HEURISTIC OPTIMIZATION OF DEMAND FORECASTING IN A FUZZY ENVIRONMENT

by

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

NN	Neural Network
ANN	Artificial Neural Network
DCO	Demand Chain Optimization
MLP	Multi Layered Perceptrons
FF	Feed Forward
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
MAE	Mean Absolute Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
MAPE	Mean Absolute Percentage Error

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ABSTRACT

Forecasting the future demand of any kind of products of the business companies is a very important and critical activity for all kinds of business organizations. For a retail chain store, demand forecasting is the major activity in their whole supply chain network. Demand has to be accurately forecasted in order to fulfill the customer requirements and in order to successfully run the business. An efficient and accurate demand forecasting system can play a major role in minimizing different kinds of costs and in increasing customer service. That means overall quality of the organization can be increased. There are hundreds of different techniques have been invented so far for efficient demand forecasting. Some are qualitative and some are quantitative methods. There are also some methods which are combination of both. Customer comes to chain retail store in order to buy products. Making products available for the customer for buying is the objective of the management of the company. Hundreds of varieties products are available in a chain retail store. There is various demand influencing factors for different kinds of products. It is very much difficult to include the quantitative effects of the influencing factors in the demand of any kind of item by applying the existing forecasting algorithms. Though, the current algorithms use both quantitative and qualitative methods in their forecasting techniques, there some limitations of the existing algorithms. There are such influencing factors in the demand of the items available in a chain retail store whose effects can not be quantified by the existing algorithms. Neural network is a very promising tool in the field of forecasting. It is a data driven method. It can identify pattern in the past data and base on that pattern it can predict or forecast the future data. Though, it is a quantitative method, judgmental decisions can be applied through this method. Forecasting using artificial neural network technique is the most advanced procedure in any kind of forecasting field. Applying artificial neural network algorithm in retail store demand forecasting is a very challenging task. In this study, the artificial neural network algorithm has been applied for forecasting future demand of a fast moving item in a chain retail store. Previous years demand data has been used in developing the algorithm. The demand pattern of the selected item has been studied initially. Network architecture has been created by using the observations of that study. The result has found to be very much encouraging. At the beginning of this research, it has been reviewed that in the retail sector the error of the current forecasting algorithms is the range of 20% to 25%. The algorithm that has been developed in this study the error is about 8% to 10%. The reduction of forecasting error will definitely contribute in the development of the chain retail stores and achieving higher profit and customer satisfaction level.

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

An efficient demand forecasting system is very much necessary and crucial for any kind of business organizations. It is also very important for any kind of non-business organizations also. Demand forecasting in any organization means to predict about the future demand of that organization's product. The product can be goods, service, information, place, property, organizations etc. So, an efficient demand forecasting process is important for a manufacturing organization, a service organization, a merchandizing organization or any other kind of organization. It is very important for a manufacturing organization or a merchandizing organization. The efficiency of whole supply chain in these types of organizations mostly depends on a perfect and effective demand forecasting system. Demand forecasting play a major role in a complete manufacturing planning. A merchandizing organization purchase products from the market or directly from the manufacturing organizations. They sell the product to the buyers. So, demand forecasting for these organizations is the most crucial in their business planning.

Chain retail store is a well established concept in the developed countries. There are thousands of chain retail stores or chain super stores in the developed countries. All most every kind of products for daily necessity is available on those stores. Grocery items, household items, food items, cosmetic items, cloth items, etc are the some common type of products that are available in the chain super store. The market share of these super stores in the total selling market is very high. In a developing country like Bangladesh super store concept is not very old. This concept has yet not established countrywide. It is established mainly in the one or two big cities like Dhaka, Chittagong. This concept is just beginning to spread countrywide. Historically, the Bangladeshi retail sector has been dominated by small independent players such as traditional, small grocery stores and others. Recently organized, multi-outlet retail concept has gained acceptance and has since then accelerated. Driven by changing lifestyles, strong income growth and favorable demographic patterns, Bangladeshi retail is expanding at a rapid pace. In Dhaka city, there are about 35 chain super stores of different brands. Chain retain stores named Agora, PQS, Nandon, Family Needs, Sapno etc. are well established. In such a store about 8000 varieties of products are available. All the super stores buy most of their products from outside. They are just selling the products. Recently, they are trying to develop their own brand in a very few variety of products. So, for these stores demand forecasting of their products is very necessary in order to make their businesses run efficiently.

1.2 RATIONALE OF THE STUDY

Demand forecasting is a very important part in the whole business plan of any kind of organizations. Forecasting is a very important topic in the operations management field. Demand forecasting is the activity of estimating the quantity of a product or service that consumers will purchase. Demand forecasting involves techniques including both informal methods, such as educated guesses, and quantitative methods, such as the use of historical sales data or current data from test markets. Demand forecasting may be used in making pricing decisions, in assessing future capacity requirements, or in making decisions on whether to enter a new market. In today's demand-driven supply chain, being successful means finding the right balance between supply and demand. Poor forecasting can lead to inaccurate demand plans, which causes excess inventory, or even more costly, inventory stock-outs. In fact a recent 2006 AMR Research note reported that a 5% improvement in demand forecasting accuracy correlates to a 10% improvement in perfect orders [1]. AMR goes further to show a 10% improvement in prefect orders can yield 50 cents better earnings per share. Demand planning and forecasting serve as the foundation for marshalling resources to cost-effectively respond to future demand and optimizing investments. In order to ensure optimal demand forecasting, those in distribution-intensive industries must capitalize on using the most appropriate forecasting model and methods that best serve the unique dynamics of their business at a specific moment in time. One size does not fit all—nor are market dynamics static such that one model that fits today's conditions will be equally suitable tomorrow.

Some important decisions by functional area that are based on demand forecasts are as follows:

- **Production:** Scheduling, inventory control, aggregate planning.
- **Marketing:** Sales-force allocation, promotions, new product introduction.
- **Finance:** Plant/equipment investment, budgetary planning.
- **Personnel:** Workforce planning, hiring, layoffs.

Most manufacturing and merchandizing companies in developing countries determine product demand forecasts and production plans using subjective and intuitive judgments. This may be one factor that leads to production inefficiency. An accuracy of the demand forecast significantly affects safety stock and inventory levels, inventory holding costs, and customer service levels. When the demand is highly seasonal, it is unlikely that an accurate forecast can be obtained without the use of an appropriate forecasting model. The demand forecast is one among several critical inputs of a production planning process. When the forecast is inaccurate, the obtained production plan will be unreliable, and may result in over or under stock problems. To avoid them, a suitable amount of safety stock must be provided, which requires additional investment in inventory and results in an increased inventory holding costs. Often forecasting demand is confused with forecasting sales. But, failing to forecast demand ignores two important phenomena [2]. There is a lot of debate in the demand planning literature as how to measure and represent historical demand, since the historical demand forms the basis of forecasting.

Stock Effects: It is the effects that inventory levels have on sales. In the extreme case of stock-outs, demand coming into store is not converted to sales due to a lack of availability. Demand is also untapped when sales for an item are decreased due to a poor display location, or because the desired sizes are no longer available. For example, when a consumer electronics retailer does not display a particular flat-screen TV, sales for that model are typically lower than the sales for models on display. And in fashion retailing, once the stock level of a particular sweater falls to the point where standard sizes are no longer available, sales of that item are diminished.

Market Response Effects: It is the effect of market events that are within and beyond a retailer's control. Demand for an item will likely rise if a competitor increases the price or if the item is promoted in weekly circular. The resulting sales increase reflects a change in demand as a result of consumers responding to stimuli that potentially drive additional sales. Regardless of the stimuli, these forces need to be factored into planning and managed within the demand forecast. In this case demand forecasting uses techniques in causal modeling. Demand forecast modeling considers the size of the market and the dynamics of market share versus competitors and its effect on firm demand over a period of time. In the manufacturer to retailer model, promotional events are an important causal factor in influencing demand. These promotions can be modeled with intervention models or use a consensus process to aggregate intelligence using internal collaboration with the sales and marketing functions.

A small retailer may not need and afford a full-fledged demand forecasting analysis. However, with increasing number of bigger retailers entering the market demand forecasting becomes feasible. Firms face a multitude of challenges due to the following factors:

- scale of forecast (how many goods to include in the forecast?)
- sporadic demand (erratic sales for many items in the store)
- introduction of new goods
- changing prices and promotions

A big retailer may have thousands of items per shop. Since forecasting is an important yet expensive task, the retailer can not forecast for all goods it sells. Though it is infeasible to manually forecast the demand of all the products, it is possible to use automated tools to do so. In most cases, quality forecasts can be obtained from the automated tool and the expert analysts can be employed to forecast few of the most important products [3]. This reduces the burden from the humans but requires lot of computing power available.

Forecasting models classically fall into one of two types: qualitative and quantitative. The primary differences between the two include the type of input data and the mathematical and statistical methods employed to generate forecasts.

Qualitative models: Qualitative models rely on subjective inputs from knowledgeable personnel, such as salespeople, account managers, and the like. This approach typically employs formal procedures for data review and consensus approval for determining the value of various forms of information. Aggregation of individual estimates and Delphi-type structured polling methods may be used to obtain consensus among a group of forecasters.

Quantitative models: Quantitative models are statistically driven, drawing heavily on historical performance data as the basic data input. The calculating logic is defined and operations are purely mathematical. Three basic model sub-types are used to configure the calculations: time series, derived and causal models.

A. Time series model: Employs a time-ordered sequence of observations of a particular variable, and uses only the history of that variable to determine future values. For example, if examination of monthly sales volumes of lawnmowers sold in Georgia revealed a linear pattern, a linear trend model would likely provide the best means for developing the forecast of future demand.

B. Derived model: Bases a new forecast on an existing forecast When an item's forecast is thought to be fundamentally the same as an existing item, characteristics of the old item can be copied to the new item with factoring up or down by a percentage to express an associated forecast. This preserves the overall trend and seasonal characteristics of the item, providing a good starting point for the new item. For example, one might forecast new lawnmowers with five-horsepower engines based on the forecast for lawnmowers with two-horsepower engines.

C. Causal model: Relies on correlation between a particular time series variable and other time series factors. If a causal relationship can be determined, one can then use that relationship to calculate the forecast. For example, causal techniques are useful in calculating 'lift' created during promotional campaigns. The relationship between base demand (demand without promotional activity) and promotional causal factors can be established through the use of sensitivity factors. For example, in promoting a product with a price discount campaign, a forecasting system using causal relationships can determine what the 'lift' or increased sales will be. Additional factors can be used, such as end-cap displays, seasonality of the product, etc. Factors are not additive but are used together to calculate the expected lift for products for a specified period, channel, or customer.

Most advanced forecasting systems use a combination of both qualitative and quantitative techniques to generate a reliable forecast. Statistical models using historical data provide an objective base of information that organizations may use as the foundation or baseline to more qualitative calculations generated by personnel with knowledge of more intangible market factors, or perceptions regarding factors impacting future market performance. During last few decades, various approaches have been developed for time series forecasting. Among them ARMA models and Box-Jenkins model building approaches are highly famous. But the classical time series methods can not deal with forecasting problems in which the values of time series are linguistic terms represented by fuzzy sets [4], [5]. Therefore, Song and Chissom [6] presented the theory of fuzzy time series to overcome this drawback of the classical time series methods. Well established time series models include: (1) **linear models**, e.g., moving average, exponential smoothing and the autoregressive integrated moving average (ARIMA); (2) **nonlinear models**, e.g., neural network models and fuzzy system models. Recently a tendency for combining of linear and nonlinear models for forecasting time series has been an active research area [7]. The recent upsurge in research activities into artificial neural networks (ANN's) has proven that neural networks have powerful pattern classification and prediction capabilities. ANN's have been successfully used for a variety of tasks in many fields of business, industry, and science [8]. They have fast become a standard class of quantitative modeling tools for researchers and practitioners. One of the major application areas of ANN's is forecasting. There is an increasing interest in forecasting using ANN's in recent years. Forecasting has a long history and the importance of this old subject is reflected by the diversity of its applications in different disciplines ranging from business to engineering. The ability to accurately predict the future is fundamental to many decision processes in planning, scheduling, purchasing, strategy formulation, policy making, and supply chain operations. As such, forecasting is an area where a lot of efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future. Forecasting has been dominated by linear methods for many decades. Linear methods are easy to develop and implement and they are also relatively simple to understand and interpret. However, linear models have serious limitation in that they are not able to capture any nonlinear relationships in the data. The approximation of linear models to complicated nonlinear relationships is not always satisfactory. In the early 1980s, Makridakis [9] organized a large-scale forecasting competition (often called M-competition) where a majority of commonly used linear methods were tested with more than 1,000 real time series data. The mixed results show that no single linear model is globally the best, which may be interpreted as the failure of linear modeling in accounting for a varying degree of nonlinearity that is common in real world problems. ANN's provide a promising alternative tool for forecasters. The inherently nonlinear structure of neural networks is particularly useful for capturing the complex underlying relationship in many real world problems. Neural networks are perhaps more versatile methods for forecasting applications in that not only can they find nonlinear structures in a problem, they can also model linear processes.

The focus of this research work is to apply artificial neural network technique in forecasting the demand of varieties of products in chain retails stores and also include the uncertainty factors in the forecasting system. The main purpose of this study is to apply non linear models of forecasting in predicting the demand which is traditionally predicted by linear models and where different factors influencing the demand have been neglected so far.

1.3 OBJECTIVES OF THE STUDY

The specific objectives of the present research work are as follows:

a. To classify the category of items from the broad category of selected daily used items.
b. To identify the influencing factors, analyze and quantify their effects on the demand level.
c. To address uncertainty in the demand.
d. To develop a heuristic optimization algorithm to efficiently forecast the demand level.
e. To compare the proposed algorithm with some existing algorithms.

Possible outcomes are:

a. A new heuristic forecasting model which can address the stochastic parameters.
b. A comparative analysis between several existing algorithms with the proposed one.
c. A computer program to forecast demand for classified category of items.

1.4 OUTLINE OF METHODOLOGY

a. Study the demand pattern of the daily used items.

b. Identify all the parameters that affect the demand pattern and level.

c. Analyze the existing algorithms along with their limitations.

d. Develop a heuristic optimization algorithm to build a forecasting model step by step.

e. Incorporate the uncertainty nature of demand through neural network logic.

f. Develop computer software to solve such algorithm.

g. Perform a comparative study with respect to existing algorithms to evaluate the performance of the proposed model.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

Forecasting is the process of estimation in unknown situations. Prediction is a similar, but more general term. Both can refer to estimation of time series, cross-sectional or longitudinal data. Usage can differ between areas of application: for example in hydrology, the terms "forecast" and "forecasting" are sometimes reserved for estimates of values at certain specific future times, while the term "prediction" is used for more general estimates, such as the number of times floods will occur over a long period. Risk and uncertainty are central to forecasting and prediction. Forecasting is used in the practice of customer demand planning in every day business forecasting for manufacturing or merchandizing companies or any other types of companies. The discipline of demand planning, also sometimes referred to as supply chain forecasting, embraces both statistical forecasting and a consensus process. Forecasting is commonly used in discussion of time-series data.

Forecasting product demand is crucial to any supplier, manufacturer, or retailer. Forecasts of future demand will determine the quantities that should be purchased, produced, and shipped. Demand forecasts are necessary since the basic operations process, moving from the suppliers' raw materials to finished goods in the customers' hands, takes time. Most firms cannot simply wait for demand to emerge and then react to it. Instead, they must anticipate and plan for future demand so that they can react immediately to customer orders as they occur. In other words, most manufacturers "make to stock" rather than "make to order" – they plan ahead and then deploy inventories of finished goods into field locations. Thus, once a customer order materializes, it can be fulfilled immediately – since most customers are not willing to wait the time it would take to actually process their order throughout the supply chain and make the product based on their order. An order cycle could take weeks or months to go back through part, item or raw material suppliers and sub-assemblers, through manufacturing of the product, and through to the eventual shipment of the order to the customer. Firms that offer rapid delivery to their customers will tend to force all competitors in the market to keep finished good inventories in order to provide fast order cycle times. As a result, virtually every organization involved needs to manufacture or at least order parts based on a forecast of future demand [10]. The ability to accurately forecast demand also affords the firm opportunities to control costs through leveling its production quantities, rationalizing its transportation, and generally planning for efficient logistics operations. In general practice, accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high cost operations and/or poor levels of customer service. In many supply chains, the most important action it can be taken to improve the efficiency and effectiveness of the logistics process is to improve the quality of the demand forecasts.

2.2 FORECASTING DEMAND IN A SYSTEM

Logistics professionals are typically interested in where and when customer demand will materialize. Consider a retailer selling through five superstores in Gulshan, Dhanmondi, Shantinagar, Mirpur, and Uttara. It is not sufficient to know that the total demand will be 5,000 units per month, or, say, 1,000 units per month per store, on the average. Rather it is important to know, for example, how much the Gulshan store will sell in a specific month, week or day, since specific stores must be supplied with goods at specific times. The requirement might be to forecast the monthly demand for an item at the Gulshan superstore for the first three months of the next year. Using available historical data, without any further analysis, the best guess of monthly demand in the coming months would probably be the average monthly sales over the last few years. Same thing applies for the months and days sales also. The analytic challenge is to come up with a better forecast than this simple average. Since the logistics system must satisfy specific demand, in other words what is needed, where and when, accurate forecasts must be generated at the stock keeping unit (SKU) level, by stocking location, and by time period. Thus, the logistics information system must often generate thousands of individual forecasts each week. This suggests that useful forecasting procedures must be fairly "automatic"; that is, the forecasting method should operate without constant manual intervention or analyst input.

In practice, however, most firms have found that the planning and operation of an effective logistics system requires the use of accurate, disaggregated demand forecasts. The manufacturing organization may need a forecast of total product demand by week, and the marketing organization may need to know what the demand may be by region of the country and by quarter. The logistics organization needs to store specific SKUs in specific warehouses and to ship them on particular days to specific stores. Thus the logistics system, in contrast, must often generate weekly, or even daily, forecasts at the SKU level of detail for each of hundreds of individual stocking locations, and in most firms, these are generated nowhere else.

An important issue for all forecasts is the "horizon;" that is, how far into the future must the forecast project? As a general rule, the farther into the future it will be looked, the more clouded the vision becomes - long range forecasts will be less accurate that short range forecasts. The answer depends on what the forecast is used for. For planning new manufacturing facilities, for example, it may be needed to forecast demand many years into the future since the facility will serve the firm for many years. On the other hand, these forecasts can be fairly aggregate since they need not be SKU-specific or broken out by stockade location. For purposes of operating the logistics system, the forecasting horizon needs to be no longer than the cycle time for the product. For example, a given logistics system might be able to routinely purchase raw materials, ship them to manufacturing locations, generate finished goods, and then ship the product to its field locations in, say, ninety days. In this case, forecasts of SKU -level customer demand which can reach ninety days into the future can tell everything it is needed to know to direct and control the on-going logistics operation. It is also important to note that the demand forecasts developed within the logistics system must be generally consistent with planning numbers generated by the production and marketing organizations. If the production department is planning to manufacture two million units, while the marketing department expects to sell four million units, and the logistics forecasts project a total demand of one million units, senior management must reconcile these very different visions of the future.

2.3 DEMAND FORECASTING PROBLEM

Forecasting needs arise in a variety of fields and applications. Whether forecasting future expenses and revenues in corporate accounting, planning manufacturing production time and cost, predicting retail sales trends or deriving an optimal trading strategy for securities, analysts are faced with the challenge of managing increasingly large and complex data sets. These data sets can contain thousands of variables making it impractical to use manual forecasting processes, where each variable is handled individually. In order to efficiently leverage the vast amount of information that exists in a data set collectively, an analyst needs flexible and scalable forecasting solutions built around a robust, reliable and accurate set of numerical algorithms.

Companies and supply chain managers should be aware of the following ties of forecasts:

- Forecasts are always wrong and should thus include both the expected measure of forecast error.
- Long-term forecasts are usually less accurate than short-term forecast; long-term forecasts have a larger standard deviation of error relative to the short-term forecasts.
- Aggregate forecasts are usually more accurate than disaggregate forecast, aggregate forecasts tend to have a smaller standard deviation of error relative to the mean than short term forecast.

Since inventory is material obtained in advance of need, any inventory control policy must be based on some anticipation or belief about which items will be needed in the future, how much will be needed, and when the need will arise. In other words, inventory control must involve some forecast of future demand, whether crude or sophisticated, explicit or implicit. Even a Kanban system involves some forecasting, in that the size or desired quantity in the Kanban container is based on a consideration of the amount of demand which could occur over the re-supply time interval [11]. In a very real sense, the ability to forecast demand and re-supply times accurately will set an upper limit on how successful or efficient the inventory control policy will be. In many cases, the most effective way to improve the inventory performance in a firm may not involve changing the inventory control algorithm, but rather would focus on improving the demand forecasts that drive the existing inventory system. That having been said, there is far more to effective inventory control than simply forecasting demand "accurately", and it is often impossible to obtain truly accurate demand forecasts. An appropriate inventory control will accept the available inventory forecasts and operate as efficiently as is possible given the inherent inaccuracies of the forecasts.

2.4 FORECASTING PROCEDURE

Forecasting involves the generation of a number, set of numbers, or scenario that corresponds to a future occurrence. It is absolutely essential to short-range and long-range planning. By definition, a forecast is based on past data, as opposed to a prediction, which is more subjective and based on instinct, gut feel, or guess. For example, the evening news gives the weather "forecast" not the weather "prediction." Regardless, the terms forecast and predictions are often used inter-changeably. For example, definitions of regression—a technique sometimes used in forecasting—generally state that its purpose is to explain or "predict.". In the below figure, forecasting procedure and need has been showed.

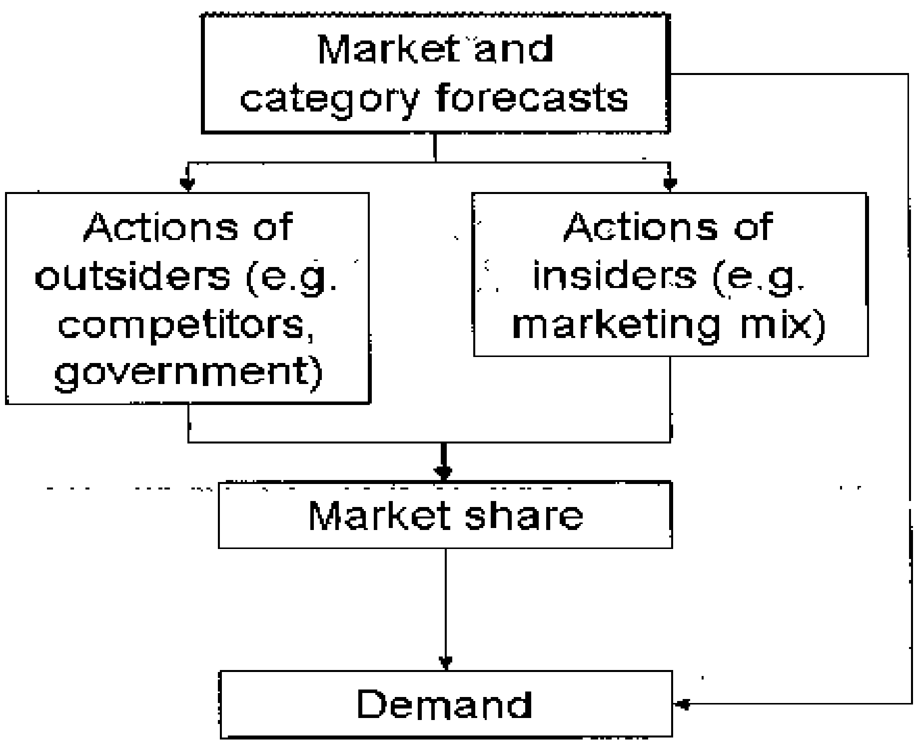

Figure 2.1: Needs for marketing forecast.

Forecasting is based on a number of assumptions:

1. The past will repeat itself. In other words, what has happened in the past will happen again in the future.

2. As the forecast horizon shortens, forecast accuracy increases. For instance, a forecast for tomorrow will be more accurate than a forecast for next month; a forecast for next month will be more accurate than a forecast for next year; and a forecast for next year will be more accurate than a forecast for ten years in the future.
3. Forecasting in the aggregate is more accurate than forecasting individual items. This means that a company will be able to forecast total demand over its entire spectrum of products more accurately than it will be able to forecast individual stock-keeping units (SKUs). For example, General Motors can more accurately forecast the total number of cars needed for next year than the total number of white Chevrolet Impalas with a certain option package.
4. Forecasts are seldom accurate. Furthermore, forecasts are almost never totally accurate. While some are very close, few are "right on the money." Therefore, it is wise to offer a forecast "range." If one were to forecast a demand of 100,000 units for the next month, it is extremely unlikely that demand would equal 100,000 exactly. However, a forecast of 90,000 to 110,000 would provide a much larger target for planning.

William J. Stevenson lists a number of characteristics that are common to a good forecast [12]:

- Accurate—some degree of accuracy should be determined and stated so that comparison can be made to alternative forecasts.
- Reliable—the forecast method should consistently provide a good forecast if the user is to establish some degree of confidence.
- Timely—a certain amount of time is needed to respond to the forecast so the forecasting horizon must allow for the time necessary to make changes.
- Easy to use and understand—users of the forecast must be confident and comfortable working with it.
- Cost-effective—the cost of making the forecast should not outweigh the benefits obtained from the forecast.

All firms forecast demand, but it would be difficult to find any two firms that forecast demand in exactly the same way. Over the last few decades, many different forecasting techniques have been developed in a number of different application areas, including engineering and economics [13]. Many such procedures have been applied to the practical problem of forecasting demand in a logistics system, with varying degrees of success. Most commercial software packages that support demand forecasting in a logistics system include dozens of different forecasting algorithms that the analyst can use to generate alternative demand forecasts. In one sense, all forecasting procedures involve the analysis of historical experience into patterns and the projection of those patterns into the future in the belief that the future will somehow resemble the past. The differences in the various approaches are in the way this "search for pattern" is conducted. Combined forecasts improve accuracy and reduce the likelihood of large errors. In a meta-analysis, Armstrong found an average error reduction of about 12% across 30 comparisons [14]. They are especially useful when the component methods differ substantially from one another. For example, Blattberg and Hoch [15] obtained improved sales forecast by averaging managers' judgmental forecasts and forecasts from a quantitative model. Considerable research suggests that, lacking well-structured domain knowledge, unweighted averages are typically as accurate as other weighting schemes [16]. Judgmental and statistical methods should be integrated. Armstrong and Collopy [17] summarize research in this area. Integration is effective when judgments are collected in a systematic manner and then used as inputs to the quantitative models, rather than simply used as adjustments to the outputs. Unfortunately, the latter procedure is commonly used.

William J. Stevenson lists the following as the basic steps in the forecasting process:

- Determine the forecast's purpose. Factors such as how and when the forecast will be used, the degree of accuracy needed, and the level of detail desired determine the cost (time, money, employees) that can be dedicated to the forecast and the type of forecasting method to be utilized.

- Establish a time horizon. This occurs after one has determined the purpose of the forecast. Longer-term forecasts require longer time horizons and vice versa. Accuracy is again a consideration.

- Select a forecasting technique. The technique selected depends upon the purpose of the forecast, the time horizon desired, and the allowed cost.

- Gather and analyze data. The amount and type of data needed is governed by the forecast's purpose, the forecasting technique selected, and any cost considerations.
- Make the forecast.
- Monitor the forecast. Evaluate the performance of the forecast and modify, if necessary.

Factors appropriate for people to weight forecasts based on experience and expertise include:

- Required forecast form
- Forecast horizon—period and interval
- Data availability
- Accuracy-level required
- Behavior or demand pattern of process being forecast
- Cost of development, installation and use
- Ease of operation
- Level of comprehension and cooperation of vested parties

The choice of a forecasting methodology is only one component of a comprehensive approach to demand forecasting. All parties in the supply chain should reach consensus regarding forecast assumptions, techniques, and final forecast numbers. With consensus, all plans within the supply chain are consistent and are able to support each other. The following basic, six-step approach to forecasting helps an organization to perform effective forecasting:

1. Understand the objective of forecasting
2. Integrate demand planning and forecasting
3. Identify the major factors that influence the demand forecast
4. Understand and identify customer segments
5. Determine the appropriate forecasting technique
6. Establish performance and error measures for the forecast

2.5 FORECASTING METHODS

Forecasting techniques range from the simple to the extremely complex. These techniques are usually classified as being qualitative or quantitative. The primary differences between the two include the type of input data and the mathematical and statistical methods employed to generate forecasts. No demand forecasting method is 100% accurate. Combined forecasts improve accuracy and reduce the likelihood of large errors.

2.5.1 QUALITATIVE METHODS

Qualitative forecasting techniques are generally more subjective than their quantitative counterparts. These techniques are more useful in the earlier stages of the product life cycle, when less past data exists for use in quantitative methods. These models rely on subjective inputs from knowledgeable personnel, such as salespeople, account managers, and the like. These approaches typically employ formal procedures for data review and consensus approval for determining the value of various forms of information. Aggregation of individual estimates and Delphi-type structured polling methods may be used to obtain consensus among a group of forecasters [18]. Qualitative forecasting methods are based on educated opinions of appropriate persons.

2.5.1.1 DELPHI METHOD

The Delphi technique uses a panel of experts to produce a forecast. Each expert is asked to provide a forecast specific to the need at hand. After the initial forecasts are made, each expert reads what every other expert wrote and is, of course, influenced by their views. A subsequent forecast is then made by each expert. Each expert then reads again what every other expert wrote and is again influenced by the perceptions of the others. This process repeats itself until each expert nears agreement on the needed scenario or numbers. The name "Delphi" derives from the Oracle of Delphi. The Delphi method is based on the assumption that group judgments are more valid than individual judgments. The Delphi method was developed at the beginning of the cold war to forecast the impact of technology on warfare. In 1944, General Henry H. Arnold ordered the creation of the report for the U.S. Air Force on the future technological capabilities that might be used by the military. Two years later, Douglas Aircraft Company started Project RAND to study "the broad subject of inter-continental warfare other than surface". Different approaches were tried, but the shortcomings of traditional forecasting methods, such as theoretical approach, quantitative models or trend extrapolation, in areas where precise scientific laws have not been established yet, quickly became apparent. To combat these shortcomings, the Delphi method was developed by Project RAND during the 1950-1960s by Olaf Helmer, Norman Dalkey, and Nicholas Rescher [19]. It has been used ever since, together with various modifications and reformulations, such as the Imen-Delphi procedure.

The following key characteristics of the Delphi method help the participants to focus on the issues at hand and separate Delphi from other methodologies:

Structuring of Information Flow: The initial contributions from the experts are collected in the form of answers to questionnaires. Their comments to these answers are also collected. The panel director controls the interactions among the participants by processing the information and filtering out irrelevant content.

Regular Feedback: Participants comment on their own forecasts, the responses of others and on the progress of the panel as a whole. At any moment they can revise their earlier statements.

Anonymity of the Participants: Usually all participants maintain anonymity. Their identity is not revealed even after the completion of the final report. This stops them from dominating others in the process using their authority or personality, frees them to some extent from their personal biases, minimizes the "bandwagon effect" or "halo effect", and allows them to freely express their opinions.

Role of the Facilitator: The person coordinating the Delphi method can be known as a facilitator, and facilitates the responses of their panel of experts, who are selected for a reason, usually that they hold knowledge on an opinion or view. The facilitator sends out questionnaires, surveys etc. and if the panel of experts accept, they follow instructions and present their views. If consensus is not reached, the process continues through thesis and antithesis, to gradually work towards synthesis, and building consensus by duplicating the procedure several times until a consensus emerged.

First applications of the Delphi method were in the field of science and technology forecasting [20]. One of the first such reports, prepared in 1964 by Gordon and Helmer [21], assessed the direction of long-term trends in science and technology development, covering such topics as scientific breakthroughs, population control, automation, space progress, war prevention and weapon systems. It was also applied successfully and with high accuracy in business forecasting. For example, in one case reported by Basu and Schroeder [22], the Delphi method predicted the sales of a new product during the first two years with inaccuracy of 3–4% compared with actual sales. Quantitative methods produced errors of 10–15%, and traditional unstructured forecast methods had errors of about 20%.

Overall the track record of the Delphi method is mixed. There have been many cases when the method produced poor results. It must also be realized that in areas such as science and technology forecasting the degree of uncertainty is so great that exact and always correct predictions are impossible, so a high degree of error is to be expected.

- Another particular weakness of the Delphi method is that future developments are not always predicted correctly by consensus of experts.
- The issue of ignorance is important. If panelists are misinformed about a topic, the use of Delphi may add only confidence to their ignorance.
- Sometimes unconventional thinking of amateur outsiders may be superior to expert thinking.
- One of the initial problems of the method was its inability to make complex forecasts with multiple factors. Potential future outcomes were usually considered as if they had no effect on each other.

Still the Delphi method can be used most successfully in forecasting single scalar indicators. Despite these shortcomings, today the Delphi method is a widely accepted forecasting tool and has been used successfully for thousands of studies in areas varying from technology forecasting to drug abuse.

2.5.1.2 UNAIDED JUDGMENT

It is common practice to ask experts what will happen. This is a good procedure to use when -

- experts are unbiased
- large changes are unlikely
- relationships are well understood by experts (e.g., demand goes up when prices go down)
- experts possess privileged information

- experts receive accurate and well-summarized feedback about their forecasts

Unfortunately, unaided judgment is often used when the above conditions do not hold. Green and Armstrong [23], for example, found that experts were no better than chance when they use their unaided judgment to forecast decisions made by people in conflict situations.

2.5.1.3 PREDICTION MARKETS

Prediction markets, also known as betting markets, information markets, and future markets have a long history. Between the end of the US civil war and world war II, well-organized markets for betting on presidential elections correctly picked the winner in every case but 1916; also, they were highly successful in identifying those elections that would be very close. More recently, in the four elections prior to 2004, the Iowa Electronic Markets (IEM) has performed better than polls in predicting the margin of victory for the presidential election winner. In the week leading up to the election, these markets predicted vote shares for the Democratic and Republican candidates with an average absolute error of around 1.5 percentage points. The final Gallup poll, by comparison, yielded forecasts that erred by 2.1 percentage points [24]. Despite numerous attempts since the 1930's, no methods have been found to be superior to markets when forecasting prices.

2.5.1.4 STRUCTURED ANALOGIES

The outcomes of similar situations from the past (analogies) may help a marketer to forecast the outcome of a new (target) situation. For example, the introduction of new products in US markets can provide analogies for the outcomes of the subsequent release of similar products in other countries. People often use analogies to make forecasts, but they do not do so in a structured manner. For example, they might search for an analogy that suits their prior beliefs or they might stop searching when they identify one analogy. The structured-analogies method uses a formal process to overcome biased and inefficient use of information from analogous situations. To use the structured analogies method, an administrator prepares a description of the target situation and selects experts who have knowledge of analogous situations preferably the one with direct experience. The experts identify and describe analogous situations, rate their similarity to the target situation, and match the outcomes of their analogies with potential outcomes in the target situation. The administrator then derives forecasts from the information the experts provided on their most similar analogies. Green and Armstrong [25] found that structured analogies were more accurate than unaided judgment in forecasting decisions in situations with eight conflicts.

2.5.1.5 GAME THEORY

Game theory has been touted in textbooks and research papers as a way to obtain better forecasts in situations involving negotiations or other conflicts. Despite a vast research effort, there is no research that directly tests the forecasting ability of game theory. However, Green [26] tested the ability of game theorists, who were urged to use game theory in predicting the outcome of eight real (but disguised) situations. In that study, game theorists were no more accurate than university students.

2.5.1.6 JUDGMENTAL DECOMPOSITION

The basic idea behind judgmental decomposition is to divide the forecasting problem into parts that are easier to forecast than the whole. One then forecasts the parts individually, using methods appropriate to each part. Finally, the parts are combined to obtain a forecast.

One approach is to break the problem down into multiplicative components. For example, to forecast sales for a brand, one can forecast industry sales volume, market share, and selling price per unit. Then reassemble the problem by multiplying the components together. Empirical results indicate that, in general, forecasts from decomposition are more accurate than those from a global approach [27]. In particular, decomposition is more accurate where there is much uncertainty about the aggregate forecast and where large numbers (over one million) are involved.

2.5.1.7 JUDGMENTAL BOOTSTRAPPING

Judgmental bootstrapping converts subjective judgments into structured procedures. Experts are asked what information they use to make predictions about a class of situations. They are then asked to make predictions for diverse cases, which can be real or hypothetical. For example, they might forecast next year's sales for alternative designs for a new product. The resulting data are then converted to a model by estimating a regression equation relating the judgmental forecasts to the information used by the forecasters. The general proposition seems preposterous. It is that the model of the man will be more accurate than the man. The reason is that the model applies the man's rules more consistently.

Judgmental bootstrapping models are most useful for repetitive complex forecasting problems where data on the dependent variable are not available (e.g. demand for a new telecommunications device) or data does not vary sufficiently for the estimation of an econometric model.

Once developed, judgmental bootstrapping models provide a low-cost procedure for making forecasts. The review in Armstrong [28] found that judgmental bootstrapping was more accurate than unaided judgment (the normal method for these situations) in 8 of the 11 comparisons, with two tests showing no difference, and one showing a small loss. The typical error reduction was about 6%. Judgmental bootstrapping also allows experts to see how they are weighting various factors. This knowledge can help to improve judgmental forecasting. For example, with respect to personnel selection, bootstrapping might reveal that some factors, such as height, weight or looks, are used, even though they are not relevant for the job. Bootstrapping also allows for estimating effects of changing key variables.

2.5.1.8 EXPERT SYSTEMS

As the name implies, expert systems are structured representations of the rules experts use to make predictions or diagnoses. For example, 'if local household incomes are in the bottom quartile, **then** do not supply premium brands'. The forecast is implicit in the foregoing conditional action statement: i.e., premium brands are unlikely to make an acceptable return in the locale. Rules are often created from protocols, whereby forecasters talk about what they are doing while making forecasts. Where empirical estimates of relationships from structured analysis such as econometric studies are available, expert systems should use that information. Expert opinion, conjoint analysis, and bootstrapping can also aid in the development of expert systems Expert systems forecasting involves identifying forecasting rules used by experts and rules learned from empirical research. One should aim for simplicity and completeness in the resulting system, and the system should explain forecasts to users. Developing an expert system is expensive and so the method will only be of interest in situations where many forecasts of a similar kind are required. Expert systems are feasible where problems are sufficiently well-structured for rules to be identified. Collopy, Adya, and Armstrong [29], in their review, found that expert systems forecasts are more accurate than those from unaided judgment. This conclusion, however, was based on only a small number of studies.

2.5.1.9 CONJOINT ANALYSIS

By surveying consumers about their preferences for alternative product designs in a structured way, it is possible to infer how different features will influence demand. Potential customers might be presented with a series of perhaps 20 pairs of offerings. For example, various features of a personal digital assistant such as price, weight, battery life, screen clarity and memory could be varied substantially such that the features do not correlate with one another. The potential customer is thus forced to make trade-offs among various features by choosing one of each pair of offerings in a way that is representative of how they would choose in the marketplace The resulting data can be analyzed by regressing respondents' choices against the product features. The method, which is similar to bootstrapping, is called 'conjoint analysis' because respondents consider the product features jointly. In general, the accuracy of forecasts from conjoint analysis is likely to increase with increasing realism of the choices presented to respondents [30]. The method is based on sound principles, such as using experimental design and soliciting independent intentions from a sample of potential customers. Unfortunately however, there do not appear to be studies that compare conjoint-analysis forecasts with forecasts from other reasonable methods.

2.5.1.10 NOMINAL GROUP TECHNIQUE

Nominal group technique is similar to the Delphi technique in that it utilizes a group of participants, usually experts. After the participants respond to forecast-related questions, they rank their responses in order of perceived relative importance. Then the rankings are collected and aggregated. Eventually, the group should reach a consensus regarding the priorities of the ranked issues.

2.5.1.11 SALES FORCE OPINIONS

The sales staff is often a good source of information regarding future demand. The sales manager may ask for input from each sales-person and aggregate their responses into a sales force composite forecast. Caution should be exercised when using this technique as the members of the sales force may not be able to distinguish between what customers say and what they actually do. Also, if the forecasts will be used to establish sales quotas, the sales force may be tempted to provide lower estimates.

2.5.1.12 EXECUTIVE OPINIONS

Sometimes upper-levels managers meet and develop forecasts based on their knowledge of their areas of responsibility. This is sometimes referred to as a jury of executive opinion.

2.5.1.13 MARKET RESEARCH

In market research, consumer surveys are used to establish potential demand. Such marketing research usually involves constructing a questionnaire that solicits personal, demographic, economic, and marketing information. On occasion, market researchers collect such information in person at retail outlets and malls, where the consumer can experience—taste, feel, smell, and see—a particular product. The researcher must be careful that the sample of people surveyed is representative of the desired consumer target.

2.5.2 QUANTITATIVE METHODS

Quantitative forecasting techniques are generally more objective than their qualitative counterparts. Quantitative forecasts can be time-series forecasts (i.e., a projection of the past into the future) or forecasts based on associative models (i.e., based on one or more explanatory variables). Time-series data may have underlying behaviors that need to be identified by the forecaster. In addition, the forecast may need to identify the causes of the behavior. Some of these behaviors may be patterns or simply random variations. Among the patterns are:

- Trends, which are long-term movements (up or down) in the data.
- Seasonality, which produces short-term variations that are usually related to the time of year, month, or even a particular day, as witnessed by retail sales at Christmas or the spikes in banking activity on the first of the month and on Fridays.
- Cycles, which wavelike variations are lasting more than a year that is usually tied to economic or political conditions.
- Irregular variations that do not reflect typical behavior, such as a period of extreme weather or a union strike.

- Random variations, which encompass all non-typical behaviors not accounted for by the other classifications.

2.5.2.1 NAÏVE FORECAST

Among the time-series models, the simplest is the naïve forecast. A naïve forecast simply uses the actual demand for the past period as the forecasted demand for the next period. This, of course, makes the assumption that the past will repeat. It also assumes that any trends, seasonality, or cycles are either reflected in the previous period's demand or do not exist. An example of naïve forecasting is presented in table 2.1.

Table 2.1: Naïve forecasting

Period	Actual Demand (000's)	Forecast (000's)
January	45	
February	60	45
March	72	60
April	58	72
May	40	58
June		40

2.5.2.2 MOVING AVERAGE

Another simple technique is the use of averaging. To make a forecast using averaging, one simply takes the average of some number of periods of past data by summing each period and dividing the result by the number of periods. This technique has been found to be very effective for short-range forecasting.

Variations of averaging include the moving average, the weighted average, and the weighted moving average. A moving average takes a predetermined number of periods, sums their actual demand, and divides by the number of periods to reach a forecast. For each subsequent period, the oldest period of data drops off and the latest period is added. Assuming a three-month moving average and using the data from table 2.1, one would simply add 45 (January), 60 (February), and 72 (March) and divide by three to arrive at a forecast for April:

$45 + 60 \div 72 = 177 \div 3 = 59$

To arrive at a forecast for May, one would drop January's demand from the equation and add the demand from April. Table 2.2 presents an example of a three-month moving average forecast.

Table 2.2: Three month moving average forecast

Period	Actual Demand (000's)	Forecast (000's)
January	45	
February	60	
March	72	
April	58	59
May	40	63
June		57

2.5.2.3 WEIGHTED MOVING AVERAGE

A weighted average applies a predetermined weight to each month of past data, sums the past data from each period, and divides by the total of the weights. If the forecaster adjusts the weights so that their sum is equal to 1, then the weights are multiplied by the actual demand of each applicable period. The results are then summed to achieve a weighted forecast. Generally, the more recent the data the higher the weight, and the older the data the smaller the weight. Using the demand example, a weighted average using weights of .4, .3, .2, and .1 would yield the forecast for June as.

$$60(.1) + 72(.2) + 58(.3) + 40(.4) = 53.8$$

Forecasters may also use a combination of the weighted average and moving average forecasts. A weighted moving average forecast assigns weights to a predetermined number of periods of actual data and computes the forecast the same way as described above. As with all moving forecasts, as each new period is added, the data from the oldest period is discarded. Table 2.3 shows a three-month weighted moving average forecast utilizing the weights .5, .3, and .2.

Table 2.3: Three month weighted moving average forecast

Period	Actual Demand (000's)	Forecast (000's)
January	45	
February	60	
March	72	
April	58	55
May	40	63
June		61

2.5.2.4 EXPONENTIAL SMOOTHING METHOD

A more complex form of weighted moving average is exponential smoothing, so named because the weight falls off exponentially as the data ages. Exponential smoothing takes the previous period's forecast and adjusts it by a predetermined smoothing constant, α (called alpha; the value for alpha is less than one) multiplied by the difference in the previous forecast and the demand that actually occurred during the previously forecasted period (called forecast error) Exponential smoothing is expressed formulaically as such:-

New forecast = previous forecast + α (actual demand − previous forecast) or $F_{new} = F_{pre} + \alpha(A_{ac} - F_{pre})$.

Exponential smoothing requires the forecaster to begin the forecast in a past period and work forward to the period for which a current forecast is needed. A substantial amount of past data and a beginning or initial forecast are also necessary. The initial forecast can be an actual forecast from a previous period, the actual demand from a previous period, or it can be estimated by averaging all or part of the past data. Some heuristics exist for computing an initial forecast. For example, the heuristic $N = (2 \div \alpha) - 1$ and an alpha of .5 would yield an N of 3, indicating the user would average the first three periods of data to get an initial forecast. However, the accuracy of the initial forecast is not critical if one is using large amounts of data, since exponential smoothing is "self-correcting." Given enough periods of past data, exponential smoothing will eventually make enough corrections to compensate for a reasonably inaccurate initial forecast. Using the data used in other examples, an initial forecast of 50, and an alpha of .7, a forecast for February is computed as such:

New forecast (February) = 50 + .7(45 − 50) = 41.5

Next, the forecast for March:

New forecast (March) = 41.5 + .7(60 − 41.5) = 54.45

This process continues until the forecaster reaches the desired period. In table 2.4 this would be for the month of June, since the actual demand for June is not known.

Table 2.4: Exponential smoothing technique

Period	**Actual Demand (000's)**	**Forecast (000's)**
January	45	50
February	60	41.5
March	72	54.45
April	58	66.74
May	40	60.62
June		46.19

An extension of exponential smoothing can be used when time-series data exhibits a linear trend. This method is known by several names: double smoothing; trend-adjusted exponential smoothing; forecast including trend (FIT); and Holt's Model. Without adjustment, simple exponential smoothing results will lag the trend, that is, the forecast will always be low if the trend is increasing, or high if the trend is decreasing. With this model there are two smoothing constants, α and β with β representing the trend component.

An extension of Holt's Model, called Holt-Winter's Method, takes into accounts both trend and seasonality [31]. There are two versions, multiplicative and additive, with the multiplicative being the most widely used. In the additive model, seasonality is expressed as a quantity to be added to or subtracted from the series average. The multiplicative model expresses seasonality as a percentage—known as seasonal relatives or seasonal indexes—of the average (or trend). These are then multiplied times values in order to incorporate seasonality. A relative of 0.8 would indicate demand that is 80 percent of the average, while 1.10 would indicate demand that is 10 percent above the average. Detailed information regarding this method can be found in most operations management textbooks or one of a number of books on forecasting.

2.5.2.4.1 SINGLE EXPONENTIAL SMOOTHING

This is also known as simple exponential smoothing. Simple smoothing is used for short-range forecasting, usually just one month into the future. The model assumes that the data fluctuates around a reasonably stable mean (no trend or consistent pattern of growth). The specific formula for simple exponential smoothing is:

$$S_t = \alpha X_t + (1 - \alpha)\, S_{t-1} \qquad (1)$$

When applied recursively to each successive observation in the series, each new smoothed value (forecast) is computed as the weighted average of the current observation and the previous smoothed observation; the previous smoothed observation was computed in turn from the previous observed value and the smoothed value before the previous observation, and so on. Thus, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depending on the value of parameter (If it is equal to 1 (one) then the previous observations are ignored entirely; if it is equal to 0 (zero), then the current observation is ignored entirely, and the smoothed value consists entirely of the previous smoothed value (which in turn is computed from the smoothed observation before it, and so on; thus all smoothed values will be equal to the initial smoothed value S_0). In-between values will produce intermediate results.

The initial value of S_t plays an important role in computing all the subsequent values. Setting it to y_1 is one method of initialization. Another possibility would be to average the first four or five observations. The smaller the value of α, the more important is the selection of the initial value of S_t.

2.5.2.4.2 DOUBLE EXPONENTIAL SMOOTHING

This method is used when the data shows a trend. Exponential smoothing with a trend works much like simple smoothing except that two components must be updated each period - level and trend. The level is a smoothed estimate of the value of the data at the end of each period. The trend is a smoothed estimate of average growth at the end of each period. The specific formula for simple exponential smoothing is:

$$S_t = \alpha * y_t + (1 - \alpha) * (S_{t-1} + b_{t-1}),\ 0 < \alpha < 1 \quad (2)$$

$$b_t = \gamma * (S_t - S_{t-1}) + (1 - \gamma) * b_{t-1},\ 0 < \gamma < 1 \quad (3)$$

Note that the current value of the series is used to calculate its smoothed value replacement in double exponential smoothing.

Initial Values

There are several methods to choose the initial values for S_t and b_t.

S_1 is in general set to y_1.

Three suggestions for b_1 are as follows:

$$b_1 = y_2 - y_1 \quad (4)$$

$$b_1 = [(y_2 - y_1) + (y_3 - y_2) + (y_4 - y_3)]/3 \quad (5)$$

$$b_1 = (y_n - y_1)/(n - 1) \quad (6)$$

2.5.2.4.3 TRIPLE EXPONENTIAL SMOOTHING

Often, time series data display behavior that is seasonal. Seasonality is defined to be the tendency of time-series data to exhibit behavior that repeats itself every L periods. The term season is used to represent the period of time before behavior begins to repeat itself. L is therefore the season length in periods. For example, annual sales of toys will probably peak in the months of November and December, and perhaps during the summer (with a much smaller peak). This pattern is likely to repeat every year, however, the relative amount of increase in sales during December may slowly change from year to year. For example, during the month of December the sales for a particular toy may increase by 1 million dollars every year. Thus, we could add to our forecasts for every December the amount of 1 million dollars (over the respective annual average) to account for this seasonal fluctuation. In this case, the seasonality is additive. Alternatively, during the month of December the sales for a particular toy may increase by 40%, that is, increase by a factor of 1.4. Thus, when the sales for the toy are generally weak, then the absolute (dollar) increase in sales during December will be relatively weak (but the percentage will be constant). if the sales of the toy are strong, then the absolute (dollar) increase in sales will be proportionately greater. Again, in this case the sales increase by a certain factor, and the seasonal component is thus multiplicative in nature (i.e., the multiplicative seasonal component in this case would be 1.4). In plots of the series, the distinguishing characteristic between these two types of seasonal components is that in the additive case, the series shows steady seasonal fluctuations, regardless of the overall level of the series; in the multiplicative case, the size of the seasonal fluctuations vary, depending on the overall level of the series.

2.5.2.4.4 Multiplicative Seasonal Model

This model is used when the data exhibits multiplicative seasonality.

In this model, it is assumed that the time series is represented by the model below:

$$Y_t = (b_1 + b_2 t)S_t + \varepsilon_t \tag{7}$$

where,

b_1 is the base signal also called the permanent component

b_2 is a linear trend component

S_t is a multiplicative seasonal factor

ε_t is the random error component

Let the length of the season be L periods.

The seasonal factors are defined so that they sum to the length of the season, i.e.

$$\sum S_t = L \tag{8}$$

The trend component b_2 if deemed unnecessary maybe deleted from the model.

2.5.2.5 REGRESSION ANALYSIS

In statistics, **regression analysis** refers to techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable and one or more independent variables. More specifically, regression analysis helps to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. Most commonly, regression analysis estimates the conditional expectation of the dependent variable given the independent variables.

Less commonly, the focus is on a quantile, or other location parameter of the conditional distribution of the dependent variable given the independent variables. In all cases, the estimation target is a function of the independent variables called the regression function. In regression analysis, it is also of interest to characterize the variation of the dependent variable around the regression function, which can be described by a probability distribution.

Regression analysis is widely used for prediction (including forecasting of time-series data). Regression analysis is also 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.

Familiar methods such as linear regression and ordinary least squares regression are parametric, in that the regression function is defined in terms of a finite number of unknown parameters that are estimated from the data. Nonparametric regression refers to techniques that allow the regression function to lie in a specified set of functions, which may be infinite-dimensional.

The performance of regression analysis methods in practice depends on the form of the data-generating process, and how it relates to the regression approach being used. Regression analysis depends to some extent on making assumptions about this process. These assumptions are sometimes (but not always) testable if a large amount of data is available. Regression models for prediction are often useful even when the assumptions are moderately violated, although they may not perform optimally. However when carrying out inference using regression models, especially involving small effects or questions of causality based on observational data, regression methods must be used cautiously as they can easily give misleading results. Classical assumptions for regression analysis include:

- The sample must be representative of the population for the inference prediction.
- The error is assumed to be a random variable with a mean of zero conditional on the explanatory variables.
- The independent variables are error-free. If this is not so, modeling may be done using errors-in-variables model techniques.

- The predictors must be linearly independent, i.e. it must not be possible to express any predictor as a linear combination of the others. The errors are uncorrelated, that is, the variance-covariance matrix of the errors is diagonal and each non-zero element is the variance of the error.
- The variance of the error is constant across observations (homoscedasticity). If not, weighted least squares or other methods might be used.

These are sufficient (but not all necessary) conditions for the least-squares estimator to possess desirable properties, in particular, these assumptions imply that the parameter estimates will be unbiased, consistent, and efficient in the class of linear unbiased estimators. Many of these assumptions may be relaxed in more advanced treatments.

Linear Regression

In linear regression, the model specification is that the dependent variable, Y_i is a linear combination of the parameters (but need not be linear in the independent variables). For example, in simple linear regression for modeling N data points there is one independent variable: X_i, and two parameters, β_0 and β_1:

Straight line: $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$, $i = 1, 2, 3, \ldots\ldots\ldots, N$ (9)

In multiple linear regressions, there are several independent variables or functions of independent variables. For example, adding a term in X_i^2 to the preceding regression gives:

Parabola: $Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \varepsilon_i$, $i = 1, 2, 3, \ldots\ldots\ldots, N$ (10)

This is still linear regression; although the expression on the right hand side is quadratic in the independent variable X_i, it is linear in the parameters β_0, β_1 and β_2.

In both cases, ε_i is an error term and the subscript i indexes a particular observation. Given a random sample from the population, we estimate the population parameters and obtain the sample linear regression model:-

$$Y_i = \beta_0 + \beta_1 X_i + e_i \quad (11)$$

2.5.2.6 EXTRAPOLATION

In mathematics, **extrapolation** is the process of constructing new data points outside a discrete set of known data points. It is similar to the process of interpolation, which constructs new points between known points, but the results of extrapolations are often less meaningful, and are subject to greater uncertainty. It may also mean extension of a method, assuming similar methods will be applicable. Extrapolation may also apply to human experience to project, extend, or expand known experience into an area not known or previously experienced so as to arrive at a (usually conjectural) knowledge of the unknown.

Extrapolation methods

A sound choice of which extrapolation method to apply relies on a prior knowledge of the process that created the existing data points. Crucial questions are for example if the data can be assumed to be continuous, smooth, possibly periodic etc.

Linear extrapolation

Linear extrapolation means creating a tangent line at the end of the known data and extending it beyond that limit. Linear extrapolation will only provide good results when used to extend the graph of an approximately linear function or not too far beyond the known data.

If the two data points nearest the point x_* to be extrapolated are (x_{k-1}, y_{k-1}) and (x_k, y_k), linear extrapolation gives the function (identical to linear interpolation if $x_{k-1} < x_* < x_k$),

$$y(x_*) = y_{k-1} + (x_* - x_{k-1})^*(y_k - y_{k-1}) / (x_k - x_{k-1}) \qquad (12)$$

It is possible to include more than two points, and averaging the slope of the linear interpolant, by regression like techniques.

2.5.2.7 ADVANCED TIME SERIES MODELS

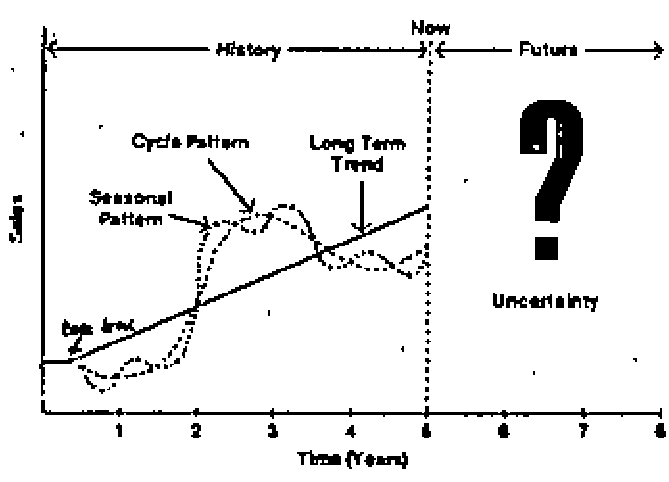

Figure 2.2: Base, trend, seasonal and cyclical effects.

In the figure 2.2 various elements of time series models has been shown.

- Base Level Model: (no Trend/Seasonal/Cyclical pattern)

  $F_{t,k} = B_t$ (forecast for the K_{th} period made at period t) (13)

  Updating after A_t known:

  $$B_t = B_{t-1} + \alpha(A_t - B_{t-1}) \quad (14)$$

- Base and Linear-Trend Model: (no Seasonal/Cyclical pattern)

  $$F_{t,k} = B_t + K \cdot T_t \quad (15)$$

  Updating after A_t known:

  $$B_t = (B_{t-1} + T_{t-1}) + \alpha\,[A_t - (B_{t-1} + T_{t-1})] \quad (16)$$

  $$T_t = T_{t-1} + \beta[(B_t - B_{t-1}) - T_{t-1})] \quad (17)$$

  β is the Trend Smooth Constant ($0 < \beta < 1$)

- Base and Seasonal Model: (no Trend/Cyclical pattern)

  $$F_{t,k} = B_t \cdot SI_{t+k} \quad (18)$$

  Updating after A_t known:

  $$B_t = B_{t-1} + \alpha(A_t/SI_{t+k} - B_{t-1}) \quad (19)$$

  $$SI^{o}_{t+k} = SI_{t+k} + \gamma(A_t/B_t - SI_{t+k}) \quad (20)$$

  γ is the Seasonal Smooth Constant ($0 < \gamma < 1$)

- Base, Trend, and Seasonal Model: (no Cyclical pattern)

  $$F_{t,k} = (B_t + k \cdot T_t) \cdot SI_{t+k} \quad (21)$$

  Updating after A_t known:

  $$B_t = (B_{t-1} + T_{t-1}) + \alpha[A_t/SI_{t+k} - (B_{t-1} + T_{t-1})] \quad (22)$$

  $$T_t = T_{t-1} + \beta[(B_t - B_{t-1}) - T_{t-1})] \quad (23)$$

  $$SI^{o}_{t+k} = SI_{t+k} + \gamma(A_t/B_t - SI_{t+k}) \quad (24)$$

  (α, β, and γ; three smoothed constants in this model)

2.5.2.8 AUTOREGRESSIVE MOVING AVERAGE (ARMA) MODEL

Given a time series of data X_t, the autoregressive moving average model (ARMA), sometimes called the Box-Jenkins model after George Box and G.M. Jenkins, is used as a tool for understanding and possibly predicting future values in the time series. The ARMA is typically applied to time series data. The model typically consists of two parts, an autoregressive (AR) part and a moving average (MA) part The model is usually then referred to as an ARMA (p,q) model where p is the order of the autoregressive part and q is the order of the moving average part .

Autoregressive model

The notation AR(p) refers to an autoregressive model of order p. Thus, an AR(p) model is written as:

$$X_t = c + \sum \varphi_i X_{t-i} + \varepsilon_t,\ i = 1, 2, 3, \ldots\ldots\ldots\ldots, p \tag{25}$$

where, φ_1, φ_2, ..., φ_p are the parameters of the model, c is a constant and ε_t is an error term. The constant term is omitted by many authors for simplicity.

Example: An AR(1) model is given by –

$$X_t = c + \varphi X_{t-1} + \varepsilon_t \tag{26}$$

An autoregressive model is essentially an infinite impulse response filter with some additional interpretation placed on it. Some constraints are necessary on the values of the parameters of this model in order that the model remains stationary. .

Example: In an AR(1) model, if $|\varphi_1| > 1$ then the model will not be well behaved.

Moving average model

The notation MA(q) refers to a moving average model of order q. This is given by –

$$X_t = \sum \theta_i \varepsilon_{t-i} + \varepsilon_t,\ i = 1, 2, 3, \ldots\ldots\ldots\ldots, q \tag{27}$$

where, the θ_1, ..., θ_q are the parameters of the model and the ε_t, ε_{t-1},... are as in the AR model, the error terms. A moving average model is essentially a finite impulse response filter with some additional interpretation placed on it.

Autoregressive moving average model

Taking the AR model and the MA model, the ARMA model can be built. The notation ARMA(p, q) refers to a model with p autoregressive terms and q moving average terms. This model subsumes the AR and MA models,

$$X_t = \varepsilon_t + \sum \varphi_i X_{t-i} + \sum \theta_i \varepsilon_{t-i}, \tag{28}$$

for φ_i, i = 1, 2, 3,......,p

for θ_i, i = 1, 2, 3,......,q

The error terms ε_t are generally assumed to be independent identically-distributed random variables sampled from a normal distribution with zero mean: $\varepsilon_t \sim N(0,\sigma_2)$ where σ_2 is the variance. These assumptions may be weakened but doing so will change the properties of the model. In particular, a change to the iid assumption would make a rather fundamental difference. ARMA models in general can, after choosing p and q, are fitted by least squares regression to find the values of the parameters which minimize the error term. It is generally considered good practice to find the smallest values of p and q which provide an acceptable fit to the data. For a pure AR model then the Yule-Walker equations may be used to provide a fit. The dependence of X_t on past values and the error terms ε_t is assumed to be linear unless specified otherwise. If the dependence is nonlinear, the model is specifically called a nonlinear moving average (NMA), nonlinear autoregressive (NAR), or nonlinear autoregressive moving average (NARMA).

2.5.2.9 BOX - JENKINS MODEL

The Box-Jenkins approach to modeling ARIMA processes was described in a highly influential book by statisticians George Box and Gwilym Jenkins in 1970 [32]. An ARIMA process is a mathematical model used for forecasting. Box-Jenkins modeling involves identifying an appropriate ARIMA process, fitting it to the data, and then using the fitted model for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data. The original Box-Jenkins modeling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process [33] often add a preliminary stage of data preparation and a final stage of model application (or forecasting).

The Box-Jenkins ARMA model is a combination of the AR and MA models:

$$X_t = \delta + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots + \varphi_p X_{t-p} + A_t - \theta_1 A_{t-1} - \theta_2 A_{t-2} - \ldots - \theta_q A_{t-q} \qquad (29)$$

Here the terms in the equation have the same meaning as given for the AR and MA model.

Data preparation involves transformations and differencing. Transformations of the data (such as square roots or logarithms) can help stabilize the variance in a series where the variation changes with the level. This often happens with business and economic data. Then the data are differenced until there are no obvious patterns such as trend or seasonality left in the data. Differencing means taking the difference between consecutive observations, or between observations a year apart. The differenced data are often easier to model than the original data.

Model selection in the Box-Jenkins framework uses various graphs based on the transformed and differenced data to try to identify potential ARIMA processes which might provide a good fit to the data. Later developments have led to other model selection tools such as Akaike's Information Criterion.

Parameter estimation means finding the values of the model coefficients which provides the best fit to the data. There are sophisticated computational algorithms designed to do this.

Model checking involves testing the assumptions of the model to identify any areas where the model is inadequate. If the model is found to be inadequate, it is necessary to go back to model selection step and try to identify a better model.

Forecasting is what the whole procedure is designed to accomplish. Once the model has been selected, estimated and checked, it is usually a straight forward task to compute forecasts. Of course, this is done by computer. Although originally designed for modeling time series with ARIMA processes, the underlying strategy of Box and Jenkins is applicable to a wide variety of statistical modeling situations. It provides a convenient framework which allows an analyst to think about the data, and to find an appropriate statistical model which can be used to help answer relevant questions about the data.

2.6 SELECTION OF FORECASTING METHODS

Practical forecasting problems have been given in the below. A forecasting method selection depends on the ability of the chosen method in solving the issues given below.

Practical problem issues with forecasting methods are:

- Inaccuracy
- Inconsistency
- Cost and Accuracy Tradeoff (simple model may perform better than complicated ones)
- Data Unavailability
- Fitness and Predictability
- A model that best "fits" the past data may not be the best "Predictive" one for the future, due to demand pattern changes

Criteria for Selecting a Forecasting Method

Cost and Accuracy:

- A trade-off between cost and accuracy- more accuracy at a cost.
- High-accuracy with disadvantages of: need more data/data may be difficult to obtain/models are more costly to design, implement, and operate/take longer time to use.
- Low-Cost approaches- statistical models, historical analogies, executive-committee consensus
- High-Cost Approaches- complex econometric models, Delphi, and market research

Data Availability:

- Is the data available/or be economically obtained?
- For a new product, a customer survey may not be practical.

Time Span:

- What operations resource be forecasted and for what purpose?
- Short-term best be forecast with simple time series model.
- Long-term best be predicted with regression or similar models.

Nature of Products and Services

- Is the product/service high cost or high volume?
- Where is the product/service in its life cycle?
- Does the product/service have seasonal demand fluctuations?

Impulse response and noise dampening

- An appropriate balance must be achieved between:
- How responsive the model to change in the actual demand data
- Desire to suppress undesirable noise in the demand data

Techniques to Support Better Forecasting

Normally associated with numbers and formulas, forecasting is a kind of magic box that uses certain inputs to determine the products that the market expects.

There are more than 100 different quantitative forecasting methods available, which all begin with the simple assumption that the past will repeat in the future.

Time-series methods extrapolate existing trends and include seasonal and cyclical indices, if necessary. They also assume that the trend, season, or cycle will have a predictable and similar effect every time. Complex econometric and regression-based methods try to isolate the individual components causing demand in order to create a forecasting model. But these models have an inherent limitation in the number of factors they use because it is impossible to include all the key data. Moreover, something that seems insignificant today all of a sudden may become a key driver.

There is no doubt that forecasting is critically important; however, relying solely on these numerical forecasting methods to drive business would be an exercise in corporate hara-kiri.

Getting the Best Forecast by Combining Judgmental and Statistical Methods

Accurate forecasting always has been a critical organizational capability for effective business planning. Good forecasts are essential for identifying and new market opportunities, anticipating future demands, effectively scheduling production, and reducing inventories.

Information technology has enabled forecasts to drive entire supply chains and enterprise resources planning systems. Simultaneously, global competition has created an environment characterized by uncertainty, rapidly shifting markets, and compressed cycle times. Customers are demanding increasingly shorter response times, improved quality, and greater product choice. The result has been a sharp rise in forecasting's complexity and historical data that are often of limited value for predicting the future.

Relying on statistical forecasts alone can be ineffective in this highly complex environment. Consider the case of Nike's $400 million failure in 2000 with demand forecasting software. According to the July 15, 2003, issue of CIO [34] magazine, nine months after implementing a much publicized i2 system, Nike leaders acknowledged that they would be taking a major inventory write-off due to inaccurate forecasts from the automated system. Nike had entirely too much inventory of slow-moving items and a major shortage of popular sellers. The problem, as it turned out, was that Nike executives relied exclusively on automated forecasts without any judgmental checks, and the automated forecasts simply were not accurate enough. Unfortunately, Nike's experience with automated statistical forecasts is not an isolated case.

When making forecasts, managers can choose from either judgmental forecasting methods, which are based on opinions, or statistical forecasting methods, based on mathematical modeling. Each category has unique strengths and weaknesses. The best forecasting approach is one that leverages the strengths of both methods. Increasingly, this is something that managers find to be effective, and it is supported by numerous research studies. However, combining judgmental and statistical forecasting requires well-established rules.

CHAPTER 3
THEORETICAL BACKGROUND

3.1 KEY FACTORS IN DEMAND FORECASTING

Sales or demand forecasting is a management function that companies often fail to recognize as a key contributor to corporate success. From a top-line perspective, accurate forecasts allow a company to provide high levels of customer service. When demand can be predicted accurately, it can be met in a timely and efficient manner, keeping both channel partners and final customers satisfied. Accurate forecasts help a company avoid lost sales or stock-out situations, and prevent customers from going to competitors. At the bottom line, the effect of accurate forecasts can be profound. All the types of items of the companies can be purchased much more cost-effectively when minute, spot market purchases last can be avoided. Such expenses can be eliminated by accurately forecasting production needs. Similarly, logistical services can be obtained at a much lower cost through long-term contracts rather than through spot market arrangements. However, these contracts can only work when demand can be predicted accurately. Perhaps most important, accurate forecasting can have a profound impact on a company's inventory levels. In a sense, inventory exists to provide a buffer for inaccurate forecasts. Thus, the more accurate the forecasts, the less inventory that needs to be carried, with the entire well understood cost savings that brings. The ultimate effects of sales forecasting excellence can be dramatic. Mentzer and Schroeter [35] describe how Brake Parts, Inc., a manufacturer of automotive aftermarket parts, improved its bottom line by $6 million per month after launching a company-wide effort to improve sales forecasting effectiveness. Nevertheless, firms often fail to recognize the importance of this critical management function. The firms have learned about sales or demand forecasting from working with hundreds of other companies, and the seven key focus points (summarized in table 3.1) that will help any company improve its forecasting performance has been given below. Although no management function can be reduced to seven keys, or 70 keys for that matter, the hope is that the ideas presented in the table will inspire senior management to look closely at their own sales forecasting practices and recognize opportunities for improvement.

Table 3.1: Seven basic keys of forecasting

Keys	Issues and Symptoms	Actions	Results
Understand what forecasting is and is not.	• Computer system as focus, rather than management processes and controls • Blurring of the distinction between forecasts, plans, and goals	• Establish forecasting group • Implement management control systems before selecting forecasting software • Derive plans from forecasts • Distinguish between forecasts and goals	• An environment in which forecasting is acknowledged as a critical business function. • Accuracy emphasized and game playing minimized
Forecast demand, plan supply.	• Shipment history as the basis for forecasting demand • Too accurate forecasts	• Identify sources of information • Build systems to capture key demand data	• Improved capital planning and customer service
Communicate, cooperate, and collaborate.	• Duplication of forecasting effort • Mistrust of the "official" forecast • Little understanding of the impact throughout the firm	• Establish cross-functional approach to forecasting • Establish independent forecast group that sponsors cross-functional collaboration	• All relevant information used to generate forecasts • Forecasts trusted by users • Islands of analysis eliminated • More accurate and relevant forecasts
Eliminate islands of analysis.	• Mistrust and inadequate information leading different users to create their own forecasts	• Build a single "forecasting infrastructure" • Provide training for both users and developers of forecasts	• More accurate, relevant, and credible forecasts • Optimized investments in information / communication systems.
Use tools wisely.	• Relying solely on qualitative or quantitative	• Integrate quantitative and qualitative methods • Identify sources of	• Process improvement inefficiency and effectiveness

	methods • Cost/benefit of additional information	improved accuracy. and increased error • Provide instruction	
Make it important.	• No accountability for poor forecasts • Developers not understanding how forecasts are used	• Training developers to under-stand implications of poor forecasts • Include forecast performance in individual performance plans and reward systems	• Developers taking forecasts seriously • A striving for accuracy • More accuracy and credibility
Measure, measure, measure.	• Not knowing if the firm is getting better • Accuracy not measured at relevant levels of aggregation • Inability to isolate sources of forecast error.	• Establish multi dimensional metrics • Incorporate multi level measures • Measure accuracy when ever and wherever forecasts are adjusted	• Forecast performance can be included in individual performance plans • Sources of errors can be isolated and targeted for improvement • Greater confidence in forecast process

Recent estimates from the U.S. Commerce Department indicate that, in the United States, \$1.1 trillion in inventory supports \$3.2 trillion in annual retail sales. This inventory is spread out across the value chain, with \$400 billion at retail locations, \$290 billion at wholesalers or distributors and \$450 billion with manufacturers. With this large stockpile of inventory, stock-outs at the retail level should be very low—one would think. But that is not the case. Studies have shown that 8.2% of shoppers, on average, have failed to find their product in stock. These stock-out events represent 6.5% of all retail sales [36]. Even after recouping some of the loss with sales of alternative product, retailers has suffered net lost sales of 3.1%. This takes an enormous toll on retail margins, not to mention customer goodwill.

A demand chain is a network of trading partners that extends from manufacturers to end consumers. The partners exchange information and finished goods flow through the network's physical infrastructure. The physical facilities include manufacturers' warehouses, wholesalers' distribution centers, retail chains' warehouses and retail outlets. A demand chain can include multiple business enterprises. As product flows through the network, the partners incur costs—but they also enjoy revenue as product changes ownership between business enterprises. It's possible to optimize the demand chain for each trading partner's portion of it, but total optimization requires a common objective that may or may not exist.

Demand chain optimization (DCO) can impact enterprise value in many ways. It can produce:

- Higher customer service levels, which lead to greater revenue and net income.
- Higher inventory turnover, which frees up working capital.
- Higher worker productivity, which lowers operating expenses.
- Higher capacity utilization, which increases the return on assets.
- Lower logistics costs, which decreases operating expenses.
- Lower costs of goods sold, which increases net income.

Each one of these will increase an enterprise's return on assets. That, in turn, leads to increased return on equity and shareholder value. The effects of DCO are broad, influencing the overall financial health of the enterprise; however, the business decisions that drive DCO are ultimately made at the stock keeping unit (SKU) level. A SKU is a specific product at a specific location. SKU management requires many decisions, such as: When SKU should be replenished? What quantity should be ordered? What customer service objective is appropriate for the selected SKU? From whom to be ordered? Could the inventory for this SKU be better utilized at another location? Should this SKU be stocked? What will happen to demand if the SKU's price is changed?

3.2 ACCURACY MEASURES

The forecast error is the difference between the actual value and the forecast value for the corresponding period.

$$E_t = Y_t - F_t \tag{30}$$

where, E_t is the forecast error at period t, Y_t is the actual value at period t, and F_t is the forecast for period t. There are many types of accuracy measures of forecasting. A suitable measure of accuracy for a given problem is not universally accepted by the forecasting academicians and practitioners. An accuracy measures is often defined in terms of the forecasting error which has been mentioned above. There are a number of measures of accuracy in the forecasting literature and each has some advantages and some disadvantages. The most frequently used measures of forecasting accuracy has been mentioned in the table 3.2:

Table 3.2: Measures of forecasting accuracy

Mean Absolute Error (MAE)	MAE = $(\sum E_t) / N$; $t = 1, 2, 3, \ldots\ldots, N$
Mean Absolute Percentage Error (MAPE)	MAPE = $(\sum (E_t/Y_t)) / N$, $t = 1, 2, 3, \ldots\ldots, N$
Percent Mean Absolute Deviation (PMAD)	PMAD = $(\sum E_t) / (\sum Y_t)$, $t = 1, 2, 3, \ldots, N$
Mean Squared Error (MSE)	MSE = $(\sum E_t^2) / N$, $t = 1, 2, 3, \ldots\ldots, N$
Root Mean Squared Error (RMSE)	RMSE = $\sqrt{((\sum E_t^2) / N)}$, $t = 1, 2, 3, \ldots\ldots, N$
Forecast Skill (SS)	SS = $1 - (MSE_{forecast} / MSE_{ref})$

Among the above all accuracy measures, some are used more often. Those have been described below:

Mean Forecast Error (MFE): Forecast error is a measure of how accurate our forecast was in a given time period. It is calculated as the actual demand minus the forecast, or

$E_t = A_t - F_t$

Forecast error in one time period does not convey much information, so it is needed to look at the accumulation of errors over time. The average value of these forecast errors over time (i.e., a **Mean Forecast Error**, or MFE) can be calculated. Unfortunately, the accumulation of the E_t values is not always very revealing, for some of them will be positive errors and some will be negative. These positive and negative errors cancel one another, and looking at them alone (or looking at the MFE over time) might give a false indication.

Mean Absolute Deviation (MAD) or Mean Absolute Error (MAE): To eliminate the problem of positive errors canceling negative errors, a simple measure is one that looks at the absolute value of the error (size of the deviation, regardless of sign). When the sign is disregarded and only the size of the error is considered, this deviation is referred as the absolute deviation. If these absolute deviations are accumulated over time and the average value of these absolute deviations has been found out, this measure is referred as the mean absolute deviation (MAD).

Mean Squared Error (MSE): Another way to eliminate the problem of positive errors canceling negative errors is to square the forecast error. Regardless of whether the forecast error has a positive or negative sign, the squared error will always have a positive sign. If these squared errors are accumulated over time and the average value of these squared errors is determined, this measure is referred as the mean squared error (MSE). The question often arises as to why the more cumbersome MSE would be used when the MAD calculations are a bit simpler. MAD does have the advantage of simpler calculations. However, there is an advantage to the MSE method. Since this method squares the error term, large errors tend to be magnified. Consequently, MSE places a higher penalty on large errors. This can be useful in situations where small forecast errors don't cause much of a problem, but large errors can be devastating.

Mean Absolute Percentage Error (MAPE): It is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy as a percentage. The difference between actual value A_t and the forecast value F_t, is divided by the actual value A_t again. The absolute value of this calculation is summed for every fitted or forecast point in time and divided again by the number of fitted point's n. This makes it a percentage error so one can compare the error of fitted time series that differ in level. For measuring the accuracy of time series forecasting MAPE is often used as benchmark.

Although the concept of MAPE sounds very simple and convincing it has two major drawbacks in practical application:

- If there are zero values (sometimes happens for example in demand series) there will be a division by zero.

When having a perfect fit, MAPE is zero. But in regard to its upper level the MAPE has no restriction. When calculating the average MAPE for a number of time series there might be a problem: a few numbers of series that have a very high MAPE might distort a comparison between the averages MAPE of time series fitted with one method compared to the average MAPE when using another method. In order to avoid this problem other measures have been defined, for example the sMAPE (symmetrical MAPE) or a relative measure of accuracy.

3.3 NEURAL NETWORK

Traditionally, the term neural network had been used to refer to a network or circuit of biological neurons The modern usage of the term often refers to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term has two distinct usages:

1. Biological neural networks are made up of real biological neurons that are connected or functionally related in the peripheral nervous system or the central nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis.

2. Artificial neural networks are made up of interconnecting artificial neurons (programming constructs that mimic the properties of biological neurons). Artificial neural networks may either be used to gain an understanding of biological neural networks, or for solving artificial intelligence problems without necessarily creating a model of a real biological system. The real, biological nervous system is highly complex and includes some features that may seem superfluous based on an understanding of artificial networks. A simple artificial neural network structure has been shown in the figure 3.1.

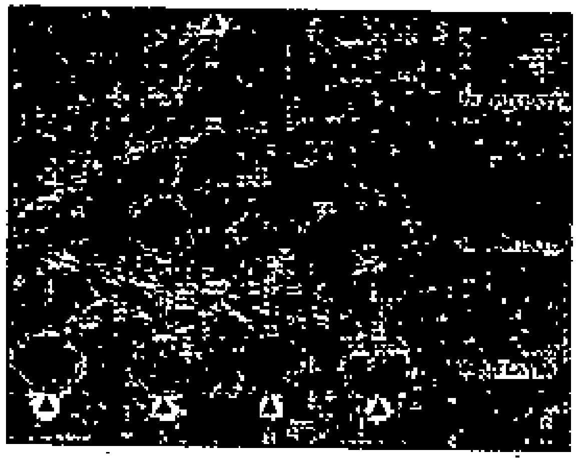

Figure 3.1: Simplified view of a feed forward artificial neural network.

3.3.1 OVERVIEW

In general a biological neural network is composed of a group or groups of chemically connected or functionally associated neurons. A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive. Connections, called synapses, are usually formed from axons to dendrites, though dendrodendritic microcircuits and other connections are possible. Apart from the electrical signaling, there are other forms of signaling that arise from neurotransmitter diffusion, which have an effect on electrical signaling. As such, neural networks are extremely complex. Artificial intelligence and cognitive modeling try to simulate some properties of neural networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems.

In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimation, optimization and control theory. The cognitive modeling field involves the physical or mathematical modeling of the behavior of neural systems; ranging from the individual neural level (e.g. modeling the spike response curves of neurons to a stimulus), through the neural cluster level (e.g. modeling the release and effects of dopamine in the basal ganglia) to the complete organism (e.g. behavioral modeling of the organism's response to stimuli).

3.3.2 HISTORY OF THE NEURAL NETWORK ANALOGY

The concept of neural networks started in the late-1800's as an effort to describe how the human mind performed. These ideas started being applied to computational models with Turing's B-type machines and the perceptron. In early 1950's, Friedrich Hayek was one of the first to posit the idea of spontaneous order in the brain arising out of decentralized networks of simple units (neurons). In the late 1940s, Donald Hebb made one of the first hypotheses for a mechanism of neural plasticity (i.e. learning) [37] and it is called Hebbian learning. Hebbian learning is considered to be a 'typical' unsupervised learning rule and it (and variants of it) was an early model for long term potentiation.

The perceptron is essentially a linear classifier for classifying data ($x \varepsilon R^n$) specified by parameters ($w \varepsilon R^n$, $b \varepsilon R$) and an output function $f = w'x + b$. Its parameters are adapted with an ad-hoc rule similar to stochastic steepest gradient descent. Because the inner product is a linear operator in the input space, the perceptron can only perfectly classify a set of data for which different classes are linearly separable in the input space, while it often fails completely for non-separable data. While the development of the algorithm initially generated some enthusiasm, partly because of its apparent relation to biological mechanisms, the later discovery of this inadequacy caused such models to be abandoned until the introduction of non-linear models into the field.

The cognitron [38] was an early multilayered neural network with a training algorithm. The actual structure of the network and the methods used to set the interconnection weights change from one neural strategy to another, each with its advantages and disadvantages. Networks can propagate information in one direction only, or they can bounce back and forth until self-activation at a node occurs and the network settles on a final state. The ability for bi-directional flow of inputs between neurons/nodes was produced with the Hopfield's network [39], and specialization of these node layers for specific purposes was introduced through the first hybrid network.

The parallel distributed processing of the mid-1980s became popular under the name connectionism. The rediscovery of the back-propagation algorithm was probably the main reason behind the repopularization of neural networks after the publication of "Learning Internal Representations by Error Propagation" in 1986 (though back-propagation itself dates from 1974). The original network utilized multiple layers of weight-sum units of the type f = g (w'x + b), where g was a sigmoid function or logistic function such as used in logistic regression. Training was done by a form of stochastic steepest gradient descent. The employment of the chain rule of differentiation in deriving the appropriate parameter updates results in an algorithm that seems to 'back propagate errors', hence the nomenclature. However it is essentially a form of gradient descent. Determining the optimal parameters in a model of this type is not trivial, and steepest gradient descent methods cannot be relied upon to give the solution without a good starting point. In recent times, networks with the same architecture as the back-propagation network are referred to as multi-layer perceptrons. This name does not impose any limitations on the type of algorithm used for learning.

The back-propagation network generated much enthusiasm at the time and there was much controversy about whether such learning could be implemented in the brain or not, partly because a mechanism for reverse signaling was not obvious at the time, but most importantly because there was no plausible source for the 'teaching' or 'target' signal.

3.3.3 THE BRAIN, NEURAL NETWORK AND COMPUTERS

Neural networks, as used in artificial intelligence, have traditionally been viewed as simplified models of neural processing in the brain, even though the relation between this model and brain biological architecture is debated. A subject of current research in theoretical neuroscience is the question surrounding the degree of complexity and the properties that individual neural elements should have to reproduce something resembling animal intelligence.

Historically, computers evolved from the Von Neumann Architecture [40], which is based on sequential processing and execution of explicit instructions. On the other hand, the origins of neural networks are based on efforts to model information processing in biological systems, which may rely largely on parallel processing as well as implicit instructions based on recognition of patterns of 'sensory' input from external sources. In other words, at its very heart a neural network is a complex statistical processor (as opposed to being tasked to sequentially process and execute).

Neural networks and artificial intelligence: An artificial neural network (ANN), also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectivity approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network.

In more practical terms neural networks are non-linear statistical data modeling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.

An artificial neural network involves a network of simple processing elements (artificial neurons) which can exhibit complex global behavior, determined by the connections between the processing elements and element parameters. Artificial neurons were first proposed in 1943 by Warren McCulloch, a neurophysiologist, and Walter Pitts, an MIT logician [41]. One classical type of artificial neural network is the Hopfield net.

In a neural network model simple nodes, which can be called variously "neurons", "neurodes", "processing element (PE)" or "units", are connected together to form a network of nodes — hence the term "neural network". While a neural network does not have to be adaptive per se, its practical use comes with algorithms designed to alter the strength (weights) of the connections in the network to produce a desired signal flow.

In modern software implementations of artificial neural networks the approach inspired by biology has more or less been abandoned for a more practical approach based on statistics and signal processing. In some of these systems, neural networks, or parts of neural networks (such as artificial neurons), are used as components in larger systems that combine both adaptive and non-adaptive elements. The concept of a neural network appears to have first been proposed by Alan Turing in his 1948 paper "Intelligent Machinery" [42].

3.3.4 APPLICATION

The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations and also to use it. This is particularly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical. Real life applications of artificial neural network have been used in the fields below:

The tasks to which artificial neural networks are applied tend to fall within the following broad categories:

- Function approximation, or regression analysis, including time series prediction and modeling.
- Classification, including pattern and sequence recognition, novelty detection and sequential decision making.
- Data processing, including filtering, clustering, blind signal separation and compression.

Application areas include system identification and control (vehicle control, process control), game-playing and decision making (backgammon, chess, racing), pattern recognition (radar systems, face identification, object recognition, etc.), sequence recognition (gesture, speech, handwritten text recognition), medical diagnosis, financial applications, data mining (or knowledge discovery in databases, "KDD"), visualization and e-mail spam filtering.

3.4 NEURAL NETWORK AND FORECASTING

The recent upsurge in research activities into artificial neural networks (ANN's) has proven that neural networks have powerful pattern classification and prediction capabilities. ANN's have been successfully used for a variety of tasks in many fields of business, industry, and science [43]. They have fast become a standard class of quantitative modeling tools for researchers and practitioners. Interest in neural networks is evident from the growth in the number of papers published in journals of diverse scientific disciplines. One of the major application areas of ANN's is forecasting. There is an increasing interest in forecasting using ANN's in recent years. Forecasting has a long history and the importance of this old subject is reflected by the diversity of its applications in different disciplines ranging from business to engineering. The ability to accurately predict the future is fundamental to many decision processes in planning, scheduling, purchasing, strategy formulation, policy making, and supply chain operations. As such, forecasting is an area where a lot of efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future. A survey of research needs for forecasting has been provided by Armstrong [44].

Forecasting has been dominated by linear methods for many decades. Linear methods are easy to develop and implement and they are also relatively simple to understand and interpret. However, linear models have serious limitation in that they are not able to capture any nonlinear relationships in the data. The approximation of linear models to complicated nonlinear relationships is not always satisfactory. In the early 1980s, Makridakis [45] organized a large-scale forecasting competition (often called M-competition) where a majority of commonly used linear methods were tested with more than 1,000 real time series data. The mixed results show that no single linear model is globally the best, which may be interpreted as the failure of linear modeling in accounting for a varying degree of nonlinearity that is common in real world problems.

ANN's provide a promising alternative tool for forecasters. The inherently nonlinear structure of neural networks is particularly useful for capturing the complex underlying relationship in many real world problems. Neural networks are perhaps more versatile methods for forecasting applications in that not only can they find nonlinear structures in a problem, they can also model linear processes. For example, the capability of neural networks in modeling linear time series has been studied and confirmed by a number of researchers [46].

In addition to the nonlinear modeling capability, ANN's also have several other features that make them valuable for forecasting tasks.

- First, ANN's are data-driven nonparametric methods that do not require many restrictive assumptions on the underlying process from which data are generated. As such, they are less susceptible to the model misspecification problem than parametric methods. This "learn from data or experience" feature of ANN's is highly desirable in various forecasting situations where data are usually easy to collect, but the underlying data-generating mechanism is not known or pre-specifiable.
- Second, neural networks have been mathematically shown to have the universal functional approximating capability in that they can

accurately approximate many types of complex functional relationships. This is an important and powerful characteristic, as any forecasting model aims to accurately capture the functional relationship between the variable to be predicted and other relevant factors or variables.

The combination of the above-mentioned characteristics makes ANN's a very general and flexible modeling tool for forecasting.

Research efforts on neural networks as forecasting models are considerable and applications of ANN's for forecasting have been reported in a large number of studies. Although some theoretical and empirical issues remain unsolved, the filed of neural network forecasting has surely made significant progress during the last decade. It will not be surprising to see even greater advancement and success in the next decade.

3.5 ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN's) are computing models for information processing and pattern identification. They grow out of research interest in modeling biological neural systems, especially human brains. An ANN is a network of many simple computing units called neurons or cells, which are highly interconnected and organized in layers. Each neuron performs the simple task of information processing by converting received inputs into processed outputs. Through the linking arcs among these neurons, knowledge can be generated and stored regarding the strength of the relationship between different nodes. Although the ANN models used in all applications are much simpler than actual neural systems, they are able to perform a variety of tasks and achieve remarkable results.

Over the last several decades, many types of ANN models have been developed, each aimed at solving different problems. But by far the most widely and successfully used for forecasting has been the feed forward type neural network.

Figure 3.1 shows the architecture of a three-layer feed forward neural network that consists of neurons (circles) organized in three layers: input layer, hidden layer, and output layer. The neurons in the input nodes correspond to the independent or predictor variables (**x**) that are believed to be useful for forecasting the dependent variable (**y**) which corresponds to the output neuron. Neurons in the hidden layer are connected to both input and output neurons and are keys to learning the pattern in the data and mapping the relationship from input variables to the output variable. With nonlinear transfer functions, hidden neurons can process complex information received from input neurons and then send processed information to the output layer for further processing to generate forecasts. In feed forward ANN's, the information flow is one directional from the input layer to the hidden layer then to the output layer without any feedback from the output layer. In developing a feed forward neural network model for forecasting tasks, specifying its architecture in terms of the number of input, hidden, and output neurons is an important task. Most ANN applications use only one output neuron for both one-step-ahead and multi-step-ahead forecasting. However, as argued by Zhang et al. [47], it may be beneficial to employ multiple output neurons for direct multi-step-ahead forecasting. The input neurons or variables are very important in any modeling endeavor and especially important for ANN modeling because the success of an ANN depends to a large extent on the patterns represented by the input variables. What and how many variables to use should be considered carefully.

For a causal forecasting problem, it is needed to specify a set of appropriate predictor variables and use them as the input variables. On the other hand, for a time series forecasting problem, it is needed to identify a number of past lagged observations as the inputs. In either situation, knowledge of the forecasting problem as well as some experimentation based on neural networks may be necessary to determine the best number of input neurons. Finally, the number of hidden nodes is usually unknown before building an ANN model and must be chosen during the model-building process. This parameter is useful for approximating the nonlinear relationship between input and output variables. Before a neural network can be used for forecasting, it must be trained.

Neural network training refers to the estimation of connection weights. Although the estimation process is very similar to that in linear regression where the sum of squared errors (SSE) or mean squared error (MSE) or mean absolute percentage error (MAPE) is minimized, the ANN training process is more difficult and complicated due to the nature of nonlinear optimization involved. There are many training algorithms developed in the literature and the most influential one is the back-propagation algorithm by Werbos [48] and Rumelhart et al. [49]. The basic idea of back-propagation training is to use a gradient-descent approach to adjust and determine weights such that an overall error function such as SSE or MSE or MAPE can be minimized. In addition to the most popular feed forward ANN's, many other types of neural networks can also be used for forecasting purposes. In particular, recurrent neural networks [50] that explicitly account for the dynamic nonlinear pattern can be a good alternative to feed forward type ANN's for certain time series forecasting problems. In a recurrent ANN, there are cycles or feedback connections among neurons. Outputs from a recurrent network can be directly fed back to inputs, generating dynamic feedbacks on errors of past patterns. In this sense, recurrent ANN's can model richer dynamics than feed forward ANN's in the same way that linear autoregressive and moving average (ARMA) models have certain advantages over autoregressive (AR) models. However, much less attention has been paid to the research and applications of recurrent ANN's and the superiority of recurrent ANN's over feed forward ANN's has not been established. The practical difficulty of using recurrent neural networks may lie in the facts that (1) recurrent networks can assume much different architecture and it may be difficult to specify appropriate model structures to experiment with and (2) it is more difficult to train recurrent ANN's due to the unstable nature of training algorithms.

An MLP is typically composed of several layers nodes. The first or the lowest layer is an input layer, where external information is received. The last or the highest layer is an output layer where the problem solution is obtained. The input layer and output layer are separated by one or more intermediate layers called the hidden layers. The nodes in adjacent layers are usually fully connected by acyclic arcs from a lower layer to a higher layer. Fig. 3.1 gives an example of a fully connected MLP with one hidden layer.

For an explanatory or causal forecasting problem, the inputs to an ANN are usually the independent or predictor variables. The functional relationship estimated by the ANN can be written as:

$$\mathbf{Y} = \mathbf{f}(\mathbf{X}_1, \mathbf{X}_2, \mathbf{X}_3, \ldots\ldots\ldots, \mathbf{X}_n), \quad (31)$$

where, $\mathbf{X}_1$, $\mathbf{X}_2$, $\mathbf{X}_3, \ldots\ldots\ldots$, $\mathbf{X}_n$ are $\mathbf{n}$ independent variables and $\mathbf{Y}$ is a dependent variable. In this sense, the neural network is functionally equivalent to a nonlinear regression model.

On the other hand, for an extrapolative or time series forecasting problem, the inputs are typically the past observations of the data series and the output is the future value. The ANN performs the following function mapping:

$$\mathbf{Y}_{t+1} = \mathbf{f}\,(\mathbf{Y}_t, \mathbf{Y}_{t-1}, \mathbf{Y}_{t-2}, \ldots\ldots\ldots\ldots, \mathbf{Y}_{t-n}) \tag{32}$$

where, $\mathbf{Y}_t$ is the observation at time t. Thus the ANN is equivalent to the nonlinear autoregressive model for time series forecasting problems. It is also easy to incorporate both predictor variables and time-lagged observations into one ANN model, which amounts to the general transfer function model. For a discussion on the relationship between ANN's and general ARMA models.

Before an ANN can be used to perform any desired task, it must be trained to do so. Basically, training is the process of determining the arc weights which are the key elements of an ANN. The knowledge learned by a network is stored in the arcs and nodes in the form of arc weights and node biases. It is through the linking arcs that an ANN can carry out complex nonlinear mappings from its input nodes to its output nodes. MLP training is a supervised one in that the desired response of the network (target value) for each input pattern (example) is always available.

The training input data is in the form of vectors of input variables or training patterns. Corresponding to each element in an input vector is an input node in the network input layer. Hence the number of input nodes is equal to the dimension of input vectors. For a causal forecasting problem, the number of input nodes is well defined and it is the number of independent variables associated with the problem. For a time series forecasting problem, however, the appropriate number of input nodes is not easy to determine. Whatever the dimension, the input vector for a time series forecasting problem will be almost always composed of a moving window of fixed length along the series. The total available data is usually divided into a training set (in-sample data) and a test set (out-of-sample or hold-out sample). The training set is used for estimating the arc weights while the test set is used for measuring the generalization ability of the network.

The training process is usually as follows. First, examples of the training set are entered into the input nodes. The activation values of the input nodes are weighted and accumulated at each node in the first hidden layer. The total is then transformed by an activation function into the node's activation value. It in turn becomes an input into the nodes in the next layer, until eventually the output activation values are found. The training algorithm is used to find the weights that minimize some overall error measure such as the sum of squared error (SSE) or mean squared error (MSE) or mean absolute percentage error (MAPE). Hence the network training is actually an unconstrained non linear minimization problem.

For a time series forecasting problem, a training pattern consists of a fixed number of lagged observations of the series. Suppose, there are N observations $Y_1, Y_2, Y_3, \ldots, Y_N$ in the training set and it is needed for one step ahead forecasting, then using an ANN with n input nodes will have N-n training patterns. The first training pattern will be composed of $Y_1, Y_2, Y_3, \ldots, Y_n$ as inputs and Y_{n+1} as the target output. The second training pattern will contain $Y_2, Y_3, Y_4, \ldots, Y_{n+1}$ as inputs and Y_{n+2} as the target output. Finally, in the last training pattern the target output will be Y_N.

3.6 ISSUES IN ANN MODELING AND FORECASTING

Developing an ANN model for a particular forecasting application is not a trivial task. Although many good software packages exist to ease users' effort in building an ANN model, it is still critical for forecasters to understand many important issues surrounding the model building process. It is important to point out that building a successful neural network is a combination of art and science and software alone is not sufficient to solve all problems in the process. It is a pitfall to blindly throw data into a software package and then hope it will automatically give a satisfactory solution.

An important point in effectively using ANN forecasting is the understanding of the issue of learning and generalization inherent in all ANN forecasting applications. This issue of learning and generalization can be understood with the concepts of model bias and variance [51].

- Bias and variance are important statistical properties associated with any empirical model. Model bias measures the systematic error of a forecasting model in learning the underlying relations among variables or time series observations.

- Model variance, on the other hand, relates to the stability of models built on different data samples from the same process and therefore offers insights on **generalizability** of the prediction model.

A pre-specified or parametric model, which is less dependent on the data, may misrepresent the true functional relationship and, hence, cause a large bias. On the other hand, a flexible, data-driven model may be too dependent on the specific data set and, hence, have a large variance.

Bias and variance are two conflicting terms that impact a model's usefulness. Although it is desirable to have both low bias and low variance, it may not be possible to reduce both terms at the same time for a given data set because these two goals are conflicting. A model that is less dependent on the data tends to have low variance but high bias if the pre-specified model is incorrect. On the other hand, a model that fits the data well tends to have low bias but high variance when applied to different data sets. Hence, a good predictive model should have an "appropriate" balance between model bias and model variance. As a model-free approach to data analysis, neural networks often tend to fit the training data well and thus have low bias. But the price to pay is the potential over fitting effect that causes high variance. Therefore, attention should be paid to address issues of over fitting and the balance of bias and variance in neural network model building.

3.6.1 MAJOR ISSUES

The major decisions a neural network forecaster must make include data preparation, input variable selection, choice of network type and architecture, transfer function, and training algorithm, as well as model validation, evaluation and selection. Some of these can be solved during the model building process while others must be considered before actual modeling starts.

Data Preparation: Neural networks are data-driven techniques. Therefore, data preparation is a critical step in building a successful neural network model Without a good, adequate, and representative data set, it is impossible to develop a useful, predictive ANN model. Thus, the reliability of ANN models depends to a large extent on the quality of data.

There are several practical issues around the data requirement for an ANN model. The first is the size of the sample used to build a neural network. While there is no specific rule that can be followed for all situations, the advantage of having large samples should be clear because not only do neural networks have typically a large number of parameters to estimate, but also it is often necessary to split data into several portions to avoid over fitting, select model, and perform model evaluation and comparison. A larger sample provides a better chance for neural networks to adequately approximate the underlying data structure. Although large samples do not always give superior performance over small samples, forecasters should strive to get as large of a sample as they can. In time series forecasting problems, Box and Jenkins [52] have suggested that at least 50 or, even better, 100 observations are necessary to build linear ARIMA models. Therefore, for nonlinear modeling, larger sample size should be more desirable. In fact, using the longest time series available for developing forecasting models is a time-tested principle in forecasting [53]. Of course, if data in the sample are not homogeneous or the underlying data generating process in a time series changes over time, then a larger sample may even hurt performance of static neural networks as well as other traditional methods.

Data Splitting: The second issue is data splitting. Typically for neural network applications, all available data are divided into an in-sample and an out-of-sample. The in-sample data are used for model fitting and selection, while the out-of-sample is used to evaluate the predictive ability of the model. The in-sample data sometimes are further split into a training sample and a validation sample. Because of the bias and variance issue, it is critical to test an ANN model with an independent out-of-sample which is not used in the neural network training and model selection phase. This division of data means that the true size of sample used in model building is smaller than the initial sample size. Although there is no consensus on how to split the data, the general practice is to allocate more data for model building and selection. That is, most studies in the literature use convenient ratio of splitting for in- and out-of- samples such as 70%:30%, 80%:20%, or 90%:10%. It is important to note that in data splitting, the issue is not about what proportion of data should be allocated in each sample. But, rather, it is about sufficient data points in each sample to ensure adequate learning, validation, and testing. Granger [54] suggests that for nonlinear modeling at least 20% of the data should be held back for an out-of-sample evaluation. Hoptroff [55] recommends that at least 10 data points should be in the test sample while Ashley [56] suggests that a much larger out-of sample size is necessary in order to achieve statistically significant improvement for forecasting problems.

Data Preprocessing: Data preprocessing is another issue that is often recommended to highlight important relationships or to create more uniform data to facilitate ANN learning, meet algorithm requirements, and avoid computation problems. Azoff [57] summarizes four methods typically used for input data normalization. They are: along channel normalization, across channel normalization, mixed channel normalization, and external normalization. However, the necessity and effect of data normalization on network learning and forecasting are still not universally agreed upon. For example, in modeling and forecasting seasonal time series, some researchers [58] believe that data preprocessing is not necessary because the ANN is a universal approximator and is able to capture all of the underlying patterns well. Recent empirical studies [59], however, find that pre deseasonalization of the data is critical in improving forecasting performance. Zhang and Qi [60] further demonstrate that for time series containing both trend and seasonal variations, preprocessing the data by both detrending and deseasonalization should be the most appropriate way to build neural networks for best forecasting performance. Neural network design and architecture selection are important yet difficult tasks. Not only are there many ways to build an ANN model and a large number of choices to be made during the model building and selection process, but also numerous parameters and issues have to be estimated and experimented with before a satisfactory model may emerge. Adding to the difficulty is the lack of standards in the process. Numerous rules of thumb are available, but not all of them can be applied blindly to a new situation. In building an appropriate model for the forecasting task at hand, some experiments are usually necessary. Therefore, a good experiment design is needed.

Network Architecture: A feed forward ANN is characterized by its architecture and determined by the number of layers, the number of nodes in each layer, the transfer or activation function used in each layer, as well as how the nodes in each layer are connected to nodes in adjacent layers. Although partial connections between nodes in adjacent layers and direct connections from input layer to output layer are possible, the most commonly used ANN is the so-called "fully connected" network in that each node at one layer is fully connected only to all of the nodes in the adjacent layers.

Output Node: The size of the output layer is usually determined by the nature of the problem. For example, in most forecasting problems, one output node is naturally used for one-step-ahead forecasting, although one output node can also be employed for multi-step-ahead forecasting, in which case iterative forecasting mode must be used. That is, forecasts for more than two steps ahead in the time horizon must be based on earlier forecasts. This may not be effective for multi-step forecasting as pointed out by Zhang et al. [61], which is in line with Chatfield [62] who discusses the potential benefits of using different forecasting models for different lead times. Therefore, for multi-step forecasting, one may either use multiple output nodes or develop multiple neural networks each for one particular step forecasting.

Input Node: The number of input nodes corresponds to the number of variables in the input vector used to forecast future values. For causal forecasting, the number of inputs is usually transparent and relatively easy to choose. In a time series forecasting problem, the number of input nodes corresponds to the number of lagged observations used to discover the underlying pattern in a time series and to make forecasts for future values. However, currently there is no suggested systematic way to determine this number. The selection of this parameter should be included in the model construction process. Ideally, it is desired to have small number of essential nodes which can unveil unique features embedded in the data. Too few or too many input nodes can affect either the learning or prediction capability of the network.

The number of input nodes is perhaps the most important parameter for designing an effective neural network forecaster. For causal forecasting problems, it corresponds to the number of independent or predictor variables that forecasters believe are important in predicting the dependent variable. For univariate time series forecasting problems, it is the number of past lagged observations. Determining an appropriate set of input variables is vital for neural networks to capture the essential underlying relationship that can be used for successful forecasting. How many and what variables to use in the input layer will directly affect the performance of neural network in both in-sample fitting and out-of-sample forecasting, resulting in the under-learning or over fitting phenomenon. Empirical results [63], also suggest that the input layer is more important than the hidden layer in time series forecasting problems. Therefore, considerable attention should be given to determine the input variables, especially for time series forecasting.

Hidden Layer and Hidden Node: The hidden layer and hidden nodes play an important role for many successful applications of neural networks. It is the hidden nodes in the hidden layer that allow neural networks to detect the feature, to capture the pattern in the data, and to perform complicated nonlinear mapping between input and output variables. Although there is substantial flexibility in choosing the number of hidden layers and the number of hidden nodes in each layer, most forecasting applications use only one hidden layer and a small number of hidden nodes. Two hidden layer networks may provide more benefits in some type of problems. Srinivasan [64] had used two hidden layer and this result in a more complicated architecture which achieves a higher efficiency in the training process. Using two hidden layer may give better results for some specific problems, especially when one hidden layer network is over laden with too many hidden nodes to give satisfactory results. In practice, the number of hidden nodes is often determined by experimenting with a number of choices and then selected by the cross-validation approach or performance on the validation set. Although the number of hidden nodes is an important factor, a number of studies have found that forecasting performance of neural networks is not very sensitive to this parameter [65]. The issue of determining the optimum number of hidden nodes is a crucial yet complicated one. In general, network with fewer hidden nodes are preferable as they usually have better generalizations ability and less over fitting problems. But network with too few hidden nodes may not have enough power to model and learn the data. The most common way in determining the number of hidden nodes is via trial and error. Several rule of thumbs have also been proposed, such as, the number of hidden nodes depends on the number of input patterns and each weight should have at least ten input patterns (sample size). In the case of one hidden layer network, several practical guidelines exist. These include 2n+1, 2n, n\2 where n is the sum of number of input nodes and output nodes.

Transfer Function: The activation function is also called the transfer function. It determines the relationship between inputs and outputs of a node and a network. In general, the activation function introduces a degree of nonlinearity that is valuable for most ANN applications. Chen and Chen [66] identify general conditions for a continuous function to qualify as activation function. Loosely speaking, any differentiable function can qualify as an activation function in theory. In practice, only a small number of "well-behaved" (bounded, monotonically increasing, and differentiable) activation functions are used. These include:

The sigmoid (logistic) function:

$F(x) = (1+ \exp(-x))^{-1}$

The hyperbolic tangent function:

$F(x) = (\exp(x)-\exp(-x))/(\exp(x)+ \exp(-x))$

The sine or cosine function:

$F(x) = \sin(x)$ or $F(x) = \cos(x)$

The linear function:

$F(x) = x$

Among them, the logistic transfer function is the most popular.

There are some heuristic rules for the selection of the activation function. For example, Klimasauskas [67] suggests logistic activation functions for classification problems which involve learning about average behavior, and to use the hyperbolic tangent functions if the problem involves learning about deviations from the average such as the forecasting problem. However, it is not clear whether different activation functions have major effects on the performance of the networks. Generally, a network may have different activation functions for different nodes in the same or different layers. Yet almost all the networks use the same activation functions particularly for the nodes in the same layer. While the majority of researchers use logistic activation functions for hidden nodes, there is no consensus on which activation function should be used for output nodes.

For forecasting applications, the most popular transfer function for hidden nodes is either logistic or hyperbolic and it is the linear or identity function for output nodes, although many other choices can be used. If the data, especially the output data, have been normalized into the range of [0, 1], then logistic function can be used for the output layer. In general, different choices of transfer function should not impact much on the performance of a neural network model.

Following the convention, a number of authors simply use the logistic activation functions for all hidden and output nodes [68]. De Groot and Wurtz [69] and Zhang and Hutchinson [70] use the hyperbolic tangent transfer functions in both hidden and output layer. Schoneburg [71] uses mixed logistic and sine hidden nodes and a logistic output node. Notice that when using these nonlinear squashing functions in the output layer, the target output values usually need to be normalized to match the range of actual outputs from the network since the output node with a logistic or a hyperbolic tangent function has a typical range of [0,1] or [-1,1] respectively. Conventionally, the logistic activation function seems well suited for the output nodes for many classification problems where the target values are often binary. However, for a forecasting problem which involves continuous target values, it is reasonable to use a linear activation function for output nodes.

Training Algorithm: Once a particular ANN architecture is of interest to the forecaster, it must be trained so that the parameters of the network can be estimated from the data. Training a neural network can be treated as a nonlinear mathematical optimization problem and different solution approaches or algorithms can have quite different effects on the training result. As a result, training with different algorithms and repeating with multiple random initial weights can be helpful in a getting better solution to the neural network training problem. In addition to the popular basic back-propagation training algorithm, users should be aware of many other algorithms These include so-called second-order approaches, such as conjugate gradient descent, quasi-Newton, and Levenberg-Marquardt [72].

The most popularly used training method is the back-propagation algorithm which is essentially a gradient steepest descent method. For the gradient descent algorithm, a step size, which is called the learning rate in ANNs literature, must be specified. The learning rate is crucial for back-propagation learning algorithm since it determines the magnitude of weight changes. It is well known that the steepest descent suffers the problems of slow convergence, inefficiency, and lack of robustness. Furthermore it can be very sensitive to the choice of the learning rate. Smaller learning rates tend to slow the learning process while larger learning rates may cause network oscillation in the weight space. One way to improve the original gradient descent method is to include an additional momentum parameter to allow for larger learning rates resulting in faster convergence while minimizing the tendency to oscillation. The idea of introducing the momentum term is to make the next weight change in more or less the same direction as the previous one and hence reduce the oscillation effect of larger learning rates Yu et al. [73] describe a dynamic adaptive optimization method of the learning rate using derivative information. They also show that the momentum can be effectively determined by establishing the relationship between the back-propagation and the conjugate gradient method.

ANN model selection is typically done with the basic cross-validation process. That is, the in-sample data is split into a training set and a validation set. The ANN parameters are estimated with the training sample, while the performance of the model is evaluated with the validation sample. The best model selected is the one that has the best performance on the validation sample. Of course, in choosing competing models, the principle of parsimony must also be applied. That is, a simpler model that has about the same performance as a more complex model, should be preferred. Model selection can also be done with all of the in-sample data. This can be done with several in-sample selection criteria that modify the total error function to include a penalty term that penalizes for the complexity of the model.

In-sample model selection approaches are typically based on some information- based criteria such as Akaike's information criterion (AIC) and Bayesian (BIC) or Schwarz information criterion (SIC). However, it is important to note the limitation of these criteria as empirically demonstrated by Swanson, White, Qi and Zhang [74]. Other in-sample approaches are based on pruning methods such as node and weight pruning [75], as well as constructive methods such as the upstart and cascade correlation approaches [76].

After the modeling process, the finally selected model must be evaluated using data not used in the model-building stage. In addition, as ANN's are often used as a nonlinear alternative to traditional statistical models, the performance of ANN's needs to be compared to that of statistical methods. As Adya and Collopy point out, "if such a comparison is not conducted, it is difficult to argue that the study has taught us much about the value of ANN's." They further propose three evaluation criteria to objectively evaluate the performance of an ANN: (1) comparing it to well-accepted (traditional) models; (2) using true out-of-samples; and (3) ensuring enough sample size in the out-of-sample (4) for classification problems and (5) for time series problems. It is important to note that the test sample served as out-of-sample should not in any way be used in the model-building process. If the cross-validation is used for model selection and experimentation, the performance on the validation sample should not be treated as the true performance of the model. Although some of the above issues are unique to neural networks, some are general issues to any forecasting method. Therefore, good forecasting practice and principles should be followed. It is beneficial to consult Armstrong's publication which provides a good source of information on useful principles for forecasting model building, evaluation, and uses.

Data Normalization: Nonlinear activation functions such as the logistic function typically have the squashing role in restricting or squashing the possible output from a node to, typically, (0, 1) or (-1, 1). Data normalization is often performed before the training process begins. As mentioned earlier, when nonlinear transfer functions are used at the output nodes, the desired output values must be transformed to the range of the actual outputs of the network. Even if a linear output transfer function is used, it may still be advantageous to standardize the outputs as well as the inputs avoid computational problems. Four methods for input normalization are summarized by Azoff [77]:

- **Along channel normalization:** A channel is defined as a set of elements in the same position over all input vectors in the training or test set. That is, each channel can be thought of as an "independent" input variable. The along channel normalization is performed column by column if the input vectors are put into a matrix. In other words, it normalizes each input variable individually.
- **Across channel normalization:** This type of normalization is performed for each input vector independently, that is, normalization is across all the elements in a data pattern.
- **Mixed channel normalization:** As the name suggests, this method uses some kind of combinations of along and across normalization.
- **External normalization:** All the training data are normalized into a specific range.

The choice of the above methods usually depends on the composition of the input vector. For a time series forecasting problem, the external normalization is often the only appropriate normalization procedure. The time lagged observations from the same source are used as input variables and can retain the structure between channels as in the original series. For causal forecasting problems, however, the along channel normalization method should be used since the input variables are typically the independent variables used to predict the dependent variable.

Training Sample and Test Sample: Training and test samples are typically required for building an ANN forecaster. The training sample is used for ANN model development and the test sample is adopted for evaluating the forecasting ability of the model. Sometimes a third one called the validation sample is also utilized to avoid the over fitting problem or to determine the stopping point of the training process. It is common to use one test set for both validation and testing purposes particularly with small data sets. In view, the selection of the training and test sample may affect the performance of ANN's. The first issue here is the division of the data into the training and test sets. Although there is no general solution to this problem, several factors such as the problem characteristics, the data type and the size of the available data should be considered in making the decision. It is critical to have both the training and test sets representative of the population or underlying mechanism. Inappropriate separation of the training and test sets will affect the selection of optimal ANN structure and the evaluation of ANN forecasting performance. The literature offers little guidance in selecting the training and the test sample. Most authors select them based on the rule of 90% vs. 10%, 80% vs. 20% or 70% vs. 30%, etc.

CHAPTER 4

PROBLEM FORMULATION

4.1 RETAIL DEMAND FORECASTING PROBLEM

One of the greatest problems faced by many companies within the retail sector is to know **when, what** and **how much** should be distributed to the point of sale. Clearly, understanding the underlying demand patterns for a particular product means that outlets can be re-stocked in sufficient time to cope with changes in consumer demand. For products that are perishable or have a very short shelf-life, this issue is more critical than for slower moving products with smaller demand requirements.

Common problems created by poor demand forecasting are:-

1. Sell-Outs & Missed Sales
2. Increased Waste
3. Markdown of Prices
4. Lower Availability across product lines
5. Customer Dissatisfaction
6. Loss of Market Share

Historically, much demand forecasting has been performed using arithmetic calculations such as moving averages, historical sales figures and/or through the application of practical business rules. This was usually because of a lack of available expertise, technology and raw computing power. For products with highly stable sales patterns these approaches can achieve, on average, a sufficient level of accuracy to not warrant more powerful techniques. However, when markets are more volatile, and goods have a shorter shelf-life, basic arithmetic techniques simply do not yield sufficiently accurate results, on a day-to-day basis, to prevent sell-outs and low availability in some stores and increased wastage and repeated markdown of prices in others. In recent years many companies have moved to more sophisticated statistical models to help with their demand forecasting problems. Often complex models have been built that allow retailers to forecast the demand for any product, in any store, for any given day. The common problem with these models is that all stores have different historical demand patterns for many products, depending on consumer demographics, store layout and other interventions like marketing campaigns. A single model is often too generic to be accurate in all cases.

Retailers face several challenges when it comes to forecasting:

- Scale of the problem (large number of stores and items to forecast).
- Intermittent demand (slow and erratic sales for many items at the store level).
- Assortment instability (frequent new-item introductions and seasonal assortment changes).
- Pricing and promotional activity.

Given these challenges, it is important to recognize where forecasting can enable better retail processes, and where forecasting alone will not solve the business problem.

Modern demand-forecasting systems provide new opportunities to improve retail performance. Although the art of the individual merchant may never be replaced, it can be augmented by an efficient, objective and scientific approach to forecasting demand. Large-scale systems are now capable of handling the mass of retail transaction data – organizing it, mining it and projecting it into future customer behavior. This new approach to demand forecasting in retail will contribute to the accuracy of future plans, the satisfaction of future customers and the overall efficiency and profitability of retail operations.

Retailers need to base their decisions on customer insight and customer understanding in order to be successful and to differentiate themselves against mega retailers. The most common way to gain customer understanding is to forecast consumer demand measured by store sales as well as by consumption data through other channels, such as shipment data or aggregated sales order data. An additional component of "demand modeling" is required before one can create forecasts or perform optimization. The process of "Demand Modeling" is executed on sales data (or other consumption data) prior to calculating forecasts or optimizing prices. The Demand Modeling process is critical, as it takes sales history time series as an input, and cleanses the data before calculating the parameter values used in the forecasting and optimization functionality. Demand modeling does not always need to run as frequent as thought. Often, model parameters change slowly (e.g. price elasticity) compared to the weekly frequency of an optimization run. Therefore, the model might be refreshed periodically, or triggered by a validation process, which continuously evaluates model quality. The parameters of the demand modeling have been given below:

- Price Elasticity
- Offer Elasticity
- Product Cannibalization
- Halo-Effect (Affinity)
- Segmentation
- Demand Influencing Factors
- Customer Decision Process
- Reference Price
- Psychological Price Thresholds
- Assortment/Face Elasticity

The effect of these parameters on the demand quantity of the product is very hard to identify by only assuming linear relationship between these parameters and demand quantity.

4.1.1 NEW OPPORTUNITIES AND CHALLENGES

From the viewpoint of a demand forecaster, the key opportunity presented by the new e-business environment is the abundance and availability of information, driven by the proliferation of information technology globally among businesses and consumers. . To exploit such an opportunity, it is needed to be aware of the value of the different types of information and subsequent exploration of this information.

1. **Information on demand throughput:** The most well-established forecasting techniques are based on historical demand. In today's business environment, changes in the marketplace are swift and sudden, and may not follow the historical pattern; hence future demand may not be predicted accurately by relying on past demand alone. Historical demand information need not be information about the past in the traditional sense, such as realized demand in the last month. Demand information about the present is commonly available. For instance, predicting demand in a time period when some customer orders are already placed can benefit from information on the incoming orders. Take for example a manufacturer serving other

businesses. If the time period is a month, then a useful indicator might be the cumulative, month-to-date shipment quantity, quantity sold, or quantity sold to end-users.

2. Information on selling price and product promotion: Changes in the selling price and the presence of product promotions are known to have a significant effect on demand in many industries. Today, in large part due to the proliferation of information and other technologies, price changes are less costly. Price changes in electronic business-to-business product catalogs or web-based retail businesses incur little incremental cost. Even in traditional retail stores, the day will soon come when a button on a computer is pressed to issue a price change, and new prices will be reflected on a liquid crystal shelf label in a physical store a few seconds later. Such opportunities imply that price changes and promotion actions may be used very frequently, and so they can no longer be analyzed separately from "normal" demand. Product promotions are getting very sophisticated. Targeted marketing, and ultimately one-on-one marketing, has created complications in the analysis of promotion effects. The traditional way of applying a general "lift factor" to nominal demand when a certain promotion is performed may not be adequate. At the very least, this "lift factor" needs to take into account the promotions target portion of the entire market, a quantity to be estimated.

3. Information on product life cycle: One of the serious challenges facing a demand forecaster in the e-business environment is ever shortening product life cycles. In many industries, a product can be expected to have a life of at most one year. As is customary, it can inherit older history from its predecessor product, which can in turn inherit history from its own predecessor and so on. This means that in order to get, say, two to three years history, a well-organized product map is needed over time. At this point in time, it has been found that many organizations do not have such product map data stored in a usable manner. The upcoming industry of product life cycle management software will no doubt provide a better infrastructure to maintain such information. However, even with a product map, one would not go too far back since the entire business environment was different. For many products, there are practically at most two or three of product history itself.

4. Information on the marketplace: As econometricians have long known, demand history is only one of many streams of information from which a forecast can be made. The e-business environment presents at least two key opportunities on forecast information. First, high level indicators of economic activities such as total production output of an industry are more up-to-date than previously possible. Data are collected continuously and automatically in electronic transactions, and should also be less error prone. This will be increasingly so as more and more business-to-business as well as business-to-consumer transactions are performed electronically. This comment applies to retail store transactions as well, where the transaction is performed electronically at the point-of-sale and will be recorded into some central database. Second, more detailed economic data are available, such as those by product types within an industry. Experience shows that detailed data are more useful as a predictor of the demand of a single product of an individual organization.

5. Information on consumers: End user sales or consumer demand is used as a source of demand information. Demand history consisting of the quantity sold, and perhaps selling price, is no longer the only piece(s) of information coming directly from past consumers. Customer database collected by an organization over time, previously limited only to expensive products such as mainframe computers or automobiles, is now likely to cover regular products such as end-user software packages or even children's products. Curiously, for these two product types, end users have very different incentives to register with the manufacturer: for future product updates in the form of software downloads, or product recalls. As more products incorporate elements of software that will go through a typical life cycle of updates, customers are more likely to register with the product manufacturer. Thus the existing customer base is no longer characterized only by a total sales number, but rather a database of information at the manufacturer's own request.

4.2 THE SCENERIO IN THE STUDY

A well established retail super store in Bangladesh has about 8000 different types of products in its one store. It has been mentioned previously the necessity of doing an error free forecasting of the products for the item available in the store. But, it is not a very easy job. The system applied in most of the retail super store for forecasting purpose is of time series quantitative methods. In the methods applied by the retail companies in Bangaldesh, linear or close to linear relationship is assumed between the demand quantity and the factors influencing the demand quantity. Most of the companies use weighted moving average or exponential smoothing techniques of demand forecasting. There are lots of inaccuracies and errors in the system that is applied by the retail companies in Bangladesh for demand forecasting of their items. The inaccuracies and errors have been mentioned below:

- First, the applied system can not identify the real factors that are actually influencing the demand of the items sold by the companies.
- Quantitative influences of the influencing factors are not determined and analyzed at all in the present system of demand forecasting.
- Uncertainty in the demand of the items is not included at all in the present system.
- The trend and seasonality are not analyzed and determined.
- The actual demand data of the earlier demand periods is not used accurately with the real effect.
- The actual relationship between the demand influencing factors and the demand quantity is not determined and analyzed.

Above mentioned failures of the present demand forecasting system in the chain retain stores in Bangladesh are responsible for one of the major problems. Due to the above problems, the stores loss their market share, sometimes there are excess inventory and sometimes there are stock out of items, customer satisfaction level decreases, cost increases etc. These problems have to be solved in order to exist in the market. There are lots of items available in a chain retail store. So, developing a demand forecasting algorithm or model for all of the items will not be possible. Because, different items will have different demand pattern, the trend and seasonal effect will also be different for varieties of products, the relationship between the demand influencing factors and demand quantity will be different for different products, demand influencing factors will be different. Different model of forecasting have to be developed for different types of products. In order to start the solution of demand forecasting problem in the retail store, one fast moving item has to select first and for that item a accurate demand forecasting model has to be developed. Then the resulting model will have to be customized for different types of products. The major problem in the present forecasting methods applied by the chain retail stores is that these methods can not actually quantify the effect of the influencing factors on the demand quantity. Because, most of the methods assume either linear relation between influencing factors and the demand quantity or they base their forecasting on an assumed non-linear relation which might not be true. The present methods cannot utilize the past actual demand data for determining the actual relation between the demand influencing factors and the demand quantity.

Another major issue is that the demand forecasting of any certain day has to make before a certain number of day so that the required order quantity can be ordered and received within time so that demand can be fulfilled effectively. During the study period, it has been found that to place an order and received that order around 10 days lead time is required. So, if the forecasting can be made about 15 days before then customer order can be fulfilled efficiently. So, the proposed algorithm will have to forecast the demand quantity for a day about 15 days before that particular day.

4.2.1 PROBLEM SOLVING PROCEDURE

In order to solve the existing demand forecasting problem in the chain retail store demand influencing factors have to be identified first. Then, a model or algorithm has to be developed so that the algorithm can identify the nonlinear relation between the demand influencing factors and demand quantity of the item selected for forecasting. The model has to be based on using past demand data so that the accurate effect of the demand influencing factors can be identified and their effects can be quantified. The algorithm should also include the uncertainty factors in the demand forecasting of any item. The developed model has to be compared with the existing methods in order to prove its superiority.

4.3 DEMAND INFLUENCING FACTORS

For developing an accurate demand forecasting algorithm for any kind of item one of the most important thing is to identify the influencing factors of that items demand. To identify all the demand influencing factors, the past demand data has to be studied intensively. It is also necessary to talk with the people in the chain retail stores and also with the customers who are actually buying the items. It is important to determine the reasons behind the buying. The buying frequency of the customers is not same throughout any given time periods. The frequency changes due to the changes in the situation.

In this study, a fast moving item in the retail store of Bangladesh has been selected. The item is **noodles**. There are different varieties of noodles. For analysis purpose, it has been assumed that all of the noodles are of same brand and of the same size. In developing the whole model past demand data of the highest sold brand and all other brands has been used.

For identifying the actual demand influencing factors past data of actual demand has been analyzed. Three years data has been collected according to day to day demand. That means total of (365*3) 1095 days actual demand data of noodles has been analyzed. The amount of data is huge in order to identify the actual demand influencing factors. The following factors have been identified as demand influencing factors:

- The period of the month is important. It has been found that the selected item is sold at a higher rate at the starting of the month. Usually from 5 to 15 of any month the sale of the item is higher than other days of the month.
- Weekend also has an effect on the demand of the item. The sale is much higher at weekends compare to week days.
- The sale of the item is higher in a holiday and any other day.
- During a festival period the overall sale is much higher.
- The weather condition of a particular day has an effect on the selling of the item. If the weather is either too hot or too much rain occurs on a particular day, then the sale is much lower than day when the weather is normal.
- The price of the item has an important effect on the demand quantity. If the price is reduced than the selling of the item increases and vice versa.
- The effect of promotional programs on the actual demand of the item is very important. The demand of the item increases during any kind of promotional programs. There are many kinds of promotional programs. Such as: free items offer, price reduction offer, discount offer, lottery offer, higher amount offer, free other items offer etc. The effect of different types of promotional programs is different. To exactly quantify the effects of promotional programs is very hard. But during the study it has been found that offer like 'get one free by buying two' has better effect on the demand than an offer like 'one any other item free by buying two'. Also offer like '10% higher amount with the same price' has also very positive effect on

the demand. So, it can be said that effect of different promotional programs are different. Offer like '10% less price if buy 3' has a very positive effect on the demand of the item.

- There are different varieties of brands available for noodles in the market. The market shares of all the brands are not equal. It has been found that one particular brand has the highest market share. The availability of this brand is very important factor in the demand of the item.
- Another important factor is that the number of people visits the store. When the number of people visit the store is high, then the selling of the item is also high. But the relation is not linear.

All the above mentioned factors are the main demand influencing factors that has been found in the study. These factors actually determine what will be the demand of the item in a particular day of the item along with the trend and other factors.

4.4 PROBLEM FORMULATION

Three years day to day demand quantity has been studied. It can be easily mentioned that the effect of all the factors on the demand of the selected item is not linear at all. There exists nonlinear relation between the factors and demand of that item. It is almost impossible to determine the relationship by applying traditional demand forecasting techniques. So, new evolutionary algorithm has to be applied in order to determine the relationship. It has been mentioned previously that neural network algorithm has a very good potential in any kind of forecasting application. So, in this study neural network will be applied for demand forecasting.

For applying neural network algorithm in the selected demand forecasting problem, the network architecture has to be built first. That means the number of output nodes, the number of input nodes, the number of hidden layer and hidden nodes, the transfer function, the training algorithm, the bite size in the input nodes, data normalization process, ratio of training sample and test sample has to be determined first.

Input Node: There are 11 input nodes in the developed neural network structure. Demand influencing factors have been divided into 11 classes. They are:

1. The day for which demand will be forecasted is a weekend or not is an input node.

2. The day for which demand will be forecasted is a holiday or not is an input node.

3. Another input node is that whether the day falls in a festival season.

4. The types of promotional activity are an important demand influencing factor. There are varieties of promotional activities. Different kinds of promotional activities have been mentioned earlier. For promotional activities, there will be two input nodes. One will be for promotional activities like free item offer, price discount and higher amount offer. Another one will be for free other items offer, lottery offer etc.

5. Availability of the selected item is also an important factor. The stock amount and amount that are displayed in the store play an important role in building demand. So, for availability of the item there will be an input node.

6. The price also plays an important role in demand in a developing country like Bangladesh. Price has multiple ranges. Price can be low, medium and high. There will be one node for price information. This node will have three different combination of input information.

7. The demand of the selected item is higher during the early period of any month because people receive their salary in that period. So, there will be one input node for that input information whether the particular day falls in the starting of the month.

8. The selected item is a fast moving item in the retail store. Its sales are more or less proportional to the number of people visited the particular retail store. This information will be given in another input node. There will be three combination of information in this node.

9. The share of different brands is not same. One particular brand has the larger market share. So, the availability of that brand is important in the selling of that item. There is one term called brand loyalty which is very important in predicting demand or developing demand for any item. So, there will be another node for this input information. It will have three different combination of input information.

10. The 11^{th} node will be weather information. The number of people visit the store has a definite relation with the weather condition of that day. If the weather is not pleasant, then there will be less number of customer visiting the store and vice versa. In Bangladesh, the weather condition might be normal, hot, slight raining, heavy raining and cold. So, this information will play an important role in predicting demand of the selected item.

Output Node: The number of output node is one. It is not very difficult to determine the number of output node for a forecasting problem. The output of the proposed algorithm will be forecasted demand of a day. Generally there are two types of forecasting: one step ahead and multi-step ahead. In the first type, the number of hidden node will be one. In the second step there can two solution processes for number of output nodes. In iterative type, the number of output node is one and in the non iterative direct process the number of output nodes is more than one. The proposed neural network algorithm has used iterative forecasting process where the number of output node will be one. The developed algorithm forecasts the demand for 15 days one by one. That means it predicts the forecast for the first day and then second day and at last for the 15^{th} day.

Hidden Layer and Hidden Node: It is an important factor in building efficient and effective neural network architecture for forecasting problem. From previous studies it has been found that one hidden is adequate and effective for forecasting problem. The more number of hidden layers will have more accurate mapping of the nonlinear relationship among the input nodes and the value of the output nodes but will make the training process more complex and time consuming. It has been thought that in the selected study field one hidden layer is enough for determining the accurate relationship mapping. The number of hidden nodes is n\2, where n is the sum of number of input nodes and output nodes. It has been chosen from some existing practical guidelines for determining the optimum number of hidden nodes.

Transfer Function: The transfer function plays a critical role in mapping the accurate relationship between input nodes and the value of the output nodes. The hyperbolic tangent function has been used as a transfer function between the input nodes and the hidden nodes and also between the hidden nodes and the output node.

Training Algorithm: The sample data has been trained in order to identify the relation form the value of the sample data. Back propagation training algorithm is the most popular training algorithm for neural network. In this study also back propagation algorithm with steepest gradient descent momentum has been used as a training algorithm. Back propagation algorithm with gradient descent steepest method has been used for training the data.

The Ratio of Training Sample Data and Validation Data: There exist some guidelines for determining the training sample and the validation sample. 80% vs 20% rule has been used in this study. That means 80% of the data has been used for training the data and the rest 20% data has been used for validation. The number of test data is 15. The developed algorithm has been tested by predicting the demand of 15 days and comparing the forecasted demand against the actual demand of those 15 days.

CHAPTER 5
SOLUTION APPROACH

5.1 PROBLEM SOLVING PROCEDURE

The objective of this study is to develop an algorithm using artificial neural network technique for forecasting the future demand of a fast moving item sold in chain retail store. An algorithm has been developed by applying neural network technique. The development of the neural network based algorithm has been made by using MATLAB software. 2008 version of MATLAB has been used in developing the algorithm. The solving procedure is as follows:

At first, the experimental data have been tested whether the data is stationary or not. Because, if the data is non-stationary then artificial neural network will give poor result. Stationary means that there is no change effect in the data. Two demand patterns have been plotted. It has been found that there is trend and also seasonal effect. So, it can be mentioned that the data is not stationary at all. But because of using large samples the non-stationarity of the data has not cause very large amount of error.

The network architecture has been specified then in order to formulate the problem into neural network structure. The network is of three layered feed forward neural network where there is only one hidden layer and one input and output layer. The number of hidden node, output node, input node, transfer function, training algorithm, training sample and test sample ratio used in the prepared neural network structure has been mentioned in the problem formulation section. 80% of the data has been used for training and rest 20% data has been used for validation.

It has been mentioned in the earlier section in this study is that building a neural network structure is an art. So, efficient neural network structure depends on nature of the individuality of the selected problem. Lots of combinations are possible. Trial and error method has to be applied in order to identify the optimum neural network structure.

Then the training data set has been trained. The training set is used for estimating the arc weights while the test set is used for measuring the generalization ability of the network. The network training is actually an unconstrained nonlinear minimization problem. The training process is as follows. First, examples of the training set are entered into the input nodes. The activation values of the input nodes are weighted and accumulated at each node in the first hidden layer. The total is then transformed by an activation function into the node's activation value. It in turn becomes an input into the nodes in the next layer that means the output activation values are found. The training algorithm has been used to find the weights that minimize some overall error measure. For training of the data, the back propagation training algorithm has been used.

5.2 HOLT – WINTER'S MODEL FOR SEASONAL / TRENDED DEMAND

It is often be the case that items in a logistics system exhibit demand patterns that include both trend and seasonality. It is possible to combine the logic of Holt's procedure for trended data and the seasonal index approach so as to forecast level, trend, and seasonality. This approach is embodied in Winter's model for trended/seasonal data. Each component term of the forecast is estimated with exponential smoothing, and separate smoothing coefficients, α, β, and γ, can be used for each estimate. In this study, the value of α, β, and γ is .10, .10, and .30 respectively. The equations have been given below. In this study, the neural network forecasting algorithm that has been developed is compared with this Holt-Winter's forecasting method for comparing performance. Because, the Holt – Winter's method is regularly applied in the retail store for forecasting of items that have both seasonality and trend effect.

$$Z'_{t+1} = (L_{t+1} + T_{t+1})\, S_{\theta[t+1-m]} \quad (33)$$

$$L_{t+1} = \alpha\,(Z_t / S_{\theta[t]}) + (1-\alpha)(L_t + T_t) \quad (34)$$

$$T_{t+1} = \beta\,(L_{T+1} - L_t) + (1-\beta)\, T_t \quad (35)$$

$$S_{\theta[t+1]} = \gamma\,(Z_{T+1} / L_{t+1}) + (1-\gamma)\, S_{\theta[t+1-m]} \quad (36)$$

where, Z'_{t+1} is the forecasted amount for the period t +1, L_{t+1} is the base level demand for the period t +1, T_{t+1} is the trend level for the period t +1, m is the number of periods in one year, $S_{\theta[t+1]}$ is the seasonal index for the period $t+1$. Here, weekly demand has been analyzed and also weekly demand has been forecasted.

Developing reasonable initial estimates of the L, T, and S values is more difficult in this procedure. Unless there are some good a priori reasons to establish these values, it will be needed at least two full seasons of historical data (usually two years worth) to be able to distinguish between trend and seasonality in the data. As an example, a simple but approximate approach is as follows.

Given two years of weekly data (Z_1 through Z_{104}), Y_1 has been computed as the average weekly demand of the first year and Y_2 as the average weekly demand of the second year. There are 52 weeks in one year. So, no. of periods in one year is 52.

Since averaging over a year de-seasonalizes the data, and also allows some of the noise to cancel, the difference between Y_1 and Y_2 has been roughly attributed to one year's accumulation of trend, so an initial estimate of T has been calculated:

$$T = (Y_2 - Y_1)/(\text{No. of periods in one year}) \tag{37}$$

The first year average, Y_1, can be thought of as the average of the initial level plus fifty one weeks with increasing trend. In other words, if seasonality and noise is ignored then:

$$Y_1 = \{L+(L+T)+(L+2T)+\ldots\ldots\ldots+(L+[m-1]T\}/m \tag{38}$$

The seasonal influence has been initially estimated from the difference between the actual demand observed in a period and an estimate based only on level and trend. For each of the m periods in a year, there are two observations to average, so:

$$S_i = (1/2) / [\{Z_i/\{L+(i-1)T\} + \{Z_{m+i}/\{L+(m+i-1)T\}, \text{ for } i = 1 \text{ to } m \tag{39}$$

Due to the manner in which these indices have been estimated, they will not generally sum to m. They should therefore be normalized before they are used. All the above principles and formulas apply if the period is day. Value of m will be 365 if the period is day. Then also the forecasted demand can be determined by using the same formulas.

CHAPTER 6

RESULTS AND COMPARISION

6.1 DEMAND PATTERN

The sales data of the 2006 and 2007 year has been plotted in order to identify and analyze the demand pattern of the item. The sales data of the 2007 and 2008 also has been plotted in order to examine the continuity of the demand pattern of the sales data throughput different time periods. It has been observed that there is trend and seasonal effect in the demand. Also the demand fluctuates randomly due to the effect of the influencing factors. The demand patterns have been shown in the following figures:

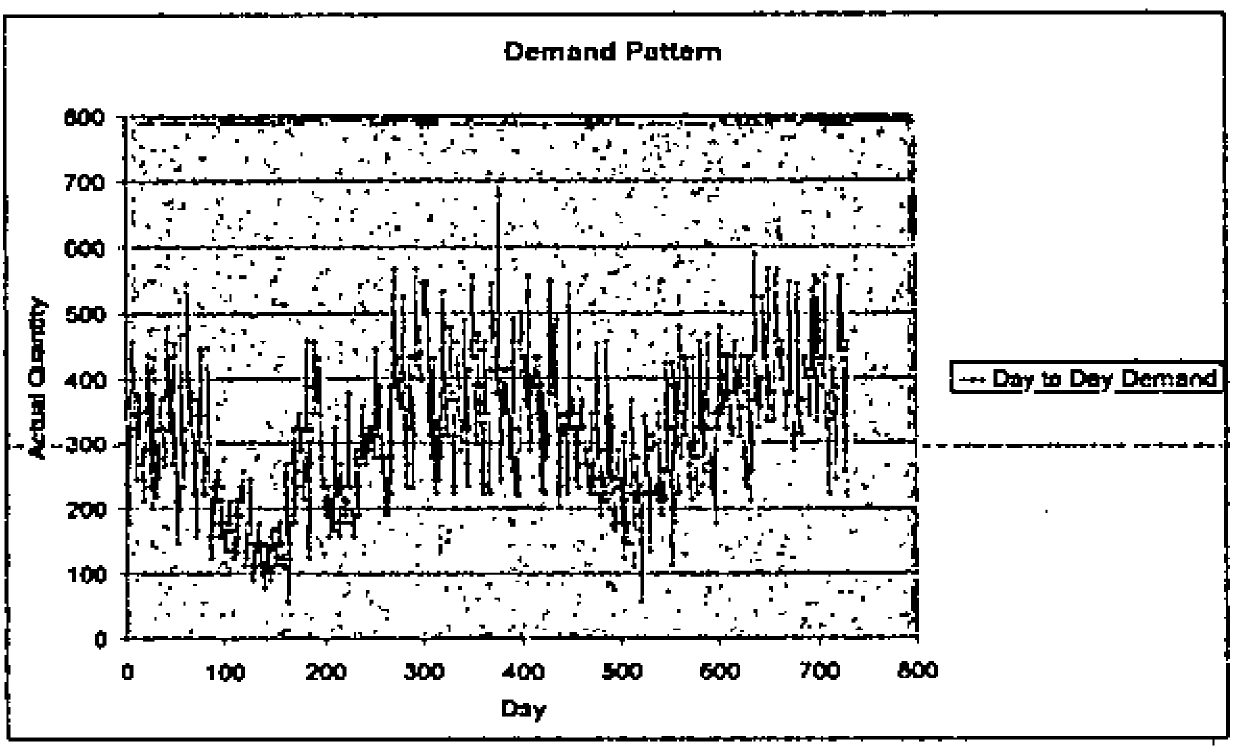

Figure 6.1: Demand pattern of the year 2006 and 2007.

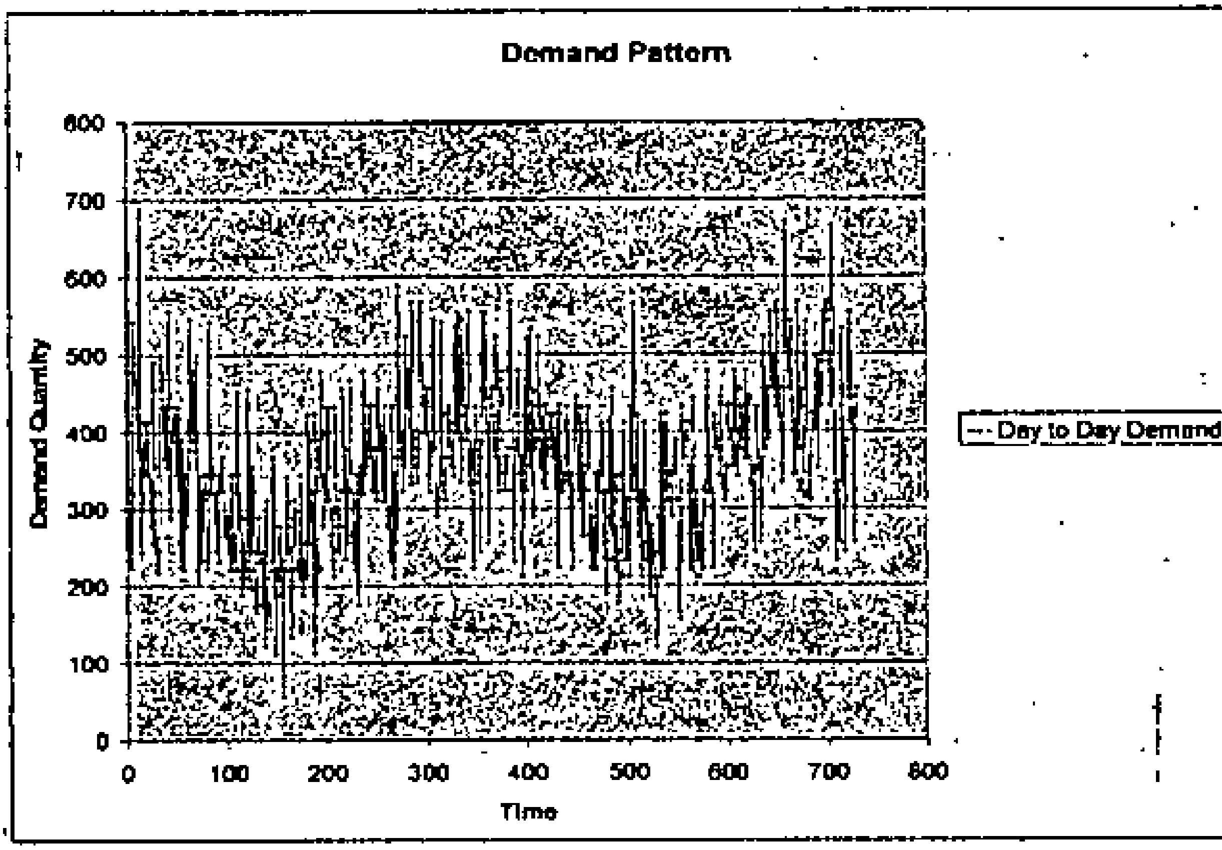

Figure 6.2: Demand pattern of the year 2007 and 2008.

It has been mentioned previously that the actual demand of three years has been collected and analyzed for identifying the demand pattern and influencing factors of demand. Theses data also have been used in developing the proposed algorithm for forecasting demand. For using the past observations in the proposed algorithm it is needed to classify each and every individual data according to the condition of all the demand influencing factors of demand. It has been found that average demand of the different months of the year varied. There is trend effect as well as seasonal effect on the demand quantity of the selected item. To quantify the seasonal effect, all the three years data have been analyzed and seasonal indices have been determined. It has been determined according to different month. One more observation is that the demand of the item for any individual day within each month varies due to the variation in the conditions or the situations of the demand influencing factors. So, it can be mentioned that accurate demand forecast for individual day can not be made by only using seasonal indices that have been determined for each month of a year. The total and average demand quantity of three years and also the seasonal indices of different months have been given in the following tables:

Table 6.1: Total and average demand of 2006 - 2008

			Total Demand		
2006	104612	2007	124149	2008	135188
			Average Demand/Month		
2006	8718	2007	10345	2008	11265

Table 6.2: Seasonal indices of different months

	2006		**2007**		**2008**		**Combined**
Month	**Demand**	**Seasonal Index**	**Demand**	**Seasonal Index**	**Demand**	**Seasonal Index**	**Index**
Jan.	9823.00	1.13	11474.00	1.11	12132.00	1.08	1.10
Feb.	9082.00	1.04	10538.00	1.02	11376.00	1.01	1.02
Mar.	9270.00	1.06	10715.00	1.04	11181.00	0.99	1.03
Apr.	5653.00	0.65	8272.00	0.80	9292.00	0.82	0.76
May	4091.00	0.47	7261.00	0.70	9870.00	0.88	0.68
Jun.	6025.00	0.69	7359.00	0.71	8369.00	0.74	0.72
Jul.	8825.00	1.01	10020.00	0.97	9640.00	0.86	0.95
Aug.	7537.00	0.86	10199.00	0.99	11630.00	1.03	0.96
Sep.	9599.00	1.10	10876.00	1.05	11282.00	1.00	1.05
Oct.	12457.00	1.43	13090.00	1.27	14610.00	1.30	1.33
Nov.	10705.00	1.23	11876.00	1.15	12890.00	1.14	1.17
Dec.	11545.00	1.32	12469.00	1.21	12916.00	1.15	1.23

6.2 RESULT OF HOLT – WINTER'S MODELS

In another study, it has been found that for retail chain demand forecasting Box – Jenkins ARIMA method has been applied. The resulting forecast error had found to be between 22% to 28%. In this study, the proposed algorithm has been compared with one of the existing algorithm that is used often in retail stores. The algorithm is Holt – Winter's forecasting model. The result of the Holt – Winter's model has been given below:

Table 6.3: Results of Holt – Winter's model (weekly demand)

Weekly Demand (Z_t)	L_t	T_t	Seasonal Index (S_θ)	Z'_t	% Error
2390					
2309					
2029					
2419					
1966					
2456					
2485					
2081					
2433					
2268					
2202					
2058					
1298					
1492					
1168					
1146					
1392					
1159					
899					
791					
862					
961					
1101					
1225					
1848					
2115					
2146					
2585					
1526					
1501					
1528					
1735					
1516					
1859					
2045					
2314					
2189					
1715					

2846					
2822					
2246					
2741					
3217					
3168					
2177					
2588					
2669					
2390					
2447					
2481					
2913					
2459					
2356			1.71		
3410			2.00		
2474			1.59		
2538			1.75		
2218			1.47		
3014			1.90		
2667			1.79		
2426			1.55		
2343			1.66		
3138			1.82		
1881			1.41		
2315			1.48		
2212			1.15		
2215			1.22		
1867			0.99		
2077			1.04		
1636			1.00		
2080			1.04		
1518			0.77		
1513			0.73		
1608			0.78		
1455			0.77		
1584			0.85		
1757			0.94		
1788			1.17		
1874			1.28		
2214			1.38		

2446			1.60		
2522			1.24		
1970			1.07		
2238			1.15		
2382			1.26		
1899			1.04		
2377			1.29		
2693			1.43		
2566			1.48		
2643			1.45		
2210			1.17		
2590			1.64		
2764			1.68		
3231			1.60		
2900			1.67		
3174			1.89		
2755			1.76		
2585			1.38		
2546			1.50		
2855			1.60		
3158			1.58		
3143			1.59		
2323			1.38		
2740			1.62		
2805	1225	7.135	1.49		
3065	1297.25	13.65	1.91	2246.35	26.7%
2760	1340.42	16.60	2.02	2714.74	1.6%
2971	1358.08	16.71	1.77	2181.53	26.6%
2499	1405.44	19.77	1.76	2501.20	-0.1%
2494	1424.52	19.70	1.55	2118.43	15.1%
3114	1460.50	21.33	1.97	2812.01	9.7%
2865	1491.88	22.33	1.83	2716.08	5.2%
2637	1519.20	22.83	1.61	2394.88	9.2%
2736	1551.83	23.81	1.69	2611.66	4.5%
2637	1580.05	24.25	1.78	2927.30	-11.0%
2465	1592.19	23.04	1.45	2282.93	7.4%
2184	1623.27	23.85	1.44	2438.83	-11.7%
2718	1634.06	22.54	1.31	1909.85	29.7%
2456	1699.05	26.79	1.29	2108.83	14.1%
1834	1743.79	28.58	1.01	1756.83	4.2%
2386	1776.83	29.03	1.13	1878.02	21.3%

2070	1836.26	32.07	1.04	1864.67	9.9%
2198	1881.15	33.35	1.08	1983.49	9.8%
1977	1927.37	34.64	0.85	1515.18	23.4%
2145	1998.86	38.32	0.83	1482.19	30.9%
2666	2091.51	43.75	0.93	1660.25	37.7%
2231	2209.43	51.17	0.84	1732.07	22.4%
1720	2300.37	55.15	0.82	2002.53	-16.4%
1476	2329.87	52.58	0.85	2239.61	-51.7%
2070	2318.25	46.16	1.09	2760.80	-33.4%
2302	2318.72	41.59	1.19	3024.99	-31.4%
2069	2316.92	37.25	1.24	3253.69	-57.3%
2600	2286.24	30.46	1.46	3696.23	-42.2%
2419	2263.36	25.13	1.19	2832.49	-17.1%
1760	2263.42	22.62	0.98	2447.10	-39.0%
2415	2236.55	17.67	1.13	2590.36	-7.3%
2312	2242.84	16.53	1.19	2836.09	-22.7%
2770	2228.06	13.40	1.10	2335.66	15.7%
2523	2268.59	16.11	1.23	2936.70	-16.4%
2834	2260.79	13.72	1.38	3250.42	-14.7%
2786	2252.95	11.57	1.41	3350.73	-20.3%
2862	2236.12	8.73	1.40	3259.09	-13.9%
2353	2224.75	6.72	1.14	2610.76	-11.0%
2471	2215.40	5.11	1.49	3652.06	-47.8%
3140	2164.76	-0.46	1.61	3627.30	-15.5%
3509	2143.10	-2.58	1.61	3429.47	2.3%
3011	2144.05	-2.23	1.59	3578.74	-18.9%
3790	2116.89	-4.72	1.86	3996.53	-5.4%
2896	2104.54	-5.49	1.64	3690.13	-27.4%
2846	2065.37	-8.85	1.38	2846.25	0.0%
2679	2056.76	-8.83	1.44	3073.92	-14.7%
3021	2029.00	-10.72	1.57	3231.34	-7.0%
3553	2009.18	-11.63	1.64	3162.95	11.0%
3650	2014.59	-9.93	1.66	3189.87	12.6%
2166	2024.42	-7.95	1.29	2792.38	-28.9%
2718	1982.68	-11.33	1.55	3198.29	-17.7%
2915	1949.92	-13.47	1.49	2884.16	1.1%

The MAPE is around 18.5 %.

The above model has been applied for day to day demand also. The MAPE has been found to be 25.2% for one year. The result for last one month (December 2008) has been given below:

Table 6.4: Result of Holt – Winter's model (day to day demand)

Actual (Z_t)	**L_t**	**T_t**	**S_θ**	**Forecast (Z'_t)**	**Error**	**% Error**
567	667.7	6.4	0.8	486.5	80.5	14.2%
543	681.3	7.1	0.9	607.0	64.0	11.8%
489	682.9	6.6	0.8	539.7	50.7	10.4%
476	684.6	6.1	0.7	498.3	22.3	4.7%
432	688.4	5.8	0.6	405.1	26.9	6.2%
489	697.2	6.1	0.6	440.4	48.6	9.9%
665	708.3	6.6	0.7	448.3	216.7	32.6%
556	735.7	8.7	0.7	507.1	48.9	8.8%
321	749.0	9.2	0.6	558.6	237.6	74.0%
234	732.2	6.6	0.6	569.4	335.4	143.3%
322	701.7	2.9	0.6	420.8	98.8	30.7%
334	692.1	1.6	0.5	309.1	24.9	7.5%
267	697.5	2.0	0.4	304.5	37.5	14.1%
256	693.1	1.4	0.5	401.4	145.4	56.8%
432	674.7	-0.6	0.7	498.6	66.6	15.4%
532	667.6	-1.3	0.8	508.2	23.8	4.5%
389	668.5	-1.1	0.7	506.7	117.7	30.3%
345	655.8	-2.2	0.7	550.3	205.3	59.5%
244	634.4	-4.1	0.6	402.7	158.7	65.0%
367	610.6	-6.1	0.6	403.5	36.5	9.9%
387	600.7	-6.5	0.6	351.8	35.2	9.1%
454	598.5	-6.1	0.7	366.6	87.4	19.3%
554	601.9	-5.1	0.9	510.2	43.8	7.9%
443	600.5	-4.7	0.8	474.1	31.1	7.0%
554	593.1	-5.0	0.8	428.9	125.1	22.6%
443	599.3	-3.9	0.7	421.6	21.4	4.8%
342	597.6	-3.7	0.5	294.7	47.3	13.8%
256	600.5	-3.0	0.4	242.1	13.9	5.4%
323	599.9	-2.8	0.6	411.2	88.2	27.3%
444	587.6	-3.7	0.8	453.2	9.2	2.1%
456	583.2	-3.8	0.7	383.0	73.0	16.0%

The actual and forecasted demand of 15 days has been shown in the following figure:

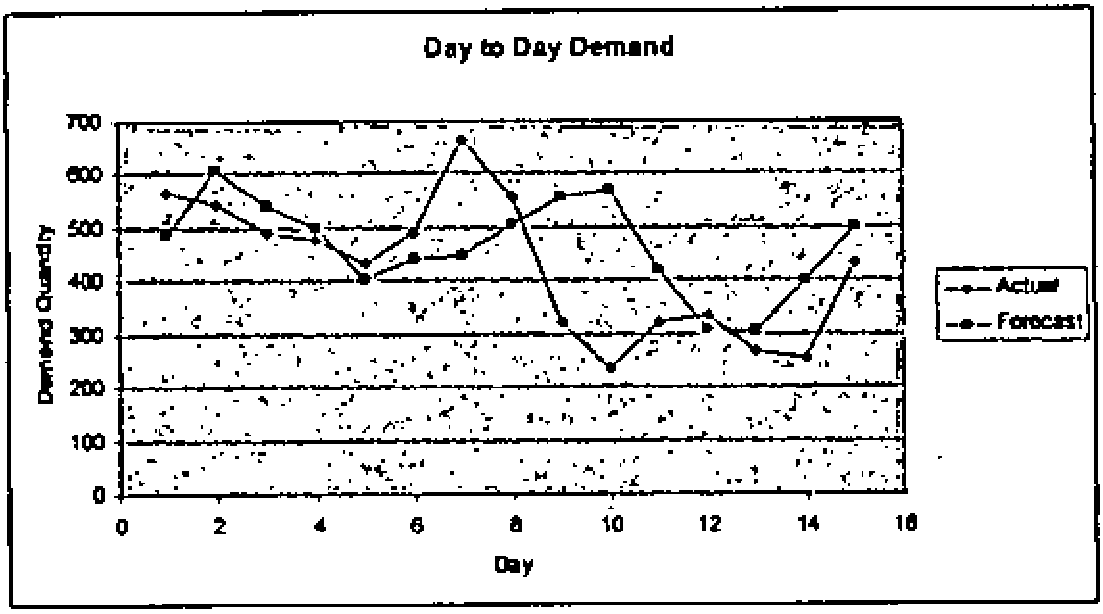

Figure 6.3: Actual demand vs forecasted demand.

6.3 RESULT OF NEURAL NETWORK

The result of neural network algorithm has been given in the following tables and figures:

Table 6.5: Actual and forecasted demand of 15 days

Actual	Forecasted	Error
567	636	12.21%
543	571	5.22%
489	461	5.89%
476	507	6.42%
432	403	6.88%
489	404	17.45%
665	793	19.34%
556	531	4.56%
321	357	11.32%
234	191	18.67%
322	311	3.44%
334	384	15.20%
267	235	12.30%
256	273	6.78%
432	407	5.88%

Table 6.6: % error and MAPE of 15 days

Day	% Error	MAPE
1	12.21	
2	5.22	
3	5.89	
4	6.42	
5	6.88	
6	17.45	
7	19.34	10.104
8	4.56	
9	11.32	
10	18.67	
11	3.44	
12	15.2	
13	12.3	
14	6.78	
15	5.88	

The graphical representation of the error has been given below:

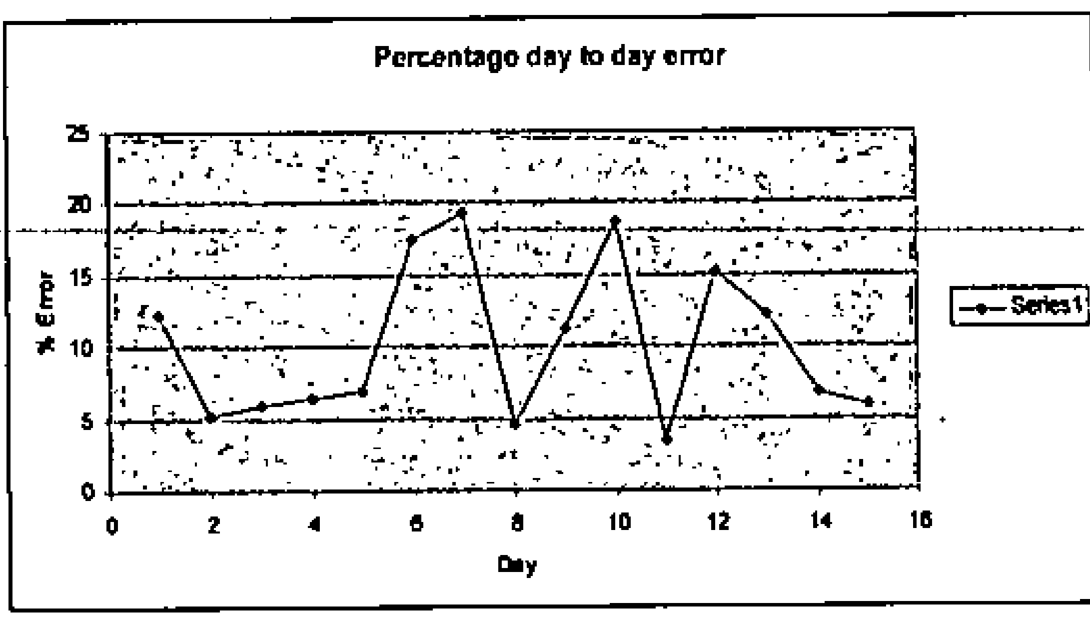

Figure 6.4: Day to day error.

The graphical representation of actual demand and forecasted demand has been shown in the following figure.

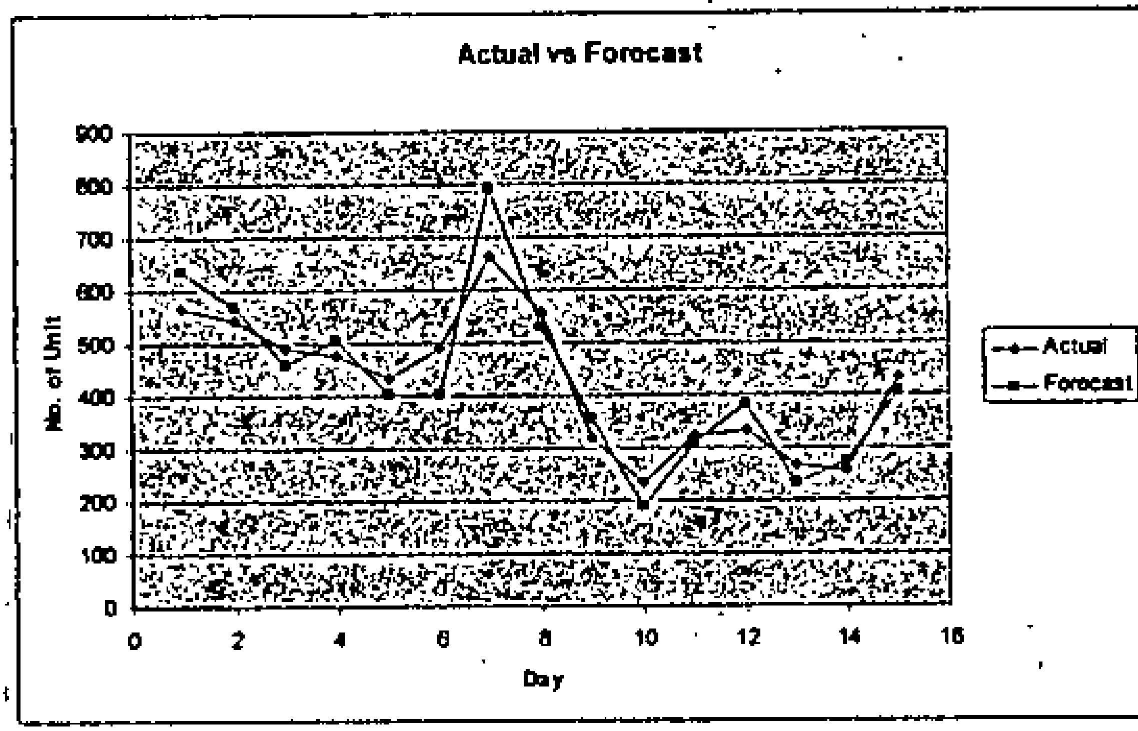

Figure 6.5: Actual demand vs forecasted demand.

6.4 COMPARISION

The proposed neural network based forecasting algorithm forecast demand on day basis and also can take into account many judgmental factors in predicting the forecast. Moreover, it forecasts the demand 15 days before so that necessary actions can be taken by the authority in case of any kind of shortage. It will definitely decrease the inventory level and by doing so it will reduce the inventory cost. By knowing the probable demand of any particular day necessary actions can be taken. In that way service to the customers can be improved, customer satisfaction level will surely rise. Forecasting developed through artificial neural network has much reduced mean absolute percentage error than any other existing algorithm used in the field of retail demand forecasting. The developed algorithm has been compared with one of the current algorithm that is Holt – Winter's model of forecasting in order to compare the accuracy of the developed neural network based algorithm. It has been found that due to the large amount of variation in day to day demand the Holt – Winter's model has large amount of forecasting error though it can accurate forecast the trend and also the seasonal effect. On the other hand, the developed algorithm has very low amount of forecast error because it takes into account the day to day change of the influencing factors. The MAPE of the neural network based algorithm is about 10.1% whereas the MAPE of Holt – Winter's model (weekly demand) is around 18.5%. If Holt – Winter's model is applied for day to day demand forecasting, then mean absolute percentage error is about 25.2% although huge amount of past data has been used for developing the forecast. For the 15 days test period, the MAPE is 29.4% for Holt – Winter's model. So, with confidence it can be mentioned that the developed algorithm will work better than the existing algorithm where there is random variation in the demand and also the trend and seasonality effect. By comparing the figure 6.3 and figure 6.5 it can be clearly mentioned that forecasted demand by neural network algorithm is much closer to the actual demand than forecasted demand by Holt – Winter's model. In the following table, the results of both models have been given.

Table 6.7: Resnlt of both models

Day	Actual Demand	Forecast by NN	Forecast by Holt–Winter's Model	% Error in NN	% Error in Holt-Winter's Model
1	567	636	487	12.21	14.2
2	543	571	607	5.22	11.8
3	489	461	540	5.89	10.4
4	476	507	499	6.42	4.7
5	432	403	405	6.88	6.2
6	489	404	441	17.45	9.9
7	665	793	448	19.34	32.6
8	556	531	507	4.56	8.8
9	321	357	559	11.32	74.0
10	234	191	569	18.67	143.3
11	322	311	421	3.44	30.7
12	334	384	309	15.2	7.5
13	267	235	305	12.3	14.1
14	256	273	402	6.78	56.8
15	432	407	499	5.88	15.4

It is clearly found that forecasting demand by neural network algorithm has less amount of error for the test period. The MAPE of developed neural network forecasting algorithm is abont 10.1% whereas the MAPE of Holt – Winter's model in forecasting day to day demand is 29.4% for the test period of 15 days. Day to day demand comparison of Holt – Winter's model and neural network algorithm has been shown in the following figure.

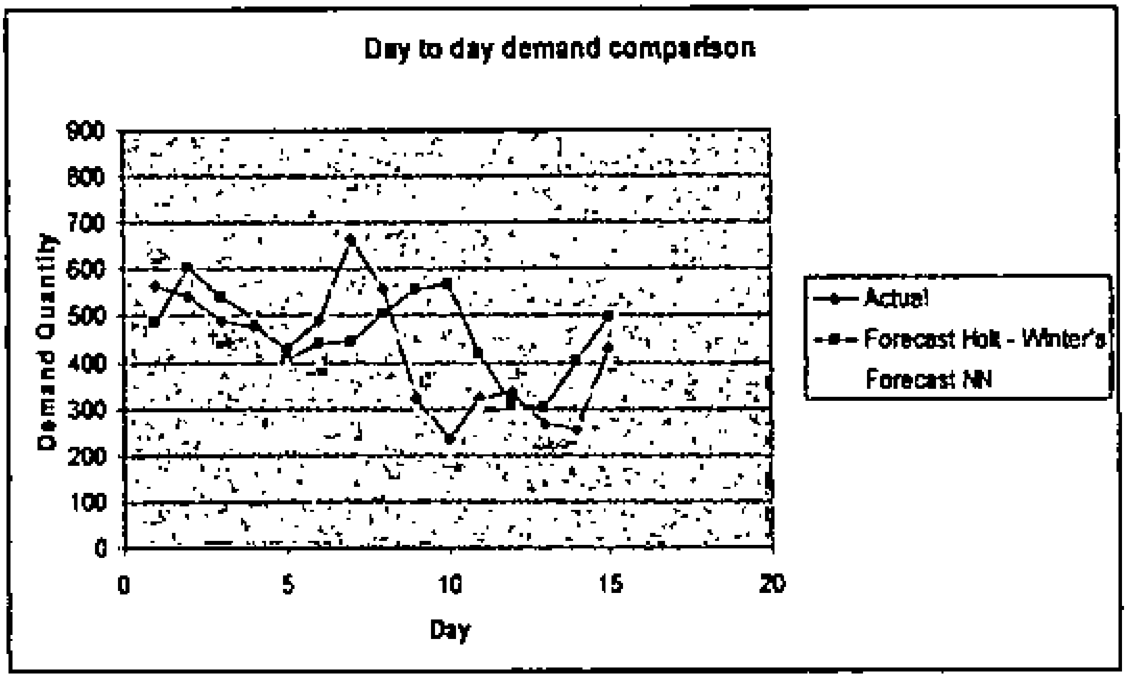

Figure 6.6: Graphical representation of actual vs forecasted demand.

It is clear that forecasted demand by neural network algorithm is closer to the actual demand quantity. The developed neural network based forecasting algorithm accurately mapping the nonlinearity of the demand pattern.

CHAPTER 7

CONCLUSION AND RECOMMENDATIONS

7.1 CONCLUSION

The objectives of this research work have been mentioned in the introductory section. The demand pattern of the selected item in the retail store has been studied and various factors have been identified as having influence behind the demand quantity. Demand forecasting is a very important part in the overall supply chain in retail organizations. The whole efficiency of retail organizations depend mainly on efficient and accurate demand forecasting. So, an algorithm which can accurately forecast the demand will have a major role in achieving the objective of any retail organizations. A neural network based algorithm has been developed in this work in order to predict the daily demand of the selected item in a retail super store. The developed algorithm is mainly quantitative method of forecasting which also takes into consideration some qualitative issues also. The developed algorithm has been compared with an existing forecasting algorithm which is used very often for retail store demand forecasting. The forecasting error of the developed algorithm is found to be very low compared to the other existing algorithms used in the field of retail demand forecasting. If the forecasting error can be decreased by 1% it is said that about 2% inventory cost can be decreased. Moreover, efficient demand forecasting will ensure that customers get their desired items in the self. In that way, customer satisfaction level will increase and better service to the customer can be given. The developed algorithm is better than most of the existing algorithm because it takes into account many factors that are ignored otherwise. It also quantifies the effect of many demand influencing factors which are very difficult to quantify. So, it can be said that the algorithm that has been developed in this research work will work efficiently.

7.2 RECOMMENDATIONS

The developed algorithm has lower amount of forecast error compared to the existing algorithms used in the field of retail sector forecasting. It takes into account the past observations as well as some underlying factors influencing the demand.

During the study period, it has been observed that some more improvements can be made in the developed algorithm. But due to the time limitation of the research work those observation cannot be applied in the developed algorithm. The recommendations have been given below:

- The demand pattern should be analyzed more in order to identify more demand influencing factors. Because, there can be some hidden demand influencing factors that has not been identified in the present study.
- Each factor that is influencing the demand has multiple level of their condition. Each of these levels has to be determined accurately. In the current study, some of these levels have been identified. But there can be more levels of the demand influencing factors.
- There is uncertainty in any kind of demand forecasting. The uncertainty can be handled more effectively with fuzzy logic. So, neuro - fuzzy logic can be applied in developing an algorithm for predicting forecast. Fuzzy logic will incorporate the uncertainty better than any other algorithm.
- For one fast moving item an algorithm has been developed. To compare the efficiency of the developed algorithm the algorithm has to be applied for other items also. The algorithm also has to be applied for different items that have different demand pattern.
- In order to optimize the individual weight accumulated in each input node particle swapping algorithm can be applied. It will take each input node weight as a particle and for overall particle set it will try to identify the optimum weight of each node. This will result in more accurate forecasting.

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APPENDICES

Training Codes:

```
function train_fn

%Data from File (Data range in excel file 2-10951)
data_all = xlsread('DatafileANN.xls','Practical','B3:M1097');
j=1;
for i = 1:1095
   data(i,:) = data_all(j,:);
   j=j+1;
end

clear data_all;

t_row = 1064;  % t_row (Number of training rows)
t_column = 11; % t_column (Number of training column)
p = data(1:t_row, 2:t_column+1);
t = data(1:t_row, 1:1);
%Formating
p = p';
t = t';
%Normalization
[pn,ps] = mapminmax(p);
[tn,ts] = mapminmax(t);

%Network Creation
net = newff(pn,tn,6, {'tansig' 'tansig'}, 'traingdm');
%Parameter Setting
net.trainParam.epochs= 50000;
net.trainParam.goal = 0.00001;
net.trainParam.show = NaN; %Hide Outputs
%net.trainParam.mem_reduc = 4;

net_backup = net;

% Training with Validation
net.divideParam.trainRatio = 0.8;
net.divideParam.valRatio = 0.2;
net.divideParam.testRatio = 0.0;
[net,tr] = train(net,pn,tn);

net = net_backup;

% Parameter Update for final Training
net.trainParam.epochs = length(tr.epoch) - 1;
net.divideParam.trainRatio = 1;
net.divideParam.valRatio = 0;
net.divideParam.testRatio = 0;

% Final Training
net = train(net,pn,tn);
```

```
save trainnet1 net ps ts data t_row t_column;
%%%%%%
xi_ori=net.iw{1,1}; % Input Layer Weight Matrix
xl_ori=net.lw{2,1};
[res_ori, min_nn, max_nn, std_nn,target, output_nn] = sim_fn(xi_ori, xl_ori, 15); % Result before
PSO

result_ann = [res_ori min_nn max_nn std_nn] % Result With NN weight
save sim_result_for_graph1 target output_nn;
%target
%Saving the Network
```

Graph.

Simulation Codes:

```
function [MAPE, MIN, MAX, STD. t, y1] = sim_fn(wi, wl, days)

load trainnet1; %Load network and Data
%Modify Network
net.iw{1,1}=wi;
net.lw{2,1}=wl;

s_start = t_row + 1 % Simulation Starts where train ends
s_end = s_start + days -1; %Simulation end

p = data(s_start:s_end, 2:t_column+1);
t = data(s_start:s_end, 1:1);
p = p'
t = t';
pn = mapminmax('apply',p,ps);
tn = mapminmax('apply',t,ts);

% Simulation
Y = sim(net,pn,[],[],tn);

% Calculation
y1 =  mapminmax('reverse',Y,ts);
err = abs(t-y1); % Absolute Error
per_err = (err ./ t) * 100 % Percentage Error


MAPE = mean(per_err);
MIN = min(per_err);
MAX = max(per_err);
STD = std(per_err);
```

Graph Codes:

```
clear;
load sim_result_for_graph1
len = length(target);
x = 1:1:len;

figure(1)
set(gcf,'DefaultAxesColorOrder',[1 0 0;0 1 0])
plot(x,target, x,output_nn);
title('Output of ANN against Actual Load');
legend('Actual', 'ANN', -1);
xlabel('Days Ahead');
ylabel('Output (Demand)');

grid on,
```

Day	Demand	Weekend	Holiday	Festival	Promotionl 1	Promotional 2	Availability	Starting of the month	Price	Total number of customer	Higher share product available	Weather Conditions
Jan1(01.01.2006)	234	no	no	no	no	no	medium	no	medium	medium	medium	cold
2	236	no	no	no	no	no	low	no	medium	medium	medium	normal
3	229	no	no	no	no	no	low	no	medium	medium	medium	cold
4	224	no	no	no	no	no	low	no	medium	high	medium	cold
5	412	no	no	no	no	no	high	yes	medium	medium	medium	normal
6	478	yes	no	no	yes	no	high	yes	medium	high	medium	normal
7	543	yes	no	yes	yes	no	high	yes	medium	high	medium	normal
8	489	no	no	yes	yes	no	high	yes	medium	high	high	normal
9	467	no	no	yes	yes	no	high	yes	medium	high	high	normal
10	433	no	no	yes	yes	no	medium	yes	medium	high	medium	normal
11	378	no	no	yes	yes	no	high	yes	medium	low	high	normal
12	398	no	no	yes	yes	no	high	yes	medium	high	high	normal
13	567	yes	no	yes	yes	no	high	yes	medium	high	high	normal
14	678	yes	no	yes	yes	no	high	yes	medium	high	high	normal
15	244	no	no	yes	yes	no	medium	yes	medium	medium	medium	cold
16	367	no	no	yes	no	no	high	no	medium	high	high	normal
17	367	no	no	yes	no	no	high	no	medium	high	high	normal
18	412	no	no	no	no	yes	high	no	medium	high	high	normal
19	345	no	no	no	no	yes	high	no	medium	high	high	normal
20	390	yes	no	no	no	yes	high	no	medium	high	high	normal
21	349	yes	no	no	no	yes	high	no	medium	high	low	normal
22	413	no	no	no	no	yes	high	no	medium	high	high	normal
23	311	no	no	no	no	yes	high	no	medium	high	medium	normal
24	278	no	no	no	no	yes	high	no	medium	high	high	normal
25	334	no	no	no	no	yes	high	no	medium	high	high	normal
26	256	no	no	no	no	no	high	no	medium	medium	medium	normal
27	456	yes	no	no	no	no	high	no	medium	high	high	normal
28	490	yes	no	no	no	no	high	no	medium	high	high	normal
29	256	no	no	no	no	no	medium	no	medium	medium	medium	normal
30	222	no	no	no	no	no	medium	no	medium	medium	medium	normal
31	218	no	no	no	no	no	medium	no	medium	medium	medium	normal

1-Feb	248	no	no	no	no	no	medium	no	medium	high	high	normal
2	321	no	no	no	no	no	medium	no	medium	high	high	normal
3	456	yes	yes	no	no	no	medium	no	medium	high	high	normal
4	499	yes	no	no	no	no	high	no	medium	high	high	normal
5	469	no	no	no	no	no	high	yes	medium	high	high	normal
6	432	no	no	no	no	yes	high	yes	medium	high	high	normal
7	367	no	no	no	no	yes	high	yes	low	high	high	normal
8	401	no	no	no	no	yes	high	yes	low	high	high	normal
9	433	no	no	no	no	yes	high	yes	low	high	high	normal
10	356	yes	no	no	no	yes	high	yes	low	high	medium	normal
11	556	yes	no	no	no	yes	medium	yes	low	medium	medium	few rain
12	289	no	no	no	no	yes	high	yes	low	high	high	normal
13	378	no	no	no	no	yes	high	yes	low	high	high	normal
14	389	no	no	no	no	yes	high	yes	low	high	medium	normal
15	401	no	no	no	no	yes	high	yes	low	high	high	normal
16	388	no	no	no	no	yes	high	no	low	high	high	normal
17	433	yes	no	no	no	yes	high	no	low	high	high	normal
18	389	yes	no	no	no	yes	high	no	low	high	high	normal
19	345	no	no	no	no	no	high	no	low	high	high	normal
20	354	no	no	no	no	no	high	no	low	high	high	normal
21	432	no	yes	no	no	no	high	no	low	high	high	normal
22	334	no	no	no	no	no	high	no	low	high	high	normal
23	226	no	no	no	no	no	medium	no	medium	medium	medium	normal
24	390	yes	no	no	no	no	medium	no	medium	medium	medium	normal
25	345	yes	no	no	no	no	medium	no	medium	high	medium	normal
26	222	no	no	no	no	no	medium	no	medium	high	medium	normal
27	345	no	no	no	no	no	medium	no	medium	high	medium	normal
28	342	no	no	no	no	no	medium	no	medium	high	medium	normal

1-Mar	278	no	no	no	no	no	medium	no	medium	high	medium	normal
2	311	no	yes	no	no	no	medium	no	medium	high	medium	normal
3	378	yes	yes	no	no	no	high	no	medium	high	high	normal
4	467	yes	no	no	no	no	high	no	medium	high	high	normal
5	547	no	no	no	no	no	high	yes	medium	high	high	normal
6	389	no	no	no	yes	no	high	yes	medium	high	medium	normal
7	435	no	no	no	yes	no	high	yes	medium	high	high	normal
8	478	no	no	no	yes	no	high	yes	medium	high	high	normal
9	376	no	no	no	yes	no	high	yes	medium	high	high	normal
10	423	yes	no	no	yes	no	high	yes	medium	high	high	normal
11	490	yes	no	no	yes	no	high	yes	medium	high	medium	normal
12	222	no	no	no	yes	no	high	yes	medium	low	medium	hot
13	202	no	no	no	yes	no	high	yes	medium	medium	medium	hot
14	234	no	no	no	yes	no	high	yes	medium	medium	medium	normal
15	342	no	no	no	yes	no	high	yes	medium	high	high	normal
16	234	no	no	no	no	no	high	no	medium	medium	medium	normal
17	324	yes	no	no	no	no	high	no	medium	medium	medium	normal
18	323	yes	no	no	no	no	high	no	medium	medium	medium	normal
19	314	no	no	no	no	no	high	no	medium	medium	medium	normal
20	345	no	no	no	no	no	high	no	medium	medium	medium	normal
21	223	no	no	no	no	no	high	no	medium	medium	medium	few rain
22	245	no	no	no	no	no	high	no	medium	medium	medium	few rain
23	323	no	no	no	no	no	high	no	medium	high	high	normal
24	543	yes	no	no	no	no	high	no	medium	high	high	normal
25	322	yes	no	no	no	no	high	no	medium	high	high	normal
26	367	no	no	no	no	no	high	no	medium	high	high	normal
27	356	no	no	no	no	yes	high	no	medium	high	high	normal
28	345	no	no	no	no	yes	high	no	medium	medium	high	normal
29	312	no	no	no	no	yes	high	no	medium	medium	high	normal
30	245	no	no	no	no	yes	high	no	medium	medium	medium	few rain
31	322	yes	no	no	no	yes	high	no	medium	high	high	hot

1-Apr	265	yes	no	no	no	yes	high	no	medium	medium	high	hot
2	232	no	no	no	no	yes	high	no	medium	medium	high	hot
3	345	no	no	no	no	yes	high	no	medium	medium	high	hot
4	324	no	no	no	no	yes	high	no	medium	high	high	normal
5	356	no	no	no	no	yes	high	yes	medium	high	high	normal
6	367	no	no	no	no	yes	high	yes	medium	high	high	normal
7	324	yes	no	no	no	yes	high	yes	medium	high	high	normal
8	267	yes	no	no	no	yes	high	yes	medium	high	high	normal
9	267	no	no	no	no	yes	high	yes	medium	high	high	normal
10	289	no	no	no	no	yes	high	yes	medium	high	high	normal
11	265	no	no	no	no	yes	high	yes	medium	high	high	normal
12	245	no	no	no	no	yes	high	yes	medium	high	high	few rain
13	222	no	no	no	no	no	medium	yes	medium	high	medium	hot
14	234	yes	no	no	no	no	medium	yes	medium	high	medium	hot
15	345	yes	no	no	no	no	medium	yes	medium	high	medium	normal
16	233	no	no	no	no	no	medium	no	medium	high	medium	normal
17	267	no	no	no	no	no	high	no	medium	high	high	normal
18	234	no	no	no	no	no	high	no	medium	high	medium	normal
19	223	no	no	no	no	no	high	no	medium	high	medium	hot
20	322	no	no	no	no	no	high	no	medium	high	medium	normal
21	453	yes	no	no	no	no	high	no	medium	high	medium	normal
22	345	yes	no	no	no	no	medium	no	medium	high	medium	normal
23	245	no	no	no	no	no	medium	no	medium	high	medium	normal
24	189	no	no	no	no	no	medium	no	medium	low	medium	normal
25	211	no	no	no	no	no	medium	no	medium	low	medium	normal
26	289	no	no	no	no	no	medium	no	medium	medium	medium	normal
27	223	no	no	no	no	yes	medium	no	medium	medium	medium	normal
28	245	yes	no	no	no	yes	medium	no	medium	medium	medium	normal
29	234	yes	no	no	no	yes	medium	no	medium	medium	medium	few rain
30	212	no	no	no	no	yes	medium	no	medium	medium	medium	few rain

1-May	456	no	yes	no	no	yes	medium	no	medium	high	medium	normal
2	310	no	no	no	no	yes	medium	no	medium	high	medium	normal
3	199	no	no	no	no	yes	medium	no	medium	high	medium	normal
4	223	no	no	no	no	yes	medium	no	medium	high	high	normal
5	356	yes	no	no	no	yes	medium	yes	medium	medium	medium	hot
6	324	yes	no	no	no	yes	medium	yes	medium	medium	high	normal
7	174	no	no	no	no	yes	medium	yes	medium	medium	high	normal
8	245	no	no	no	no	yes	medium	yes	medium	medium	high	normal
9	167	no	no	no	no	yes	medium	yes	medium	medium	medium	normal
10	178	no	no	no	no	yes	medium	yes	medium	medium	medium	normal
11	231	no	no	no	no	yes	medium	yes	medium	high	medium	normal
12	289	yes	no	no	no	yes	high	yes	medium	high	high	normal
13	234	yes	no	no	no	yes	high	yes	medium	high	high	normal
14	234	no	no	no	no	yes	high	yes	medium	high	high	normal
15	176	no	no	no	no	no	high	yes	medium	medium	high	hot
16	213	no	no	no	no	no	high	no	medium	medium	high	hot
17	243	no	no	no	no	no	high	no	medium	high	high	hot
18	123	no	no	no	no	no	high	no	medium	high	medium	normal
19	312	yes	no	no	no	no	high	no	medium	high	medium	normal
20	212	yes	no	no	no	no	high	no	medium	high	medium	normal
21	167	no	no	no	no	no	high	no	medium	high	medium	normal
22	176	no	no	no	no	no	high	no	medium	medium	high	few rain
23	145	no	no	no	no	no	high	no	medium	medium	medium	few rain
24	221	no	no	no	no	no	high	no	medium	high	high	normal
25	233	no	no	no	no	no	high	no	medium	high	high	normal
26	367	yes	no	no	no	no	medium	no	medium	medium	medium	hot
27	299	yes	no	no	no	no	medium	no	medium	high	high	normal
28	111	no	no	no	no	no	medium	no	medium	high	high	normal
29	211	no	no	no	no	no	medium	no	medium	medium	medium	normal
30	222	no	no	no	no	no	medium	no	medium	high	medium	normal
31	210	no	no	no	no	no	medium	no	medium	high	medium	normal

1-Jun	278	no	no	no	no	no	medium	no	medium	high	high	normal
2	189	yes	no	no	no	no	medium	no	medium	medium	medium	normal
3	234	yes	no	no	no	no	medium	no	medium	medium	medium	normal
4	167	no	no	no	no	no	medium	no	medium	medium	medium	few rain
5	56	no	no	no	no	no	medium	yes	medium	low	medium	rain
6	223	no	no	no	yes	no	medium	yes	medium	medium	medium	normal
7	221	no	no	no	yes	no	medium	yes	medium	medium	medium	normal
8	267	no	no	no	yes	no	medium	yes	medium	high	medium	normal
9	342	yes	no	no	yes	no	medium	yes	medium	high	medium	normal
10	308	yes	no	no	yes	no	medium	yes	medium	high	medium	normal
11	276	no	no	no	yes	no	medium	yes	medium	high	medium	normal
12	223	no	no	no	yes	no	medium	yes	medium	high	medium	normal
13	134	no	no	no	yes	no	medium	yes	medium	medium	medium	few rain
14	223	no	no	no	yes	no	medium	yes	medium	medium	medium	few rain
15	289	no	no	no	yes	no	medium	yes	medium	medium	high	normal
16	312	yes	no	no	yes	no	medium	no	medium	medium	high	normal
17	298	yes	no	no	yes	no	medium	no	medium	medium	medium	normal
18	298	no	no	no	yes	no	medium	no	medium	high	medium	normal
19	223	no	no	no	yes	no	medium	no	medium	medium	medium	normal
20	232	no	no	no	yes	no	medium	no	medium	medium	medium	normal
21	222	no	no	no	yes	no	medium	no	medium	medium	medium	normal
22	212	no	no	no	no	no	medium	no	medium	medium	medium	normal
23	345	yes	no	no	no	no	medium	no	medium	medium	high	hot
24	256	yes	no	no	no	no	medium	no	medium	medium	medium	normal
25	189	no	no	no	no	no	medium	no	medium	medium	medium	normal
26	234	no	no	no	no	no	medium	no	medium	medium	medium	normal
27	212	no	no	no	no	no	medium	no	medium	medium	medium	normal
28	256	no	no	no	no	no	medium	no	medium	high	medium	normal
29	215	no	no	no	no	no	medium	no	medium	high	medium	normal
30	423	yes	no	no	no	no	medium	no	medium	high	medium	normal

1-Jul	345	yes	no	no	no	no	medium	no	medium	high	medium	normal
2	256	no	no	no	no	no	medium	no	medium	high	medium	normal
3	389	no	no	no	no	no	medium	no	medium	high	medium	normal
4	323	no	no	no	no	no	medium	no	medium	high	medium	normal
5	322	no	no	no	no	no	medium	yes	medium	high	medium	normal
6	112	no	no	no	no	no	medium	yes	medium	medium	medium	few rain
7	423	yes	no	no	no	no	medium	yes	medium	medium	medium	few rain
8	389	yes	no	no	no	no	high	yes	low	high	high	normal
9	178	no	no	no	no	no	high	yes	low	high	high	normal
10	378	no	no	no	no	no	high	yes	low	high	high	normal
11	354	no	no	no	no	yes	high	yes	low	high	high	normal
12	390	no	no	no	no	yes	high	yes	low	high	high	normal
13	223	no	no	no	no	yes	high	yes	low	medium	high	few rain
14	478	yes	no	no	no	yes	high	yes	low	medium	high	few rain
15	445	yes	no	no	no	yes	high	yes	low	high	high	normal
16	278	no	no	no	no	yes	high	no	low	high	high	normal
17	345	no	no	no	no	yes	high	no	low	high	high	normal
18	322	no	no	no	no	yes	high	no	low	high	high	normal
19	432	no	yes	no	no	yes	high	no	low	high	high	normal
20	312	no	no	no	no	yes	high	no	low	high	high	normal
21	432	yes	no	no	no	yes	high	no	low	medium	high	normal
22	401	yes	no	no	no	yes	medium	no	low	high	medium	normal
23	267	no	no	no	no	yes	high	no	low	high	high	normal
24	234	no	no	no	no	yes	high	no	low	medium	medium	few rain
25	234	no	no	no	no	no	high	no	medium	medium	medium	normal
26	213	no	no	no	no	no	high	no	medium	medium	medium	normal
27	245	no	no	no	no	no	high	no	medium	medium	medium	normal
28	432	yes	no	no	no	no	high	no	medium	high	medium	normal
29	345	yes	no	no	no	no	high	no	medium	high	medium	normal
30	278	no	no	no	no	no	high	no	medium	high	high	normal
31	245	no	no	no	no	no	medium	no	medium	medium	medium	normal

1-Aug	222	no	no	no	no	no	medium	no	medium	medium	medium	normal
2	278	no	no	no	no	no	medium	no	medium	medium	medium	normal
3	324	no	no	no	no	no	high	no	medium	high	high	normal
4	456	yes	no	no	no	no	medium	no	medium	medium	medium	normal
5	435	yes	no	no	no	no	high	yes	medium	high	high	normal
6	235	no	no	no	no	no	high	yes	medium	high	high	normal
7	332	no	no	no	no	no	high	yes	medium	high	medium	normal
8	378	no	yes	no	no	no	high	yes	medium	high	medium	normal
9	256	no	no	no	no	no	medium	yes	medium	medium	medium	normal
10	324	no	no	no	no	no	medium	yes	medium	medium	medium	normal
11	390	yes	no	no	no	no	medium	yes	medium	medium	medium	normal
12	467	yes	no	no	no	no	high	yes	medium	high	high	normal
13	267	no	no	no	no	no	high	yes	medium	high	medium	normal
14	321	no	no	no	no	no	high	yes	medium	medium	medium	normal
15	232	no	no	no	no	no	medium	yes	medium	medium	medium	normal
16	256	no	no	no	no	no	high	no	medium	high	medium	normal
17	222	no	no	no	no	no	medium	no	medium	medium	medium	normal
18	345	yes	no	no	no	no	medium	no	medium	medium	high	few rain
19	256	yes	no	no	no	no	medium	no	medium	medium	medium	few rain
20	176	no	no	no	no	yes	medium	no	medium	medium	medium	normal
21	289	no	no	no	no	yes	medium	no	medium	medium	medium	normal
22	323	no	no	no	no	yes	medium	no	medium	high	medium	normal
23	355	no	no	no	no	yes	high	no	medium	high	high	normal
24	321	no	no	no	no	yes	high	no	medium	high	high	normal
25	478	yes	no	no	no	yes	high	no	medium	high	high	normal
26	435	yes	no	no	no	yes	high	no	medium	high	high	normal
27	345	no	no	no	no	yes	high	no	medium	high	high	normal
28	356	no	no	no	no	yes	high	no	medium	high	high	normal
29	356	no	no	no	no	yes	high	no	medium	high	high	normal
30	402	no	no	no	no	yes	high	no	medium	high	high	normal
31	367	no	no	no	no	yes	high	no	medium	medium	high	normal

1-Sep	432	yes	no	no	no	yes	high	no	medium	medium	high	normal
2	435	yes	no	no	no	yes	high	no	medium	medium	medium	normal
3	324	no	no	no	no	yes	high	yes	medium	high	high	normal
4	378	no	no	no	no	yes	high	yes	medium	high	high	normal
5	342	no	no	no	no	no	high	yes	medium	medium	high	normal
6	312	no	no	no	no	no	high	yes	medium	medium	high	normal
7	322	no	no	no	no	no	high	yes	medium	medium	medium	normal
8	432	yes	no	no	no	no	high	yes	medium	medium	medium	normal
9	456	yes	no	no	no	yes	high	yes	medium	high	high	normal
10	378	no	no	no	no	yes	high	yes	medium	high	high	normal
11	409	no	no	no	no	yes	high	yes	medium	high	high	normal
12	389	no	no	no	no	yes	high	yes	medium	medium	high	normal
13	310	no	no	no	no	yes	medium	yes	medium	medium	medium	normal
14	334	no	no	no	no	yes	medium	yes	medium	medium	high	normal
15	389	yes	yes	no	no	yes	high	yes	medium	medium	high	normal
16	434	yes	no	no	no	yes	high	no	medium	high	high	normal
17	355	no	no	no	no	yes	high	no	medium	high	high	normal
18	278	no	no	no	no	yes	high	no	medium	high	high	normal
19	290	no	no	no	no	yes	medium	no	medium	medium	medium	normal
20	245	no	no	no	no	no	medium	no	medium	medium	medium	normal
21	232	no	no	no	no	no	medium	no	medium	medium	high	normal
22	378	yes	no	no	no	no	high	no	medium	medium	high	normal
23	432	yes	no	no	no	no	high	no	medium	high	high	normal
24	211	no	no	no	no	no	high	no	medium	high	high	normal
25	345	no	no	no	no	no	high	no	medium	high	high	normal
26	256	no	no	no	no	no	high	no	medium	medium	medium	normal
27	299	no	no	no	no	no	high	no	medium	medium	medium	normal
28	367	no	no	no	no	no	medium	no	medium	medium	medium	normal
29	523	yes	no	no	yes	no	medium	no	medium	high	medium	normal
30	589	yes	no	no	yes	no	medium	no	medium	high	medium	normal

1-Oct	389	no	no	no	yes	no	medium	no	medium	medium	medium	normal
2	376	no	no	no	yes	no	medium	no	medium	medium	medium	normal
3	323	no	no	no	yes	no	medium	no	medium	medium	medium	normal
4	398	no	no	no	yes	no	medium	no	medium	medium	medium	normal
5	399	no	no	no	yes	no	medium	no	medium	high	medium	normal
6	356	yes	no	no	yes	no	medium	yes	medium	high	medium	normal
7	523	yes	no	no	yes	no	high	yes	medium	high	high	normal
8	456	no	yes	yes	yes	no	high	yes	medium	high	high	normal
9	432	no	no	yes	yes	no	high	yes	medium	high	medium	normal
10	478	no	no	yes	yes	no	high	yes	medium	high	high	normal
11	432	no	no	yes	yes	no	high	yes	medium	high	high	normal
12	332	no	no	yes	yes	no	medium	yes	medium	medium	medium	normal
13	567	yes	no	yes	yes	no	medium	yes	medium	high	medium	normal
14	534	yes	no	yes	yes	no	medium	yes	medium	high	high	normal
15	378	no	no	yes	no	no	high	yes	medium	medium	high	normal
16	356	no	no	no	no	no	medium	no	medium	high	medium	normal
17	356	no	no	no	no	no	high	no	medium	medium	medium	normal
18	334	no	no	no	no	no	high	no	medium	medium	high	few rain
19	378	no	no	no	no	no	high	no	medium	medium	high	normal
20	543	yes	no	yes	no	no	high	no	medium	high	high	normal
21	555	yes	no	yes	no	no	high	no	medium	high	high	normal
22	567	no	no	yes	no	yes	high	no	medium	high	high	normal
23	436	no	no	yes	no	yes	high	no	medium	high	medium	normal
24	444	no	no	yes	no	yes	high	no	medium	high	medium	normal
25	435	no	no	yes	no	yes	high	no	medium	high	high	normal
26	398	no	no	yes	no	yes	high	no	medium	medium	high	normal
27	456	yes	no	yes	no	yes	high	no	medium	high	medium	normal
28	438	yes	no	yes	no	yes	high	no	medium	high	medium	normal
29	343	no	no	no	no	no	medium	no	medium	medium	medium	normal
30	322	no	no	no	no	no	medium	no	medium	medium	medium	normal
31	356	no	no	no	no	no	medium	no	medium	medium	medium	normal

1-Nov	378	no	no	no	no	no	medium	no	medium	medium	medium	normal
2	432	no	no	no	no	no	medium	no	medium	high	medium	normal
3	546	yes	no	no	no	no	high	no	medium	high	medium	normal
4	378	yes	no	no	no	no	high	no	high	medium	high	normal
5	312	no	no	no	no	no	high	yes	high	medium	high	normal
6	290	no	no	no	no	no	high	yes	high	high	high	normal
7	312	no	no	no	no	no	high	yes	high	medium	medium	normal
8	316	no	no	no	no	no	high	yes	high	medium	medium	normal
9	356	no	no	no	no	no	high	yes	high	high	high	normal
10	456	yes	no	no	no	no	high	yes	high	high	high	normal
11	543	yes	no	no	no	no	high	yes	high	high	high	normal
12	345	no	no	no	no	no	medium	yes	high	high	medium	normal
13	322	no	no	no	no	no	medium	yes	high	high	medium	normal
14	312	no	no	no	no	no	medium	yes	high	high	medium	normal
15	345	no	no	no	no	no	medium	yes	high	high	medium	normal
16	367	no	no	no	no	no	medium	no	high	high	medium	normal
17	423	yes	no	no	no	no	medium	no	high	high	medium	normal
18	432	yes	no	no	no	no	high	no	high	high	high	normal
19	402	no	no	no	no	no	high	no	high	high	high	normal
20	411	no	no	no	no	no	high	no	high	high	high	normal
21	356	no	no	no	no	no	high	no	high	medium	high	normal
22	354	no	no	no	no	no	high	no	high	medium	high	normal
23	342	no	no	no	no	no	medium	no	high	medium	medium	normal
24	456	yes	no	no	no	no	medium	no	high	high	high	normal
25	534	yes	no	no	no	no	high	no	high	high	high	normal
26	423	no	no	no	yes	no	high	no	medium	high	medium	normal
27	401	no	no	no	yes	no	high	no	medium	high	medium	normal
28	554	no	yes	no	yes	no	high	no	medium	high	high	normal
29	443	no	no	no	yes	no	high	no	medium	medium	medium	normal
30	335	no	no	no	yes	no	high	no	medium	medium	medium	normal

1-Dec	456	yes	no	no	yes	no	high	no	medium	medium	high	normal
2	546	yes	no	no	yes	no	high	no	medium	high	high	normal
3	456	no	no	no	yes	no	high	no	medium	high	high	normal
4	422	no	no	no	yes	no	high	no	medium	medium	high	normal
5	389	no	no	no	yes	no	high	yes	medium	medium	high	normal
6	432	no	no	no	yes	no	high	yes	medium	high	high	normal
7	401	no	no	no	yes	no	high	yes	medium	high	high	normal
8	487	yes	no	no	yes	no	high	yes	medium	high	high	normal
9	556	yes	no	no	yes	no	high	yes	medium	high	high	normal
10	333	no	no	no	yes	no	high	yes	medium	low	high	cold
11	322	no	no	no	yes	no	high	yes	medium	medium	high	cold
12	223	no	no	no	yes	no	high	yes	medium	low	high	cold
13	267	no	no	no	yes	no	high	yes	medium	low	high	cold
14	334	no	no	no	no	no	high	yes	medium	medium	medium	normal
15	432	yes	no	no	no	no	high	yes	medium	medium	high	normal
16	412	yes	no	no	no	no	high	no	medium	medium	high	normal
17	389	no	no	no	no	no	high	no	medium	high	medium	normal
18	345	no	no	no	no	no	medium	no	medium	medium	medium	normal
19	244	no	no	no	no	no	medium	no	medium	medium	medium	normal
20	367	no	no	no	no	no	high	no	medium	medium	medium	normal
21	387	no	no	no	no	no	high	no	medium	high	high	normal
22	454	yes	no	no	no	no	high	no	medium	high	high	normal
23	554	yes	no	no	no	yes	high	no	medium	high	high	normal
24	443	no	no	no	no	yes	high	no	medium	high	high	normal
25	554	no	yes	no	no	yes	high	no	medium	high	high	normal
26	443	no	no	no	no	yes	high	no	medium	high	medium	normal
27	342	no	no	no	no	yes	high	no	medium	medium	high	cold
28	256	no	no	no	no	yes	high	no	medium	medium	medium	cold
29	323	yes	no	no	no	yes	high	no	medium	medium	medium	cold
30	444	yes	no	no	no	yes	high	no	medium	medium	high	normal
31	456	no	no	no	no	yes	medium	no	medium	high	medium	normal

Day	Demand	Weekend	Holiday	Festival	Promotionl 1	Promotional 2	Availability	Starting of the month	Price	Total number of customer	Higher share product available	Weather Conditions
Jan1(01.01.2007)	432	no	no	yes	no	yes	high	no	medium	high	high	normal
2	421	no	no	yes	no	yes	high	no	medium	high	high	normal
3	389	no	no	yes	no	yes	high	no	medium	high	medium	normal
4	367	no	no	yes	no	yes	high	no	medium	high	medium	normal
5	523	yes	no	yes	no	yes	high	yes	medium	high	high	normal
6	477	yes	no	yes	no	yes	high	yes	medium	high	high	normal
7	322	no	no	yes	no	yes	high	yes	medium	medium	high	cold
8	345	no	no	yes	no	yes	high	yes	medium	high	high	cold
9	389	no	no	yes	no	yes	high	yes	medium	high	high	cold
10	467	no	no	yes	no	yes	high	yes	medium	high	high	normal
11	435	no	no	yes	no	yes	high	yes	medium	high	high	normal
12	478	yes	no	yes	no	yes	high	yes	medium	high	high	normal
13	324	yes	no	no	no	no	high	yes	medium	high	medium	normal
14	345	no	no	no	no	no	medium	yes	medium	high	medium	normal
15	324	no	no	no	no	no	medium	yes	medium	medium	medium	cold
16	367	no	no	no	no	no	medium	no	medium	medium	medium	normal
17	378	no	no	no	no	no	medium	no	medium	medium	medium	normal
18	456	no	no	no	no	no	high	no	medium	high	high	normal
19	534	yes	no	no	no	no	high	no	medium	high	high	normal
20	567	yes	no	no	no	no	high	no	medium	high	high	normal
21	324	no	no	no	no	no	high	no	medium	high	medium	normal
22	231	no	no	no	no	no	high	no	medium	medium	high	cold
23	311	no	no	no	no	no	high	no	medium	medium	high	normal
24	278	no	no	no	no	no	medium	no	medium	medium	medium	normal
25	421	no	yes	no	no	no	medium	no	medium	high	medium	normal
26	456	yes	no	no	no	no	high	no	medium	high	medium	normal
27	478	yes	no	no	no	no	high	no	medium	high	high	normal
28	411	no	no	no	no	no	high	no	medium	high	high	normal
29	345	no	no	no	no	no	medium	no	medium	medium	medium	normal
30	324	no	no	no	no	no	medium	no	medium	medium	medium	normal
31	213	no	no	no	no	no	medium	no	medium	low	medium	cold

1-Feb	324	no	no	no	no	no	high	no	medium	medium	medium	normal
2	421	yes	no	no	no	no	high	no	medium	high	high	normal
3	456	yes	no	no	no	no	high	no	medium	medium	medium	normal
4	324	no	no	no	no	no	high	no	medium	high	medium	normal
5	467	no	no	no	yes	no	high	yes	medium	high	high	normal
6	521	no	no	no	yes	no	high	yes	medium	high	high	normal
7	478	no	no	no	yes	no	high	yes	medium	high	high	normal
8	356	no	no	no	yes	no	high	yes	medium	high	high	normal
9	533	yes	no	no	yes	no	high	yes	medium	high	high	normal
10	435	yes	no	no	yes	no	high	yes	medium	high	medium	normal
11	289	no	no	no	yes	no	medium	yes	medium	low	medium	few rain
12	453	no	no	no	yes	no	medium	yes	medium	high	medium	normal
13	378	no	no	no	yes	no	medium	yes	medium	high	medium	normal
14	369	no	no	no	yes	no	high	yes	medium	high	medium	normal
15	401	no	no	no	yes	no	high	yes	medium	high	high	normal
16	432	yes	no	no	yes	no	high	no	medium	high	high	normal
17	523	yes	no	no	yes	no	high	no	medium	high	high	normal
18	389	no	no	no	yes	no	high	no	medium	high	medium	normal
19	367	no	no	no	yes	no	high	no	medium	high	medium	normal
20	354	no	no	no	yes	no	high	no	medium	high	medium	normal
21	432	no	yes	no	yes	no	high	no	medium	high	medium	normal
22	334	no	no	no	no	no	high	no	medium	high	medium	normal
23	326	yes	no	no	no	no	medium	no	medium	medium	medium	few rain
24	435	yes	no	no	no	no	medium	no	medium	high	medium	normal
25	345	no	no	no	no	no	medium	no	medium	high	medium	normal
26	390	no	no	no	no	no	medium	no	medium	high	medium	normal
27	401	no	no	no	no	no	medium	no	medium	high	medium	normal
28	423	no	no	no	no	no	high	no	medium	high	high	normal

1-Mar	378	no	no	no	no	no	high	no	medium	high	high	normal
2	421	yes	no	no	no	no	high	no	medium	high	high	normal
3	378	yes	no	no	no	no	high	no	medium	high	medium	normal
4	367	no	no	no	no	no	high	no	medium	high	medium	normal
5	423	no	no	no	no	no	high	yes	medium	high	high	normal
6	389	no	no	no	no	no	high	yes	medium	high	high	normal
7	224	no	no	no	no	no	high	yes	medium	low	high	few rain
8	376	no	no	no	no	no	high	yes	medium	medium	high	few rain
9	435	yes	no	no	no	no	high	yes	medium	high	high	normal
10	423	yes	no	no	no	no	high	yes	medium	high	high	normal
11	322	no	no	no	no	no	high	yes	medium	high	medium	normal
12	322	no	no	no	no	no	high	yes	medium	medium	medium	normal
13	345	no	no	no	no	no	high	yes	medium	medium	medium	normal
14	335	no	no	no	no	no	high	yes	medium	medium	medium	normal
15	342	no	no	no	no	no	high	yes	medium	high	high	normal
16	367	yes	no	no	no	no	high	no	medium	high	medium	normal
17	432	yes	no	no	no	no	high	no	medium	high	high	normal
18	345	no	no	no	no	yes	high	no	medium	high	medium	normal
19	314	no	no	no	no	yes	high	no	medium	medium	medium	normal
20	345	no	no	no	no	yes	high	no	medium	medium	medium	few rain
21	223	no	no	no	no	yes	high	no	medium	low	medium	rain
22	245	no	no	no	no	yes	high	no	medium	medium	medium	few rain
23	323	yes	no	no	no	yes	high	no	medium	high	high	normal
24	389	yes	no	no	no	yes	high	no	medium	high	high	normal
25	422	no	no	no	no	yes	high	no	low	high	high	normal
26	445	no	no	no	no	yes	high	no	low	high	high	normal
27	421	no	no	no	no	yes	high	no	low	high	high	normal
28	345	no	no	no	no	yes	high	no	low	medium	medium	normal
29	312	no	no	no	no	yes	high	no	low	medium	medium	normal
30	342	yes	no	no	no	yes	high	no	low	medium	medium	few rain
31	431	yes	no	no	no	yes	high	no	low	high	high	normal

1-Apr	265	no	no	no	no	yes	high	no	low	medium	medium	normal
2	322	no	no	no	no	yes	high	no	low	medium	high	normal
3	345	no	no	no	no	yes	high	no	low	medium	high	normal
4	324	no	no	no	no	yes	medium	no	low	high	medium	normal
5	356	no	no	no	no	yes	medium	yes	low	high	medium	normal
6	412	yes	no	no	no	yes	high	yes	low	high	high	normal
7	432	yes	no	no	no	yes	high	yes	low	high	high	normal
8	267	no	no	no	no	no	high	yes	low	medium	high	normal
9	223	no	no	no	no	no	high	yes	low	medium	high	few rain
10	289	no	no	no	no	no	high	yes	low	medium	high	few rain
11	223	no	no	no	no	no	medium	yes	low	medium	medium	few rain
12	265	no	no	no	no	no	medium	yes	low	medium	medium	few rain
13	222	yes	no	no	no	no	medium	yes	low	low	medium	rain
14	345	yes	no	no	no	no	medium	yes	low	high	medium	normal
15	245	no	no	no	no	no	medium	yes	low	high	medium	normal
16	322	no	no	no	no	no	medium	no	low	high	medium	normal
17	345	no	no	no	no	no	high	no	medium	high	high	normal
18	321	no	no	no	no	no	high	no	medium	high	medium	normal
19	345	no	no	no	no	no	high	no	medium	high	medium	normal
20	410	yes	no	no	no	no	high	no	medium	high	high	normal
21	398	yes	no	no	no	no	high	no	medium	high	high	normal
22	235	no	no	no	no	no	medium	no	medium	medium	medium	normal
23	322	no	no	no	no	no	medium	no	medium	medium	medium	normal
24	189	no	no	no	no	no	medium	no	medium	low	medium	rain
25	256	no	no	no	no	no	medium	no	medium	medium	medium	few rain
26	289	no	no	no	no	no	medium	no	medium	medium	medium	normal
27	367	yes	no	no	no	no	high	no	medium	high	high	normal
28	412	yes	no	no	no	no	high	no	medium	high	high	normal
29	234	no	no	no	no	no	high	no	medium	medium	medium	few rain
30	312	no	no	no	no	no	medium	no	medium	medium	medium	normal

1-May	456	no	yes	no	no	no	medium	no	medium	high	medium	normal
2	310	no	no	no	no	no	medium	no	medium	high	medium	normal
3	221	no	no	no	no	no	medium	no	medium	high	medium	normal
4	323	yes	no	no	no	no	medium	no	medium	high	medium	normal
5	342	yes	no	no	no	no	medium	yes	medium	medium	medium	normal
6	178	no	no	no	no	no	medium	yes	medium	low	medium	hot
7	245	no	no	no	no	no	medium	yes	medium	medium	medium	hot
8	243	no	no	no	no	no	medium	yes	medium	medium	medium	hot
9	342	no	no	no	no	no	medium	yes	medium	medium	medium	normal
10	213	no	no	no	no	no	high	yes	medium	medium	high	normal
11	345	yes	no	no	no	no	high	yes	medium	high	high	normal
12	411	yes	no	no	no	no	high	yes	medium	high	high	normal
13	234	no	no	no	no	no	high	yes	medium	high	medium	normal
14	312	no	no	no	no	no	high	yes	medium	high	medium	normal
15	256	no	no	no	no	no	high	yes	medium	medium	high	hot
16	213	no	no	no	no	no	high	no	medium	medium	high	hot
17	311	no	no	no	no	no	high	no	medium	medium	medium	hot
18	387	yes	no	no	yes	no	high	no	medium	high	medium	normal
19	432	yes	no	no	yes	no	high	no	medium	high	high	normal
20	324	no	no	no	yes	no	high	no	medium	high	high	normal
21	356	no	no	no	yes	no	high	no	medium	high	high	normal
22	565	no	yes	no	yes	no	high	no	medium	high	high	normal
23	345	no	no	no	yes	no	high	no	medium	medium	high	normal
24	312	no	no	no	yes	no	medium	no	medium	medium	medium	normal
25	343	yes	no	no	yes	no	medium	no	medium	high	medium	normal
26	421	yes	no	no	yes	no	high	no	medium	medium	medium	normal
27	265	no	no	no	yes	no	high	no	medium	medium	high	hot
28	321	no	no	no	yes	no	high	no	medium	medium	high	hot
29	211	no	no	no	yes	no	medium	no	medium	low	medium	hot
30	321	no	no	no	yes	no	medium	no	medium	medium	medium	normal
31	312	no	no	no	yes	no	medium	no	medium	high	medium	normal

1-Jun	389	yes	no	no	yes	no	high	no	medium	high	high	normal
2	412	yes	no	no	yes	no	high	no	medium	high	high	normal
3	234	no	no	no	yes	no	high	no	medium	medium	high	few rain
4	312	no	no	no	yes	no	high	no	medium	high	medium	normal
5	231	no	no	no	no	no	medium	yes	medium	medium	medium	normal
6	211	no	no	no	no	no	medium	yes	medium	medium	medium	normal
7	187	no	no	no	no	no	medium	yes	medium	medium	medium	normal
8	267	yes	no	no	no	no	medium	yes	medium	high	medium	normal
9	278	yes	no	no	no	no	medium	yes	medium	high	medium	normal
10	211	no	no	no	no	no	medium	yes	medium	high	medium	normal
11	242	no	no	no	no	no	medium	yes	medium	high	medium	normal
12	156	no	no	no	no	no	medium	yes	medium	high	medium	normal
13	121	no	no	no	no	no	medium	yes	medium	medium	medium	few rain
14	167	no	no	no	no	no	medium	yes	medium	medium	medium	normal
15	289	yes	no	no	no	no	high	yes	medium	medium	medium	normal
16	290	yes	no	no	no	no	medium	no	medium	medium	medium	normal
17	212	no	no	no	no	no	high	no	medium	medium	high	normal
18	423	no	yes	no	no	no	high	no	medium	high	high	normal
19	245	no	no	no	no	no	high	no	medium	high	medium	normal
20	222	no	no	no	no	no	high	no	medium	medium	medium	hot
21	222	no	no	no	no	no	high	no	medium	medium	medium	hot
22	323	yes	no	no	no	no	high	no	medium	medium	high	normal
23	423	yes	no	no	no	no	high	no	medium	medium	high	normal
24	312	no	no	no	no	no	high	no	low	medium	high	normal
25	345	no	no	no	no	no	high	no	low	medium	high	normal
26	346	no	no	no	no	no	high	no	low	high	high	normal
27	342	no	no	no	no	no	high	no	low	high	high	normal
28	312	no	no	no	no	no	high	no	low	high	medium	normal
29	289	yes	no	no	no	no	medium	no	low	high	medium	normal
30	356	yes	no	no	no	no	medium	no	low	high	high	normal

1-Jul	345	no	no	no	no	no	medium	no	low	high	medium	normal
2	367	no	no	no	no	no	medium	no	low	high	medium	normal
3	389	no	no	no	no	no	medium	no	low	high	medium	normal
4	312	no	no	no	no	no	medium	no	low	high	medium	normal
5	222	no	no	no	no	no	medium	no	low	high	medium	normal
6	156	yes	no	no	no	no	medium	yes	low	medium	medium	few rain
7	278	yes	no	no	no	no	medium	yes	low	medium	medium	few rain
8	232	no	no	no	no	no	high	yes	medium	high	medium	normal
9	432	no	yes	no	no	no	high	yes	medium	high	high	normal
10	378	no	no	no	no	no	high	yes	medium	high	high	normal
11	367	no	no	no	no	yes	high	yes	medium	high	high	normal
12	390	no	no	no	no	yes	high	yes	medium	high	high	normal
13	389	yes	no	no	no	yes	high	yes	medium	high	high	normal
14	412	yes	no	no	no	yes	high	yes	medium	medium	high	normal
15	389	no	no	no	no	yes	high	yes	medium	medium	high	normal
16	321	no	no	no	no	yes	high	no	high	high	high	normal
17	267	no	no	no	no	yes	high	no	high	high	high	normal
18	222	no	no	no	no	yes	high	no	high	high	high	normal
19	410	no	yes	no	no	yes	high	no	high	high	high	normal
20	443	yes	no	no	no	yes	high	no	high	high	high	normal
21	367	yes	no	no	no	yes	high	no	high	high	high	normal
22	201	no	no	no	no	yes	high	no	high	high	high	normal
23	322	no	no	no	no	yes	medium	no	high	medium	medium	few rain
24	234	no	no	no	no	yes	medium	no	high	high	high	normal
25	267	no	no	no	no	yes	high	no	high	medium	medium	few rain
26	213	no	no	no	no	no	high	no	high	high	medium	normal
27	245	yes	no	no	no	no	high	no	high	high	medium	normal
28	278	yes	no	no	no	no	high	no	high	high	medium	normal
29	223	no	no	no	no	no	high	no	high	high	medium	normal
30	245	no	no	no	no	no	high	no	high	high	medium	normal
31	324	no	no	no	no	no	high	no	high	high	high	normal

1-Aug	322	no	no	no	no	no	medium	no	high	high	medium	normal
2	367	no	no	no	no	no	medium	no	medium	high	medium	normal
3	456	yes	no	no	no	no	medium	no	medium	high	medium	normal
4	478	yes	no	no	no	no	high	no	medium	high	medium	normal
5	345	no	no	no	no	no	high	yes	medium	high	medium	normal
6	322	no	no	no	no	no	high	yes	medium	high	high	normal
7	367	no	no	no	no	no	high	yes	medium	high	high	normal
8	223	no	no	no	no	no	high	yes	medium	high	high	normal
9	256	no	no	no	no	no	high	yes	medium	medium	medium	few rain
10	378	yes	no	no	no	no	medium	yes	medium	medium	medium	normal
11	421	yes	no	no	no	no	medium	yes	medium	medium	medium	normal
12	378	no	no	no	no	no	medium	yes	medium	high	medium	normal
13	390	no	no	no	no	no	high	yes	medium	high	high	normal
14	389	no	no	no	no	no	high	yes	medium	high	medium	normal
15	343	no	no	no	no	no	high	yes	medium	high	medium	normal
16	378	no	no	no	no	no	high	yes	medium	medium	medium	normal
17	435	yes	no	no	yes	no	high	no	medium	high	high	normal
18	457	yes	no	no	yes	no	high	no	medium	high	high	normal
19	342	no	no	no	yes	no	high	no	medium	high	high	normal
20	312	no	no	no	yes	no	high	no	medium	high	medium	normal
21	324	no	no	no	yes	no	high	no	medium	high	medium	normal
22	323	no	no	no	yes	no	high	no	medium	medium	medium	normal
23	355	no	no	no	yes	no	medium	no	medium	high	medium	normal
24	432	yes	no	no	yes	no	medium	no	medium	high	high	normal
25	435	yes	no	no	yes	no	high	no	medium	high	high	normal
26	389	no	no	no	yes	no	high	no	medium	high	high	normal
27	399	no	no	no	yes	no	high	no	medium	high	high	normal
28	378	no	no	no	yes	no	high	no	medium	high	high	normal
29	356	no	no	no	yes	no	high	no	medium	high	medium	normal
30	402	no	yes	no	yes	no	high	no	medium	high	medium	normal
31	478	yes	no	no	yes	no	high	no	medium	high	high	normal

1-Sep	432	yes	no	no	yes	no	high	no	medium	medium	medium	normal
2	342	no	no	no	yes	no	high	no	medium	high	high	normal
3	401	no	no	no	yes	no	high	no	medium	high	high	normal
4	378	no	no	no	yes	no	high	no	medium	high	medium	normal
5	455	no	no	no	yes	no	high	yes	medium	high	high	normal
6	389	no	no	no	yes	no	high	yes	medium	high	high	normal
7	369	yes	no	no	yes	no	high	yes	medium	high	high	normal
8	432	yes	no	no	yes	no	high	yes	medium	high	medium	normal
9	376	no	no	no	no	no	high	yes	medium	medium	medium	normal
10	365	no	no	no	no	no	high	yes	medium	high	high	normal
11	478	no	yes	no	no	no	high	yes	medium	high	high	normal
12	389	no	no	no	no	no	high	yes	medium	medium	medium	normal
13	366	no	no	no	no	no	medium	yes	medium	high	medium	normal
14	445	yes	no	no	no	no	medium	yes	medium	high	medium	normal
15	443	yes	no	no	no	no	high	yes	medium	high	high	normal
16	334	no	no	no	no	no	high	no	medium	high	high	normal
17	332	no	no	no	no	no	high	no	medium	high	medium	normal
18	278	no	no	no	no	no	high	no	medium	high	medium	normal
19	301	no	no	no	no	no	medium	no	medium	high	medium	normal
20	245	no	no	no	no	no	medium	no	medium	medium	medium	normal
21	432	yes	no	no	no	no	medium	no	medium	high	high	normal
22	431	yes	no	no	no	no	high	no	medium	high	high	normal
23	313	no	no	no	no	no	medium	no	medium	medium	high	normal
24	323	no	no	no	no	no	medium	no	medium	medium	high	normal
25	256	no	no	no	no	no	medium	no	medium	medium	medium	normal
26	278	no	no	no	no	no	medium	no	medium	medium	medium	few rain
27	322	no	no	no	no	no	medium	no	medium	medium	medium	normal
28	456	yes	no	no	no	no	medium	no	low	high	medium	normal
29	523	yes	no	no	no	no	medium	no	low	high	medium	normal
30	378	no	no	no	no	no	medium	no	low	high	medium	normal

1-Oct	423	no	no	no	no	no	medium	no	low	high	medium	normal
2	455	no	no	no	no	no	medium	no	low	high	medium	normal
3	389	no	no	no	no	no	medium	no	low	medium	medium	normal
4	398	no	no	no	no	no	medium	no	low	high	medium	normal
5	554	yes	no	no	no	no	medium	no	low	high	medium	normal
6	543	yes	no	no	no	no	medium	yes	low	high	medium	normal
7	523	no	no	yes	no	no	medium	yes	low	high	medium	normal
8	456	no	no	yes	no	no	high	yes	low	high	high	normal
9	478	no	no	yes	no	no	high	yes	low	high	high	normal
10	499	no	no	yes	no	no	high	yes	low	high	high	normal
11	432	no	no	yes	no	no	high	yes	low	high	high	normal
12	554	yes	no	yes	yes	no	medium	yes	low	high	high	normal
13	567	yes	no	yes	yes	no	medium	yes	low	high	high	normal
14	445	no	no	yes	yes	no	medium	yes	low	high	high	normal
15	421	no	no	yes	yes	no	high	yes	low	high	high	normal
16	456	no	no	yes	yes	no	high	no	low	high	medium	normal
17	356	no	no	no	yes	no	high	no	low	high	medium	normal
18	334	no	no	no	no	no	high	no	medium	high	medium	normal
19	456	yes	no	no	no	no	high	no	medium	high	medium	normal
20	543	yes	no	no	no	no	high	no	medium	high	high	normal
21	555	no	no	yes	no	no	high	no	medium	high	high	normal
22	670	no	no	yes	no	yes	high	no	medium	high	high	normal
23	556	no	no	yes	no	yes	high	no	medium	high	high	normal
24	478	no	no	yes	no	yes	high	no	medium	high	high	normal
25	456	no	no	yes	no	yes	high	no	medium	high	high	normal
26	543	yes	no	yes	no	yes	high	no	medium	high	high	normal
27	532	yes	no	yes	no	yes	high	no	medium	high	high	normal
28	438	no	no	yes	no	yes	high	no	medium	high	medium	normal
29	343	no	no	yes	no	yes	high	no	medium	medium	medium	normal
30	345	no	no	yes	no	yes	high	no	medium	medium	medium	normal
31	412	no	no	no	no	yes	high	no	medium	medium	medium	normal

1-Nov	378	no	no	no	no	no	medium	no	medium	medium	medium	normal
2	413	yes	no	no	no	no	medium	no	medium	high	medium	normal
3	567	yes	no	no	no	no	high	no	medium	high	medium	normal
4	323	no	no	no	no	no	medium	no	medium	medium	high	normal
5	432	no	no	no	no	no	medium	yes	medium	medium	medium	normal
6	453	no	yes	no	no	no	medium	yes	medium	high	high	normal
7	378	no	no	no	no	no	high	yes	medium	high	medium	normal
8	316	no	no	no	no	no	high	yes	medium	medium	medium	normal
9	432	yes	no	no	no	no	high	yes	medium	high	medium	normal
10	512	yes	no	no	no	no	high	yes	medium	high	medium	normal
11	543	no	no	no	no	no	high	yes	medium	high	high	normal
12	345	no	no	no	no	no	medium	yes	high	high	high	normal
13	322	no	no	no	no	no	medium	yes	high	high	medium	normal
14	312	no	no	no	no	no	medium	yes	high	high	medium	normal
15	367	no	no	no	no	no	medium	yes	high	high	medium	normal
16	367	yes	no	no	no	no	medium	no	high	high	medium	normal
17	423	yes	no	no	no	no	medium	no	high	high	medium	normal
18	401	no	no	no	no	no	high	no	high	high	medium	normal
19	402	no	no	no	no	no	high	no	high	high	medium	normal
20	432	no	no	no	no	no	high	no	high	high	medium	normal
21	498	no	yes	no	no	no	high	no	high	high	high	normal
22	354	no	no	no	no	no	high	no	high	high	medium	normal
23	445	yes	no	no	no	no	high	no	high	medium	high	normal
24	489	yes	no	no	no	no	medium	no	high	medium	medium	normal
25	433	no	no	no	no	no	medium	no	high	high	high	normal
26	453	no	no	no	yes	no	high	no	high	high	high	normal
27	490	no	no	no	yes	no	high	no	medium	high	medium	normal
28	554	no	yes	no	yes	no	high	no	medium	high	medium	normal
29	502	no	no	no	yes	no	high	no	medium	high	high	normal
30	554	yes	no	no	yes	no	high	no	medium	high	medium	normal

1-Dec	567	yes	no	no	yes	no	high	no	medium	high	high	normal
2	543	no	no	no	yes	no	high	no	medium	high	high	normal
3	489	no	no	no	yes	no	high	no	medium	high	medium	normal
4	476	no	no	no	yes	no	high	no	medium	high	high	normal
5	432	no	no	no	yes	no	high	yes	medium	high	high	normal
6	489	no	no	no	yes	no	high	yes	medium	high	high	normal
7	665	yes	no	no	yes	no	high	yes	medium	high	high	normal
8	556	yes	no	no	yes	no	high	yes	medium	high	high	normal
9	321	no	no	no	yes	no	high	yes	medium	medium	high	cold
10	234	no	no	no	yes	no	high	yes	medium	low	high	cold
11	322	no	no	no	yes	no	high	yes	medium	medium	high	cold
12	334	no	no	no	yes	no	high	yes	medium	medium	high	cold
13	267	no	no	no	yes	no	high	yes	medium	low	high	cold
14	256	yes	no	no	yes	no	high	yes	medium	low	medium	normal
15	432	yes	no	no	yes	no	high	yes	medium	medium	high	normal
16	532	no	yes	no	yes	no	high	no	medium	high	high	normal
17	389	no	no	no	no	no	high	no	medium	high	medium	normal
18	345	no	no	no	no	no	medium	no	medium	medium	medium	normal
19	244	no	no	no	no	no	medium	no	medium	medium	medium	cold
20	367	no	no	no	no	no	high	no	medium	medium	medium	normal
21	387	yes	no	no	no	no	high	no	medium	high	high	normal
22	454	yes	no	no	no	no	high	no	medium	high	high	normal
23	554	no	no	no	no	yes	high	no	medium	high	high	normal
24	443	no	no	no	no	yes	high	no	medium	high	high	normal
25	554	no	yes	no	no	yes	high	no	medium	high	high	normal
26	443	no	no	no	no	yes	high	no	medium	high	medium	normal
27	342	no	no	no	no	yes	high	no	medium	medium	high	cold
28	256	yes	no	no	no	yes	high	no	medium	low	medium	cold
29	323	yes	no	no	no	yes	high	no	medium	medium	medium	cold
30	444	no	no	no	no	yes	high	no	medium	medium	high	normal
31	456	no	no	no	no	yes	medium	no	medium	high	medium	normal