



Research Paper

DEMAND FORECASTING USING NEURAL NETWORK FOR SUPPLY CHAIN MANAGEMENT

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The demand forecasting technique which is modeled by artificial intelligence approaches using artificial neural networks. The consumer product causes 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

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

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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).

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 moving-average, exponential smoothing, and the Box-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 (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 (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 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. 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. 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).

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.

Demand Forecasting

The demand forecasting is use 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.

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, \dots, 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.

$$O = f(\text{net}) = f\left(\sum_{j=1}^n w_j x_j\right) \quad \dots(1)$$

where w_j is the weight vector, and the function $f(\text{net})$ is referred to as an activation (transfer) function. The variable net is defined as a scalar product of the weight and input vectors,

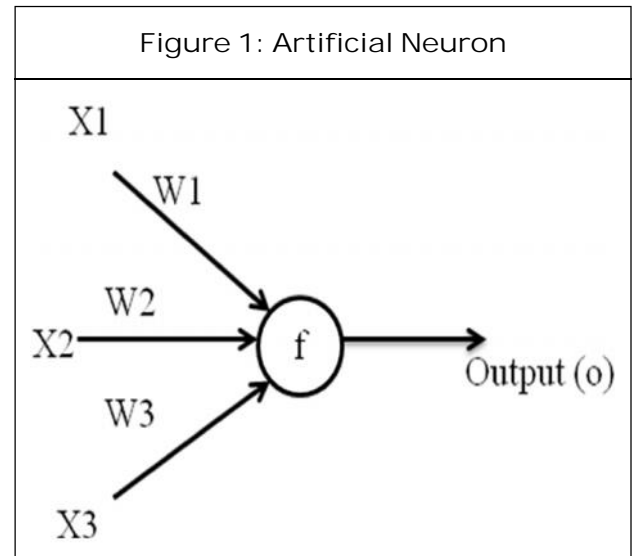
$$\text{net} = w_x^T = w_1 x_1 + \dots + w_n x_n \quad \dots(2)$$

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

$$O = f(\text{net}) = \begin{cases} 1 & w^T x \geq \mu \\ 0 & \text{Otherwise} \end{cases} \quad \dots(3)$$

where μ 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. 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 approximate.

Back Propagation Training Algorithms

MATLAB toolbox is used for neural network implementation for functional approximation for demand forecasting. Different back propagation algorithms in use in MATLAB ANN toolbox are:

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

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:

$$H = J^T J \quad \dots(4)$$

And the gradient can be computed as

$$G = J^T e \quad \dots(5)$$

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.

$$X_{k+1} = X_k - [J^T J + \lambda I]^{-1} J^T e \quad \dots(6)$$

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.

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 previous year 2011 to 2013 in above table, previous data already consumed in large company, and

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

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.

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 $r = \text{abs}(\text{frcst} - \text{target})$ and also calculate the percentage error using formula are

$$pe = (\text{forecasting } r / \text{target}) * 100;$$

The data of fuel filter available from previous year 2011 to 2013 in above table, previous data already consumed in large company, and month wise data consumptions are show in above table and find the next year data for the

S. No.	Month	Base Year Data (2011)	Forecasting Data (2013)	Target Data (2012)	Forecasting Error	% Error
1.	Jan	53.0	68.70	69.0	0.29	0.42
2.	Feb	58.0	62.67	63.0	0.32	0.51
3.	Mar	59.0	65.44	65.0	0.44	0.69
4.	Apr	62.0	67.99	70.0	2.00	2.86
5.	May	63.0	71.03	69.0	2.03	2.94
6.	Jun	56.0	71.56	72.0	0.43	0.59
7.	Jul	59.0	64.11	64.0	0.11	0.18
8.	Aug	61.0	70.07	71.0	0.92	1.29
9.	Sep	63.0	74.94	75.0	0.05	0.07
10.	Oct	64.0	75.77	76.0	0.22	0.29
11.	Nov	61.0	75.33	73.0	2.33	3.19
12.	Dec	59.0	65.21	75.0	9.78	13.04

Figure 2: Graph Plotted Between Actual Demand and Forecasting Demand

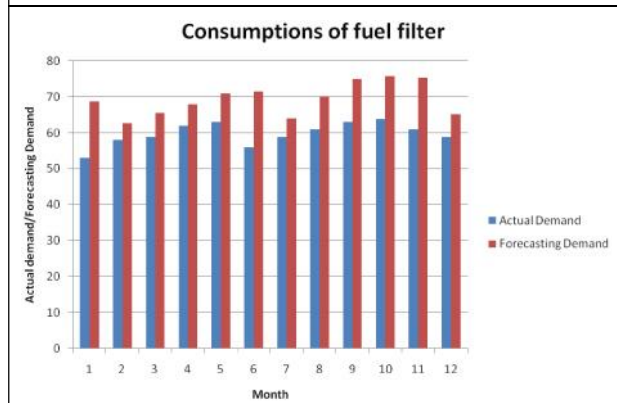


Figure 4: Graph Plotted Between Actual Demand and Forecasting Demand

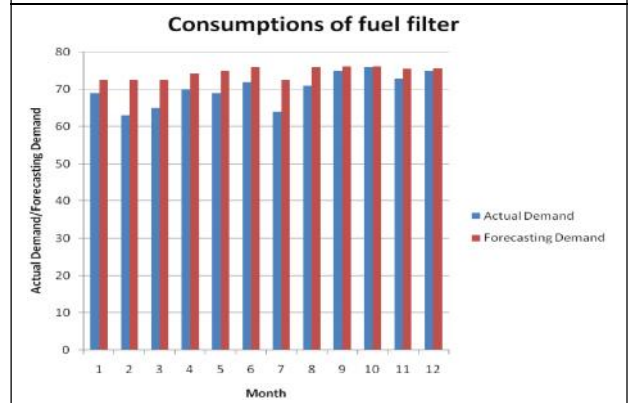


Figure 3: Forecasting Error with Respect Month

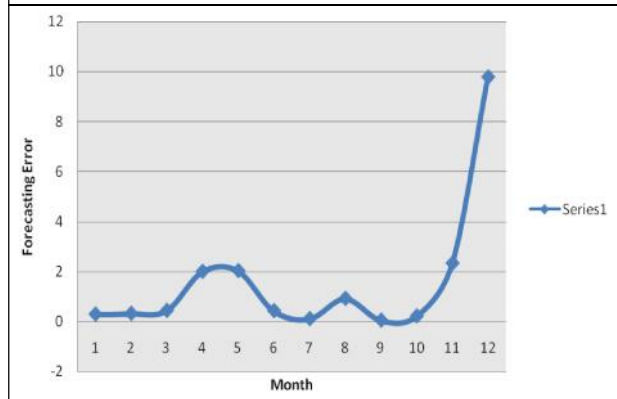


Figure 5: Forecasting Error with Respect Month

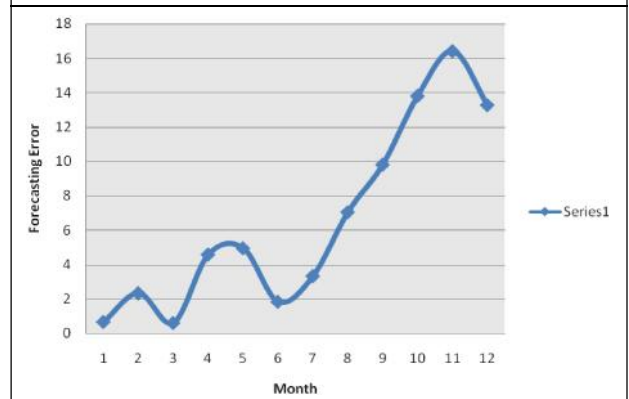


Table 3: Prediction of Next Year Consumptions (2014)

S. No.	Month	Base Year Data (2011)	Forecasting Data (2013)	Actual Data (2013)	Forecasting Error	% Error
1.	Jan	69.0	72.69	72.0	0.69	0.96
2.	Feb	63.0	72.63	75.0	2.36	3.15
3.	Mar	65.0	72.63	72.0	0.63	0.88
4.	Apr	70.0	74.39	79.0	4.60	5.83
5.	May	69.0	75.02	80.0	4.97	6.21
6.	Jun	72.0	76.13	78.0	1.86	2.38
7.	Jul	64.0	72.64	76.0	3.35	4.408
8.	Aug	71.0	76.06	69.0	7.06	10.23
9.	Sep	75.0	76.18	86.0	9.817	11.40
10.	Oct	76.0	76.18	90.0	13.81	15.35
11.	Nov	73.0	75.58	92.0	16.41	17.84
12.	Dec	75.0	75.71	89.0	13.28	14.92

supply chain management, now we will first all consider the base year data of 2012 in 12th month to calculate next year data of 2014 but 2013 data are available but can not consider as a forecasting data only consider as a target data.

To calculate the forecasting error between actual data of 2013 and forecasting data 2014 and also formula available for the calculating of forecasting error in MATLAB coding

forecasting $r = \text{abs}(\text{frcst} - \text{target})$ and also calculate the percentage error using formula are

$$pe = (\text{forecasting } r / \text{target}) * 100;$$

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 forecasting

mechanism 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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