Chapter 2

Literature Review

2.1 INTRODUCTION

Demand Forecasting is the practice of estimating the quantity of a product or service that is likely to be purchased by a consumer over a specified time period. Demand forecasting has grown to be indispensable in making decisions with regard to production, sales, investment, expansion, employment of manpower etc., both in the short run as well as in the long run. It seeks to investigate and measure the forces that determine sales for existing and new products. Companies plan their business, production or sales in anticipation of future demand.

The literature review covers the following areas of the past work:

- Supply Chain Management
- Demand forecasting techniques
- Demand forecasting for slow moving items
- Demand forecasting for new products
- Forecast accuracy measures

The literature review about the supply chain management is discussed in section 2.2. Demand forecasting techniques and about fast moving consumer goods are covered in section 2.3. Demand forecasting of slow moving items is discussed in section 2.4. Section 2.5 discusses about demand forecasting of new products. Forecast accuracy measurement is discussed in section 2.6

2.2 SUPPLY CHAIN MANAGEMENT

Morgan and Monczka (1996) has stated that supply chain management seeks improved performance through better use of internal and external capabilities in order to create a seamlessly coordinated supply chain, thus elevating inter-company competition to inter-supply chain competition .

Supply chain management (SCM), as defined by Lambert and Cooper (2000), is the integration of key business processes from end user through original suppliers, services and information that add value for customers and other stakeholders. From this perspective, integrating business processes within and across organizational boundaries is a core element of SCM as explained by Gadde and Hakansson (1994).

Lee et al (1997) discussed that supply chain partners aim to minimize the disruptions associated with the bull-whip effect by integrating processes and promoting information sharing. Simchi-Levi et al (2000) discussed about this effect, caused by disparities between supply and demand in the supply chain, typically leads to inefficiencies, added costs, increased waste, and loss of productivity in the form of stock-outs, bloated inventories, delayed material deliveries, and under-utilized production capacities.

Cachon and Fisher (2000) described that by integrating their processes and promoting information exchange, supply chain partners can develop common plans and forecasts to synchronize production with shipment and delivery schedules with a view to reducing costs, lead-times, safety-stocks, and inventories, increasing inventory turns, revenues and profit margins, and improving operational performance, flexibility, reliability, quality and productivity. Integration is defined as the merging of parts into a whole, and supply chain integration, at its normative ideal, refers to the adoption and use of collaborative and coordinating structures, processes, technologies and practices among supply chain partners for building and maintaining a seamless conduit for the precise and timely flow of information, materials and finished goods.

Researchers have conceptualized supply chain integration in terms of its scope, support function, management direction, and means used to accomplish it. Scope refers to the extent to which a focal organization has integrated its processes both internally and externally with its trading partners, and has, for example, been examined as arcs of integration by Frohlich and Westbrook (2001).

It is widely argued that competition is no longer between organizations, but among supply chains. Effective supply chain management (SCM) has become a potentially valuable way of securing competitive advantage and improving organizational performance .Organizations began to realize that it is not enough to improve efficiencies within an organization, but their whole supply chain has to be made competitive. It has been pointed out by Moberg et al (2002) that understanding and practicing supply chain management (SCM) has become an essential prerequisite to staying in the competitive global race and to growing profitably. Jones (1998) has stated that many organizations have begun to recognize that SCM is the key to building a sustainable competitive edge for their products or services in an increasingly crowded marketplace

Despite the increased attention paid to SCM and the expectations from SCM, the literature does not offer much evidence of successful implementations. Boddy et al. (1998) found that more than half of the respondents to their survey considered that their organizations had not been successful in implementing supply chain partnering. Spekman et al. (1998) noted that 60% of supply chain alliances tended to fail. Many researchers have emphasized the importance of information sharing in SCM practices. Lalonde (1998) considers sharing of information as one of five building blocks that characterize a solid supply chain relationship. According to Stein and Sweat (1998), supply chain partners who exchange information regularly are able to work as a single entity. Together, they can understand the needs of the end customer better and hence can respond to market change quicker.

The term supply chain management (SCM) was originally introduced by consultants in the early 1980s (Oliver and Webber, 1992) and has subsequently gained tremendous attention (La Londe, 1998).
The technologies and tools used to enable integration have also been used to characterize supply chain integration. Trent and Monczka (1998) termed that integration has been classified in terms of the directionality of its management. Frohlich (2002) describes e-integration as the integration of suppliers and customers using the Internet. Van Donk and

Van Der Vaart (2005) identify four dimensions in which process integration practices can be observed – flow of goods, planning and control, organization, and flow of information.

Paulraj et al. (2006) also view supply chain as a complex construct that encompasses four facets – relational integration, process integration, information integration, and cross-functional teams.Wang et al (2006) use the term virtual integration to describe information technology enabled collaborative operations and joint planning and control between manufacturers and suppliers.

Gadde and Hakansson (1993) discussed that supply strategy is inherently broader than manufacturing strategy, because it incorporates interactions among various supply chain members. Each focal organization has its own unique network that comprises a unique set of actors, resources, and activities, which together constitute its identity. It also takes a position in comparison with other organizations and networks; the position of a company with respect to others reflects its capacity to provide values to others such as productiveness, innovativeness, competence as explained by Hakansson and Snehota (1995).

Supply chain collaboration has become an important strategy in various businesses. McCarthy and Golicic (2002) discussed that supply chain collaboration encourages exchanging information to improve sales performance. Lee et al.(2000) stated that proper information exchange between supply chains partners may help in reducing the bullwhip effect and make the supply chain more responsive to dynamic market conditions.

Hayes and Wheelwright (1984) posted that a business strategy needs to be supported by various functional level strategies that are internally consistent. Each function needs to be strategically integrated into the whole for a firm to be competitive. This theoretical model underlies much of the strategic research that has been done in the operations and supply chain fields.

Ipek Kocoglu , Salih Zeki Imamoglu *et al*. (2011) evinced the influence of supply chain integration (SCI) on information integration and sharing . The results suggested that the role played by Supply Chain Integration is critical in Data Integration and Information sharing.

Marianna Marra et al. (2012) have reviewed the published literature in Supply Chain Management. They have reviewed 58 journal articles systematically and have commented the way in which knowledge management applications are applied in the supply chain

Per J. Agrell et al. (2013) have discussed that supply chain management is effective if it relies on information integration and implementation of best practice techniques. They have reviewed the state of the two stage network models and have reviewed the advanced applications in the SCM modeling.

2.3 DEMAND FORECASTING TECHNIQUES

Demand Forecasting is an activity of estimating the future demand of a product that a consumer will purchase over a specific period of time. It is generally associated with forecasting sales and manipulating demand. A firm can make use of the sales forecasts made by the industry as a powerful tool for formulating sales policy and sales strategy. Thus it is an important component of the strategic decision making field of the company. To make good forecast, in-depth understanding of the different forecasting methods is of utter importance for practical implementation.

Exponential smoothing is commonly used in automatic forecasting systems. However, when only a small amount of historical data is relevant to future demands, the ad hoc startup methods used in exponential smoothing produce unexpected results. With large data sets, an exponentially smoothed average implicitly weighs the data in a declining manner, similar to discounting. This pattern is important in that it minimizes a measure of forecast error as demonstrated by John O.McClain (1981).

When statistical forecasts were nearly optimal, adjustment had little effect. When the forecasts were less accurate, adjustment improved accuracy. These results suggest the value of graphical review and adjustment of statistical forecasts as explained by Thomas R.Willemain (1989)

Sari (2008) demonstrated a cost-benefit analysis of obtaining the supply chain data which acts as a base line to engage in information sharing. Success in demand forecasting is a critical factor so that the cost-cutting and improved customer service objectives in planning processes and production scheduling are met as discussed by Spedding & Chan (2000).

In recent decades, numerous time series forecasting models have been proposed. A review of the same in the last 25 years may be seen in De Gooijer and Hyndman (2005).

Time series forecasting software tools usually offer a variety of techniques, some of which provide the user the possibility to automatically define parameters. In real business settings however, where it might be necessary to forecast thousands of time series, it is necessary to provide the decision-maker with expert systems that either deal with the automatic parameterization of certain forecasting models or the most suitable forecasting model selection from a set of models.

On the other hand, the forecasting error concept with different time series forecasting models have appeared in recent decades which may be classified into various families. Among these Montgomery, Johnson, & Gardiner (1990) find the family of the exponential smoothing models which have been widely used in the practice, along with the ARIMA models which have been extensively used in the research. Despite the wide range of models, experience has shown that there is no forecasting model which works better than the rest in any given situation by Collopy & Armstrong (1992). Therefore, a suitable selection of the model to be used for each time series may increase forecasting accuracy.

Two approaches have been suggested for forecasting items in a product line by Byron and John (1992). The top-down (TD) approach uses an aggregate forecast model to develop a summary forecast, which is then allocated to individual items on the basis of their historical relative frequency. The bottom-up (BU) approach employs an individual forecast model for each of the items in the family.

Improvements in accuracy do not necessarily result in more valuable forecasts. Forecasts are of little value; no matter how accurate they are, if they are not used. Many planners distrust forecasts. To help ensure that forecasts are used, forecasters have to determine what types of forecasts are needed. Forecasting reports should be simple and easy to interpret. A preliminary report should be distributed for suggestions to resolve possible problems before the final presentation. After the forecasting numbers are distributed, forecasters should follow up to see how forecasts are used. Such group efforts in preparing forecasts typically improve both the accuracy and the acceptability and thus the value of forecasts has been explained by Chaman L. Jain (1993)

Christine A. Martin et al (1989) explained that using quantitative methods, one-year-ahead forecasts are more accurate than two-years-ahead forecasts. Also, aggregation of data series appears to reduce forecasting accuracy slightly.

The demands for products vary and the demand patterns of individual product groups are highly seasonal. The appropriate forecasting models based on the forecast errors and accuracy is applied to the individual product groups as experimented by Pisal Yenradee and Anulark Pinnoi (2001).

Spiros Makrydakis et al (1998) have shown that Quantitative forecasting techniques will sometimes call for analyzing time series so as to examine the underlying context of data over a large period of time. A time series is an observation of data at different points in time. Examples include analysis of daily stock prices, weekly sales goals, and monthly expenses. This technique usually measures historical data using line charts to forecast future events, allowing an economist to identify characteristics in data that can be used in making predictions about future outcomes.

In Simple Moving Average Method, every data point carries equal weight in making the forecast. This is one of the major limitations of this method which is corrected by Weighted Moving Average (WMA), in which more weight/preference is given to the more recent observations. As indicated in the work by R. Panneerselvam (2010), assigning weights to the more recent demand values than the previous ones provide more accuracy making Weighted Moving Average a better method than Simple Moving Average for Dynamic Selection.

The simple moving average introduced in the previous section suffers from two drawbacks as shown by Charles Chase Jr (2009) .First, the averaging process seems rather capricious in that an observation is given full weight for one period, and none the next, when it reaches the K^{th} or “oldest” position. Second, if we use a large number of terms, we have to keep them all around until they are finally removed from the average.

With smoothing methods, more importance is placed on the most recent data than on the historical data. The Single Exponential Smoothing Technique identifies the Trend pattern in the data. Like if there is a trend in the data, it will use the recent observations to make up the bulk of the forecast, and the forecast is more likely to reflect the trend.

Regression analysis is used to understand which among the independent variables are related to the dependent variable, and to explore the forms of these relationships. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent and dependent variables. Aspy Palia et al (2004) concluded in their study that Multiple Regression method can also be used for FMCG products; however, it involves a number of parameters to be given as the input which makes forecast a difficult and time-consuming process.

There are more complex time-series techniques as well, such as ARIMA. These are heavier duty statistical routines that can cope with data with trends and the seasonality in them. They involve heavy and powerful algorithms.

Prajakta S. Kalekar (2004) explained that Simple Exponential Smoothing is used for short-range forecasting and it also tries to smoothen or filter out random errors by giving exponentially decreasing weights to the data relating to the periods that have passed into history but trend still exists in the demand pattern of many products which is corrected by the Adjusted Exponential Smoothing. Moving averages and simple exponential smoothing techniques are easy to execute. That is a part of the great advantage of time-series methods: they're generally simple, cheap to run, and relatively easy to interpret.

Giulio Zotteria, Matteo Kalchschmidt (2007) described that demand forecasting is a major issue in several industrial sectors. A relevant choice for companies is the proper level of forecast aggregation. Forecasters need to properly identify what is the object of the forecasting process, in terms of time bucket (e.g., forecasts are produced on a daily level or on weekly one), set of items the demand refers to (e.g., single item or group of items), set of locations the demand refers to (e.g., single store or chain of stores).

Michael Lawrencea and Paul Goodwin (2006) have demonstrated that 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. While previously judgement was thought to be the enemy of accuracy, today judgement is recognized 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 subjected to many biases. Much of the research has been directed at understanding and managing these strengths and weaknesses.

Robert Fildes and Paul Goodwin (2006) have explained in their work that forecasts play a key role in the management of the supply chain. In most organizations such forecasts form part of an information system on which other functions, such as scheduling, resource planning and marketing depend. Forecast accuracy is, therefore, an important component in the delivery of an effective supply chain. Typically, the forecasts are produced by integrating managerial judgment with quantitative forecasts within a Forecasting Support System (FSS). However, there is much evidence that this integration is often carried out poorly with deleterious effects on accuracy.

Cheng Zhang (2007) believed that the simulation and analytical approaches can help firms make better decision on business model design and inter-organizational collaboration in supply chains.

Hong Liu Ping Wang(2007) established that Simulation model of bullwhip effect when order-up-to inventory policy is employed, which investigate demand variability caused by forecasting technology such as Moving Average (MA) method, Exponentially Weighted Moving Average (EWMA) method or Mean Square Error-optimal (MSE-optimal) forecasting method.

Consumer Goods with their wide range of products and short product life-cycles, show very wide variations in sales trends. Small changes in the business scenario might reflect large variations in sales patterns. Due to these different sales trends exhibited by the products, it becomes necessary while forecasting sales, to choose a forecasting model which is sensitive to the trends shown in the historical sales data. A company must fit the best suited forecasting model to each specific product to obtain the optimal forecast. This, however, is not the case, and the general practice is to use a single forecasting model for different products. Such practice may result in obtaining higher forecast error values.

Michael Lawrence and Konstantinos Nikolopoulos along with Robert Fildes and Paul Goodwin (2009) have experimented that the most common approach to forecasting demand in these companies involves the use of a computerized forecasting system to produce initial forecasts and the subsequent judgmental adjustment of these forecasts by the company's demand planners, ostensibly to take into account exceptional circumstances expected over the planning horizon. Making these adjustments can involve considerable effort and time, but they improve accuracy.

The exponential and Holt-Winters techniques are sensitive to unusual events or outliers as shown by Sarah Gelper et al (2007). Outliers affect the forecasting methods in two ways. First, the smoothed values are affected since the update equations involve current and past values of the series including the outliers. The second effect of outliers is on the selection of the parameters used in the recursive updating scheme. These parameters regulate the degree of smoothing and are chosen to minimize the sum of squared forecast errors.

Forecasting techniques are often used as much for their explanatory power as for their predictive power for practical implementation. Understanding of trend, level and seasonal behavior of the data provided would result in a better forecast. Paul Goodwin (2010) indicated that the winter's method was designed to handle data where there is a conventional seasonal cycle across the course of a year, such as monthly seasonality. James Taylor (2006) has extended the conventional winters' method to deal with double and triple seasonal cycles.

As shown by Anne Koehler et al (2008), there are two variations to winter's method of forecasting that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series. With the additive method, the seasonal component is expressed in absolute terms in the scale of the observed series, and in the level equation the series is seasonally adjusted by subtracting the seasonal component. Within each year the seasonal component will add up to approximately zero. With the multiplicative method, the seasonal component is expressed in relative terms (percentages) and the series is seasonally adjusted by dividing through by the seasonal component. Within each year, the seasonal component will sum up to approximately.

Stavros Asimakopoulos et al (2013) have examined the factors for the efficient adoption and use of the forecasting support systems in product forecasting. The y have laid the foundation for an enhanced model of adoption and use for the practical development of FSS designs and services

Badi H. Baltagi (2013) has reviewed the panel data forecasting literature. He has reviewed starting from the simple forecasts to ARMA models to the regressions as well. He has provided some suggestions for the future work.

2.4 DEMAND FORECASTING FOR SLOW MOVING ITEMS

A.A. Syntetos, J.E. Boylan (2001) studied the causes of the unexpected performance of the Croston Method and developed first step towards it. Certain limitations are identified in Croston's approach and a correction in his derivation of the expected estimate of demand per time period is presented. In addition, a modification to his method that gives approximately unbiased demand per period estimates is also introduced.

Adel A. Ghobbar, Chris H. Friend (2003) presented a predictive error-forecasting model which compares and evaluates forecasting methods based on their factor levels when faced with intermittent demand. This paper deals with techniques applicable to predicting spare parts demand for airline fleets.

Levén and Segerstedt (2004) suggested a modification of the Croston method where a demand rate is directly calculated when a demand has happened. In this paper unknown but real demand data is used to compare these variants of the Croston method. The idea with the modification is that time between demand and demand size is not independent.

Aris A. Syntetos, John E. Boylan (2006) assessed the empirical stock control performance of intermittent demand estimation procedures. The forecasting methods considered are the simple moving average, single exponential smoothing, Croston's method and a new method developed by the authors of this paper. The nature of the empirical demand data set (3000 stock keeping units) is discussed and the stock control model to be used for experimentation purposes is specified.

J.E. Boylan, A.A. Syntetos (2007) studied the accuracy of a Modified Croston procedure. The modified procedure uses a new method for estimating the mean demand and a smoothing method for estimating the variance of the forecasted demand rate. It is found that the smoothed variance estimate is based on an invalid measure of forecast accuracy. Moreover it is shown that the method of forecasting mean demand produces biased forecasts.

A.A. Syntetos, Konstantinos Nikolopoulos et al. (2009) studied the effect of integrating management judgement into intermittent demand forecasts. The work analyses monthly intermittent demand forecasts for the UK branch of a major pharmaceutical company for which it uses statistical forecasting system to produce forecasts that are subsequently and judgmentally adjusted based on marketing intelligence.

Matthew Lindsey, Robert Pavur (2009) proposed a technique for forming reliable prediction intervals for the future demand rate of existing products with observed demand of zero using methodology adapted from software reliability. By using the demand information from a group of products which includes slow-moving products, prediction intervals for the future demand rate of the products with an observed demand of zero were constructed.

Ruud Teunter, Babangida Sani (2009) tried to link the Croston method with inventory control i.e., using the generated forecast to calculate the inventory control parameters. The numerical study shows that the calculated order-up-to levels lead to service levels that are close to their targets.

George Nenes et al. (2010) discussed that the demand for the vast majority of items is intermittent and lumpy, thus not allowing the use of the usual normal or Poisson distributions. Using gamma distribution models and simple quantitative tools, an efficient procedure for approximate but quite accurate determination has been determined that achieve the desired fill rates in the proposed periodic review system

Ralph Snyder (2002) presented a paper on Forecasting sales of slow and fast moving inventories. The Croston approach is critically appraised in this paper. Corrections are made to underlying theory and modifications are proposed to overcome certain implementation difficulties. A parametric bootstrap approach is outlined that integrates demand forecasting with inventory control.

Liljana Ferbar Tratar (2009) stated that exponential smoothing methods are very commonly used for forecasting demand if initial values as well as smoothing constants are treated as decision variables, a considerable reduction in forecast error can be achieved.

Ralph D. Snyder and J. Keith Ord (2010) developed some new models for forecasting intermittent demand time series based on a variety of count probability distributions which were coupled with a variety of dynamic specifications to account for potential serial correlation.

Aris A. Syntetos and John E. Boylan (2010) have analyzed the most well-cited intermittent demand estimation procedures in terms of the variance of their estimates. Detailed derivations are offered along with a discussion of the underlying assumptions.

Peter Wallström et al. (2010) concluded through principal components analysis [*PCA*], that a single measure of forecast errors does not present the total different dimensions of the errors and complementary error measures must be used.

Teunter et al. (2011) show that Croston approach is not suitable to deal with obsolescence issues. The work proposes to update demand probability instead of demand interval.

Ward Romeijnders, Ruud Teunter et al. (2012) suggested a two-step method for forecasting spare parts demand using information on component repairs. A new two-step forecasting method is proposed that takes the additional repair information into account. The first step forecasts for each type of component, the number of repairs per time unit of that component and the number of spare parts (of the type under consideration) needed per repair of that component while in the second step these forecasts are combined to forecast total demand for a spare part.

Nezih Altay et al (2012) investigated the effects of three different types of correlation on forecasting and stock control of intermittent demand items. They showed that correlation in intermittent demand plays a role in forecast quality and stock control performance and also shows that high intermittency levels intensify these changes in service level.

Ralph D. Snyder et al (2012) examined different approaches to demand forecasting for products, paying particular attention to the need for inventory planning. It has been concluded that the inventory planning should be based upon dynamic models using distributions that are more flexible than the Poisson scheme.

M. Zied Babai et al (2012) showed that the intermittent demand is characterized by occasional demand arrivals interspersed by time intervals during which no demand occurs. These demand patterns pose considerable difficulties in terms of forecasting and stock control due to their compound nature, which implies variability both in terms of demand arrivals and demand sizes. The results show that the aggregation forecasting approach results in higher achieved service levels as compared to the classical forecasting approach

Inaba, T. (2012) has proposed an inventory management policy with a demand forecasting algorithm. In this algorithm, the discrete probability distribution is assumed and the parameters to define the distribution are estimated dynamically so that it adapts demand pattern changes during the sales season.

Nikolaos Kourentze (2013) studied intermittent demand forecasts with neural networks. This study proposes a neural network (NN) methodology to forecast intermittent time series. These NNs are used to provide dynamic demand rate forecasts which do not assume constant demand rate in the future and can capture interactions between the non-zero demand and the inter-arrival rate of demand events overcoming the limitations of Croston's method.

2.5 DEMAND FORECASTING FOR NEW PRODUCTS

Louis Fourt and Joseph Woodlock (1960) described novel methods of using consumer panel statistics to predict the success of new grocery products. The method presented a reliable and easily usable prediction model for test markets or initial national marketing. It had the desirable feature of separating the very good and the very bad quickly. Hence it proved a reliable method for early selection of the most promising fraction of innovation.
Frank M. Bass (1969) presented a model for new product growth of consumer durables. The basic assumption of the model is that the timing of consumer’s initial purchase is related to the number of previous buyers. A behavior rationale for model is offered in terms of innovative and imitative behavior.

Wheelwright and Clark (1992) stated that there is a well developed stream of research that examines new product development, with an emphasis on examining the integration of R&D and manufacturing functions .The focus of the majority of these studies is on the processes used to create new products, often with an emphasis on moving from a traditional “functional silos” approach to a more coordinated or concurrent approach.

In the recent past, Klaus K. Brockhoff and Vithala R. Raob (1993) came up with a sub model that draws upon several existing models of product positioning and customer and channel behavior, it specifically shows the effects of preannouncing a product long before it will be available on the market. They showed specific ways of including these effects in the estimation of the potential demand for new products. The sub model implicitly showed the time-dependent effects on the intermediary’s acceptance of the new product.

Everett M. Rogers (1995) presented on Innovation and different elements of Diffusion. Byunggryong Kang I, Hojoong Kim et al. (1996) developed a widely applicable innovation diffusion model based on a conceptual framework characterizing several factors determining market demand for technological products. They discussed the major underlying factors of market penetration and actual demand such as the level of income, price, stock and depreciation and tastes or consumer preferences.

Cachon and Fisher (2000) proposed to boost market demand, several types of promotions and information sharing between partners may improve the availability and of goods in the supply chain. But the benefit of information sharing is highly dependent on the quality and proper use of the available data as described by Raghunathan (2001).

Ching-Chin, Ao Ieong Ka Ieng et al. (2010) proposed a decision-support system, the New Product Forecast System (NPFS), to help execute the standard forecast procedure for new product sales forecasts. NPFS has four modules: Data Handling, Forecasting Model, Learning Platform and Forecasting. Each of these modules has specific functionalities for dealing with the kinds of problems encountered with new product sales forecasts.

S. David Wu, Karl G. Kempf et al. (2010) developed a model that perpetually reduces forecast variance as new market information which is acquired over time. The model extends Bass's original idea of product diffusion to a more comprehensive theoretical setting. It describes how forecast variances can be reduced when combining predictive information from multiple diffusion models.

Usha Ramanathan, Luc Muyldermans (2010) have applied structural equation modeling to investigate the impact of promotions and other factors on the sales of soft drinks. SEM is a multivariate statistical analysis technique, which looks for relationships between various constructs. The SEM model links sales performance with four latent constructs (promotional factors, seasonal factors, special days and customer preference) each measured through a number of indicator variables.

Jongsu Lee et al. (2012) have devised a model for new products based on the reservation price data and Bayesian's rule. The model is estimated by using reservation price data through a consumer survey, and the forecast is updated with sales data as they become available using Bayer's rule. It has concluded that consumer reservation price can be used to forecast the demand for a new product.

2.6 FORECAST ACCURACY MEASURES

Peter J. Brockwell et al (2002) has described that forecast error can be a calendar forecast error or a cross-sectional forecast error, when we want to summarize the forecast error over a group of units. If the average forecast error for a time-series of forecasts for the same product or phenomenon is observed, then that is called as a calendar forecast error or time-series forecast error. If the same has been observed for multiple products for the same period, then that is a cross-sectional performance error. It has been shown that, by combining forecasts, the forecast error can be reduced.

Neil R. Ericsson (1992) indicated that parameter constancy and the mean square error (mse) are two commonly used measures of the forecast performance of empirical macro-models. While forecasting for the same product using different methods, errors of variable magnitude may be involved in actual demand and forecast. A number of methods are available to calculate these errors. It has been shown by Zhuo Chen and Yuhong Yang (2004) that Mean Square Error better capture the information for normally distributed forecast than other error calculating techniques.

Gardner (1990) has identified and has proposed that percentage based measures have the disadvantage of being infinite or undefined if $Yt = 0$ for any t in the period of interest, and have an extremely skewed distribution, where the data involves small counts (which is common with intermittent demand data) it is impossible to use these measures as occurrences of zero values of *Yt* occur frequently. Excessively large (or infinite) MAPEs were avoided in the results by only including data that were positive as explained by Makridakis and Hibon (2000). However, this is an artificial solution that is impossible to apply in practical situations.

Chen and Kung (1984) have presented on how the forecasting accuracy can be improved by integrating qualitative and quantitative forecasting approaches. In the business setting, demand forecasting must be considered as a process to obtain information that will be used in different decision making processes. It has been noticed that only a handful of studies compared Multiple Forecast accuracy measures by Tashman (2000).

Nikolopoulos and Assimakopoulos (2003) discussed in short that reducing errors in forecasts helps minimize the risk that the firm assumes to cover its customers demands.

Zhuo Chen and Yuhong Yang , in their work (2004) have looked into the issue of evaluating forecast accuracy measures and proposed well motivated divergence based accuracy measures. It also examines the performance of several familiar accuracy measures. In addition, their study suggests that individually tailored measures may improve the performance of differentiating between good and poor forecasters.

The comparison of different performance measures is a very challenging task since there is no obvious way to do it objectively according to Rob J Hyndman and Anne B Koehler's work (2006), Scaled Errors become the standard measures for the Forecast accuracy, under some circumstances.

Dr. Ron Tibben-Lembke (2004) highlighted some basic forecasting methods, explaining how to set parameters for those methods, and how to measure forecast accuracy. This work also introduced the method of Running Sum of Forecast Errors (RSFE) and Tracking Signal (TS) and talks about its advantages over MAD.

Guoshan Liu and Yuanyuan Lu (2008) have proposed that the key factor to increase enterprise profits and reduce the costs to make reasonable demand forecasting, the accuracy of which can directly influence the effect of decision-making for an enterprise.

Mark Chockalingam (2010) has discussed the process of measuring forecast accuracy, the pros and cons of different accuracy metrics, and the time-lag with which accuracy should be measured. Also, he suggests a method to identify and track forecast bias .He has also explained the benefits of short-term and long-term planning of forecasts and has also compared the characteristics of MAPE (Mean Absolute Percentage Error) and WAPE (Weighted Average Percentage Error).

Matteo Kalchschmidt and Pamela Danese (2011) have investigated the impact of how forecasting is conducted on forecast accuracy and operational performances (i.e. cost and delivery performances). Besides, it highlights the importance of a proper forecasting-process design that should be coherent with how users intend to exploit forecast results and with the aim that should be achieved, that is not necessarily improving forecast accuracy.

Fabio Busetti and Juri Marcucci (2013) have performed various tests of Mean Square Prediction Errors (MSPE) and of Forecast Encompassing (FE) using simulations for regression models. They inferred that the test is oversized when the out of sample observations are small and the presence of regressors resulted in loss of power of the tests but the size properties were not affected.

2.7 SUMMARY

From the above existing literature, it has been inferred that various research activities and improvements are in progress day by day in the area of forecasting demand for the varieties of products and for the accuracy measurement of forecast. In spite of these developments, lot of scope still prevails in the demand forecasting and forecasting accuracy measurement areas.

The demand forecasting of consumer goods products have been done using the traditional way of quantitative techniques based on the nature and frequency of demand of the products.

Demand for the slow moving items has been predicted using the croston's method which is widely used since years together. Forecasting demand for slow moving items still remains a challenge and numerous researches are carried out on the same.

New products demand prediction still remains as an area of concern since accurate forecasting could not be done. Most of the new products are forecasted based on the various survey measures.

Forecast accuracy measurement is still an area of criticality and no specific measure has been widely accepted in industries till date. Any measures used are either industry specific or organization specific and still improvements are going on in this area.

Understanding the present and past scenario, an attempt has been made in this work to develop forecasting models for consumer goods, slow moving items and for new products. The forecast accuracy measurement has also been included in the scope of this work and an attempt has been made on the same as well. The chapter Methodology discusses about the work performed in achieving the research objectives.

2.8 GAPS IN THE LITERATURE

The following points are identified as the gaps in the Literature and have been addressed in the Methodology of this work.

- Improper static demand forecasting models resulting in inaccurate forecasts.
- Ineffective demand forecasting for slow moving items.
- Low utilization of promotions in the forecasting process.
- Imperfect Forecast Accuracy Measure