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Research Article

Research on Supply Chain Performance Evaluation of Fresh Agriculture Products Based on BP Neural Network

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Abstract: Evaluating supply chain performance of fresh agricultural products is one of the key techniques and a research hotspot in supply chain management and in fields related. The paper designs a new evaluation indicator system and presents a new model for evaluating supply chain performance of fresh agriculture product companies. First, based on analyzing the specific characteristics of the supply chain performance evaluation of fresh agriculture products, the paper designs a new evaluation indicator system including external and internal performance. Second, some improvements, such as adjusting dynamic strategy and the value of momentum factor, are taken to speed up calculation convergence and simplify the structure and to improve evaluating accuracy of the original BP evaluation model. Finally the model is realized with the data from certain supply chains of three fresh agriculture product companies and the experimental results show that the algorithm can improve calculation efficiency and evaluation accuracy when used for supply chain performance evaluation of fresh agriculture product companies practically.

Keywords: BP neural network, evaluation indicator system, fresh agriculture products, performance evaluation, supply chain management

INTRODUCTION

In the 1990s, along with the rapid development of economic globalization and the acceleration of competition, companies around the world, especially for fresh agriculture products companies, start to compete in the area of supply chain to cater for the extremely diversified customer demands, because the practice of supply chain can enhance company's competitiveness and offers great economic benefits. So how to carry out supply chain performance evaluation for fresh agriculture products companies including evaluation indicator system construction and evaluation method design has become a hotspot for the researchers related (Feng and Ma, 2010).

There are mainly following methods used for the overall evaluation of the performance of supply chain:

- **BP neural network method:** BP neural network learning algorithm adopts gradient search technology so as to minimize the error mean square value between actual output value and desired output value; the method is adept in the processing of uncertain information. If the input mode is close to training sample, the evaluation system is able to provide correct reasoning conclusion. The method has such advantages as wide applicability and high evaluation accuracy, but it also has some disadvantages like easy to fall into local minimum in the computation, low rate of convergence and etc., (Lee and Amandal, 2013).
- **Data Envelopment Analysis (DEA):** Starting from the perspective of relative efficiency, evaluates each decision-making unit and the indicators selected are only relied on input and output. As it doesn't rely on specific production function, it is effective for dealing with the evaluation with various kinds of input and output indicators, suitable for the analysis of benefit, scale economy and industry dynamics. But it is complicated in computational method, subject to certain limitations in application (Luong and Phien, 2012).
- Grey correlation analysis is a multi-factor statistical analysis method, which takes the sample data of each factor as basis to describe the strength, size and order of relationship among factors with grey correlation; If the situation of change of two factors reflected by sample data is relatively consistent, they have relatively large correlation; otherwise, the correlation is relatively small. The merits of this method lie in that it is intellectually clear, able to reduce the loss caused by information asymmetry to a great extent and less requires for data with less workload; however, its main demerits are that it requires for human determination of the optimal values of each indicator, it has strong subjectivity and it is

difficult to determine the optimal values of some indicators (Mu and Dahoon, 2013).

- Analytic Hierarchy Process (AHP) effectively combines qualitative analysis with quantitative analysis, not only able to guarantee the systematicness and rationality of model, but also able to let decision makers make full use of valuable experience and judgment, so as to provide powerful decision-making support for lots of regulatory decision making problems. The method has such strengths as clear structure and simple computation, but due to its strong subjective judgment, the method also has shortcomings like low evaluation accuracy (Feng and Ma, 2010).
- Multi-hierarchy comprehensive evaluation of fuzzy mathematics, its principle of is to firstly evaluate various kinds of factors of the same thing, dividing into several big factors according to certain attribute. Then carry out initial hierarchical comprehensive evaluation on certain big factor and carry out high hierarchical comprehensive evaluation on the result of initial hierarchical comprehensive evaluation based on that. The key of successful application lies in correctly specifying the factor set of fuzzy evaluation and reasonably form fuzzy evaluation matrix, obtaining evaluation result according to matrix calculation result. Make use of fuzzy comprehensive evaluation method can obtain the value grade of evaluated object or mutual precedence relationship; however, the method requires to establish appropriate evaluation matrix of evaluation object, which will obtain different evaluation matrixes due to the inconformity of different experts, leading to the inconformity of final evaluation results (Xi and Shi, 2010; Crook, 2013).

BP neural network algorithm is popular used in supply chain performance evaluation, for its high evaluation accuracy, but it leaves behind the question of slow convergence speed in calculation. The paper takes some measures including adjusting the value and dynamic strategy of momentum factor and dynamic strategy to modify and improve BP neural network model to overcome the question of slow convergence speed of original BPNN. In doing so a new algorithm for evaluating supply chain performance of fresh agriculture products companies is advanced.

MATERIALS AND METHODS

Analysis and establishment of evaluation indicator system: As the supply chain of fresh agriculture products needs to focus on quality safety and circulation efficiency, meanwhile, trying to reduce the loss in the logistics process, which is a special and complicated supply chain, the similarity of general supply chain and the specialty of fresh agriculture products shall be combined to establish evaluation indicator system of performance. Integrating the general idea of performance evaluation of supply chain and performance evaluation of logistics system, combining existing research literature, this study will, from such two aspects as evaluation of internal and external performance, establish the evaluation indicator system of the performance of supply chain of fresh agriculture products, which includes 4 hierarchies, 2 categories, 6 second-grade indicators, 16 third-grade indicators; see Table 1 for details (Feng and Ma, 2010; Lee and Amandal, 2013; Mu and Dahoon, 2013).

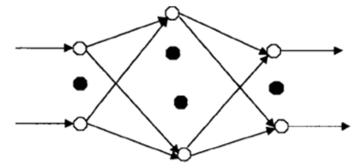

Fig. 1: Basic structure of BP neural network

Derivation of supply chain evaluation algorithm:

Working principle of BP neural network algorithm: Up till now, hundreds of artificial neural network models are put forward from different views of research, among which multi-hierarchy feed forward error back propagation BP neural network is the most-widely used network model in actual research. Basic three-layer BP neural network structure is shown as Fig. 1.

From the picture we can see that three-layer BP neural network is mainly comprised of input layer, hidden layer and output layer. Adjustable weight ω connects the layers. There can be several hidden layers, forming multi-layer BP neural network. The input of BP neural network is recorded as x_i (k), the actual output of network is recorded as y_i (k), the ideal output of network is recorded as Y_i (k), the subscripts i, j indicate the nodes of input layer of network respectively and k is the running iterations of BP neural network. Its approximation error is defined as Formula 1 in which L is the quantity of output layer nodes; in this way, the function characteristic of BP neural network can be described as formula 2 (Lucy and Lee, 2012):

$$E = \frac{1}{2}\sum_{j=1}^{L}(Y_j(k) - \gamma_j(k))^2 \tag{1}$$

$$\gamma_j(k) = f(x_i(k), \omega) \tag{2}$$

In formula 2, function f is obtained through the composition of weights of each network layer and node function, generally being very complicated non-linear function BP neural network training is to dynamically adjust the connecting weight ω to make formula 3 workable. The learning of weight ω adopts the fastest grads descent principle, i.e., the variable quantity of weights is in proportion to the negative gradient

Table 1: Evaluation indicator system of supply chain performance

Target hierarchy	First-class indicator	Second-class indicator	Third-class indicator
Performance of supply chain of fresh agriculture products	External performance	Customer service level	Timeliness of delivery
			Accuracy of delivery
			Security
			Customer dissatisfaction rate
		Adaptability of logistics service	Applicability of products
			Applicability of time
			Applicability of quantity
		Integration of logistics service	Integration level of service
			Intimacy of cohesion
	Internal performance	Enterprise input	Assets input
			Personnel expenditure
			Logistics cost
		Internal operation	Informational level
			Resource utilization
			Logistics operation
		Enterprise income	Cost benefit
			Business growth rate
			Profit growth rate

direction of approximation error E. See reference 2 for specific calculation:

$$\lim_{k\to\infty} E = \lim_{k\to\infty} \frac{1}{2}\sum_{j=1}^{L}(Y_j(k)-\gamma_j(k))^2 = 0 \tag{3}$$

Algorithm improvement in adjusting the value of momentum factor α: The introduction of momentum is, in essence, to exert a recursive low pass filter on $\partial E_{all}/\partial$ (•), so as to "attenuate" the error of "high-frequency oscillation" and expand the "direct current" component of error gradient along "the bottom of canyon"; secondly, the investigation of iterative correction formula of network parameter (one of the parameters representing ω, θ, S) can be expressed by formula 4 (Deaph, 2011):

$$\begin{aligned}\bar{X}(k) &= \bar{X}(k-1) - \eta(k-1)\frac{\partial E_{all}}{\partial \bar{X}(k-1)} + \alpha\Delta \bar{X}(k-1) \\ &\approx \bar{X}(k-1) + \eta(k-1)\{-\frac{\partial E_{all}}{\partial \bar{X}(k-1)} + \frac{\alpha\eta(k-2)}{\eta(k-1)}(-\frac{\partial E_{all}}{\partial \bar{X}(k-2)})\}\end{aligned} \tag{4}$$

The above parameters are expressed by vectors, which shows that the introduction of momentum makes the approximation similar to the conjugate gradient search process, but $\frac{\partial E_{all}}{\partial \bar{X}\,(k-1)}$ and $\frac{\partial E_{all}}{\partial \bar{X}\,(k-2)}$ are not in the form of conjugate gradient; in these circumstances, the value of momentum factor α can be adjusted as follows:

- While the learning errors of recent continuous S' times are increasing, α = 0, stop the amplified action on "direct current component".
- Otherwise, the value of α keeps unchanged, maintaining the restrain on "high-frequency oscillation".

Generally, as there are change points of learning speed in "oscillation area" in error curved surface, in order to avoid the over slowness of learning process towards "oscillation area", the value α shall not be too big; (0.1-0.3) will be appropriate.

Algorithm improvement in dynamic strategy of momentum factor α: Stagnation is the fundamental cause resulting in the inadequacy of BP neural network algorithm. Based on the deterministic and random selections, this study adjusts the transition probability dynamically to build the selection strategy more conducive to the overall search.

The pheromone in the path occurs continuous change in the evolutionary process. The pheromone of better solution searched is strengthened to increase the selection possibility of next iteration and some better solutions is forgotten gradually because fewer ants pass in the start-up phase so as to affect the overall search capabilities of the algorithm. If the BP neural network are stimulated properly to try the path occasionally in the selection strategy, it is conducive for the overall search of the solution space. Thus, the inadequacy of basic BP neural network algorithm is overcome effectively. See formula 5 for the improved selection strategy in this study. In formula 5, X_{ij} meets the requirements of formula 6:

$$P_{ij}^{k}(t) = \begin{cases} \arg\max\{\left|\tau_{ij}(t)\right|^{\alpha}\cdot\left|\eta_{ij}(t)\right|^{\beta}\}, & q \le q_0, j \in allowed_k; \\ \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\cdot\left[\eta_{ij}\right]^{\beta}\cdot X_{ij}(t)}{\sum\limits_{k\in allowed_k}\left[\tau_{ik}(t)\right]^{\alpha}\cdot\left[\eta_{ik}\right]^{\beta}\cdot X(t)}, & j \in allowed_k, others \end{cases} \tag{5}$$

$$X_{ij} = \frac{m\cdot N_c}{m\cdot N_c + \delta\cdot Q_c(i,j)\cdot\eta(i,j)/\max\eta} \tag{6}$$

Adaptive change of algorithm steps: In order to make the learning step better carry out adaptive change, adjustment shall be carried out according to different conditions. Specific change steps are as shown below:

- Under the guiding of non-monotone linear search method: Calculate the error change of forward and backward iteration process, see formula 7:

$$\Delta E_{all}(k) = E_{all}(k) - \max_{0\le i\le r_g}\{E_{all}(k-i)\}$$
$$\Delta E_{all}(k-1) = E_{all}(k-1) - \max_{0\le i\le r_g}\{E_{all}(k-i)\} \quad (7)$$

- If the learning errors of recent continuous S times are decreasing, the step change is formula 8 which $\beta_1 \ge 1$; if the learning errors of recent continuous S times are increasing, the step change is formula 9 which $\beta_2 \le 1$; otherwise, time varying coefficient L needs to be calculated through formula 10:

$$\eta_k = \beta_1 * \eta_{k-1} \quad (8)$$

$$\eta_k = \beta_2 * \eta_{k-1} \quad (9)$$

$$L(k) = C1 * \frac{-\Delta E_{all}(k)}{E_{all}(k-1)} + C2 * Sgn(-\Delta E_{all}(k)) * \frac{|\Delta E_{all}(k) - \Delta E_{all}(k-1)|}{|\Delta E_{all}(k-1)|} \quad (10)$$

If $\Delta E_{all}(k\text{-}1) = 0$, then take the first item only; if $L(k) \ge \beta 1\text{-}1$, then $L(k) = \beta 1\text{-}1$, If $L(k) \le \beta 2\text{-}1$, then $L(k) = \beta 2\text{-}1$. Based on this, step change is formula 11:

$$\eta_k = (1 + \mathrm{L(k)}) * \eta_{k-1} \quad (11)$$

In the above formulas, k represents learning times, $E_{all}(k)$ is the error after the k^{th} times of learning (define according to Cauchy error estimation form), Sgn (•) represents sign function, η is learning steps, S, $C1$, $C2$ are predetermined constants.

The essence of the above step change strategy is to change the step according to the features of "flat area" and "oscillation area" of error curved surface: the increase and decrease of step in "oscillation area" are adjusted with the percentage of forward and backward error change, so the learning process can be better closed to "optimal route"; while in the "flat area", rapid increase and decrease shall be implemented on step to accelerate the convergence of learning process. Therefore, in the actual calculation of this study, the value of β_1 is among (Deaph, 2011; Lee and Amandal, 2013) and the value of β_2 is among (0.1, 0.4).

RESULTS AND DISCUSSION

Data acquisition and pre-processing: Choose m typical supply chains of fresh agriculture products companies, make use of statistical data to compute the values of n indicators of each supply chain and compute corresponding overall evaluation score of each supply chain with n indicator weights through determination and normalization processing of experts, so as to obtain m training mode pairs, training the model of this study with such m training mode pairs. Subsequently, model in this study can be applied to the performance evaluation of supply chain of fresh agriculture products companies. Every time when inputting 18 third-class evaluation indicators of supply chain to be evaluated, we can obtain the performance of supply chain of the fresh agriculture products companies.

The questionnaires of all the evaluation indicators were made and surveyed to the enterprises and consumers related to get the score of each indicator for different supply chains of fresh agriculture products companies. The original data acquired by the survey are pre-processed to the scope of the BP algorithm and the final scope of the score is (0, 5).

Experimental results and analysis: Limited to paper space, the evaluation of intermediate results is omitted here, only providing secondary evaluation results and final comprehensive evaluation results of three typical chains, see Table 2.

In order to illustrate the value of the presented algorithm and some other algorithms which are popular used for performance evaluation are realized with the same calculation platform in the study. The indicators of the calculation platform can be listed as follows Intel i3 2120, 2GB DDR3, AMD Rade on HD 7450 and 3.3 GHz CPU and windows XP. The Table 3 can shows that the evaluation accuracy and time consuming of the different algorithms. Form the table we can see clearly that the algorithm in the study has greater value than that's of BP neural network (Lee and Amandal, 2013) and fuzzy algorithms (Crook, 2013) in evaluation accuracy or time consuming. In realization practice, the paper takes some obvious indicators as sample to

Table 2: Evaluation results of secondary grade indicators of some supply chains

	Customer service level	Adaptability of logistics service	Integration of logistics service	Enterprise input	Internal operation	Enterprise income
1	3.332	3.761	3.421	3.598	4.021	3.876
2	4.218	4.318	3.892	4.282	4.208	3.998
3	4.651	4.458	4.321	4.093	4.587	4.602

Table 3: Realization results of different algorithms

	Algorithm in the paper	Fuzzy model	Ordinary BP neural network
Evaluation accuracy	94.97%	71.33%	82.76%
Time consuming (S)	13	16	817

calculate evaluation accuracy in order to make our comparison more believable.

CONCLUSION

It is shown through empirical research that the model for evaluating the supply chain performance of fresh agriculture products companies based on BP neural network established in this study is practicable, effective and feasibility and is able to effectively conquer some shortcomings of traditional evaluation models, as well as equipped with capabilities like self-learning, self-adaptation, strong fault tolerance and ability of expression, able to reduce some human subjective factors to the hilt, so as to improve the reliability of the performance evaluation of enterprises, making evaluation results more objective and accurate.

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