Industrial Forecasting Support Systems and Technologies in Practice: A Review

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Abstract

With the present changing and uncertain economic and marketing scenario the available resources must be utilised by the most optimum way, so that the predetermined goal is achieved. There are number of tools and techniques that are used directly and as support system in the business for success. Forecasting is also a powerful tool and technique which is used as support system to the industrial environment so that future of the business can be predicted accurately. It provides the basis to plan the future requirements for men, machine and materials, time, money etc. so that the wastage will be least.This paper presents the reviews of different works in the area of industrial forecasting support systems and tries to find out latest developments and technologies available in industries and show how they are beneficial to achieve an accurate forecasting.

Index terms— forecasting, support systems, techniques

1 Introduction

ith the changing of the structure of business, reliable prediction of sales is of immense benefit to a business because it can improve the quality of the business strategy and decrease costs due to waste, thereby increasing profit. To improve an enterprise's competitiveness, we must make correct decisions using the available information. This "Forecasting" is viewed as an important part of decision making. It is defined as the estimation of future activities like the estimation of type, quantity and quality of future work. These estimates provide the basis to plan the future requirements for men, machine and materials, time, money etc. Forecasts are predictions or estimation of change, if any in characteristic economic phenomena which may affect one's business plans. Prediction is an estimate of future event through subjective considerations other than just the past data. For prediction good subjective estimation is based on managers' skill, experience and judgement. There is an influence of one's own perception and bias in prediction. So it is less accurate and has low reliability. Forecasts have great importance now days because:

? The forecasts are very important for organizations to help to meet the upcoming needs of their customers. ? Majority of the activities of the industries depends upon the future sales. ? Projected demand for the future assists in decision making with respect to investment in plant and machinery, market planning and programmes. ? To schedule the production department activity for effective utilisation of the plant capacity. ? To prepare material, tool and spare part planning so that it will be available at right place, at right quantity and at right place when desired. ? It provides information about the demand of the different products in order to obtain a balanced production in terms of quantity required of different product as a function of time. ? To provide a future trend,this is very much essential for product design and development. Thus, in this changing and uncertain economic and marketing scenario forecasting helps to predict the future with accuracy. Sometimes it is appropriate to forecast demand directly. When direct prediction is not feasible, or where uncertainty and changes are expected to be substantial, marketing managers may need to forecast the size of a market or product category. Also, they would need to forecast the actions and reactions of key decision makers such as competitors, suppliers, distributors, collaborators, governments, and themselves, especially when strategic issues are involved. These actions can help to forecast market share.

There are numerous ways to forecast, ranging from the simple, unsophisticated methods of intuition to complex approaches such as econometric models. However, the forecasting techniques can be divided into two types, namely: a) Qualitative Forecasting Techniques Qualitative forecasting techniques are subjective, based on the opinion and judgment of consumers, experts; appropriate when past data is not available. Qualitative forecasting analyses can be used to formulate forecasts for new products for which there are no historical data; to devise or adjust mid-or longrange forecasts for corporate planning. There are three situations in which qualitative methods are preferable to quantitative ones. These are when: 1) Data are insufficient or are known to be unreliable. 2) It is not possible to construct a suitable numerical model. 3). Time is insufficient to initiate and operate a quantitative analysis.

2 Jury / Expert Evaluation Techniques

This method is based on judgment of the executives about the future. Expert evaluations use the experience of people, such as executives, sales people, marketing people, distributors, or outside experts, who are familiar with a product line or a group of products and estimates for future. The executives exercise their judgment and give their opinions. By rough averaging of these opinions, the final forecast is made.

3 Survey of Experts Opinion

In the jury method opinions of executives gives rise to forecast. In survey of Experts Opinion method, experts in the concerned field inside or outside the organization are approached for making estimates. The opinions of outside expertise may include opinions given in newspapers, trade journals, Opinions of wholesalers and distributors, agencies etc.

4 3.

In this method the sales forecasting is done by the sales force. Each salesman develops the forecast for his respective territory, the territorywise forecasts are consolidated at each branch area level and the aggregate of all these forecast is taken as the corporate forecast. It is a grass root method.

5 4.

6 Consumers Opinion Method

In this method, actual users of the product are directly contacted by the investigators and their preferences and attitude towards the product as well as future requirements are ascertained.

7 Market Share Method

The market share of the firm may also serve as a guide to sales forecasting. The firms first work out the industry forecast, apply the market share factor to estimate the company's sales forecast. The market share factor is developed based on past trend, company's present competitive position, brand preference etc.

8 6.

Each member of the panel of experts who is chosen to participate writes an answer to the question being investigated and all the reasoning behind this forecast. The answers of the panel are summarized and returned to the members of the panel, but without the identification of which expert came up with each forecast Quantitative forecasting models are used to estimate future demands as a function of past data; appropriate when past data are available. The method is usually applied to short-intermediate range decisions. When a forecaster uses an endogenous quantitative forecasting technique, there is an implicit assumption that there will be no systematic changes or departures from previously occurring patterns. If there is reason to believe this assumption is no longer valid, qualitative techniques provide the means to adjust the Delphi Method

9 Global

10 Sales

Force Composite Method forecasts by tapping the experience and judgment of people knowledgeable about the product being forecast and the environment affecting the forecast. In other words, one could say that qualitative forecasting emphasizes predicting the future, rather than explaining the past.

11 Sales Trend Analysis

In this method the firm uses its own record of past several years' sales to estimate the future sales. It involves the plotting of the sales figures for the past several years and stretching of the line or the curve as the case may be. The extrapolation will give the figures for the coming years.

12 Casual Method

This method tries to identify the factors which cause variation in the demand. There analyst tries to find out the method that best explain the level of sales of the product. This process called econometric forecasting.

13 Time series

The variable to be forecast has behaved according to a specific pattern in the past and that this pattern will continue in the future. D = F(t)Where, D is the variable to be forecast and f(t) is a function whose exact form can be estimated from the past data available on the variable. The value of the variable for the future as a function of its values in the past D t+1 = f (D t , D t-1 , D t-2 ...)

14 4.

A moving average may be defined as an average of some fixed or predetermined number of observations in a time series which moves through the series by dropping the top item of the previous averaged group and adding the next item below in each successive average. The calculation depends upon the period to be odd or even.

15 5.

It is similar to moving average method and used fairly extensively. In fact it is an improvement over moving average method. It tries to overcome the limitations of moving average method and eliminates the necessity of keeping extensive records of past data. The fundamental concept of Exponential method is that new estimate=odd estimate of latest actual demand +? (latest demand-odd estimate of latest actual demand)

6.

16 Least Square Method

Under this method a mathematical relationship is established between the time factor x and the variable y. Let y denote demand and x the period of a certain product. Then relationship is given by y = a + bx.Where, a and b are constants.

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18 Aims and Objectives

Organizations use forecasting methods of production and operations management to implement production strategies. Forecasting involves using several different methods of estimating to determine possible future outcomes for the business. Planning for these possible outcomes is the job of operations management. Additionally, operations management involves the managing of the processes required to manufacture and distribute products. Important aspects of operations management include creating, developing, producing and distributing products for the organization. The aims and objectives of the present study are as follows:

? To provide the business with valuable information that the business can use to make decisions about the future of the organization.

? To improve the accuracy and quality of the production forecast.

? To encourage and achieve a greater level of engagement in the production forecast process, by using data, where available and appropriate, as input to the forecast system.

? To plan production to meet customer requirements.

? To effectively correlate deliveries of materials and supplies with production schedules.

? To plan about the potential demands with the level of investment in plant, equipment and inventory to be created to manage the business.

19 III.

20 Literature Review

The literature surveys have been done considering support systems and techniques prevalent in industries. The works of various authors from diverse fields have been referred from 1992 onwards. Some of the most important and relevant findings have been presented. Mahmoud et al. (1992) [1] argue about the gap between forecasting theorists and practitioners and suggested the answers for the question for the successful implementation of forecasting in the organizations, which is hampered by gaps in communication and understanding between forecast preparers and forecast users. Two approaches of Rogers's and Bass models were compared by Wright and Charlett (1995) [2] and found that bass model is more successful forecasting tool than Rogers's approach. Similarly, Winklhoferet al. (1996) [3] G application in industrial area and identified their major methodological characteristics. Korpcla and Tuominen (1996) [4] worked onanalytic hierarchy process-based approach to demand forecasting and proposed decision support system which offers many improvements compared to traditional methods. Fleischmann et al. (1997) [5] surveyed the recently emerged field of reverse logistics. The management of return flows induced by the various forms of reuse of products and materials in industrial production processes has received growing attention throughout this decade. They subdivided the field into three main areas: distribution planning, inventory control, and production planning, and discussed the implications of the emerging reuse efforts, review the mathematical models proposed in the literature, and point out the areas in need of further research.

A work was presented by Diebold (1998) [6] on the macroeconomic forecasting, the Non-structural forecasting based largely on reduced-form correlations and Structural forecasting spects, which aligns itself with economic theory, and theirimpact on the product forecasting. Focussing on the inter department coordination of an organisation Celikbaset al. (1999) [7] considered two possible organizational structures centralized and decentralized. In the decentralized system, the marketing department provides a forecast to manufacturing. Whereas in the centralized system, marketing and manufacturing jointly decide on the production quantity. They showed that it is possible to set penalties so that a coordinated decentralized system outperforms a centralized system when there are no tangible costs to the firm for the efforts expended by the marketing department.

The various characteristics and effectiveness of the Delphi technique reviewed by Rowe and Wright (1999) [8]. They concluded that Delphi technique sometimes performs better than statistical groups and standard interacting groups. But, the technique has shown no clear advantages over other structured procedures. Sutanto (2000) [9] studied the role of Human resource management in supporting the production plan to achieve the target. The main task of human resource management is to support other departments to have the best people. Therefore, Forecasting helps to have the best people in the right place at the right time so that production does not suffer at any time.

By using winter's decomposition and Auto-Regressive Integrated Moving Average (ARIMA) forecasting models, Yenradeea et al. **??**2001)[10] discussed the demand forecasting and production planning for Highly Seasonal Demand Situations. It was found that the decomposition and ARIMA models provide lower forecast errors. The forecasted demand and safety stock were subsequently used as input to determine the production plan that minimize the total overtime and inventory holding costs based on a fixed workforce level and an available overtime and the total costs could be reduced by 13.2%.

A new systematic approach was presented by Svetinovic and Godfrey (2001) [11] based on the use of functional and quality attributes to recover, document, and apply knowledge about how and why software systems evolve. In this discussion was done on how the study of software evolution in terms of attributes makes it possible to draw parallels between software evolution and other types of evolution This help us to analyze their similarities and to map their results and methodologies from these other fields to software evolution and how the use of attributes can make knowledge about how a system has evolved more easily applicable to other attribute-based techniques of software engineering.

A comparison of the focus forecasting and exponential smoothing was done by Gardner et al. (2001) [12] and found that Exponential smoothing is substantially more accurate than Demand Solutions. Forecasting rules are arbitrary, with no statistical rationale therefore, users of Focus Forecasting have much to gain by adopting statistical forecasting methods. A work was presented by Smaros (2001) [13] on the support for Collaborative Planning, Forecasting and Replenishment offered by electronic marketplaces as well as distributed, peer-to-peer, information systems. When comparing the centralized market place model to the decentralized peer-to-peer model, it becomes clear that the market places are not the solution to CPFR. If the standardization considered, it appears that companies would be better off choosing a peer-to-peer solution for CPFR rather than relying on electronic marketplaces to provide the necessary support for their collaboration efforts.

A work was presented by Charles N. Smart(2002) [14] highlighting the importance of accurate demand forecasting for inventory planning to optimize stocking levels to ensure that the right service part or product is available at the right place at the right time, in the right quantity. Accurate demand forecasting results in the improved customer service and satisfaction. Out of stock and not having the right part in stock at the right time, can be costly, especially when the customers are an infrequent purchaser and thus accurate forecasting needed to control business. Smaros (2002) [15] focussed on the Collaborative Planning Forecasting and Replenishment (CPFR) process. In their study, more emphasis is given to exchange ideas among the different people to get a good forecast and finally the product life-cycle model can be used to select and combine the most suitable approach to collaboration in different market situations.

Choudhury et al.(**??**002) [16] worked on Forecasting of engineering manpower through fuzzy associative memory neural network with ARIMA: a comparative study, focussed on the requirement of(D D D D) G

The performance of a vendor managed inventory (VMI) supply chain with a traditional "serially linked" supply chain was compared by Disney and Towill (2003) [19]. They found that vendor managed inventory responds significantly better at responding to volatile changes in demand caused due to discounted ordering or price variations. A work was presented by Hsu et al. (2003) [20] on Litterman Bayesian vector auto regression (LBVAR) model for production prediction based on the interaction of industrial clusters. The LBVAR model possesses the superiority of Bayesian statistics in small sample forecasting and holds the dynamic property of the vector auto regression (VAR) model. Result showed, the LBVAR model was found to be capable of providing outstanding predictions for these two technology industries in comparison to the auto regression (AR) model and VAR model. Siliverstovs and Dijk (2003) [21] compared the forecasting performance of linear autoregressive models, autoregressive models with structural breaks, self-exciting threshold autoregressive models and Markov switching autoregressive models in terms of point, interval and density. The results of point forecast evaluation tests support the established notion in the forecasting literature on the favourable performance of the linear AR model. The Markov switching models give more accurate interval and density forecasts than the other models, including the linear AR model. Thus the non-linear models may outperform linear competitors in terms of describing the uncertainty around future realizations of a time series.

A work was presented by G. Peter Zhang (2003) [22] on Time series forecasting using a hybrid ARIMA and neural network model, focussed on combined effect of ARIMA and ANN model and a model proposed to take advantage of the unique strength of ARIMA and ANN models in linear and nonlinear modelling. Timmermann and Granger (2004) [23] worked on Efficient market hypothesis and forecasting concluded that Forecasters constantly search for predictable patterns and affect prices when they attempt to exploit trading opportunities therefore stable forecasting patterns unlikely to persist for long periods of time and will self-destruct when discovered by a large number of investors this gives rise to non stationarities in the time series of financial returns and complicates both formal tests of market efficiency and the search for successful forecasting approaches.

A new approach presented by Smaros and Hellstrom (2004) [24]to reduce significantly time spent on forecasting by working with an entire assortment at a time instead of producing a forecast for each product individually. The implementation of a less timeconsuming forecasting method has enabled the company to involve its salespeople in forecasting and in this way gain access to their product and market knowledge. Its forecasting accuracy and time spent on forecasting before and after the implementation are measured. The results demonstrate a remarkable increase in forecasting efficiency as well as improved communication. HuiZou, Yuhong Yang (2004) [25] worked on combining time series models for forecasting used an algorithm with ARIMA Model to improve prediction accuracy when there is much uncertainty in finding.

The performance of Artificial Neural Networks (ANN) and ARIMA models in forecasting of seasonal Time series compared by Kihoro et al.(2004) [26].The r esults showed that the ANN is relatively better than ARIMA models in forecasting ability but the nature of the data may influence the results. The main problem with ANN is the lack of explanation capabilities and of a proper building methodology to define the network architecture. Most of the ANN modelling process is basically empirical and proposed an easier ARD rule, which seems to be working well empirically. This rule may be investigated further and perhaps a theory developed to be included in Time Series modelling methodology for Artificial Neural Networks.

Onkal and Bolger (2004) [27] examined the potential differences in perceived usefulness of various forecasting formats from the perspectives of providers and users of predictions. Experimental procedure consists of asking participants to assume the role of forecast providers and to construct forecasts using different formats, followed by requesting usefulness ratings for these formats. 95% prediction intervals were considered to be the most useful format, followed by technical man power for the plant in next five years by using ARIMA and FAM Method. Karel van Donselaar (2002) [17] studied the Winters' method for forecasting of seasonal demand and found that the quality of the forecasts deteriorates, if the relative demand uncertainty increases or if the amount of historical demand data decreases. Mathematical modelling as well as simulation was used to assess the added value of product-aggregation. It turns out that impressive improvements can be achieved, especially in case demand uncertainty is high.

A work was presented by Winklhofer and Diamantopoulos (2002) [18] on A Multiple Indicators and Multiple Causes (MIMIC) model in which managerial evaluations of forecasting effectiveness are modelled as a function of different forecast performance criteria, namely, accuracy, bias, timeliness and cost. The data from a survey of export sales forecasting practices and several hypotheses linking the aforementioned criteria on effectiveness are tested and indicate that evaluations of forecasting effectiveness are equally influenced by short-term accuracy and absence of overestimating bias, while timely delivery of the forecast to management is somewhat less important, while in Long-term accuracy, underestimation and timing of production of the forecast are not found to impact on effectiveness. A work on the effects of judges' forecasting on their later combination of forecasts for the same outcomes was published by Harvey and Harries (2004) [28]. The judges' ability to combine forecasts that they receive from more knowledgeable advisors is impaired when they have previously made their own forecasts for the same outcomes. Also, People responsible for integrating forecasts from more knowledgeable advisors should not explicitly include their own forecasts among those that they combine and should consider avoiding making their own forecasts altogether, the cognitive mechanisms responsible for these effects.

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A work was presented by Marcellinoet series forecast and compared the empirical iterated and direct forecasts from linear uni-variate and bi-variate models by applying simulated out-of-sample methods. Iterated forecasts was more efficient if the one-period ahead model is correctly specified, but direct forecasts are more robust to model misspecification. **??**ilson and Gilbert (2005) [30] in their paper great emphasis were given to the emotional, psychological effect on the future events. One cause of the impact bias was focalism, the tendency to underestimate the extent to which other events will influence our thoughts and feelings. Another was people's failure to anticipate how quickly they will make sense of things that happen to them in a way that speeds emotional recovery. Affective forecasts were important because people use many decisions on them. It may be overestimating the impact of negative events creates unnecessary dread and anxiety about the future and results in costs to affective forecasting errors. Chandra and Grabis (2005) [31] focussed on the bullwhip effect. The results obtained do not provide evidence that magnitude of the bullwhip effect is larger for higher order autoregressive processes, but the magnitude of the bullwhip effect is similar for the first order and the seasonal autoregressive demand processes. A new methodology was presented by Horet al. (2006) [32] using Auto Regressive Integrated Moving Average (ARIMA) model to predict daily load pattern. The work served as an initial step to investigate the impacts of climate change and weather extremes on electricity demand patterns and the electricity network. The forecasted load will be used as input to transmission network model to study security and grid reinforcement of the power network as the result of climate change. The model has fitted to an in sample training data and the results were then verified with actual electricity data. The mean absolute percentage error (MAPE) for each month generally lies within 1-3%.

A work on the long term forecasting was presented by Granger and Jeon (2007) [36]. Long-term forecasting is likely to be dominated by trend curves, particularly the simple linear and exponential trends. However, the forecasts will be unsatisfactory with breaks in their parameter values at some unknown points. They investigate whether or not simple methods of long-run forecasting can ever be successful, after one takes into account the uncertainty level associated with the forecasts.

A comparison of support vector regression (SVR) with the existing neural-network approaches and the autoregressive integrated moving average (ARIMA) model were done by Kuan-Yu Chen (2007) [37]to find out the feasibility of SVR and find out that SVR performs better than the ARIMA models. Similarly, A work was presented by Nikolopoulos et al.(2007) [38] on Forecasting with cue information: A comparison of multiple regression with alternative forecasting approaches done on Multiple linear regression (MLR) method and which was less accurate than a other methods when deals with the complex non-linearity's data. Bianco et al. (2007) [39] used Ensemble Kalman Filter to calibrate porosity fields used in a model for oil reservoir production. The dependence of Ensemble Kalman Filter effectiveness on the number of fields included in the statistical ensembles was performed by using three ensembles of 50, 100 and 135 members and investigated the connection between Ensemble Kalman Filter effectiveness and the size of the ensemble for a real problem. The limited number of ensembles considered did not give the chance to lead al.(2005) [29] on the "Iterated" multi period-ahead time Robert Fildes(2006) [33] analysed the different journals and showed that the comparative approach to establishing improved forecasting methods through examining multiple hypotheses has been successfully adopted and was unusual when compared to other journals. There were little cross-fertilisation between journals. Organisational issues and the effects of forecast error have been ignored. These two issues directly impact the gap between theoretical contributions and forecasting practice, a gap that remains unbridged. Michael Lawrence et al. (2006) [34] reviewed the past 25 years has seen phenomenal growth of interest in judgemental approaches to forecasting and a significant change of attitude on the part of researchers to the role of judgement. Judgement is recognised as an indispensable component of forecasting and much research attention has been directed at understanding and improving its use. Human judgement can be demonstrated to provide a significant benefit to forecasting accuracy but it can also be subject to many biases. Syntetosa and Boylan (2006) [35] presented work on the stock control performance of intermittent demand estimators. The nature of the empirical demand data set evaluated and the stock control model specified for experimentation purposes. The performance of the new intermittent demand forecasting method was found better than the other forecasting methods. [40] for wheat production forecastingand proposed a model. By comparing the results it was found that proposed model yields better results than the other method. Guoet al. (2008) [41] studied the characteristic of the preprocessing of sample data using wavelet transformation for forecast. The experimental results suggested that the proposed hybrid method is typically a reliable forecasting tool for time series technique superior to standard SVM model. Two automatic forecasting algorithms were described by Hyndman and Khandakar (2008) [42].The first was based on innovations state space models that underly exponential smoothing methods and second is a step-wise algorithm for forecasting with ARIMA models. These algorithms are applicable to both seasonal and non-seasonal data, and compared using four real time series.

Datta et al. (**??**008) [43] focussed on the forecasting and risk analysis in supply chain. Advanced forecasting tools were applied for decision support in supply chain management and results suggest that advanced methods may be useful to predict oscillated demand but their performance may be constrained by current structural and operating policies as well as limited availability of data. Improvements to reduce demand amplification may decrease the risk of out of stock but increase operating cost or risk of excess inventory. A work was presented by Jushan and Serena (2008) [44] on forecasting economic time series using targeted predictors studied two refinements to the method of factor forecasting by applying the method of principal components to 'targeted predictors' selected using hard and soft thresh holding rules. They considered the methodof quadratic principal components that allow the link function between the predictors and the factors to be non-linear. Second, the factors used in the forecasting equation were estimated.

A work on the long-term forecasting and trend forecasting was published by Dong and Pedrycz (2008) [45]. Technique based on the fuzzy clustering was used to construct information granules on a basis of available numeric data present in the original time series. A forecasting model developed which captures the essential relationships between such information granules and in this manner constructs a fundamental forecasting mechanism and yield better results when processing a large number of data. Eric Sucky (2009) [46] presented a work on the bullwhip effect in supply chains. The variability of orders increases as they move up the supply chain from retailers to wholesalers to manufacturers to suppliers. They showed that while analyzing the bullwhip effect in supply chains, the influence of risk pooling has to be considered, Otherwise bullwhip effect will overestimated. **??**amzacebi et.al (2009) [47] focussed on the two methods, first was iterative method, in which subsequent period information was predicted through past observations and then the estimated value was used as an input for the prediction of the next period. The process was carried out until the end of the forecast horizon in multi-periodic time series forecasting. In the second, direct forecast method, successive periods predicted all at once and yield better results as only observed data was utilized in order to predict future periods.

A work was presented by Goldstein and Gigerenzer (2009) [48] on forecasting rules and shown that simple statistical forecasting rules make better predictions than more complex rules, especially when the future values of a criterion is highly uncertain. They provide evidence that some of the fast and frugal heuristics that people use intuitively are able to make forecasts that are better than those of knowledgeintensive procedures. Petervon Stackelberg (2009) [49] studied Timelines when used to lay out historical data and cycles, and found that waves pattern along a common temporal scaleprovide a far deeper, more nuanced understanding of the dynamics of change. Timelines patterns can be used in a "hypothesis-toforecast" process to identify potential long-term patterns of change and make long-range forecasts whereas, Traditional forecasts are well suited for relatively shortterm futures but, exploratory forecasts are better suited to forecasting longer-term futures.

A work on forecasting aggregate demand was published by Widiarta et al. (**??**009) [50]. The aggregate demand series composed of several correlated sub aggregate components, each of which was assumed to follow a stationary time series process, which was correlated over time. They analytically showed that there is no difference in the relative performance of TD and BU forecasting strategies when the time series for all of the sub aggregate components follow a first-order univariate moving average process with identical coefficients of the serial correlation term.

Sanders et al. (**??**009) [51] investigate forecast smoothing in the USDA's cotton production forecasts and demonstrated how forecasting practitioners and farm managers should correct the forecasts. Forecasts provide an important and cost effective source of public forecast information, a graphical technique used for identifying and analyzing smoothing in forecast revisions. Simple scatter plots in Excel provide a test for the existence of smoothing, and the corresponding regression line provides the corrective adjustments needed to remove the impact of smoothing so that producers frequently can use agency forecasts to aid in planning and decision making.

A work was presented by Borade and Bansod (2009) [52] on the supply chain management practices for improving business or supply chain performance. G They discussed vendor managed forecasting with the help of case study. They showed how a small enterprise improves supply chain performance by using demand related information obtained from retailer. The results obtained in the study shows that vendor managed forecasting in supply chain reduces the demand variation and improves inventory management significantly.

Concentrated on the forecasting approach of foreign trade unit value indices Lutero and Marini (2010) [53] presented their work.In their work the automatic selection strategy of TRAMO evaluated in comparison with a standard ARIMA model and then, a direct forecasting approach experimented. They show that the automatic selection process of the ARIMA model carried out by TRAMO provides acceptable forecasts, on average better than those from the classical Airline model. . Berlec(2010) [54] presented a procedure for forecasting the lead times of production orders on the basis of past actual lead time data. The proposed procedure for forecasting lead times was an empirical distribution of possible lead times for a production order. On the basis of this distribution, the probable lead time of a production order was forecast, taking into account a confidence interval. Subsornet al. (2010) [55] investigated the best-fitting forecasting model for national rubber production forecasting.The methods used in their study was based on non-neural network training and neural network training techniques and compared with the actual rubber production data for the best-fitting forecasting model.

A new version of support vector machine (SVM) was presented by Qi Wu(2010) [56] named v -SVM. The new proposed model construct the nonlinear system of product demand series by combining the chaos theory, evaluated and the simulation results demonstrated that Cv-SVM is effective in dealing with multi-dimension data and finite samples. Also, Cv-SVM has better MAE, MAPE and MSE than ARMA, GA v-SVM and ECGA v-SVM. Syntetos et al. (2010) [57] studied that the efficiency of inventory systems does not relate directly to demand forecasting performance, as measured by standard forecasting accuracy measures. It should always be evaluated with respect to its consequences for stock control through accuracy implications metrics, in addition to its performance on the standard accuracy measures. They addressed the issue of judgementally adjusting statistical forecasts for 'fast' demand items, and the implications of such interventions in terms of both forecast accuracy and stock control.

A work was presented by Smith and Mentzer (2010) [58] on the relationship between forecasting support system, the procedures that guide forecast creation, and their fit with the capabilities of the forecasting support system user. The results showed a positive relationship between the user's assessment of system quality and access and a dependent variable measuring forecast performance. Forecasting practitioners confirms a positive relationship between specific forecasting support system characteristics and the system user's perceptions of system quality and access.

A new approach named cycle forecasting EWMA (CF-EWMA) was published by Bing Ai et al. (2010) [59]. The new approach deal with the problem of large deviations in the first few runs of each cycle. In case of mixed-product drifted process, they concentrated on the time lost on irregular break down during the production time, these uneven breakdowns deviate the results from the target value which will lead to a possible high rework rate and lots of waste wafers.

A work on the trend and seasonality patterns of a selected product in a retail trading chain was presented by Hasinet al. (2011) [60]using traditional Holt-Winter's model, artificial neural network (ANN) with fuzzy uncertainty and then the errors, measured in terms of MAPE. The error level in Holt-Winter's approach was higher than those obtained through fuzzy ANN approach because of influence of several factors on demand function in retail trading system. It was also observed that as forecasting period becomes smaller, the ANN approach provides more accuracy in forecast.

A work was presented by Theodosiou (2011) [61] on hybrid forecasting method based on the disaggregation of time series components. The prediction of each component were done individually and the reassembling of the extrapolations to obtain estimation for the data. Generalized Regression Neural Networks (GRNN) used to perform out-of sample extrapolations of the seasonal and residual components and shown good results. Leitner and Leopold (2011) [62] reviewed several literatures and found that in most experiments the forecasting abilities of individuals were compared to rational forecasts or forecasts of statistical models. In such a way results were very poor and the inability to incorporate supportive information was the main cause of forecasting inefficiency.

Similarly, Polerand Mula(2011) [63] presented a new automatic selection procedure of time series forecasting model proposed and the selection criterion has been tested using the set of monthly time series of the M3 Competition and two basic forecasting models. Cardin and Castagna (2011) [64] presented a new application of discrete-event simulation as a forecasting tool for the decision support of the production activity control of a complex manufacturing system. The specificity of such an application of simulation is the short term of the forecast. This specificity implies that the initial state of the simulation takes into account the actual state of the system. The development on a realsize flexible manufacturing system shows the technical feasibility of the developed concepts and the potential benefits on the productivity of a single example. [65] on the forecasting of the challenging world future scenarios discussed the behaviour of the supply and consumption of energy and food, two of the main commodities that drive the world system. They suggest that unless the currently prevailing focus on economic growth is changed into that of sustainable prosperity, human society may run into a period of serious economic and social struggles with unpredictable political consequences.

A new methodology was presented by Rossi and Sekhposyan (2011) [66] to identify the sources of models' forecasting performance. The methodology decomposed the models' forecasting performance into asymptotically uncorrelated components that measure instabilities in the forecasting performance, predictive content, and over-fitting. The results showed the new methodology is useful for understanding the causes of the poor forecasting ability of economic models for exchange rate determination.

A new hybrid SARIMA wavelet transform method for sales forecasting was presented by Choi et al. (2011) [67] combined the classic SARIMA method and wavelet transform (SW). Experiments were conducted by using real sales data, hypothetical data, and publicly available data sets and the time series features which influence the forecasting accuracy and new method shown good results. Petrie and Bannister (2011) [68] presented a method for merging flow-dependentfore cast error statistics from an ensemble with static statistics for use in high resolution variational data assimilation. In their study EnRRKF the forecast error statistics in a subspace defined by an ensemble of states forecast by the dynamic model and then merged in a formal way with the static statistics and then used in a variational data assimilation setting.

Mukhopadhyay et al. (**??**011) [69] presented aStackelberg model of pricing of complementary goods under information asymmetry. They show that information sharing benefit the leader firm but hurt the follower firm as well as the total system if the follower firm shares information unconditionally. They then devise a simple scheme which was beneficial for both the system. Babai et al. (2011) [70] analysed a single echelon single item inventory system. Where Demand was modelled as a compound Poisson process and the stock was controlled according to a continuous time order-up-to (OUT) level policy. They proposed a method for determining the optimal OUT level for cost oriented inventory systems and results showed that there was a significant difference in accuracy for slow moving items. Hsiao and Wan (2011) [71] suggested two modified simple averaging forecast combination methods-a mean corrected and a mean and scale corrected method. They concluded that due to the fact that real data was usually subjected to structural breaks, rolling forecasting scheme has a better performance than fixed window and continuously updating scheme and methods that use less information appear to perform better than methods using all the sample information about the covariance structure of the available forecasts.

Lee and Tong (2011) [72] worked on Forecasting time series using a methodology based on autoregressive integrated moving average and genetic programming. They proposed a hybrid forecasting model for nonlinear time series by combining ARIMA with genetic programming (GP) to improve upon both the ANN and the ARIMA forecasting models. Finally, some real data sets are adopted to demonstrate the effectiveness of the proposed forecasting model.

Xiang et al. (**??**011) [73] presented work on Multiagent Bayesian forecasting of structural timeinvariant dynamic systems with graphical models. They proposed a model called dynamic multiply sectioned Bayesian network and showed that as long as the DMSBN is structural time-invariant (possibly parametric time-variant), the forecast is exact and its time complexity is exponentially more efficient than using dynamic Bayesian networks (DBNs). Cheikhrouhou et al. (2011) [74] presented a judgemental collaborative approach for demand forecasting in which the mathematical forecasts, considered as the basis, were adjusted by the structured and combined knowledge from different forecasters. Factors corresponding to these events were evaluated through a fuzzy inference system to ensure the coherence of the results. They show that by structuring and combining the judgements of different forecasters to identify and assess future events, companies can experience a high improvement in demand forecast accuracy.

A methodology was proposed by Chang et al. (2012) [75] to evaluate individual and alternative mean forecasts using efficient estimation methods, and compared individual replicable forecasts with alternative mean forecasts. The empirical analysis showed that replicable and non-replicable forecasts could be distinctly different from each other, that efficient and inefficient estimation methods, as well as consistent and inconsistent covariance matrix estimates, could lead to significantly different outcomes, alternative mean forecasts could yield different forecasts from their individual components, and the relative importance of econometric model versus intuition could be evaluated in terms of forecasting performance.

A work was presented by Xu Yaboaet al. (2012) [76] on the safety in combination with production. Combination forecasting model can be used to the actual forecast, in order to achieve the prior risk forecasting of production safety trends and has shown the good results. Obahet al.(2012) [77] working on Simplified Models for Forecasting Oil Production: Niger Delta Oil Rim Reservoirs Case, studied Many factors affect both the reliability and accuracy of production forecasts; the static or geological uncertainties, the Year 2013 dynamic uncertainties and operational uncertainties. In their study a generic dynamic simulation study was carried out to generate oil production profiles from oil rim reservoirs in the Niger Delta. Donate et al. (2012) [78] in this paper an novel Evolutionary Artificial Neural Networks (EANNs) approach used to build an ensemble of neural networks, under four different combination methods: mean, median, softmax and rank-based. Based on the experimental results they suggested that the fitness weighted n-fold ensemble improves the accuracy of the forecasts, outperforming both then no weight n-fold ensemble and the simpler hold out validation(0-fold) EANN. Also, advised the use of a 4-fold ANN ensemble that evolved using weighted cross-validation and that uses a rank-based combination method to build the final forecasts.

Lehneret al. (2012) [79] presented a method, the inferred probability method, for quantitatively measuring the accuracy of forecasts in documents that use imprecise language to describe both forecast events and forecast certainties. They applied the inferred probability method to 14 documents that examine significant and complex political events which were considered the premier analysis product. Test focused on three things: first, whether the inferred probability method yielded accuracy results that are in the same range as more traditional forecasting studies in the same general topic area. Second, whether the accuracy results were biased by a readers' knowledge of the topic area, and third whether the accuracy results were sensitive to errors in assigning ground truth.

Subramanian and Ramanathan (2012) [80] reviewed the applications of Analytic Hierarchy Process in operations management. AHP has been largely applied to macro and people oriented problems, the most addressed decision themes were product and process design and, managing the supply chain. They presented a comprehensive listing of AHP applications in operations management and develop a framework for identifying the decision areas that have better research gaps to be studied by future researchers. A two-step forecasting method separately updates the average number of parts needed per repair and the number of repairs for each type of component was proposed by Romeijnders et al.(2012) [81].The method was tested in an empirical, comparative study for a service provider in the aviation industry. They showed that proposed method performs considerably better than Croston's method and forecasts errors cab be reduced up to 20% by planned maintenance and repair operations.

on Technological-Organizational -Environmental frame-work, Interorganizational Relationships and Unified Theory of Acceptance and Use of Technology was proposed and empirically validated. Matteo Kalchschmidt (2012) [83] compared the different perspectives by designing and testing different sets of propositions that underline the aforementioned perspectives. More than 500 companies collecting data was analyzed via the 4th edition of the Global Manufacturing Research Group (GMRG IV) questionnaire and the results demonstrated that each perspective has some empirical support.Qin and Nembhard (2012) [84] worked on the stochastic diffusion of a product in the market as a geometric Brownian motion (GBM) process that has a time-varying drift rate. The model calibrated so that it was able to feature different product types and diffusion conditions. The model demonstrated robust performance over a wide range of conditions despite model uncertainty and gave both qualitative and quantitative information for manufacturers and service providers to design strategies for stochastic PLC conditions as well as dynamic production planning.

A work on Multi-objective integrated production and distribution planning of perishable products was presented by Amorim et al. (2012) [85]. They integrated production and distribution planning approaches at operational level and formulate a model for the case where perishable goods have a fixed and a loose shelflife. The results showed that the economic benefits derived from using an integrated approach were much dependent on the freshness level of products delivered.Xu et al.(2012) [86]developed a product modularization model based on real options theory to determine the optimal modular production strategies under market uncertainty. They showed that when the market is more volatile, it is optimal for a firm to postpone modularization, and when a firm's investment efficiency at the preparation stage is higher, the firm can start modular production earlier with relatively low product modularity. An increase in market uncertainty will stimulate the firm to improve its product modularity. [82] studied the factors that influence the diffusion of e-collaboration in SCM among the SMEs. They proposed a research model to examine a stage-based e-collaboration diffusion process in SMEs. An integration technology adoption model based Beutel and Minner (2012) [87] presented two data-driven frameworks to set safety stock levels when demand depends on several exogenous variables. The first approach used regression models to forecast demand and the second approach used Linear Programming. Both the methods exercised to a common problem and results were compared. They showed a considerable improvement of the overly simplifying method of moments is possible and the ordinary least squares approach yields a better performance than the LP-method. But, the LP approach provides more robust inventory levels, if some of the standard assumptions of ordinary least squares regression are violated. Money et al. (2012) [88] Based on Support Vector Regression Method was presented by WANG Guanghui (2012) [89]. They introduced the basic theory and computing process of time series forecasting based on Support Vector Regression (SVR), optimizing the parameters of SVR by Genetic Algorithm (GA) and then Applied SVR to forecast the demand and finally, compared to the RBF neural network method.. They showed that SVR is superior to RBF in prediction performance and the suitable and effective method for demand forecasting of supply chain.

22 Chan et al. (2012)

Xu and Ouenniche (2012) [90] proposed a Multi-Criteria Decision Analysis (MCDA) based framework to address the problem of relative performance evaluation of competing forecasting models. They show that the multidimensional framework provides a valuable tool to apprehend the true nature of the relative performance of competing forecasting models and the ranking of the best and the worst performing models do not seem to be sensitive to the choice of importance weights or outranking methods. A review of literature on Sustainable business development (SBD) in manufacturing and services was done Gunasekar an and Spalanzani (2012) [91]. The papers on Sustainable business development were critically examined including tools, techniques and strategies that would be helpful for SBD in future.A work on Singular spectrum analysis (SSA) was presented by Claudio (2013) [92] to decompose and forecast failure behaviours, using time series related to time-to-failure data. Results were compared with previous approaches and show that SSA is a promising approach for data analysis and for forecasting failure time series.

Bao et al. (??013) [93] studied the forecasting and optimization decisions in an experimental cobweb economy. They performed experimental study on the basis of: (1) subjects form forecasts only, (2) subjects determine quantity only, (3) they do both and (4) they are paired in teams and one member was assigned the forecasting role while the other was assigned the optimization task. They showed that the performance was the best in treatment 1 and the worst in Treatment 3. Given a price forecast, subjects were less likely to make conditionally optimal production decisions in Treatment 3.

A work was presented by Douglas et al. (??013) [94] on Forecasting Innovation Pathways (FIP) for new and emerging science and technologies, offer a framework to analyze NESTs to help ascertain likely innovation pathways. They devised a 10-step framework based on extensive Future-oriented Technology Analyses ("FTA") experience, and describing the nanobiosensor experience in contrasted with that of deep brain stimulation in relative quantitative and qualitative emphases analytically in two case studies. The paper reflects on the systematic FTA framework for emerging science and technologies, for its intended goal, that is to support decision making.

Ubilavaand Helmers (2013) [95] examined the benefits of nonlinear time series modelling to improve forecast accuracy of the El Nino Southern Oscillation (ENSO) phenomenon. A smooth transition autoregressive (STAR) modelling framework was adoptedto assess the potentially smooth regimedependent dynamics of the sea surface temperature anomaly. They showedthat the superiority of forecast performance of STAR over the linear autoregressive models, especially apparent in short-and intermediateterm forecasts. Fye et al. (??013) [96] evaluated technological forecasts to determine how forecast methodology and eight other attributes influence accuracy, also evaluated the degree of interpretation required to extract measurable data from forecasts. They found that quantitative forecast methods were more accurate than forecasts using qualitative methods, and forecasts predicting shorter time horizons were more accurate than predicting for longer time horizons. Forecasts about computers and autonomous or robotic technologies were more accurate than those about other technologies, and of the nine attributes, only methodology and time horizon had a statistically significant influence on accuracy. Gorr and Schneider (2013) [97] applied receiver operating characteristic analysis to micro-level, monthly time series from the M3-Competition. Forecasts from competing methods were used in binary decision rules to forecast exceptionally large declines in demand. Using the partial area under the ROC curve (PAUC) criterion, they found that complex univariate methods (including Flores-Pearce 2, Forecast PRO, Automat ANN, Theta, and Smart (FCS) perform best for this purpose. Thedecision-rule combination forecasts using three top methods generally perform better than the component methods. From the evidence M3-Competition suggests that practitioners should use complex univariate forecast methods for operations-level forecasting, for both ordinary and large-change forecasts. A work was presented by Heinecke et al. (2013) [98] on the categorisation of stock keeping units (SKUs) and apply the most appropriate methods in each category. A bias adjusted modification to CRO (Syntetos-Boylan Approximation, SBA) has been shown in a number of Environment), was developed using expert elicitation techniques.a case of silver nano particles (Ag NPs) in aquatic environments studied. They showed that Bayesian networks provide a robust method for formally incorporating expert judgments into a probabilistic measure of exposure and risk to nanoparticles, particularly when other knowledge bases may be lacking, and Within the bounds of uncertainty as currently quantified, nanosilver may pose the greatest potential risk as these particles accumulate in aquatic sediments. G empirical studies to perform very well and be associated with a very 'robust' behaviour. The solutions were compared by means of experimentation on more than 10,000 SKUs from three different industries. The results enable insights to be gained into the comparative benefits of these approaches.

Asimakopoulos and Dix (2013) [99] examined the critical factors for the effective adoption and use of forecasting support systems (FSS) in product forecasting. Using the technologies-in-practice model based on evidence from professional designers, users and organizational documents, found that FSS adoption and use depend on certain situational factors, such as organizational protocols, communication among stakeholders, and product knowledge availability and their outputs can be used as springboard for organizational actions. A work on forecast accuracy was presented by Davyden koand **??**ildes (2013) [100]. They showed that many existing error measures are generally not suited to the task, due to specific features of the demand data. A metric based on aggregating performance ratios across time series using the weighted geometric mean yield better results and has the advantage of treating over-and under-forecasting even-handedly, has a more symmetric distribution.

IV.

23 Discussion

From the review of literatures it is found that the main purpose of forecasting is to estimate the upcoming demand in order for the organizations to make plan to create the products. The goal is to create as accurate forecasts as possible since accurate forecasts can be very profitable as forecasts help companies to meet the upcoming demand. If forecasts are too low, profits are most likely lower due to lost sales. Forecasts which are too high will create excess inventory which will increase the inventory carrying costs and products might have to be sold at a discount and discarded as obsolescence. From the literature surveys following points are considered:

? Traditional forecasting methods include a few explanatory variables, most of which can easily be expressed in quantitative terms.

? Classical forecasting methods are both deterministic and structurally stable leading to error in forecasting because of constant change which is selectively studied, and interpreted from a special view point. ? The bullwhip effect is due to the retailer's need to forecast. It is clearly seen that the increase in variability will be greater for longer lead times. However, the size of the impact does depend on the forecasting methods. The bullwhip effect is larger in case of Exponential forecasting method than Moving Average with the same average data age and for certain demand processes. ? The experimental results show that the forecasting errors made by various neural-networks models used only data-driven methods without model identity, and that any prior assumptions about the properties of the data would be much smaller than that of traditional ARIMA model. ? The neural network method is objective as compared to subjective fuzzy time series methods, since in case of neural network interpretation is done by only designed artificial neural network model. It can easily handle the inaccuracy and any degree of nonlinearity in the data. ? Hybrid method is typically a reliable forecasting tool for application within the forecasting fields of time series from social system, while the one without wavelet analysis evaluated showed poor ability in forecast.

V.

24 Conclusion

From the study of literature survey it has been observed that in order to reduce equipment costs, cycle G time, the correlation between task times and flexibility ratio needs a great attention on accurate forecasting. Forecast of manufacturing is a very complex problem, which is influenced by many factors. How to identify the factors such as technology, labour and investment, etc., and considers them into the forecast model is the problems which will be researched in the future. Success or failure of the project greatly depends upon the accurate forecasting; therefore method adopted must be perfect and best suited according to the circumstances. Because a wrong forecast may results in the total wastage of money, power and time.The inability to incorporate supportive information is the main cause of forecasting inefficiency and remains a clear challenge for all those engaged in the design of forecast support systems. Quantitative method produce better results than the Qualitative methods when rich historic data is available, simple, and accurate and less time consuming. [1] [2] [3]

[2]Industrial Forecasting Support Systems and Technologies in Practice: A Review

1

Figure 1: Figure 1 :

1

S.No.	Techniques	Description
1.		

Figure 2: Table 1 :

2

S.NO.	TECHNIQUES	DESCRIPTION
1.		

Figure 3: Table 2 :

Figure 4:

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