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Research Article

Research on Food Demand Prediction Algorithm Based on Supply Chain Management

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Abstract: An improved BP neural network algorithm for food demand prediction based on supply chain management is presented to realize market and sale management target effectively for food enterprises. First, the working principle of BP neural network algorithm is analyzed to explore the root reasons of its low convergence speed; Second, the paper integrates genetic algorithm with BP algorithm to present a new algorithm, then improves it through encoding chromosome, formatting fitness function, designing selection operator, redesigning crossover operator, designing mutation operator, integrating BP algorithm and optimal individual, improving calculation process step by step; Finally, a supply chain of a food enterprise is taken for experimental sample to illustrate the calculation performance of the improved algorithm and the simulation results indicate that the improved algorithm not only can solve the problem of low convergence speed, but also can improve the demand prediction accuracy and can be used for predicting supply chain demand for food enterprises practically.

Keywords: BP neural network algorithm, food demand prediction, genetic algorithm, supply chain management

INTRODUCTION

In the food enterprise, inventory is a reservoir to regulate the imbalance between the production and demand. Demand prediction is an important part of inventory management, which is the foundation of the inventory set. Used for the prevention of the large number of sudden orders, extension of delivery time and other problems and it also played a big role in enhancing the production satisfaction, increasing marginal benefit from customers, reducing response time and enhancing the credibility of enterprises. With the increasing competition in current market, the rapid high-tech development, shrink of food product life cycles and the complexity of food product mix, coupled with the various characteristics and storage requirements of different food, all of these factors, affect supply chain and require increasing demand prediction accuracy to avoid losses caused by shortages of stock, which however increases the cost of supply chain. Demand prediction based on supply chain management will not affect normal production and be able to avoid blind excessive procurement only. Therefore, accurate demand prediction for food enterprises is an effective way to improve supply chain management performance and is a hotspot for the researchers related (Drezner, 2011).

At present, the popular demand prediction methods for food supply chain adopted by enterprises and researchers are can divided to two categories: one is single prediction method, such as grey prediction method, adopting neural network prediction method, markov prediction method, prediction method based on quantity of value, time series prediction method; Another methods is using multiple prediction methods and combing their results according to certain form, i.e., combination prediction method. Besides, there are researchers presents some other methods, such as scenario analysis method. Specific methods have their own advantages and disadvantages:

Delphi method: Is always used for new product and long-term prediction, technology prediction and profits prediction. Its advantages includes it can draw on the wisdom of the masses and be beneficial to a reliable and comprehensive prediction. And its disadvantages includes lack of objective standard because of its main reference to subjective judgment and with low reliability (Feng and Ma, 2008).

Business personnel evaluation method: It can convene all the business personnel of each stage of logistics, such as transporting, purchasing, planning and warehousing to estimate the demand of certain logistics. And its disadvantages includes low quality of some business personnel and easiness of neglecting market demand change trend and entire economic situation (Xi *et al*., 2005).

Time series method: It is to use sale volume data of past time and certain mathematical methods with present demand data to predict future demand and development change trend. The methods includes: index correction method, epitaxial smoothing technique and moving average method (Lee *et al*., 2000):

- Index correction method is to conduct prediction value based on actual and past data and the method is only applicable to the time column which is unremarkable in seasonal change and trend (Luong and Phien, 2007)
- Epitaxial smoothing technique, when the impact of seasonal fluctuation and change trend on prediction value are under considered and the seasonal elements and trend are different from random character obviously, the method can be used and has better prediction accuracy, it is sensitive to demand on season also (Disney *et al*., 2006).
- Moving average method, Several data points in the method should be chosen to eliminate seasonal effect. The method is widely used, but the method is only can be used to predict the demand without obvious descending and ascending of value change and it is can not be used for long-term prediction (Duc *et al*., 2008).

Prediction based on BP Neural Network algorithm: Based on Kolmogorov theorem, for any given L2 type continuous function f:[0,1] → R_m, f can be simulated accurately with three-layer BP neural network algorithm. According to this theory, based on original BP neural network algorithm, recording structures evolved by factors in three layers, adding node evolution factors and choosing the optimal factors of the network structure can realizes the supply chain demand prediction (Cai *et al*., 2015).

BP neural network algorithm when used in supply chain demand prediction has fairly good prediction accuracy, but the algorithm has some disadvantages, such as slow convergence speed, falling in local optimum easily and above disadvantages has limited the application of BP algorithm in food demand prediction. Genetic algorithm is used to improve and modify BP neural network algorithm to solve the disadvantages mentioned above, the specific improvements include encoding chromosome, formatting fitness function, designing selection operator, redesigning crossover operator, designing mutation operator, integrating BP algorithm and optimal individual, improving calculation process step by step. By doing so, it not only can overcome the disadvantages mentioned above, but also simplify the structure of BP algorithm and the guarantee the final prediction accuracy, then a new food demand prediction algorithm based on supply chain management is presented.

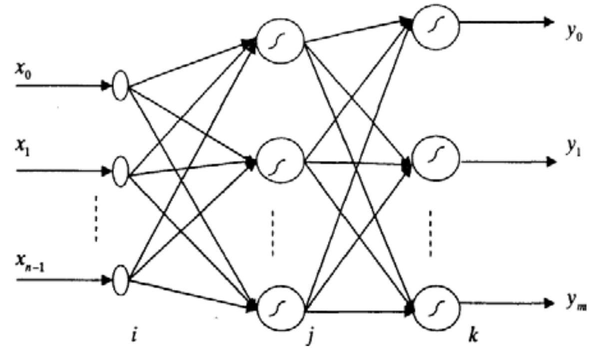

Fig. 1: The working topology of BP neural network algorithm

MATERIALS AND METHODS

This study was conducted in School of Business Administration, Jiangxi University of Finance and Economics, Nanchang, Jiangxi, China in 2015.

The working principle of BP algorithm: Generally, BP algorithm is comprised of three layers, i.e., output layer, hidden layer and input layer and every layer is connected each other and the node in the same layer is not connected. Generally, the number of nodes in input layer takes the dimension of input vector and the number of nodes in output layer generally takes the dimension of output vector; Now there is no standard method to confirm how many nodes in hidden layer and it should be confirmed by cut-and-try methods repeated. Based on Kolmogorv law, BP algorithm with three-layers (one hidden layer with sufficient nodes) can approximate and simulate any nonlinear continuous curve function with arbitrary precision on a closed set. So, the paper takes three-layers BP algorithm as example to illustrate its topological structure, shown as in Fig. 1 (Zhang *et al*., 2013).

It can suppose that the input vector X is the set $x \in R^n$, in the input vector $x = (x_0, x_1, x_2 \ldots, x_{n-1})^T$; and there have n_1 neurons (nodes) in hidden layer, the output of the input vector is $x' \in R^{n1}$, $x' = (x'_0, x'_1, x_2 \ldots, x'_{n-1})^T$; and there have m neurons in output layer, output $y \in R^m$, $y = (y_0, y_1, y_2 \ldots, y_{n-1})^T$, threshold is θ_j, the weight between input layer and hidden layer is $w_{i,j}$; threshold is θ'_k, the weight between hidden layer and output layer is $w_{j,k}$; therefore, the output of neurons (nodes) in three layer of BP algorithm meet Eq. (1) (Courant, 2012):

$$\begin{cases} x'_j = f(\sum_{i=0}^{n-1} w_{ij}x_i - \theta_j), & j = 0,1,2\ldots,n_1 - 1 \\ y'_k = f(\sum_{i=0}^{n1-1} w'_{jk}x'_j - \theta'_k), & k = 0,1,2\ldots,m-1 \end{cases} \quad (1)$$

The algorithm can complete the mapping and simulation calculation from n dimensional space vector to m dimension obviously and in mapping and simulation calculation activation function $f(x)$ is single-stage. Sigmoid function is described as Eq. (2) and activation function $f(x)$ is a continuous differentiable function, described as Eq. (3) (Zhang *et al*., 2013):

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

$$f^{'}(x) = f(x)(1-f(x)) \tag{3}$$

Improving BP neural network algorithm with genetic algorithm: BP neural network algorithm takes gradient descent and has strong ability in local search but poor ability in global search; Corresponding to this, genetic algorithm is a global optimization search method and has poor ability in local search but strong ability in global search. The paper integrates BP and genetic algorithms to exploit their own advantages complementary and develop their own strength and overcome their own disadvantages each other. The most important concept for two algorithm integration is that it should find a relative optimal solution to train BP algorithm with genetic algorithm; And then take this parameter as the initial parameter of BP algorithm to conduct the network calculation training enhance the calculation and simulation ability of BP algorithm.

The important problems to be solved for genetic algorithm used for improving BP network are formation of fitness function, mutation operator, encoding of chromosome, crossover operator, design of selection operator and, as well as the integration of BP algorithm and best individual.

Encoding chromosome: Learning steps of BP algorithm is the optimization learning calculation process of two continuous parameters, i.e., weight and threshold of BP algorithm. BP network fall into local optimization easily if choosing unsuitable initial parameters. Genetic algorithm is adopted in the paper to confirm the initial parameter value of BP algorithm to overcome the defect of BP network, that is falling into local optimization easily. In the chromosome encoding process, if it adopts binary encoding on parameters, the generated string may be too long and may revert to real number string in decoding process, which may influence the learning accuracy and the running time of the genetic and BP algorithm. So, real number decoding is adopted in the study, i.e., $X = (w_{n1,1}$,… $w_{n1,2}$, θ_1,…, θ_{n1}, w_{m1} … w_{mn1}, θ'_1, …, $\theta'_m)$ is the code string form (Guo *et al*., 2012).

Formatting fitness function: Basically in the evolution search genetic algorithm never use external information and only use fitness function as reference and use the fitness value to judge and search the excellence of each individual in the group with fitness value. So, choosing fitness function is very critical because it will influence on the convergence speed of genetic algorithm directly and whether the algorithm can be able to find the optimal solution. Generally, objective function can transform to fitness function. The network error is defined as Eq. (4) in the study. And error function is also can be the objective function in the study. Because the larger the fitness value is, the smaller the objective function value is and the smaller the fitness value is, the larger the objective function value is. Fitness function should be the reciprocal objective function, Eq. (5) is fitness function:

$$E_A = \sum_{p=1}^{P} E^{(P)} = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=0}^{m-1}(d_k^{(p)} - y_k^{(p)})^2 \tag{4}$$

$$F(E_A) = 1/E_A \tag{5}$$

Designing selection operator: Selection strategy in the improved genetic algorithm adopts commonly-used proportion to choose operator, it can suppose that M is the group size and F_i is the fitness of individual i, then Eq. (6) can express the probability P_i of individual i being selected:

$$P_i = F_i / \sum_{i=1}^{M} F_i \qquad (i = 1,2,3,...,M) \tag{6}$$

Designing crossover operator: The paper adopts real number encoding, so arithmetic crossover strategy is adopted for crossover operator. It can suppose that two individuals $\boldsymbol{X_A^t}$ and $\boldsymbol{X_B^t}$ exist, it can conduct arithmetic crossover between two individuals and generate two new individuals after crossover calculation, Eq. (7) and Eq. (8) can express the crossover calculation, in Eq. (7) and Eq. (8) α is a parameter and can be a variable or a constant which is depend on evolution generation:

$$X_A^{t+1} = \alpha X_B^t + (1-\alpha)X_A^t \tag{7}$$

$$X_B^{t+1} = \alpha X_A^t + (1-\alpha)X_B^t \tag{8}$$

Designing mutation operator: Uniform mutation strategy is adopted by mutation operator and it can suppose that for an individual $X = x_1\ x_2\ \ldots\ x_k\ \ldots x_t$, if using x_k means mutation point, the value range of mutation point is $[U^k_{\min}, U^k_{\max}]$, it can obtain a new individual $X = x_1\ x_2\ \ldots\ x'_k\ \ldots x_t$, after the mutation point conduct mutation calculation on the individual X, in which Eq. (9) shows a new gene value of every mutation point, in Eq. (9) r means a random number which meets the uniform probability distribution within the value range of [0, 1]:

Table 1: The prediction results of the improved algorithm

Year	Quarter	Actual demand	Model prediction demand	Error (%)
2003	1	5788	5847	1.0
2004	2	5854	5934	1.4
2005	3	6002 unit	6089 unit	1.4
2006	4	6544 unit	6715 unit	2.6
2007	1	6853 unit	6967 unit	1.7
2008	2	7188 unit	7283 unit	1.3
2009	3	7667 unit	7763 unit	1.3
2010	4	7993 unit	8198 unit	2.6
2011	1	8636 unit	8734 unit	1.1
2012	2	8547 unit	8689 unit	1.7
2013	4	9337 unit	9578 unit	2.6
2014	3	9774 unit	9834 unit	0.6

Table 2: The prediction results comparison of different algorithms

	Moving average Algorithm	Ordinary BP Algorithm	Improved BP Algorithm
The overall prediction error	15.08%	6.46%	1.86%
The prediction error of the first quarter	17.87%	5.22%	1.45%
The prediction error of the second quarter	14.65%	7.01 %	1.76%
The prediction error of the third quarter	14.36%	4.48%	1.92%
The prediction error of the forth quarter	16.77%	7.01%	3.09%
Time consumption (S)	5	189	6

$$x_k^{'} = U_{\min}^k + r(U_{\max}^k - U_{\min}^k) \tag{9}$$

Integrating BP algorithm and optimal individual: After genetic algorithm training finished, following steps should be conducted:

- Searching the individuals and their the largest fitness value
- Decoding their individual components into different corresponding parameter values
- Training genetic algorithm with BP algorithm until the termination condition of genetic algorithm is obtained (Guo *et al*., 2012).

Improving calculation steps: The calculation steps of the improved algorithm can be listed as follows:

- Establish sample set and try to reduce the dimensions of samples through factor analysis
- Calculate the fitness value of every individual in the same group and save its optimal fitness value
- Turn to step 4 if the optimal fitness value of the individual meets convergence conditions or reaches the evaluation generation required; Turn to step 2 after such genetic operations as crossover, selection and mutation
- Decode the fitness values of each individual gotten in step 3 into different network parameters to work as the initial parameters values of BP algorithm
- Modify the parameters of current BP network neural algorithm
- Exit calculation loop if reaching the calculation accuracy condition of BP network neural algorithm; otherwise, turn to step 5 to calculate continually.

RESULTS AND DISCUSSION

With C language the presented prediction algorithm is realized in the study. The demand of some quarters from 2003-2014 of certain food product enterprise is taken for example to conduct demand prediction; the specific prediction results is shown in Table 1 and 2. Table 1 shows some of the prediction results with the presented algorithm in the study and Table 2 shows algorithm performance of moving average algorithm (time series method), general BP neural network algorithm and presented BP algorithm in the study when they are used in practice of food supply chain demand prediction. The simulation experiments are carried out by. The configurations of the personal computer used in the study can be listed s follows: Inspiron 3847-R7938, 3.2GHz CPU and 8GB (4GX2) DDR3 1600MHZ memories.

Analyzing the prediction results shown in Table 1 and 2 which are practical food supply chain demand prediction of a certain food enterprise, it appears the obvious seasonal change characteristics of supply chain demand of food product enterprise, such as two tables can show that the prediction error of the fourth quarter is much larger than that of the other three quarters and it turns out to be the same with prior prediction. Furthermore, compared with moving average algorithm (time series method), general BP neural network algorithm, the food demand prediction algorithm presented in the study has higher prediction accuracy and effective algorithm calculation efficiency.

CONCLUSION

Food demand prediction based on supply chain management algorithm presented in this study takes advantages of the powerful ability of BP neural network in high prediction accuracy, strong non-linear simulation ability and popular application scope and improves the calculation method and simplifies algorithm network structure through genetic algorithm to speed up the convergence rate of BP neural network algorithm in calculation process. And it can obtain a new food supply chain demand prediction algorithm with high prediction accuracy and feasible practical application based on BP neural network algorithm. Taking a certain food product enterprise as experimental sample, the experimental and simulation results indicates that the presented algorithm based on BP neural network algorithm can be used for demand prediction in food supply chain. In other words, the methods of improving BP neural network algorithm in the study also has reference significance for the other application of BP neural network algorithm.

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