American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-6, Issue-12, pp-142-147
www.ajer.org
Research Paper Open Access

Development of ANN Models for Demand Forecasting

Shubham Bhadouria, *Arvind Jayant
Department of Mechanical Engineering, SLIET Deemed University, Longowal, 148106, India
(CFTI under MHRD Govt. of India)
**Corresponding author E-mail address:* arvindjayant@sliet.ac.in

ABSTRACT: *The supply chain of every enterprise comprises a highly distributed environment, in which complex processes evolve in a network of companies and this distributed environment creates a lot of fluctuation and uncertainty in the supply chain. Demand forecasting is the downstream part of the supply chain. Accurate forecasting of the future demand of the product will eliminate the uncertainty and makes the supply chain stable. Therefore, demand forecasting is very critical for any organization to make the correct decisions and to achieve the benefits in this regularly changing business scenario. The objective of this work is to study the basics of Artificial Neural Network (ANN) and its application in supply chain management and develop an ANN model which will predict the future demand with high accuracy as compared to the conventional Forecasting methods. To demonstrate the effectiveness of the present study, demand forecasting issue was investigated on a gear manufacturing company as a real-world case study. Three ANN models with TANSIGMOID, LINEAR and LOGSIGMOID transfer function has been developed using MATLAB software for forecasting the demand. A comparative analysis of different ANN models and various traditional forecasting methods like exponential smoothing, moving average and weighted moving average method has been done on the basis of the results obtained from the various forecasting models.*

Keywords: *Artificial Neural Network (ANN); Supply Chain Management (SCM); MATLAB; Demand forecasting.*

Date of Submission: 18-11-2017 Date of acceptance: 14-12-2017

I. INTRODUCTION

Supply chain management is an important competitive strategy used by modern enterprises. Supply chain management is the coordination of production, inventory, location, and transportation among the participants in a supply chain to achieve the best mix of responsiveness and efficiency for the market being served (wiley, 2010). Demand forecasting is the integral part of the supply chain. In under-forecasting, the losses arise from the potential loss of regular and companion products, though increases in production and shipment costs can make up for the shortfalls. In the case of over-forecasting, the losses come from discounts that must be offered to dispose of excess inventory. Both scenarios lead to uncertainty in supply chain. Thus, correct forecast is a big challenge. Accurate forecasting of the future demand of the product will eliminate the uncertainty and makes the supply chain stable. Therefore, demand forecasting is very critical for any organization to make the correct decisions and to achieve the benefits in this regularly changing business scenario.

The ability to predict the future demand on the basis of previous data is an important tool to support decision making of company. Forecasting through conventional forecasting methods yields less accuracy due to the fluctuating nature of demand. Artificial Neural Network (ANN) has the ability to implicitly detect complex nonlinear relationships between dependent and independent variables thus can be used to predict the future demand with better accuracy.

II. LITERATURE REVIEW

Demand forecasting has tempted the focus of much research work. There is a large number of literature on sales forecasting in industries such as pulpwood (Anandhi et al. 2012), supermarket (Slimani & Farissi, 2015), server manufacturing (Saha & Lam, 2014). However, very few literatures were focused on the gear manufacturing sector. Leung (1995) have studied the neural networks in supply chain management and explains the ways in which it can contribute to supply chain management. Artificial neural network can be used to solve the problems related to Optimization, forecasting, modeling and simulation, globalization and decision making. Bansal et al. (1998) have studied the neural networks based forecasting techniques for inventory control applications. Apichottanakul et al. (2009) have developed an artificial neural network to forecast the market share of Thai rice. Soroush et al. (2009) have reviewed on application of artificial neural network (ANN) in supply chain management and its future. ANN was applied in the field of optimization, forecasting, decision making and Simulation. Zhu Ying & Xiao Hanbin (2010) have studied the Model of Demand Forecasting Based on Artificial Neural Network and developed a three layers ANN model for forecasting the market demand. Kandananond (2012) have studied the consumer product demand forecasting based on artificial neural network and support vector machine. Lau (2013) have developed a demand forecast model using a combination of surrogate data analysis and optimal neural network approach and proposed a mathematical approach minimum description length (MDL) to determine optimum neural network that provide the accurate demand forecast. Kourentzes (2013) have studied the intermittent demand forecasts with neural networks. Neural network based methodology was proposed to forecast intermittent time series. Wang et al. (2014) have studied the neural network with adaptive evolution differential equation for time series data. Slimani & Farissi (2015) have studied the Artificial Neural Networks for forecasting the demand and a neural network is proposed in order to predict the consumer's demand and implement this demand forecasting in a two-echelon supply chain with a game theoretic approach. Ratna & Nisha (2015) have studied an artificial neural network based demand forecasting system for uncertainty elimination in two echelon supply chains. Vhatkar & Dias (2016) have studied the oral-care goods sales forecasting using artificial neural network model. Lolli et al. (2017) have studied the Single-hidden layer neural networks for forecasting intermittent demand. More investigation in comparing and pooling of conventional and neural network can offer some improvement in performance and its feasibility of collaboration.

In the present work, demand analysis for a gear manufacturing industry has been carried out using artificial neural network based on different transfer functions.

III. METHODOLOGY

3.1 Artificial Neural Network

An Artificial Neural Network is a mathematical or computational model based on biological neural network. It is composed of a large number of highly interconnected processing elements (neurons) working together to solve specific problems. There are three main components in the ANNs; neurons, interconnections, and learning rules. Neural networks learn from real-life cases. It has the ability to implicitly detect complex nonlinear relationships between dependent and independent variables and best suited for the complex information processing. Black box nature of ANN is the big disadvantage of the ANN. It is mainly used for Optimisation, forecasting, simulation, decision making, pattern recognition and clustering.

An ANN network is formed by combining two or more neurons. The different architectures may be classified as: feed forward network and recurrent network. Learning algorithms can be divided into the two categories: supervised learning and unsupervised learning. Hit and trial method was used to find the optimum the number of hidden layers and hidden neurons.

3.2 Back propagation Training algorithms

MATLAB16 is used for neural network implementation for demand forecasting. Various back propagation algorithms available in MATLAB ANN tool box are:

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

IV. DEVELOPMENT OF ANN MODELS FOR DEMAND FORECASTING

Product demand is always prone to fluctuation thus making the supply chain inefficient and ineffective. Therefore, demand forecasting is an important and crucial part of downstream activity of any supply chain. Fluctuation of product demand causes uncertainty in supply chain. Thus, accuracy of sales forecast of a product in a supply chain is certainly an important key to competitiveness. Therefore, there is a need to develop an efficient and precise model for forecasting the future demand. Accuracy of sales forecast of a product in a supply chain is definitely an important key to competitiveness. Therefore, there is a need to develop an efficient and precise model for forecasting the demand. In the present work, three ANN models based on three transfer function (tan- sigmoid, log- sigmoid, linear) has been developed. The monthly sales data of last 3 years i.e. from 2014 to 2016 of worm gear box (8.5”) has been collected from the XYZ Company and then demand for the next year has been computed. The sales data of worm wheel gear box from 2014 to 2016 are as follows

Table 1 Sales data of Worm wheel gear box (8") from 2014 to 2016

Month		Year	
	2014	2015	2016
January	60	67	72
February	57	63	75
March	58	65	72
April	62	70	79
May	63	69	80
June	59	72	78
July	58	64	74
August	61	71	72
September	64	73	88
October	64	72	87
November	61	73	78
December	64	72	89

For our Neural Network model, we used a Multi-Layer Perceptron (MLP) network with a single hidden layer. ANN model was constructed using tan sigmoid, linear and log sigmoid transfer function. Input for the model was demand of all the months of previous year 2014 when we are forecasting demand for all the months of the year 2016 and then this forecasted demand of year 2016 obtained from the model became the input to the model to forecast the demand of next year 2017. The number of neurons in the hidden layer was varied between 2 and 20 before finally being set at 10 neurons. The number of output neurons was 1. To set the momentum, network was run with the different values of momentum before settling on 0.001 which gave us the best results. The ANN was implemented using MATLAB 16. The training algorithm was TRAINLM and adaptive learning function was LEARNGDM and performance function is the mean square error (MSE). The number of epochs while training was set at 1000 by which point the network was sufficiently trained.

The forecasted demand of the product for the year 2016 and 2017 when transfer function is TANSIGMOID are shown in table 2 and 3 respectively. The forecasted demand of the product for the year 2016 and 2017 when transfer function is LINEAR are shown in table 4 and 5 respectively. The forecasted demand of the product for the year 2016 and 2017 when transfer function is LOGSIGMOID are shown in table 6 and 7 respectively.

Table 2 Prediction of next year 2016 demand in case of TANSIGMOID transfer function

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Input data	60	57	58	62	63	59	58	61	64	64	61	64
Target data	67	63	65	70	69	72	64	71	73	72	73	72
Forecasted	67	63.0005	63.9837	68.8479	68.5054	72.0001	63.9837	72	72.3311	72.3311	72	72.3311
data												
	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Input data	67	63.0005	63.9837	68.88479	68.5054	72.0001	63.9837	72	72.3311	72.3311	72	72.3311
Target	72	75	72	79	80	78	74	72	88	87	78	89
data												
Forecasted	72.0086	75.001	73	80.9446	80	76.0049	73	75.9989	88.0017	88.0017	75.9989	88.0017
data												

Table 4 Prediction of next year 2016 demand in case of LINEAR transfer function

		Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	Input data	60	57	58	62	63	59	58	61	64	64	61	64
	Target	67	63	65	70	69	72	64	71	73	72	73	72
	data												
	Forecasted	68.5658	63.8921	64.8654	71.73	72.4147	66.4912	64.8647	70.4602	72.7412	72.7412	70.4602	72.742
	data												
Table 5 Prediction of next year 2017 demand in case of LINEAR transfer function													
		Jan	Feb	Mar	Apr	Ma	Jun	July	Aug	Sep	Oct	No	De

						y	e					v	c
	Input data	67	63.0005	63.9837	68.88479	68.5054	72.0001	63.9837	72	72.3311	72.3311	72	72.3311
	Target	72	75	72	79	80	78	74	72	88	87	78	89
	data												
	Forecasted	72.196	72.0003	72.0011	80.5967	84.3976	72.0105	72.0011	74.4684	85.7767	85.7767	74.4684	85.7797
	data												

Table 6 Prediction of next year 2016 demand for LOGSIGMOID transfer function

		Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	Input data	60	57	58	62	63	59	58	61	64	64	61	64
	Target	67	63	65	70	69	72	64	71	73	72	73	72
	data												
	Forecasted	72.1091	63.3597	63.966	69.9597	68.3494	71.9425	63.966	70.0479	71.965	71.965	70.0479	71.965
	data												

Table 7 Prediction of next year 2017 demand for LOGSIGMOID transfer function

		Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
	Input data	67	63.0005	63.9837	68.88479	68.5054	72.0001	63.9837	72	72.3311	72.3311	72	72.3311
	Target	72	75	72	79	80	78	74	72	88	87	78	89
	data												
	Forecasted	72.0403	75.7309	75.281	80.0414	79.9991	78.1761	75.281	79.9772	87.3837	87.3837	79.9772	87.3837
	data												

V. Results And Discussion

While forecasting the demand for the year 2016, MAD is 0.5009, MAPE is 0.71390, MSE is 0.4393 in case of TANSIGMOID transfer function and MAD is 1.577680, MAPE is 2.25303, MSE is 4.7434 in case of LINEAR transfer function and MAD is 1.024545, MAPE is 1.48506, MSE is 3.202 in case of LOGSIGMOID transfer function. Comparison shows that the ANN model with the TANSIGMOID transfer function is best model for forecasting the demand for the year 2016. The various errors occur during forecasting demand for 2016 is shown in table 8 and fig 1.

While forecasting the demand for the year 2017, MAD is 1.16257, MAPE is 1.51048, MSE is 2.6460 in case of TANSIGMOID transfer function and MAD is 2.48710, MAPE is 3.13985, MSE is 8.8474 in case of LINEAR transfer function and MAD is 2.91400, MAPE is 3.76319, MSE is 24.110 in case of LOGSIGMOID transfer function. Comparison shows that the ANN model with the TANSIGMOID transfer function is best model for forecasting the demand for the year 2017. The various errors occur during forecasting demand for 2016 is shown in table 8 and fig 1.

Table 8 Errors using different transfer function for forecasting the demand of 2016

	Transfer Functions	Mean absolute deviation(MAD)	Mean absolute percentage error(MAPE)	Mean square error(MSE)
	TANSIGMOID	0.5009	0.71390	0.4393
	LINEAR	1.577680	2.25303	4.7434
	LOGSIGMOID	1.024545	1.48506	3.202

Table 8 Errors using different transfer function for forecasting the demand of 2016

Transfer functions	Mean absolute deviation(MAD)	Mean absolute percentage error(MAPE)	Mean square error(MSE)
TANSIGMOID	1.16257	1.51048	2.6460
LINEAR	2.48710	3.13985	8.8474
LOGSIGMOID	2.91400	3.76319	24.110

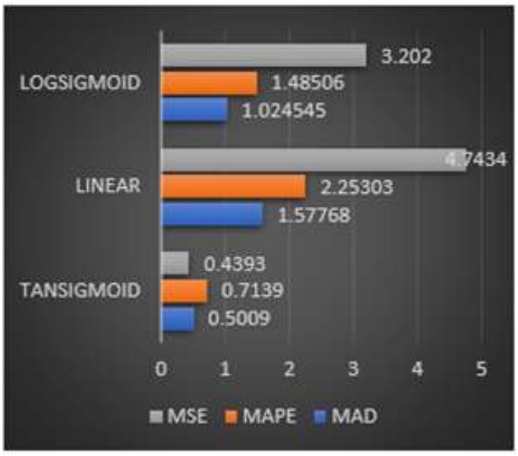

Fig 1Graph showing errors using different transfer function for forecasting the demand of 2017

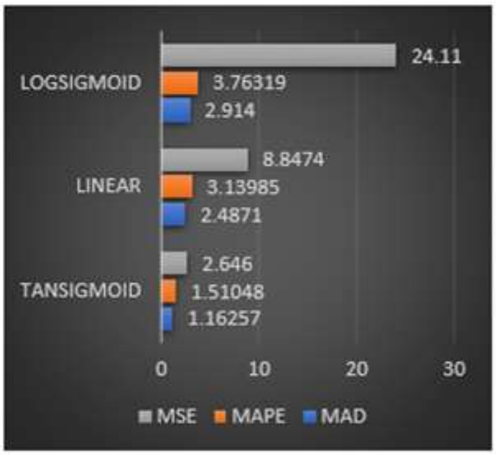

Fig 2 Graph showing errors using different transfer function for forecasting the demand of 2017

VI. MANAGERIAL IMPLICATION

In the present research, ANN models with TANSIGMOID, LINEAR and LOGSIGMOID transfer function has been develop using MATLAB software for forecasting the future demand of the product and these models are further validated by comparing the results of ANN models with the traditional forecasting methods like Exponential smoothing method, Moving average method and Weighted moving average method. ANN models developed forecast the demand with high accuracy and thus reduce the fluctuation of the supply chain as the demand forecasting is the integral part of the supply chain.

The objective of this research was to find out the importance of ANN models in forecasting the future demand of the product and to compare the ANN models with the traditional forecasting methods. Predicting the future demand with the traditional forecasting methods yields low accuracy and greater fluctuation. Thus, it is necessary to develop some models which will forecast the demand with high accuracy. ANN models developed in the present work predict the demand with high accuracy and reduce the fluctuation of supply chain. Managers can use these proposed ANN models for predicting the future demand of their company's product and make their supply chain stable and reliable.

VII. CONCLUSIONS

Three ANN models based on TANSIGMOID, LINEAR and LOGSIGMOID transfer function has been developed by using the MATLAB software for forecasting the future demand using the data of worm gear box. Demand forecasted by the ANN models are validated by the conventional forecasting techniques like exponential smoothing method, moving average method and weighted moving average. MAD, MAPE and MSE are used for estimating the accuracy of the models. Results revealed that, forecasting of 2017 demand, in case of TANSIGMOID transfer function, the value of MAD, MAPE and MSE are 1.16257, 1.51048 and 2.646 respectively while in case of LINEAR transfer function, the value of MAD, MAPE and MSE are 2.4871, 3.13985 and 8.8474 respectively and in case of LOGSIGMOID transfer function, the value of MAD, MAPE and MSE are 2.9140, 3.76319 and 24.11 respectively. Thus, the ANN model with TANSIGMOID transfer function is far better and more accurate than ANN model with LINEAR and LOGSIGMOID transfer function in terms of MAD, MAPE and MSE.

In relation to the traditional forecasting methods for forecasting the 2016 demand, the values of MAD, MAPE and MSE are 5.19, 6.45 and 38.83 respectively in case of Exponential smoothing method while the values of MAD, MAPE and MSE are 4.83, 5.96 and 35 respectively in case of Moving average method and the values of MAD, MAPE and MSE are 4.94, 6.09 and 37.05 respectively in case of Weighted moving average method. Thus, Moving average method is best suited for forecasting the future demand of year 2016 as compared to the Exponential smoothing method and weighted moving average method in our case study. It can be concluded that the ANN models outperform the traditional forecasting model in predicting the demand and forecast the demand with greater accuracy.

ACKNOWLEDGEMENT

The authors are very thankful to the case company for providing necessary data for this research.

REFERENCES

[1]. Ying, Z. and Hanbin, X., 2010, August. Study on the model of demand forecasting based on artificial neural network. In Distributed Computing and Applications to Business Engineering and Science (DCABES), 2010 Ninth International Symposium on (pp. 382-386). IEEE.
[2]. Wang, L., Zeng, Y. and Chen, T., 2015. Back propagation neural network with adaptive differential evolution algorithm for time series forecasting. Expert Systems with Applications, 42(2), pp.855-863.
[3]. Udo, G.J., 1992. Neural networks applications in manufacturing processes. Computers & industrial engineering, 23(1-4), pp.97-100.
[4]. Slimani, I., El Farissi, I. and Achchab, S., 2015, December. Artificial neural networks for demand forecasting: Application using Moroccan supermarket data. In Intelligent Systems Design and Applications (ISDA), 2015 15th International Conference on (pp. 266-271). IEEE.
[5]. Sharda, R. and Wang, J., 1996. Neural networks and operations research/management science. European journal of operational research, 93(2), pp.227-229.
[6]. Arvind Jayant, H.S. Ghagra (2013), Supply Chain Flexibility Configurations: Perspectives, Empirical Studies and Research Directions" International Journal of Supply Chain Management (UK), Volume 2, Number 1, March 2013, pp 21-29.
[7]. Arvind Jayant, P Gupta, S K Garg (2011). "An Application of Analytic Network Process to Evaluate Supply Chain Logistics Strategies", International Journal of Analytic Hierarchy Process (USA). Vol.4, Issue 1.pp149-163.ISSN 1936-6744
[8]. Sabuncuoglu, I., 1998. Scheduling with neural networks: A review of the literature and new research directtions. Production Planning & Control, 9(1), pp.2-12.
[9]. Anandhi, V., Chezian, R.M. and Parthiban, K.T., 2012. Forecast of demand and supply of pulpwood using artificial neural network. International Journal of Computer Science and Telecommunications, 3(6), pp.35-38.
[10]. Radzi, N.H.M., Haron, H. and Johari, T.I.T., 2006. Lot sizing using neural network approach. Second IMT-GT Regional.
[11]. Kourentzes, N., 2013. Intermittent demand forecasts with neural networks. International Journal of Production Economics, 143(1), pp.198-206.
[12]. Saha, C., Lam, S.S. and Boldrin, W., 2014, January. Demand forecasting for server manufacturing using neural networks. In IIE Annual Conference. Proceedings (p. 1031). Institute of Industrial and Systems Engineers (IISE).
[13]. Paul, S. and Azeem, A., 2011. An artificial neural network model for optimization of finished goods inventory. International Journal of Industrial Engineering Computations, 2(2), pp.431-438.
[14]. Hobbs, B.F., Helman, U., Jitprapaikulsarn, S., Konda, S. and Maratukulam, D., 1998. Artificial neural networks for short-term energy forecasting: Accuracy and economic value. Neurocomputing, 23(1), pp.71-84.
[15]. Ratna, S. and Nisha, S., an artificial neural network based demand forecasting system for uncertainty elimination in two-echelon supply chains.
[16]. Arvind Jayant, P Gupta and S K Garg (2014) "Simulation Modeling and Analysis of Network Design for Closed-Loop Supply Chain: A Case Study of Battery Industry" Procedia Engineering, Vo.97, pp 2213-2221.
[17]. Sustrova, T., 2016. An Artificial Neural Network Model for Wholesale Company's Order-Cycle Management. International Journal of Engineering Business Management, 8, p.2.
[18]. Sabuncuoglu, I. and Gurgun, B., 1996. A neural network model for scheduling problems. European Journal of Operational Research, 93(2), pp.288-299.
[19]. He, W., 2013. An inventory controlled supply chain model based on improved BP neural network. Discrete Dynamics in Nature and Society, 2013.
[20]. Arvind Jayant, Mohd. Azhar, Priya Singh (2014) "Interpretive Structural Modeling (ISM) Approach: A State of the Art Literature Review" International Journal of Research in Mechanical Engineering & Technology, Vol.4 (3), pp 15-21. ISSN 2249-5770
[21]. Apichottanakul, A., Piewthongngam, K. and Pathumnakul, S., 2009, December. Using an artificial neural network to forecast the market share of Thai rice. In Industrial Engineering and Engineering Management, 2009. IEEM 2009. IEEE International Conference on (pp. 665-668). IEEE.
[22]. Arvind Jayant, M.S.Dhillon (2014) "Use of Analytic Hierarchy Process (AHP) to Select Welding Process in High Pressure Vessel Manufacturing Environment" International Journal of Applied Engineering Research 10 (8), 586-595.
[23]. Arvind Jayant, A.Singh, and V.Patel (2011), "An AHP Based Approach for Supplier Evaluation and Selection in Supply Chain Management" International Journal of Advanced Manufacturing Systems, Volume 2, No. 1, pp. 1-6
[24]. Gaafar, L.K. and Choueiki, M.H., 2000. A neural network model for solving the lot-sizing problem. Omega, 28(2), pp.175-184.
[25]. Kandananond, K., 2012. Consumer product demand forecasting based on artificial neural network and support vector machine. World Academy of Science, Engineering and Technology, 63, pp.372-375.
[26]. Arvind Jayant, Md. Azhar (2014) "Analysis of Barriers to Implement Green Supply Chain Management (GSCM) Practices: An Interpretive Structural Modeling (ISM) Approach" Procedia Engineering, Vo.97, pp 2157-2166
[27]. Chiu, M. and Lin, G., 2004. Collaborative supply chain planning using the artificial neural network approach. Journal of Manufacturing Technology Management, 15(8), pp.787-796.

Shubham Bhadouria. "Development of ANN Models for Demand Forecasting." American Journal of Engineering Research (AJER), vol. 06, no. 12, 2017, pp. 142-147.