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Designing an Efficient Model to Predict Demand in the Supply Chain

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Abstract
The present study intended to design an efficient model for demand prediction in supply chain. In this regard, first effective variables on prediction of demands in supply chain of selected product were identified, then artificial neural network model and fuzzy- neural model (in form of two creative models of ANFIS and FSOM) were designed, then demand of one of the Kalleh company's product was predicted by these three models were estimated and calculated values were compared with real values of demand and the optimized model was offered by extraction of estimated errors. Results showed that variables of the amount of produced product per unit of time with 0.68 coefficient, total advertising costs of company with 0.54 coefficient, price of the product compared to similar products with -0.74 coefficient, number of company's agents in counties with 0.51 coefficient, number of similar products and competitive products with -0.43 coefficient and total rate of competitors with -0.32 coefficient were among effective variables on product demand in supply chain. The results of comparison of efficiency and errors of the mentioned three models in demand prediction of supply chain also showed that the exactness of combined model of ANFIS was very high in prediction and errors: RMSE, MSE, NMSE, MAPE and MAD and R2 were in a very low level. After this method, there was combined model of fuzzy-neural networks of FSOM method and finally artificial neural network method. Also the two prediction methods based on fuzzy logic (fuzzy- neural network model ANFIS with TS value of 2.1 and fuzzy- neural network models FSOM with TS value of 4.3) had tracking signal (TS) lower than 6, thus, it can asserted that they are suitable for prediction but artificial neural network method with TS higher than 10 (equals to –10.65) is not a suitable method for demand prediction.

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INTRODUCTION

Supply chain management is one of the One of the emerging field of management that is developing and progressing day to day and seeks to find ways to decrease production cycle and to offer services until the customer receives the product; in addition, increasing the quality of products and services is considered. Moreover, to achieve it, supply chain management benefits from the newest advances in management science and technology and today, all countries need to apply it [1].

Supply chain includes all activities related to the flow and transfer of goods from raw materials stage to the final users and information flows associated with it. Supply chain management also consisted of a set of all organization's activities (Strategic and operational) which its aim is to integrate suppliers, manufacturers, distributors, and storekeepers , as well as appropriate and right production and distribution of products in terms of number, location, time and cost to meet customer needs [2].

One update, application and important issue in supply chain management is assessment of demand range or prediction of demand which has always occupied the minds of thinkers in this area and some studies have been conducted in this field. But models designed to predict demand had always faced a relatively high degree of error due to their lack of continuous space and the need for the use of fuzzy logic in them and these models are not suitable and useful for organizations. Therefore, the present study with understanding the importance of this subject and its problem intended to design a model with a combination of and fuzzy logic and neural networks and predicting supply chain demand through it for the first time. In this chapter, the totality of the study such as statement of the subject and the main issue of the research, hypotheses and questions and aims, the necessity of its conduction have been addressed.

In terms of structure, the most important problem that supply chain encounters is the number of decision-making centers for production, conversion and flow of goods. This will intensify the fluctuation of demands in the chain. As we move from the end of the stage toward the beginning of the stage (first supplier) the fluctuations of

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demand will intensify. This phenomenon is known as THE BULL WHIP EFFECT. Thus, a lot of inventory accumulation occurs among members of the chain that increase costs and final price of goods and decrease the competition power of the chain [3].

Thus, it is observed that prediction of demand is a main resource of uncertainty in the supply chain. Prediction of demand is affect by some factors such as competition, prices, current conditions, development of technology and public level of customers' commitment. Another factor of uncertainty in the supply chain is time of delivering that is depended on factors such as failure of machines in the production line process, traffic density that is involved in the transport and difficulties of materials quality that may create production delays [4].

Due to the importance of management and prediction of demand in the supply chain especially in competitive organizations, this study attempted to design an efficient model to predict demands of organizations with a combination of fuzzy logic and neural network models and with the lowest error level. Therefore, one of the key issues proposed in each supply chain is that how we can predict future demands by having the information of previous demands. Prediction of demand is importance because it is a basis for many activities such as planning production, controlling inventory and marketing.

Thus, in this study to design an efficient model for prediction of demand in the supply chain, one of the efficient methods of stimulation that is neural networks was used and to enrich the model and minimize predicted errors and due to the existence of discrete spaces and instability in various areas and predictive variables, fuzzy data were used. In other words, a combination model of fuzzy logic and neural network was designed.

Literature review

Fayyazbakhsh and Razzazi [5] in an article entitled "designing network and planning demand in the supply chain", paid attention to theoretic subjects of this field and discussed linear models of network design with the aim of locating and determining and allocating capacity of physical structures of the supply chain.

Nakhaei et al. [6] in their article "applications of neural networks in supply chain management", generally defined neural networks and described and analyzed the methods that one can use neural networks in supply chain management on the basis of five identified characteristics of supply chain models (optimism, prediction, modeling and simulation, generalization and decision support) in which using neural networks is possible. Hill [7] showed that neural networks significantly outperform classic methods of prediction when predicting seasonal and monthly data (presence of seasonal pattern). However in theory, neural networks can lead to better outputs from time series with the presence of seasonal patterns and procedures.

Nelson et al. [8] showed that with the presence of seasonal fluctuations, neural networks are not able to perform modeling well. Foster et al. [9] showed the superiority of exponential smoothing method to neural networks in prediction of monthly and annual data. Winter's exponential smoothing model had a better prediction in most applications. Chon et al. [10] used neural networks to predict the maximum demand in an electronic company and concluded that the model enjoyed a high efficiency and MSE and MAPE error indicators were 19 and 8 respectively. Feng and Koziak [11] have reviewed existence methods for selecting prediction models and their evaluation. They also offered a procedure for selecting and evaluating neural networks models and Regression analysis. Results of the study done by Mostard et al. [12] showed that in case of small groups of products, expert judgment methods work better than the methods that are based on demand's data. Comparative results were limited to this case study and further tests require determining the amount of reliability of basic information [12]. Georgiadis et al. [13] in a study titled "optimized design of supply chain networks based on temporal changes of demand" intended to consider problems of the design of supply chain networks such as possibility to produce multi products with common resources through using mathematical formula. Obtained results represented the value of this model which is able to calculate complex interactions existing in such networks.

MATERIAL AND METHODS

Variables and research model

By combining artificial neural networks and fuzzy logic, a fuzzy system is designed that will be capable of learning. This system works as follow: in each training cycle, during the movement towards front, the output nodes are normally computed until the final layer and then result parameters are determined by the lowest sum of squared errors. Then, after calculating the error, during backward movement, the ratio of error is spread on condition parameters and their number will be corrected by error downward slope method. Various structures have been offered for implementation of a fuzzy system by neural networks and Adaptive

Neural-Fuzzy Inference Systems (ANFIS) is one of the most powerful systems which was proposed by JARIS (Hamilton, 2003). Architecture of ANFIS has been shown in picture.

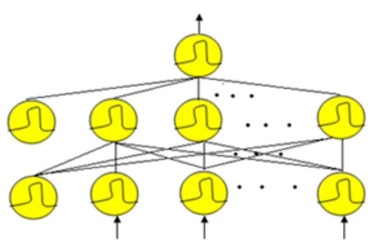

Figure 1. Architecture of ANFIS

After designing the model and predicting under study demand of supply chain, to test the efficiency of designed model, prediction error is computed. Thus, mean squared error (MES), mean absolute deviation

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(MAD) and mean absolute percentage error (MAPE) were computed.

RESULTS

To consider results, first effective variables on demand prediction in supply chain selected product were identified, and then artificial network model and fuzzy-neural network (in form of two created models of ANFS and fuzzy self-assembled neural networks (FSOM)) were designed, demand of considered product was estimated by these two models and was compared with real amounts of demand and by deriving estimated errors, the optimized model was offered.

1-Identifying important and effective variables on prediction of demand in supply chain:

By studying theoretical bases and models and similar studies that some of them were referred in this study, variables which affect the demand in supply chain were extracted. These variables were finalized by inquiries from industrial and academic experts' opinions in order to be entered in regression model. Initial and effective variables are:

- The amount of produced product per unit of time (X1).
- Total advertising costs of company (X2).
- Price of the product compared to similar products (Equal to the difference between the price of product in Kaleh company and the mean price competitors) (X3).
- Number of company's agents in counties (X4).
- Total marketing costs of the product (X5).
- Number of similar products and competitive products (X6).
- Total rate of competitors' products (X7).
- Export rate of the product i(X8).

Information related to the above variables was extracted from financial notes and documents of Kalleh Company and commercial ministry in a weekly form in an 80 period (80 recent weeks). Regression method is one of the most suitable methods for considering the existence or nonexistence of the significant relationship and specifying the importance of each above variable.

Tables of outcomes from SPSS software in estimating multi-variable regression are as following:

Table 1. Coefficients of dependent variables

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	T	Sig.
Constant	3.435	0.869		3.955	0
X1	0.682	0.284	0.599	3.39	0.001
X2	0.54	0.5	0.481	4.108	0
X3	-0.742	0.27	-0.693	-3.995	0
X4	0.512	0.379	0.48	5.357	0
X5	0.211	0.495	0.181	1.31	0.094
X6	-0.433	0.36	-0.392	-2.975	0.009
X7	-0.321	0.495	-0.277	3.31	0.004
X8	0.054	0.1112	0.044	0.975	0.834

As it is observed from the above table, the obtained t in all variables except two variables marketing costs (X5) and export range of product (X8) was higher than 1.96 and significance level of lower than 0.05, so the results show that the six variables are included in effective variables group on product demand in supply chain and these variables are: the amount of produced product per unit of time (X1) with .68 coefficient, total advertising costs of company (X2) with .54 coefficient, price of the product compared to similar products (X3) with -.74 coefficient, number of company's agents in counties (X4) with .51 coefficient, number of similar products and competitive products (X6) with - .43 coefficient and total rate of competitors (X7) with - .32 coefficient.

2- Design of combined model of fuzzy- neural network (ANFIS) for predicting demand of supply chain:

The proposed model in first part is designed with combining Adaptive Neural Networks ANN and Fuzzy Inferential System FIS. To simplify, ANFIS is assumed that this system has two inputs y and x and an output z. for a first-order fuzzy Takagy Sugeno model, it is possible to state a set of model rules with the law of fuzzy if-then as follows:

First rule: if x equals A1 and y equals B1, then z1=p1x+q1y+r

Second rule: if x equals A2 and y equals B2, then z2=p2x+q2y+r

Where ri,qi,pi (i=1,2) are linear parameters in tally part of first-order fuzzy Takagy-Sugeno.

ANFIS structure (fuzzy- neural network model) includes five layers:

First layer, input nodes: each node in this layer produces membership amounts that belong to a suitable fuzzy set by membership function.

$$i = 1.2 \qquad O_{1,i} = \mu_{Ai}(x)$$

$$i = 3,4 \qquad O_{2,i} = \mu_{Bi-2}(x)$$

Where y and x of non-fuzzy inputs to the group i. Ai, Bi (small, large, …) are linguistic labels that are identified by membership functions µAi و µBi respectively. Here, bell form and gauss fuzzy-element are used. Parameters of this membership function which are known as premise parameters should be determined in this layer.

Second layer, rule groups: in this layer, operator and (AND) are used to receive output (firing strength) that represents the initial part of that rule. Firing strength is known as the amount of the degree that the initial part of a fuzzy rule has met and forms the output function of that rule. Therefore, O2K of this layer are the products of degrees related to the first layer.

$$O_{2K} = \mu_{Ai}(x) * \mu_{Bj}(y)$$

Third layer: moderate groups: the main aim of this layer is determining the ratio of the rule's firing strength to the sum of all rules' firing strengths. Consequently, is known as normalized firing strength.

$$O_{3,i} = \overline{W} = \frac{wi}{\sum_{k=1}^{4} w_k}$$

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Forth layer: consequent groups: the forth distribution layer of rule i is calculated from the total output and is defined as following:

$$O_{4,i} = \overline{W}_i f_i = \overline{W}_i (p_i x + q_i y + r_i)$$

Where output is node i from pervious layer. {pi,qi,ri are coefficients of this linear combination, they are also parameters of tally part of fuzzy Takagy-Sugeno.

Fifth layer: output groups: this single node calculates the overall output as the summation of all incoming signals. Thus, in this layer, none-fuzzy process changes the results of each fuzzy rule to a non-fuzzy output.

$$O_{5,i} = \overline{W}_i f_i = \frac{\sum_{i=1}^{4} w_i f_i}{\sum_{i=1}^{4} w_1}$$

Figure (2) shows a simple algorithm of the performance and relationship between layers that has been designed in fuzzy-neural network model.

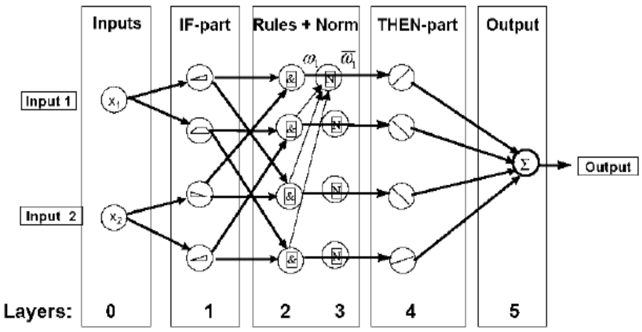

Figure 2. A simple picture of ANFIS model

This network is trained based on controlling learning. Thus, our aim is training adaptive networks that are able to estimate unknown functions obtained from training information and to find an exact amount for above mentioned parameters.

3- Modeling data, evaluating methods and estimating errors and comparing efficient neural networks and fuzzy-neural models (ANFIS) for demand prediction in supply chain.

As it is stated, for designing fuzzy neural networks models, multi-layer forward neural networks (MFNN) with learning algorithm after back-propagation and Sugeno fuzzy inference systems with input function "difference between the two sigmoid functions" and linear output function and for defuzzification, mobile average function was used.

Commonly, some performance standards are used for showing learning of data relations at network. About prediction issues, these standards are often related to the error between predicted outputs and real desired output. Assume that for a pattern with p input (a set of p patterns), the predicted output of a d_p nerve, the real output d_p and average of real output in all patterns is d. following table shows some common performance standards for prediction issues. The fist third cases are from standard mean error family: mean squared error (MSE), root-mean-square error (RMSE) and normalized mean-square error (NMSE). Errors for penalizing large errors and for neutralizing the effect of positive and negative values of difference were rooted. R2 is determinate coefficient and has a relationship with NMSE and it is NMSE=1-R2. Value of R2 is between zero to one and value one shows complete match of data, while value zero shows the performance that can expect from the value mean of real output d as a basis for predictions. The next two standards are about absolute error: mean absolute error (MAE) and mean absolute percentage error (MAPE). Other standards such as maximum of absolute error are usually used for showing the range of performance of the model. As each performance evaluation standard evaluates a specific aspect, for evaluating the performance of network, the sixth mentioned standards have been used. Results of performance evaluation standards for training data through using various methods have been shown in Table 2. Comparison of performance evaluation, efficiency and errors of the three modes, ANFIS, FSOM and neural networks for prediction of demand in supply chain.

Prediction methods of demand	R2	MAD	MAPD	NMSE	MSE	RMSE
Fuzzy neural networks ANFIS	0.99999	4.0646	0.8483	0.000001	66.65	6.453
Fuzzy-neural networks FSOM	0.99998	8.774	2.665	0.000027	78.88	8.095
Neural networks	0.99765	99.995	153.52	0.00775	1854	65.65

To determine whether a prediction method estimates the demand from its real value or its lower value, bias quantity is defined as following:

$$bias_n = \sum_{t=1}^{n} E_t$$

Fluctuation of bias around zero shows that error has a random pattern. Tracking signal is calculated according to the below formula:

$$TS_t = \frac{bias_t}{MAD_t}$$

If tracking signal for each period of t is higher than +6 or lower than -6 represents too prediction and too little prediction respectively. So the above mentioned method is not a suitable method for prediction and another method should be chosen.

In table (3), values of TS and bias fluctuation about three research model have been offered:

Table3. Comparison of TS and bias fluctuation of three models ANFIS, FSOM and neural networks for prediction in supply chain.

Both prediction fuzzy-logic based methods have tracking signal of lower than 6; thus, it can be asserted that they are suitable for prediction but adaptive neural

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network method with tracking value of higher than 10 is not a suitable method for predicting demand in supply chain.

As it is seen in above tables, both methods of fuzzy-neural networks methods are superior to neural networks methods in terms of performance standards. Among the two creative fuzzy- neural network methods in this research, ANFIS model is superior to FSOM model.

Table 3. Comparison of TS and bias fluctuation of three models

Prediction methods of demand	Bias	TS
Fuzzy- neural networks ANFIS	8.526	2.1
Fuzzy- neural networks FSOM	36.5904	4.32
Neural networks	-1060.63	-10.65

DISCUSSION AND CONCLUSION

Demand prediction in supply chain has a major role on optimizing production, marketing and market strategy. Additionally, it has an effective role on government policies. Due to the importance of prediction, the present research attended to design an efficient model for predicting demand in supply chain. A model that can minimize error prediction.

According to the importance of identifying main and effective variables for demand prediction in supply chain for managers and researchers, in first part of the study, first effective variables for demand prediction were identified, then artificial neural network model and fuzzy-neural model (in form of two creative models of ANFIS and FSOM) were designed, demand of one of the under study company's product was predicted by these two predicted models and calculated values were compared with real values of demand and the optimized model was offered by extraction of estimated errors.

The eight initial variables were identified as effective variables on demand prediction in supply chain based on theoretical studies and driven results from related literature and inquiries from experts and by considering a regression model, the variables' relationship with dependent variable of demand in supply chain was estimated and driven results showed a significant relationship between the above six variables and demand prediction. Indeed, variables: the amount of produced product per unit of time (X1) with.

68 coefficient, total advertising costs of company (X2) with .54 coefficient, price of the product compared to similar products (X3) with -.74 coefficient, number of company's agents in counties (X4) with .51 coefficient, number of similar products and competitive products (X6) with -.43 coefficient and total rate of competitors (X7) with -.32 coefficient are among effective variables on product demand in supply chain.

After identifying effective variables on demand, two combined models 1- ANFIS and 2- self-assembly neural networks (SOM) and fuzzy system (FSOM) were designed for predicting demand in supply chain. After designing these models and stating their equations and relationship, for considering the amount of efficiency of designed models and extracting and calculating the their amount of error and exactness in demand prediction and choosing an optimized method, methods evaluation and error estimation in modeling data part were considered by using real data related to variables during 80 weeks and results of the three artificial neural network models and the two combined fuzzy-neural methods were considered and the efficiency of 3-multiple models on demand prediction in supply chain was calculated.

Comparison of performance evaluation and errors of the three models of ANFIS, FSOM and neural networks in demand prediction show that the exactness of combined model of ANFIS is very high in prediction and different errors: RMSE, MSE, NMSE, MAPE and MAD and R2 are in a very low level. After this method, there is combined model of FSOM method and finally neural network method. Also the two prediction methods are based on fuzzy logic (fuzzy- neural network model ANFIS with TS value of 2.1 and fuzzy- neural network models FSOM with TS value of 4.3) have tracking signal (TS) lower than 6, thus, it can asserted that they are suitable for prediction but artificial neural network method with TS higher than 10 (equals to – 10.65) is not a suitable method for demand prediction.

Finally, by using the three research models, the value of predicted product demand was compared with the real value.

As it was stated, the designed models for demand prediction of product were used during 80 weeks. In this section we will consider the significant or non-significant relationship between estimated predictions by the three models. In this regard, Pearson correlation coefficient and SPSS software were used. The most common correlation coefficient is Pearson correlation which is calculated as below:

$$r_{pearson} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y - \bar{y})^2}}$$

Test of whether the correlation coefficient of population is equal to zero or not is done as below:

$H_0 : \rho = 0$

$H_1 : \rho \neq 0$

Test statistics has t- student distribution with df n-2

$$t = \frac{\rho}{\sqrt{\frac{1-\rho^2}{n-2}}}$$

In following, first the relationship between predictions by the two models of fuzzy-neural networks ANFIS and fuzzy self-assmbly neural networks FSOM are stated.

H0 and H1 hypotheses are defined as below:

H0: There is no significant relationship between the results of demand prediction in the two models of ANFIS and FSOM.

H1: There is a significant relationship between the results of demand prediction in the two models of ANFIS and FSOM.

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Table 4. Results of Pearson correlation coefficient for comparing demand prediction in the two models of ANFIS and FSOM

		ANFIS	FSOM
ANFIS	Pearson Correlation	1	0.601
	Sig. (2-tailed)		0.004
	N	80	80
FSOM	Pearson Correlation	0.601	1
	Sig. (2-tailed)	0.004	
	N	80	80

Since the level of significance is lower than error level (.0004 < .05), H0 is accepted. So with 95% level of confidence, it can be asserted that there is a significant relationship between the performed prediction by the two fuzzy- neural models of ANFIS and FSOM for demand in supply chain. Estimated correlation coefficient is also equal to .601 which shows a relatively strong relationship and correlation between the two predictions.

Consideration of the prediction relationship between the two fuzzy-neural network models of ANFIS and artificial neural networks:

H0 and H1 hypotheses are as below:

H0: there is no significant relationship between the prediction results demand in the two models of ANFIS and ANN.

H1: there is significant relationship between the prediction results demand in the two models of ANFIS and ANN.

In table (5) features of correlation coefficient for considering the existence or non-existence of the relationship between prediction by the two models of ANFIS and ANN have been offered.

Table 5. Results of Pearson correlation coefficient for comparing demand prediction in the two models of ANFIS and ANN

		ANFIS	ANN
ANFIS	Pearson Correlation	1	0.109
	Sig. (2-tailed)		0.511
	N	80	80
ANN	Pearson Correlation	0.109	1
	Sig. (2-tailed)	0.511	
	N	80	80

Since the level of significance is higher than error level (.51 >.05), H0 is rejected. So with 95% level of confidence, it can be asserted that there is no significant relationship between the performed prediction by the two fuzzy- neural models of ANFIS and artificial neural network ANN for demand in supply chain.

Consideration of the prediction relationship between the two models of artificial neural network and fuzzy self-assembly neural networks FOSM and

H0 and H1 hypotheses are as below:

H0: there is no significant relationship between the prediction results demand in the two models of FSOM and ANN.

H1: there is significant relationship between the prediction results demand in the two models of FSOM and ANN.

In table 6 features of correlation coefficient for considering the existence or non-existence of the relationship between prediction by the two models of FSOM and ANN have been offered.

Table 6. Results of Pearson correlation coefficient for comparing demand prediction in the two models of FSOM and ANN.

		FSOM	ANN
FSOM	Pearson Correlation	1	0.084
	Sig. (2-tailed)		0.143
	N	80	80
ANN	Pearson Correlation	0.084	1
	Sig. (2-tailed)	0.143	
	N	80	80

Since the level of significance is higher than error level (.14 >.05), H0 is rejected. So with 95% level of confidence, it can be asserted that there is no significant relationship between the performed prediction by the two fuzzy- neural models of FSOM and artificial neural network ANN for demand in supply chain.

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