Hadhramout University Journal of Natural & Applied Sciences

Volume 17 | Issue 2 Article 3

2020

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Abstract

Supply chain management plays a significant role for running business efficiently, as it integrates management of materials and information flows between supply chain parties Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy inference system (ANFIS) are expert systems widely used to deal with imprecise and vague data. In this paper FIS and ANFIS are implemented to deal with the uncertainty regarding demand, lead time and inventory level in continuous inventory control system in order to obtain the optimal order quantity and reorder point. These two models are compared with Economic Order Quantity (EOQ) model at different service level to study their impacts on the inventory costs. A case Study of Yemen Company for Industry and Commerce has been selected in this paper. The simulation results showed the superiority and efficiency of the proposed FIS and ANFIS models in comparison to stochastic EOQ model with7 %saving of total inventory cost and no shortages with expectation of raising the customers' loyalty.

Keywords: Fuzzy Inference System, Adaptive neuro-fuzzy, Continues Inventory model**.**

Introduction:

In every organization, supply chain management plays a significant role for keeping the business running. The term supply chain management refers to cooperative management of materials and information flows between supply chain partners, to reach goals that cannot be achieved acting individually [14]. This paper focuses on the supply chain from the perspective of inventory management.

Inventory management always targets to minimize the total inventory cost and maximize the customer service level. Inventory management strives hard to avoid overstock or ending up with shortage therefore it is necessary to decide when to order (reorder point) and how much to order (order quantity) to control the inventory system. Conventional inventory models assist in determining how much and when to order .However, these models assume certain or uncertain demand and lead time. In reality both demand and lead time are uncertain due to change of orders, random capacity of suppliers, or unpredictable events etc. Due to the impact of the imprecise and uncertain factors, the inventory decisions have increased the complexity procedures. Therefore, it is necessary to apply a suitable control system to deal with such imprecise.

Fuzzy Inference System (FIS) and Adaptive Neuro Fuzzy inference system (ANFIS) are expert systems widely used to deal with imprecise and vague data. In this paper FIS and ANFIS are implemented to deal with the uncertainty regarding demand, lead time and inventory level in continuous inventory control system in order to obtain the optimal order quantity and reorder point. These two methods are compared with the conventional model to study their impacts on the inventory costs.

Literature Review:

Fuzzy inventory model and adaptive neuro fuzzy inventory have been discussed recently by many researches. In this section most significant researches have been presented. Maryam Ramezani and G. A. Montazer (2006) [12] proposed a fuzzy expert decision support system for solving the vendor selection problem with multiple objectives, the basic important factors considered for supplier selection are price, quality and delivery time. Hamid Reza (2012) [14] proposed an integration of weighted association rule and FIS to develop an intelligent model of inventory control system. The model provides a general framework to predict safety stock.Tanthatemee, Phruksaphanrat (2012) [15] presented a fuzzy inventory control system for a single item continuous control system. The model can deal with both uncertain demand and availability of supply. The developed fuzzy model was used to determine the order quantity and the reorder point. Mohammed Mira 2016 [11] proposed Fuzzy Inventory System (FIS) that can deal with both demand and lead time uncertainty, the developed fuzzy rules were used to extract the fuzzy order quantity. The fuzzy model reduced the total inventory cost almost by 26%.H.Bautista, J.L. Martinez, M.B. Bernabé, D.

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Sanchez & F. Sanchez (2016) [4] proposed fuzzy expert system for the integration of collaborative supply chains. Tugba E., Semih and Cengiz (2008) [6] showed a new forecasting mechanism which is modeled by Artificial Intelligent approach including the comparison of both artificial neural network (ANN) and adaptive neuro fuzzy inference system to manage fuzzy demand .The results indicate that ANFIS method performs more efficiency than ANN structure. Michael Chang, Chung Chan and Evan Lin (2011) [10] used Artificial Neural Network (ANN) and Fuzzy Neural Networks (FNN) to forecast the order quantity and compared with some traditional time series forecasting technologies such as moving average and exponential smoothing methods .The results indicate that FNN method has better forecast accuracy than the others.Amir Azizi, Yazid b. Ali and Loh Wei Ping (2012) [3] introduced two approaches based on Bayesian inference and adaptive neuro-Fuzzy inference system (ANFIS) were utilized for models development to estimate the effect of uncertain variables as setup time, machinery breakdown time, lead time of manufacturing, and scraps of production line in the tile industry. The results demonstrated that the ANFIS was superior than the Bayesian model. Aengchuan and Phruksaphanrat [2] made a comparison between the three methods: Fuzzy Inference System (FIS), Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) with different membership functions in solving inventory control problem with two inputs and one output. The results showed that the ANFIS model with Gaussian membership functions gave the best solution for inventory minimum total cost. Ahmed Abdel-Aleem, Mahmoud EL-sharief and Hassan (2017) [1] studied and analyzed the optimal lot size in a real production system by using Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS). Pawel Więceka (2016) [12] introduced a proposal for a combined application of fuzzy logic and genetic algorithms to control the procurement process. In this study a comparative analysis based on FIS, ANFIS and a conventional inventory model for a continuous inventory system is presented. The main objective is to determine the order quantity and reorder point taking into account the demand, lead time and inventory level uncertainties, which can maximize the customer satisfaction and minimize the inventory cost.

Methodology:

This paper is divided into two stages, the first stage is Fuzzy inference system FIS and the second stage Adaptive Fuzzy Inference system. Yemen Company for Industry and Commerce has been selected to collect the required data from. This company is considered to be one of the largest manufacturer companies in Yemen, which handle a variety of data. The gathered data depends on historical data and an interview with expert managers in inventory field. The bullet points below summarized the procedures and the tools that was used in conducting thesis.

- Construct a FIS for three inputs (demand, lead time and inventory levels) and two outputs (order quantity and reorder point).
- Construct two models for adaptive fuzzy inference systems, the first one is to obtain the optimal order quantity with the same three variables input (demand, lead time and inventory levels), the second is for obtaining the optimal reorder point with the same three variables input (demand, lead time and inventory levels).
- The simulated results of FIS and ANFIS are compared with the conventional model based on the historical data of the company.

Inventory Control System:

Inventory is one of the most expensive and important assets of many companies. The main objective of Inventory management is to reduce inventory costs by dropping on-hand inventory levels. On the other hand, customers become dissatisfied when stock outs occur. Thus, balance is essential between low and high inventory levels.

There are two general types of inventory systems: a continuous (fixed–order quantity models) and fixed–time period models. These two models are designed to achieve that the stock will be available throughout the year on an ongoing basis.

In a continuous inventory system, inventory level for every item must be continually monitored. Whenever the inventory level falls to a predetermined level called as reorder point (ROP), a replenishment order of fixed quantity called economic order quantity (EOQ) is placed. Thus EOQ (Q) and ROP (R) are the two decision variable involved in solving the problem of how much to buy and when to buy [13]. This work introduces a new approach for a continuous inventory monitoring and control system for uncertain demand and lead-time and inventory level with the use of artificial intelligence techniques. These include, in particular, fuzzy inference system and Adaptive neuro fuzzy system.

Inventory Costs:

The objective of most inventory models is to minimize the total cost. The significant costs that effect on the total inventory cost are carrying / holding cost and ordering cost. Thus, if we minimize the sum of the ordering and carrying cost, the inventory cost will be minimized.

Carrying cost is the cost of holding items in an inventory, this cost represents the costs of capital tied up, warehouse space, insurance, taxes, and so on. It is computed using equation (1).

Total Carrying cost $= (Q/2) \times C_h$ (1)

Where:

Q : Order quantity.

C_h : Holding cost per unit per period.

Ordering costs are expenses incurred when a purchase order is initiated for procurement or replenishment of inventories and it is computed using equation (2).

Total Ordering cost $= (D/Q) \times C_o$ (2)

Where,

Q : Order quantity.

C_o : Ordering cost per time

D : Estimated demand for the product within a specified time horizon.

Fixed Order Quantity Inventory Model:

A fixed-order quantity system is one of the most important models in inventory management. This model assumes that both demand, D, and lead time, L, occur at a constant rate and their values are known with certainty. However, D and L are rarely fixed, and demand is often higher than expected. An amount of safety stock depends on the service level desired,is added to the ROP calculation to avoid this uncertainty. This model is called a Fixed Order Quantity with Safety Stock. The first decision in the fixed-order quantity model is to select the optimal order quantity, Q^* .The optimal order quantity, Q^*, is the point that minimizes the inventory cost, where inventory cost is the sum of ordering cost and carrying cost .

$$Q^* = EOQ = \sqrt{\frac{2D\,C_o}{C_h}} \qquad (3)$$

The second decision is the reorder point R is which determined based on the demand rate during the lead time. Safety stock is added to the reorder point calculation. The purpose of the safety stock is to cover the random variations in demand and lead time. The reorder point and the safety stock can be computed as:

$$R = \bar{d}\,L + SS \qquad (4)$$

$$SS = z\sigma_d\sqrt{L} \qquad (5)$$

Where

R : Unit of reorder point.

$\bar{d}$: Average daily demand

L : Lead time (time between placing an order and receiving the items).

SS : Safety stock.

σ_d : The standard deviation of usage during lead time.

z : The number of standard deviation corresponding to the service level probability

Fuzzy Inference System:

Fuzzy set theory provides a framework for considering parameters that are vaguely or unclearly defined or whose values are imprecise or determined based on subjective beliefs of individuals (Tanthatemee & Phruksaphanrat, 2012 [15].

The expert system is defined as" a computing system capable of representing and reasoning about some knowledge rich domain with a view to solving problems and giving advice. Fuzzy inference uses the fuzzy logic to composite if-then rules of rule base and to convert the input variables into the output variables. The common fuzzy inference model that has been frequently used is called Mamdani and Sugeno model.

The Mamdani model is formed by four blocks as shown in Figure 1. The forthcoming subheadings explain the purpose of each block.

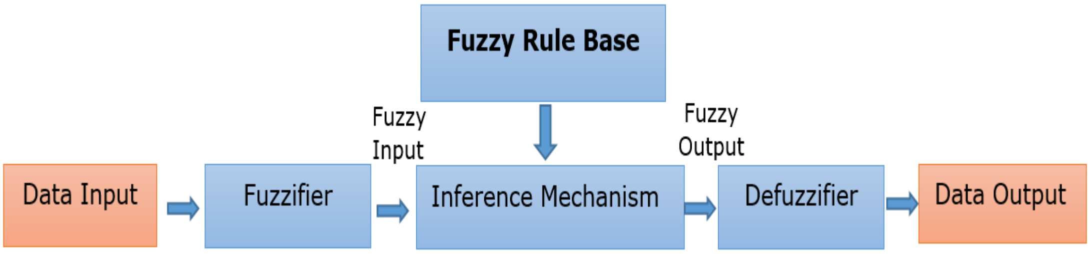

Figure 1. Mamdani type fuzzy logic system.(H. Bautista-S, J.L. Martinez, M.B. Bernabé, D. Sanchez & F. Sanchez [4])

Fuzzification:

The fuzzification process is to represent the non-fuzzy input values in a fuzzy values by interpreting the inputs from numerical values to a linguistic variables such as low, medium, high. This is achieved by the application of the membership functions related to each fuzzy set in the rule input space. The numerical input values of the input parameters are assigned to membership values to fuzzy sets.

Rules Base:

The rule is interpreted as an "implication" and consists of the "antecedent" (if part) and "consequent" (then part). The general form of fuzzy rule is given in the following:

$$if\ x\ is\ A\ , Then\ y\ is\ B \qquad (6)$$

Inference Mechanism:

The task of the inference mechanism is to take fuzzy values and generate a fuzzy output using the fuzzy rules base. The maximum-minimum operation is used in the inference mechanism to calculate the output fuzzy value. Equation (7) shows the maximum- minimum operation.

$$\boldsymbol{\mu}_{(\boldsymbol{output})} = \boldsymbol{Max}[\boldsymbol{Min}\ [\boldsymbol{\mu_A}(\boldsymbol{input_1}\ ), \boldsymbol{\mu_B}(\boldsymbol{input_2}\ ) \ldots]] \qquad (7)$$

Defuzzification:

In this block the output is converted to a numerical value. There are several defuzzification methods and the most popular one is the centroid technique (Center Of Gravity COG) and it is represented in Equation 8.

$$\boldsymbol{y_{01}} = \frac{\sum \boldsymbol{y1}(\boldsymbol{\mu}(\boldsymbol{y1}))}{\sum \boldsymbol{\mu}(\boldsymbol{y1})} \qquad (8)$$

Where,

y_1 :

$\mu(y1)$:

y_{01} :

Adaptive Neuro Fuzzy Inference System:

ANFIS was introduced by Jang [6]. ANFIS is a combination of artificial neural network (ANN) and fuzzy inference system (FIS).Adaptive neuro-fuzzy system makes use of a hybrid-learning rule to optimize the fuzzy system parameters of a first order Sugeno system (Benmiloud,) [2].ANFIS system allows the user to choose or modify the parameters of the membership functions based on the data. The parameters are adjusted automatically by the neuro adaptive learning techniques like back propagation algorithm or hybrid method (which is a combination of back propagation and least squares method). These techniques allow the fuzzy inference system to learn information about the data set (V.Vaidhehi, 2014) [18].

ANFIS Architecture:

The ANFIS architecture consists of five-layers as illustrated on Figure 2. In order to understand the ANFIS, assume that the fuzzy inference system under consideration has two inputs, x_1 and x_2, and one output, y . A rule is set with two fuzzy if-then rules which can be expressed as:

$$Rule1: \quad if\ x_1\ is\ A_{11}\ and\ x_2\ is\ A_{21} Then\ f = p_1x_1 + q_1x_2 + r_1 \qquad (9)$$

$$Rule2: \quad if\ x_1\ is\ A_{12}\ and\ x_2\ is\ A_{22} Then\ f = p_2x_1 + q_2x_2 + r_2 \qquad (10)$$

Where $A_{11}, A_{12,} A_{21} and\ A_{22}$ the fuzzy sets and f are the outputs within the fuzzy region specified by the fuzzy rule, $p_i, q_i and\ r_i$ are the design parameters of the output/consequent part that are determined during the training process. Each layer has a specific functionality.

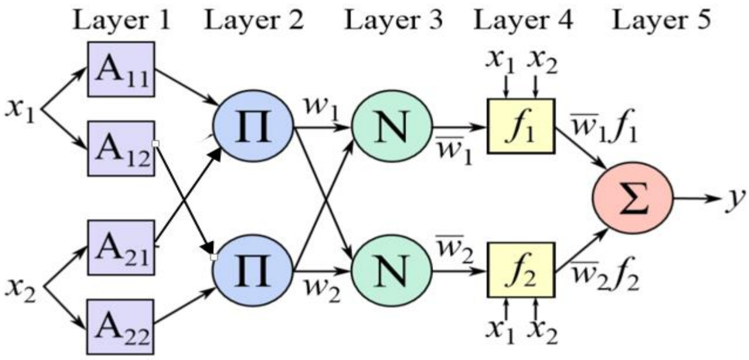

Figure 2.The ANFIS architecture consists of five-layer. (Jang, J. R. 1993 [18])

Layer 1: Input nodes. Each node of this layer generates a degree of-membership score of each input in the appropriate fuzzy sets.

$$o_{1,i} = \mu_{Ai}(x_i) \qquad ,i = 1,2 \tag{11}$$

Where x_i are crisp inputs to node i, and $A_i$are the linguistic labels (small, large, etc.) characterized by membership functions$\mu_{Ai}(x_i)$.

Layer 2: Rule nodes. In the second layer, the AND operator is applied to obtain one output that represents the result of the degree to which the antecedent part of a fuzzy rule is satisfied in terms of a firing strength. The outputs $O_{2,i}$ of this layer are the products of the degrees of membership from Layer 1:

$$o_{2,i} = w_i = \mu_{A1,i}(x_1) \times \mu_{A2,i}(x_2) \qquad ,i = 1,2 \tag{12}$$

Layer 3: Average nodes. In the third layer, the main objective is to calculate the ratio of each rule's firing strength to the sum of the firing strengths of all the rules (R). This is the normalized firing strength ($\overline{w_i}$):

$$o_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{r=1}^{R} w_r} \qquad ,i = 1,2 \tag{13}$$

Layer 4: Consequent nodes. The function of the fourth layer nodes is to compute the contribution of each rule toward the total output using the function defined as:

$o_{4,i} = \overline{w}f_i = \overline{w}_i\ (p_i x_1 + q_i x_2 + r_i)$	$,i = 1,2$	(14)

Where $\overline{w_i}$is the input from the previous layer and $p_i, q_i and\ r_i$are the parameters in the consequent part of the Sugeno-model rules.

Layer 5: Output nodes. A single node computes the overall output by summing all the incoming signals. This defuzzification process transforms each rule's fuzzy result into a crisp output:

$$o_{5,i} = \sum_{r=1}^{R} \overline{w}\ f_i \tag{15}$$

Hybrid Learning Algorithm (HLA):

This algorithm is a combination of the gradient descent and the least squares methods which are used to minimize the error in the learning stage. The HLA consists of two passes known as forward and backward passes. In the forward pass, the information flows forward until$o_{4,i}$ and the consequent parameters are determined by the least square approach. In the backward pass, the error signals propagate backward and the antecedent parameters are updated using gradient descendent approach (Jang, 1993) [6].Figure3 presents the steps which is applied to construct ANFIS model.

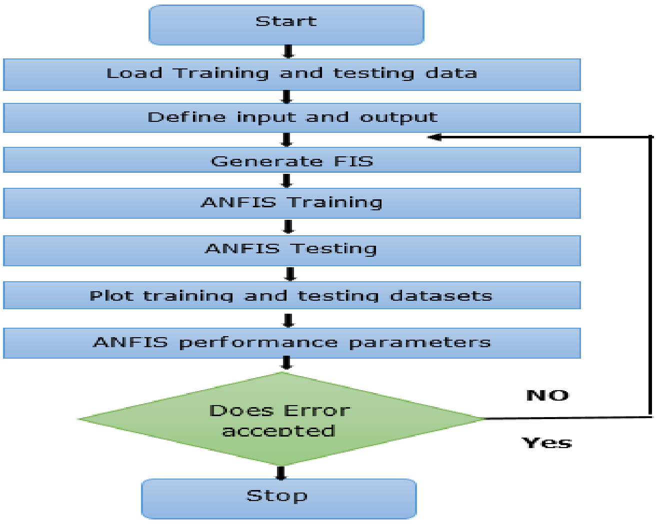

Figure 3. Flowchart of the developed ANFIS .(Abdel-Aleem, A. El-Sharief, A. Hassan, and G. El-Sebaie,2017) [1]

Case Study:

Yemen Company for Industry & Commerce (YCIC) is one of the largest manufacturers of Biscuits, Sweets, Cakes and Cookies. YCIC was established in 1970. YCIC has five factories with 32 different production lines, and annual capacity of (120000 MT). The company produces a broad variety of products about more than 60 different products.Historical MRO (Maintenance, repair, and operating inventory data of Yemen Company for Industry & Commerce has been investigated. One of the items that the inventory management must monitor continuously is called MAKE-UP-CARTIDGE MC291BK, which is the ink that is used to type expiry date code on the products. Date code ink is highly affected on the production process. Date code equipment is installed vertically or horizontally to the packing machine. However, if there is no enough ink the packing operation will be suspended as a result a bottleneck occurs and the whole production line might be stalled. The more demand of finished products, the ink bottle is more consumed. Therefore, the demand of date code ink bottle is uncertain and randomly fluctuated. In addition, Both lead time and inventory level are uncertain too. The company policy is to raise the inventory level to protect shortage. Service level that the company wants to guarantee with customers is more than 98%. Customer Service Level and safety stock is one of the available methods of solving the inventory problem under uncertain lead time and demand.

Fuzzy Inference System Model:

Fuzzy system has been developed to obtain the order quantity and reorder point based on input variables of demand, inventory level and lead time. We use linguistic terms to illustrate the situation of input and output variables and construct a fuzzy rule base. These linguistic terms were decided by expert managers, who have been worked in the inventory management department for more than 15 years. Then, the developed fuzzy rules were used to extract the fuzzy order quantity and reorder point.

Fuzzy Inputs Variables:

Three fuzzy input variables are defined: demand, lead time and inventory level which are described by membership functions μ_D ,μ_L and μ_I respectively. These variables are represented by linguistic variables. These linguistic terms were decided by expert managers, who have been worked in the inventory management department for more than 15 years. Trapezoidal and triangular membership functions are used to fuzzify the crisp input variables.

Fuzzy Demand

Demand is determined based on observation and test using normal distributions of historical data. The monthly demand has normal distribution. The demand is assumed to be represented by 3 linguistic values; low, medium and high. The universe of discourse of the demand input space is designed from the real data of annual demand within the interval [0, max (D)], where max (D) is the expected maximum demand that had been ordered. Demand membership function is based on these parameters [$0, \bar{d}-\sigma_d, \bar{d}, \bar{d}+\sigma_d, \max(D)$]

Fuzzy Lead time:

Fuzzy lead time is determined based on observation and test using normal distributions of historical data .Appendix C shows the normal distribution of the lead time using Minitab software with average lead time 15 and 5 standard deviations .The universe of discourse of Lead time is designed based on real data within the interval [0, max (L)], where max (L) is maximum lead time of supply from the current suppliers of determined planning horizon. And it is represented by 3 linguistic values; normal, medium, high.

Fuzzy Inventory Level:

Fuzzy inventory level is determined based on the daily demand during the lead time, and it is assumed to be represented by 3 linguistic values; low, medium and high. The universe of discourse of the inventory level space is the set of real numbers within the interval [0, 3(D× L)], where D is the daily demand and L is average lead time. Inventory level membership function is based on these parameters [$0, (D \times L), 2(D \times L), 3(D \times L)$] [19].

Fuzzy Outputs Variables:

Two output variables are constructed order quantity Q and reorder point R and they are described by membership functions μ_Q and μ_R respectively. These variables are represented by linguistic variables .Trapezoidal and triangular functions are used to fuzzify the crisp output variables.

Fuzzy Order Quantity:

Fuzzy order quantity is assumed to be represented by 3 linguistic values; low, medium, high. Linguistic values of order quantity is designed from available of supply because in real situation of uncertain supply order quantity should be in the possible range of supply so the universe of discourse for order quantity output is in the interval [0, max(S)], where max(S) is the maximum availability of supply from historical data. The parameters that are used to represent are 3 linguistic values; low, medium and high are $(0, 0.5Q, Q, 2Q)$.

Fuzzy Reorder Point:

Reorder point is assumed to be represented by 3 linguistic values; low, medium and high.The universe of discourse of the reorder point space is the set of real numbers within the interval [0, 2R]. Three Linguistic values of reorder point are designed based on reorder point. The parameters (0, R-SS, R, R+SS, 2R) are used.

Construct Fuzzy Rule Base:

Fuzzy inference type of the proposed system is Mamdani. In this paper demand, lead time and inventory level are in "if part" of rules and quantity order and reorder point are in "then part". Since demand, lead time and inventory level, each of them, consist of three linguistic variables, thus we have 3×3× 3= 27"If – Then" rules for designing fuzzy rule base. Table1 illustrated the 27 fuzzy rules which are constructed to determine the order quantity and reorder point. These fuzzy rules which show the expert's opinions for estimating the order quantity of date-code ink bottle and its reorder point under different conditions.

Table 1. Fuzzy rules show the expert's opinions for estimating the order quantity and reorder point

Rule number	IF part			THEN part	
	Demand	Lead time	Inventory level	Order quantity	Reorder point
1	Low	Normal	Low	Low	Low
2	Low	Normal	Medium	Low	Low
3	Low	Normal	High	Low	Low
4	Low	Medium	Low	Medium	Medium
5	Low	Medium	Medium	Low	Low
6	Low	Medium	High	Low	Low
7	Low	High	Low	High	Medium
8	Low	High	Medium	Medium	Medium
9	Low	High	High	Medium	Medium
10	Medium	Normal	Low	Medium	Medium
11	Medium	Normal	Medium	Medium	Low

12	Medium	Normal	High	Low	Low
13	Medium	Medium	Low	High	Medium
14	Medium	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Medium	Low
16	Medium	High	Low	High	High
17	Medium	High	Medium	High	Medium
18	Medium	High	High	Medium	Medium
19	High	Normal	Low	High	Medium
20	High	Normal	Medium	Medium	Low
21	High	Normal	High	Medium	Low
22	High	Medium	Low	High	High
23	High	Medium	Medium	Medium	Medium
24	High	Medium	High	Medium	Medium
25	High	High	Low	High	High
26	High	High	Medium	High	High
27	High	High	High	Medium	Medium

Inference Mechanism:
The inference mechanism was executed with the help of fuzzy tool box of MATLAB. Fuzzy output was generated using the fuzzy rules base. The maximum-minimum operation Equation (6) is used in the inference mechanism to calculate the output fuzzy value of order quantity (y_1) and reorder point (y_2) . These outputs can be expressed using equation 7 as follows:

$$\mu_Q\,(y_1) \quad = \quad (\mu_{D1}\,(x_1) \wedge \mu_{L1}(x_2) \wedge\; \mu_{I1}(x_3)) \vee \ldots (\,\mu_{Dn}(x_1)\mu_{Ln}(x_2) \wedge \mu_{In}(x_3))$$
$$\mu_R\,(y_2) \quad = \quad (\mu_{D1}\,(x_1) \wedge \mu_{L1}(x_2) \wedge\; \mu_{I1}(x_3)) \vee \ldots (\,\mu_{Dn}(x_1)\mu_{Ln}(x_2) \wedge \mu_{In}(x_3))$$

Where $\wedge$ is the minimum operation and $\vee$ is the maximum operation. D_i , L_i , I_i , Q_i and R_i are fuzzy subsets defined by the corresponding membership functions μ_D , μ_L , μ_I , μ_Q and μ_R . $x_1, x_2 and x_3$ are demand, lead time and inventory level respectively.

Finally, a defuzzification method, the center-of gravity method is used here to convert the fuzzy inference output into a non-fuzzy value order quantity y_{01} and reorder point y_{02} .The non-fuzzy value for order quantity and reorder point can be expressed using equations 8 as follows:

$$y_{01} = \frac{\sum y_1(\mu_Q(y_1))}{\sum \mu_Q\,(y_1)}$$
$$y_{02} = \frac{\sum y_2(\mu_R(y_2))}{\sum \mu_R\,(y_2)}$$

These operation is implemented using Fuzzy Tool Box of MATLAB using Rule Viewer inference which is display the whole fuzzy inference process [5].

The final experimental results of FIS model will be discussed later in section 8.

Adaptive Fuzzy Inference System:
Neuro –fuzzy Designer generates a single- output Sugeno Inference System. Therefore the ANFIS model for this study will be divided into two models one to obtain the order quantity output.The other model is for obtaining the reorder point output Figure3. The same input data for (demand, lead time and inventory level) will be given to the two models.

Anfis Model for Order Quantity:
The ANFIS model for order quantity consists of three inputs demand, lead time and inventory level and a signal -output order quantity. The datasets of these variables was generated rondamly based on the normal distribution of the historical data using EXCEL software.The steps of Anfis structure that had been followed to create the model is shown in Figure 3.

Load Data:
50 items of data have been generated randomly for all variables .The dataset is categorized into three groups observations 30 assigned for training 10 for testing,and 10 for verifying. The training set was assigned to build the ANFIS model. The verifying data set was used to confirm that the trained model is a suitable representation of the target system and to avoid over-fitting of the system to the training data set.

Generation of Fuzzy Inference System:
In this heading the loaded data is fuzzified, Grid partitioning is used to divide the data space into rectangular sub spaces called “grids” based on

the number of membership functions and their types. For selecting the best type of membership function, different membership functions as nonlinear functions were considered for the input uncertainties. The most popular membership functions, which are widely used, namely, triangular, trapezoidal were examined. And each membership function was examined in relation to three different structures.
The first one was studied with three linguistic values defined as low, medium, and high. The second was examined by four linguistic values: very low, low, medium, high. Finally the third was examined by five linguistic values: very low, low, medium, high, and very high. The number of fuzzy rules increases exponentially, when the number of input variables increases. For example, if there are m membership functions for every input variable and a total of n input variables for the problem, then the total number of fuzzy rules needed is m^n.

Training Process:

The training adjusted the membership function parameters and displayed the error plots. ANN was utilized for training, testing, and checking for each uncertainty .Hybrid learning algorithm includes both Gradient descent and the least square of error was employed.
The number of iteration is set to be 40 to do the training process through the hybrid learning algorithm. The purpose of iteration is to see if there is any possibility to more error reduction, and make sure the error not increasing and no overfitting. The training process was stopped when the maximum epoch number is reached.
The training process has five-layers architecture. Figure 4clarifies the training process in each layer .
Input node layer: the output of three input variables is denoted by$o_{1,i}$ equation 11.

$$o_{1,i} = \mu_{Ai}(D)$$
$$o_{1,i} = \mu_{Ai}(L)$$
$$o_{1,i} = \mu_{Ai}(I)$$

Where,

D : demand
L : Lead time
I : inventory level
o_i : output for each cluster i
A_i : Linguistic variable (low, medium ,high)

Rule nodes (inference layer or rule layer):The weight of each cluster is found in step 2. The output of each input was obtained from step 1 and multiplies to other factors. The number of rules are 27rules equation 12.

$$o_{2,i} = w_i = \mu_i(D) \times \mu_i(\mathrm{L}) \times \mu_i(I)$$

Where,

w_i : weight of cluster i

Normalized layer (Average nodes layer) :Defuzzification method was done through the weighted average in step 3. The output i is the ratio of the weight of cluster i to the summation of all weights equation 13.

$$o_{3,i} = \overline{w}_i = \frac{w_i}{\sum_{i=1}^{27} w_k}$$

Consequent nodes layer (aggregation layer):$\overline{w}_i$ is multiplied by the output of the cluster i in the step 4 as presented in equation below equation 14.

$$o_{4,i} = \overline{w} f_i$$

Where,

f_i : the output of the cluster i.

Total output layer: In the step 5, the overall output as the summation of all incoming signals is computed using equation 15.

$$o_{5,i} = \sum_{i=1}^{27} \overline{w}\, f_i$$

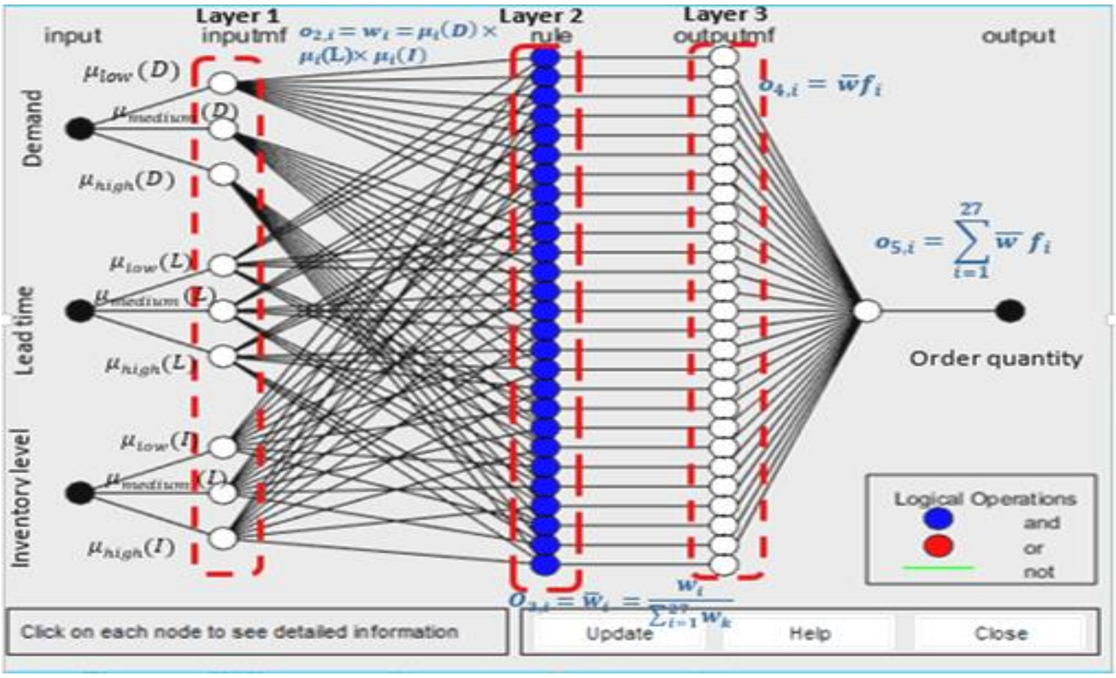

Figure 4. Training process in each layer

Model Validations:

Model validation is the process done to the FIS after training to check if the FIS model predicts the data set applied to it with in the specified error or not [12]. Table2 shows the results of the simulation study to find the best definition of the constructed ANFIS to various alternative structures. The best structure was determined by the lowest value of check error. The checking error is the difference between the checking data output value, and the output of the fuzzy inference system corresponding to the same checking data input value. The checking error records the RMSE for the checking data at each epoch. Based on the simulation the best ANFIS structure for obtaining the order quantity is the Triangular type with three membership function with check error 0.131588.The average testing error for the training is 0.110813and average testing error for the testing data set is 0.10909.

Table 2. ANFIS results related to various alternative structures

		Training error	Check error	Test error
Triangular	3membership function	0.110813	**0.131588**	0.10909
	4 member ship function	0.158060	0.183917	0.10114
	5 member ship function	0.136659	0.129361	0.13579
Trapezoidal	3membership function	0.188025	0.150193	0.150193
	4 member ship function	0.192438	0.199239	0.659500
	5 member ship function	0.274042	0.204440	0.383270

ANFIS Model for Reorder Point:

The ANFIS structure for reorder point is the same as constructing the ANFIS model for order quantity except the output is the reorder point. The training process was executed .Table 3 shows the results of the simulation study to find the best definition of the constructed ANFIS for the different scenarios. The best ANFIS structure for obtaining the reorder point is the Triangular type with three membership functions with check error **0.10765** with average testing error for the training is 0.096715 and average testing error for the testing data set is 0.049099.

Table 3. ANFIS results related to various alternative structures

		Training error	Check error	Test error
Triangular	3membership function	0.096715	**0.10765**	0.049099
	4 member ship function	0.421380	0.10826	0.20796
	5 member ship function	0.168550	0.18925	0.23862
Trapezoidal	3membership function	0.28660	0.32150	0.30761
	4 member ship function	0.23818	0.26069	0.20100
	5 member ship function	0.21356	0.1954	0.20775

FIS for ANFIS Models:

The most suitable and efficient membership functions, which was Triangular with three membership functions for both models. The estimated parameters for each linguistic value (low ,medium and high) for demand ,lead time and inventory level are shown in the followings tables:

Table 4. Estimated membership function for fuzzy demand for ANFIS model

Linguistic variable	Membership functions
$\mu_D\ normal$	[-102.5 1434 2971]
$\mu_D medium$	[1434 2971 4507]
$\mu_D high$	[2971 4507 6044]

Table 5. Estimated membership function for fuzzy lead time for ANFIS model

Linguistic variable	Membership functions
$\mu_D\ normal$	[-3.5 6 3000]
$\mu_D medium$	[6 15.5 25]
$\mu_D high$	[15.5 25 35]

Table 6. Estimated membership function for fuzzy inventory level for ANFIS model

Linguistic variable	Membership functions
$\mu_D\ normal$	[-305 0 305.5]
$\mu_D medium$	[0 305.5 611]
$\mu_D high$	[305 611 916]

RESULTS:

In order to test the performance of the proposed FIC model and ANFIS model, historical data was used and compared to the results of the EOQ with safety stock model. Five data sets of annual demand were examined. Lead time is considered to be the average lead time 15.Inventory level is considered to be zero , Ordering cost and holding cost per unit per period of the case study factory are 250$ &12$ respectively. The standard deviation of daily demand is 7 units. Workdays per year is 300 days. The Z value associated with a 98% and 99% probability of not stocking out is 2.053, 2.326 respectively.

EOQ and reorder point with safety stock for conventional model can be calculated using Eq.(3) &Eq.(5). Holding cost, ordering cost and total cost can be calculated using Eq.(1) ,(2). The results are tabulated as follows:

Table 7. Total cost of EOQ model with different service level 98% and 99%

98% Service level			99% Service level		
Holding cost	**Order cost**	**Total cost**	**Holding cost**	**Order cost**	**Total cost**
3042	2368	5410	3126	2368	5494
3018	2346	5364	3102	2346	5448
3168	2498	5666	3252	2498	5750
3060	2387	5447	3144	2387	5531
2964	2250	5214	3048	2250	5298

FIS Results:

The same data set was implemented and simulated using The Rule viewer .The results of the Fuzzy Control for EOQ and ROP are shown in Table 8. Ordering cost , holding cost and total cost are computed using Equations (1)& (2) respectively.

Table 8. holding & order costs for FIS model

Holding cost	Order cost	Total cost
3438	1632	5070
3420	1609	5029
3492	1786	5278
3450	1652	5102
3492	1503	4995

ANFIS Results:

The same data set was implemented and simulated using The Rule viewer .The results of the ANFIS for order quantity and reorder point are shown in Table 9. Ordering cost and holding cost and total cost are computed using Equations (1), (2) respectively.

Table 9. holding & order costs for ANFIS model

Holding cost	Order cost	Total cost
3840	1461	5301
3762	1463	5225
4302	1449	5751
3906	1459	5365
3576	1468	5044

Comparative Analysis:

The comparison results of costs for 5 data sets at service level 98%, 99%, FIS and ANFIS are shown in Figure 5 – Figure 8

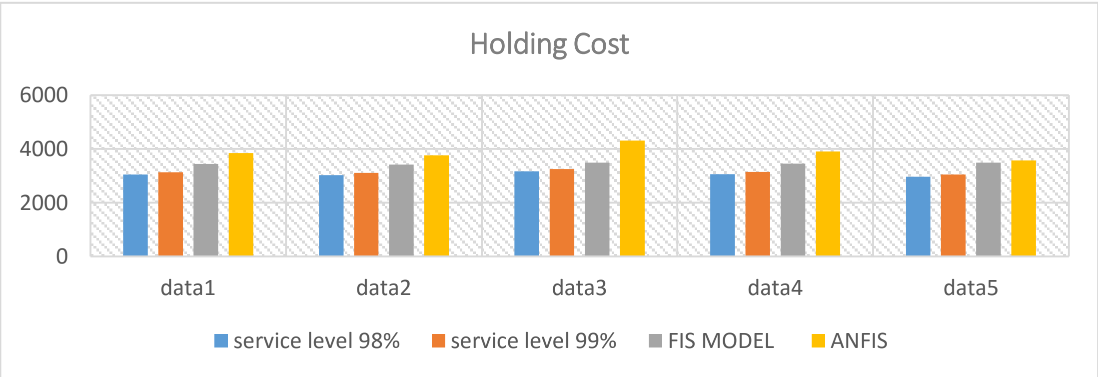

Figure 5. Comparison of holding cost of 5 data sets between stochastic EOQ models at service level 98%, 99%, FIS model and ANFIS model

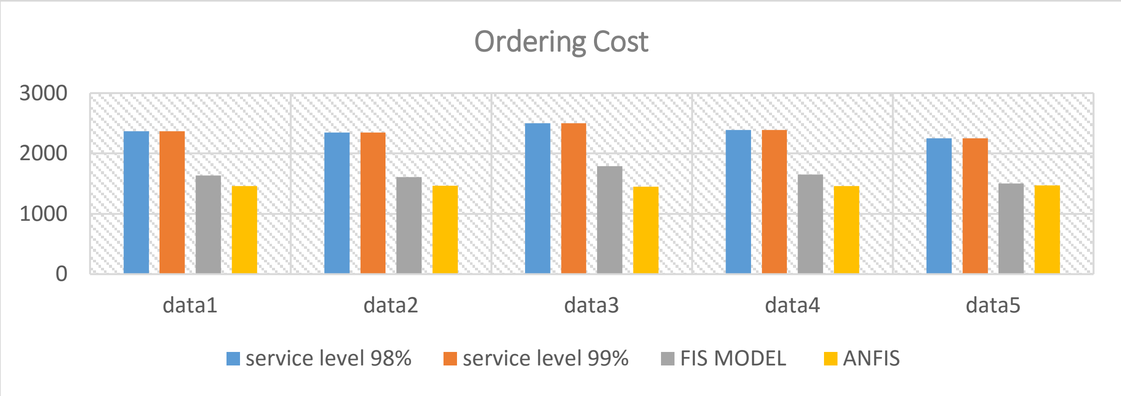

Figure 6. Comparison of ordering cost of 5 data sets between stochastic EOQ models at service level 98%, 99%, FIS model and ANFIS model

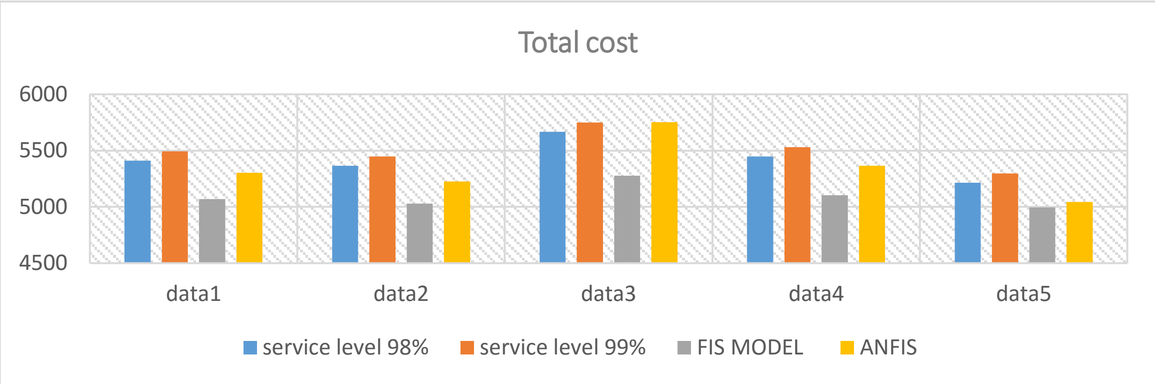

Figure 7. Comparison of total cost of 5 data sets between stochastic EOQ models at service level 98%, 99%, FIS model and ANFIS model

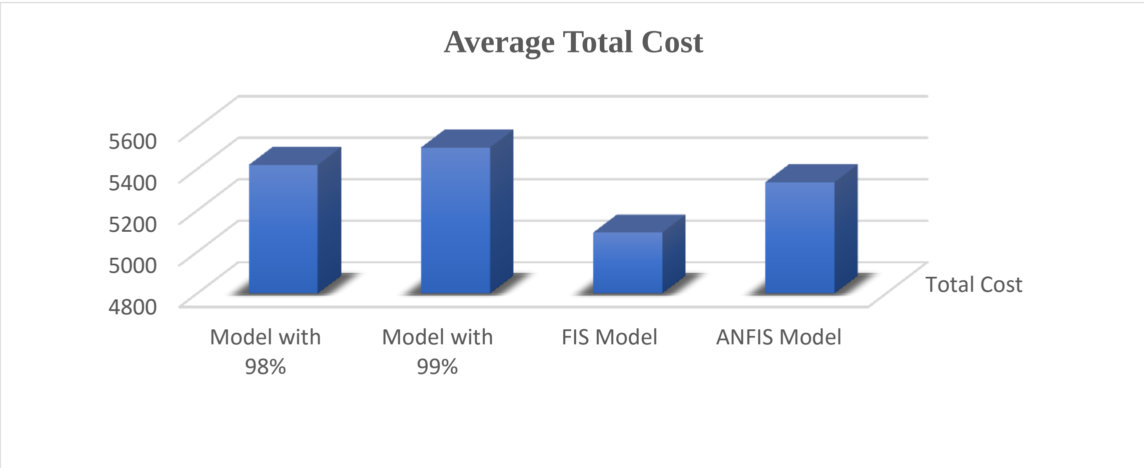

Figure 8. Comparison of average total cost of 5 data sets between stochastic EOQ models at service level 98%, 99%, FIS model and ANFIS model.

Figure 5 revealed that holding cost of EOQ models at service level 98%, 99% have lower cost than FIC model and ANFIS model. It means that the FIC model and ANFIS have higher average inventory level than stochastic EOQ models.
Figure 6 revealed that ordering cost of EOQ models at service level 98%, 99% have higher cost than the FIC model and ANFIS model. It means that the FIC model and ANFIS have less frequency of orders.

In addition , the FIC model and ANFIS model have lower average total inventory cost than EOQ models at service level 98%, 99% as presented in Figure 8 . Cost saving of average EOQ model at each service level, FIC model and ANFIS are calculated as shown in Table 10&11. These results confirm that the FIC model and ANFIS are better than the current stochastic models.

Table 10. Comparison of average total cost of EOQ model at service level 98% with FIC &ANFIS model

EOQ Model	FIS Model	ANFIS Model	Saving Cost FIS	Saving Cost ANFIS
5420	5094	5337	6%	2%

Table 11. Comparison of average total cost of EOQ model at service level 98% with FIC &ANFIS model

EOQ Model	FIS Model	ANFIS Model	Saving Cost FIS	Saving Cost ANFIS
5504	5094	5337	7.4%	3%

The FLC model can save 6% , 7.4% when comparing with stochastic models of EOQ at service level 98%, 99% respectively. The saving cost is increased when service level is increased because shortage is reduced. The ANFIS model can save 2% , 3% when comparing with stochastic models of EOQ at service level 98%, 99% respectively.
Finally The FIC model and ANFIS can control both reorder point and order quantity to the appropriate level under fluctuation circumstances so shortages never occur. While EOQ model shows a huge inventory cost and it cannot respond effectively under fluctuation. This is because the model is built based on wrong assumption and whenever a fluctuation happens, it will be late to order and shortages may occur. So, FIC model and ANFIS model are more flexible than stochastic models at any service level.

Conclusion:

In this paper a Mamdani Fuzzy Inference Model FIS and Adaptive Neuro Fuzzy System ANFIS based on continuous inventory control system were introduced. MATLAB was used to construct the two models.

Mamdani Fuzzy Inference Model FIS was constructed based on three uncertain inputs (demand, lead time and inventory level) and two outputs order quantity and reorder point, Linguistic values were used to represent both inputs and output Fuzzy Rules were constructed according to the historical experience. Adaptive Neuro Fuzzy System ANFIS was divided into two phases the first one was to build a model in order to obtain the order quantity and the second model is for obtaining the reorder point. The same three inputs (demand, lead time and inventory level) were taken in to consideration. Learning of ANFIS is based on Hybrid learning. The data is divided using Grid Partitioning technique.
The performance of the two models were examined by comparing them with EOQ model at different service levels. The results clearly show that FIC model and ANFIS model save the total inventory cost. Moreover, the shortages will not occur which means increasing customer satisfaction.
FIS &ANFIS models are more flexible than the stochastic model .Both models allow a user to modify or readjust parameters easily when the situation has been changed.

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التحكم في المخزون باستخدام نظام الاستدلال الضبابي ونظام الاستدلال العصبي التكيفي الضبابي في ظل ظروف غير مؤكدة

علي عبد المجيد علي أرزاق محمد علي كليب

الملخص

تؤثر إدارة سلسلة التوريد تأثيرًا مهمًا في إدارة الأعمال بكفاية، حيث تدمج إدارة المواد وتدفق المعلومات بين أطراف سلسلة التوريد. في هذه الورقة البحثية، يتم تنفيذ نظامي الاستدلال الضبابي FIS والاستدلال العصبي الغامض التكيفي ANFIS للتعامل مع عدم اليقين فيما يتعلق بالطلب، والمهلة الزمنية ومستوى المخزون في نظام مراقبة المخزون المستمر من أجل الحصول على كمية الطلب المثلى ونقطة إعادة الطلب .يعد نظام (FIS) ونظام الاستدلال العصبي الغامض التكيفي (ANFIS) أنظمة خبيرة تستخدم على نطاق واسع للتعامل مع البيانات غير الدقيقة والغامضة. تتم مقارنة هذين النموذجين مع نموذج كمية الطلب الاقتصادي (EOQ) على مختلف مستوى الخدمة لدراسة تأثيرهما في تكاليف المخزون. تم اختيار دراسة حالة الشركة اليمنية للصناعة والتجارة في هذه الورقة البحثية. أعطى نظامي FIS و ANFIS نتائج أفضل مقارنة بنموذج كمية الطلب الاقتصادي العشوائية (Stochastic EOQ) مع توفير 7 ٪ من إجمالي تكلفة المخزون وعدم وجود نقص في الإمداد و توقع زيادة ولاء العملاء.

الكلمات الرئيسية: نظام الاستدلال الضبابي FIS ، الاستدلال العصبي الغامض التكيفي ANFIS ، نموذج المخزون المستمر