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An Investigation on Machine Learning Approaches in Supply Chain Forecasting: A Survey

K. Prahathish, J. Naren, Dr.G. Vithya, S. Akhil, K. Dinesh Kumar
and S. Sai Krishna Mohan Gupta

Abstract--- *Forecasting necessitates the important decision making in Supply Chain network. Recently, machine learning techniques has leveraged towards increasing the forecast accuracy thereby reducing errors. In this work, brief analysis over various machine learning techniques in demand forecasting, demand uncertainty, intermittent demand, reducing bullwhip effect, available in the literature has been surveyed. Demand across echelons of the chain varies as each participant creates various demands. Hence, there is a need for forecasting such scenarios where meeting uncertainties in the future might effectively contribute to the efficient functioning of Supply Chain.*

Keywords--- *Supply Chain, Forecast, Demand, Artificial Neural Network, Logistics, Support Vector Machine, Bullwhip Effect, Inventory.*

I. INTRODUCTION

Forecasting is done in almost every day-to-day activity in order to meet future requirements. With growing economic activities in the country, businesses have to sustain with a huge task in the field of Operations Management. Supply Chain(s) (SC) forms the integral part of managing goods, services, transportation and information sharing with the stakeholders especially has become a source of utmost importance (Zhao et al., 2002[27])

Typically, an SC is inclusive of echelons such as Supplier, Manufacturer, Distributer, Retailer and end Customer, and the necessary flow of information to the upstream end and downstream flow of materials, products, and services explained in Fig. 1. Each echelon may have its own SC or logistics within its network contributing to several layers in operation. The end customer creates a demand for the product that entirely initiates the SC of operations in motion (A.A. Syntetos et al., 2015[1].

Demand for information, goods, and services are created across every player in the chain. This demand however is not constant and highly fluctuates and is distorted. Forecasting such demand distortion which is often non-linear in extended SC is indeed helpful for decision makings in the field of Operations Management and Research. Intermittent demand (ID) or sporadic demand refers to zero and or non- zero demand that a product experiences over an irregular period of time and frequency of such demand is highly variable. So, forecasting ID becomes a crucial

K. Prahathish, B.Tech Computer Science and Engineering, School of Computing, SASTRA Deemed University, Thanjavur, India. E-mail: prahathishk97@gmail.com
J. Naren, Assistant Professor, School of Computing, SASTRA Deemed University, Thanjavur, India. E-mail: naren.jeeva3@gmail.com
Dr.G. Vithya, Professor, School of Computing, KL University, Vijayawada. E-mail: vithyamtech@gmail.com
S. Akhil, B.Tech Information Technology School of Computing, SASTRA Deemed University Thanjavur, Tamil Nadu, India. E-mail: 121015123@sastra.ac.in
K. Dinesh Kumar, B.Tech Information Technology School of Computing, SASTRA Deemed University Thanjavur, Tamil Nadu, India. Email: 121015119@sastra.ac.in
S. Sai Krishna Mohan Gupta, B.Tech Information and Communication Technology School of Computing, SASTRA Deemed University, Thanjavur, Tamil Nadu, India. Email: saikrishna@sastra.ac.in

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factor in inventory that influences lead time of service. Variants of Neural Network(NN) for ID forecasting outcasts the traditional methods overcoming its limitations with respect to forecast accuracy and has profound itself to be effective.

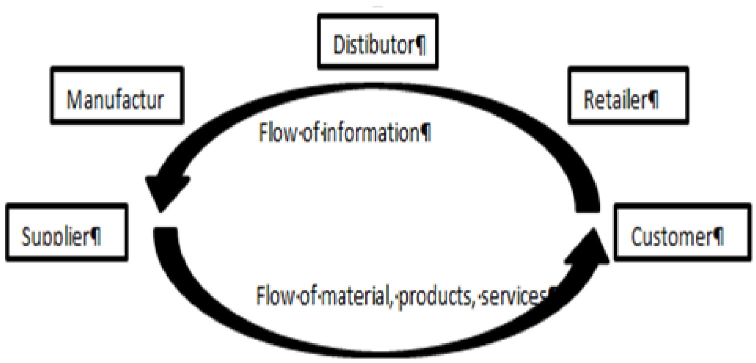

Fig. 1.1: A Supply Chain Network

Supply and demand is the key to any successful business for delivering their products or services to their reputed customers. Supply of necessary goods, which are either in transit or in warehouses within the network efficiently, is completely governed by a logistics department of an organization. Any industry should be aware of what product to hold and what not to hold depending upon varying demand.

Machine Learning (ML) strategies have paved the way for forecasting the future requirements in the recent era. The very purpose of this paper is to illustrate the emerging trends in forecasting using learning approaches of Artificial Neural Network (ANN), Support Vector Machines (SVM), Extreme Learning Machines and other such equivalent or modified networks which are contributed to the literature. Hill et. al. [5] (1994), observed the adoptions of ANN models in place of future predictions using statistical learning and decision making models. One of the main reasons to adopt ML techniques for prediction analysis is the non- linearity (Weiland and Leighton, 1988[5]) in time series data, which efficiently maps the input data to output data. It is understood that it is almost impossible to cover every literature available subjected to this topic. Only those selective techniques that have forecasting metrics to SC using Machine Learning have been concentrated.

Comparison of "traditional" forecasting techniques as categorized by R. Carbonneu et al.[17] with the current advanced techniques of NN and SVM are beyond the scope of this study. This survey subjects only to literature works in methodologies of machine learning in SC Management

II. INFORMATION SHARING AND ITS EFFECT

Presently, IT advancements have enormously boosted the information sharing in the market. Sharing of information regards to customers demand that is being processed and communicated by the members acting in the SC. Businesses and E- Commerce have become competitive and have to be "agile" (Gunasekaran and Ngai, 2004[2]) enough to produce a quality product in terms of product life cycle, robustness, quality etc. and efficient integration of SC is the most sought area in recent era. Investments in IT has improvised almost every sector and it is seen as the "glue" which knits business together (Sanders and Premus, 2002[15]). Information sharing leads to collaborative practices. Increasing and improvising the accuracy of forecasts is one among the main aim of collaboration (Raghunathan, 1999[20]). Many such collaborative practices have been adopted like CPFR abbreviated as Collaborative Planning, Forecasting and Replenishment (Ireland and Bruce,2000[18]).

Inventory refers to current stocks held by a company which are in intermediate storage place like a warehouse and shall be made to transit once orders are placed. Approaches to reducing inventory can be done by collaborative planning (De Koket al., 2005[21]) which has potential in influencing customer service levels. Achieving such a factor, ML exploits the usage of forecasting demand in SC, and several literature works have proven that it has hugely impacted inventory. Sharing of demand and inventory have also bloomed a collaboration practice called Vendor Managed Inventory (VMI) which has marginally reduced information distortions and the famous "Bullwhip effect", a termed coined by Procter & Gamble (P&G) during 1990's which means amplification in signals of orders (customer's order) get increased as one moves towards the upstream end of the chain. The reduction in amplification is believed to lie in information sharing mechanisms such as Demand Information Sharing and VMI acros SCs (X.Wang and S.M. Disney[26]).Forrester (1961)[10] made this approach to industrial metrics. Strong academic research has been devoted to this area. Readers can view, The bullwhip effect: Progress, trends and directions, X.Wang and S.M. Disney[26] for a detailed study. Several papers have devoted their work to reduce the Bullwhip Effect (BWE), which shall be seen in the next section

III. LITERATURE REVIEW

Methodologies of ML that has been exploited by several authors have aforementioned the mathematical background behind ANN, SVM etc. in their works. This current work avoids the explanation of working of such techniques and just surveys over some recognized works that has helped effectively forecasting SC. Forecasting approaches have been exhaustively discussed in the works of A.A. Syntetos et al.[1], "Supply Chain Forecasting: Theory, practice their gap and future". Readers can The findings of the survey have been tabulated in Table 1. for a brief overlook of the works described below.

Dong and Wen (2006) [25], proposed a model of Recurrent Neural Network (RNN) in order to reduce the uncertainty in inventory. The proposed model is compared with Multi Layer Feed Forward Neural Network and made a prediction of time series simulated data and a real world practical sale of paper of a papermaking enterprise. Only the influencing factors like season and paper category were taken into consideration for building the proposed NN model. Significant reductions in errors were achieved in forecasting which were compared against the traditional techniques. One such first step in forecasting is concluded by the fact that it shall be helpful of inventory related decision making.

R. Carbonneu et al. (2008) focuses distorted demand signal processing as it travels the extended SC (Tan (2001)[14]; Davis and Spekman (2004)[7]). The ML techniques such as NN, RNN, and SVM have been used to compare against the "traditional" techniques such as Naïve, Average, Moving Average, Trend, Multiple Linear Regression which were the actual existing statistical forecasting methods. The objective rather lied to forecast future demand to match for compensating manufacturer's lead time by using the orders of the manufacturer. The data used are the simulated data (developed in MATLAB Simulink) for an extended SC and an actual foundries data from a Canadian statistical database called Statistics Canada. The demand signal created at the customer end gets processed eventually getting distorted at each levels in the extended SC. The data has been observed, trained and tested over various days, periods and the results were tabulated for the same. Comparisons of the techniques mentioned were tabulated on the basis of Mean Average Error (MAE). The results were concluded that the ML techniques were the best performers with more accurate forecasting efficiency in terms of reduced error percentages. Variations within the accuracy ML techniques were almost the same with no such marginality being observed.

R.S. Gutierrez et al. (2008)[19]compared NN modeling with the existing mathematical predictors of ID such as (i) single exponential smoothing, (ii) Crostan's (CR) methods (Crostan 1972[12]), (iii) Syntetos and Boylan Approximation (SBA) (Syntetos and Boylan, 2001[5]). Adoption of the *Multi Layer Perceptron* (MLP) consisting of three main layers (1 input, 3 hidden and 1 output) and having it trained by back propagation algorithm. Industrial data consisting of 24 time series consisting 967 demand observation of a Stock.

Keeping Unit (SKU) of a distributor in Monterry, Mexico usually inter demand intervals of an ID is highly varies. Hence non-linearity of NN property again comes to play. Based on the average non-zero demand size the NN model seemed to be almost superior to those the existing methods of ID. The author summarises by concluding that superiority in NN model performance has been observed when compared existing methods in regard to error measures such as *Mean Absolute Percentage Error* (MAPE), *Percentage Best* (PB) and *Relative Geometric Root-Mean-Square Error* (RGRMSE) [Syntetos and Boylan,2005[5]].

Anandhi and R. M. Chezian[24] forecasted the price of pulpwood (eucalyptus) using ANN by the help of the tool MATLAB predicted the future costs from the data being collected from Tamil Nadu Newsprint and Papers Limited (TNPL) in Karur District, Tamil Nadu. The data is trained using Back Propagation algorithm called Levenberg–*Marquardt* training, a learning based on supervised training algorithm. It predicted the future prices using previous year's data. Detailed specifications regarding hidden layers, numbers of iterations etc have been detailed in the paper. The motive behind one such study is to aid the farmers and relevant traders in the field and once this study has been validated, it shall help the Government to take initiatives for decision making for the future. Again, in their study [25], SVM architecture was adopted to predict the demand and supply of pulpwood obtained from the same paper-manufacturing firm TNPL

Nikolaos Kourentzes[16]tried to forecast the ID using a proposed NN model in comparison with the existing conventional ID forecasting metrics proposed by that of Crostan's and Syntetos and Boylan. The dataset comprised of 3000 time series of automotive parts from one such industry with each series containing 36 Observations. The previous records dating upto 3 years were considered and out of which 100 samples were taken as sample data and another 100 such samples were taken for simulation. Inventory metrics were also taken into consideration given the fact that forecasting imparts a huge weightage in this area. ID usually consists of zero or non-zero demand for every inter-demand interval which is usually highly varying. The existing models could not take the interdependency in non- zero demand and inter-demand intervals because of its non-linear relationship. Although several corrections to Crostan's model were later made (A. Rao [4],Syntetos and Boylan[5]), the proposed NN models were able to capture the non-linearity. Two architectures of NN model proposed were NN-Rate and NN- Dual that takes the non-zero demand and inter-demand intervals as inputs. The proposed NN-Dual architecture produced demand and interval forecasts whereas the NN-Rate avoided the forecast biasing and produced a single linear output of Demand Rate. Detailed discussion regarding forecasting and inventory metrics are discussed in this paper. The results obtained forecasting the proposed NN models were compared against the Crostan's variants and conventional models of forecasting. NN models were poor contesters in forecasting accuracy while in terms of Inventory metrics, they achieved higher service levels. A Service level directly affects key decision making in SC Management. One should not conclude the fact that these results obtained shall apply universally across all such forecasting metrics. The forecasting measures were taken restricted to a particular dataset forecasted over a distinct time-series, trained for a particular period and tested the same predicting future demand. In this case, service levels were quite higher viz-à-viz the conventional variants of Crostans'

Efforts made by SanjitaJaipuria and S.S. Mahapatra to reduce Bullwhip Effect (BWE) are an attempt to forecast and reduce the Mean Squared Error (MSE) and the BWE. The architecture using Discrete Wavelet Transform (DWT) integrated with ANN is proposed.

The main purpose of introducing the DWT as explained by the authors is to capture the pattern in data which makes the learning simpler. The output of the DWT signals is fed as the inputs of ANN. A comparative study of proposed DWT-ANN model with Auto Regression Integrated Moving Average (ARIMA) (Box and Jenkins, 1970[9]) has been done using an example dataset available from open literature and tested with a dataset from three manufacturing firms. Conclusions drawn from study shows that the MSE is far lesser in DWT- ANN model than the Box Jenkin's ARIMA approach.

BWE is measured as the ratio of variance in order to variance in demand. If BWE is greater than one, then BWE is said to exist Every forecasting technique tries to make the BWE to be lesser than 1 and the proposed DWT-ANN architecture has proven to be better at making BWE lesser than the ARIMA models at most of the cases during testing.

Also, there exists another factor calledNet Stock Amplification (NSAmp) which is defined as the ratio of variance of net stock to variance of demand. The DWT- ANN model also reduces this factor in all the three cases of testing. Overall, the study concludes that reduction in BWE and NSAmp forecasted by proposed DWT-ANN model shall significantly increase customer service levels and thereby reducing overall cost of SC.

F. Lolli et al.[8] were the first to use a concept called Extreme Learning Machine, a machine learning approach that adopts faster and simpler learning in forecasting ID. This paper concentrates on comparison study of proposed neural network model and a back-propagated NN with the existing benchmark NNs (feed-forward, time delay, and recurrent) and the famously known estimators of ID (Crostan, Syntetos and Boylan) using different input patterns and cross combinations of several estimators.

The dataset consisted of 24 different time series data of ID. Although in the study, the extreme learning machine could not achieve much forecasting efficiency as the models trained using back propagation. However, the computational efforts are much simpler and easier than the other existing NN models. Hence investigation regarding such learning algorithms can be adopted for future works which shall significantly reduce time and energy.

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Table 1: Comparison of various Machine Learning Techniques surveyed

Author(s)	Problem scenario	Data	Technique s used	Results
Xiaoni Dong and Guangrui Wen.	Prediction of sales for Inventory Management	Sales of paper from papermaking enterprise.	RNN compare d with Multi Layer Feed- forward NN	Higher accuracy, prediction achieved using RNN helping inventory decision making.
R. Carbonneau et al.	Forecasting the processing of Distorted Demand signal.	Foundries monthly sales data from Statistics Canada	NN, RNN, SVM comp ared with “tradi tional ” meth ods.	RNN, SVM outperformed “traditional” models improving forecast accuracy for foundries dataset.
R.S. Gutierrez et al.	Forecasting lumpy demand	Industrial demand observations for SKUs by an electronics distributor in Monterrey, Mexico	NN (3 layered) compared with traditional methods of ID	NN found to be superior than the traditional ones (CR, SBA and single exponential smoothing) for forecasting error measures.
V. Anandhi and R. M.Chezian	Forecasting the Price of Pulpwood – Eucalyptus	Pulpwood costs from TNPL, Tamil Nadu	1. ANN with LVBP Algorithm 2. SVM	Predicted the future costs of pulpwood by training previous years’ using MATLAB.
Nikolaos Kourentzes	Intermittent Demand (ID) Forecasting	Simulated set of 1000 items used by Syntetos and Boylan (SBA)	NN-Dual and NN-Rate compared with Croston (CR) based methods (Tradition al)	NN Models proposed achieved poor forecasting accuracy. On contrary, obtained higher service levels (inventory metrics) outperforming Croston’s variants.
SanjitaJaipuria and S. S.Mahapatra	Demand Forecasting method to reduce Bullwhip Effect (BWE) in SC	Collected from open literature from anonymous firms.	Integrat ed DWT-ANN compare d with ARIMA	Proposed models achieve higher forecast accuracy and less error which reduce BWE and NSAmp when compared to ARIMA model thereby reducing total cost of SC.
F. Lolli et al.	Extreme Learning machine approach forecasting ID.	24 Weekly ID of spare parts in Automotive Sector	Extreme Learning Machines compared with standard CR, SBA and set of ANN’s like feed forward, time delay and recurrent.	NN does have better performance comparatively but adopting Extreme Learning Machines offers less computational efforts than ANN models.
Karin Kandananond	Consumer Product demand forecasting	Six different consumer based products from Thailand	ANN and SVM	SVM outperformed ANN for non-correlated dataset in terms of error measurement of MAPE.

Real time demand of six consumer based products from a product based company in Thailand (used for training) was studied by Karin Kandananond[13]and forecasted the demand for the next upcoming future were predicted using proposed SVM and ANN architecture. The architectures however utilized only correlated data obtained from a single pattern. The SVM had better forecasting accuracy in terms of MAPE when compared with its ANN counterpart. This was only in the case the data was correlated. The results were different when the similar time series data was worked with no correlation

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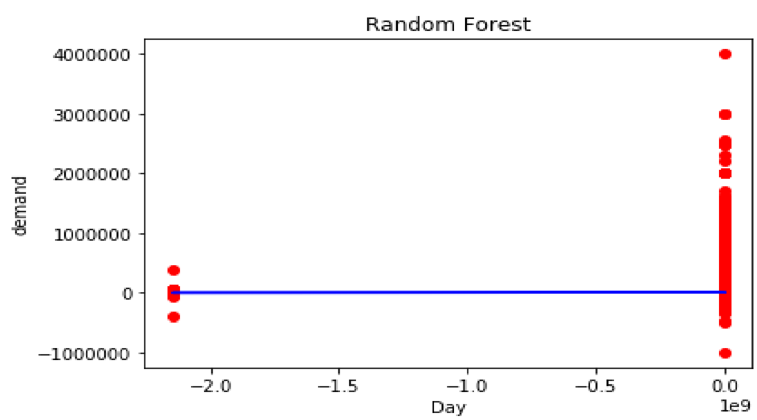
IV. DISCUSSION

The literature reviews of several works as discussed above have been briefly discussed in a tabulated format in Table 1. Every literature work tried to capture the essence of machine learning technique and investigated the same with a sole purpose to reduce errors, decrease overall SC cost, decrease inventory, improve SC information sharing, reduce lead time. The list does not end here. The measures taken to forecast future consumption of resources directly affects the SC decisions and thereby increasing customer service levels.

V. RESULTS



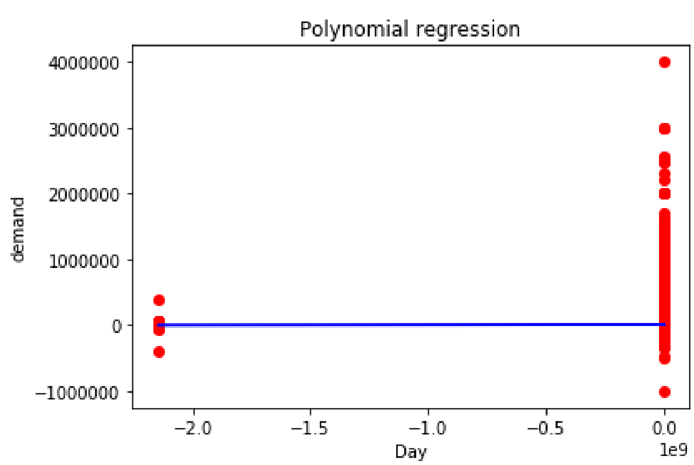


Figure 1.2: Graph depicting Machine Learning Algorithms

Inference: The above graph shows the prediction of product for one month day wise using random forest and polynomial regression

VI. CONCLUSION

In the field of Operations Management, decision making is the heart for the businesses to sustain and exist. Such vital decisions are influenced by forecasting future consumption of demand across various echelons of SC. The survey encompasses a wide range of forecast data starting from the supplier end or the upstream end of the chain and various other participants in the network. There is also a study conducted on consumer-based products, which forecasts consumption at the customer end. Hence, forecasting techniques that have been heavily exploited using ML learning have proven to have higher degree of accuracy and robustness when compared with the conventional statistical models. Several other variants of ANN can be integrated with neuro-fuzzy, deep convolution nets can be adopted which are also a broader area of study that prompts research gaps . Future works can be narrowed towards integration of ML using Big Data analytics (A. L'Heureux et al.[3]).

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