Algorithm Research for Supply Chain Demand Prediction - Taking Fresh Agricultural Product Enterprises as Example

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ABSTRACT: *Supply chain demand prediction plays a very important role for enterprises to realize sales and markets management target effectively, especially for fresh agricultural product enterprises. A new model for supply chain demand prediction for fresh agricultural product enterprises is presented based on improved BP neural network. First the advantages and disadvantages of BP neural network algorithm are analyzed when it is used in supply chain demand prediction; Second, Legendre wavelets algorithm is used to speed up the convergence and improve the prediction accuracy of original BP neural network algorithm and based on this the paper advances a new supply chain demand prediction model for fresh agricultural product enterprises. Finally, certain fresh agricultural product enterprise is taken for example to verify the validity and feasibility of the model and the experimental results show that the model can improve prediction accuracy and decrease the calculation time and can be used for supply chain demand prediction practically.*

Categories and Subject Descriptors:
F.1.1: [**Machine learning**]: Neural Network; **C.2.3:** [**Operations research**]: Supply Chain

General Terms:
Neural Networks, Supply Chain

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1. Introduction

Prediction is a kind of anticipation or estimate on the flow or units that may occur in aspects of production, shipping or sale. Prediction on future demand constitutes the basis for all the strategic and planning decision in the supply chain. All the pushing processes are carried out according to the prediction on customers' demand, while all the pulling processes are carried out according to the response to market demand. Under the above two situations, the first step adopted by managers of supply chain is to predict future demand of customers. In today's society, suppliers are confronted with endless plan and decision-making problems. Accurate demand prediction can reduce the uncertainty of inventories and provide the basis for decision making. With any great products, if there is lack of accurate prediction on actual market demand, it will cause short supply or oversupply, thus influencing the inventories level and operation cost of enterprises. Therefore, prediction on demand is an important element driving the entire supply chain; low error rate of prediction is the common goal pursued by the industry. Especially for fresh agricultural product enterprises, due to strict requirement for the storage period of products, in case of prediction error on inventories demand, enterprises will suffer heavy loss, so carrying out prediction study on supply chain demand taking fresh agricultural product enterprises as example has an important theoretical value and practical significance [1, 2].

2. Literature Review

At present, the mainstream prediction methods adopted by researchers and enterprises in the industry on supply chain demand prediction are roughly categorized as two categories: one is single prediction method, such as adopting neural network prediction method, grey prediction method, markov prediction method, time series prediction method, prediction method based on quantity of value; the other is combination prediction method, i.e. making use of the prediction results of multiple prediction methods and combing according to certain form. Besides, there are scholars putting forward other methods, like scenario analysis method, set pair analysis prediction, and etc. Specific methods and their merits and demerits are as follows [2]. (1) Delphi Method, the method, also called expert investigation method, is often used for long-term and new products sales prediction, profits prediction and technology prediction. Its process mainly includes: first, according to the goal and demand of prediction, prepare opinion consultation table. Second, choose those experts, who engage in professional job related to prediction topic, are proficient in specialty and possess analysis ability, as consultation objects. Third, repeatedly consult experts' opinion. Finally, make prediction conclusion. The merit of this method is drawing on the wisdom of the masses, beneficial to a comprehensive and reliable prediction. But the demerit is the lack of objective standard due to main reference to subjective judgment, with low reliability [3, 4]. (2) Business Personnel Evaluation Method, While carrying out prediction, convene all the business personnel of each stage of logistics, like planning, purchasing, warehousing and transporting, to make estimate on demand of certain logistics in the future, and then comprehensively deal with the estimate data of everyone, forming the prediction on future. The merit of this method is that business personnel know the best about logistics demand conditions and market dynamics, the conditions and predicted number they depend on are close to the practical situation. The demerit is that the quality of some business personnel is low, and their prediction often neglects the entire economic situation and market demand change trend. The empirical formula is: estimated average value $= (A + 4 \times B + C) / 6$, among which A is the most optimistic estimate, B is the most possible estimate and C is pessimistic estimate [5, 6]. (3) Time Series Method, Time series method is to make use of sales volume data of past period or other level-one data and adopt certain mathematical methods, with existing demand data, to predict future development change trend and demand. Existing time series methods used for logistics demand prediction include three kinds: moving average method, index correction method and epitaxial smoothing technique. ① Moving average method means that every point moving averagely in time series is arithmetic average or weighted average of a series of continuity points. Several data points need to be selected to eliminate seasonal effect or irregular or the common effect of above two parties. While predicting with simple moving average method, prediction of this period is equal to the sum of actual occurrence amount of past periods dividing prediction periods used; the moving average method is widely used, but it's only applicable to the demand trend prediction with no obvious ascending or descending of value change, and is not applicable to long-term prediction [6]. ② Index correction method is to estimate future prediction value according to actual data of past periods and weighted average of prediction value, mainly applicable to time column not remarkable in trend and seasonal change [7, 8]; ③ Epitaxial smoothing technique, if considering the impact of trend value and seasonal fluctuation on prediction value, and the trend and seasonal elements in the data are obvious different from random character, we can carry out correction and expansion on the model in index correction method to better predict. This method is high in prediction precision but has a sensitive demand on season [7, 8]. (4) Supply Chain Prediction based on BP Neural Network, There are lots of variables in classical BP algorithm and other training algorithms which can confirm an ANN structure only training the ANN weighted value of fixed structure (including connection weight and node transformation function). According to Kolmogorov theorem, as to any given L2 type continuous function f: $[0, 1]\, n \rightarrow Rm, f$ can be accurately realized by three-layer feed forward neural network, thus it can only consider the weighted value and nodes of evolving network while not affecting evolution results. Based on this, on the basis of BP original algorithm, add node evolution factor, record structures evolved by factors of every layer, and choose the optimal factor and its network structure, thus avoiding local optimum obtained due to adding or cutting. According to the experiment, different prediction precision also influences the nodes of neuron of network layer, so prediction system can be dynamically established as required [9.10].

BP neural network algorithm has fairly good in accuracy when used in supply chain demand prediction but leaves behind the question of slow convergence speed of BPNN so as to be hard to put into effect in the actual project. The paper takes Legendre wavelets algorithm to modify and improve BP neural network model to overcome the question of slow convergence speed of original BPNN. In so doing, not only the problem of convergence speed of BPNN has been solved, but also the simplicity of the model structure and the accuracy of the predicted are ensured, then a new prediction model of supply chain demand is advanced.

3. Derivation of Supply Chain Demand Prediction Algorithm

3.1 Legendre Wavelets Neural Network

Wavelets can provide multi-resolution proximity for function differentiation as well as localization of space and frequency. Therefore, wavelets neural network based on wavelets analysis theory is more adaptable to learn locally non-linear and rapidly changing functions. Legendre wavelets is Formula 1, in which m, the order of Legendre polynomial and t, the time, are defined in the interval $[0, 1)$ to satisfy Formula 2. In Formula 2, $L_m(t)$ is the Legendre polynomial, in which $L_0(t) = 1$, $L_1(t) = t$ and the others satisfy the Recursion Formula 3. It can be proved that for different values of n, Legendre wavelets remain orthonormal [10].

$$\psi_{nm}(t) = \psi(k, \hat{n}, m, t), \quad k = 2, 3..., \quad \hat{n} = 2n - 1 \qquad n = 1, 2...2^{k-1} \tag{1}$$

$$\psi_{nm}(t)=\begin{cases}[m+\frac{1}{2}]^{1/2}\,2k/2L_m(2^k t-\hat{n}), & \frac{\hat{n}-1}{2^k}\le t\le\frac{\hat{n}+1}{2^k} \\ 0 & Others\end{cases} \quad (2)$$

$$L_{m+1}(t)=\frac{2m+1}{2m-1}\,tL_m(t)-\frac{m}{m+1}L_{m-1}(t) \quad (3)$$

From Formula 3, it can be known that a function $f(t)$ defined in the interval $[0, 1)$ can be approximated to be Formula 4, in which C and $\psi(t)$ are Formula 5 and Formula 6 respectively.

$$f(t)\approx\sum_{n=1}^{2k-1}\sum_{m=0}^{M-1}\rho_{nm}\psi_{nm}(t)=C^T\psi(t) \quad (4)$$

$$C=[c_{10}, c_{11},..., c_{1M-1}, c_{20}, c_{2M-1}, c_{2^{k-1}0}, c_{2^{k-1}M-1} \quad (5)$$

$$\psi(t)=[\psi_{10}(t), \psi_{11}(t),..., \psi_{1M-1}(t) \;......\; \psi_{2^{k-1}M-1}(t) \quad (6)$$

By setting as the activation function of neural network, a Legendre wavelets neural network can be constructed through Formula 5 with a structure as follows:

①**Input layer:** to input digitalized original signals.

②**Preprocessing layer:** to divide the digitalized original signals inputted into 2^{k-1} groups, which will enter the corresponding Legendre wavelets basic function to get training.

③**Hidden layer:** divided into 2^{k-1} group nodes with each having M Legendre wavelets basic functions to receive signals after preprocessing respectively. The weight for the hidden layer nodes are the proximity of Legendre wavelets coefficients.

④**Output layer:** to receive the output of the hidden layer. The output layer is linear nodes which are added to get the result.

3.2 Algorithm Model Design

In solving the Legendre wavelets, the values of M and k can be increased for better accuracy. The increase of value of k is equivalent to subdivide the interval $[0, 1)$ further while the increase of value of M is equivalent to increase the coefficient of the highest order of the polynomial on the correspondingly subdivided intervals. Considering the actual accuracy requirement and the of the printer and the calculated amount of the model, 3 is given to M and 2 is given to k in the actual solution. According to Formulas 4, 5 and 6, there are six Legendre wavelets basic functions, as is shown in Formula 7. Figure 1 offers its network structure.

$$\begin{aligned}
&\psi_{10}=2^{1/2}\\
&\psi_{11}=6^{1/2}(4t-1),\quad 0\le t\prec 1/2\\
&\psi_{12}=10^{1/2}[\tfrac{3}{2}(4t-1)^2)-\tfrac{1}{2}]\\
&\psi_{20}=2^{1/2}\\
&\psi_{21}=6^{1/2}(4t-3),\quad 1/2\le t\prec 1\\
&\psi_{22}=10^{1/2}[\tfrac{3}{2}(4t-3)^2)-\tfrac{1}{2}]
\end{aligned} \quad (7)$$

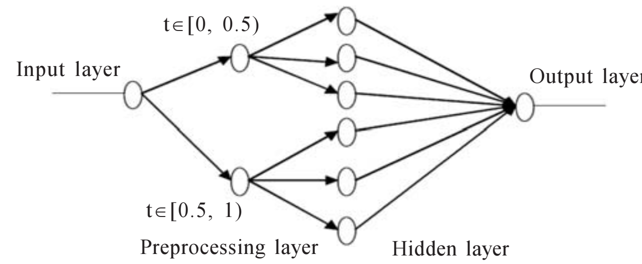

Figure 1. Diagram of network structure

3.2 The Solutions for the Model Calculation

The solutions for the model calculation of the improved BP neural network when it is used for supply chain demand prediction practice can be listed as follows.

(1) **Network training:** The network training employs BPNN algorithm by assigning the values of Y, M, and C from the transformation YMC value database as input value and that of X, Y, Z as output. In this algorithm, both weight value and threshold value are randomly picked out in the range of -0.5~0.5, with adequate adjustment with regard to the real convergence.

(2) **Initialization:** to initialize the weight coefficient with a small random number.

(3) **Circulation:** to set an iteration number and load data to undergo network training. The weight coefficient required is acquired once the accuracy of designated color blocks is reached.

(4) Keep the value of weight coefficient of Legendre wavelets neural network and conclude the training.

4. Experimental Simulation of the Algorithm

The proposed prediction model is realized with C language. This paper takes the demand of certain quarter in 10 years from 2002-2011 of certain fresh agricultural product enterprise to carry out model application and demand prediction; specific prediction results see Table 1 and Table 2, in which Table 1 is the part of the prediction results of the improved algorithm in the paper, and Table 2 is the prediction result comparison among time series method (moving average Algorithm) [6], general BP neural network[9] and improved algorithm in the paper in the practical application and the experiment is conducted through PC. PC configurations are as follows: P4 2.5G CPU and 512M memories and the population number of genetic algorithm is supposed to be 60, the largest evolutionary generations is 80, crossover probability is 0.9, mutation rate is 0.01, target function takes the minimum total costs sum.

Through the prediction results of practical supply chain demand of the above three tables, the supply chain demand of fresh agricultural product enterprise appears to be obvious seasonal change characteristics, such as all of three tables can reflect that the prediction error of the fourth quarter is large while that of the other three quarters are small, which turns out to be the same with prior prediction. Moreover, compared with time series

Year	Quarter	Actual Demand	Model Prediction Demand	Relative Error
2002	3	6000 unit	6078 unit	1.3%
2003	4	6544 unit	6743 unit	3.0%
2004	1	6843 unit	6923 unit	1.2%
2005	2	7121 unit	7254 unit	1.9%
2006	3	7652 unit	7741 unit	1.12
2007	4	7980 unit	8190 unit	3.8%
2008	1	8623 unit	8715 unit	1.1%
2009	2	8534 unit	8676 unit	1.7%
2010	4	9321 unit	9563 unit	2.6%
2011	3	9765 unit	9809 unit	0.5%

Table 1. The Prediction Results of the Improved Algorithm

	Moving average Algorithm	Ordinary BP Algorithm	Improved BP Algorithm
The overall Prediction Error	14.02%	4.21%	1.86%
The Prediction Error of the first Quarter	13.66%	4.09%	1.43%
The Prediction Error of the second Quarter	13.99%	4.18%	1.42%
The Prediction Error of the third Quarter	13.21%	3.97%	1.84%
The Prediction Error of the Forth Quarter	16.56%	5.98%	3.23%
Time consumption (S)	6	143	7

Table 2. The Prediction Results Comparison of different Algorithms

method with BP neural network prediction model before improvement, the supply chain prediction model based on genetic algorithm and BP neural network put forward in this paper has higher prediction precision and less time consumption.

5. Study Conclusion

Supply chain demand prediction method put forward in this paper makes full use of the strength of BP neural network in high prediction precision, wide application scope and strong non-linear reflecting ability in the aspect of supply chain demand, also advancing BP neural network structure and operation method through Legendre wavelets, highly improving the convergence rate of BP neural network in computational procedure, obtaining supply chain demand prediction model with high prediction precision and feasible practical operation based on BP neural network. Prediction simulation result taking certain fresh agricultural product enterprise as example shows that the model can be used as demand prediction tool in supply chain.

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