EVALUATING THE OPTIMIZATION OF PREDICTION FOR BALANCE FOR SUPPLY CHAIN

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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 work is to propose a forecasting technique which is modelled by artificial intelligence approaches using artificial neural network based transfer functions. It was concluded that It can be concluded from the above results that Tansig Transfer Function with Bayesian Back propagation Training Function outperforms better with minimum error while forecasting load on weekly basis. This algorithm is then used for analysis of yearly data of a clothing shop located in Bhopal.

I. KEY WORDS: ANN, DEMAND FORECASTING, TRAINING FUNCTION, MSE.

II. INTRODUCTION.

Neural networks are an emerging technology of artificial intelligence based on the success of modern biological research on human brain tissues. The simulation of the structure and behaviour of the human brain is the principle. Neural network technology Advanced in the exploration of some of the limits of artificial intelligence (AI) that has been successfully applied in many areas and cannot demonstrate the effectiveness and accuracy of other IA techniques. Indeed, many aspects of Supply chain management have used neural network technology, but so far few people have combined these two concepts and routinely explained neural network technology in the management of neural networks.

With a lot of development of neural networks, it was found that no matter how the organizational structure of the network it is, it is always has the following two characteristics:

1.1 SELF-LEARNING

Neural networks can be modified according to the external environment of their behavior to adapt to the external environment, mainly due to their learning process. Learning is often the first step in using neural networks. When a series of information is entered, neural networks can adjust their internal parameters (or their weighting coefficient) and possibly generate a series of consistent outputs.

1.2 GENERATION

Once self-learning is complete, the response of a neural network to the reduction of input information and its local defects is no longer sensitive. This mechanism can result in a high fault tolerance on the neural network and reduce the quality requirements of input data. The main advantages of the BP neural network are simple, easy to implement and have the ability to generalize and tolerate errors of approximation of arbitrary nonlinear mappings. However because an anticipatory neural network is a typical BP network, some applications are limited.

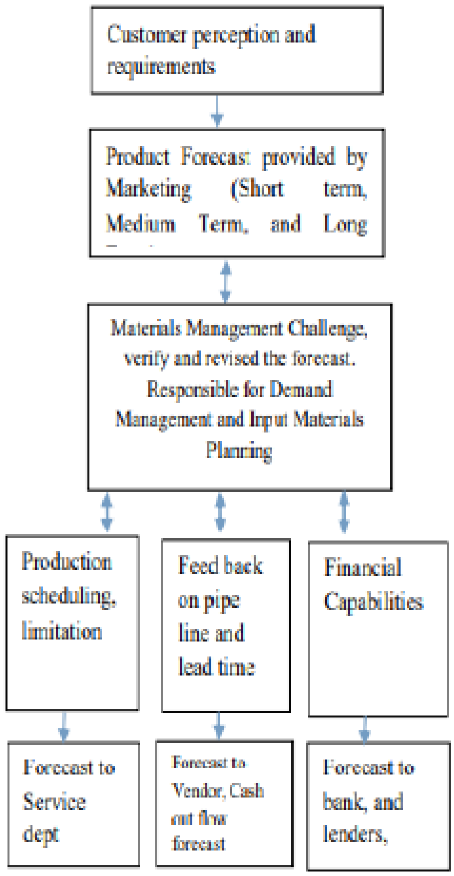

Figure 1 General flow of forecast

1.3 FORECASTING

Uncertainty has long been the main obstacle for decision makers. The uncertainty in the supply chain is mainly due to changes in product demand, delays in deliveries and mechanical failures. Due to imprecise forecasts of local aspects of the supply chain, the whole supply chain will experience considerable fluctuations and this volatility will increase. As a result, the question of how to improve forecast accuracy and reduce supply chain management uncertainty has become a key issue. As we all know, the information supporting our decisions is generally insufficient, which has become an insurmountable obstacle to other forecasting techniques such as expert systems, statistical methods and time series. However, the black box function in the neural network can avoid this obstacle and achieve a more satisfactory predictive result. Furthermore, the neural network is essentially a non-linear system. Most supply chain forecasting issues are complex and non-linear. They make impotent linear prediction tools while the neural network is even simpler.

LITERATURE REVIEW

K.Metaxiotis et al. [1] this paper provides an overview of AI technology researchers and their current use in predicting short-term electrical load (STELF). The history of KI in STELF is described and leads to a discussion of different approaches and current research directions. The document concludes with an exchange of views and an assessment of the future prospects of the AI in this area. This review shows that while artificial intelligence technologies are still considered a new methodology, they have proven to be very advanced and offer real practical benefits in many of their applications.

Muhammad Qamar Raza et al. [2] this article provides a review of the complete and systematic literature on short-term load prediction techniques based on artificial intelligence. The main objective of this study is to examine, identify, evaluate and analyze the performance of load prediction models based on artificial intelligence (AI) and research gaps. The accuracy of the predictive model based on ANN depends on the number of parameters, e.g. The predictive model architecture, the combination of inputs, the activation functions and the learning algorithm in the network, as well as other exogenous variables that influence the inputs of the predictive model. The published literature presented in this paper demonstrates the potential of artificial intelligence techniques for an efficient charge prediction to realize the intelligent grid and the concept of construction. The prediction of electric charge plays a crucial role in the realization of the concept of the next generation of energy systems, such as smart grid, efficient energy management and better planning of energy systems. Consequently, a high predictive accuracy is required for multiple time horizons associated with the regulation, distribution, planning and provisioning of the units of the electric network.

Fahad Javed et al. [3] in this article, we try to find answers to two main questions to predict the burden of individual consumers: first, do current STLF models (short-term load forecasting) work effectively for individual household forecasts? Secondly, anthropological and structural variables improve the predictive accuracy of individual consumers. Our analysis shows that a single multidimensional model prediction is more efficient for all houses that use anthropological and structural data variables than a prediction based on traditional global metrics. We have provided many empirical evidence to support our statements. The electricity grid is changing. With the smart grid, demand response programs will make the network more resilient and economical. However, a system that allows consumers to participate directly in demand management requires new efforts to predict consumers of electrical equipment.

Chao-HungWang [4] the forecast of tourist demand in a sector of services with limited capacity was a big problem in this region. This study presents two models for forecasting tourist demand. Both models are based on artificial intelligence (AI). The neural network theory was first applied in 2000 to predict tourist demand and was empirically tested by Hong Kong's raw data. This work provides empirical evidence using gray theory and fuzzy time series that do not require large samples or long time series. These IA models were estimated for tourists from Hong Kong, United States and Germany to Taiwan for the period 1989-2000. The GM (1, 1) model allows accurate prediction when the sample data shows a stable slope trend. However, the Markov modification model can effectively improve the GM model (1, 1) if the sample data show significant variations.

OBJECTIVE

- The aim of the work is to propose a new forecasting mechanism which is modeled by artificial intelligence approaches including the comparison of both artificial neural networks based training functions.
- To decide the effectiveness of the proposed approach to the demand forecasting issue is demonstrated using real-world data from a company which is active in durable consumer goods industry in Bhopal.
- To obtain input data from a clothing store in the new market, Bhopal will produce and request data for the fiscal period from April 2017 to March 2018 for the next year.

METHODOLOGY

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.

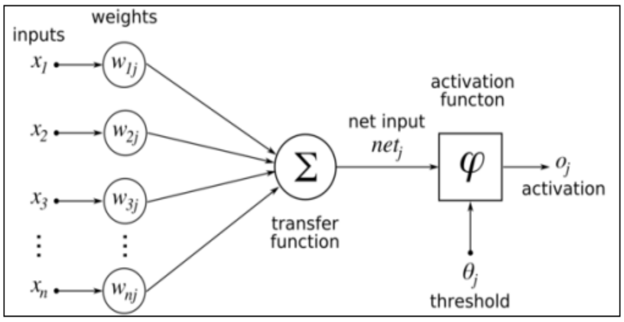

Figure 2: Artificial Neuron

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in the signal flow from inputs $x_1, x_2, ..., x_n$ 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.

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

Where w_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,

$$net = W_X^T = W_1 X_1 + \cdots .WnXn$$

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

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

is called the threshold level; and this type of node is called a linear threshold unit. In different types of$\theta$where 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 MATLAB toolkit is used to implement neural networks for functional forecasting for demand forecasting. The MATLABANN toolkit uses different backward propagation algorithms:

a) Gradient descent in series (guided)
b) Variable learning rate (trained, traingdx)
c) Conjugate gradient algorithms (traincgf, traincgp, traincgb, traincg)
d) Levenberg-Marquardt (train)

4.1 DATA COLLECTION

To assess the performance of the neural network method empirically, a daily data set is collected from the clothing store for the fiscal year from April 2017 to March 2018. In this article, we want their stores. We used the information from the Bhopal Madhya Pradesh market station. Using the ANNs already highlighted in the previous section, the data set was divided into a training set and a set of tests. The data that represents the quantity, the rate and the gross amount for a given commodity of a given size for a sales date are described below. These data are a sample of data for the entire year from April 2017 to March 2018.

Data of a clothing store located in Bhopal

RESULTS

5.1 Analysis

The model was trained with ''Levenberg–Marquardt optimization'' as well as Bayesian Back propagation Training Function learning algorithm. The network was simulated for various numbers of hidden layers and hidden neurons in order to minimize the error between actual and forecasted values

Input for the demand model for neural networks:

1. Previous weekly sale (2017-2018)
2. Monthly sale analysis The output of the neural network corresponds to the expected demand for the next weekly sale. M-file programs are designed to predict demand with the ANN MLP model and the RBF network.

5.2 Result analysis with different training function of neural network

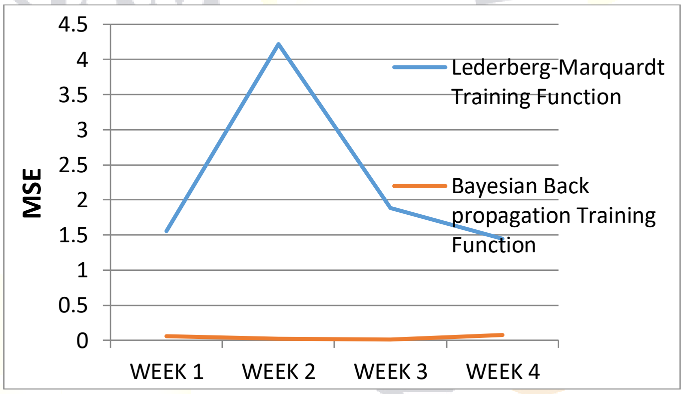

Figure 3 MSE with Bayesian Back propagation Training Function and Lederberg-Marquardt Training Function

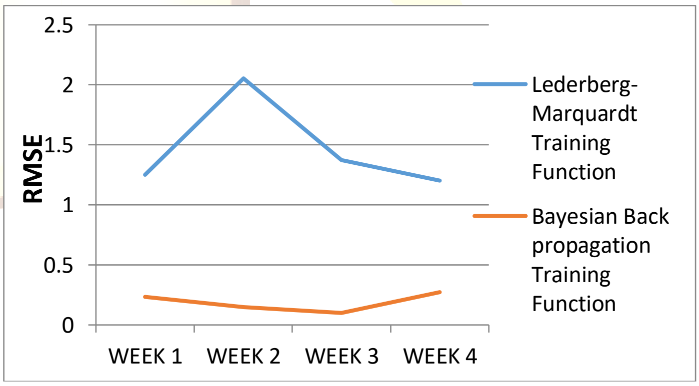

Figure 4 RMSE with Bayesian Back propagation Training Function and Lederberg-Marquardt Training Function

5.2.1 Discussion:

- The MSE (Mean Square Error) with Bayesian Back propagation Training Function in forecasting demand is calculated to be minimum for the third week of May to June that is 0.01 with corresponding RMSE (Root Mean Square Error) to be 0.1.
- The MSE (Mean Square Error) with Lederberg-Marquardt Training Function in forecasting demand is calculated to be minimum for the fourth week of May to June that is 1.44558 with corresponding RMSE (Root Mean Square Error) to be 1.20232
- However when we compare these minimum values of both the training functions Bayesian Back Propagation training function is found to be a better option for forecasting demands

5.3 Result analysis with different transfer function of neural network of the above mentioned training functions.

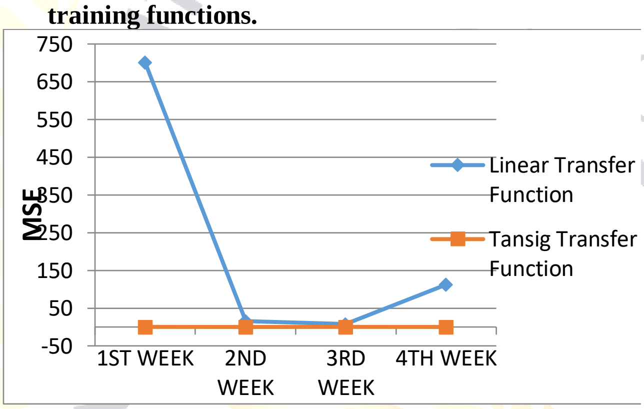

Figure 5 MSE with Linear and Transig Transfer function of Bayesian Back propagation Training Function

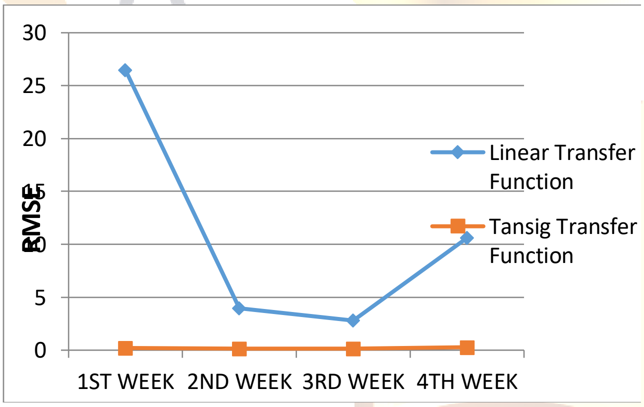

Figure 6 RMSE with Linear and Transig Transfer function of Bayesian Back propagation Training Function

5.3.1 Discussion:

- The MSE (Mean Square Error) with Bayesian Back propagation Training Function when performed with linear transfer function in forecasting demand is calculated to be minimum for the third week of May to June that is 7.83527 with corresponding RMSE (Root Mean Square Error) to be 2.7991.
- The MSE (Mean Square Error) with same Training Function when performed with Transig Transfer function in forecasting demand is calculated to be minimum for the second week of May to June that is 0.02167with corresponding RMSE (Root Mean Square Error) to be 0.14720. However when we compare these minimum values of both the transfer functions of Bayesian Back Propagation training function, It can be concluded that from both the functions linear transfer function is better than Transig Transfer function as it generates less MSE after forecasting the Demand

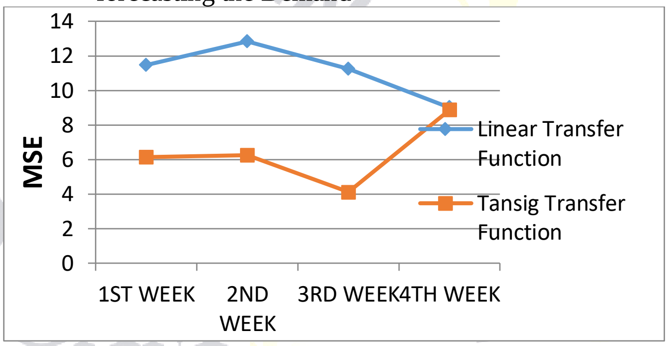

Figure 7 MSE with Linear and Transig Transfer function of Levenberg-Marquardt Training Function

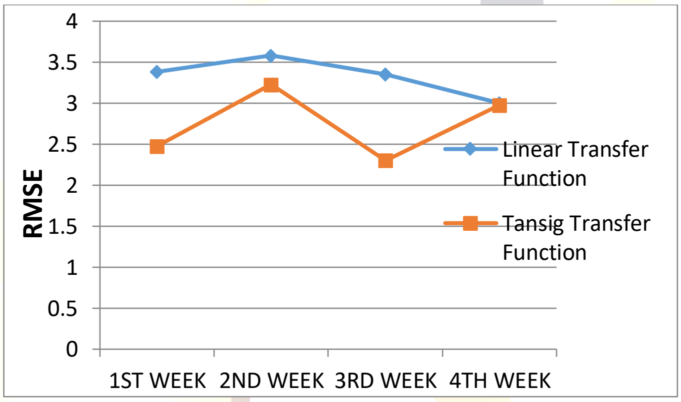

Figure 8 RMSE with Linear and Transig Transfer function of Levenberg-Marquardt Training Function

5.3.2 Discussion:

- The MSE (Mean Square Error) with Levenberg-Marquardt Training Function when performed with linear transfer function in forecasting demand is calculated to be minimum for the fourth week of May to June that is 9.0074 with corresponding RMSE (Root Mean Square Error) to be 3.0012.
- The MSE (Mean Square Error) with same Training Function when performed with Transig Transfer function in forecasting demand is calculated to be minimum for the second week of May to June that is 4.1212

with corresponding RMSE (Root Mean Square Error) to be 2.3007.

- However when we compare these minimum values of both the transfer functions of Levenberg-Marquardt Training Function, It can be concluded that from both the functions linear transfer function is better than Transig Transfer function as it generates less MSE after forecasting the Demand.

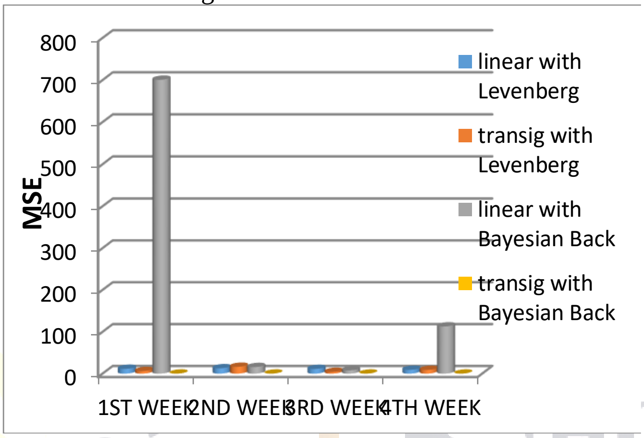

Figure 9 Comparison of various transfer functions for weekly analysis

It can be concluded from the above results that Tansig Transfer Function with Bayesian Back propagation Training Function outperforms better with minimum error. Hence this function is selected for further analysis of demand forecasting in the retail shop.

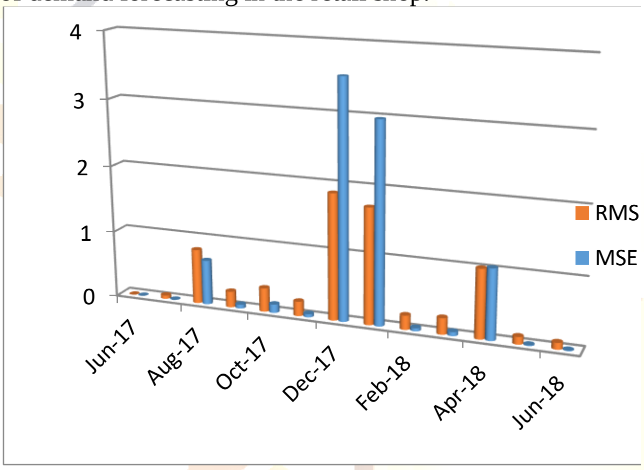

Figure 10 RMSE and MSE for various months using Bayesian Back propagation Training Function with Tansig Transfer Function

- Minimum MSE has been calculated in the month June-july 2017 with Bayesian Backpropagation Training Function with Tansig Transfer Function which is approx. 0.002.This concludes the effectiveness of the proposed methodology.

CONCLUSION

For the optimum balancing the supply chain in demand and sale better forecasting is important factor and by using AI. Technique is easy and appropriate way to identify the realistic demand of future in various conditions by using previous data of demand and supply with inventory record by whole seller. The result of the evaluation shows that ANN is more efficient technique in AI.

In which Lederberg –Marquand and Bayesian back propagation training function is used and it served that in Bayesian back propagation training function is much suitable showing a realistic forecasting with transing function compared to Linear function.The above result date shows that the transing training function is minimum MSE average and it's about 0.66it shows that transing is much more efficient function as compared to Linear transfer function Bayesian back propagation training function in a ANN.

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