance evaluation based on fuzzy neural network.

The final output of the combination model of enterprise performance evaluation based on fuzzy neural network contains 4 arrays, which is F={excellent, good, middle, poor} = {(0.85,1),(0.7,0.85),(0.6, 0.7),(0, 0.6)}. In this empirical research, the model of financial indicators based on BP neural network has 3 layers that are input layer, hidden layer and output layer. Each neural element of them is 23, 1 and 14 respectively. BP neural network training curve close to 10^{-5} infinitely in this case, as show in Figure 3, neural network can be used for simulation training on the data, that is to say, sample data can be input to the adjusted BP neural network.

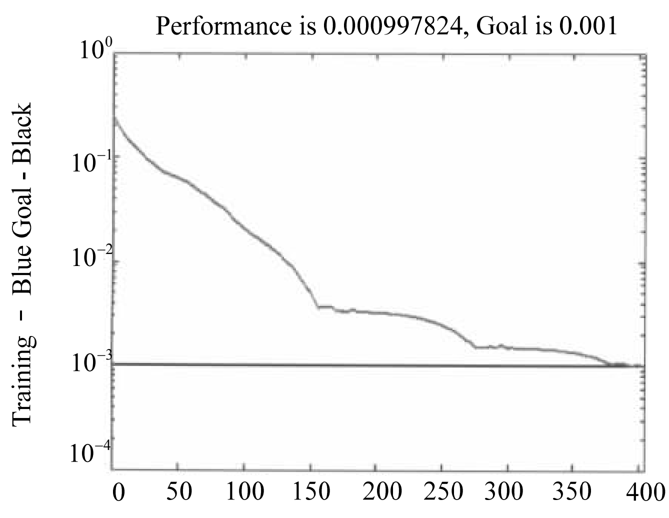

Figure 3 : Training error curve

Fuzzy neutral network is used to construct the non-financial indexes model in this empirical research. The model has 3 layers that are input layer (7 input elements), output layer (1 output element) and fuzzy layer (28 fuzzy neuron). In the next step, the training output of BP neutral network and fuzzy neutral network will be stored as the input of the combination model of enterprise performance evaluation based on fuzzy neural network. In this model, input layer has 2 elements (financial standing and non-financial standing), fuzzy layer has 8 neurons, output layer has 1 result variable.

Figure 4 is the curve of training mean variance resulting from the data training by using this model. 20 steps training can make the training error data close to 0 and maintain in the trend to 0 infinitely. It can be say that the training result is excellent.

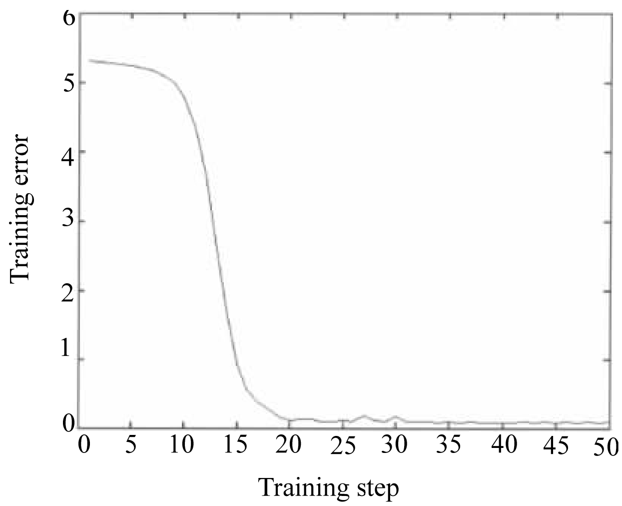

Figure 4 : The curve of training mean variance

Final evaluation of training result should depend on the accuracy test of network evaluation (σ test) by the following formula:

$$\sigma = \frac{H}{S} \quad \textbf{(15)}$$

Where *H* is the number of enterprise satisfying the condition that the network model output corresponding to the actual output. *S* is the total number of evaluated enterprise. The value of σ in this experiment is 0.87, high accuracy. It is need to analyses the accuracy of BP neutral network and fuzzy neutral network. Figure 3 shows that the σ based on BP neutral network is 0.73 less than the fuzzy neutral network. In addition, the final output error of combination model based on fuzzy neutral network is 0.0367 less than BP neutral network significantly. It is result that the combination model based on fuzzy neutral network has higher accuracy than BP neutral network.

TABLE 3 : Comparison between two models

	accuracy (σ)	**final error**
BP neutral network	0.73	0.0428
Fuzzy neutral network combination model	0.87	0.0367

CONCLUSIONS

The combination model based on fuzzy neutral network has good reliability and feasibility on enterprise performance evaluation. With the introducing of the neutral network, the combination model based on fuzzy neutral network has good performance in robustness and adaptability. Actually, in the enterprise management practice, managers can actually build portfolio model based on fuzzy neural network combined with the enterprise, thus reducing the subjective malicious or benign interference during the evaluation process. However, this technology used in practical application is affected by data source, management attitude and other uncertain factors, so it is need to improve it, combining with the genetic algorithm is worthy of being researched in further step.

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