Logistics Forecasting Using Improved Fuzzy Neural Networks System

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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 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 fuzzy system can be calculated by the following formula

$$Y = \sum_{j=1}^{P} \omega_j g_j$$  \hspace{1cm} (3)

Where $g_j$ is the output value of the network $NN_j$ and $\omega_j$ 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 $NN_i$ 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:

$$\omega_j^i = \begin{cases} \text{on} & j = S \\ \text{off} & j \neq S \end{cases}$$  \hspace{1cm} (4)

Namely,

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

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 \((X_s, W^s)\) 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 \(NN_j\) \((j=1, \ldots, P)\) is gained.

Step 4. Train the networks \(NN_1 \sim NN_p\). Assume that \(NN_i\) \((i=1, \ldots, P)\) corresponds to the \(S\)-th rule, thus, all of the samples in the \(S\)-th cluster is the training data for the network \(NN_i\). Then, back-propagation algorithm is applied to train the networks \(NN_1 \sim NN_p\).

2.3 Applying Wavelet Transformation and Wavelet Network in the Networks \(NN_j\)

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

\[
\omega_j(a, b) = \int_{-\infty}^{\infty} f(t) \cdot h(a, b, t) dt \quad 5)
\]

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

\[
h(a, b, t) = \frac{1}{\sqrt{a}} h_{basic}\left(\frac{t-b}{a}\right)
\]

Here \(h_{basic}(t)\) is called basic wavelet or mother wavelet, \(\sqrt{a}\) 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

\[
f(x) \approx \sum_{j=1}^{n} \omega_j \phi\left(x - \frac{b_j}{a_j}\right) \quad 6)
\]

Formula (6) is a general mathematic description for wavelet network, where \(n\) is the number of network nodes, \(\phi(\bullet)\) is basic wavelet, \(b_j\) is translation factor, \(a_j\) is dilation factor and \(\omega_j\) 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 weighted 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 \(X=(x_1, x_2, \cdots, x_n)\) and output vector is \(Y=(y_1, y_2, \cdots, y_m)\) and the number of its neurons is \(n, q, m\) respectively and the link weights of the network are \(\omega_j, \omega_j\) and \(b_j\). Thus, the nonlinear function \(f(\bullet)\) in formula (6) can be fitted using basic wavelet \(h(a, b, t)\).

So, we have

\[
f(\bullet) = \sum_{j=1}^{m} \omega_j b_j \left(\frac{\sum_{i=1}^{n} (\omega_i x_i) - b_j}{a_j}\right) \quad 7)
\]

where \(a_j, b_j\) are the dilation factor and translation factor respectively, and \(q\) is the number of wavelets 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

\[
E = \frac{1}{2} \sum_{i=1}^{P} \sum_{k=1}^{q} (d_{ik} - y_{ik})^2 \quad 8)
\]

where \(y_{ik}\) is the actual value of \(l\)th sample on the \(k\)th output node in the network, and \(d_{ik}\) is the ideal value of the \(k\)th 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

\[
h(t) = \cos(1.75t) \exp\left(-\frac{t^2}{2}\right) \quad 9)
\]

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 \(\omega_j, \omega_j\) 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 $NN_j$ ($j=1, \ldots, P$).

3. FUZZY NEURAL NETWORKS SYSTEM FOR LOGISTICS DEMAND FORECASTING

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 lie in $[0, 1]$ range in advance using reasonable estimation of the maximum and minimum values for each input.

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