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M.H. Fazel Zarandi
Polytechnic of Iran, zarandi@cic.aut.ac.ir

Milad Avazbeigi
Polytechnic of Iran, miladavazbeigi@cic.aut.ac.ir

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M.H. Fazel Zarandi
Department of Industrial Engineering, Amirkabir University of Technology (Polytechnic of Tehran), P.O. Box 15875-4413, Tehran, Iran
zarandi@cic.aut.ac.ir

Milad Avazbeigi
Department of Industrial Engineering, Amirkabir University of Technology (Polytechnic of Tehran)
miladavazbeigi@cic.aut.ac.ir

ABSTRACT

The bullwhip effect in nowadays Supply Chains has become a major source of problems and has attracted supply chain scientists attentions. This paper explores the concept of bullwhip effect in supply chains throughout a completely new approach. Assuming all demands are fuzzy in supply chain, fuzzy If-Then rules are used to show the bullwhip effect. Application of fuzzy logic is due to the fuzzy nature of supply chain problems. The new approach can be the source of inspiration for new solutions to the bullwhip effect in supply chains base on fuzzy logic and fuzzy If-Then rules. Fuzzy time series are widely used in this paper. First for data generation, we apply a modified version of Hwang fuzzy time series with a neural network for defuzzification and finally to show the bullwhip effect, we use Lee fuzzy time series which is based on Fuzzy If-Then rules, Genetic Algorithm and Simulated Annealing.

Keywords

Supply Chains, Bullwhip effect, Fuzzy Time Series, Fuzzy if-Then rules, Genetic Algorithm.

INTRODUCTION

Supply chain (SC) is defined as the chain linking each entity of the manufacturing and supply process from raw materials through to the end user (New and Payne, 1995; Scott and Westbrook, 1991). In recent years, with growth and expansion of new international and multi-national businesses, supply chain management (SCM) has attracted many attentions. Also with growing complexity of new supply chains, bullwhip effect in supply chains has become an important critical issue.

Bullwhip is a relatively new phase coined by Lee, Padmanabhan and Whang (1997 a, b) to describe the demand amplification phenomenon which was already well known at Procter and Gamble as long as 1919 (Denis, Zhou and Disney, 2007). However, the most seminal contribution to understanding the bullwhip phenomenon was Forrester's work in 1958. Forrester in his work discusses causes of bullwhip effect and possible remediation.

Next, several researchers such as Blinder (1982), Blanchard (1983), Burbidge (1984), Caplin (1985), Blinder (1986) and Kahn (1987) also recognize the existence of the bullwhip effect in supply chains.

Literature review shows there are two works which apply the concept of fuzzy logic to bullwhip effect. The first is the work of Carlsson and Fuller (2001). They assume each echelon in SC uses an order up policy which let them to put an imprecise order to up-stream echelon. They also let the echelons make their orders more precise as the delivery time point gets closer. Finally, they show if all echelons share their information, bullwhip effect can be reduced. However, the uncertainty of demands and lead times are not considered. Moreover, they show the bullwhip effect by using a crisp ordering policy. The second is the work of Zarandi, Pourakbar and Turksen (2007). They define their problem in a fully uncertain fuzzy environment which demands and lead times are also fuzzy besides order quantity. Finally, they present an agent-based solution for reduction of bullwhip effect.

This paper tries to show the bullwhip effect in a fuzzy environment, using fuzzy If-Then rules which is not considered in previous works. The rest of paper is organized as follows: First we provide some preliminary definitions of fuzzy time series. Next, we briefly describe two fuzzy time series which are applied in this paper. Finally we propose our new approach based on fuzzy if-then rules to show bullwhip effect.

FUZZY TIME SERIES

Preliminary definitions

In this section, we briefly review the concepts of fuzzy time series. Song and Chissom (1993a, 1993b, 1994a and 1994b) presented the concepts of fuzzy time series based on the fuzzy set theory (Zadeh, 1965).

Definition 1 (Song and Chissom, 1993a) Fuzzy time series:

A fuzzy set *A* defined in the universe of discourse $U, U = \{u_1, u_2, \cdots, u_n\}$ can be represented as follows:

$$A = f_A(u_1)/u_1 + \cdots + f_A(u_n)/u_n \qquad (1)$$

where, f_A is the membership function of the fuzzy set $A, f_A : U \to [0,1],$ and $f_A(u_i)$ denotes the degree of membership of u_i belonging to the fuzzy set *A*, $f_A(u_i) \in [0,1],$ and $1 \le i \le n$. Let $Y(t)(t = \cdots 0,1,2,\cdots)$ be the universe of discourse and be a subset of R. Assume that $f_i(t) \quad (i = 1,2,\cdots)$ is defined in the universe of discourse $Y(t)$, and assume that $F(t)$ is a collection of $f_i(t)(i = 1,2,\cdots)$, then $F(t)$ is called a fuzzy time series of $Y(t)(t = \cdots 0,1,2,\cdots)$.

Definition 2 (Song and Chissom, 1993a) Current and next state of the fuzzy logical relationship:

Let $F(t)$ be a fuzzy time series, where:

$$F(t) = F(t-1) \circ R(t, t-1) \qquad (2)$$

and $R(t, t-1)$ is a fuzzy relation, and ''∘'' is the Max–Min composition operator. Then, $F(t)$ is caused by $F(t-1)$ and it is denoted by the fuzzy logical relationship $"F(t-1) \to F(t),"$ where $F(t-1)$ and $F(t)$ are fuzzy sets. In this case, $F(t-1)$ and $F(t)$ are called the current state and the next state of the fuzzy logical relationship, respectively.

Definition 3 (Lee, Wang and Chen, 2008) Nth-order fuzzy logical relationship:

Let $F(t)$ be a fuzzy time series. If $F(t)$ is caused by $F(t-1), \cdots F(t-n)$ then the nth-order fuzzy logical relationship is represented by:

$$F(t-n), \cdots, F(t-2), F(t-1) \to F(t)$$

where, $F(t-n), \cdots, F(t-2), F(t-1)$ and $F(t)$ are fuzzy sets, $"F(t-n), \cdots, F(t-2), F(t-1)"$ is called the current state of the nth-order fuzzy logical relationship, and $F(t)$ is called the next state of the nth-order fuzzy logical relationship. A set of *nth*-order fuzzy logical relationships having the same current state forms a *nth*-order fuzzy logical relationship group.

FUZZY TIME SERIES LITERATURE

Traditional forecasting methods can deal with many forecasting cases, but they cannot solve forecasting problems in which the historical data are linguistic values (Hwang, Chen and Lee, 1998).

Fuzzy time series forecasting emerged as a proper approach for predicting the future values in a situation where the information are imprecise and vague or linguistic values. Song and Chissom (1993a) successfully employed the concept of fuzzy sets having linguistic variables presented by Zadeh (1965) and the application of fuzzy logic to approximate reasoning by Mamdani to develop the foundation of fuzzy time series forecasting. Song and Chissom (1993b, 1994a and 1994b) implemented their developed time invariant and time variant models on the historical time series data of student enrollments of University of Alabama. Chen (1996) presented a simplified time invariant method for time series forecasting by using the arithmetic operations in place of max–min composition operations used by Song and Chissom (1993b). Song, Leland and Chissom (1996) considered the fuzzy valued probability distributions and extended the concept of time series to fuzzy stochastic fuzzy time series. Hwang et al. (1998) proposed a method using heuristic rule to handle forecasting problem based on fuzzy time series. Further. Cheng, Chang and Yeh (2006) used two approaches to improve the fuzzy time series forecasting: (a) by minimization based on entropy principle approach to partition the universe of discourse and building the membership function and, (b) by using trapezoid fuzzification approach. Also Lee et al. (2008), focused on determining the length of fuzzification intervals. They used simulated annealing and genetic algorithm to determine the length of intervals. Their model has proved a good accuracy in prediction and higher flexibility in application over different data sets.

In this paper we apply Lee et al. (2008) and Hwang et al. (1998) fuzzy time series in order to show the bullwhip effect in a supply chain. In the next section we introduce the two fuzzy time series. It should be noted that Hwang et al. (1998) fuzzy time series is used with some modifications. The modification is presented right after introduction of the original method.

Fuzzy time series and bullwhip effects

In this paper, we use fuzzy time series for two different purposes:

First, in a multi-echelon supply chain in order to put an order to upstream echelon, each echelon uses an order up policy. We use Hwang et al. (1998) fuzzy time series for this purpose. The vague and fuzzy nature of demands, are the main motivations behind the application of fuzzy time series in this case. The underlying reason in using Hwang et al. (1998) fuzzy time series is that their fuzzy time series does not need complex and time consuming calculations and also has an acceptable accuracy for generation of training and test data for the next phase of research.

Second, by applying Hwang et al. (1998) fuzzy time series, we generate pairs of data in a multi-echelon supply chain. Each pair of data represents the order quantity of an echelon and upstream echelon. We, first, use these pairs of data as training data set for determining the length of intervals by Lee et al. (2008) fuzzy time series and, then as test data set to show the bullwhip effect. The underlying reason in using Lee et al. (2008) fuzzy time series is the similarity between the structure of the fuzzy time series and pairs of data.

Hwang et al. (1998) fuzzy time series

As we said, we use Hwang et al. (1998) Fuzzy Time Series with some modifications. Here we just bring the main defuzzification process of Hwang et al. (1998) and the new method proposed for defuzzification. Hwang et al. (1998) proposed the following method for defuzzification of fuzzy outputs as the final step of their algorithm.

(1) If the grades of membership of the fuzzified forecasted variation have only one maximum u_i, and the midpoint of u_i is m_i, then the forecasted variation is m_i. If the grades of membership of the fuzzified forecasted variation have more than one maximum $u_1, \cdots, u_k$ and their midpoints are $m_1, \cdots, m_k$ respectively, then the forecasted variation is $(m_1 + \cdots + m_k)/k$.

(2) If the grades of membership of the fuzzified forecasted variation are all 0, then we set the forecasted variation to 0.

Modification of Hwang et al. (1998) for data generation

For the first pair of data, the input data to Hwang et al. (1998) fuzzy time series is demand of the first echelon which is generated by Monte Carlo simulation. For defuzzification of fuzzy output of Hwang et al. (1998) fuzzy time series, we have adopted Neural Network instead of method introduced in Hwang et al. (1998). Each participant in supply chain, first, uses Hwang et al. (1998) fuzzy time series to determine the next order quantity using order-up policy, then s/he uses trained Neural Network for defuzzification and, finally, passes the order quantity to up-stream echelon. For training Neural Network(NN) as defuzzification method, we adopted Back-Propagation method. The number of inputs to NN is determined by number of intervals in Hwang et al. (1998) method. The window basis in Hwang et al. (1998) Model is 4. Table 1 summarizes the results of prediction. Figure 2 shows the real data generated by Monte Carlo method versus predicted data which is the output of modified Hwang et al. (1998) fuzzy time series. The results show the average error of modified Hwang et al. (1998) fuzzy time series for test data set is 2.88% which is an acceptable average error in compare to other models in literature. Result shows, because of the proved accuracy and robustness of the proposed model, besides the application of modified Hwang et al. (1998) for proving bullwhip effect, the proposed model can be applied for other applications too.

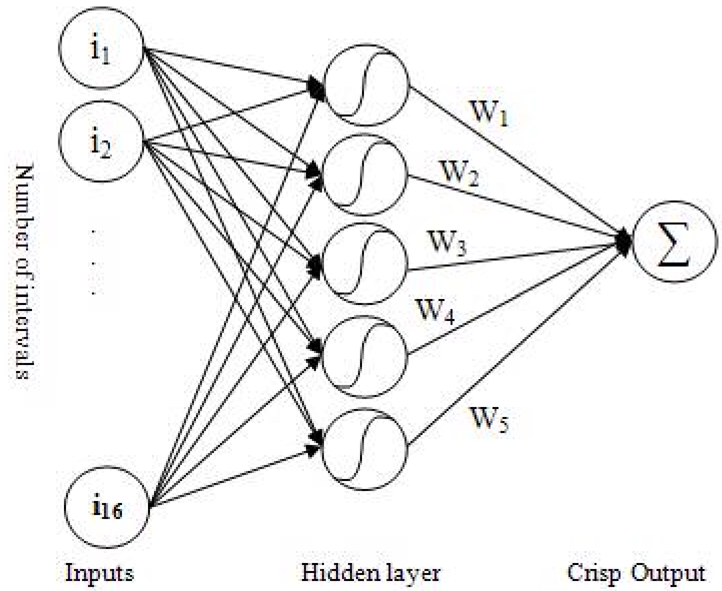

Figure 1. Defuzzifier neural network

#	Predicted Data	Real Data	Error	MSE
231	2576.7193	2548	0.0113	824.7981925
232	2572.5688	2568	0.0018	20.87393344
233	2592.5744	2477	0.0467	13357.44194
234	2501.3216	2477	0.0098	591.5402266
235	2501.6752	2452	0.0203	2467.625495
.	.	.	.	.
.	.	.	.	.
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296	2457.7493	2457	0.0003	0.56145049
297	2461.2222	2480	0.0076	352.6057728
298	2506.4043	2470	0.0147	1325.273058
299	2494.5817	2590	0.0368	9104.651975
300	2614.6513	2468	0.0594	21506.60379
#		Average	2.88%	8329.349

Table 1. The result of testing the Neural Network

Now, we describe the ordering policy in detail. Hayman and Sobel (1984) in their work show that when customer's demand is an ARIMA process, such a policy minimizes the total expected holding and shortage costs over an infinite horizon. We assume that all echelons use the following policy to determine the order quantity, which they have to put on up-stream echelon.

$$\widetilde{D}_{k+1,t} = \widetilde{D}_{k,t} + (\widetilde{S}_{k,t} - \widetilde{S}_{k,t-1}) \tag{3}$$

where

$$\widetilde{S}_{k,t} = \widetilde{m}_{k,t} + z_k \sqrt{v_{k,t}} \tag{4}$$

while

$$\tilde{m}_{k,t} = E(\sum_{i=1}^{\tilde{l}_k} \tilde{D}_{k,t+i} \mid \tilde{D}_{k,t}) \quad (5)$$

$$v_{k,t} = Var(\sum_{i=1}^{\tilde{l}_k} \tilde{D}_{k,t+i} \mid \tilde{D}_{k,t}) \quad (6)$$

$$z_k = \phi^{-1}(h_k /(p_k + h_k)) \quad (7)$$

In our model, we set h=1, p=2, w=4, Number of Intervals=16, and lead time=4. For simplification we assume all participants in supply chain use these values as their inventory management system setup arguments.

Using cited ordering policy and trained Neural Network we generate data pairs. The output of this phase would be a matrix including the demands of supply chain participants. We continue data generation in order to achieve data needed for training and testing of Lee et al. (2008) method.

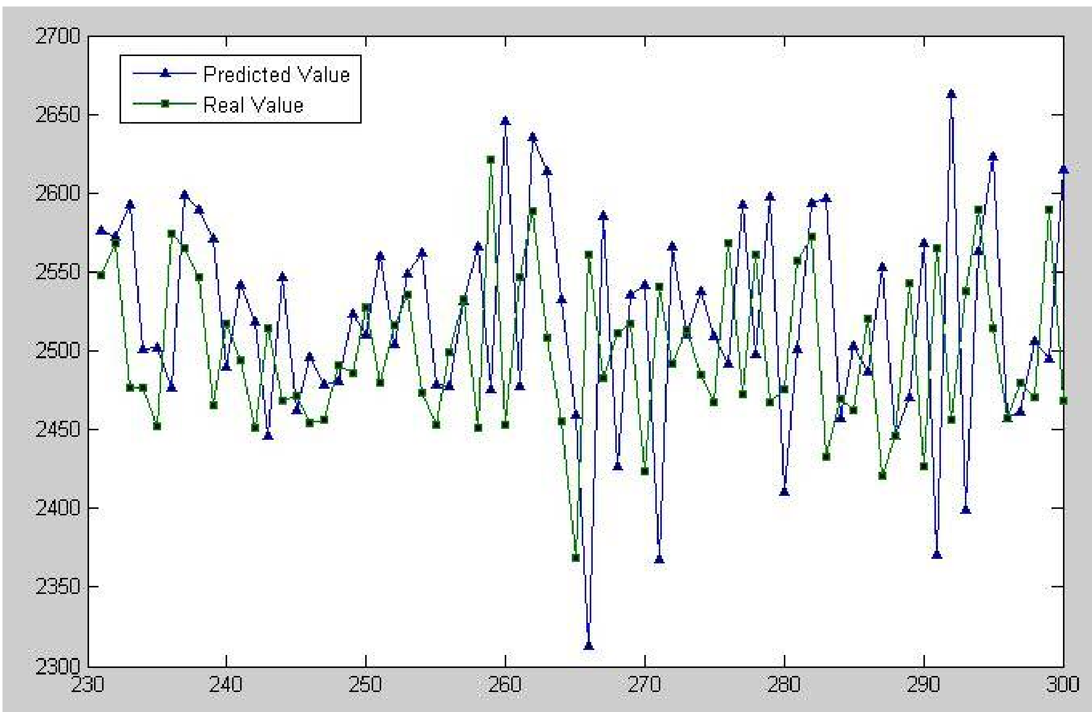

Figure 2. Actual and the forecasted amount by the proposed approach generated data by Monte Carlo method

Lee et al. (2008) fuzzy time series

In contrast to Hwang et al. (1998) fuzzy time series, Lee et al. (2008) fuzzy time series is applied for the pairs of data. The main reason that we don't use this method directly in the beginning of research is the lack of data; we don't have the demand of second echelon, third echelon, and so forth at the beginning. Using Fuzzy Logic and Fuzzy Inference Systems for prediction values affects significantly on variation of data and usually the variation of the main data and predicted data have a considerable difference. However, our aim is to show the bullwhip effect in a supply chain using Fuzzy If-Then rules. Hence, we need a model with high accuracy to predict values in order to minimize the negative effect of prediction method on variation of values.

We don't describe the Lee et al. (2008) fuzzy time series in detail. This fuzzy time series, applies genetic algorithm and simulated annealing to determine the intervals length of the new fuzzy time series, then by the help of new intervals, we predict the value of next period t.

RESULTS OF EXPERIMENTS

Figure 3, shows the integration and relationships of all methods introduced in previous sections to prove the bullwhip effect. In this section we bring the result of experiment using Fuzzy If-Then rules. For each prediction, we apply Lee et al. Fuzzy Time Series (2008). The population size is set to 35 and means, each time we create a population, we generate 35 chromosomes. Each chromosome represents a set of intervals. The number of intervals is also the input to the model; *m* and *n* are the number of intervals for defuzzification of inputs which are set to 12 and 20 respectively. The *K* as the window basis in Lee et al. (2008) model and is set to 7.

The fitness type is set to average forecasting error rate (AFER). The mutation rate is set to 0.05 and mutation process happens by the help of SAM. The crossover rate is 0.8. The parameters of SA are 0.0001 for Tfrozen, 10000 for Tinitial and 0.9 for α.

For each pair of data generated by Hwang et al. (1998) model and defuzzified by a trained neural network, we first use Lee et al. (2008) Fuzzy Time series to determine the intervals, then by generated intervals for each echelon and introduced "Dynamic fuzzy inference system" we predict the next values of demand. We use 100 data records for Genetic Algorithm and around 250 data records for test.

The following figures (Figure 4, Figure 5, Figure 6 and Figure 7) show the bullwhip effect clearly. The fluctuation of demands increases from first echelon to the last one. However, in order to compare the bullwhip effect mathematically we need to define a measure in order to quantify the effect. For this aim we apply the measure which is used in Zarandi et al. (2007) paper. The simplest metric is comparing the sample variance, but it has some difficulties. Suppose we are studying the bullwhip effect in a three echelon supply chain. By the simple variance, the bullwhip effect exists in supply chain if and only if variance of third echelon was bigger than the second echelon variance and so on. At the same time, result of experiments also indicates that the degree of magnification is decreasing when moving up-stream. To quantify this, Zarandi et al. (2007) use the metric of Li et al. (2005). This metric is based on the relative comparison of the variance of sample points and is expressed as:

$$A_{i,j} = \frac{Var(D_i) - Var(D_j)}{Var(D_j)} \qquad (8)$$

Therefore, when this metric is used, if $|A_{k+2,k+1}| > |A_{k+1,k}|$, it is said that the information transformation propagates from stage k to $k+2$ in an increasing magnitude. Otherwise, if $|A_{k+2,k+1}| < |A_{k+1,k}|$, we say that information transformation propagates from stage k to $k+2$ in a decreasing magnitude. To compute $Var(D_i)$, the formulas of sample variance and mean of fuzzy numbers have been used. The results are shown in Table 2.

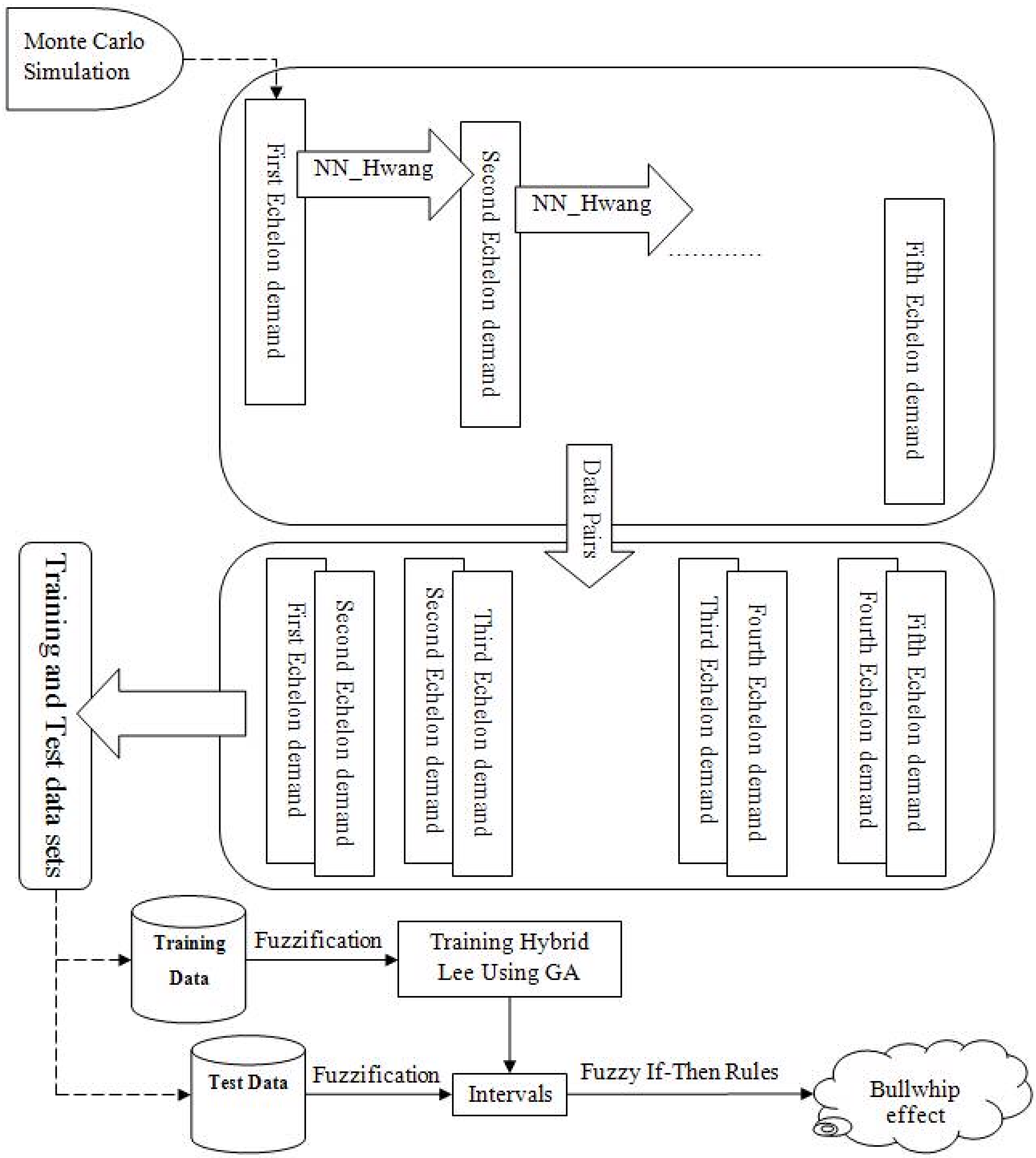

Figure 3. A fuzzy If-then rules approach to show Bullwhip Effect in Supply Chains

	First Echelon	Second Echelon	Third Echelon	Fourth Echelon	Fifth Echelon
Demand Variance	2614.3234	5473.8902	7360.7307	9812.4931	11125.8221
Metric Value		0.5224	0.2563	0.2498	0.1180

Table 2. Value of sample variance and BW metric for different stages.

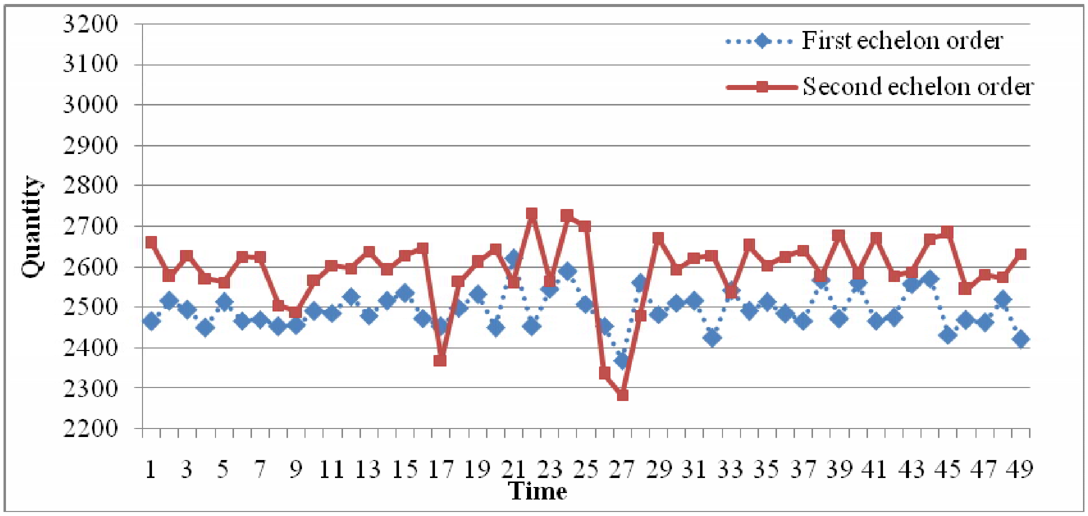

Figure 4. Order quantity of first and second echelon during time.

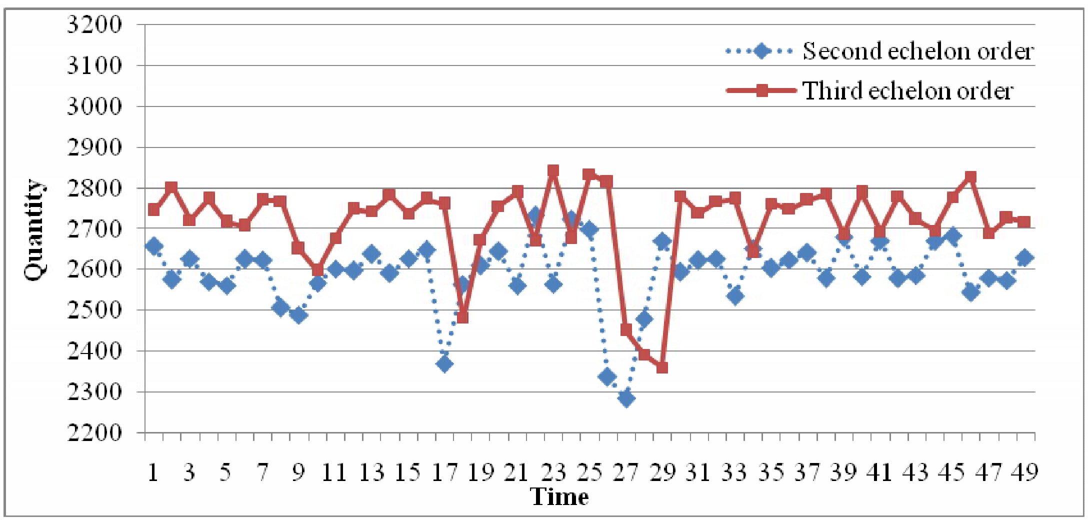

Figure 5. Order quantity of second and third echelon during time.

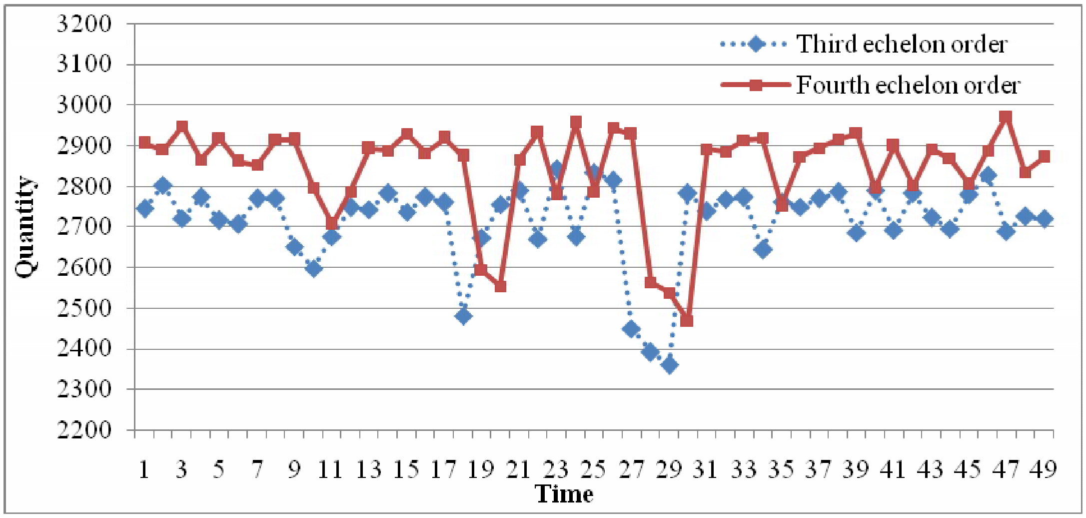

Figure 6. Order quantity of third and fourth echelon during time

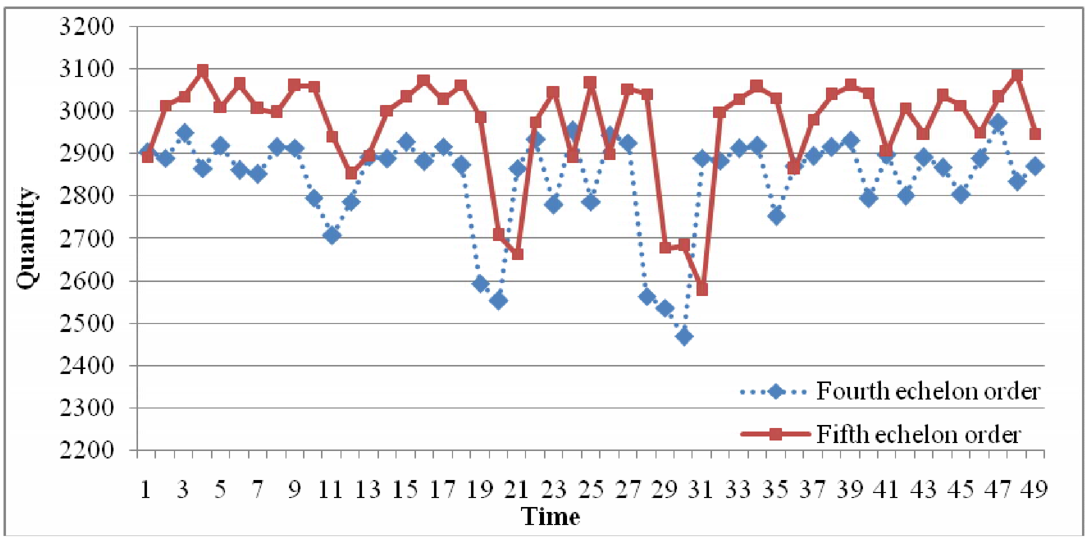

Figure 7. Order quantity of fourth and fifth echelon during time.

order quantity as we move from the first echelon in supply chain to up-stream supply chain is 2614.3234, 5473.8902, 7360.7307, 9812.4931 and 11125.8221. As numbers show, the variance of demand increases from 2614.3234 to 11125.8221. We find the theoretical SC shows the bullwhip effect. □

CONCLUSIONS

The paper shows the bullwhip effect in a supply chain throughout fuzzy If-Then rules, a new way rather than traditional simulation methods. The literature shows the method is completely a new method using fuzzy If-Then rules to show the bullwhip effect in a supply chain. The method can be the source of inspiration for new solution for bullwhip effect using fuzzy logic. In this research, following contributions can be addressed.

The first is the application of fuzzy time series for data generation. Hwang fuzzy time series is used for this aim and for defuzzification purpose a neural network is designed and applied. The second contribution is presentation of a new application for Lee fuzzy time series. This fuzzy time series is introduced in Lee. And finally the last contribution is the application of fuzzy If-Then rules to prove the bullwhip effect in a supply chain.

For future works, other architecture of supply chains can be considered; means other supply chain with different levels and multiple echelons in each level. Also in this research, the fuzziness of lead time is not considered, which can be an important element in a fuzzy turbulent environment. Base on fuzzy logic and fuzzy time series, new method can be invented to overcome the bullwhip effect in a supply chain.

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