ARTIFICIAL NUERAL NETWORK APPROACH TO INDUSTRIAL DEMAND FORECAST

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Abstract: An efficient and accurate demand forecast becomes imperative for enhancement of commericial competitive advantage at al the stages of supply chain , escpically in the absence of collaborative supply chain management.Procurement decisions in the upstream supply chain to buy right quantity at right time for effective inventory management decisions depend on the accurate prediction of demand The objective of the paper is to propose a forecasting technique which is modelled 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.

Keywords: Demand forecasting, Artificial Neural network, AI techniques, Multilayer Perceptron, Radial Basis Network

I. INTRODUCTION

Demand forecast is one of the most pivotal functions of the organisation. In Upstream side of supply chain Sound and accurate forecast helps to make the important inventory management decision of when to buy and how much to buy Keeping demand and supply in balance, effective forecast reduce excess and shortage of inventories and improve profitability. The overestimated demand results in excess production which in turn leads to extra stock keeping locking up of undesirable and unproductive inventory. On the other hand, underestimated demand causes unfulfilled orders, foregone sales, lost opportunities and reduced customer satisfaction. Either overestimated or underestimated demand will 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 major decisions on all organization functions like procurement, manufacturing, logistics, marketing, financial planning, etc. are all dependent on the forecasted results. Hence, to reduce the impact of demand uncertainty on the overall profitability of an organization, effective forecasting mechanism is very essential. The cability to forecast the future based on historical data is an important 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.[1] accurate demand forecast is a real challenge for participant in supply chain [2].

Forecasting techniques can be broadly classified under 3 heads: Qualitative method, time series method, and causal method. Qualitative methods are highly subjective and depends on the opinion of subject matter expert. Time series methods forecast the future demand based on historical data. Causal methods are aimed at exploring the correlation between different factors on which the demand depends.

Due to its strategic importance in the organizational functions, demand forecasting has attracted the attention of many research works. Many prior studies have explored the suitability of forecasting customer demand based on been based on the prediction of customer demand based on time series models such as moving-average, exponential smoothing, and the Box-Jenkins method, and casual models, such as regression and econometric models.
When Traditional forecasting methods are used forecasting accuracy achieved is very is limited .Many research workers have tried to adopt different algorithms and novel techniques to overcome the limitation of limited forecasting accuracy.
Artificial neural network (ANN) algorithms, which is one of the important Artificial Intelligence Techniques, has been found to be useful tool for demand forecasting due to its 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. [3][4]. In this study, an industrial valve manufacturing company has been chosen for demand analysis. The data has been used to carry out demand forecast using neural network based on Multi layer Perceptron algorithm. The results have been compared with demand forecast obtained from traditional techniques.

II. PROPOSED METHODOLOGY

2.1 Demand forecasting

Naive Forecast, Average, Moving Average, Trend and Multiple Linear Regression are some of Traditional time series demand forecasting models. The naive forecast is simplest and the most straight forward forecasting model which uses the latest value of the variable of interest as a best estimate for the future value. Naïve forecasting is used a s reference method to evaluate the performance of the other different forecasting techniques. The average of a defined number of previous periods will give the moving average forecast. 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 models try to predict the change in demand using a number of past changes in demand observations as independent variables.

2.2 Artificial Neural Network

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 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. [5]. 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 [6].ANN is a technology that has been mainly used for prediction, clustering, classification, and alerting of abnormal patterns [7]. The capability of learning examples is probably the most important property of neural networks in applications and can be used to train a neural network with the records of past response of a complex system [8].

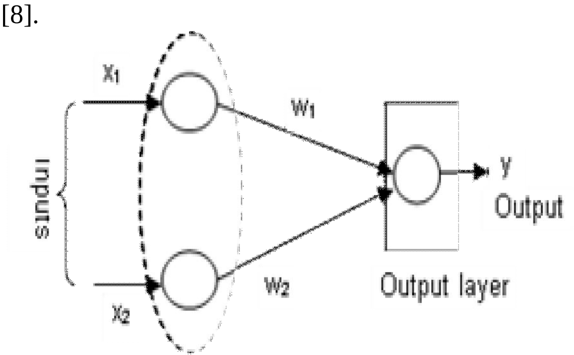

Fig.1 Non-Linear model of Neuron (Courtesy: Haykin, 1994.)

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 element 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[9]

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. [10].. 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 [11].

1.3 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)

The Levenberg-Marquardt algorithm appears to be the fastest and most efficient method for training moderate-sized Feed forward neural networks.

1.4 Radial Basis network

This section presents an overview of radial basis function neural networks and their application for prediction of product demand.

Radial basis function (RBF) networks are feed-forward networks trained using supervised training algorithm.

They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function hidden units.

Popularized by Moody and Darken (1989), RBF networks have proven to be a useful neural network architecture. The major difference between RBF networks and back propagation networks (that is, multi layer perceptron trained by Back Propagation algorithm) is the behavior of the single hidden layer.

III. 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.

3.1. Dataset for demand forecast

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 for this product category is compiled. This group of 72 data items will form the time series for forecasting the demand for these types of valves. Table 1 shows the sample data collected. This data will be divided into 2 parts, one for training the ANN and other for testing and validation.

It is considered that time series and historical demand of the valves will reflect on the effect of all parameters based on which the demand can be arrived at.

3.2 Forecasting variable

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 programmes are written for demand forecasting using ANN MLP model and RBF network.

IV. RESULTS AND DISCUSSION

Using TRAINLM method, optimum number of neurons is computed. Fig. 2 shows the Mean Square Error for different number of neurons and it is identified that the MSE is minimum for 20 neurons. Following parameters are used for calculation:

Number of neurons in hidden layer = 20
Learning rate = 1.0.
Momentum = 0.8.

Table 1. Sample of Bi-monthly Sales Data for 6''X 150 GTV 102

Year	Month	Domestic Sales Qty (Nos)
200	Jan-Feb	162
	Mar-April	194
	May-June	168
	July-Aug	150
	Sept-Oct	193
	Nov-Dec	220
2002	Jan-Feb	202
	Mar-April	156
	May-June	159
	July-Aug	165
	Sept-Oct	110
	Nov-Dec	190
2003	Jan-Feb	195
	Mar-April	126
	May-June	125
	July-Aug	136
	Sept-Oct	95
	Nov-Dec	119
2004	Jan-Feb	138
	Mar-April	196
	May-June	159

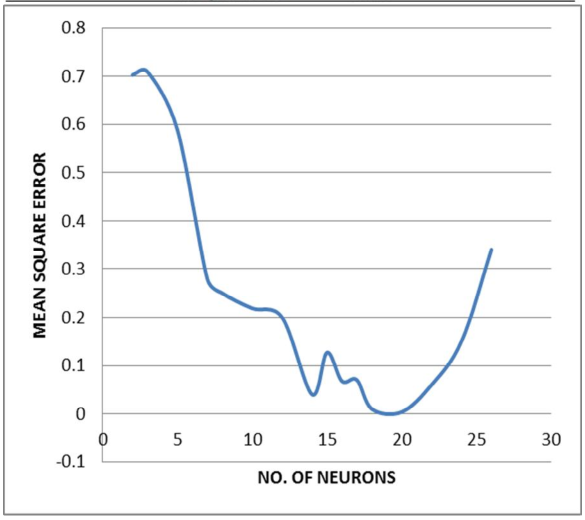

Fig 1. Identification of optimum no. of neurons

Number of epochs=1000.
Using the above parameters, and experimental data set the neural network is trained. Out of the data set, 13values are taken for testing. Similarly forecast values are computed using MATLAB tool box using RBF network and results are tabulated as shown below.

Mean absolute error is calculated between the actual sales and forecast sales using the output obtained by running M-file programme. The results of forcast are presented in the form of tables and graphs comparing the forecast error using MLP and RBF

Table 2. 6" X 150 GTV102 Actual Sales Vs. Demand Forecast Using MLP (Trainlm Method)

Table 2 shows the actual sales, forecast demand quantity for the corresponding period using ANN method. The table also lists the percentage absolute error.

Actual Sales (Qty)	Forecast Demand(Qty)	Absolute Error(%)
150	157.25	4.83
159	166.55	4.75
195	186.21	4.51
119	127.2	6.89
155	162.76	5.01
170	164.27	3.37
125	118.67	5.06
135	139.6	3.41
165	176.5	6.97
150	158	5.33
159	166.5	4.72
145	152.27	5.01
148	156.78	5.93

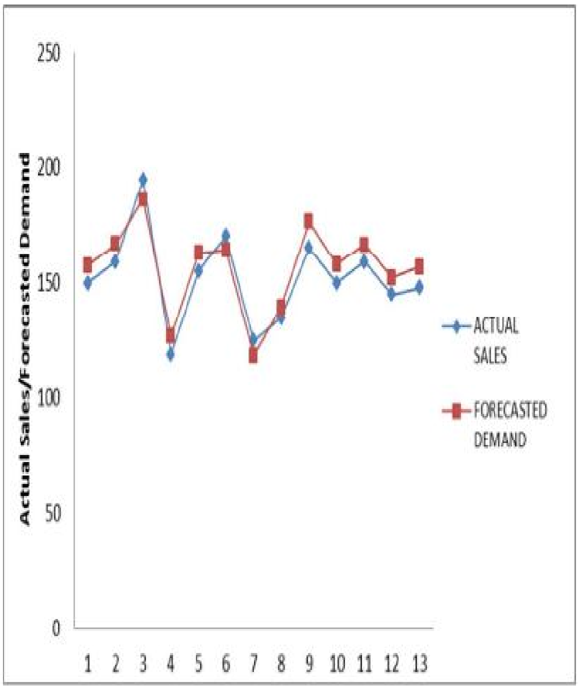

Fig 2. Actual sales vs. Demand forecast using MLP (Trainlm Method)

Fig 2 shows the actual sales and forecast demand for the 13 time periods which are used as test data in the ANN modeling.

Table 3. 6" X 150 GTV102 Actual Sales Vs. Demand Forecast Using RBF network

Actual Sales (Qty)	Forecast Demand(Qty)	Absolute Error(%)
150	156.96	4.64
159	164.35	3.36
195	188.36	3.41
119	125.68	5.61
155	160.91	3.81
170	164.54	3.21
125	118.43	5.26
135	140.15	3.81
165	173.28	5.02
150	156.66	4.44
159	164.35	3.36
145	155.46	7.21
148	154.28	4.24

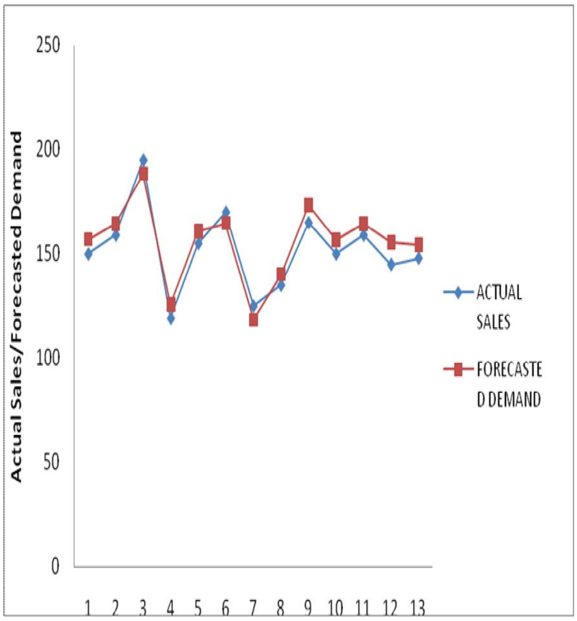

Fig 3. Actual sales vs. Demand forecast using RBF network .

Demand forecast calculations are also done using two of traditional methods – 3 period moving averages and multiple regression method. Fig 4. Compares the absolute error of prediction using MLP, RBF and other two traditional methods.. It is clear that prediction accuracy is far higher in the case of ANN method than the traditional methods. It is observed that Radial Basis Function Neural Network gives the best forecasting accuracy due to the network architecture

Table 3 .Analysis Of Results Using ANN training Methods and traditional Demand Forecasting technique

Method Of Forecasting	Mean Absolute Error(%)
ANN Forecast with RBF architecture	4.42
ANN Forecast (MLP architecture)	4.91
3 Period Moving Average	9.69
Multiple Regression	8.02

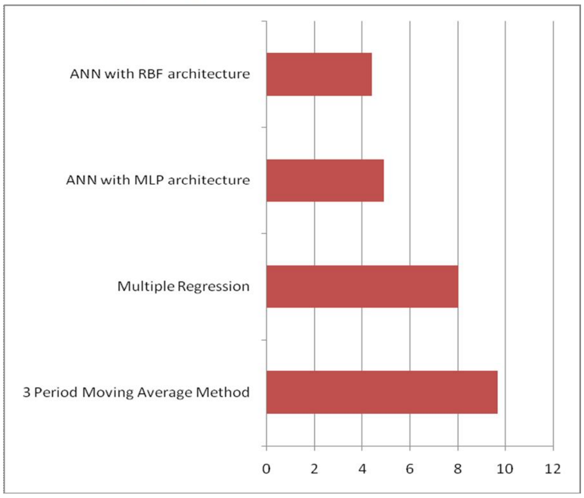

Fig 4. Comparison of prediction accuracy of ANN demand forecast with traditional methods

CONCLUSION

The objective of this research was to study the effectiveness of forecasting the demand signals in the supply chain with ANN method and compare the prediction accuracy with traditional demand forecast 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 ANN method performs more effectively than traditional forecasting methods in estimation of the more reliable predictions for our case. It is observed that Radial Basis Function Neural Network gives the best forecasting accuracy due to the network architecture. 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 recurrent neural networks to make a similar approach and better the accuracy of prediction.

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