Asian Review of Mechanical Engineering
ISSN: 2249-6289 (P) Vol.6 No.2, 2017, pp.19-26

DOI: https://doi.org/10.51983/arme-2017.6.2.2429

Inventory Control by Linear and Non Linear Demand Forecasting

R. V. Patil[1] and A. N. Chapgaon[2]
[1]PG Student, [2]Head of the Department,
Department of Mechanical Engineering, AMGOI Vathar, Maharashtra, India
E-Mail: rohit29291@gmail.com

***Abstract* - Now a day, supply chain practices are widely adopted in Indian industries .Research points out examination of success factors and implementations of the system in Indian industries. However, the adoption in Small and Medium Enterprises is not very common. Interestingly, multinational firms and large enterprises can invest huge capital for implementing latest information technology tools to share the information and carry day-to-day operations, but the investment and implementation is quite difficult for SMEs. This inspires us to investigate effect of new age supply chain technology like VMI practices in SMEs and other industries. VMI entails forecasting demand through joint efforts of customer and supplier, maintaining a targeted service level for customers, initiating and shipping supply orders, material control and customer order fulfillment.**

In this study, the results of adopting a partial vendor managed inventory practice, along with latest decision support tool like ANN, are presented. Outcomes of case study shows that deployment of vendor managed forecasting improves forecasting accuracy, reduces bullwhip, minimizes total supply chain cost, improves profits and most importantly improves customer satisfaction index

Overall five statistical models and five neural network models are adopted and compared. Study illustrates how a neural network aptly learns the case dynamics, and improves system performance. The results presented in this section demonstrates the effectiveness of the Focused Time Lagged Recurrent Neural Networks (FTLRNN) model compared to traditional and other neural network models. The significant finding of this research is results of forecasting error and other supply chain performance measures. Further study reveals that when we bracket the overstock and under stock cost in the supply chain cost, a forecast with minimum forecasting error may not lead to reduced supply chain cost or improved profits. This study also introduces a mixed model where the error obtained from statistical model is mixed with the forecast obtained by neural model and a new forecast is obtained. The analysis shows that the developed model could further improve supply chain performance in VMI setting.

Keywords: **Decision support system (DSS),**

I. INTRODUCTION

Organizations have multiple objectives like enhanced competitiveness, better customer service, increased profitability and so on. Organizations have relied upon business performance improvement methodologies viz. Quality Circles, Just in Time, Concurrent Engineering, Business Process Reengineering, Total Quality Management, Six Sigma etc. to seek these objectives. These approaches often focus on any one operational area of organization. But, today's global environment demands integration of several operations. The approach that integrates and coordinates all business operations in to a seamless process is called Supply Chain Management (SCM). Basically, it is the management of material, money, men, and information within as well as across the supply chain. In a traditional supply chain, each member is responsible for his own inventory control and production or distribution related activities. One fundamental problem for all members in a traditional supply chain (such as retailers, distributors, manufacturers, raw material suppliers) is deciding the production quantity which will satisfy its customer demand. In recent years, organizations have started working collaboratively to solve this problem. While working in a collaborative environment, supply chain members need to have a commonly agreed goal and an information sharing mechanism.

This supply chain mechanism is popularly known as Vendor Managed Inventory (VMI). It is a supply initiative where the supplier or manufacturer assumes the responsibility of tracking and replenishing a customer's inventory. The manufacturer himself decides the quantity to be delivered on the basis of information about sales and the stock level in the distribution center. Pending orders and replenishment schedules are also taken into consideration .The customer, on the other hand, has to share vital information to enable the manufacturer to formulate realistic order proposals and make reliable provisions.

The key characteristics of VMI are, thus, short replenishment lead times along with frequent and punctual deliveries that optimize production and transport planning. The other benefits that are to be obtained in successful VMI relationship differ for suppliers and customers. The suppliers will have a more stable demand from the customer and an increase in information flow. This will lead to improvement in production flexibility for the supplier. The customer on the other hand, will have lower inventory levels, reduced administration cost, increased service levels and reduced stock outs.

II. RESEARCH PROBLEMS AND SCOPE OF THE STUDY

In the traditional supply chain, orders are placed upstream from each supply chain member (retailer, distributor, and manufacturer) to other and, in turn, the member supplies the material downstream. Based on the projected demand of customers, retailers place an order to the distributor. The distributor places an order to a manufacturer based on demand forecast of retailers. The order placement and material passing process in a supply chain is subject to delays, and can take months to complete the cycle. By that time, the demand of the customer changes from what was originally forecasted. In addition, there are a host of problems related to transportation facilities, unnecessary transportation cost and problem of setting priorities to urgent and non-urgent orders. These problems could be mitigated with Vendor Managed forecasting systems. Therefore, there is a recognized need to increase an understanding of collaborative forecasting in supply chain management.

This study concentrates on the front-end function i.e. forecasting, and reveals how the adoption of partial Vendor Managed Inventory practices improves the supply chain performance. In this study, a forecast was developed by sharing daily demand information using a decision support tool like Artificial Neural Network (ANN).The outcome of case study shows that deployment of vendor managed forecasting improves forecasting accuracy, reduces bullwhip, minimizes total supply chain cost, improves profits and most importantly, improves customer satisfaction index.

Vendor Managed Forecasting and its Impact on Supply Chain Performance

A case study was undertaken in Indian SME to study adoption of VMI and its impact on supply chain performance. The case company was a small-scale enterprise engaged in manufacturing and marketing products. Detailed investigations revealed that the inventory carrying cost was exorbitant. On interrogation, it was found that one of the reasons behind higher inventory cost was the order placement and replenishment system. The retailers were ordering the required quantity once in five days. In other words, the inventory-carrying cost was higher and the ordering frequency was less. The cost behavior for year 2014-15 was analyzed. It was found that the major problem was inefficient forecast of demand from retailers. As a result of distorted forecasts, the company was suffering a huge loss. Retailers were happy with the existing strategy; however, management was keen to reduce the inventory cost and, ultimately the, total supply chain cost. So, the company decided to manage the retailer's inventory. Before adopting a new strategy, the performance of supply chain was measured.

III. PERFORMANCE MEASUREMENT

Performance measurement is done by calculating forecasting accuracy.

All supply chain decisions were based on forecast of customer demand. Therefore forecasting accuracy was taken as one of the measures. The degree of the accuracy was measured by calculating absolute error, mean absolute deviation, and mean absolute percentage error and tracking signal. In this study, Absolute Error, Mean Absolute Deviation, Mean Absolute Percentage Error and Tracking Signal were taken as evaluating measures. Using historical data, a forecast was obtained from neural network as well traditional models. This forecast was used by the manufacturer to decide the quantity to be supplied to the retailer. To find the differences in the forecasted demand and actual demand, the following formulae were used.

Forecasting Accuracy:

1. Percent Error. (P.E.)

$$\grave{e} = 100 * |f_t - d_t| / d_t \qquad (1)$$

2. Mean Absolute Percentage Error. (MAPE)

$$\ddot{e} = 1/n \sum_{t=1}^{n} |f_t - d_t| / d_t * 100 \qquad (2)$$

3. Absolute Error.

$$\Delta = | f_t - d_t | \qquad (3)$$

4. Mean Absolute Deviation. (M.A.D.)

$$\partial = 1/n \sum_{t=1}^{n} |f_t - d_t| \qquad (4)$$

5. Tracking Signal. (T.S.)

$$T.S. = \sum_{t=1}^{n} |f_t - d_t| / \partial_t \qquad (5)$$

where, n was number of observations, f_t was forecast for period t, d_t was demand for period t.

Linear Forecasting Models

1. Cyclical Forecasting Models
2. Exponential Smoothing Method
3. Winter's Smoothing Model
4. Trend corrected exponential smoothing method Model
5. Fourier Smoothing Model

Nonlinear Forecasting Models

1. Radial Basis Function Neural Network (RNN)

2. Multi-layer Perceptron Neural Network Models (MNN)
3. Self-Organizing Feature Maps (SNN)
4. Jordan –Elman Neural Network (JNN)
5. Focused Time Lagged Recurrent Neural Networks (FNN)

If the retailer had a prior knowledge of the demand, the ordering quantity was modified and the company supplied revised order quantity. For example, in case of biggest Indian festival Diwali, it is known that people do not buy bread much; therefore, there would less sale of product. If the forecast suggested supplying, say 450 quantities, and the retailer was sure that this much quantity would not be sold, this information was shared with the company. The company then sent a modified ordering quantity to the retailer. Similarly, for all situations, wherever there was a wide deviation in forecasted demand and actual demand, this methodology was adopted.

Thus, neural network based forecasts and information sharing about the demand patterns helped to modify the demand and execute the supply chain decisions. The methodology is depicted in Figure 3.2

The forecast obtained from F.T.L.R.N model was very close to the actual data. It was felt that, the results could be further improved if we incorporate the error observed in forecasting back to model and then make a forecast. The lowest forecasting errors were found for exponential model and F.T.L.R.N models. This indicated the closeness of these models with the existing system. In order to improve the profit, C.S.I. and to reduce the total supply chain cost it was decided to add the error from exponential model to the F.T.L.R.N. model and obtain the new forecast. This was done at the end of the year to get a new model of forecasting and to get a new direction of research. The model was coined as a Mixed model.

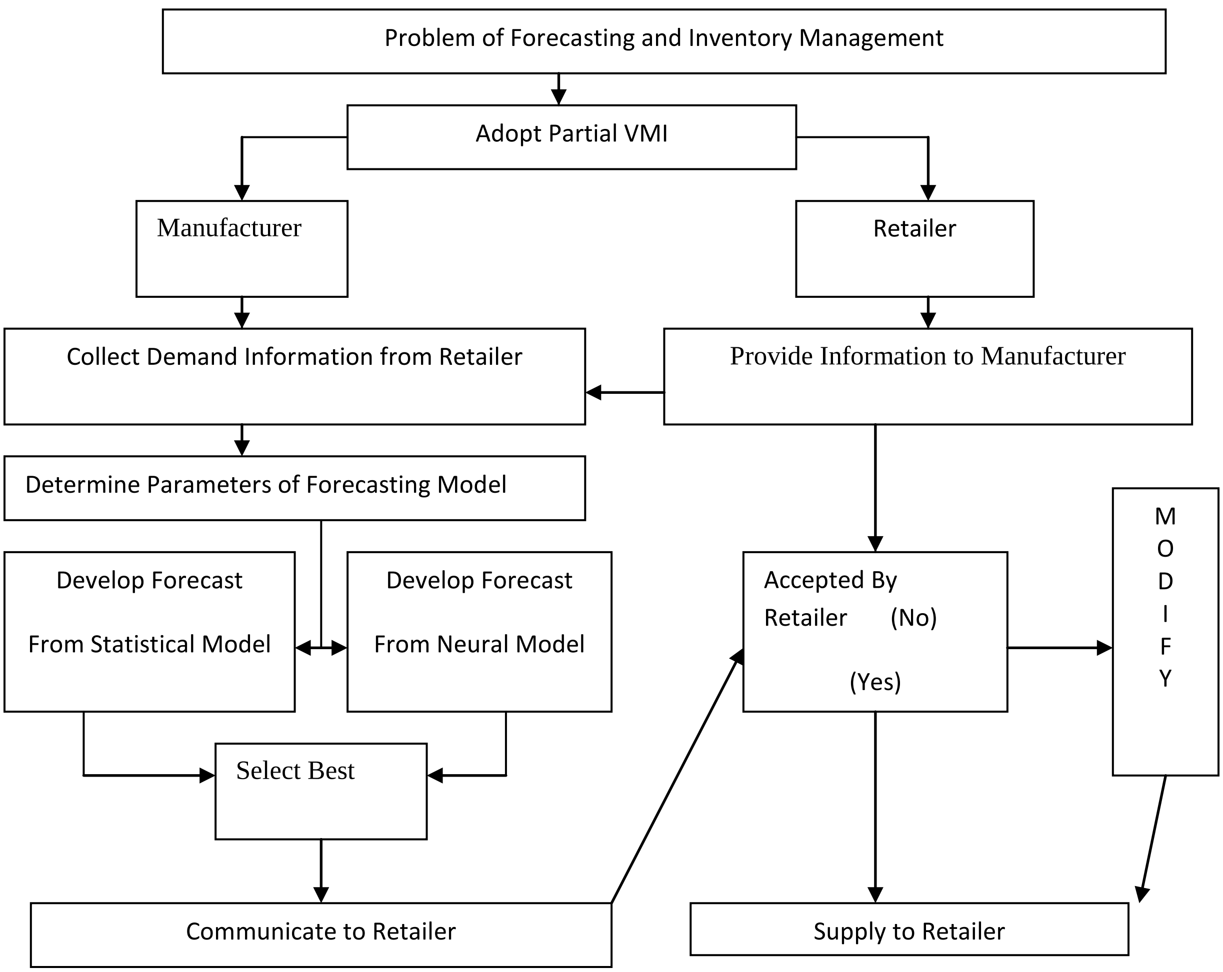

Fig.1 Decision Support System

IV. OBSERVATIONS

A case study was undertaken to validate the benefits of VMI adoption. In this study partial VMI was adopted. By sharing the demand related information of the retailer, the manufacturer projected the demand. Inventory replenishment decisions were taken on the basis of these forecasts and the impact on performance of supply chain was evaluated.

At the outset, the cost elements and inventory behaviors were analyzed. The various cost elements were as follows

ɳ – Number of orders,
ƒ was forecasted quantity supplied to retailer;
ɗ was actual demand at retailers end
ɧ – carrying cost per unit per day = 0.20
ƻ – resale cost for overstock per unit = 1.00
ʉ- burden for stock outs per unit = 2.20
ɱ – production cost per unit = 12.00
ɵ- ordering cost per order = Rs. 200
ƥ – processing cost per unit = 1.50
ſ – shipping cost per unit = 2.50

V. RESULTS

Vendor Managed Forecasting and its Impact on Supply Chain Performance.

Today organizations rely on supply chain software for demand forecasting and other inventory management decisions. These software have inbuilt algorithms for forecasting which are based on statistical or neural network models. But these supply chain software are costly and the company was not able to afford it. Therefore, the forecasts were manually developed based on statistical and neural network models.

The performance of each forecast was analyzed. First, the accuracy was measured. The findings are as shown in Figure 2 and Figure 3.

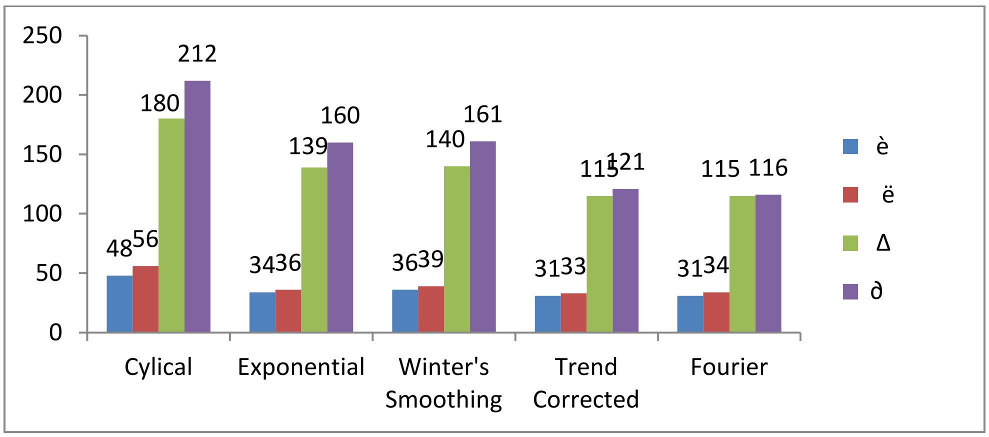

Fig.2 Forecasting Accuracy for Statistical Models

Similarly accuracy of neural network models was as shown below.

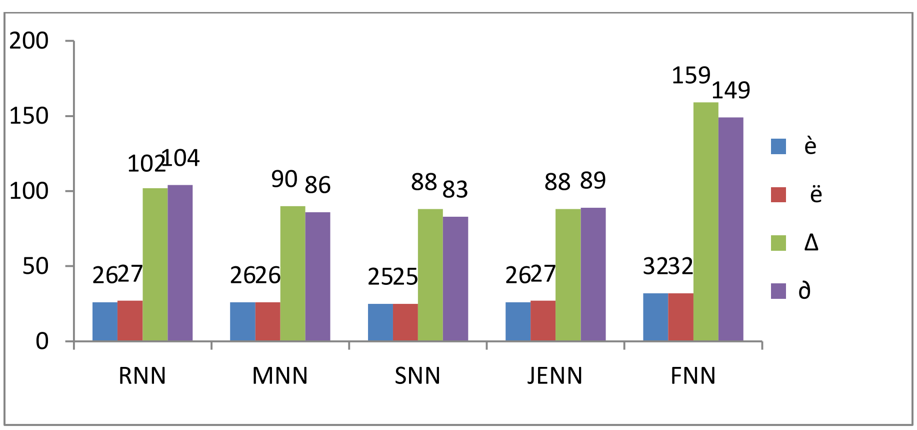

Fig3 Forecasting Accuracy for Neural Network Models

The tracking signal range for all models was as given below as shown in Figure 3 and Figure 4

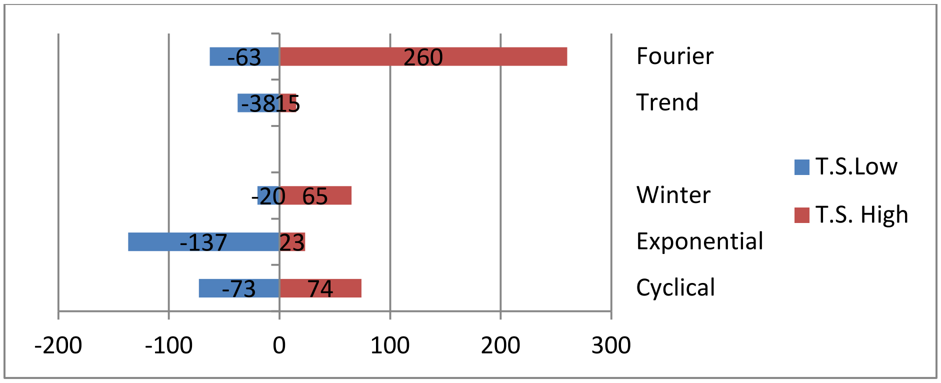

Fig.4 Tracking signal range for Linear Models

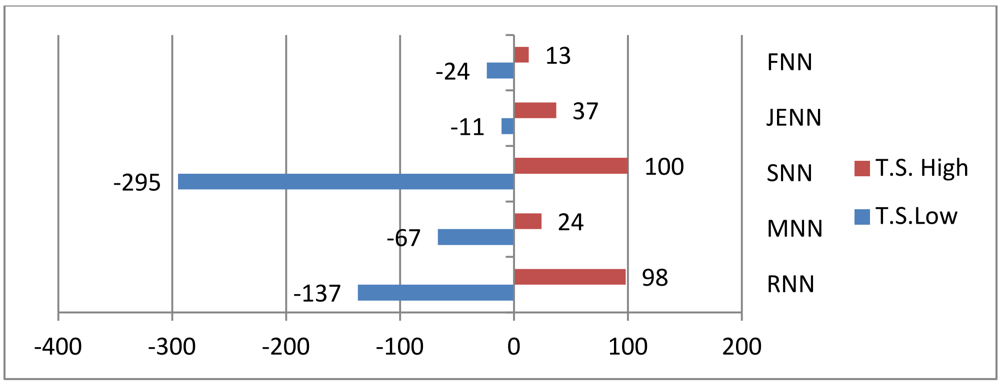

Fig.5 Tracking Signal range for Nonlinear models.

The effect of forecasts on inventory levels and customer satisfaction index was as follows.

Table 1 Effect of Forecasts Obtained from Neural Network Models on Inventory levels and Customer Satisfaction Index.

TABLE 1 EFFECT OF FORECASTS

	FNN	JENN	SNN	MNN	RNN
Over Stock	7.89%	9.03%	8.77%	7.99%	7.75%
Under Stock	24.31%	8.25%	8.35%	9.87%	12.79%
Service Level	49.45%	42.5%	12.79%	41.75%	41.20%

Similarly, the effect of statistical forecasts was observed.

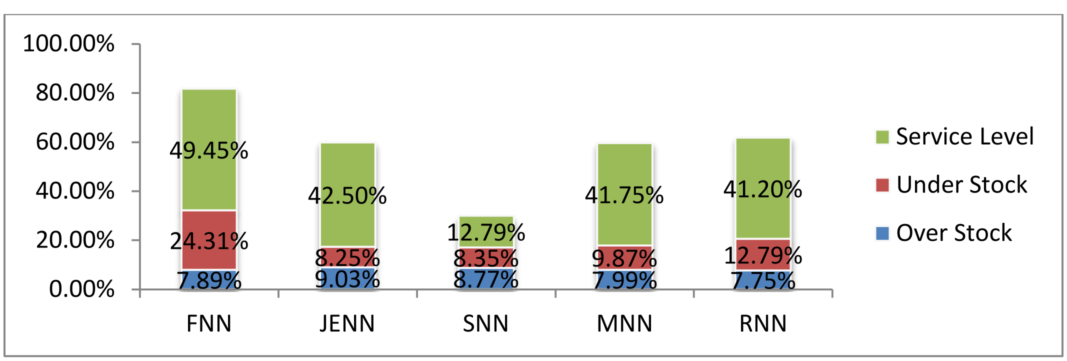

Fig.6 Effect of Forecasts Obtained from Neural Network Models on Inventory levels and Customer Satisfaction Index

Similarly, the effect of forecasts obtained from statistical methods were observed

TABLE 2 EFFECT OF FORECASTS OBTAINED FROM STATISTICAL MODELS ON INVENTORY LEVELS AND CUSTOMER SATISFACTION INDEX

	Fourier	Trend	Winter	Exponential	Cyclical
Over Stock	9.33%	7.07%	17.9%	7.48%	7.00%
Under Stock	19.79%	20.22%	17.32%	16.28%	17.08%
Service Level	34.06%	34.06%	43.15%	30.76%	30.21%

Similarly, the effect of statistical forecasts was observed.

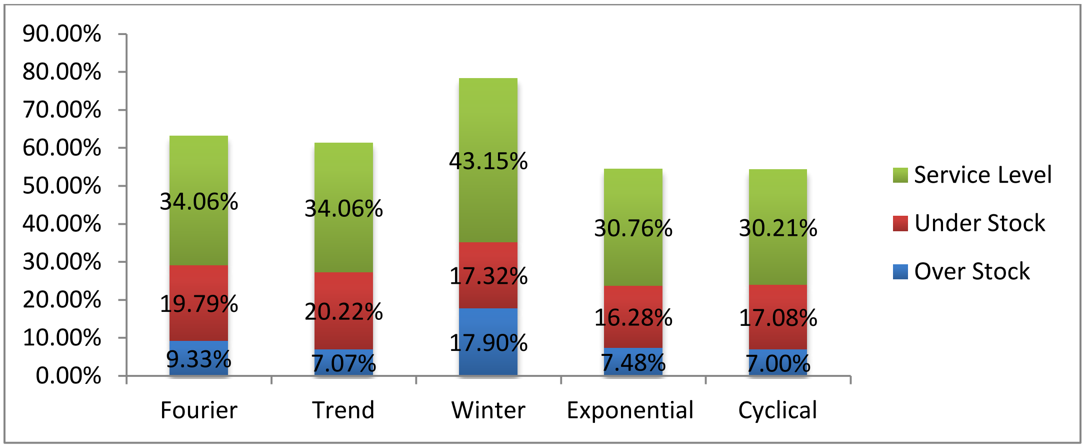

Fig.7 Effect of Forecasts Obtained from Statistical Models on Inventory levels and Customer Satisfaction Index

V. DISCUSSION

Five statistical forecasting models that are discussed in literature were chosen for forecasting the demand. Using each model, the forecasts were made. The company wanted a forecast, which could reduce the stock outs and overstocks. To be more specific, a forecast was needed which could learn the system and then predict the demand. Therefore, in addition to statistical forecasts, neural network models that are discussed in literature were used for forecasting. From the statistical analysis shown in Figure 2, it can be seen that highest value of errors were obtained for winter's model. The value of absolute error (A.E) was 180, mean absolute deviation (M.A.D) was 212, percentage error (P.E) was 48% and mean absolute percentage error (M.A.P.E) was 56%. While minimum error values were for cyclical forecaster. Absolute error was 115, Mean absolute deviation was 116, percentage error was 31% and mean percentage error was 34%. The obvious reason behind this may that the product is seasonal in nature and a perfect forecasting function might have been derived with this model. Errors obtained with Exponential models were very close to that of Cyclical models. While Errors obtained with Holt and Fourier Smoothing models were moderate.

For neural network models, as shown in Figure 3 the lowest error is observed for S.O.F.M. network. Here, A.E was 88; M.A.D. was 83; P.E was 25 % and M.A.P.E was 25 %. The highest error was found for F.T.L.R.N model. For the model, A.E was 159; M.A.D. was 149; P.E was 32 % and M.A.P.E was 32%. In fact, for almost all neural network models error was very less as compared to statistical models. Even the highest mean absolute percent error value i.e. 32 % obtained from neural model, specifically, from F.T.L.R.N model was less than that of all statistical models. It can be seen that the results from M.L.P., Jordon-Eleman, and S.O.F.M. models were analogous. Therefore, it can be inferred that forecasting accuracy is improved with neural network models.

Tracking signal (T.S) helps to identify whether there is over or under forecasting. Figure 4 and Figure 5 reveals the value of tracking signal for all models. It was observed that Jordon-Eleman and F.T.L.R.N. model provided the forecasts within a controllable limit. These models exhibited narrow tracking signal range. Tracking signal range for Jordon model was -11 to + 37 and T.S for F.T.L.R.N model was -24 to +13. Wider tracking signal range was observed for Fourier smoothing model, Exponential smoothing model and R.B.F model. Whereas, Cyclical, Winter's and M.L.P model shows moderate T.S range. It must be mentioned that F.T.L.R.N. model gave the highest values of percent errors but lowest values of tracking signal range. Similarly for Holt model, the deviation in percent error was large but the T.S range (-38 to 15) was the lowest among statistical models. In case of neural network models, percent error value for S.O.F.M. model was minimal but the tracking signal range (-295 to +100) was very high for this model.

Hence, it can be concluded that it is not customary that minimum-forecasting error leads to minimum tracking signal range.

When inventory levels and customer satisfaction index as shown in Table 1 and Table 2 were analyzed, significant differences were found for different models. A close look at these results reveals that the percentage of excess inventory was almost similar for statistical and neural network models. The only exception was Winter's model, which shows 17.9 % excess inventory. The percentage of short inventory was very high in case of statistical models. For most of the neural network models, shortages were in single digits. Only F.T.L.R.N. Model yielded high percentage of short inventory i.e. 24.31%. Thus it can be concluded that use of neural network models for forecasting can do considerable saving in inventory.

VI. CONCLUSIONS

The current business environment has compelled Indian industries to work collaboratively with their supply chain partners. This research was carried out to get insights on collaborative business practice i.e. Vendor Managed Inventory in Indian Industries. The specific aim of this research was to examine the applicability and potential of VMI in small and medium enterprises in India. This research adds to the existing literature on VMI practices.

The third study was undertaken to verify the results obtained from the survey of VMI practices in Indian SMEs. In this case study, outcomes of partial adoption of VMI system in a small-scale enterprise were analyzed. It was observed that step-by-step adoption of VMI enabled the enterprise under study to obtain the benefits that are proposed theoretically. This study focused on front-end function of VMI i.e. Vendor Managed Forecasting. In this study, a simple information sharing mechanism between retailer and case industry was developed. Using demand related information and by deploying statistical and neural network models, vendor managed forecasts were developed. From the results, it is observed that properly trained neural network yields better forecasts and helps to improve supply chain performance. Finally, it is concluded that vendor managed forecasting helps to decrease inventory levels, reduce total supply chain cost and improve customer satisfaction simultaneously. The observations of this study have important managerial implications. It is known that precise forecasting depends on forecasting horizons, information technology requirements and in-house expertise. Large organization can easily take care of all these factors. However, for small enterprise it is difficult to invest in special software and support staff. In such an event, small enterprise can go for partial adoption of VMI and develop decision support tool based on neural networks to improve the business performance. The results of this study can be easily replicated with other small enterprises.

REFERENCES

[1] A. Abraham and B. Nath, "A neuro-fuzzy approach for modeling electricity demand in Victoria," *Applied Soft Computing* ,Vol. 1, pp.127–138, 2001.

[2] L. Aburto, and R. Weber, " Improved Supply Chain Management based on hybrid demand forecasts," *Applied Soft computing*, Vol. 7 , pp. 136-144, 2007.

[3] D. Achabal, S. Mclntyre, S. Smith and K. Kalyanam, "A decision support system for vendor managed inventory," *Journal of Retailing*, Vol. 76, No.4, pp. 430– 454, 2000.

[4] I. Alon, M. Qi, and R.J. Sadowski , "Forecasting aggregate retail sales: a comparison of artificial neural networks and traditional methods," *Journal of Retailing and Consumer Services* ,Vol. 8, pp. 147-156, 2001.

[5] P. Arce, J. Antognini, W. Kristjanpoller and L. Salinas., "An Online Vector Error Correction Model for Exchange Rates Forecasting," *Proceedings of the International Conference on Pattern Recognition Applications and Methods (ICPRAM-2015)*, pp. 193-200, 2015.

[6] A.F. Atiya, S.M. El-Shoura, S.I. Shaheem, and M.S. El-Sherif , "A comparison between neural-network forecasting techniques – Case study: River flow forecasting ,"*IEEE Transactions on Neural Networks* ,Vol. 10, No. 2, pp. 402-409, 1999.

[7] A. Azadeh, S.F. Ghaderiand S. Sohrabkhani, " Forecasting electrical consumption by integration of Neural Network, Time series and ANOVA," . *Applied Mathematics and Computation* , Vol. 186 , No. 2 , pp.1753-1761, 2007.

[8] R.K. Bannor and M. Melkamu, ARFIMA, ARIMA And ECM Models Forecasting Of Wholesale Price Of Mustard In Sri Ganganagar District Of Rajasthan Of India, *Journal of Business Management & Social Sciences Research* , Vol. 5, No.1 , pp 1-13, 2016.

[9] M. Barratt and A. Oliveira, " Exploring the experiences of collaborative planning initiatives," *International Journal of Physical Distribution & Logistics Management,* Vol. 31, No.4, pp.266 – 289, 2001.

[10] J.E. Biegel, .*Production Control - A Quantitative Approach* , Prentice Hall India Ltd. , Delhi ,pp. 15, 1987.

[11] G.E.P. Box, G.M. Jenkins and G.C. Reinsel, *Time Series Analysis Forecasting and Control* , Pearson Education Asia , Delhi ,pp 131-180 , 2004.

[12] P.C. Chang , C.H. Liu and Y.W. Wang, a . "A hybrid model by clustering and evolving fuzzy rules for sales decision supports in printed circuit board industry, " *Decision Support Systems* ,Vol. 42 , pp.1254–1269, 2006.

[13] P.C. Chang , C.Y. Lai and K.R. Lai, ".A hybrid system by evolving case-based reasoning with genetic algorithm in wholesaler's returning book ,". *Decision Support Systems* , 42,,pp. 1715–1729, 2006.

[14] P.C. Chang , Y.W. Wang and C.H. Liu, "The development of a weighted evolving fuzzy neural network for PCB sales forecasting ,". Expert *Systems with Applications* , Vol. 32 , pp.86–96, 2007.

[15] K.K. Chang, "Applying Fourier Transform and Linear Time Invariant Analysis to Brain Imaging Data, Project for Machine Learning," . Available at *\www.cs.cmu.edu/~kkchang/paper/Chang.2005.10-701.brainImaging.rtf* -Si , 2005.

[16] Y.M. Chiang, F.H. Chang, B.J. Dao Jou and P.F. Lin, "Dynamic ANN for precipitation estimation and forecasting from radar observations,". *Journal of Hydrology* , 334 , pp. 250-261, 2007.

[17] S. Chopra and P. Meindl. *Supply Chain management .Strategy, Planning and Operation* .Pearson Education Asia, 2001.

[18] C.W. Chu and G.P . Zhang, ''A comparative study of linear and nonlinear models for aggregate retail sales forecasting". *International Journal of Production Economics,* Vol. 86 , pp. 217–231, 2003.

[19] C.W. Chu and G.P. Zhang, ''A comparative study of linear and nonlinear models for aggregate retail sales forecasting ,"*International Journal of Production Economics,* Vol.86 , pp. 217–231, 2003.

[20] C.W.Chu and G.P. Zhang, ''A comparative study of linear and nonlinear models for aggregate retail sales forecasting," *International Journal of Production Economics,* Vol. 86 , pp. 217–231, 2003.

[21] F. Costantino ,G. Gravio, A. Shaban, and M. Tronci, "SPC forecasting system to mitigate the bullwhip effect and inventory variance in supply chains," *Expert Systems with Applications* ,Vol. 42, pp 1773–1787, 2015.

[22] M. Dekker, K. Donselaar and P. Ouwehand , "How to use aggregation and combined forecasting to improve seasonal demand forecasts," .*International Journal Production Economics* , Vol. 90 , pp. 151–167, 2004.

[23] S.V. Dudul, "Identification of liquid saturated steam heat exchangers using focused time lagged recurrent neural network, "*IETE Journal of Research* , Vol. 53, No.1, pp. 69-82, 2007.

[24] R. Frankel, T.J. Goldsby and J.M. Whipple, "Grocery Industry Collaboration in the wake of ECR," *The International Journal of Logistics Management*, Vol. 13 ,No. 1, pp.57 – 72 , 2002.

[25] E.W. Frees and T.W. Miller, "Sales forecasting using longitudinal data models ," *International Journal of Forecasting* , Vol. 20 , pp. 99–114, 2004.

[26] S. Georgakarako, D. Koutsoubas and V. Valavanis "Time series analysis and forecasting techniques applied on loliginid and ommastrephid landings in Greek waters,". *Fisheries Research*, Vol.78 , pp. 55–71, 2006.

[27] A. Haq and G. Kannan, Effect of forecasting on the multi echelon distribution inventory supply chain cost using neural network, genetic algorithm and particle swarm optimization. *International Journal of Services Operations and Informatics* , Vol. 1 (1/2) , pp. 1-22, 2006.

[28] P.J. Harrison, "Short term demand forecasting," *Applied Statistics*, Vol. 14 , pp. 102-139, 1965.

[29] S. Haykin, Neural Networks –A comprehensive foundation, Pearson Education, Delhi ,pp .443, 2006.

[30] C.C. Holt, F.J. Modigliani, F. Muth, and H.A. Simon, *Planning Production, Inventories and Work Force*. Prentice Hall, Englewood Cliffs, N.J., 1963.

[31] L. Horvath,." Collaboration: the key to value creation in supply chain management," .*Supply Chain Management: An International Journal*, Vol. 6, No.5, pp.205 -207, 2001.

[32] J. Krajewski ,L. ,Ritzman ,." Operations Management Strategy and Analysis," Pearson Education Asia, Delhi, pp. 491-Vol. 542, 2000.

[33] R.J. Kuo, P. Wub, C.P. Wang , " An intelligent sales forecasting system through integration of artificial neural networks and fuzzy neural networks with fuzzy weight elimination," *Neural Networks* , Vol. 15 , pp. 909–925, 2002.

[34] A.A. Kurawarwala , H. Matsuo, Product growth models for medium-term forecasting of short life cycle products . *Technological Forecasting and Social Change* ,Vol. 57 , pp. 169-196, 1998.

[35] M. Macas, , F. Moretti, A. Fonti, A. Giantomassi, G. Comodi, M. Annunziato, S. Pizzuti , A. Capra, . The role of data sample size and dimensionality in neural network based forecasting of building heating related variables, *Energy and Buildings*, DOI: 10.1016/j.enbuild.2015.11.056, 2016.

[36] T. Michinaka, H. Kuboyama, K. amura ,H. Oka, and N. Yamamoto, *Forecasting Monthly Prices of Japanese Logs.*, Vol.7, No.94 , pp 1-19, 2016.

[37] H.Min, G. Wei, F. Mingming, ".Multivariate Chaotic Time Series Prediction Based on Radial Basis Function Neural Network," *Advances In Neural networks* , Vol. 3, pp. 741 – 746, 2006.

[38] P. MISHRA, P.K. SAHU, K. PADMANABAN ,K.P. VISHWAJITH and B.S. DHEKALE,*Study of Instability and Forecasting of Food Grain Production in India. International Journal of Agriculture Sciences*, Vol.7, No. 3 , pp.-474-481, 2015.

[39] Y.S.Murat and H. Ceylan ,. '' Use of artificial neural networks for transport energy demand modeling, "*Energy Policy* ,Vol. 34 ,pp. 3165–3172, 2006.

[40] N. Myhr and R.E. Spekman," Collaborative supply-chain partnerships built upon trust and electronically mediated exchange," .*Journal of Business & Industrial Marketing*, Vol. 20, (4/5), pp. 179 – 186, 2005.

[41] P. Potočnik, E. Strmčnik. and E. Govekar., "Linear and Neural Network-based Models for Short-Term Heat Load Forecasting.," *Journal of Mechanical Engineering* , Vol. 61, No. 9 , pp. 543-550, 2015.

[42] A. Raveh, and C.S. Tapiero, "Finding common seasonal patterns among time series. *Journal of Econometrics*, " Vol. 12 ,pp..353–363, 1980.

[43] R.D. Snyder , A.B. Koehler, R.J. Hyndman, and J.K. Or, "Exponential smoothing models: Means and variances for lead-time demand," .*European Journal of Operational Research*, Vol. 158, pp. 444–455, 2004.

[44] S.T. Thomassey , A. Fiordaliso, "A hybrid sales forecasting system based on clustering and decision trees,". *Decision Support Systems*, 42, pp. 408– 421, 2006.

[45] T.Y. Wang, and C.Y. Huang , "Improving forecasting performance by employing the Taguchi method,". *European Journal of Operational Research* ,Vol. 176 , pp.1052–1065, 2007.

[46] T.Y. Wang, and C.Y. Huang , " Improving forecasting performance by employing the Taguchi method," *European Journal of Operational Research* ,Vol. 176 , pp.1052–1065, 2007.

[47] H. Winklhofera and A. Diamantopoulos,." A model of export sales forecasting behavior and performance: development and testing,'" International *Journal of Forecasting*, Vol. 19, pp. 271–285, 2003.

[48] P.M. Yelland, "Stable seasonal pattern models for forecast revision: A comparative study,". *International Journal of Forecasting*, Vol. 22, pp. 799–818, 2006.

[49] X. Zhao, T. Xie, and W.J. Zhang, " The impact of information sharing and ordering co-ordination on supply chain performance," *Supply Chain Management An International Journal*, Vol. 7, No.1 , pp. 24-40, 2002.