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ANALYSIS OF THE FACTORS CONTRIBUTING TO EFFICIENT INVENTORY MANAGEMENT USING FUZZY WEIGHTED MULTI EXPERT NEURAL NETWORK SYSTEM

Nivetha Martin[1], Pandiammal.P[2]
Assistant Professor, Department of Mathematics, Arul Anandar College (Autonomous), Karumathur
Assistant Professor, Department of Mathematics, GTN Arts College (Autonomous), Dindigul

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Abstract-- Inventory is an idle resource which is maintained by all manufacturing sectors for promoting the production run, but management of inventory is indeed a difficult task for the production sectors as both the deficit and surplus of items put the sectors into trouble. To avoid the hurdles in controlling inventory, the decision makers of the production companies must formulate suitable strategies to handle such situations of risk. To support the process of decision making, the factors contributing to the efficiency of inventory management is investigated using fuzzy multi expert neural network system which is advantageous then Fuzzy neural networks. This paper also aims in determining the prime factors contributing to inventory administration which would duly assist in framing suitable frameworks.

Keywords: Inventory management, Fuzzy, Weighted Multi Expert, Neural network

I. INTRODUCTION

The ultimate objective of any manufacturing sector is profit maximization and costs minimization for which the production run has to be continuous, to make so, the inventory levels have to be monitored and the replenishment of the stock has to be made without any interruption; In general the manufacturing sectors face many obstacles with regard to inventory handling from several internal and external dimensions. Inventory Management is synonyms with inventory control which is the process of regulating the stocks within definite limits. The tactics of inventory handling have been discussed in theoretical aspects along with the formulation of inventory models which play a vital role in finding the optimal order quantity of each inventory item. These mathematical models just consider only the costs parameters but not the other influencing aspects. This clearly shows that the factors contributing to inventory management cannot be analyzed via these inventory models, therefore these influential factors have to be profoundly examined in a more insightful manner for which the concept of Neural network a mathematical inference making tool is used in this paper. Neural Networks are predominantly used in decision making which is the resultant of inference making and analysis. Weighted multi expert neural network (WMENN) is a kind of network and it is extended to fuzzy WMENN using fuzzy neural networks.

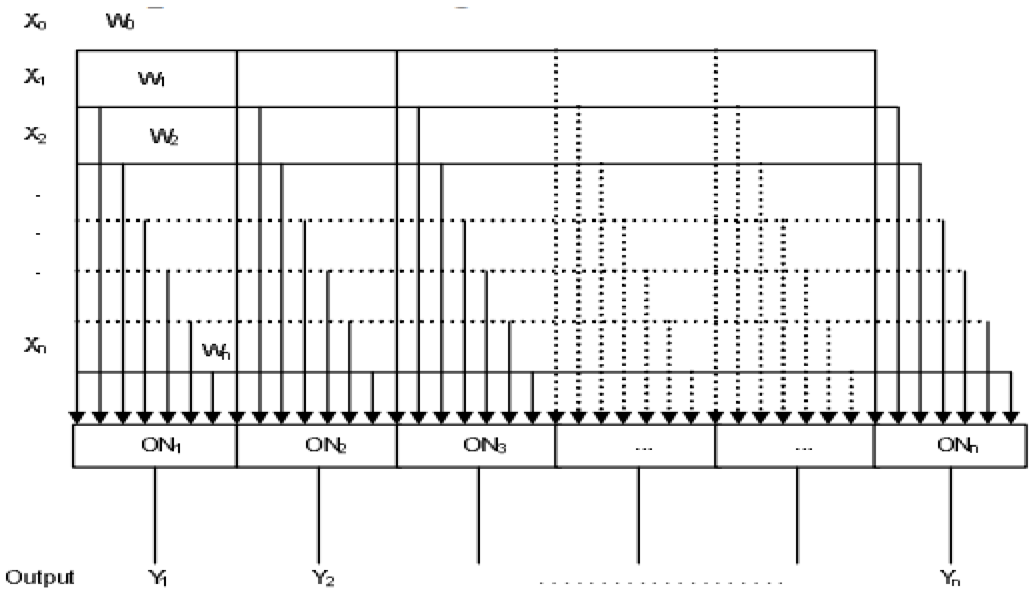

Fig 1. Multi Expert Neural Network System with Opinion's weights

The learning of neural networks is either supervised or unsupervised in which the learning is guided by specific patterns or in latter the classification of the pattern is done by the networks itself. The working of neural networks is purely based on biological functioning. The components of the system are the neurons, the simple computational units which are highly interrelated and the intensity of the bondage is quantified by numerical, but in this paper the expression of association is done by linguistic variables which then quantified by hexagonal fuzzy numbers. The paper is structured as follows: section 2 contains the preliminaries; section 3 confers the factors contributing to Inventory management along with the adaptation to the proposed method; section discusses the results and concludes the paper.

II. PRELIMINARIES

The elementary concepts that are used in this paper are listed below [7,11].

2.1 The bias is the value of the aggregate of weights of inputs around which the output of the neuron is highly sensitive to get altered in the sum. In case of neural networks the bias is -1.

2.2 The sigmoid function or sigmoidal curve or logistic function is the function

$$S_\beta = \frac{1}{1+e^{-x}}$$

2.3 A fuzzy set $\tilde{A}$ is defined by $\tilde{A}$ = {(x, $\mu_{\tilde{A}}(x)$) : x ∈ X, $\mu_{\tilde{A}}(x) \in [0, 1]$}. In the pair {(x, $\mu_{\tilde{A}}(x)$)}, the first element x belong to the classical set A, the second element $\mu_{\tilde{A}}(x)$, belong to the interval [0, 1], called membership function or grade of membership. The membership function is also a degree of compatibility or a degree of truth of x in $\tilde{A}$.

2.4 A fuzzy number is any fuzzy subset of the real line R, whose membership function satisfies the following conditions, is a generalized fuzzy number

$\mu_{\tilde{A}}(x)$ is a continuous mapping from R to the closed interval [0, 1].

$\mu_{\tilde{A}}(x) = 0, -\infty < x \le a_1$,

$\mu_{\tilde{A}}(x) = L(x)$ is strictly increasing on $[a_1, a_2]$,

$\mu_{\tilde{A}}(x) = 1, a_2 \le x \le a_3$,

$\mu_{\tilde{A}}(x) = R(x)$ is strictly decreasing on $[a_3, a_4]$,

$\mu_{\tilde{A}}(x) = 0, a_4 \le x < \infty$, where a_1, a_2, a_3 and a_4 are real numbers.

2.5 Hexagonal Fuzzy Numbers

A depiction of a fuzzy number of the H = (*a1,a2,a3,a4,a5,a6*) such that all ai's are real numbers and *a1≤a2≤a3≤a4≤a5≤a6* is called as Hexagonal Fuzzy number with the membership function as

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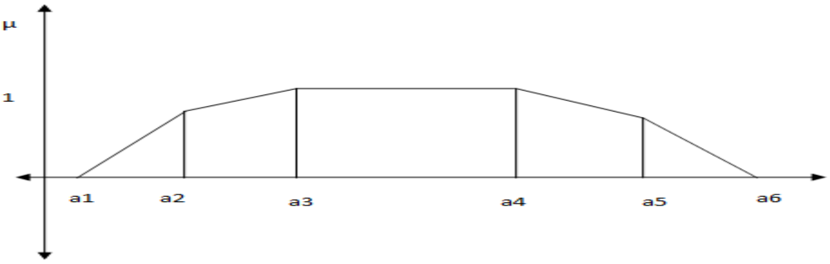

$$\mu(\tilde{A}\,x) = \begin{cases} \frac{1}{2}\frac{x-a1}{a2-a1} & for\ a1 \le x \le a2 \\ \frac{1}{2} + \frac{1}{2}\frac{x-a2}{a3-a2} & for\ a2 \le x \le a3 \\ 1 & for\ a3 \le x \le a4 \\ 1 - \frac{1}{2}\frac{x-a4}{a5-a4} & for\ a4 \le x \le a5 \\ \frac{1}{2}\frac{a5-x}{a6-a5} & for\ a5 \le x \le a6 \\ 0 & \text{otherwise} \end{cases}$$

III. DEFUZZIFICATION OF HEXAGONAL FUZZY NUMBER

The hexagonal fuzzy number is defuzzfied by median method where

$$A = (a_1 + a_2 + a_3 + a_4 + a_5 + a_6) / 6$$

3. Factors Contributing to Efficient Inventory management and the adaptation to the proposed method

The factors are considered for study are as follows

HX C1 Periodical stock check
HX C2 Resourceful Man power
HX C3 Sufficient Flow of Cash
HX C4 Installation of Inventory Monitoring software
HX C5 upholding warehouses
HX C6 Vibrant forecasting techniques of demand
HX C7 Quick Information sharing of inventory levels

The factors taken are considered as inputs

X1 Periodical stock check
X2 Resourceful Man power
X3 Sufficient Flow of Cash
X4 Installation of Inventory Monitoring software
X5 upholding warehouses
X6 Vibrant forecasting techniques of demand
X7 Quick Information sharing of inventory levels

FIVE EXPERT'S OPINION ARE OBTAINED IN TERMS OF LINGUISTIC VARIABLES WHICH ARE TABULATED AS FOLLOWS

Expert	X0	X1	X2	X3	X4	X5	X6	X7
E1	H	H	M	M	H	H	M	H
E 2	M	M	H	M	H	H	M	H
E 3	H	M	H	H	H	L	H	H
E 4	H	H	M	H	M	H	H	H
E 5	H	H	M	L	L	H	H	H

THE HEXAGONAL WEIGHTS OF LINGUISTIC VARIABLES

Low	(0.1,0.15,0.2,0.25,0.3,0.35)
Medium	(0.35,0.4,0.45,0.5,0.55,0.6)
High	(0.6,0.7,0.8,0.9,1,1)

Expert	X0	X1	X2	X3	X4	X5	X6	X7
E1	(0.6,0.7, 0.8,0.9,1, 1)	(0.6,0.7,0. 8,0.9,1,1)	(0.35,0.4 ,0.45,0.5, 0.55,0.6)	(0.35,0.4,0.4 5,0.5,0.55,0. 6)	(0.6,0.7,0. 8,0.9,1,1)	(0.6,0.7,0. 8,0.9,1,1)	(0.35,0.4,0. 45,0.5,0.55, 0.6)	(0.6,0.7,0.8,0 .9,1,1)
E 2	(0.35,0.4 ,0.45,0.5, 0.55,0.6)	(0.35,0.4,0 .45,0.5,0.5 5,0.6)	(0.6,0.7, 0.8,0.9,1, 1)	(0.35,0.4,0.4 5,0.5,0.55,0. 6)	(0.6,0.7,0. 8,0.9,1,1)	(0.6,0.7,0. 8,0.9,1,1)	(0.35,0.4,0. 45,0.5,0.55, 0.6)	(0.6,0.7,0.8,0 .9,1,1)
E 3	(0.6,0.7, 0.8,0.9,1, 1)	(0.35,0.4,0 .45,0.5,0.5 5,0.6)	(0.6,0.7, 0.8,0.9,1, 1)	(0.6,0.7,0.8, 0.9,1,1)	(0.6,0.7,0. 8,0.9,1,1)	(0.1,0.15,0 .2,0.25,0.3, 0.35)	(0.6,0.7,0.8, 0.9,1,1)	(0.6,0.7,0.8,0 .9,1,1)
E 4	(0.6,0.7, 0.8,0.9,1, 1)	(0.6,0.7,0. 8,0.9,1,1)	(0.35,0.4 ,0.45,0.5, 0.55,0.6)	(0.6,0.7,0.8, 0.9,1,1)	(0.35,0.4,0 .45,0.5,0.5 5,0.6)	(0.6,0.7,0. 8,0.9,1,1)	(0.6,0.7,0.8, 0.9,1,1)	(0.6,0.7,0.8,0 .9,1,1)
E 5	(0.6,0.7, 0.8,0.9,1, 1)	(0.6,0.7,0. 8,0.9,1,1)	(0.35,0.4 ,0.45,0.5, 0.55,0.6)	(0.1,0.15,0.2 ,0.25,0.3,0.3 5)	(0.1,0.15,0 .2,0.25,0.3, 0.35)	(0.6,0.7,0. 8,0.9,1,1)	(0.6,0.7,0.8, 0.9,1,1)	(0.6,0.7,0.8,0 .9,1,1)

THE DEFUZZIFIED TABULATED VALUES ARE

Expert	X0	X1	X2	X3	X4	X5	X6	X7
E1	0.84	0.84	0.48	0.48	0.84	0.84	0.48	0.84
E 2	0.48	0.48	0.84	0.48	0.84	0.84	0.48	0.84
E 3	0.84	0.48	0.84	0.84	0.84	0.23	0.84	0.84
E 4	0.84	0.84	0.48	0.84	0.48	0.84	0.84	0.84
E 5	0.84	0.84	0.48	0.23	0.23	0.84	0.84	0.84

THE AVERAGE OF THE WEIGHTAGE GIVEN BY THE EXPERTS IS

E1	E2	E3	E4	E5
0.71	0.66	0.72	0.74	0.64

The input is taken as the average of the weightage given by the experts together with the bias -1 as in neural network.

X0	X1	X2	X3	X4	X5	X6	X7
-1	0.695	0.624	0.574	0.646	0.718	0.696	0.84

The corresponding output is given by
$Y_i = S_\beta \left(\sum_{i=0}^{5} W_i \ X_i \right)$ where W_i is the weight given by the experts.
$S_\beta (a) = (1 + \exp(-\beta a))^{-1}$

The tabulation of the output Yi is as follows

Y1	Y2	Y3	Y4	Y5
0.92	0.93	0.92	0.93	0.90

The altogether opinion of the experts pertaining to the factors causing hurdles in weather prediction happens to be > 0.1 To make an inference the following fuzzy set along with the membership function is defined.

$\mu : E \rightarrow [0,1]$, where $E = \{ E1,E2,E3,E4,E5\}$

$$\mu(E) = \begin{cases} 0 & \text{if } E_i < 0.60 \\ 0.91 & \text{if } 0.60 \le E_i < 0.65 \\ 0.94 & \text{if } 0.65 \le E_i < 0.7 \\ 0.97 & \text{if } 0.7 \le E_i < 0.75 \\ 1 & \text{if } 0.75 \le E_i < 1 \end{cases}$$

A COMPARISON TABLE IS FORMULATED FOR DECISION MAKING.

Expert	Average Weight	Weighted Multi Expert Neural Network System	μ (E)	Difference
E1	0.71	0.92	0.97	0.05
E 2	0.66	0.93	0.94	0.01
E 3	0.72	0.92	0.97	0.05
E 4	0.74	0.93	0.97	0.04
E 5	0.64	0.90	0.91	0.01

IV.CONCLUSION

The expert's opinion is considered for further analysis if the difference is less than or equal to 0.01, in that case the opinion of the expert E2 and E5 are taken into account with regard to the context of inventory management. This paper advocates the method of inference making by incorporating the linguistic variables as input weights. This proposed methodology reflects the realm of the expert's opinion on any aspect. This paper can also be extended with the comparative analysis of various fuzzy numbers

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