Supply Chain Inventory Strategies Using Fuzzy Neural Network

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Abstract

In the fast-changing business environment, supply chains are affected by the production and inventory strategies, which influence the amount of information needed by the chains. The firms must therefore determine the best supply chain inventory strategies for their products. The lack of precise market demand and reliable supplier's stock level makes it inappropriate to use the statistically-based inventory model to determine inventory strategies for the new product supply chain. This paper therefore presents a fuzzy neural network model to describe the uncertain market demand and supply reliability. By the joint replenishment and periodic review, we determine, under the consideration of long-term effect, the possible quantities of supply and customer's demands in the multi-echelon acyclic network supply chain.

Keywords: Fuzzy neural network, supply chain, inventory management

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1. Introduction

Supply chain refers to the production and distribution process at production facility before the production is finished. According to the relevant literature, supply chains can be further divided into four processes: material control, production, stockpile inventory, and distribution. In most of the previous literature, the probability distribution approach has been used to describe the processes. However, due to the lack of accuracy of many key variables, the traditional probability distribution methods (e.g., Normal, Binomial, etc.) may produce incorrect empirical result.

This paper extends the model of Hsu et al. (2003) to utilize fuzzy set to determine customer demand and supplier's stock level under the uncertainty so that the total inventory combinations can be obtained. Moreover, neural network is employed in this study to precisely estimate capacity to lower the overall costs and to increase profits for businesses.

2. Methodology

The study applies fuzzy set to the uncertain customer demand and the supplier's stock. By applying the possibility theory index model, we determine the size of fuzzy set by calculating fuzzy addition, fuzzy subtraction, fuzzy multiplication, fuzzy maximum, and fuzzy minimum.

2.1 Fuzzy set applied in the supply chain

The research first applies a standard membership function in the fuzzy set to describe the uncertain factors in the overall supply chain, including the customer's demand and the supplier's stock level. In Figure 1, we assume the fuzzy numbers in the triangle (D_1, D_m, D_r) are the customer's demand; in Figure 2, we assume (s, S) type fuzzy numbers (F_1, F_m) are the possibility of the supplier's stock level. D_m represents the most possible demand. The customer's demand usually falls within a fixed range in a certain period of time. Let the middle point of the average be the most possible demand. D_1 and D_r denote the range of possible customer's demand, calculated by subcontracting/summing a standard deviation of demands, respectively. To the suppliers, if the stock level is lower than the average, they could experience a run-out at any time. Therefore, we assume F_1, the lowest value of the possible supply is the average of overall data; similarly, let F_m, the highest value of the possible supply be the average of overall data plus standard deviation. Apparently, the more inventory, the more likely the supply fulfillment is closed to 1.

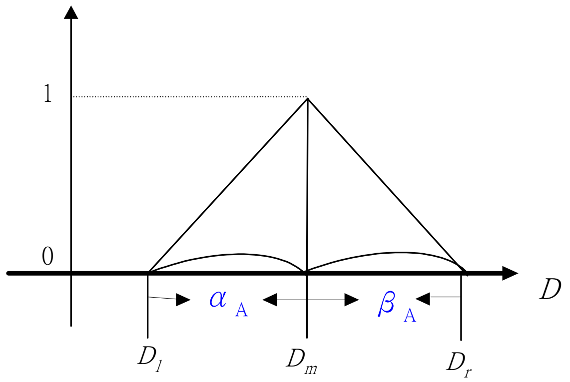

Figure 1. Fuzzy set of the customer demand

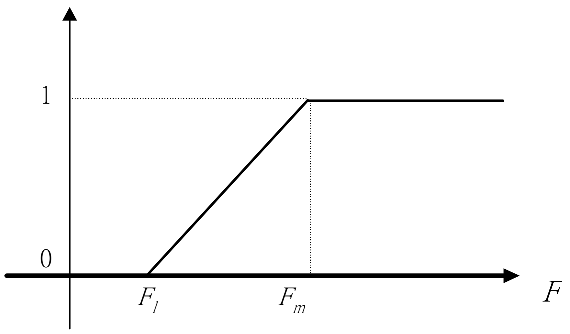

Figure 2. Fuzzy set of the supplier's stock level and supply fulfillment

In the research, the overall supply chain strategy is based on the joint replenishment decision (Edward, 1974), and the order cost is assumed to be negligible under the total cost consideration. The holding cost and backorder cost will be the only two cost items considered under the fuzzy independent inventory control system. As far as the holding cost is concerned, the timing and the quantities are the two important factors. If the fuzzy demand is satisfied by the stock level, then the holding costs equal to the holding quantities times the unit holding costs. As for the backorder costs, quantities are the only factor to be considered. If the fuzzy demand cannot be satisfied by the stock, shortage may occur. In that case, the backorder costs = (fuzzy demand - stock level) x the unit backorder costs.

The definitions of the variables are as follows:

h_i : unit holding cost at production facility *i*

b_i : unit backorder cost at production facility *i*

t : time

R : review period

S_t : stock level in period *t*

d_t : $d = (d_1 \oplus d_2 \oplus \ldots \oplus d_r)$ is the periodically cumulative demand in the review period, determined by the information of similar products, people at higher levels or domain experts.

$\oplus$, $\oplus$, $\otimes$, Min, Max: denote fuzzy add, fuzzy subtraction, fuzzy multiplication, fuzzy minimum and fuzzy maximum, respectively.

In the supply chain, the holding cost and backorder cost at production facility *i*, can be calculated:

$$H_i(S,d) = \frac{h_i}{2} \otimes \left\{ Max\left(0, \left(\sum_{t=1}^{R} S_t - d_i \right) \right) \right\}$$

$$F_i(S,d) = b_i \otimes \{ Max(0, (d - S_t)) \}$$

2.2 Using neural network to predict the suppliers' capacity

2.2.1 Neural network training

Neural network can be classified as supervised and unsupervised learning schemes according to its learning characteristics. Supervised learning scheme obtains training samples in the problem areas, including input variables and output variables, and learns internal corresponding rules of input and output variables in order to be applied in the new cases. This research employs supervised neural network approach with the involvement of learning vector quantification and back-propagation.

In this research, a four-layered structure of neural network is proposed as follows:

1. Input Variables Layer
2. Input Fuzzy Layer
3. Hidden Layer
4. Output Variables Layer

2.2.2 Neural network test

Once being constructed, neural network test is performed by dividing into three stages:

1. Convergence test: In the neural network learning

process, the test supervises if error function or energy function converges in a reasonable way.

2. Examination test: After learning, the test analyzes the error types in order to improve the neural network process.

3. Experiments and discussion

An example, as Figure 3, is used to illustrate the model in the research.

- Production facility: 6
- Total outside supplies: 3
- The outside suppliers' stock level: The possibility of the outside suppliers' stock level is S-type fuzzy sets (average, average + standard deviation)
- Customer demand: 750 items per week. The triangle fuzzy set represents customer demand (average-standard deviation, average, average+standard deviation).

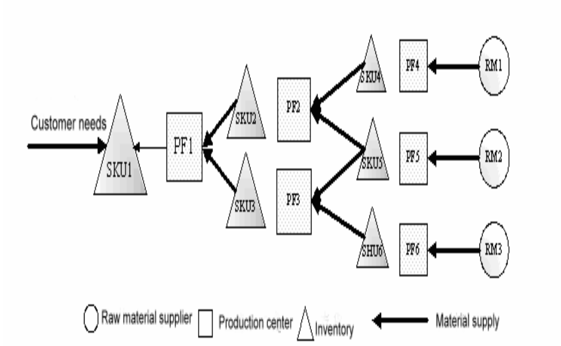

Figure 3. Example supply chain

MatLab is used as an experimental tool to examine the proposed model. It must first be fuzzificated and then trained by neural network to predict the suppliers' capacity. In the research, the above-mentioned four fuzzy input nodes are input factors while the capacity represents the output factor. Take the first production facility as an example and the procedures are as follows:

Step 1 To obtain customer demand, we first find the average located in the middle of the triangle fuzzy set and then calculate standard deviation. On the right and left angle of the triangle fuzzy set are D_l (= Avg-Std) and D_r (= Avg+Std,) respectively.

Step 2 To obtain the possibility of the suppliers' stock level, calculate the average and standard deviation. In the S-type fuzzy set, the lowest and highest degrees are F_1 (= Avg) and F_m (= Avg.+Std), respectively.

3. Evaluation test: After the system is constructed, the test decides if the goal of the project has been fulfilled.

Step 3 Fuzzy operations such as fuzzy add, fuzzy subtract, fuzzy multiply, and fuzzy maximization are employed to manipulate the above factors to calculate the fuzzy number of the holding cost and backorder cost.

Step 4 There are four input nodes: the node at hidden layer is 9, and the node at the output layer is 1, as shown in Figure 4.

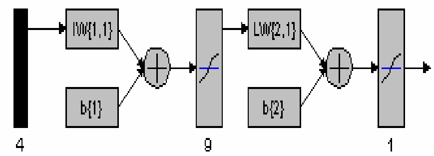

Figure 4. Example fuzzy neural network

Step 5 After the convergence test, perform neural network training, and establish the optimal stopping condition.

Step 6 Examination test: After learning, the test analyzes the error types of neural network using input training data to improve the process (see Table 1).

Step 7 Evaluation test: After the system is constructed, using input test data, the test decides if the goal of the project has been fulfilled.

Table 1. Data comparison

Target Data	58	59	49	67	57	53	71	68	59	60
Predicted Data	58	59	50	66	57	53	66	68	59	66

4. Conclusion

This study has applied fuzzy set to describe customer demand and suppliers' stock level with uncertainties. The study considers shortage and backordering costs and applies a fuzzy neural network model to predict the capacity at each production facility. MatLab is used as an experimental tool. To improve the entire supply chain more, additional algorithms must be derived to estimate the minimal inventory costs under capacity constrain.

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