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ABSTRACT

In this paper, we proposed and trained a fuzzy neural network system to estimate future logistics demand. The structure of neural network in the system is similar to that of BP network, except that here the nonlinear sigmoid functions in the networks are replaced by fuzzy reasoning process and wavelet functions respectively. Moreover, the trained network system is put into practical logistics demand forecasting. The experimental results show that it has good properties such as a fast convergence, high precision and strong function approximation ability and is good at predicting future logistics amount.

Keywords: logistics demand, forecasting, fuzzy logic, wavelet neural networks

1. INTRODUCTION

In reality, it is significant to estimate future logistics amount as to a logistics manager in a company. Accurate prediction of logistics amount will help the managers to make decision more right. The indefinite nature of the market means that there is a significant need for accurate forecasts of future business, both short- and long-term. Hence, managers, researchers and policy makers have recognized the necessity of accurate forecast of logistics demand. They have tried to apply various kinds of mathematical techniques to reflect the quantitative relationship between a specific demand and its impact factors. On the other hand, another approach to set up a relationship model for the dependent variable only based on its past data or performance. The relationship model is then used to estimate future data.

Previous relationship modeling methods have been largely based on time-series models and multivariate regression analyses. In summary, there are many forecast approaches in the world, each of which has remarkable superiority and unavoidable weakness.

Back-propagation (BP) neural network can establish function approximation for specific input and output relationship without a given model. Nevertheless, the traditional BP network has some weaknesses that are easy to relapse into local minimum point and its computation convergence speed is somewhat slower, which affect the enhancement of reliability and accuracy of prediction model. Thus, we put forward a novel prediction model for the logistics demand based on the combination of fuzzy logic and neural network. We combine fuzzy reasoning theory with neural network in order to improve the precision and convergence speed of the prediction model. So, a neural network-driven fuzzy reasoning system is proposed on the basis of improved Takagi-Sugeno reasoning model. The system consists of $P+1$ neural networks, the networks $NN_1 \sim NN_P$ denote the functions in the conclusion parts of the P rules respectively, and this type of networks are called expert networks; NN_{P+1} is used to calculate the fitness of each rule corresponding to input vector, this type of networks is called gate network. Thus, the topology structure of the neural network-driven fuzzy reasoning system is determined.

We think that it is feasible to model the relationship among the time-series historic data of logistics demand using fuzzy neural networks system. Namely, making no assumption about other impact factors, time-series forecast models based on fuzzy neural networks can use historical data as the input and output variables to form a univariate or multivariate mathematical function to reflect the relationship among these statistical data.

2. FUZZY NEURAL NETWORKS SYSTEM

2.1 Introduction to Fuzzy Neural Networks

In recent years, artificial neural network, a commonly used nonlinear function approximation tool, has shown huge advantages in forecasting, pattern identification, optimization technique and signal processing for its good properties such as nonlinear, flexible and valid self-organization study et al. Back-propagation (BP) neural network, a typical case of neural networks, is used most widely and is more mature than other networks. Unlike the classic mathematic methods, BP networks can approximate the specific input and output relationship without a certain model. Therefore, we usually attempt to set up a BP ANN model for logistics demand prediction. Nevertheless, traditional BP network has some weaknesses that it is easy to relapse into local minimum point and computation convergence speed is somewhat slower, which affect the enhancement of reliability and precision of prediction model. So, we intend to combine fuzzy reasoning theory with neural networks in order to improve the precision and convergence speed of simulation model.

Thus, a neural network-driven fuzzy reasoning system is proposed on the basis of improved Takagi-Sugeno reasoning model. The system consists of P+1 neural networks, the networks NN_1~NN_P denote the functions in the conclusion parts of the P rules respectively, and NN_{P+1} is used to calculate the fitness of each rule corresponding to input vector.

As there are a good deal of practical application of fuzzy neural networks are reported up to now, its superiority for solving complicated non-linear problems has been proved by these researches and taken seriously by scholars gradually.

In this paper, we intend to approximate and fit the functional relationship between the among the statistic data of logistics demand using the neural network driven fuzzy reasoning system abovementioned, and corresponding learning algorithm of fuzzy neural networks system is proposed there. Thus, a prediction model of logistics demand based on fuzzy neural networks system is hereby founded and is put into practice.

2.2 Fuzzy Neural Networks System

As to a fuzzy system with n-input and single output, a regular style of fuzzy rules is:

If x_1 is A^j_1, x_2 is A^j_2, …, x_n is A^j_n, then y is B_j, where A^j_1, A^j_2, …, A^j_n and B_j is fuzzy subsets. In the conclusion part, the model substituting fuzzy set B_j with a function is commonly called Takagi-Sugeno (TS) model.

If x_1 is A^j_1, x_2 is A^j_2, …,x_n is A^j_n, then $y=f_j(x)$, where $f_j(x)$ is a linear combination of input variables, namely

$$f_j(x) = c_j^1 x_1 + c_j^2 x_2 + \cdots + c_j^n x_n + c_j^{n+1} \tag{1}$$

The model divide input space into linear spaces because the input variables are independent each other. When we use the two models abovementioned to divide input space into nonlinear spaces, it is necessary to have an elaborate division at first. But, it will result in the rapid increase of the number of fuzzy rules. To avoid the happening of such a situation, it is convenient to adopt the number of following model:

$$\text{If } X \in P_j \text{, then } y = f_j(X) \tag{2}$$

Where X= (x_1, x_2, … , x_n), P_j is a partial space divided from input space. In the formula (2), the membership function cannot be determined as formula independently, so we only acquire the joint membership function in the condition part using neural networks, similarly, the function in the conclusion part can also be expressed by neural networks. Thus, a fuzzy system based on neural networks is proposed and its structure is shown in Fig 1.

The system consists of P+1 neural networks, where NN_1~NN_P denote the functions in the conclusions of the P rules, NN_{P+1} is used to calculate the fitness of each rule corresponding to input vector. The output of the

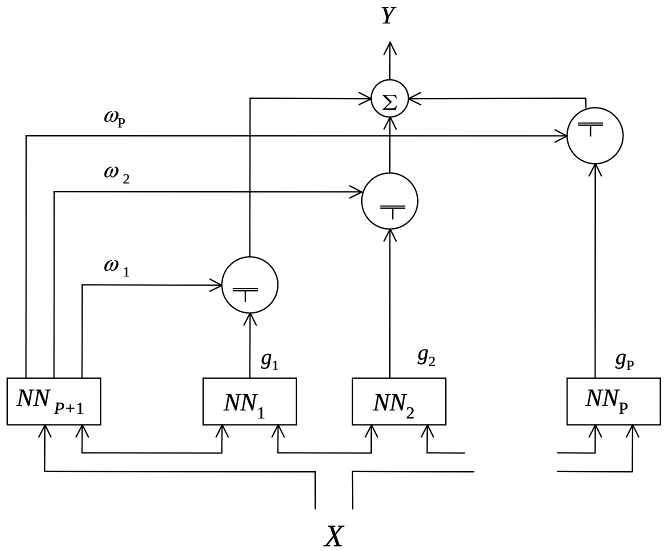

Fig.1 A fuzzy neural networks system

fuzzy system can be calculated by the following formula

$$Y = \sum_{j=1}^{P} \omega_j g_j \tag{3}$$

Where g_j is the output value of the network NN_j and ω_j is its corresponding fitness. The system is called an NN-driven fuzzy reasoning system.

We stipulate three kind of function of the fuzzy system as follows:

1) Determine the number of fuzzy rules by the use of K-means clustering method.

2) Design and train the neural network NN_{P+1} to calculate the fitness of each rule corresponding to input vector.

3) Design and train the neural network NN_j to denote the nonlinear function in the conclusion part in the fuzzy system.

The steps of establishing and training the fuzzy system are as follows:

Step 1. Collect training sample for the fuzzy system.

Step 2. Use K-means method to cluster input vectors, and each cluster corresponds to a rule. Because the samples are clustered into P teams, there are P fuzzy rules for the fuzzy reasoning system.

Step 3. Train the network NN_{P+1}, which has n inputs and P outputs in its structure. The training samples can be constructed using the following method:

If the training sample X_i is clustered into the S-th team, we have:

$$\omega_j^i = \begin{cases} on & j = S \\ off & j \neq S \quad j = 1,2,\cdots,P \end{cases} \tag{4}$$

Namely,

$$W^i = (\omega_1^i, \omega_2^i, \cdots, \omega_{s-1}^i, \omega_s^i, \omega_{s+1}^i, \cdots, \omega_P^i)^T$$

Where *on*/*off* correspond to 1 or 0 respectively. But the output of the activation function in the neural networks is not absolutely 1 or 0. Here we replace them with 0.9/0.1, which can accelerate the training process of networks. Thus, we can construct training sample (X_i, W^i) for the network NN_{P+1}. After a certain number of training, the final fitness vector $W = (\omega_1, \omega_2, \cdots, \omega_P)^T$ for each network NN_j (j=1, …, P) is gained.

Step 4. Train the networks NN_1~NN_P. Assume that NN_s (s=1, …, P) corresponds to the S-th rule, thus, all of the samples in the S-th cluster is the training data for the network NN_s. Then, back-propagation algorithm is applied to train the networks NN_1~NN_P.

2.3 Applying Wavelet Transformation and Wavelet Network in the Networks NN_j

In nature, wavelet transform is a kid of integral transform among various parameters:

$$\omega_f(a,b) = \int_{-\infty}^{+\infty} f(t) \bullet h(a,b,t)dt \qquad 5)$$

where $f(t)$ is a function with compact support set, $h(a,b,t)$ is called wavelet such that

$$h(a,b,t) = \frac{1}{\sqrt{|a|}} h_{basic}(\frac{t-b}{a})$$

Here $h_{basic}(t)$ is called basic wavelet or mother wavelet, $1/\sqrt{a}$ is the coefficient of normalization, and a, b are dilation and translation factor of $h(a,b,t)$. As to a signal or function $f(t)$, the identification of its local structure can be conducted by adjusting those two parameters to change the size and place of wavelet bases window to realize.

From the wavelet theory and latest research reports, we know that an arbitrary function $f(x) \in L^2(R^n)$ can be approximated closely as

$$f(x) \approx \sum_{j=1}^{n} \omega_j \varphi(\frac{x-b_j}{a_j}) \qquad (6)$$

Formula (6) is a general mathematic description for wavelet network, where n is the number of network nodes, $\varphi(\bullet)$ is basic wavelet, b_j is translation factor, a_j is dilation factor and ω_j is link weight of the network.

Wavelet networks is a type of novel feedforward network on the basis of wavelet analysis theory. It utilizes wavelet space as the characteristic space of style identification, and realizes the feature identification by the weighed sum of the inner product for basic wavelet and signal vector. Because it is a combination of time-frequency localization characteristic of wavelet transform and self–study function of artificial neural network, it owns such capabilities as valid function approximating and error bearing. The function relationship of formula (6) can be realized by using linear superposition of nonlinear basic wavelet, namely, we can approximate formula (6) using the limited terms of wavelet series.

Assume that there is a three-layer wavelet network whose input vector is X=(x_1, x_2,⋯, x_n) and output vector is Y=(y_1, y_2,⋯, y_m) and the number of its neurons is n, q, m, respectively and the link weights of the network are ω_{ij} and ω_{jk}.Thus, the nonlinear function $f(\bullet)$ in formula (6) can be fitted using basic wavelet $h(a,b,t)$. So, we have

$$f(\bullet) = \sum_{j=1}^{q} \omega_{jk} h\left[\frac{\sum_{i=1}^{n}(\omega_{ij}x_i) - b_j}{a_j}\right] \qquad (7)$$

where a_j, b_j are the dilation factor and translation factor respectively, and q is the number of wavelons in the hidden layer.

Put the input and output vector of P samples into the network, and calculate the output values and the system error of the network. To assess the approximation results, we select the least squares objective function as a figure of merit, namely

$$E = \frac{1}{2}\sum_{l=1}^{P}\sum_{k=1}^{m}(d_{lk} - y_{lk})^2 \qquad (8)$$

where y_{lk} is the actual value of lth sample on the kth output node in the network, and d_{lk} is the ideal value of the kth output node accordingly.

In the training process of wavelet network, we select Morlet mother wavelet as the basic wavelet approximating the nonlinear function such that

$$h(t) = \cos(1.75t)\exp(-\frac{t^2}{2}) \qquad (9)$$

The steps of wavelet network training are as follows:

Step 1.Initializing the parameters of the wavelet network. Using random generator, the link weights of the network ω_{ij}, ω_{jk} and the dilation factor a_j and translation factor b_j of basic wavelets are evaluated with random number.

Step 2.Project study samples data into the network.

Step 3.Carry out the self-study of network and gain the output vector and error of network.

Step 4.Calculate the instantaneous gradient vector.

Step 5.Carry out error back-propagation and revise the parameters of the networks.

Step 6. While the absolute value of the error is less than the precision, stop the training process. Otherwise, turn to Step 3.

Step 7.Put the trained wavelet network into the practice.

The functions in the conclusion part of the fuzzy reasoning system are all expressed by wavelet neural networks NN_j (j=1, …, P) .

3. FUZZY NEURAL NETWORKS SYSTEM FOR LOGISTICS DEMAND FORECATING

In the work here, this novel networks system is applied to model logistics forecasting. What we should do firstly is to decide the variables denoting the input-output relationship for it. Generally, whichever networks can be used in time-series prediction if it can accept actual input and brings out actual output. If the prediction objective is a future point in a single time-series, it is feasible to use the former n-1 points before this point as the historic data to estimate its value. In a time series, every n neighboring point can be used as training samples. Here, the proposed fuzzy neural networks system is used as a time-series prediction model for logistics demand. Namely, every n-1 neighboring point can be used as training sample and put into the system to estimate the value of the n-th point.

So, the training sample data and testing data of fuzzy neural networks for logistics forecasting are collected and constructed. In the process of practical application, for the difference in the dimension and magnitude of sample data, all inputs are scaled to lied in [0, 1] range in advance using reasonable estimation of the maximum and minimum values for each input.

Table 1. Comparison between prediction and the actual value of rail freight amount in China

Year	1989	1990	1991	1992	1993	1994	1995	1996	1997
Actual	151489	150681	152893	157627	162663	163093	165855	168803	169734
Prediction	151390	150540	157512	157432	160565	162187	166238	169126	170163

We apply the trained networks system in the study of actual logistics forecasting and by comparison with historical statistics data to test its properties. The experimental results are contrast to that of actual data and shown in Table 1. The experimental results show that although there a certain error in the prediction values to some extents, the simulation model can forecast logistics demand properly and accurately.

4. CONCLUSIONS

In this paper, we proposed and trained an improved fuzzy neural networks system with the data of past logistics demand data. The structure of the networks in the system is similar to that of BP network, except that here the nonlinear sigmoid functions in the networks are replaced by fuzzy reasoning process and wavelet functions respectively. Moreover, the trained network is put into practical logistics demand forecasting. The experimental results show that the fuzzy neural network has good properties such as a fast convergence, high precision and strong function approximation ability. Furthermore, it also demonstrates that the fuzzy neural network system is good at predicting future logistics amount because of its non-strict requirements for input variables and not needing plenty of sample data, which ensure that it is suitable for the actual forecasting and outperforms other classic prediction methods and is significant to in applied in the planning of logistics system in both a company and a city.

REFERENCES

[1] Parlos, A. G., “An accelerated learning algorithm for multiplayer perceptron networks”, *IEEE Transaction on Neural Networks*, Vol. 5, pp. 493-497, 1994.

[2] Tong, R. M., “A control engineering review of fuzzy systems”, *Automatic*, Vol. 13, No. 6, pp 559-569, 1997.

[3] Kim, K. H., Park, J. K., et al., “Implementation of hybid short-term forecasting system using network and fuzzy expert systems”, *IEEE Transaction on Power Systems*, Vol. 10, No. 3, pp1534-1539, 1995.

[4] Cybenko, G., “Approximation by superpositions of a sigmoidal function”, *Math. Control Signals Syst.*, Vol. 2, pp 303-314, 1989.

[5] Wang, L. X., Mendel J. M., “Fuzzy basis functions, universal approximation and orthogonal least-squares learning”, *IEEE Transaction on Neural Networks*, No. 3, pp807-814, 1992.