AN AGGREGATE PRODUCTION PLAN BASED ON A NEURAL NETWORK FORECASTING MODEL FOR PREMIUM GROCERY ITEMS IN BANGLADESH

By

Syeda Kumrun Nahar

A Thesis
Submitted to the
Department of Industrial & Production Engineering
in Partial Fulfilment of the
Requirements for the Degree
of
M.Sc. in Industrial and Production Engineering

DEPARTMENT OF INDUSTRIAL & PRODUCTION ENGINEERING
BANGLADESH UNIVERSITY OF ENGINEERING & TECHNOLOGY
DHAKA, BANGLADESH

September 2018

The thesis titled **An Aggregate Production Plan Based on a Neural Network Forecasting Model for Premium Grocery Items in Bangladesh** submitted by **Syeda Kumrun Nahar**, Student No. 0413082013, Session- April 2013, has been accepted as satisfactory in partial fulfillment of the requirement for the degree of Master in Industrial and Production Engineering on September 22, 2018.

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Declaration

It is hereby declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

Syeda Kumrun Nahar

This work is dedicated
to my loving

Parents

&

Husband

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Acknowledgement

At first the author expresses her heartiest thanks to the Almighty for giving the patience and potentiality to dispatch this thesis in light. The author has the pleasure to express her sincere gratitude and profound indebtedness to her supervisor Dr. Shuva Ghosh, Assistant Professor, Department of Industrial & Production Engineering, BUET, Dhaka, for his continuous support, guidance and valuable suggestions throughout the progress of this work.

The author expresses her heartiest thanks to the organization for providing necessary data and support to complete the research.

The author is profoundly indebted to her parents and husband for encouraging and providing moral support to complete this thesis smoothly. Special thanks are due to all staff members of the machine shop and welding shop for proving their supports in carrying out the experimental work.

Abstract

Demand fluctuation, shorter shelf life, and business competition make the grocery market one of the most vulnerable markets. In-order to overcome this situation, accurate demand forecasting is essential. Considering current situation, this study aims to develop a forecasting model considering the factors that influence the demand for premium grocery items in Bangladesh and also develop an optimized aggregate model considering the forecasted demand. The model is developed for two premium grocery items. In order to identify the factors, a structured questionnaire based survey has been conducted. From the survey, 12 factors are identified that influence demand. The most influencing factors are identified by using factor analysis. The factors are price, per capita income, and number of competitors, market share, product quality, product availability, seasonal variations, festival season, and promotional activities. Considering these factors, a feed- forward neural network forecasting model with the back-propagation algorithm is prepared. The selected factors are used as input for the model and demand data including the factors that have collected and used as input. Two years of data have used to train the model. Using the model, future 12 months demand is calculated. The model is developed for two premium grocery items. Based on the result, an optimized aggregate plan is developed.

Chapter-1

INTRODUCTION

1.1 Background

In today’s intense competition, a company must have a reasonable estimate of how vital indicators are going to behave in the future. One of the most important key indicators is demand. An efficient forecasting system of demand can improve resource utilization and reduce inventories as well. Grocery items producers are very much concerned with demand forecasting. Predicting customer demand in the highly competitive grocery business has become extremely difficult. In the consumer-centric environment of today's business world, enterprises seeking good sales performance often need to maintain a balance between meeting customer demand and controlling inventory costs. Carrying a more massive inventory allows customer demand to be satisfied at all times, but can result in over-stocking. Lower inventory levels, in contrast, may reduce inventory costs, but can result in missed sale opportunities, reduced customer satisfaction, and other problems. In order to avoid such situations, accurate demand forecasting could be used to determine the required inventory level and avoid the problem of under or over-stocking. Improving the accuracy of forecasts has, therefore, become an essential aspect of operating a business. Adebanjo et al. stated that the ability to forecast consumer demand accurately is of great importance to companies in the consumer market, as this enables companies to determine the number of items that need to be produced [1] Typically, high-performance companies focus on robust demand forecasting approaches; however, the challenge of demand forecasting varies significantly according to company and industry. Demand forecasting varies industry to industry due to the variation in demand pattern and the influence of varying factors. The Grocery industry is one of the kinds that face demand fluctuations. The demand variation occurs in this sector due to price variation, promotional activity, no. of different alternatives, product availability, and quality, etc. In such cases, simple trend and seasonality based forecasting are not appropriate. The incorporation of different factors will provide accurate forecasts in such cases. Accurate forecast leads to an accurate aggregate plan. An accurate aggregate plan helps in achieving optimized production and effective utilization of resources while minimizing total cost.

1.1.1 Condition of Grocery Market

In their recent bestseller, Kotler et al. state that today’s businesses must strive to fulfill customers’ needs in the most convenient way while minimizing the time and energy that consumers spend in searching for, ordering, and receiving goods and services. Grocery markets are concerned about forecasting because of the rapid changing of demand. It is a highly competitive market. The frequency of an increase in the number of competitors and the reduction of market share is another important concern for the companies. In-order to boost market demand, several types of promotions with various price structures can be offered in retail markets [3]. In executing these promotions, retailers and suppliers exchange a variety of sales and promotion related information. All the available data may not be useful for forecasting or decision making [4]. Also, the quality and availability of the product influence consumers' buying behavior. Per capita income is another important factor that also affects consumer buying actions. Accurate and timely forecast in this business drives success. To achieve a better understanding about what type of data to collect or exchange between different supply chain partners, it is vital to understand the structure of demand and how different factors influence sales. Forecasting with many predictors provides the opportunity to exploit a much richer base of information than is conventionally used for time series forecasting. Another, less obvious (and less researched) opportunity is that using many predictors might provide some robustness against the structural instability that plagues low-dimensional forecasting.

1.1.2 Prospects of grocery (agro-processing) market in Bangladesh

Bangladesh, is a developing consumer product market now. Consumer spending has influenced growth in Rising per capita income. The current value of food processing sector in Bangladesh USD 2.2 Billion. The annual growth rate between the fiscal years 2004-2005 and 2010-2011 has grown annually at an average rate of 7.7%. The rapidly growing current middle-class population of over 30 million signifies that the food processing sector in Bangladesh will grow in the future. It indicates that the growth achieved in food processing is only along with the economic growth of Bangladesh, and the sector has further prospective. According to Bangladesh Agro Processor's Association (BAPA), the export of agro-based products from Bangladesh grown to USD 60 million in 2010-2011 to USD 224 million in 2014-2015. The food processing sector is expected to grow positively in the coming years. Though, the growth trends are positive, the influence of the food manufacturing or food processing industry in Bangladesh has remained mostly fixed at around 2% of the GDP since 2004-2005 [5]. There are many reasons behind this issue, one important reason is that, they have limited shelf life, and the absence of accurate forecasting creates a dilemma among manufacturers. Due to the dilemma, the manufacturer sometime faces overstock and sometime under-stock. An accurate forecasting technique in this sector can solve the problem and bring a balance between demand and production.

1.1.3 Currently employed forecasting approaches

A good forecasting model leads to improve the customer's satisfaction, reduce cost, increase sales revenue, and make production plan efficiently [6]. From a study, it has found that, of several large companies in the food industry, which aimed to improve forecasting practice, identified that 48% of food companies are poor at forecasting [1]. The methodologies that have used in sales forecasting are typically time series algorithms that can be classified as linear or nonlinear, depending on the nature of the model they are based on [7]. There is an extensive body of literature on sales forecasting in such industries as textiles and clothing and fashion, books, and electronics [7-12]. However, very few studies center on sales or demand forecasting in the grocery items.

There are currently at least 70-time series forecasting models using linear and, or nonlinear structures for quantitative demand forecasting [13]. In the recent literature, it is well established that there is a need for investigative studies on the most appropriate forecasting model for every situation since there is no universal model that will make accurate predictions for all problems. Historically, many scientific papers have focused on modeling, analysis, and forecasting approaches of time series that show irregular variations, seasonality, and trends [14-17]. Many theoretical and heuristic models are developed and evaluated empirically in recent decades [18]. In general, the linear mathematical models are preferred over more complex models, as linear models have the important practical advantage of accessible interpretation and implementation [19]. On the other hand, if linear models fail to perform well in both sample fitting and out-of-sample forecasting, more complex nonlinear models should be considered [20]. The most common and useful mathematical model used to predict demand is ANN. It has successfully applied in sales or demand forecasting. Kue et al. used this tool to forecast sales for a beverage company and found that this approach is better than ARIMA [11]. Chang et al. applied a fuzzy BPN to forecast sales for the Taiwanese printed circuit board industry [12]. Hyunchul et al. first used independent component analysis to screen variables before employing an ANN algorithm to predict sales for a Korean shopping mall. They also showed that the proposed forecasting scheme is superior to a forecasting method in which principal component analysis is first used to screen variables before an ANN algorithm is applied [21]. In addition, the ANN is compared with the Box-Jenkins models using international airline passenger traffic, domestic car sales, and foreign car sales in the USA. It was concluded that the Box-Jenkins models outperformed the ANN models in short-term forecasting, although the ANN models outperformed the Box-Jenkins for long-term forecasting [22]. Chakraborty et al. presented an ANN approach to multivariate time series analysis, using it to accurately predict flour prices in three US cities, demonstrating the superior performance of the approach [23]. ANNs have also been applied successfully to problems concerning sales of food products, such as predicting the impact of promotional activities and consumer choice on the sales volumes and were found to perform better than linear models [24]. Another exciting example is by Ainscough et al. that compared ANNs to linear regression for studying the same effects on yogurt [25]. Zhang did a comprehensive review of the literature concerning the utilization of ANNs in forecasting problems in various areas. This method performed equally well with linear methods in 30% and better in 56% of the cases reviewed. In a subsequent study by Stock et al. linear and nonlinear methods were compared and it had found that in terms of forecasting performance, combinations of nonlinear methods are better than combinations of linear methods. Additionally, feed-forward neural networks (FNNs) that constitute a distinctive ANN architecture performed equally well or better than traditional methods in more than half of the cases [26]. Overall, it can be inferred that, among other methods, ANN has been successfully used in forecasting.

1.1.4 Aggregate production plan

After successfully forecasting the demand, another essential aspect that needs to be performed is the development of an efficient aggregate plan. It ensures proper utilization of resources while fulfilling demand. Aggregate Plans are necessary to the company goals or conditions (e.g., target levels for customer service, inventory, employment, etc.) and considers demand forecast, facility capacity, inventory levels, workforce size, and other related inputs. The job of the planning department is to determine, the best way to meet forecasted demand by adjusting the rates of production output for a facility; the levels of workforce and inventories; and the estimated costs incurred by the firm based on these manufacturing-related activities over the next 3 to 18 months. Thus, when generating an Aggregate Plan, the operations manager must address questions like the following [27]:

1. Should inventories be used to engross changes in demand during the planning bound?
2. Should changes be lodged by varying the size of the workforce?
3. Should part-timers be used, or should overtime and idle time absorb variations?
4. Should subcontractors be used on shifting orders so a steady workforce can be sustained?

One of the most important objectives of an AP is to meet forecasted demand. Once this is achieved, the focus turns into minimizing the total procurement-related costs over the planning horizon. “However, other strategic issues maybe sometimes more important than low cost, for example, to smooth employment levels, to drive down inventory levels, or to meet a high level of service, regardless of cost” [27].

1.2 The rationale of the Study

In the current situation, the grocery market is one of the most competitive markets. Limited life cycle and variation of demand are the most concerning issue for the decision-makers. The accuracy of forecasted demand is also questionable because most of the forecast they performed are based on time-series analysis. Whereas, different forecasting techniques apply to different categories of products. This study is concerned about developing an appropriate forecasting model for grocery items, especially agro-processing items. Here, the association of various factors with demand would be consider making the forecast more accurate and reliable. Another essential aspect is capacity planning after predicting demand; in this study, this phenomenon would be considered. Furthermore, an optimized aggregate plan will be developed. The scopes of the study are mentioned below:

- This study is applicable for decision making regarding the forecasting of grocery items.
- This study will also help them in decision making regarding resource utilization and inventory planning..

1.3 The objective of the Study

From the literature review, it is clear that there is no sufficient work done on forecasting of grocery items, considering the factors influencing the demand. It is also necessary for them to have an optimized aggregate plan. It would help in meeting the forecasted demand while ensuring optimized use of resources. Considering the situation the objective of the study has been set. The objectives of the study are mentioned below:

1. To identify the factors influencing the demand for grocery items in Bangladesh.
2. To develop a forecast model to predict the uncertain demand of premium grocery items in Bangladesh using Artificial Neural Network, considering the identified factors.
3. To develop a mathematical model of aggregate planning based on forecasted demand

1.4 Structure of the Thesis Paper

The thesis outline is as follows; chapter one provides the necessary background of choosing the topic and the sector. It also gives some insights regarding the previously performed work related to forecasting and also insight about the aggregate plan. The rationale and main objectives of the study are also mentioned in this chapter. Chapter two provides, detail literature review about forecasting, forecasting techniques, Artificial

Neural Network (ANN), factors influencing demand, and aggregate production plan. Chapter three depicts the methodology adopted for the study. In chapter four, data collection, factor selection, forecasting model development, and detail about the optimized aggregate plan has discussed. In chapter five, the findings from the developed forecasting model and aggregate production plan has been discussed. Chapter six is the concluding part.

Chapter-2

LITERATURE REVIEW

2.1 Introduction

In this chapter, an in-depth literature review related to the work has presented. This review involves topics like; forecasting, artificial neural network (ANN), and aggregate plan, including detailed literature about them.

2.2 Forecasting

Forecasting refers to the formation of expectations about future states or processes of specific historical entities. Forecasting involves the estimation or calculation of expected future events or developments from a conceptual model. At the most informal level, the conceptual model can be a heuristic model based on individuals' life experiences and the particular social, cultural, and economic circumstances in which they live, as in the formation of expectations about the routine activities and rituals to take place on a given day. At the other end of the spectrum, the conceptual model can be analytic, formal, and complex based on numerical measurements, equations, simulations, and projections [28].

There are two primary reasons for the need for a forecast in any field. They are [28]:

1. **Purpose** – Any action devised in the PRESENT to take care of some contingency accruing out of a situation or set of conditions set in the future. These future conditions offer a purpose or target to be achieved to take advantage of or to minimize the impact of these future conditions.
2. **Time** – To prepare a project, to organize resources for its implementation, to implement, and complete the project; all these need time as a resource. Some situations need very little time, and some other situations need several years. Therefore, if the future forecast is available in advance, appropriate actions can be planned and implemented.

2.2.1 Types of forecasting methods

Forecasting techniques are divided into two broad categories: quantitative and qualitative. The methods in the quantitative type include mathematical models such as moving average, straight-line projection, exponential smoothing, regression, analysis, decomposition, Box-Jenkins, expert systems, and neural network etc. The qualitative category includes subjective or intuitive models such as jury or executive opinion, sales force composite, and customer expectations [29, 30]. Various forecasting methods are briefly discussed below [29, 30]:

- **Quantitative Forecasting Methods:**

• **Regression Analysis:** This method statically relates sales to one or more explanatory (independent) variables such as; price changes, competitive information, economic data etc.

• **Exponential smoothing:** This method uses past sales, trends, and seasonality to make an exponentially smoothed weighted average.

• **Moving average:** This method uses the average of specified number observations to derive a forecast.

• **Box-Jenkins:** From past sales data and forecasting errors and autoregressive moving average forecasts are developed using the autocorrelated structure.

• **Trend line analysis:** This method fits a line to the sales data by minimizing the squared error between the line and actual past sales data.

• **Decomposition: This method d**ivides the sales data into seasonal, cyclical, trend, and noise components and projects them in the forecast.

• **Straight-line projection** is a graphic extrapolation of the previous data, which is projected the forecast into the forecast to calculate future data.

• **Life-cycle analysis** bases the forecast upon the life cycle of products, which the introduction, growth, maturity, or decline stage of the life cycle.

• **Simulation**: The simulation model is a mathematical model of the actual entity.

• **Expert systems** In this method, decision rules are developed using the knowledge of one or more experts to derive a forecast.

• **Neural networks** look for patterns in the previous history of sales and analytical data to reveal connections. These connections are used to produce the forecast.

- **Qualitative Forecasting Methods**

• **Jury of executive opinion** comprises combining top executives' opinions regarding upcoming.

• **Salesforce:** This method individually combines the forecast of sales personnel.

• **Customer expectations** Customers' expectations are collected by the salespeople and used as a tool to forecast.

• **Delphi model** This method takes the benefit of the knowledge of experts, though maintains secrecy among participants.

• **Naïve model** assumes that the next period will be similar to the present. The prediction is grounded on the most recent observation of data.

2.2.2 Forecasting horizon

There are three types of forecasting horizon for managerial decision makingThese three types of forecasting horizon are briefly discussed below [31]:

Short-term forecasts are typically made for strategic reasons includes production planning and control, short-term cash requirements and changes that required to be made for seasonal sales fluctuations. This latter factor can be crucial for production, whereas the general trend may be of less consequence. This type of forecast is for periods of less than one year, with an average length of one to three months.

Medium-term forecasts Medium-term forecast are essential in the area of budgeting and it is from this forecast that company budgets are built up. Incorrect forecasting can have severe consequences for the organization, the organization will be overstocked and will have overspent on production. Many bankruptcies among smaller firms took-place due to a lack of attention in medium-term forecasts. The period for a medium-term forecast usually is one year.

Long-term forecasts This method is used for strategic decision making such as; government policy, social change, and technological change. They are, therefore, concerned more with prevailing trends, and in the light of these trends, attempt to predict sales over periods higher than two years.

2.2.3 Application of forecasting in different areas

Nowadays, forecasting has been extensively used in different areas such as; short-term or long-term load forecasting of gas and electricity, estimation of tourist flow, demand forecasting of industrial, food, garments and other products, etc. In a study, it has mentioned that the fashion industry is a fascinating sector for sales forecasting. Indeed, the longtime-to-market, which contrasts with the short-life cycle of products, makes the forecasting process very challenging [32]. In the business operations of the foodstuff retail segment, forecasting accuracy is even more critical to the quality of the decision-making process because retailing is widely `recognized as a competitive industry in both mature and developing markets [33-35]. Load forecasting can provide a basis for the gas supply planning, achieving the maintenance plan and distribution dispatching of the gas pipe network. The accurate prediction will improve operational efficiency, save energy, and reduce costs. Thus the natural gas consumption forecasting has been widely researched [36-38]. The rapid growth of tourists flow in the short term will be a heavy burden for sightseeing spots, airports, and hotels during holidays. Since various vital decisions, such as tourism planning, transportation, and accommodation, have been made based on the results of holiday daily tourist flow forecasting, an optimal solution of the allocation of social resources in such areas is crucial [39]. Wind speed forecasting is of boundless significance for wind farm management and safe integration into the electric power grid [40]. These are some examples regarding the area where forecasting is used.

2.2.4 Factors influencing demand

The variations in consumer demand are caused by factors like price, promotions, changing consumer preferences, or weather [41]. There are lots of factors influencing the market for grocery items. These factors are mentioned below:

a. Price: The price is defined as the money that customers exchange in terms of service or product, or the value they receive [42]. The consumer considers the amount when they purchase a product or service. How a consumer perceives a price – as high, as low, as fair – has a strong effect on both purchase intentions and purchase fulfillment. Lee et al. studied the effects of consumer perception of price fairness on its purchase decision and referred to it as a proper predictor for the purchase decision of consumers [43].

b. Promotion: Trade promotion can encourage resellers to carry a brand, give it shelf space, promote it in advertising, and push it to consumers [44].

c. Quality of product: Consumers often judge the quality of the product or service based on a variety of informational signals that they associate with the product. Some of these signals are intrinsic to the product or service; others are extrinsic. Either singly or together, such signals provide the basis for perceptions of product and service quality [45]. Product quality is a crucial factor in assessing purchase intention. It is a constant process of improvement that the continuous changes increase product performance and consequently, the satisfaction of customers' needs. Quality should be improved every moment [46]. Chi et al. concluded that if a product has better quality, the customer will be more inclined to purchase it [47]. Some parameters that are used to check the quality of rice are [48];

   i. **Moisture content:** moisture content has a marked effect on all aspects of paddy and rice quality and paddy must be milled at the proper moisture content to obtain the maximum head rice produce. Paddy is at its optimal milling potential at the moisture content of 14% wet weight basis.

   ii. **Purity degree:** purity is associated to the presence of dockage in the grain. Dockage refers to material other than paddy and includes chaff, stones, weed seeds, soil, rice straw, stalks, etc.

   iii. **Whiteness:** whiteness is a combination of varietal physical characteristics and the degree of milling. In milling, the whitening and polishing significantly affect the whiteness of the grain. During whitening, the silver skin and the bran layer of the brown rice are removed.

iv. **Gel consistency:** gel consistency measures the tendency of the cooked rice to harden after cooling. The harder gel consistency is associated with harder cooked rice, and this feature is particularly evident in high-amylose rice.

v. **Milling degree:** milling degree is computed based on the amount of bran removed from the brown rice. To obtain the weight of brown rice, dehull the paddy samples using the Laboratory Huller. Estimate the percent milling degree using the following equation:

$$\%Milling\ degree=\frac{wt\ of\ milled\ rice}{wt\ of\ brown\ rice}\times 100$$

d. **Availability of products:** Availability is becoming an increasingly important issue for consumers seeking out time-saving grocery solutions. Consumers are increasingly relying on factors that make shopping easier and quicker and improving availability is one strategy for delivering against these expectations [49].

e. **Seasonality:** As it relates to inventory management, it is defined as a particular time series with repetitive or predictable patterns of demand. The extent of interest typically measures seasonality for small time periods, such as days, weeks, months, or quarters. It is expected that almost all orders has some seasonal variations.

f. **Festival Season:** During the festival season, demand for some grocery items increases rapidly. Festival season plays a dominant rule in the behavior of a consumer of grocery items in this country. There are lots of festivals, including the wedding season, when the demand for grocery items increases.

g. **Market share:** A higher current market share can be interpreted by future consumers as a signal of more top relative quality and will tend to increase future demand.

h. **No. of Competitors:** Competition is widespread throughout the market process. It is a condition where "buyers incline to compete with other buyers, and sellers incline to compete with other sellers." In offering goods for an exchange, buyers competitively bid to purchase specific quantities of specific products that are available or might be handy if sellers were to choose to provide such products. The more the no. of competitors, there is more opportunity for consumers to choose.

i. **Brand name:** Branding are essential in creating mental structures that help consumers organize their knowledge about products and services in a way that clarifies their decision making and, in the process, provides value to the firm [42].
j. **Per capita income:** Per capita income is commonly used to measure an area's average income. This is used to see the wealth of the population with those of others. Per capita income is commonly used to measure a country's standard of living.

2.3 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) utilize interconnected mathematical nodes or neurons to form a network that can model complex functional relationships [50]. Its development started in the 1940s to help cognitive scientists to understand the complexity of the nervous system. It has been evolved steadily and was adopted in many areas of science. ANNs are numerical structures inspired by the learning process in the human brain. They are constructed and used as alternative mathematical tools to solve a diversity of problems in the fields of system identification, forecasting, pattern recognition, classification, process control, and many others [51]. It is used in a wide range of membrane process applications [52].

2.3.1 ANN architecture

The underlying architecture consists of three types of neuron layers: input, hidden, and output layers. In feed-forward networks, the signal flow is from input to output units, strictly in a feed-forward direction. The data processing can extend over multiple (layers of) units, but no feedback connections are present. Recurrent systems contain feedback connections. Unlike feed-forward networks, the dynamical properties of the network are essential. The network will evolve to a steady-state while the activation values of the units undergo a relaxation process, in which these activations do not change anymore. In other applications, the changes in the activation values of the output neurons are significant, because dynamical behavior constitutes the output of the network [53].

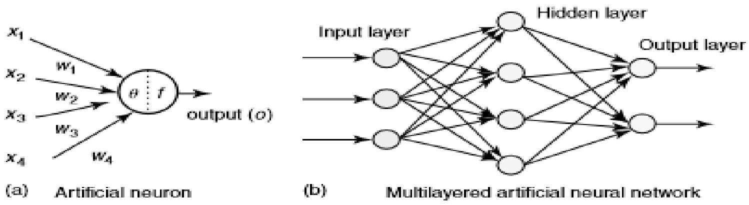

Fig. 2.1: Single and Multilayered neural network

A neural network has to be configured in such a way that a set of inputs after processing produces the set of outputs. Various methods are available to provide the strength of the connections. One way is to set the weights for the network, using previous knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations in neural networks may be classified into three distinct categories such as; supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, an input vector is presented at the inputs together with a set of anticipated responses, one for each node, at the output layer. The term supervised initiates from the fact that the desired signals on individual output nodes are provided by an external teacher [54].

The application of supervised learning are seen in the backpropagation algorithm, the delta rule, and the perceptron rule. In unsupervised learning, a (output) layer is trained to respond to clusters of patterns within the input. In this paradigm, the system is supposed to discover statistically prominent features of the input layer. Unlike the supervised learning, there is no a priori set of categories into which the patterns are to be classified; instead, the system must develop its representation of the input layer. In reinforcement learning, prior knowledge is not provided. The learner instead must discover which steps yield the most reward by trying them. In the most exciting and challenging cases, efforts may affect not only the immediate premium, but also the following state and, through that, all subsequent rewards. These two characteristics, trial-and-error search and delayed reward, are the two most important distinguishing features of reinforcement learning [55].

2.3.2 ANN learning

The external environment also interacts with the network during "learning" or training of ANN. In this phase, a learning rule is used to change the elements of the matrix and other adaptable parameters that the network may have. In this context, "learning" and "adaptation" are seen as mere changes in the network parameters. In ANN models, the external environment will typically provide a set of "training" input vectors. There are two main types of learning: supervised and unsupervised.

In **supervised** learning, the external environment also provides the desired output for each one of the training input vectors, and it is said that the external environment acts as a teacher. A particular case of supervised learning is reinforcement learning where the external environment only provides the information that the network output is good or bad, instead of giving the correct output. In the case of reinforcement learning, it is said that the external environment acts as a critic.

In **unsupervised** learning, the external environment does not provide the desired network output nor classifies it as good or bad. By using the correlation of the input vector, the learning rule changes the network weights in order to group the input vector into groups such that similar input vectors will produce related network outputs since they will belong to the same groups. Ideally, the learning rule finds the number of clusters and their respective centers, if they exist, for the training data. This learning method is also called self-organization.

Apart from these rules, there are different types of learning algorithms are used to update the weights. Some of the learning algorithms are discussed below:

a. Hebbian learning

The most influential work in connectionism’s history is the contribution of Hebb, where, he presented a theory of behavior-based, as much as possible, on the physiology of the nervous system. Most of the neural network learning techniques are modified form of Hebbian learning rule. If two neurons are active concurrently, their interconnection must be strengthened based on this idea, this rule works. If we consider a single layer network, one of the connected neurons will be an input unit and one an output unit. If the data are represented in bipolar form, it is easy to express the desired weight update as:

$$w_i(new) = w_i(old)+x_i o \ldots\ldots\ldots\ldots\ldots(2.1)$$

where, o is the desired output for i=1 ton(inputs). Basic Hebbian learning continually strengthens its weights without bound (unless the input data is normalized correctly) [56].

b. Perceptron learning rule

The perceptron is a single layer neural network whose weights and biases could be trained to produce a correct target vector when presented with the corresponding input vector. The training technique used is called the perceptron learning rule. Perceptrons are especially suited for simple problems in pattern classification. Suppose we have a set of learning samples consisting of an input vector x and a desired output, d(k). For a classification task, the d(k) is usually +1 or−1. The perceptron-learning rule is elementary and can be stated as follows:

1. Start with random weights for the connections.
2. Select an input vector x from the set of training samples.
3. If output, $y_k \neq d(k)$ (the perceptron gives an incorrect response), modify all connections wi according to: $\delta w_i = \eta(d_k - y_k)x_i$; ($\eta$= learning rate)
4. Go back to step 2.

The procedure is very similar to the Hebb rule; the only difference is that when the network responds correctly, no connection weights are modified [55].

c. Backpropagation learning

The simple perceptron is just able to handle linearly separable or linearly independent problems. We will learn a little about the direction of thee error of the network is moving only taking the partial derivative of the error of the network work, concerning each weight. If we take the negative of this derivative (i.e., the rate change of the error as the value of the weight increases) and then proceed to add it to the weight, the error will decrease until it reaches a local minimum. It makes sense because if the derivative is positive, this tells us that the error is increasing when the weight is increasing. The obvious thing to do then is to add a negative value to the weight and vice versa if the derivative is negative. Because the taking of these partial derivatives and then applying them to each of the weights takes place, starting from the output layer to hidden layer weights, then the hidden layer to input layer weights, this algorithm has been called the back-propagation algorithm.

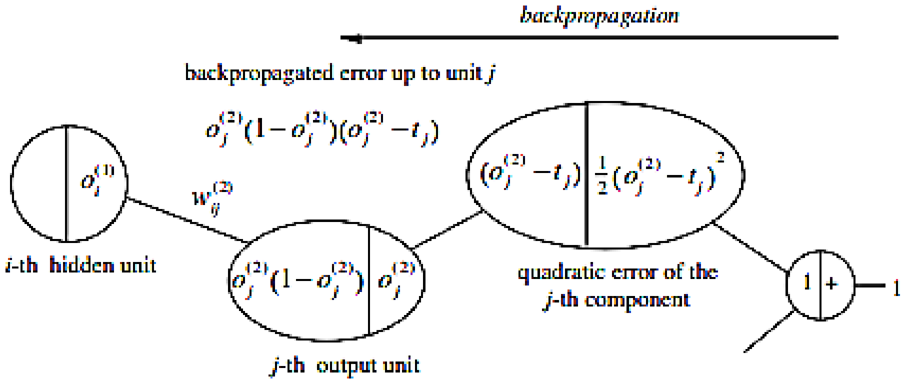

Fig.2.2: Backpropagation path up to output j.

A neural network can be trained in two different modes: online and batch modes. The online method weights are updated for each input data sample, and the weights are modified after each sample. An alternative solution is to calculate the weight update for each input sample but store these values during one pass through the training set, which is called an epoch. At the end of the epoch, all the contributions are added, and only then the weights will be updated with the composite value. This method adapts the weights with a cumulative weight update, so that it will follow the gradient more closely. It is called the batch-training mode. Training involves feeding training samples as input vectors through a neural network, calculating the error of the output layer, and then adjusting the weights of the network to minimize the error. The average of all the squared errors (E) for the outputs is computed to make the derivative easier. Once the error is computed, the weights can be updated one by one [55]. In the batched mode variant, the descent is based on the gradient ∇E for the total training set,

$$\Delta w_{ij}(n) = -\eta * \frac{\delta E}{\delta w_{ij}} + \alpha * w_{ij}(n-1) \qquad (2.2)$$

2.3.3 Training and testing neural networks

The best training process is to accumulate a wide range of examples, which show all the different characteristics of the problem. Generally, the network is trained for a prefixed number of periods or when the output error decreases below a particular set error. Special care is to be taken not to overtrain the network. By overtraining, the network may become too adapted in learning the samples from the training set, and thus may be unable to accurately classify samples outside of the training set [55].

2.4 Holt-Winters model

If the data have no trend or seasonal patterns, then simple exponential smoothing is appropriate. If the data exhibit a linear trend, then Holt's linear model is appropriate. However, if the data are seasonal, these models on their own cannot address the problem adequately. Holt's model was extended by Winters to capture seasonality directly. The new model could be extended, easily and flexibly, to the forecasting of multiple components in a variety of combinations and had many desirable characteristics: it was easy to program, fast to compute, required minimal data storage, put declining weight on old data, used simple initial conditions, had robust parameters, was automatically adaptive, model formulations were easy and the math was tractable. On the other hand, one of the criticisms of exponential smoothing models is that no covariates are used in the models, i.e., the data are assumed to be self-explanatory. Exponential smoothing models cannot deal with highly nonlinear problems that have an unknown functional relationship.
Consequently, there are difficulties when it comes to fitting the data. Holt-Winters' model, HW, is based on three smoothing equations: one for the level, one for trend, and one for seasonality. The seasonality can be modeled in an additive or multiplicative way [57]. The basic equations for the HW multiplicative model are as follows:

$$Level : I_t = \alpha \frac{y_t}{S_{t-m}} + (1-\alpha)(I_{t-1} + b_{t-1}) ....(2.3)$$

$$Trend : b_t = \beta(I_t - I_{t-1}) + (1-\beta)b_{t-1} ....(2.4)$$

$$Seasonal : S_t = \gamma y_t / (I_{t-1} + b_{t-1}) + (1-\gamma)S_{t-m} ......(2.5)$$

$$Forecast : \hat{y}_{t+h/t} = (I_t + b_t h)S_t - m + h_m ....(2.6)$$

Where m is the length of seasonality, *lt* represents the level of the series; *bt* denotes the growth, *st* is the seasonal component, h_m= [(h-1)mod m]+1, The parameters (α, β* and γ) are usually restricted to lie between 0 and 1.

2.5 Aggregate planning

Aggregate planning is the calculation of production rate and the best tactics to meet the demand through considering sales forecasts, production capacity, inventory levels and workforce for a medium period, often from 3 to 18 months in advance [58]. According to Chen et al. [59], the objective of an APP is not limited to maximize the revenue of the company, but it may also be used to maximize the resource utilization, to minimize the changes in production rate or to minimize the modifications in workforce level. Hence it is essential to specify the objective function correctly on an APP. In some cases, multiple objective functions are used to obtain a more realistic model for some real [60].

Aggregate production planning with matching capacity (via adjustment of production load, inventory, and employment levels) to changing demand, over a finite planning horizon, in order to achieve long-run profitability. It requires complete and accurate information about machine capacity, labor utilization, levels (inventory, safety stock, human resources adjustment, subcontract, storage), time (regular/overtime), costs (production, inventory, overtime/idle time, subcontracts, shortage, lost sales, breakdown, backorder, hiring/ firing/training) [61]:.

There are several Aggregate production models available, such as; Single-objective models focus on minimizing the total cost of the plan [62], bi-objective models, the minimization of total cost is the primary objective and a second objective is incorporated, such as maximization of service level (equivalently, minimization of back-ordering levels and lost sales because of stock-outs), or minimization of one of the following: changes in labor level, variability of total cost, financial risk [63-64]. Moreover, multi-objective models consider a combination of objectives simultaneously [64-67]. The Models that are used to solve aggregate planning include linear decision rule, transportation model, dynamic programming, lot sizing model, linear programming[68], heuristics [69], simulation [70], goal programming [71], micro spreadsheet analysis [72], multi-objective optimization [73], fuzzy formulation models [74,75], genetic algorithms (GAs) [76], and multiple criteria mixed-integer programming. Based on Holt et al., in [77], in the area of models for planning/scheduling production-inventory systems, two types of models can be identified:

- Static models which are based on a finite planning limit, considering deterministic demand. In this scenario, the receding planning limit is more significant than the period by the period plan.
- Dynamic models consider an indefinite planning limit, with proper forecasting in demand; this based on the framework that period by period decisions are based on a receding forecast over a planned time horizon.

2.5.1 Application of APP in different areas

Wang and Liang [78] utilized a fuzzy multi-objective linear programming model in the multi-product APP problem. They also presented a mathematical model to show the feasibility of the method. The model offers a compromise solution and the decision maker's overall levels of satisfaction. Leung and Chan [79] presented the aggregate production planning problem with different operational constraints and three production plants in North America and one in China. Mirzapur Al-e-Hashem et al. [80] studied a supply chain problem by considering multiple a multi-site, multi- period, multi-product aggregate production planning (APP) problem under uncertainty. In order to deal with APP including two conflicting objectives simultaneously, the proposed model was solved as a single-objective mixed integer programming model applying the LP-metrics method. The results showed the proposed model can achieve an efficient production planning in a supply chain.

Chapter-3

METHODOLOGY

3.1 Introduction

This chapter indicated the research methodology that provides the necessary steps followed to perform this study. Here below, given the flow chart represents the overall steps involved in this study.

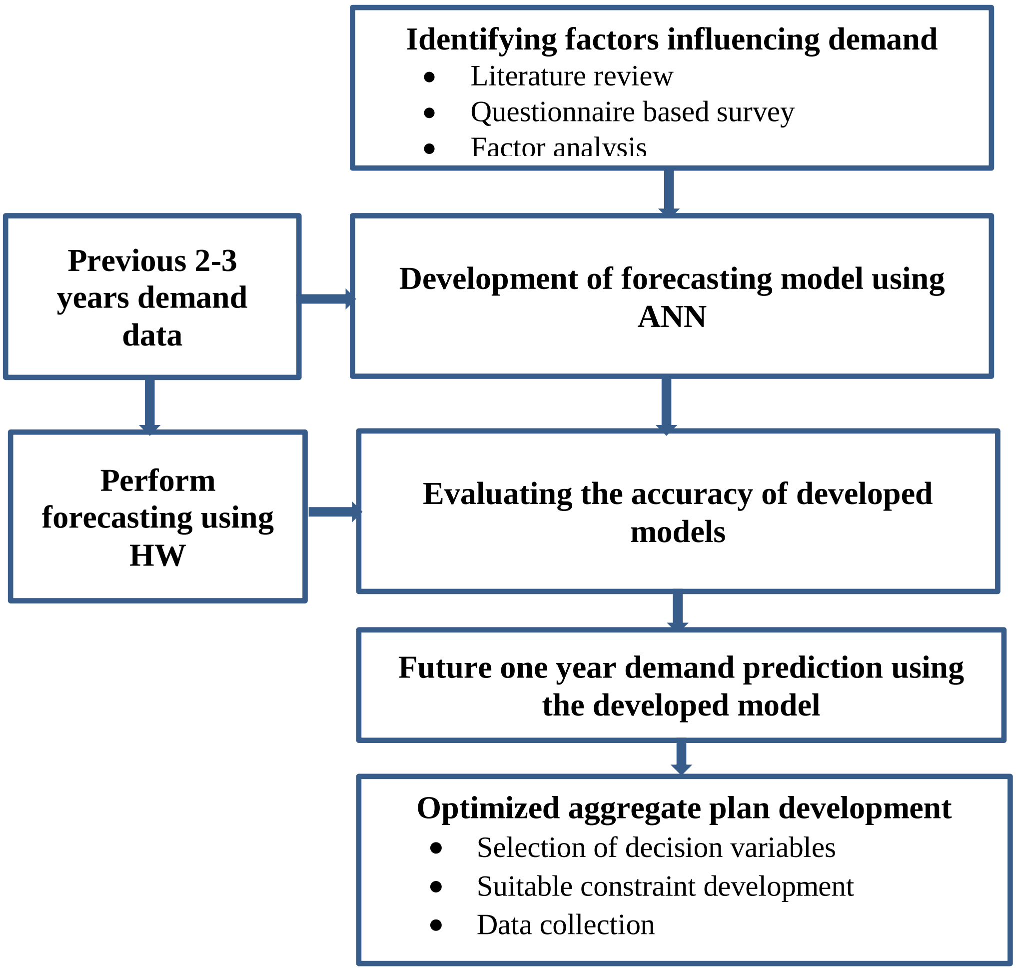

Figure 3.1: Methodology adopted for the study

3.2 Identifying Factors Influencing Demand

One of the objectives of the study is to identify the factors influencing demand. Several factors have a direct or indirect impact on customer preference. The demand of premium grocery items varies mostly with the factors. For identifying the factors, an extensive literature review has been performed. From the literature, some factors have been found. After performing a literature review, a questionnaire has been made which is verified by the experts. After that, the questionnaire has been sent to the selected manufacturing company. From the questionnaire-based survey, 12 factors have been found, which the company personnel found more important. To select the most crucial factor, Factor analysis has been performed.

3.2.1 Factor analysis

Factor analysis is a statistical model that allows explaining the correlations between a large number of observed correlated variables through a small number of uncorrelated unobservable ones: the factors. Factor analysis is generally an exploratory/descriptive method that requires many subjective judgments by the user. It is a widely used tool.
The process of factor analysis is as follows: an inter-item correlation matrix is created, and through principal factor or principle component analysis, the number of variables is reduced to a smaller number of components.

•Factor loadings: the correlation between the components and the original variables or items. Items with components loadings of >0.3–0.4 and with only one component may be retained [81]. Items should 'load on' only one component to be included
•Eigenvalues are calculated by squaring and adding the loadings on each factor. Each item has an eigenvalue of 1, hence the factor must have an eigenvalue of >1 if it is to be logically retaining
•Percentage variance: the total variance within the correlation matrix that the factor accounts for. It is calculated by dividing the eigenvalue by the number of variables
•Cumulative percentage variance: variance accounted for by all the factors. The larger this is, the more variance that is accounted for by the analysis

•Communality: squaring and adding the loadings for each item or variable calculates this. It is an indicator of the proportion of variance for each item that each factor accounts for.

3.3 Developing Forecasting Model Using ANN

Another objective of the study is to develop a forecasting model. Many researchers have utilized ANN for developing forecasting models in the diverse field including food items. Artificial neural networks (ANNs) utilize interconnected mathematical nodes or neurons to form a network that can model complex functional relationships [16]. Considering the benefit of this approach over other methods, it has been chosen to develop a forecasting model for premium grocery items. The first for model development is the selection of input nodes. The inputs are the selected factors. Data related to the factors has been collected and supplied to the model. Previous two to three years of demand data has been collected for the model. For the study, two different ANN models have been contrasted for two different premium grocery items ("Chinigura" and "Bashmoti"), considering the feed-forward back-propagation algorithm. The network architecture of Product "Chinigura" and "Bashmoti" are depicted below in fig.3.2:

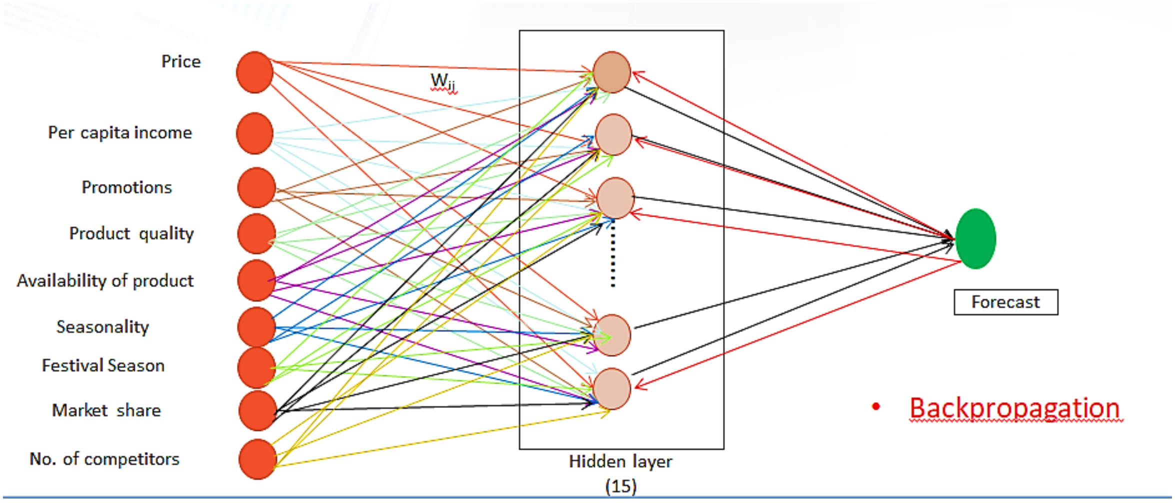

Fig. 3.2: Network architecture for this research

From the figure, it can be seen that there are eight inputs, 15 hidden neurons and one output layer. Here, the inputs are the factors mentioned identified from questionnaire based survey.

3.4 Forecasting Using HW Method

Another analysis using the Halt-Winter method (HW) is performed to compare with ANN. HW Model was first developed in the early 1960s and is an up gradation of the exponential smoothing method. All data values in a series contributing to the calculation of the prediction model. This method is used when there are a trend and seasonality in the data.

In general, HW technique is an elaborate extension of the exponential smoothing method because it sums up this approach to manage trend and seasonality.

If St denotes the smoothed series, α denotes the smoothing parameter, the exponential S smoothing constant is between, $0 < \alpha < 1$.

The smoothed series is given by the Eq. 3.1

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} \text{.................}(3.1)$$

For both product, “Chinigura” and “Bashmoti” forecasting is performed using Halt-Winter method. After the models are specified, their performance characteristics have been verified or validated by comparing its forecasts with historical data using accuracy measures. This analysis has been performed using Xcel solver. The adjustment parameters of the forecasting model are given below:

Table 3.1: Adjustment parameters for HW

Model	Parameters	Product “Chinigura”	Product “Bashmoti”
HW	A	0.636788	0.234868
	B	0.13856	0.4108
	Γ	2.16E-07	0.925851

These values have been found using the evolutionary engine of excel solver, here convergence is 0.0001, the mutation rate is 0.075 and the population size is 100.

3.5 Evaluating the Accuracy of Developed Model

When forecasting method is in use, one wants to know how well the method predicts what it is supposed to predict. Accuracy is the most common reason to use a specific type of forecast error. The second reason to use a specific forecast error is that it is relatively easy to interpret the error measure. To evaluate the forecast accuracy of the model's statistics such as different statistics are used. They are described below:

a. Mean Squared Error (MSE)

Mean Squared Error (MSE) a standard measure for forecasting errors and its variance is Mean Squared Error (MSE). MSE is related to the standard deviation of forecast errors and is, therefore, an appropriate error for mathematical operations. The mean forecast error deviates from zero and therefore is the mean error present which can be compared to the standard deviation. If instead, the mean error is assumed to be equal to zero the term for mean forecast error is deleted. However, due to the squared function, MSE is more sensitive to outliers and errors smaller than one.

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(\mathrm{e}_t - \overline{e_t})^2 \text{................}(3.2)$$

b. Mean Absolute Deviation (MAD)

MAD takes the absolute value of forecast errors and averages them over the entirety of the forecast time periods. Taking an absolute value of a number disregards whether the number is negative or positive and, in this case, avoids the positives and negatives canceling each other out.

$$MAD = \frac{1}{T}\sum_{t=1}^{T}|\,\mathrm{e}_t - \overline{e_t}\,| \text{...................}(3.3)$$

c. Mean Absolute Percentage Error

It provides an indication of how significant the forecast errors are in comparison to the actual values of the series. Especially useful when the e_t values are large can be used to compare the accuracy of the same or different methods on two different time series data.

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\frac{|\,\mathrm{e}_t - \overline{e_t}\,|}{e_t} \text{..................}(3.4)$$

d. Tracking Signal

The ratio of the cumulative algebraic sum of the deviations between the forecasts and the actual values to the mean absolute deviation. Used to signal when the validity of the forecasting model might be in doubt.

$$TS = \frac{\frac{1}{T}\sum_{t=1}^{t}(\mathrm{e}_t - \overline{e_t})}{MAD} \text{..................}(3.5)$$

3.6 Optimized Aggregate Plan

After verifying and checking the developed ANN forecasting model, this study aims to develop an optimized aggregate plan. This optimized aggregate plan is a linear programming model with necessary constraints. The objective function comprises production cost, overtime cost, cost of subcontracting and inventory holding cost. Hiring and firing cost are not considered because of company policy.

Chapter-4

DATA COLLECTION AND MODEL DEVELOPMENT

4.1 Introduction

The first objective aims to identify the factors influencing the demand for selected grocery items. The data concerning the factors has been collected from a renowned grocery item manufacturing company using a structured questionnaire. The demography of studied organization, respondent's profile, detail analysis regarding the selection of factors, ANN model development, and optimized aggregate plan development has been mentioned in this chapter.

4.1.1 Demography of studied organization

The study has been performed in a reputed food processing company, "X." It started its operation in 1981. Around 84,000 employees are employed there. The company is producing more than 400 food products of 10 different, which include grocery items. They collect the demand for products by market survey. From the record of the company's previous two-three years demand data of grocery item "Chinigura" and two years data of grocery item "Bashmoti" has been collected. From a structured questionnaire-based survey factor influencing the demand for the products and data related to these factors have been collected.

4.1.2 Demography of the respondents

Findings from the demography of the respondents are stated below. This described percentage participants of different positions, ages, and years of experience in a selected company.

Table 4.1: Demography of the respondents

Designation	Total Respondent	Percentage	Age	Percentage	Experience	Percentage
Marketing personnel	50	35.0	35+	19.0	3+	45.0
Operation personnel		22.0	24+	17.0	5+	27.7
Engineer		25.0	40+	14.9	15+	17.0
Finance personnel		18.0	50+	4.5	10+	18.0

From the table, it is evident that total respondent is 50; among them, 35% is from marketing and sales department, 22% are from operations, 25% from production and only 18% from the finance department. Their age and experience are also mentioned, respectively.

4.2 Factor selection

From the questionnaire, 12 factors are found. The importance of the factors has been ranked based on a Likert scale of 1 to 5. Here, 5 depicts most influencing, and 1 depicts the least influencing factors. Rests are arranged accordingly. After that, factor analysis has been performed to select the most influencing factors. From this analysis, nine factors have been selected. The descriptive statistics of the selected factors are mentioned below:

Table 4.2: Descriptive statistics of the selected factors

Factors	Mean	Standard Deviation	Maximum	Minimum
Price	4.3	0.7943	5	3
Per capita income	4.16	0.7943	5	3
Promotional activity	4	0.9468	5	2
Festival Season	3.8	0.9613	4	2
Market share	3.46	0.5713	4	2
No. of competitors	3.2	0.7143	5	2
Product availability	3.7	0.9878	5	2
Product quality	3.46	0.7302	5	2
Seasonal Variation	3.3	0.7523	4	2

From the table, it can be inferred that the mean price is 4.3, which is the highest. Seasonal variations, promotional activities, and per capita income have mean four and above. Standard deviation, standard error, etc. of all the factors are mentioned in the table. The Cronbach's alpha test has been performed to check the validity of data, and it is found that for all data, Cronbach's alpha value is >0.69, which implies the data are validated for study. The factor loading and eigenvalues of selected factors are mentioned below:

Table 4.3: Result of factor analysis of selected factors

Factors	Factor loading	Eigenvalue
Price	0.887	2.043
Per capita income	0.623	1.491
Promotional activity	0.846	1.437
Festival season	0.645	2.210
market share	-0.817	2.988
no. of competitors	-0.667	2.651
Seasonal variations	-0.638	2.523
Product availability	0.753	2.392
Product quality	-0.688	2.265

Here, the selected factors have factor loading value > 0.4, and also eigenvalue has been used to select the most demand influencing factors.

4.3 Forecasting model development

The forecasting model has been developed using ANN, considering the factors affecting demand. The network consists of input, activation function, hidden layer, learning algorithm, and output. The task has been performed using MATLAB 15 software. The network structure and learning conditions adopted for this study are mentioned below in the table. :

Table 4.4: The network structure and learning conditions

Network structure	
Network type	Feed-forward backpropagation
Transfer function	TANSIG
Training function	TRAINLM (Levenberg Marquardt (LM) algorithm)
Learning function	LEARNGDM

Learning conditions	
Learning Scheme	Supervised learning
Learning rule	Gradient descent rule
Learning rate	0.001
Maximum epochs	1000

The application randomly divides input vectors and output vectors into three sets as follows:

a. 70% is used for training
b. 10% is used to validate that the network is generalizing and stop training before overfitting
c. The last 20% is used as a completely independent test of network generalization.

4.3.1 Input layer

This layer is responsible for receiving information (data), signals, features, or measurements from the external environment. These inputs (samples or patterns) are usually normalized within the limit values produced by activation functions—this normalization results in better numerical precision for the mathematical operations performed by the network. There are nine input neurons for the selected products. These are the selected factors that affect the demand for the selected products. Data related to the factors has been collected from the selected company.

Among the selected factors, price, market share, no.of competitors, per capita income, and promotional activity are quantitative by nature. Suitable indexes are developed for qualitative factors. In the case of seasonality, the seasonality index has been developed. For developing a quality index, five essential factors that determine the level of quality of rice have been selected. These factors are [48]:

a. Grain dimension: Grain size and shape (length-width ratio) is a varietal property. Long slender grains usually have higher breakage than short, bold grains and consequently have a lower milled rice recovery.
b. Amylose content: High amylose grains cook dry, are less tender and become hard upon cooling. In contrast, low-amylose rice cooks moist and sticky.

c. Whiteness: Whiteness is a combination of varietal physical characteristics and the degree of milling.
d. Gel consistency: Gel consistency measures the tendency of the cooked rice to harden after cooling.
e. Milling degree: The degree of milling is a measure of the percent bran removed from the brown rice kernel. Milling degree affects milling recovery and influences consumer acceptance.

The respective weightage and level of the factors in each month for an individual product have been collected. The data are based on a Likert scale of 1 to 5. Here, 1 means the lowest acceptable limit, and 5 means the highest acceptable limit. The equation is;

$$\text{Quality index} = F_1W_1 + F_2W_2 + F_3W_3 + F_4W_4 + F_4W_4\ F_5W_5$$

Here,
F_i= level of factor i of an individual product in each month
W_i= weightage provided to factor i by selected company
In the case of festival season index development at first deseasonalizaton and trend elimination of demand, data has been performed. After that average of those months which are found to have festival demand has been calculated. Deseasonalize and trend adjusted demand data of each month is divided by this average to get the festival index of each month.
The data of product availability are incorporated as a percentage. From the response collected from the company based on a Likert scale (1= lowest availability and 5= highest availability), this percentage has been developed. Data of input neurons are represented in appendix1.

4.3.2 Activation function

Sigmoid function has been used as an activation function. A sigmoid function is a mathematical function having an "S" shape (sigmoid curve). The following formula gives the sigmoid function:

$$S_x = \frac{1}{1+e^{-x}} ....(4.1)$$

Sigmoid function exhibits smoothness and has the desired asymptotic properties. The sigmoid curve is shown in figure 4.1. As x goes to minus infinity, S(x) goes to 0. As x goes to infinity, S(x) goes to 1. As, x =0, S(x) =0.5.

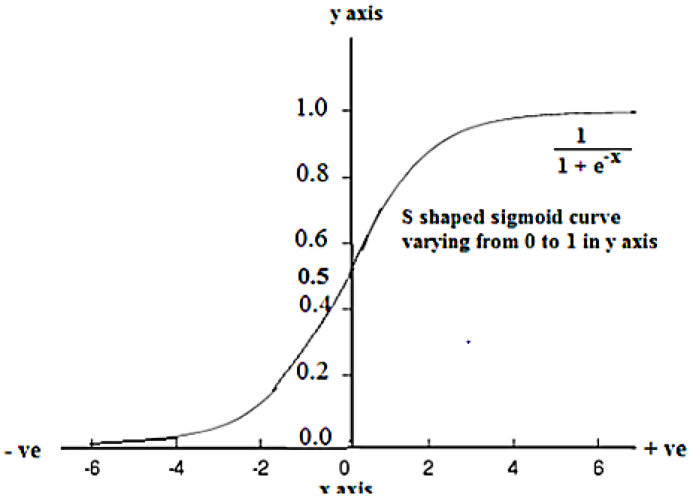

Fig. 4.1: Sigmoid function

4.3.3 Hidden layer

Hidden, intermediate, or invisible layers, these layers are composed of neurons that are responsible for extracting patterns associated with the processor system being analyzed. These layers perform most of the internal processing from a network. In the hidden layer, the sigmoid data represented as t1(i), t2(i)…….tn(i) are multiplied with initially assumed weights represented as wi . The initially assumed weights were from 0 to 1. Each node is multiplied with weights as follows:

$$Y_i = \sum t_i W_i + bias(+1) ....(4.2)$$

4.3.4 Learning algorithm

In this model supervised learning algorithm has been used. From the literature review, it is found that the Backpropagation algorithm is suitable for this kind of analysis, and it is more efficient. The backpropagation algorithm works well with the large data set, and in such learning, algorithm errors are distributed throughout the network. The backpropagation network could be easily modified to accommodate more features or to include spatial and temporal information. For that reason, the backpropagation algorithm has been a learning algorithm.

4.3.5 Output layer

The layer where the processed output information is computed and presented is called the output layer. Different computations performed in the output layer are given below:
Steps Computations performed to evaluate the performance of ANN

I. Zi is processed by multiplication of output Yi from the hidden layer with initially assumed weight Wk. There are nine values Z(1), Z(2)……….Z(9). Zi = Yi * Wk
II. Compute the Error between actual input data and the ANN output data using the formula given below:

$$\textbf{Error(i)} = \frac{Original\ data(i) - ANN\ output\ (i)}{Original\ data(i)} \ldots\ldots\ldots(4.3)$$

III. The backpropagation technique was adopted by computing the summation in the hidden layer using updated weights.
IV. If original independent input data and the corresponding ANN output are the same, the research has predicted correctly without any deviations. It happens only when an error is 0.
V. If there is a difference between the original input data and the corresponding ANN output, there are some deviations. The errors were worked out to understand how far the ANN output was away from the original data. Then update the weights and follow the backpropagation technique of computing summations.

4.4 Optimized Aggregate Plan Development

The final objective of the study is to develop an optimized aggregate plan. Aggregate planning is the middle term production planning level. The model proposed considers a planning horizon of 12 months, and solutions should be monthly reviewed (rolling-horizon) due to planning uncertainty. Following assumptions were considered in the model development:

a. 20% of total production is safety stock
b. Fixed capacity inline

c. Subcontracting cost include administrating, ordering and transportation cost
d. Multiple suppliers with different capacity and cost

The aggregate planning model involves the following decision variables:

1. Production volume (inregular shifts) of each family in each month of planning horizon;
2. Number of overtime shifts and units which must be used in each production line; and
3. Production Volume (in subcontract) of each family in each month of the planning horizon.

It is important to reinforce that the model will not suggest how to allocate the overtime shifts. The factory manager will decide which weeks of the month these shifts should be used. The following is a detailed description of the linear programming model.

Parameters	**Variables**
i= Product category	X_{it}= Total production of product i (Regular)
t= period (month)	Y_{it}= Total subcontracting production
d_{it}= Demand of i at month t	Z_{it}= Production at overtime hour
P_i= Production cost/unit	J_{it}= Total subcontracting production of i at month T
L_i= Cost to hold one unit of i	C_i=Production capacity of the company for a specific product
Si= Subcontracting cost/unit	I_{it}= Inventory level
C= cost of overtime production/unit	N_t= Normal shift of production
c_{it}= Available production capacity under subcontracting	O_{it}= Overtime shift of production
	O_T= Available overtime hours in a month
a_i= Required Production time	S_{it}= No.of product sold in month t
SS_{it}= Safety stock of product i at month t	

Mathematical Model:

Minimize,

$$\sum_{i=1}^{2}\sum_{t=1}^{T}P_iX_{it}+\sum_{i=1}^{2}\sum_{t=1}^{T}S_iY_{it}+\sum_{i=1}^{2}\sum_{t=1}^{T}L_iI_{it}+\sum_{t=1}^{T}(\mathrm{C}\,Z_{it})$$

Subject To,

$X_{it}+Y_{it}+Z_{it}=1.2*d_{it}$ **……………………..(i)**

$X_{it}\le C_i$ **……………….(ii)**

$I_{it}=I_{it-1}+X_{it}+Y_{it}+Z_{it}-d_{it}$ **……………………….(iii)**

$N_t=\sum_{i=1}^{2}a_i.X_{it}$ **…………………………..(iv)**

$O_{it}=\sum_{i=1}^{2}a_i.Z_{it}$ **…………………………..(v)**

$Y_{it}\le c_{it}$ **……………………(vi)**

$O_{it}\le O_T$ **…………………..(vii)**

$S_{it,}X_{it},Y_{it},I_{it},O_{it,}Z_{it}\ge 0$ **……………(viii)**

Here, the objective function includes production cost, subcontracting cost, inventory holding cost, and overtime workforce production cost. In production cost material cost, standard work hour costs are included. The constraint (i) represents that production quantity, overtime production and subcontracted unit should meet the demand. The production unit should be less than the available capacity of the selected product of a particular company is represented by constraint (ii). Constraint (iii) signifies the inventory unit that should always be maintained. Normal production time and overtime production time are maintained by constraint (iv) and (v). The subcontractor's capacity is maintained by constraint (vi). Overtime work hours should be less than the available hour provided by the company is represented by constraint no. (viii). Here, a single subcontractor has been considered.

Chapter-5

FINDINGS AND ANALYSIS

5.1 Introduction

In this chapter, findings from the developed neural network forecasting model, comparison between the developed model and Holt Winter model, and findings from the developed optimized aggregate plan will be discussed.

5.2 Findings From Developed Forecasting Model

In order to accurately forecast the demand for premium grocery items, an ANN forecasting model has been developed considering the identified factors. The quantitative factors are provided with their corresponding value collected from the selected company. The qualitative factors are ranked from 1 to 5. Here, 1= lowest and 5=highest. In order to train and check the model previous two to three years of data of demand for two selected products have been collected and used to check the validity of the model. The result is shown in appendix 1. The actual demand and forecasted demands of product "Chinigura" and "Bashmoti" are shown below in figure 5.1 and 5.2:

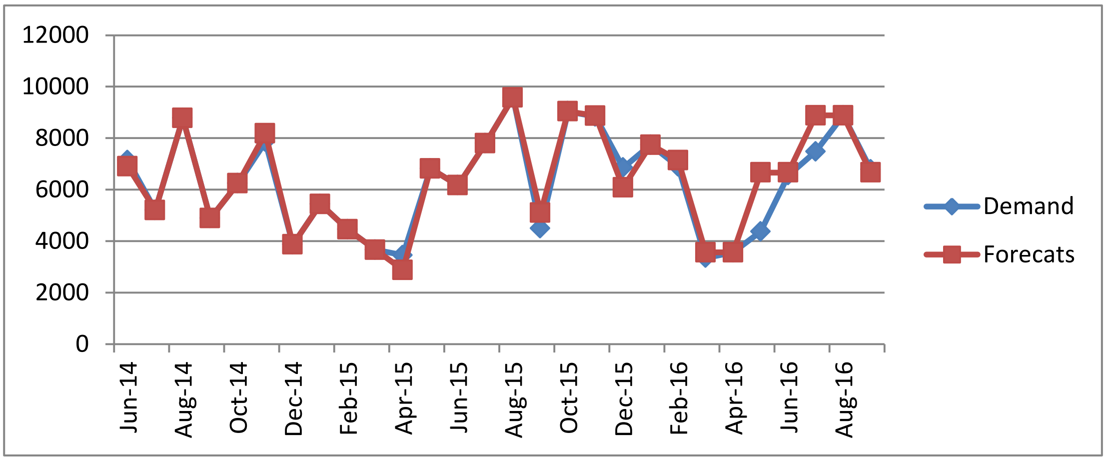

Fig. 5.1: Actual vs. forecasted demand of product "Chinigura"

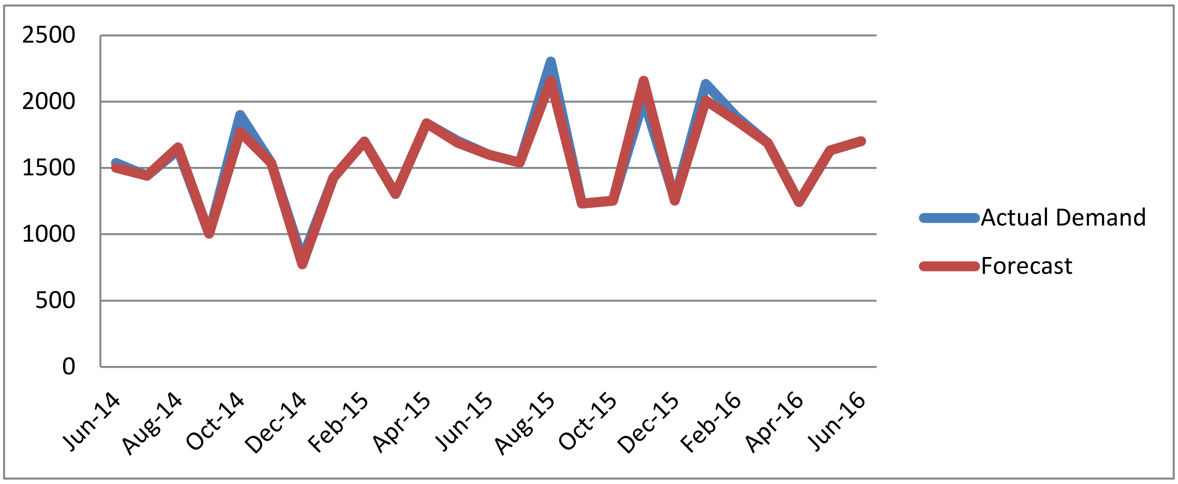

Fig. 5.2: Actual vs. forecasted demand of product "Bashmoti."

From figure. 5.1 and 5.2, it can be inferred that the forecasted demand is pretty close to the actual demand. The regression plot of training, validation, and test condition for both product Y and Z are mentioned below in figure 5.3 and 5.4:

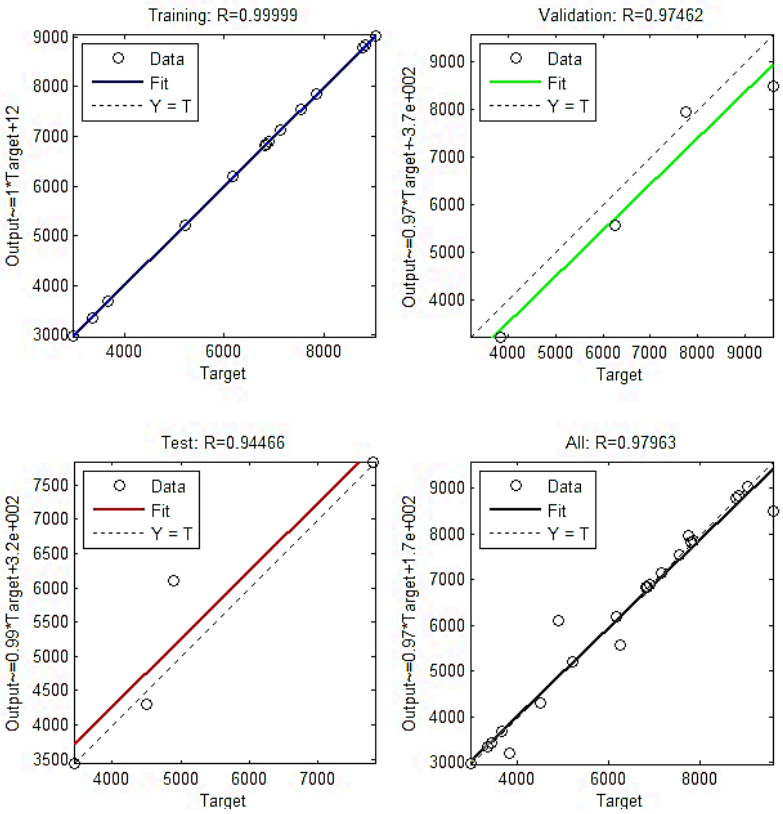

Fig. 5.3: Regression plots for product "Chinigura."

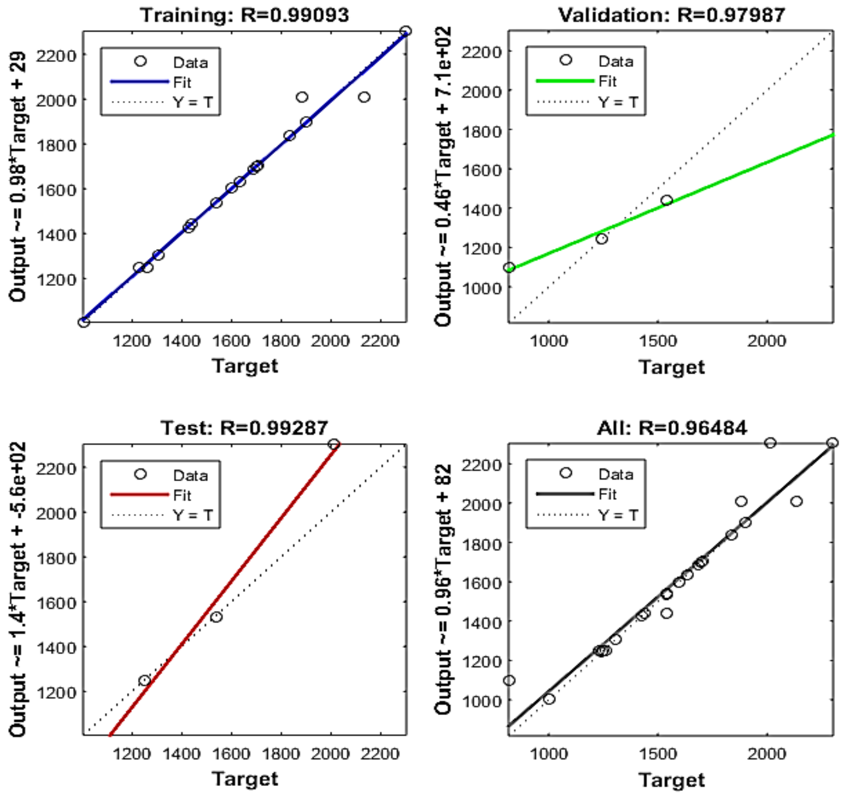

Fig. 5.4: Regression plots for product "Bashmoti."

Close inspection of figures 5.3 and 5.4 shows that in all conditions such as; training, validation, and test the regression value above 0.9. Regression values closer to 1 are considered to be satisfactory. Therefore from this analysis, it can be inferred that the accuracy of the forecasting model is satisfactory.

5.3 Comparison between ANN and Holt-Winter Method (HW)

Similar to ANN, historical data of demand are used in the HW method. The only difference is that here only two factors can be considered, such as; trend and seasonality, whereas in ANN, nine factors have been considered. For comparison, the forecasted demand found from 12 months data is shown for both methods below in table 5.1.

Table 5.1: Comparison of forecasted demand found from ANN and HW

Month	Actual demand	Forecasted demand from ANN (“Chinigura”)	Forecasted demand from HW (“Chinigura”)	Actual demand	Forecasted demand from ANN (“Bashmoti”)	Forecasted demand from HW (“Bashmoti”)
Dec-14	3869	3869	6130	817	773	1510
Jan-15	5441	5441	6409	1426	1426	1421
Feb-15	4451	4451	5675	1699	1699	1334
Mar-15	3664	3664	4707	1304	1304	1368
Apr-15	3451	2880	4149	1836	1836	1555
May15	6819	6819	6838	1704	1689	1639
Jun-15	6168	6168	7380	1601	1601	1637
Jul-15	7796	7796	8981	1541	1541	1743
Aug-15	9577	9577	11129	2303	2158	1710
Sep-15	4498	5095	7591	1230	1230	1842
Oct-15	9036	9036	10010	1252	1252	1780
Nov-15	8833	8870	10795	2014	2158	1694

In the table, 12 months of forecasted demands are shown using both methods. Here, forecasted demands found from ANN are closer to actual demand than HW.

The performance of a forecasting model is evaluated by some accuracy measures, such as root mean squared error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE). The values of these parameters for both models are shown below in table 5.2. Details of analyses are mentioned in appendix 2.

Table.5.2: Values of different errors for ANN and HW

Product category	Forecasting method	MAD	MAPE	RMSE
Chinigura	ANN	136.4008	2.678799	265.26
	HW	1300.102	22.72614	1544
Bashmoti	ANN	30.52993	1.67724	58.65
	HW	407.8457816	108.092619	480.22

The value of MAPE is 2.68% and 1.68% in the case of the ANN model, whereas the value of MAPE found for the HW model is 22.72% and 108.09% respectively for product “Chinigura” and “Bashmoti”. Similarly, other errors are lower in the case of ANN.

5.4 Forecasting Demand Using ANN Model

The main objective of the research is to predict future demand using the developed model. From the ANN model future, one year demand from (October 2016 to September 2016) has been calculated. The demand found for both products are shown below:

Table 5.3: Forecasted demand found from ANN model

Month	The demand for Product "Chinigura" (d_{it})	The demand for "product "Bashmoti" (d_{it})
Oct-16	8892	1864
Nov-16	9239	1552
Dec-16	8900	1564
Jan-17	7185	1006
Feb-17	5202	2295
Mar-17	5415	1542
Apr-17	4859	856
May-17	8100	1510
Jun-17	7741	1704
Jul-17	5152	1096
Aug-17	4829	1788
Sep-17	7624	1712

In calculating future demand, the input factors are also modified according to their trend and pattern.

5.5 Findings From Optimized Aggregate Plan

The ultimate aim of the research is to develop an optimized aggregate plan. For that purpose, a mathematical model considering different costs has been developed. The model is a constrained linear optimization model. The optimization of the model has been performed using MATLAB optimization function (linprog). Using the demand data from table.5.3, the mathematical model has been checked and cost has been calculated. The values of other variables have been collected from the company. The values of various variables are mentioned below in table 5.4

Table 5.4: Values collected for different variables of the aggregate model

Variable	Product "Chinigura"	Product "Bashmoti"
P_i	610	820
L_i	120	164
Si	620	835
a_i	3 minutes	13 minutes
C	6100	1500
c_{it}	3500	1200
T	12 months	12 months
O_T	30 hour	30 hour

Here, the safety stock is considered to be 20% of production. From the minimization model, the total cost has been calculated for each month. Result found from the aggregate model for two products Chinigura (Y) and Bashmoti (Z) are delineated below:

Table 5.5: The value of various decision variables found from the aggregate planning model

Month	Production unit (X_{it})		Subcontracting unit (Y_{it})		Overtime production unit (Z_{it})		Overtime work hour (O_{it})		Inventory Level (I_{it})		Total cost	
	Y	Z	Y	Z	Y	Z	Y	Z	Y	Z	Y	Z
Oct-16	3836	782	4446	932	610	150	25	25	1438	310	5.6586e+06	1.65E+06
Nov-16	6.01E+03	783	3079	619	150	150	6.15	25	1540	310	5.86E+06	1.40E+06
Dec-16	5783	788	2967	938	150	150	7.5	25	1483	312	5.64E+06	1.66E+06
Jan-17	3380	450	3623	600	182	150	6.15	25	1208	200	4.84E+06	1.08E+06
Feb-17	2949	1071	3099	1103	150	121	6.15	20	1033	368	3.94E+06	2.32E+06
Mar-17	3099	776	3249	926	150	150	6.15	25	1083	308	4.13E+06	1.64E+06
Apr-17	2765	363	2915	513	150	150	6.15	25	972	171	3.71E+06	9.36E+05
May-17	4643	709	4793	859	150	150	6.15	25	1597	285	6.13E+06	1.53E+06
Jun-17	4494	918	4644	1023	150	143	6.15	23.8	1548	341	5.95E+06	1.84E+06
Jul-17	3301	507	3451	657	150	150	6.15	25	1151	219	4.43E+06	1.18E+06
Aug-17	2747	1028	2897	1073	150	178	6.15	29.6	966	358	3.73E+06	2.05E+06
Sep-17	4425	1012	4575	1027	150	138	6.15	23	1525	343	5.86E+06	1.93E+06

The result obtained from the mathematical model is shown in the table. Here, optimized value for different decision variables of product Chinigura and Bashmoti, found from the model, has been identified. From this result, the company can make a decision regarding the unit to be produced in standard production time, unit to be outsourced, overtime production unit, and inventory level. Here, the total cost for producing the product 'Chinigura' is $59.87\times10^{6,}$ and for product 'Bashmoti' is 27.64×10^{6}. From the analysis of the company it is found that the total costs are 64.84×10^{6} and 31.29×10^{6} Tk. It shows that they can save money if they follow the developed aggregate plan.

5.6 Discussion on Findings

The model has been developed considering the factors identified from the questionnaire-based survey. Data related to the factors has been collected and supplied to the model to predict future demand. Data has been collected for two products. Factors are supplied as input to the neural network forecasting model. Previous two to three years of data have been used to train the model. The training method used for the model is supervised learning. The developed network is a feed-forward neural network with backpropagation algorithm. Using the model future one year, demand has been calculated. The accuracy of the model has been compared with the HW method. Another objective of the research is to develop an optimized aggregate plan. The aggregate plan has been developed. The developed model is a linear programming model, where minimizing cost is the main objective. In the model subcontracting cost and overtime cost are also considered. The supplier considered here is a fixed supplier. The model has been checked using the forecasted demand. The model estimated better than the company's traditional approach.

Chapter-6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusion

Forecasting is essential for both the manufacturing and service industries. Day to day, the companies are emphasizing more and more on forecasting. There are lots of forecasting techniques available. However, all the techniques are not applicable for all the products. The variation occurs due to demand variation and the influence of different factors in the demand for different products. One of the most important markets is the grocery market, where different types of products with demand variation can be found. This market is a growing market in Bangladesh. Lots of renowned and unknown companies produce products. One of the most vulnerable items in grocery items is an agro-processed product; for example, rice. The demand for such a product varies more rapidly. There are also lots of factors that influence the demand for such products. However, the lack of accurate forecasting techniques makes the situation worse. Companies are now trying to find out a more accurate technique to overcome such problems. This study focuses on identifying an accurate forecasting model for such products and also to develop an optimized aggregate plan for them. The conclusions derived from this work are mentioned below:

- To develop an accurate forecasting model to predict demand for premium grocery items, it is necessary to identify the factors that influence the demand for selected products. An extensive literature review has been performed to gain preliminary knowledge regarding the factors. After that, a structured questionnaire-based survey has been performed in a selected company. From the survey, 12 factors have been identified. After that, factor analysis has been performed to select the most influencing factors. From that, nine factors are found most influencing. These factors are price, per capita income, promotional activity, product quality, product availability, seasonal variation, festival season, market share, no. of competitors.
- Another objective of the study is to develop a forecasting model. To develop a model ANN has been chosen for its' accuracy in working both linear and non-

linear situations. A feed-forward model with a backpropagation algorithm has been developed. The identified factors have been supplied as input for the model. Data related to the input have been collected from the selected manufacturing company. Previous two to three years of data have been supplied in the model for training. The output of the model is the forecasted demand. The developed model has been compared with the HW model to check its accuracy based on some parameters. It is found that the developed model outperformed the HW method.

- The remaining objective of the model is to develop an optimized aggregate plan. The developed plan is the cost model with a linearity function. The main decision variables are in-house production quantity, subcontracting quantity and overtime hours. This optimized model shows a better estimation than the company's traditional method.

6.2 Recommendation for Future Study

The study has been performed in such a sector where less study had been done. Viewing the necessity of performing such a study in this sector, the objective of the study has been set. Great endeavor and efforts have been given in conducting the study however there are some limitations of the study. These limitations provide an opportunity for future researchers to work in this field. The limitations are mentioned below;

- The study has been performed in a company. It would be more accurate if the study can be performed in more than one company.
- The study would be more accurate if the data from the consumers can be gathered.
- The more the number of demand influencing factors, the more accurate would be the forecast it.

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Appendix 1
Secondary questinnaire
Questionnaire for Demand influencing factors
Participant's details:

Name:

Age:

Department:

Position:

Work experience:

Factor related Questions

1. **How is the demand pattern of grocery items in the company:**

   a. **Fluctuating** b. **Non- Fluctuating**

2. **From your observation, which factors influences demand of grocery items such as; 'Chinigura rice' and Basmoti rice' in this company**:

Mark the boxes which you find suitable for your answer. Here, 1= Least influence, 2= Mild influence, 3= Moderate influence, 4= High influence and 5= Highest influence.

a. **How much influence 'Price' shows in demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

b. **How much influence 'Inflation' shows in demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

c. **Mention the amount of influence of 'Per Capita Income' in demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

d. **How much influence 'Consumer Preference Index (CPI)' shows in demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

e. **How much 'Quality of the product' influences the demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

f. **The influence of 'Availability of the product' on the demand of 'Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

g. **How much 'Market Share' influences the demand of Chinigura' and 'Basmoti':**

   [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

h. **The influence of 'No. of competitors' in the market influences the demand of respective products:**

[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

i. The influence of 'Import' of the products from outside influences the demand of respective products:

[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

j. How much influence 'Discount/promotion' have in demand of these items:

[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

k. How much influence 'Seasonality' have in demand of these items:

[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

l. How much influence 'Festival season' such as, eid, puja and marriage season shows in demand of these items:

[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5