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FORECASTING OF DEMAND USING ARTIFICIAL NEURAL NETWORK FOR SUPPLY CHAIN MANAGEMENT

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ABSTRACT

The demand forecasting technique which is modeled by artificial intelligence approaches using artificial neural networks. The consumer product causers the difficulty in forecasting the future demand and the accuracy of the forecast In performance of the artificial neural network an advantage in a constantly changing business environment and demand forecasting an organization in order to make right decisions regarding manufacturing and inventory management. The learning algorithm of the prediction is also imposed to better prediction of time series in future. The prediction performance of recurrent neural networks a simulated time series data and a practical sales data have been used. This is because of influence of several factors on demand function in retail trading system. It was also observed that as forecasting period becomes smaller, the ANN approach provides more accuracy in forecast.

Keywords: Demand Forecasting, Artificial Neural Network, Time Series Forecasting

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 reduces service levels. Both scenarios lead to inefficient supply chain. Thus, the accurate demand forecast is a real challenge for participant in supply chain. 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. 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. Demand analysis for a valve manufacturing industry which typically represents a make to order industry has been carried out using neural network based on different training methods. A company may hold inventories of raw materials, parts, work in process, or finished

products for a variety of reasons, such as the following. To create buffers against the uncertainties of supply and demand; To take advantage of lower purchasing and transportation costs associated with high volumes; To take advantage of economies of scale associated with manufacturing products in batches; To build up reserves for seasonal demands or promotional sales; To accommodate product flowing from one location to another (work in process or in transit).

II. LITERATURE REVIEW

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 assumptions that demand forecasting are 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 movingaverage, exponential smoothing, and the BoxJenkins 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 (Sun et al., 2008; and Fan et al., 2011), books (Tanaka et al., 2010), and electronics (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 et al. (1997) studied bullwhip effect which is due to the demand variability amplification along a SC from retailers to distributors. Chen et al. (2000) analyzed the effect of exponential smoothing forecast by the retailer on the bullwhip effect. Zhao et al. (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 (TugbaEfedil 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 approximates of functions (Garetti and Taisch, 1999). Al-Saba et al. (1999) and 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. Abort 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. KuoandXue (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. hang 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 (Jeremy Shapiro, 2001).

III. METHODOLOGY

In the present research work new outline of investigation using Neural Network, this technique is planned to investigate the influence of demand forecasting to predictions of next year consumptions for the average.The demand forecasting is done by ANN method. 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.

3.1 Artificial Neural Network

In This project is used ANN method. The development of ANN based on studying the relationship of input variables and output variables basically the neural architecture consisted of three or more layers, input layer, output layer and hidden layer. The function of this network was described as follows.

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in the signal flow from inputs x_1 , ..., $x_n$is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (O). The neuron output signal O is given by the following relationship.

$$O = f(net) = f\left[\sum_{j=1}^{n} w_j \,.\, x_j\right] \ldots\ldots\ldots (1)$$

wherew_j is the weight vector, and the function f(net) is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors,

$$net = W_X^T = W_1 X_1 + \cdots . WnXn \ldots..(2)$$

where T is the transpose of a matrix, and, in the simplest case, the output value O is computed as:

$$O = f(net) = \begin{cases} 1 & W^T X \geq \theta \\ 0 & otherwise \end{cases} \ldots(3)$$

whereθ is called the threshold level; and this type of node is called a linear threshold unit. In 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

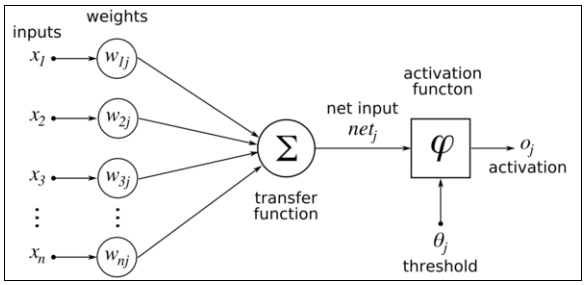

Figure 1: Artificial Neuron

3.2 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)

3.3 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:

$H = J^T J$ ……..(4)

And the gradient can be computed as

$G = J^T e$ ……..(5)

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.

$X_{(k+1)}=X_k -[J^T J +\mu I]^{-1} J^T e$ ……....(6)

This algorithm appears to be the fastest method for training moderate-sized Fed 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.

IV. RESULTS

The monthly sales data of the distributor, between the years of 2011-2013, are used to train the networks as inputs and outputs, and then the demand pattern forecasts for 12 months of 2014 are made based on time series analysis. Matlab 7.0 is used for ANN simulation. We have a product data available from 2011 to 2013. The data of fuel filter available from privious year 2011 to 2013 in above table, privious data alrady consumed in large company, and month wise data consumptions are show in above table and find the next year data for the supply

chain managment, now we will first all consider the base year data of 2011 in 12th month to calculate next year data of 2012 but 2012 data are available but can not consider as a forecasting data only consider as a target data.

Table 1: Product Data of Fuel Filter for the Year 2011 to 2013

Month	Year		
	2011	2012	2013
January	53	69	72
February	58	63	75
March	59	65	72
April	62	70	79
May	63	69	80
June	56	72	78
July	59	64	76
August	61	71	69
September	63	75	86
October	64	76	90
November	61	73	92
December	59	75	89
TOTAL	718	842	958

To calculate the forecasting error between actual data of 2012 and forecasting data 2013 and also formula available for the calculating of forecasting error in MATLAB coding.

Forecasting r =abs(frcst-target')and also calculate the percetage error using formula are pe=(forecasting r/target)*100;

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Table 2: Prediction of Next Year Consumptions (2013)

S. No.	Month	Base Year Data (2011)	Forecasting Data (2013)	Target Data (2012)	Forecasting Error	% Error
1.	JANUARY	53.0	68.70	69.0	0.29	0.42
2.	FEBRUARY	58.0	62.67	63.0	0.32	0.51
3.	MARCH	59.0	65.44	65.0	0.44	0.69
4.	APRIL	62.0	67.99	70.0	2.00	2.86
5.	MAY	63.0	71.03	69.0	2.03	2.94
6.	JUNE	56.0	71.56	72.0	0.43	0.59
7.	JULY	59.0	64.11	64.0	0.11	0.18
8.	AUGUST	61.0	70.07	71.0	0.92	1.29
9.	SEPTEMBER	63.0	74.94	75.0	0.05	0.07
10.	OCTOBER	64.0	75.77	76.0	0.22	0.29
11.	NOVEMBER	61.0	75.33	73.0	2.33	3.19
12.	DECEMBER	59.0	65.21	75.0	9.78	13.04

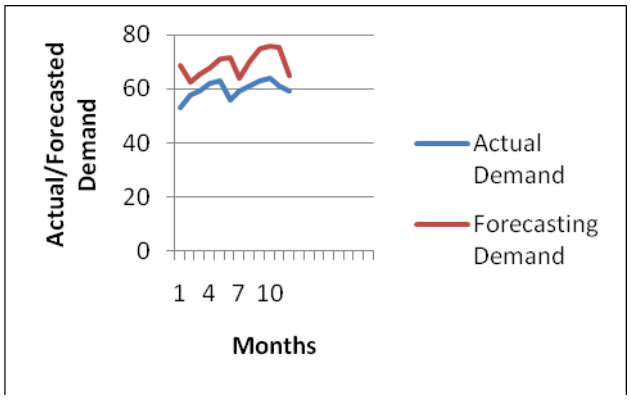

Figure 2: Graph Plotted between Actual Demand and Forecasting Demand

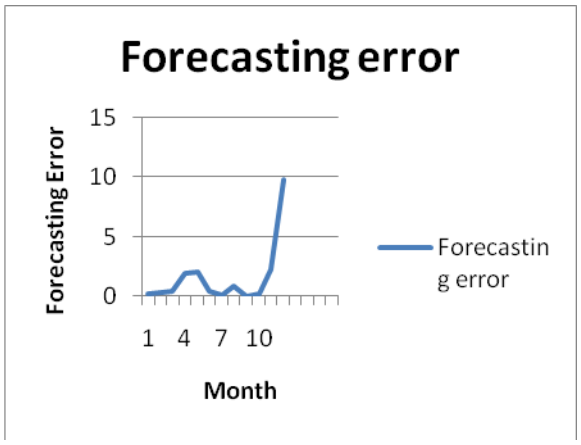

Figure 3: Forecasting Error with Respect Month

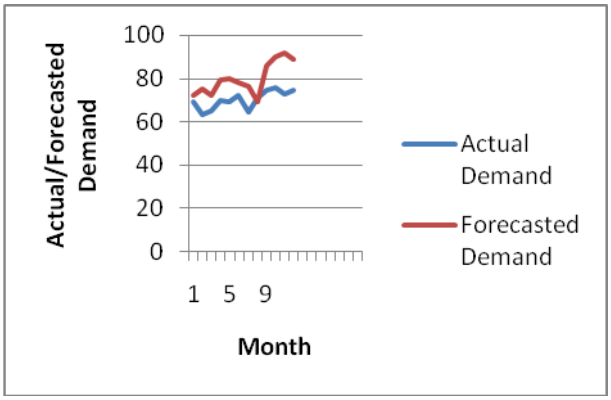

Figure 4: Graph Plotted Between Actual Demand and Forecasting Demand

V. CONCLUSION

In this project we have observed performance of product demand forecasting. The project is consumer product for future average. 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 cooperative forecastingmechanism based on ANN and training methods. The proposed methodology, demand forecasting issue was investigated on a manufacturing company as a real-world case study. The result indicates a TrainLM method performs more effectively than the other tanning method and the more reliable forecast for our case. The proposed methodology can be considered as a successful decision support tool in forecasting. The ability to increase forecasting accuracy will result. Future research can possibility of using Artificial Neural Network to make a similar approach and better the accuracy.

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