Journal of Naval Science and Engineering
2009, Vol. 5, No.2, pp. 20-34

A HYBRID FUZZY TIME SERIES AND ANFIS APPROACH TO DEMAND VARIABILITY IN SUPPLY CHAIN NETWORKS

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Abstract

The variability of the demand information between the stages of the supply chain networks and the increase in this variability (i.e., Bullwhip Effect) triggers several system defects which directly influence total performance of the chain. In this paper the response of demand variability to the proposed hybrid system; which consists of fuzzy time series forecasting model and ANFIS based decision process, in supply chain networks is analyzed using a near beer game simulation model under relatively medium variate demand data.

TEDARİK ZİNCİRİ AĞLARINDA TALEP DEĞİŞKENLİĞİNE MELEZ BİR BULANIK ZAMAN SERİSİ VE ANFIS YAKLAŞIM

Özetçe

Tedarik zinciri ağlarında safhalar arasındaki talep bilgisi değişkenliği ve bu değişkenlikteki artış (Kırbaç Etkisi) zincirin toplam performansına etki eden birkaç sistem kusurunu tetikler. Bu makalede göreli orta değişken talep bilgisi altında, tedarik zinciri ağlarındaki talep değişkenliğinin önerilen bulanık zaman serileri tahmin modeli ve ANFIS tabanlı karar sürecinden oluşan melez sisteme verdiği tepki, bir benzetim modeli ile analiz edilmiştir.

Keywords: Supply Chain, Forecasting, Bullwhip Effect, Fuzzy Time Series, ANFIS.

Anahtar Kelimeler: Tedarik Zinciri, Tahmin, Kırbaç Etkisi, Bulanık Zaman Serileri, ANFIS.

1. INTRODUCTION

Supply chain networks (SCN) are dynamic complex systems including many sophisticated activities such as constant on time information flow, scheduling, production, distribution and decision making processes which are all required for satisfying the demand of customer. A simple definition for these complex systems can be expressed as “the network of organizations that are involved, through upstream and downstream linkages, in the different process and activities that produce value in the form of products and services in the hand of ultimate customer” [1]. Performance of SCN directly concerns with accurate and appropriate demand information together with promptly and adequately decision making in each and every stage which are also vital for survivability of SCN [2].

The variability of the demand information between stages and increase in this variability as demand information moves from first stage to the upstream stages of SCN (i.e., bullwhip effect (BE)) engenders several system defects such as overload errors in production activities, redundant inventory levels, defective labor force, cost increases, and etc. From 1952 till 2009 many studies have been done about this undesirable phenomenon which can be categorized under three groups. But, it must be stressed that there is no absolute boundaries between the categories developed as each study with its main purpose, may also partially include research interest of other categories. The first category consists of studies that showed and proved the existence of BE such as studies of Forrester [3, 4] and Sterman [5, 6, 7]. The studies in the second category illustrates the causes and suggests possible solutions for this phenomenon such as well-known studies of Lee et al.[8, 9, 10, 11], Towill [12, 13] and Dejonkheere *et al.* [14, 15, 16]. And the last category covers studies those have been made for quantifying the BE such as the studies of Chen *et al.* [17, 18, 19, 20], and also Lee *et al.* However, in all three categories very few of them interested in fuzzy and neuro-fuzzy system (NFS) approaches to BE such as Carlssson and Fuller [21, 22, 23, 24] and Efendigil *et al.* [25].

Lee *et al.* [8, 9, 10, 11]; focusing on the operational causes of the problem and proving the existence by documentary evidences provided from several companies from different sectors, declared four major causes and triggers of BWE as;

- demand forecast updating,
- order batching,
- price fluctuations and,
- rationing game.

This study rather than evaluating effects all of causes, specifically stresses on relatively controllable ones; the decision making process, demand forecast updating, and aims to analyze the response of BE to the proposed hybrid system made up of an Adaptive Neuro-Fuzzy Inference System (ANFIS) based demand decision process together with Fuzzy Time Series forecasting (FTS) model using a simple two stage SCN Matlab simulation model.

The following sections of the paper are organized as follow. In section 2, ANFIS, FTS model are introduced. In section 3, SCN simulation is introduced. In section 4 the response of BE to the proposed hybrid system is analyzed under selected data. Finally in section 5, research findings are illustrated and conclusions are presented.

2. ANFIS AND FTS MODEL

2.1 ANFIS

ANFIS is the implementation of fuzzy inference system (FIS) to adaptive networks for developing fuzzy rules with suitable membership functions to have required inputs and outputs [26]. FIS is a popular and cardinal computing tool to which fuzzy if-then rules and fuzzy reasoning compose bases that performs mapping from a given input knowledge to desired output using fuzzy theory. This popular fuzzy set theory based tool have been successfully applied to many military and civilian areas of including decision analysis, forecasting, pattern recognition, system control, inventory management, logistic systems, operations management and so on. FIS basically consist of five subcomponents [26]; a rule base (covers fuzzy rules), a database (portrays the membership functions of the selected fuzzy rules in the rule base), a decision making unit (performs inference on selected fuzzy rules), fuzzification inference and defuzzification inference. The first two subcomponents generally referred knowledge base and the last three are referred to as reasoning mechanism (which derives the output or conclusion). An adaptive network is a feed-forward multi-layer Artificial Neural Network (ANN) with; partially or completely, adaptive nodes in which the outputs are predicated on the parameters of the adaptive nodes and the adjustment of parameters due to error term is specified by the learning rules [26].

Generally learning type in adaptive ANFIS is hybrid learning. This learning model is appropriate for the systems having unsteady nature like SCN. Jang defined this learning type as the learning that involves parameter updating after each data is given to the system.

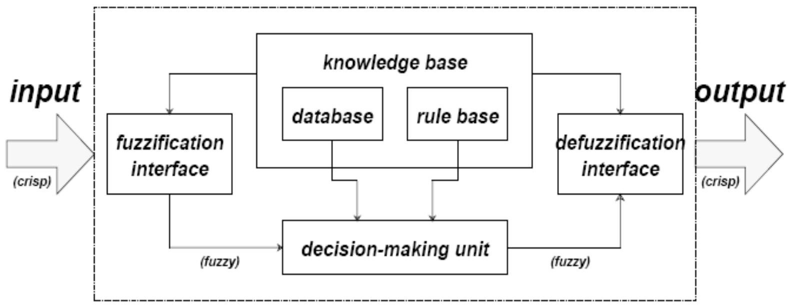

Figure 1: FIS **[26]**.

2.2 FTS Forecasting Model

Demand forecasting (which sound basis for decision making process) is among the key activities that directly affect the SCN performance. As the demand pattern varies from system to system, determination of the appropriate forecasting model that best fits the demand pattern is a hard decision in management of SCN. More importantly, the usage of proper demand forecasting model that is adequate for the demand pattern is a cornerstone for smoothing BE in SCN.

As the nature of prediction contains uncertainty or vagueness; which are the facts to be deal with for accurate demand forecasting, it best fits for the applications of fuzzy logic and fuzzy set theory [29] which directly pertinent to the aim of this study. When historical demand data that will use to calculate the desirable forecast value are linguistic values and (or) are in small amounts (just like cases in dynamic systems like SCN), FTS model best fit the aspect [28, 29, 30, 31, 32, 33]. A definition of fuzzy time series is given by Lee and Chou [34] as follow:

Definition: Let $X(t)\,(=...,1,2,....)$; a subset of real line R, be the universe of discourse on fuzzy sets $\widetilde{A}_i(t)\ (i=1,2,\ldots)$ are defined and $FTs(t)$ is the collection of $\widetilde{A}_i(t)\ (i=1,2,\ldots)$. Then $FTs(t)$ is called a fuzzy time series on $X(t)\,(=...,1,2,....)$.

FTS model can simply be summarized as follow [33, 35]:

- First, the variation between two historical data is to be calculated and minimum/maximum variation values (i.e., $D_{\min}/D_{\max}$) are to be determined,
- Next step is to define the universe discourse (U_d) with following equation using $D_{\min}$ and $D_{\max}$.

$$U_d = [D_{\min} - D_1 \,,\, \mathrm{D}_{\max} + D_2] \qquad \textbf{(7)}$$

where D_1 and D_2 are positive appropriate values that fits for separating U_d into equally length intervals.

- Then, fuzzy sets on U_d are to be defined and variation data is to be fuzzified. Defining fuzzy time series $FTs(t)$ as

$$FTs(t) = {p_{Z1}}/{u_1} + {p_{Z2}}/{u_2} + ... + {p_{Zm}}/{u_m} \qquad \textbf{(8)}$$

where the memberships p_{zi} are $0 \le p_{zi} \le 1$. The fuzzy sets $\tilde{S}_i$ of U_d then can be represented as;

$$\tilde{S}_i = \left\{ {p_{Z1}}/{u_1} + {p_{Z2}}/{u_2} + ... + {p_{Zm}}/{u_m} \right\} \qquad \textbf{(9)}$$

Fuzzifications of variations are determined according to interval u_i of U_d that they fit.

- Next step includes composing the relation matrix; $R(t)$, which is governed by operation ($O^w(t)$) and criterion matrixes ($Z(t)$), and defuzzifying the calculated variation which will be used for estimating the forthcoming value using the relation of the chance value gathered from relation matrix . In this step the windows basis; w ($w = 2, 3, ..., \text{n}$), have to be determined which shows the number of periods of variations that will be used for forecasting. For period t, $O^w(t), Z(t)$ and $R(t)$ is defined respectively as follow:

$$Z(t) = FTs(t-1) = [Z_1,\ \ Z_2,\ Z_3, ...Z_n] \qquad \textbf{(10)}$$

$$O^{w}(t)=\begin{bmatrix} FTs(t-2) \\ FTs(t-3) \\ . \\ . \\ FTs(t-w-1) \end{bmatrix}=\begin{bmatrix} O_{11} & O_{12} & \ldots & O_{1m} \\ O_{21} & O_{22} & \ldots & O_{2m} \\ . & . & . & . \\ . & . & . & . \\ O_{w1} & O_{w2} & \ldots & O_{wm} \end{bmatrix} \quad \textbf{(11)}$$

$$R(t)=\begin{bmatrix} O_{11} \text{ x } Z_1 & O_{12} \text{ x } Z_1 & \ldots & O_{1m} \text{ x } Z_m \\ O_{21} \, x \, Z_2 & O_{22} \text{ x } Z_2 & \ldots & O_{2m} \text{x} Z_m \\ . & . & . & . \\ . & . & . & . \\ O_{w1} \text{ x } Z_1 & O_{w2} \text{ x } Z_2 & \ldots & O_{wm} \text{ x } Z_m \end{bmatrix} \quad \textbf{(12)}$$

Let $O_{ik} \text{ x } Z_k = R_{ik}$ (for $1 \leq \text{i} \leq w$ and $1 \leq k \leq m$) then, (9) can be rewritten as;

$$R(t)=\begin{bmatrix} R_{11} & R_{12} & \ldots & R_{1m} \\ R_{21} & R_{22} & \ldots & R_{2m} \\ . & . & . & . \\ . & . & . & . \\ R_{w1} & R_{w2} & \ldots & R_{wm} \end{bmatrix} \quad \textbf{(13)}$$

And, the estimated variation will be determined with the following equality.

$$Fv(t)=[r_1, r_2, ...r_m] \quad \textbf{(14)}$$

where $r_j = Max(R_{ik})$

- Last step of the model implies defuzzification of the predicted variations and computing the forecast value for the desired time period. The forecast value for the period t; F_t is computed as;

$$F_t = Fv(t) + A_{t-1} \qquad \textbf{(15)}$$

where A_{t-1} is the onestep back actual observation value of the time series.

3. THE SIMULATION MODEL

The SCN simulation model used in the study for evaluating the impacts of proposed system using is a two stage near beer distribution game extended with ANFIS decision making process and FTS model; which is improved from the beer game model of Sterman [5, 6] and its revised version of Paik's [36] (the base model for comparison that includes inventory/capacity restrictions and specific delay functions). MatLab is used as the simulation tool. A comparison is made between the base model and the proposed model using the same input values for relatively medium demand variation ($\mu = 50;\ 15 \le \sigma_d < 20\,units$), which is determined with the demand standard deviations. This study quantifies BE as a ratio of standard deviations of subsequent stages to reflect the amount of variability [2].

$$BWE_{i \leftrightarrow k} = \frac{Max[\sigma_i, \sigma_k]}{Min[\sigma_i, \sigma_k]};\ k = R, \mathrm{F} \qquad \textbf{(16)}$$

where, σ denotes the standard deviation of orders placed to upstream stage and subscripts C, R, F denote the customer, the retailer and the factory respectively.

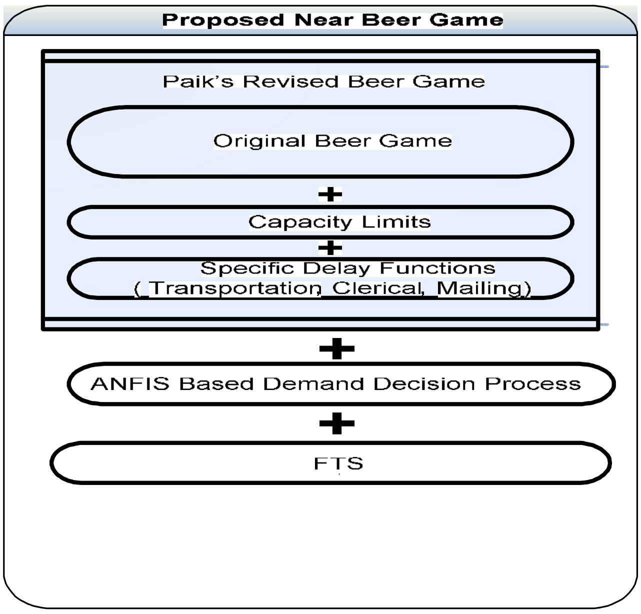

Figure 3: Proposed near beer game

The ordering/production decision process rule in each phase of the base model is simple but effective as it takes almost all factors reflecting behaviors of SCN [7, 45].

$$\begin{aligned} OD_{i,t} &= FW_t + \alpha(DINV_{i,t} - INV_{i,t}) \\ &+ \theta\ \beta(SD_{i,t} - SA_{i,t}) \end{aligned} \quad \textbf{(17)}$$

where, OD is the order decision, FW is the forecast value determined from the selected forecasting model, INV and $DINV$ are inventory and desired inventory, SA and SD are the supply line and desired supply line, θ and β represents the adjustment parameters for inventory and supply line respectively. The maximum, mean and minimum values of the parameters used in the decision rule which have been estimated by Sterman [5, 6, 7] are illustrated in the following table.

Parameters	α	θ	β
Minimum	0.00	0.00	0.00
Mean	0.36	0.26	0.34
Maximum	1.00	0.80	1.05

Table 1. Estimated values

The proposed model performs an ANFIS based decision process in each phase of SCN to determine order quantities (or production quantities in factory stage) using the forecast values gathered from the FTS model together with inventory and pipeline information which, also are the same inputs used in the base model. Figure 4 illustrates the system structure of the proposed model (for the detailed formulation see [2]).

4. APPLICATION

Proposed model simulation is performed for the parameter combination that gives the best results for the base model ($\alpha = 0.36$, $\beta = 0.34$ and $\theta = 0.26$). In simulation, FIS for the decision making is obtained by training ANFIS with randomly generated demand data sets that includes 200 values representing demand for a 200 periods. The membership function selected for all inputs is Gaussian membership function and for output is linear. The partition method used is Grid partition. Generated and calculated demand values (order/production decision) derived from the simulation runs of the base and proposed models are illustrated in Figure 5 and 6 respectively at the end of Section 5.

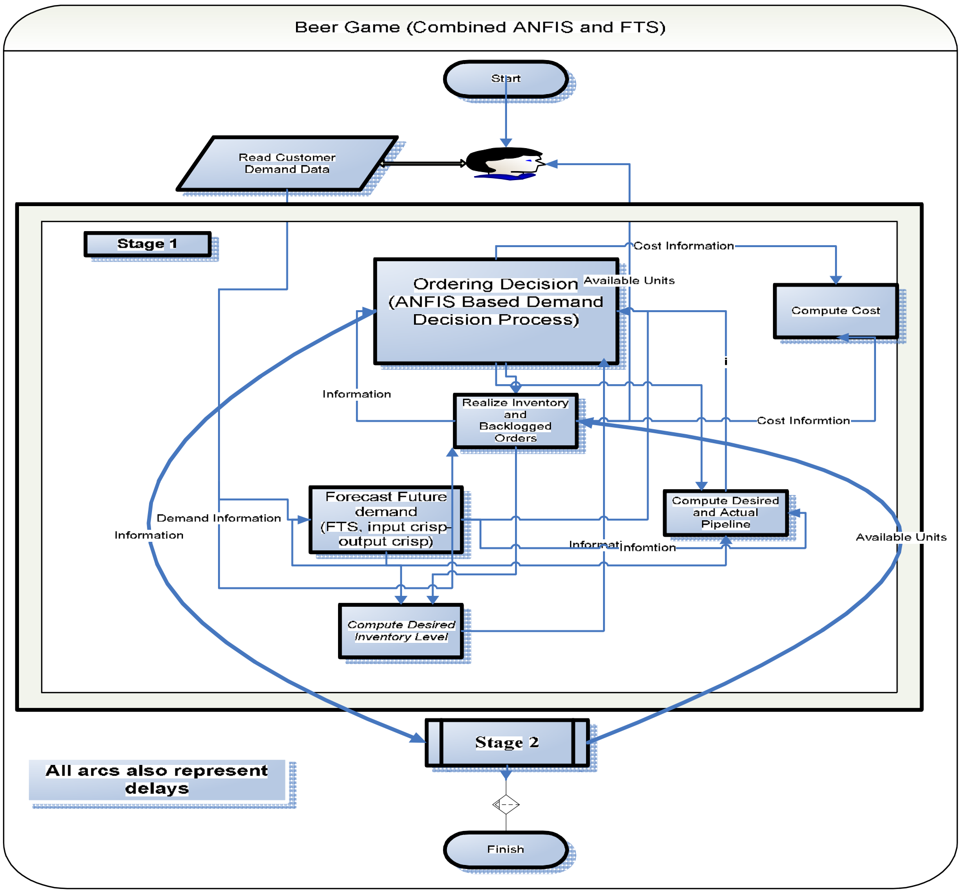

Figure 4: System structure of the hybrid model

5. Research Findings and Conclusion

Demand decision and forecasting processes are the mainstays for successful and robust SCN. Here, a hybrid approach consists of ANFIS and FTS are used for decision and forecasting processes in a simple two echelon SCN simulation and the response of BE is examined in terms of standard deviations. The simple application performed in the study showed that, usage of ANFIS together with FTS model easily monitored the demand and provided remarkable decreases in demand variability through the SCN. The standard deviation and BE values from the base and proposed model are illustrated in Table 2.

$\mu = 50$	**Base Model**	**Proposed Model**
σ_D	**18.96**	**18.96**
σ_R	49.58	20.59
σ_F	24.32	14.78
$BE_{C \leftrightarrow R}$	**2.615**	**1.086**
$BE_{C \leftrightarrow F}$	**1.283**	**1.283**

Table 2. Standard deviation and BE values

Further studies can be made by fuzzifying every parameter and variable in the SCN simulation as to improve the proposed system.

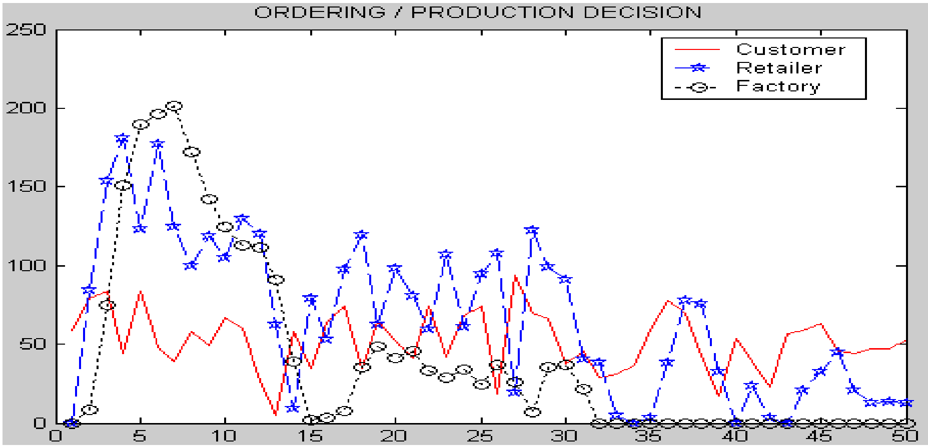

Figure 5: Order/Production decisions for the base model

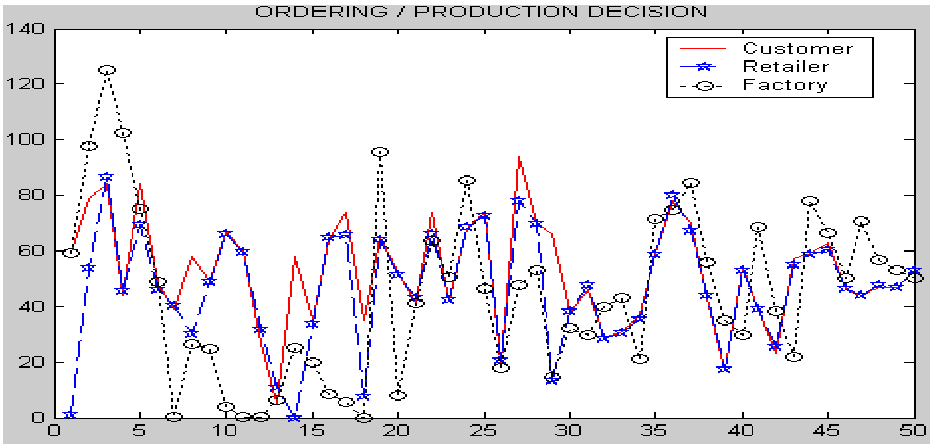

Figure 6.Order/Production decisions for the proposed model

REFERENCES

[1] Christopher M., Logistic and Supply Chain Management, Pitman Publishing, London, UK, 1994, pp.30.

[2] Tozan H, Vayvay O., A Hybrid Grey and ANFIS Approach to BWE in Supply Chain Networks, *WSEAS Transactions on Systems*, 8, 2009, pp. 461--470.

[3] Forrester J., Industrial Dynamics: A Major Breakthrough for Decision Makers, *Harvard Business Review*, 36, 1958, pp. 37--66.
[4] Forrester J., Industrial Dynamics, MIT Press, Cambridge, MA, 1961.
[5] Sterman, J. D., Instructions for Running the Beer Distribution Game, System Dynamics Group Working Paper D- 3679, MIT, Sloan School of Management, Cambridge, MA, 1984.
[6] Sterman J.D., Modeling Managerial Behavior: Misperception of Feedback in a Dynamic Decision Making Experiment, *Management Science*, 35, 1989, pp.321-399.
[7] Sterman J.D., Deterministic Chaos in an Experimental Economic System, *Journal of Economic Behavior and Organization*, 12, 1989, pp.1-28.
[8] Lee H. L., Padmanabhan V., Whang S., The Bullwhip Effect in Supply Chains, *MIT Sloan Management Rev.*, 38, 1997a, pp. 93-10 2.
[9] Lee H. L., Padmanabhan V., Whang S., Information Distortion in a Supply Chain: The bullwhip effect, *Management Science*, 43, 1997b, pp. 546--558.
[10] Lee H. L., Aligning Supply Chain Strategies with Product Uncertainties, *California Management Review*, 44, 2002, pp. 105-119.
[11] Lee H. L., Padmanabhan V., Whang S., Information Distortion in a Supply Chain: The bullwhip effect, *Management Science*, 50, 2004, pp. 1875--1886.
[12] Towill D. R.: System Dynamics Background, Methodology and Applications-Part1: Background and Methodology, *IEE Computing & Control Engineering Journal*, 4 (5), 1993, pp. 201--208.
[13] Towill D. R.: System Dynamics Background, Methodology and Applications-Part 2: Applications, *IEE Computing & Control Engineering Journal*, 4 (5), 1993, pp. 261--268.
[14] Dejonckheere J., Disney S.M., Lambrecht M., Towill D.R., Transfer Function Analysis of Forecasting Included Bullwhip in Supply Chains, *Int.J. Production Economics*, 78, 2002, pp. 133-144.
[15] Dejonckheere J., Disney S.M., Lambrecht M., Towill D.R., Measuring and Avoiding the Bullwhip Effect: A control theoretic approach, *European Journal of Operational Research*, 147 2003, pp.567-590.
[16] Dejonckheere J., Disney S.M., Lambrecht M., Towill D.R., The Impact of Information Enrichment on the Bullwhip Effect in Supply Chains: A control engineering perspective, *European Journal of Operational Research*, 153, 2004, pp. 727-750.
[17] Chen F., Drezner Z., Ryan J., Simchi-Levi D., Quantifying the bullwhip effect: The impact of forecasting, lead time and information, working paper, Department of IE/MS North Western University, Evanston, IL. And School of IE, Purdue University, Lafayette, IN, (1998).
[18] Chen F., Decentralized supply chains subject to information delays, *Management Science*, 45, 1999, pp. 1076--1090.
[19] Chen F., Drezner Z., Ryan J., Simchi-Levi D., Quantifying the bullwhip effect: The impact of forecasting, lead time and information, *Management Science*, 46, 2000 pp.436--443.
[20] Chen F., Samroengraja R., The impact of exponential smoothing forecasts on the bullwhip effect, *Naval Research Logistics*, 47, 2000, pp. 269--286.
[21] Carlsson C., Fullér R., Soft computing and the bullwhip effect, *Economics and Complexity*, 2 1999, pp. 1--26.

[22] Carlsson, C., Fullér, R., Reducing the bullwhip effects by means of intelligent, soft computing methods, *In Proceeding of the 34th Hawaii International Conference on System Science*, 2001, pp. 1--10.
[23] Carlsson, C., Fullér, R., A position paper on the agenda for soft decision analysis, *Fuzzy Sets and Systems*, 131, 2002, PP. 3--11.
[24] Carlsson C., Fedrizzi M, Fullér R., Fuzzy logic in management, Kluwer Academic Publishers, Boston, 2004.
[25] Efendigil T., Önüt S., Kahraman C., A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comprehensive analysis, *Expert Systems with Applications*, 36, 2008, pp..6697--6707.
[26] Jang J-S. R., ANFIS: Adaptive network based fuzzy inference system, *IEEE Transactions on Fuzzy Systems*, Man and Cybernetics, 23, 1993, pp. 665--685.
[27] Maduko, A., Developing and testing a neuro-fuzzy classification system for IOS data in asthmatic children, PhD. Thesis, Texas University, 2007.
[28] Kahraman C., Fuzzy Applications in Industrial Engineering, (Studies in Fuzziness and Soft Computing, Vol. 201), *Springer Verlag* , NJ USA, 2006
[29] Song Q., Chissom B. S., Forecasting Enrollments with Fuzzy Time Series, *Fuzzy Sets and Systems*, 54, 1993, pp. 1--9.
[30] Song Q., Chissom B. S., Fuzzy Time Series and Its Models, *Fuzzy Sets and Systems*, 54, 1993, pp. 269--277.
[31] Song Q., Chissom B. S., Forecasting Enrollments with Fuzzy Time Series Part II, *Fuzzy Sets and Systems*, 62, 1994, pp. 1--8.
[32] Wang C.H., Predicting Tourism Demand Using Fuzzy Time Series and Hybrid Grey Theory, *Tourism Management*, 25, 2004, pp.367--374.
[33] Tozan H., Vayvay Ö., Fuzzy and Neuro-Fuzzy Approaches to Whiplash Effect in Supply Chains, *Journal of Naval Science and Engineering*, 4 , 2008, pp. 27--42.
[34] Lee H-S., Chou M-T., Fuzzy Forecasting Based on Fuzzy Time Series, *International Journal of Computer Mathematics*, 81, 2004, pp. 781--789.
[35] Hwang J., Chen S. M., Lee C. H., Handling Forecasting Problems Using Fuzzy Time Series, *Fuzzy Sets and Systems*, 100, 1998, pp. 217--228.
[36] Paik S.K., Analysis of the Causes of Bullwhip Effect in Supply Chain: A Simulation Approach, *George Washington University Press*, 2003