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Demand forecasting Using Artificial Neural Network Based on Different Learning Methods: Comparative Analysis

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Abstract----To gain commercial competitive advantage in a constantly changing business environment, demand forecasting is very crucial for an organization in order to make right decisions regarding manufacturing and inventory management. The objective of the paper is to propose a forecasting technique which is modeled by artificial intelligence approaches using artificial neural networks. The effectiveness of the proposed approach to the demand forecasting issue is demonstrated using real-world data from a company which is active in industrial valves manufacturing in Mumbai. A comparative analysis of different training methods of neural network is carried using the results obtained from the demand forecasting model

Key words:--- Demand forecasting, Artificial Neural network, AI techniques, Multilayer Perceptron

I. INTRODUCTION

Demand and sales forecasting is one of the most important functions of manufacturers, distributors, and trading firms. Keeping demand and supply in balance, they reduce excess and shortage of inventories and improve profitability. When the producer aims to fulfil the overestimated demand, excess production results in extra stock keeping which ties up excess inventory. On the other hand, underestimated demand causes unfulfilled orders, lost sales foregone opportunities and reduce service levels. Both scenarios lead to inefficient supply chain. Thus, the accurate demand forecast is a real challenge for participant in supply chain.(A.A. Syntetos et al., 2010)

The ability to forecast the future based on past data is a key tool to support individual and organizational decision making. In particular, the goal of Time Series Forecasting (TSF) is to predict the behavior of complex systems by looking only at past patterns of the same phenomenon.(J.H. Friedman et al.,1991) Forecasting is an integral part of supply chain management. Traditional forecasting methods suffer from serious limitations which affect the forecasting accuracy. Artificial neural network (ANN) algorithms have been found to be useful techniques for demand forecasting due to their ability to accommodate non- linear data, to capture subtle functional relationships among empirical data, even where the underlying relationships are unknown or hard to describe. (P.C. Chang et al.,2006), (R. Fildes et al.,2008) Demand analysis for a valve manufacturing industry which typically represents an make to order industry has been carried out using neural network based on different training methods and a comparative study has been presented.

Section 2 presents a critical view of past work on forecasting studies in SC and the use of ANN in demand forecasting. Section 3 describes the techniques used in the proposed methodology. A real-world case study from a valve manufacturing company is presented in Section 4. Section 5 gives the results of the neural techniques and empirical evaluations. Section 6 concludes this paper by giving important extensions and future directions of work.

II. LITERATURE

Qualitative method, time series method, and causal method are 3 important forecasting techniques. Qualitative methods are based on the opinion of subject matter expert and are therefore subjective. Time series methods forecast the future demand based on historical data. Causal methods are based on the assumption that demand forecasting is based on certain factors and explore the correlation between these factors.

Demand forecasting has attracted the attention of many research works. Many prior studies have been based on the prediction of customer demand based on time series models such as moving-average, exponential smoothing, and the Box-

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Jenkins method, and casual models, such as regression and econometric models.

There is an extensive body of literature on sales forecasting in industries such as textiles and clothing fashion (Y.Fan et al., 2011), (Z.L. Sun et al.,2008) ,books (K. Tanaka et al., 2010),and electronics (P.C. Chang et al.,2013). However, very few studies center on demand forecasting in industrial valve sector which is characterized by the combination of standard products manufactures and make to order industries.

Lee, Padmanabhan, and Whang (1997) studied bullwhip effect which is due to the demand variability amplification along a SC from retailers to distributors. Chen, Ryan, and Simchi-Levi (2000) analyzed the effect of exponential smoothing forecast by the retailer on the bullwhip effect. Zhao, Xie, and Leung (2002) investigated the impact of forecasting models on SC performance via a computer simulation model.

Dejonckheere et al.,(2003) demonstrated the importance of selecting proper forecasting techniques as it has been shown that the use of moving average, naive forecasting or demand signal processing will induce the bullwhip effect . Autoregressive linear forecasting, on the other hand, has been shown to diminish bullwhip effects, while outperforming naive and exponential smoothing methods (Chandra and Grabis, 2005).

Although the quantitative methods mentioned above perform well, they suffer from some limitations. First, lack of expertise might cause a mis-specification of the functional form linking the independent and dependent variables together, resulting in a poor regression (Tugba Efedil et al., 2008). Secondly an accurate prediction can be guaranteed only if large amount of data is available. Thirdly, non-linear patterns are difficult to capture. Finally, outliers can bias the estimation of the model parameters. The use of neural networks in demand forecasting overcomes many of these limitations. Neural networks have been mathematically demonstrated to be universal approximaters of functions(Garetti&Taisch, 1999).

Al-Saba et al. (1999) & Beccali, et al (2004), refer to the use of ANNs to forecast short or long term demands for electric load . Law (2000) studied the ANN demand forecasting application in tourism industry. Aburto and Weber (2007) presented a hybrid intelligent system combining autoregressive integrated moving average models and NN for demand forecasting in SCM and developed an inventory management system for a Chilean supermarket. Chiu and Lin (2004) demonstrated how collaborative agents and ANN could work in tandem to enable collaborative SC planning with a computational framework for mapping the supply, production and delivery resources to the customer orders. Kuo and Xue (1998) used ANNs to forecast sales for a beverage company. Their results showed that the forecasting ability of ANNs is indeed better than that of ARIMA specifications. Chang and Wang (2006) applied a fuzzy BPN to forecast sales for the Taiwanese printed circuit board industry. Although there are many papers regarding the artificial NN applications, very few studies center around application of different learning techniques and optimization of network architecture.

III. PROPOSED METHODOLOGY

A. *Demand forecasting.*

Traditional time series demand forecasting models are Naive Forecast, Average, Moving Average Trend and Multiple Linear Regression. The naive forecast which uses the latest value of the variable of interest as a best guess for the future value is one of the simplest forecasting methods and is often used as a baseline method against which the performance of other methods is compared. The moving average forecast is calculated as the average of a defined number of previous periods.. Trend-based forecasting is based on a simple regression model that takes time as an independent variable and tries to forecast demand as a function of time. The multiple linear regression model tries to predict the change in demand using a number of past changes in demand observations as independent variables..

B. Neural Network

Neural Networks (NNs) are flexible non-linear data driven models that have attractive properties for forecasting. Statistical methods are only efficient for data having seasonal or trend patterns, while artificial neural techniques can accommodate the data influenced by the special case, like promotion or extreme crisis demand fluctuation. (Nikolaos Kourentzes , 2013) Artificial intelligence forecasting techniques have been receiving much attention lately in order to solve problems that are hardly solved by the use of traditional methods. ANNs have the ability to learn like humans, by accumulating knowledge through repetitive learning activities. Animal brain's cognitive learning process is simulated in ANNs.

ANNs are proved to be efficient in modeling complex and poorly understood problems for which sufficient data are collected (Dhar & Stein, 1997). ANN is a technology that has been mainly used for prediction, clustering, classification, and alerting of abnormal patterns (Haykin, 1994). The capability of learning examples is probably the most important property of neural networks in applications and can be used to train

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network with the records of past response of a complex system (Wei, Zhang & Li, 1997).

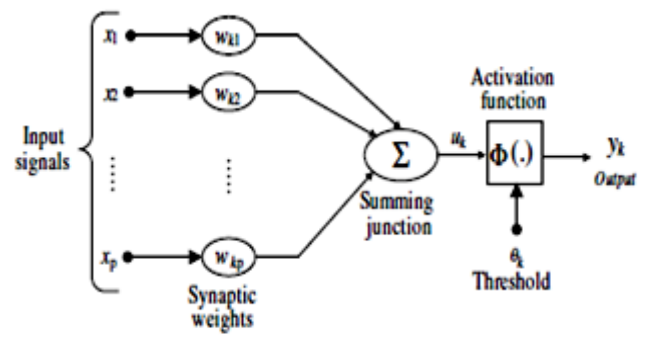

Fig.1 Non-Linear model of Neuron(Courtesy: Haykin, 1994.)

The basic element in an ANN is a neuron. The model of a neuron is depicted in Fig. 1 (Haykin, 1994). In mathematical terms, a neuron k can be described as in Eqs. (1) and (2):

$$u_k = \sum_{j=1}^{p} w_{kj} x_j \qquad \text{----\{1\}}$$

$$y_{k-\phi(u_k-\theta_k)} \qquad \text{------\{2\}}$$

where $x_1, x_2, \ldots, x_p$ are the input signals; $w_{k1}, w_{k2}, \ldots, w_{kp}$ are the synaptic weights of neuron k, and, u_k is the linear combiner output while θ_k denotes the threshold. Furthermore, $\emptyset$ is the activation function; and y_k is the output signal of the neuron (Haykin, 1994)

Of the different types of neural networks , most commonly used is the feed-forward error back-propagation type neural nets. In these networks, the individual elements neurons are organized into layers in such a way that output signals from the neurons of a given layer are passed to all of the neurons of the next layer. Thus, the flow of neural activations goes in one direction only, layer-by-layer. The smallest number of layers is two, namely the input and output layers. More layers, called hidden layers, could be added between the input and the output layer to increase the computational power of the neural nets. Provided with sufficient number of hidden units, a neural network could act as a 'universal approximator.(Real Carbonneau et. al. 2006)

Neural networks are tuned to fulfill a required mapping of inputs to the outputs using training algorithms. The common training algorithm for the feed-forward nets is called 'error back-propagation'(Rumelhart et al., 1986). The learning method can be divided into two categories, namely, unsupervised learning and supervised learning. Error back propagation method is supervised learning model where the error between the expected output and the calculated output is computed and minimized by adjusting the weights between two connection layers starting backwards from the output layer to input layer.

The correct number of hidden units is dependent on the selected learning algorithm. A greater quantity of hidden layers enables a NN model to improve its closeness-of-fit, while a smaller quantity improves its smoothness or extrapolation capabilities. (Choy et al., 2003). It was concluded that the number of hidden neurons is best determined by trial and error method . According to some literature studies, the number of hidden layer nodes can be up to 2n + 1 (where n is the number of nodes in the input layer), or 50% of the quantity of input and output nodes (Lenard, Alam, & Madey, 1995; Patuwo, Hu, & Hung, 1993; Piramuthu, Shaw, & Gentry, 1994)

C. *Back Propagation Training Algorithms*:

MATLAB tool box is used for neural network implementation for functional approximation for demand forecasting.

Different back propagation algorithms in use in MATLAB ANN tool box are:

- Batch Gradient Descent (traingd)
- Variable Learning Rate (traingda, traingdx)
- Conjugate Gradient Algorithms (traincgf, traincgp, traincgb, trainscg)
- Levenberg-Marquardt (trainlm)

1) *Batch Gradient Descent (Traingd)* : The batch steepest descent training function is traingd. The weights and biases are updated in the direction of the negative gradient of the performance function. There are seven training parameters associated with traingd: epochs, show, goal, time, min_grad, max_fail, and lr. The learning rate lr is multiplied times the negative of the gradient to determine the changes to the weights and biases.

*2) Variable Learning Rate (Traingda)***:** With standard steepest descent, the learning rate is held constant throughout training. The performance of the algorithm is very sensitive to the proper setting of the learning rate. If the learning rate is set too high, the algorithm may oscillate and become unstable. If the learning rate is too small, the algorithm will take too long to converge. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface.

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The performance of the steepest descent algorithm can be improved if the learning rate is adjusted during the training process. An adaptive learning rate will attempt to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface. (Mathworks, 2000)

3). Conjugate Gradient Algorithms (Traincgf) : The basic back propagation algorithm adjusts the weights in the steepest descent direction (negative of the gradient). This is the direction in which the performance function is decreasing more rapidly. It turns out that, although the function decreases more rapidly along the negative of the gradient, this does not necessarily produce the fastest convergence. In the conjugate gradient algorithms a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. Depending on the search functions we have different training algorithms like traincgf, traincgp, traincgb, trainscg. (Mathworks, 2000)

4). Levenberg-Marquardt Algorithm (trainlm): Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed forward networks), then the Hessian matrix can be approximated as

$$H = J^{T}J$$

and the gradient can be computed as

$$G = J^{T}e$$

where is J the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The Jacobian matrix can be computed through a standard back propagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update

$$X_{k+1}=X_{k} - [\, J^{T}J+\mu I]^{-1}\, J^{T}e$$

This algorithm appears to be the fastest method for training moderate-sized Feed forward neural networks (up to several hundred weights). It also has a very efficient MATLAB implementation, since the solution of the matrix equation is a built-in function, so its attributes become even more pronounced in a MATLAB setting. (Mathworks, 2000)

IV. EMPIRICAL EVALUATION

The real time data for the inventory management of an existing valve manufacturing company will be used to validate the concepts on the demand forecasting .

A. *Data set and forecasting variable*

The company under study is a pioneer in the Indian valve industry and has developed innovative and high quality products for various applications. The company produces more than fifty types of valve assemblies of different valve types, gate valve, ball valve, globe valve, check valve etc. Among this wide product range, one of fast moving items is earmarked for the demand forecasting analysis. 10’’X 150 class gate valve –GTV 101 series is selected for study. Past historical bimonthly sales data from 2001 till 2012 for these product category is compiled. This group of 72 data items will form the time series for forecasting the demand for these types of valves. This data will be divided into 2 parts, one for training the ANN and other for testing and validation.

TABLE1.

SAMPLE OF BI-MONTHLY SALES DATA FOR 10’’X 150 GTV 101

Year	Month	Domestic Sales Qty (Nos)
200	Jan-Feb	48
	Mar-April	64
	May-June	52
	July-Aug	42
	Sept-Oct	55
	Nov-Dec	70
2002	Jan-Feb	65
	Mar-April	63
	May-June	76
	July-Aug	66
	Sept-Oct	63
	Nov-Dec	70
2003	Jan-Feb	60
	Mar-April	42
	May-June	40
	July-Aug	44
	Sept-Oct	55

B. *Forecasting variable*

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MATLAB ANN tool box is used for neural network implementation for functional approximation of demand forecasting.
Input for the neural network demand forecasting model:

1. Previous bimonthly sale
2. 2^{Nnd} previous bimonthly sale (sales of last 3^{rd} and 4 th month)
3. Moving average of last 2 bimonthly sales
4. Moving average of last 3 bimonthly sale

Output of neural network is the forecasted demand for the next bimonthly sale. Mfile programs are written for demand forecasting using ANN MLP model using different training methods.

TABLE 2.

IDENTIFICATION OF OPTIMUM NUMBER OF NUERONS FOR MLP

No. of nodes	Mean Square Error
2	0.70
3	0.71
5	0.59
7	0.28
8	0.25
10	0.22
12	0.20
14	0.04
15	0.13
16	0.07
17	0.07
18	0.01
20	0.004
22	0.06
24	0.15
26	0.34

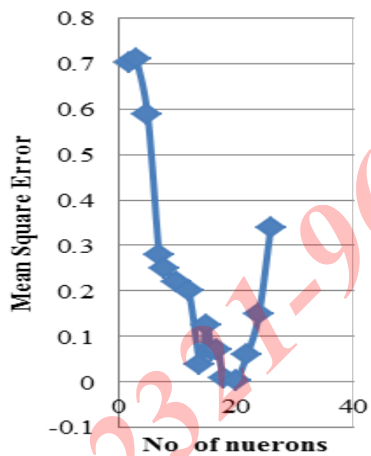

Fig 1. Identification of optimum no. of neurons

C. *Procedure for demand forecasting calculation*:

- Run the program using the training method trainlm and optimize the number of nodes in the hidden layer where we will achieve the training goal or very good mean square error performance.
- For this number of hidden nodes , run the program using different learning algorithms like TRAINLM, TRAINGD, TRAINGDA.
- Tabulate the test data , that is the actual quantity and forecasted test data result. Find the mean absolute error.
- Compare the \mean absolute percentage error from all the above training methods.

Using TRAINLM method, optimum number of neurons is computed. Table 2 lists Mean Square Error for different number of neurons and it is identified that the MSE is minimum for 20 nuerons. By means of many trial and error experiments ,the proper parameters are chosen as following:
Number of neurons in hidden layer = 20
Learning rate = 1.0.
Momentum = 0.8.
Number of epochs=1000.

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TABLE 3
10 X 150 GTV101 ACTUAL SALES Vs.
DEMAND FORECAST MLP (TRAINLM METHOD)

Actual Sales (Qty)	Forecast Demand(Qty)	Relative Error(%)
63	64.772	2.81
44	41.36	6.00
62	59.23	4.47
54	50.20	2.67
68	64.28	5.47
56	51.55	7.95
74	71.58	3.27
70	75.26	3.81
65	67.34	3.60
55	53.43	2.85
56	57.76	3.14
45	42.36	0.09
56	53.78	3.96

TABLE 4
10 X 150 GTV101 ACTUAL SALES Vs.
DEMAND FORECAST MLP (TRAINGD METHOD)

Actual Sales (Qty)	Forecast Demand(Qty)	Relative Error(%)
63	63.13	0.20
44	54.69	24.29
62	66.00	6.44
54	57.68	6.82
68	64.40	5.29
56	71.20	27.15
74	58.91	20.39
70	57.66	17.64
65	55.27	14.97
55	53.67	2.41
56	51.36	8.29
45	52.43	16.52
56	56.85	1.51

TABLE 5
10 X 150 GTV101 ACTUAL SALES Vs.
DEMAND FORECAST MLP (TRAINGDA METHOD)

Actual Sales (Qty)	Forecasted Demand(Qty)	Relative Error(%)
63	58.03	7.89
44	60.17	-36.75
62	69.39	-11.92
54	62.91	-16.51
68	61.33	9.81
56	63.41	-13.23
74	58.64	20.76
70	57.64	17.66
65	57.05	12.24
55	54.81	0.34
56	45.99	17.87
45	56.35	-25.22
56	58.82	-5.03

TABLE 6
10 X 150 GTV101 ACTUAL SALES Vs.
DEMAND FORECAST MLP (TRAINCGF METHOD)

Actual Sales (Qty)	Forecast Demand(Qty)	Relative Error(%)
63	63.66	1.05
44	58.00	31.82
62	50.63	18.34
54	61.37	13.65
68	71.29	4.84
56	52.21	6.77
74	53.52	27.67
70	68.59	2.01
65	61.12	5.98
55	53.85	2.10
56	53.01	5.33
45	51.59	14.65
56	62.06	10.82

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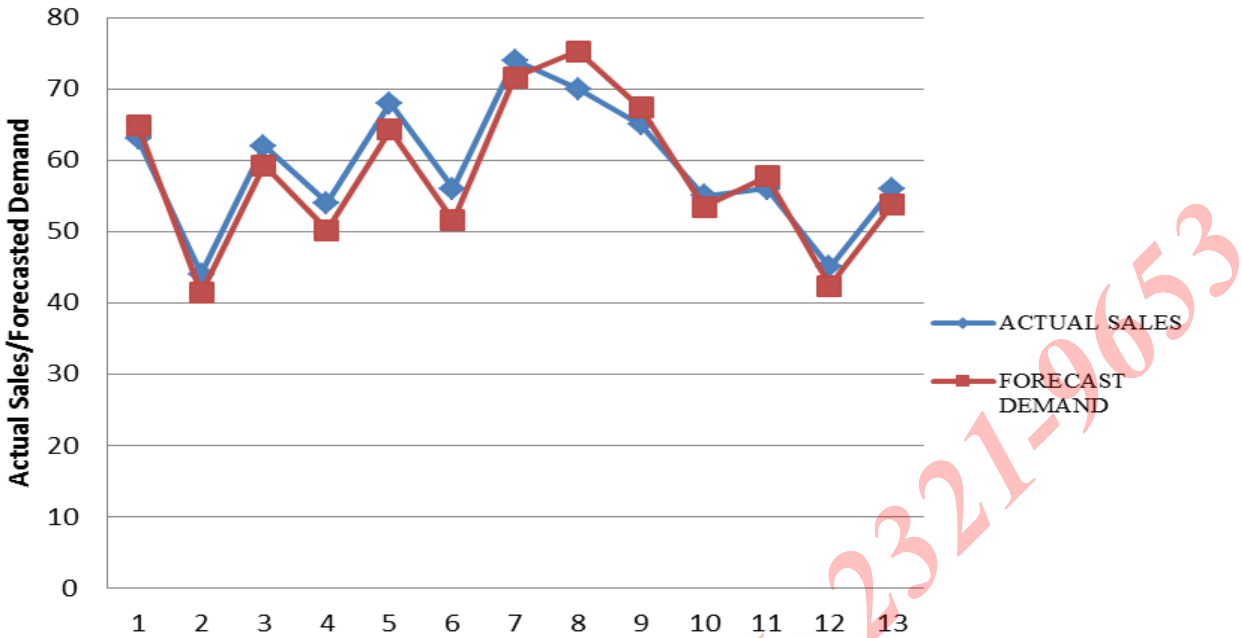

Fig 3. Actual sales vs. Demand forecast using MLP (Trainlm Method)

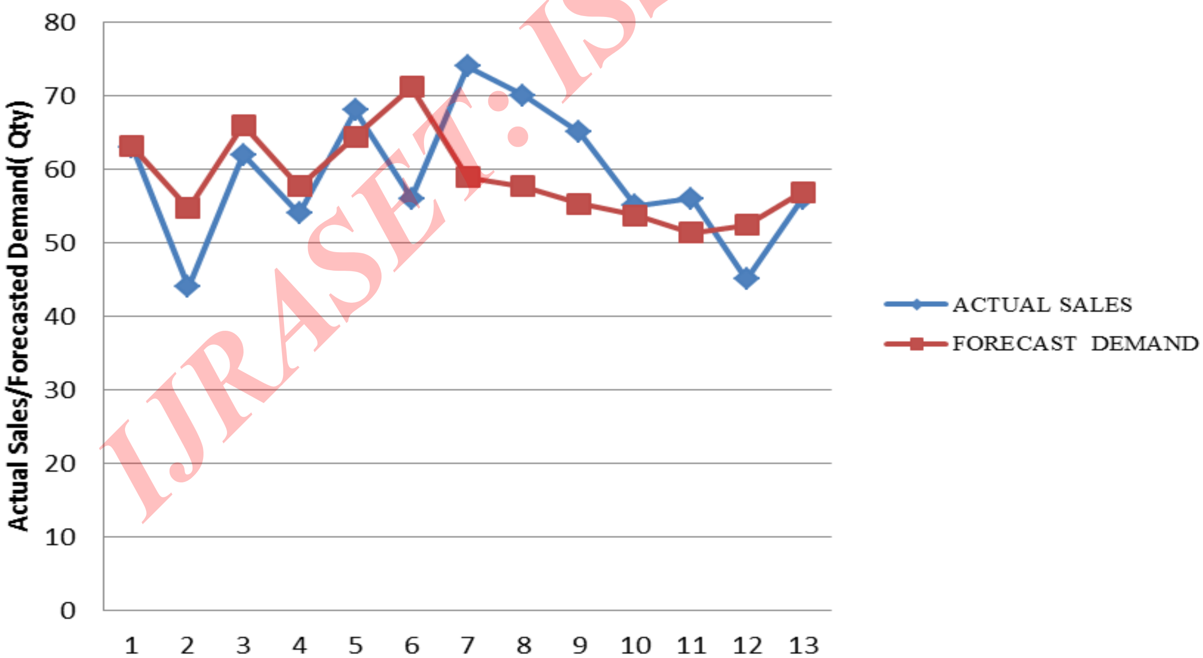

Fig 4. Actual sales vs. Demand forecast using MLP (Traingd Method)

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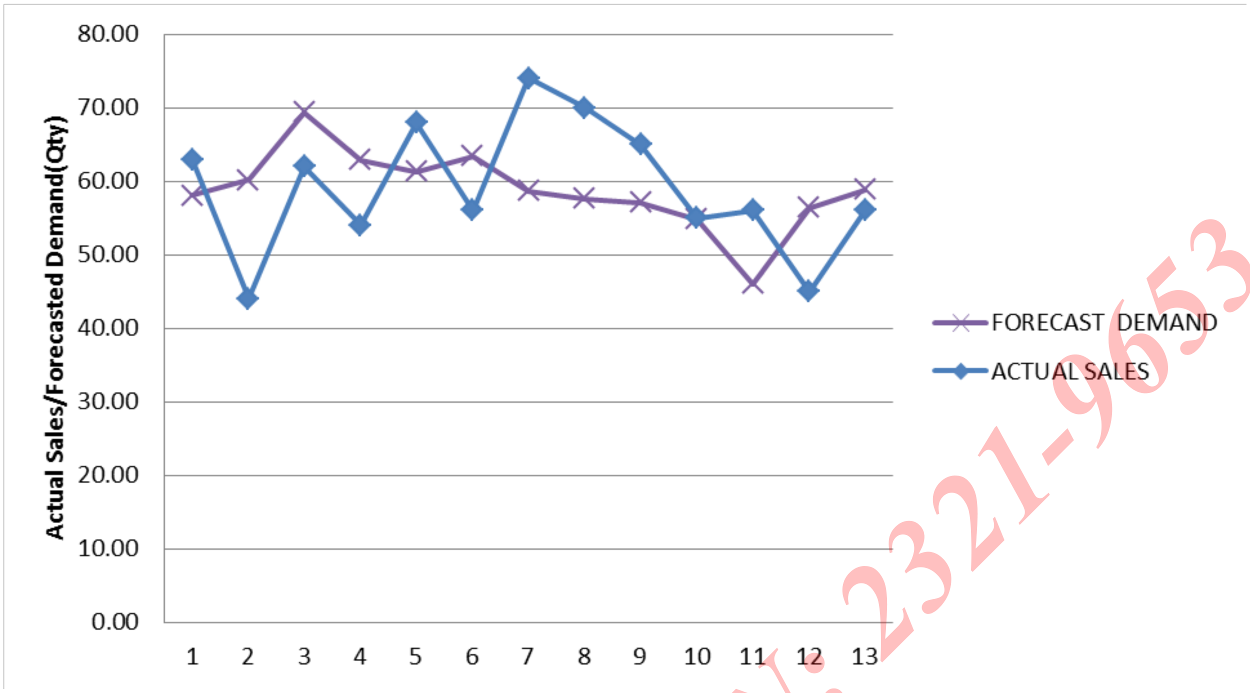

Fig 5. Actual sales vs. Demand forecast using MLP (Traingda Method)

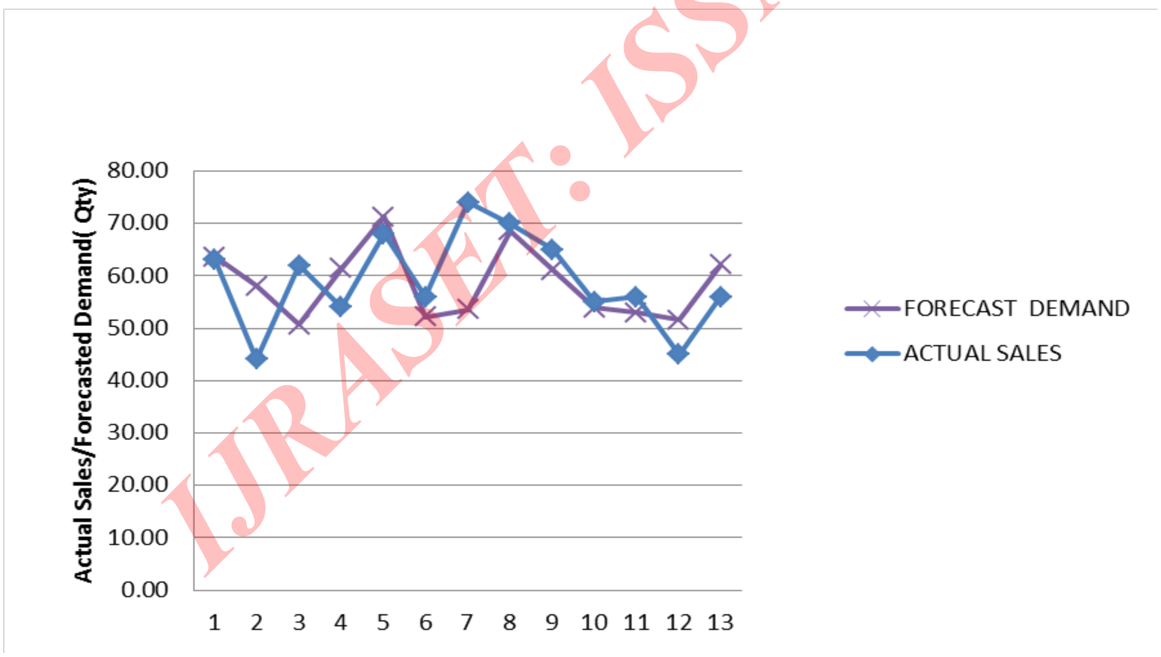

Fig 6. Actual sales vs. Demand forecast using MLP (Traincgf Method)

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TABLE 7
ANALYSIS OF RESULTS USING DIFFERENT ANN TRAINING METHODS FOR DEMAND FORECASTING

Method Of Forecasting	Mean Absolute Error(%)
MLP - TRAINLM	4.91
MLP- TRAINGD	11.69
MLP- TRAINGDA	15.02
MLP- TRAINCGF	11.16

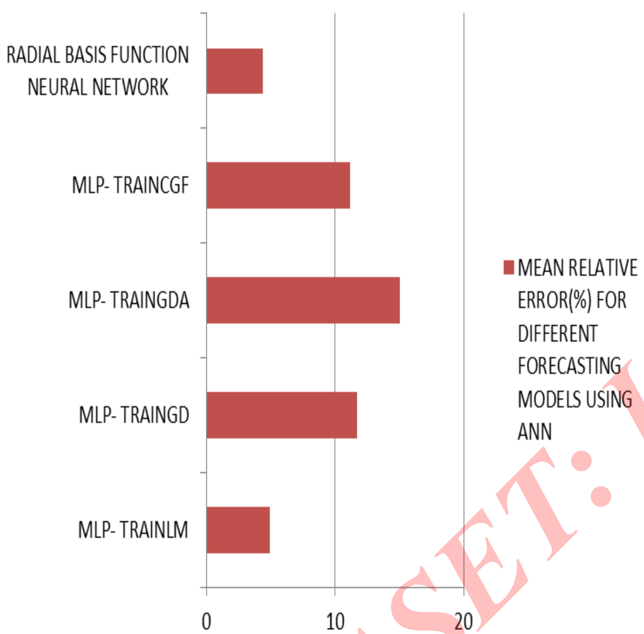

Fig 7 . Mean Absolute Error (%) in demand forcast for different training using ANN

V. RESULTS AND VALIDATION

The network is trained using different training methods. Table 2 to table No. 6 tabulate the test result using the training methods TRAINLM, TRAINGD, TRAINGDA & TRAINCGF. These results are graphically represented in Fig 3 to Fig 6. Average absolute error of each training method is listed in table 7 which compares the predictive accuracy of the different ANN training models. Fig 7 is a bar chart representation of Mean absolute error. Overall, the performance of TRAINLM training method has been significantly better than that of other training methods

VI. CONCLUSION

The objective of this research was to study the effectiveness of forecasting the demand signals in the supply chain with ANN method and identify the best training method.. This study has developed a comparative forecasting mechanism based on ANN and different training methods. To demonstrate the effectiveness of the proposed methodology, demand forecasting issue was investigated on a valve manufacturing company as a real-world case study. Evaluation results indicate that TrainLM method performs more effectively than other training methods in estimation of the more reliable forecasts for our case. The ability to increase forecasting accuracy will result in lower costs and higher customer satisfaction because of more on-time deliveries. The proposed methodology can be considered as a successful decision support tool in forecasting customer demands. Future research can explore the possibility of using other ANN types like radial basis neural networks to make a similar approach and better the accuracy of prediction.

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