Examination Roll Number: 21291761036

PROJECT REPORT

on

"TO CONDUCT ABC ANALYSIS AND TO FORECAST THE DEMAND OF FMCG PRODUCTS AND SUGGEST OPTIMUM PROCUREMENT STRATEGY"

Submitted as part of an assignment in

MASTER OF OPERATIONAL RESEARCH

Undertaken at

Mohit & Company
Pakka Bagh, Gangapur
Bareilly -243003, India

UNIVERSITY OF DELHI
DEPARTMENT OF OPERATIONAL RESEARCH

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ACKNOWLEDGEMENT

It is a great sense of satisfaction and a matter of privilege for me to work at Mohit & Company. I wish to express my heartiest thanks to Mr. Mohit Gupta for providing me with the opportunity to undertake this project in their esteemed organization. During the project work, I was in constant interaction with Mr. Gupta, who was highly cooperative throughout the project.

I would especially like to thank our Professors, **Prof (Dr.) Preeti Wanti Srivastava, Prof (Dr.) K.K. Aggarwal, and Prof (Dr.) Chandra K. Jaggi** for their valuable guidance, precious time, and support in the completion of this project.

Lastly, I would like to thank all my batchmates and seniors for their cooperation and help without which I would not have been able to complete the project successfully.

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COMPANY PROFILE

Basic Information

Year Of Establishment - 1995

Legal Status of the Firm – Proprietorship

Nature of Business – Super Stockist

Mohit & Company is a wholesale-based company which deals in trading/lending of most kinds of FMCG items only in large quantity across areas in Bareilly, Badaun, Pilibhit, Shahjahanpur and other nearby areas. It has wide range of products from Bambino, Lion, Madhusudan, Niine, Wagh Bakri, etc. They have a motive to provide and make available varieties of daily use items to wholesalers and satisfy their bulk orders on weekly or monthly basis at minimum price possible. The organization buys products directly from the manufacturers and deals in around 150+ products for wholesale quantity. Mainly they buy from Gujarat tea processor and packers Ltd-New Delhi, Bambino Agro industry Ltd-Gurgaon, Niine pvt Ltd-New Delhi, Pushp brand India pvt Ltd-Indore, Creamy foods pvt Ltd-New Delhi, etc.

Mohit & Company was established in 1995, by Mr. Mohit Gupta, the proprietor of the firm and they have covered a long way since then. They have been in the market for over 28 years and since then they have been extending their client base all over the region and other nearby states. They currently experience a good turnover of over 15-18 crores annually. Taking their ideas into action, they have seen an upward growth in past few years. They have a team of over 15 workers, who are very efficient and well trained in this profession. They work tirelessly to fulfil all the consignments taken by the company. Moreover, the inventory of products is stored in a very well- maintained storage, taking care of all the necessary requirements of storage for these kinds of product

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Chapter 1

Introduction
to
Operational Research

1.1 - WHAT IS OPERATIONAL RESEARCH?

Operations research attempts to provide those who manage organized systems with an objective and quantitative basis for decision. As its name implies, operation research involves “research on operations”. Thus, operations research is applied to problems that concern how to conduct and coordinate the operations (i.e., the activities) within an organization. OR starts when mathematical and quantitative techniques are used to substantiate the decision being taken. The main activity of a manager is decision making. In our daily life we make the decisions without even noticing them. The decisions are taken simply by common sense, judgment, and expertise without using any mathematical or any other model in simple situations. But the decisions we are concerned here with are complex and heavily responsible. Examples are public transportation network planning in a city having its own layout of factories, residential blocks or finding the appropriate product mix when there exist many products with different profit contributions and production requirement etc.
Operational Researchers apply their skills of incisive analysis and numeracy to real world problems. They take tools from different disciplines such as mathematics, statistics, economics, psychology, engineering etc. and combine these tools to make a new set of knowledge for decision making. Today, O.R. became a professional discipline which deals with the application of scientific methods for making decisions, and especially to the allocation of scarce resources. The main purpose of O.R. is to provide a rational basis for decision making in the absence of complete information, because the systems composed of humans, machines, and procedures may not have complete information.

O.R. specialists are involved in three classical aspects of science; they are as follows:

- Determining the system’s behavior.
- Analyzing the systems behavior by developing appropriate models
- Predict future behavior using these models.

The emphasis on analysis of operations distinguishes the O.R. from other research and engineering. O.R. is an interdisciplinary discipline which provided solutions to problems of military operations during World War II, and successful in other operations. Today business applications are primarily concerned with O.R. analysis for the possible alternative actions. The business and industry benefitted from O.R. in the areas of inventory, reorder policies, optimum location and size of warehouses, advertising policies, etc.

1.2 - HISTORY OF OPERATIONAL RESEARCH

The origin of OR takes us back to the time Of World War II, the military management in England called upon a team of scientists to study strategies and tactical problems associated with air and land of the country. Their objective was to decide upon the most effective utilization of limited military resources. The applications included, among others, studies to integrate radar technology into aerial combat operations from the research and development being done in laboratories & workshops. The military services began assembling scientists, engineers, and mathematicians – not to mention a smattering of lawyers, actuaries, and schoolteachers. The establishment of this scientific team marked the first formal operations research activity. The name "Operational Research" was apparently coined because the team was dealing with research on (military) operations, since its birth, this new decision-making field has been characterized using deciding upon the best utilization of limited resources.

By the mid-1950s, as O.R. assumed the mantle of a profession, it began to adopt into its methodology a variety of emerging mathematical methods such as linear programming, inventory theory, search theory and queuing theory. In 1951 a committee on Operations Research formed by the National Research Council of USA, and the first book on "Methods of Operations Research", by Morse and Kimball, was published. In 1952 the Operations Research Society of America came into being. Success of Operations Research in army attracted the attention of the industrial mangers who were seeking solutions to their complex business problems.

Now a days, almost every organization in all countries has staff applying operations research, and the use of operations research in government has spread from military to wide variety of departments at all levels. The growth of operations research has not limited to the U.S.A. and U.K., it has reached many countries of the world. India was one the few first countries who started using operations research. In India, Regional Research Laboratory located at Hyderabad was the first Operations Research unit established during 1949. At the same time another unit was set up in Défense Science Laboratory to solve the Stores, Purchase and Planning Problems. In 1953, Operations Research unit was established in Indian Statistical Institute, Calcutta, with the objective of using Operations Research methods in National Planning and Survey. In 1955, Operations Research Society of India was formed, which is one of the first members of International Federation of Operations Research societies. Today Operations Research is a popular subject in management institutes and schools of mathematics.

1.3 - BASIC CONCEPT OF OR

- **FORMULATING THE PROBLEM**

Both the consumer's and the researcher's problem must be formulated. The person (or group) who controls the operations under study is referred to as the decision-maker. In formulating the consumer's problem, an analysis must be made of the system under his control, his objective, and alternative course of action. Others affected by the decision under study must be identified and their pertinent objectives and course of action must be uncovered. What we have called the overall viewpoint is closely connected with the attempt to define objectives. O.R. tries to consider as broad a scope of objectives as possible. In most general terms, the research problem is to determine which alternative course of action is most effective relative to the set of pertinent objectives. Consequently, in formulating the research problem a measure of effectiveness must be specified and its suitability must be established.

- **CONSTRUCTING A MATHEMATICAL MODEL**

This model expresses the effectiveness of the system under study as a function of a set of variables at least one of which is subject to control. The general form of an O.R. model is $E = f(x1, y1)$ Where E represents the effectiveness of the system, xj represents the variables of the system, which are subject to control and yj those variables that are not subject to control. The restriction on values of the variables is expressed in a supplementary set of equations and/or inequations.

- **DERIVING A SOLUTION FROM THE MODEL**

There are essentially two types of procedures for deriving an optimum (or an approximation to an optimum) solution from a model: analytical and numerical. Analytical procedures consist of the use of mathematical deduction. This involves the application of various branches of mathematics such as calculus or modern algebra. Analytic solutions are obtained "in the abstract" i.e., the substitution of numbers for the symbol is generally made after the solution has been obtained.

- **TESTING THE MODEL AND SOLUTION**

A model is never more than a partial representation of reality. It is a good model if, despite its incompleteness, it can accurately predict the effect of changes in the system on the system's overall effectiveness. The adequacy of the model can be tested by determining how well it predicts the effect of these changes. The solution can be evaluated by comparing results obtained without applying the solution with results obtained when it is used. These evaluations may be performed retrospectively using past data, or by a trial run or pre-test. Testing requires careful analysis as to what are and what are not valid data.

- **ESTABLISHING CONTROLS OVER THE SOLUTION**

A solution derived from a model remains a solution only as long as the uncontrolled variables retain their values and the relationship between the variables in the model remains constant. The solution itself goes “out of control” when the value of one or more of the uncontrolled variables and/or one or more of the relationships between variables has changed significantly. The significance of the change depends on the amount by which the solution is made to deviate from the true optimum under the changed conditions and the cost of changing the solution in operation. To establish controls over the solutions, one must then develop tools for determining when significant changes occur, and rules must be established for modifying the solutions to consider these changes.

- **IMPLEMENTATION**

The tested solution must be translated into a set of operating procedures capable of being understood and applied be the personnel who will be responsible of their use. Required changes in existing procedure and resources must be specified and carried out. The steps enumerated are seldom, if ever, conducted in the order presented. Furthermore, the steps may take place simultaneously. In many projects, for example, the formulation of the problems is not completed until the project itself is virtually complete. There is usually a continuous interplay between these steps during the research.

1.4 – STAGES OF DEVELOPMENT

The stages of development of O.R. are also known as phases and process of O.R, which has six important steps. These six steps are arranged in the following order:

Step I: Observe the problem environment: The first step in the process of O.R. development is the problem environment observation. This step includes different activities; they are conferences, site visit, research, observations etc. These activities provide sufficient information to the O.R. specialists to formulate the problem.

Step II: Analyse and define the problem: This step is analysing and defining the problem. In this step, in addition to the problem definition the objectives, uses and limitations of O.R. study of the problem also defined. The outputs of this step are clear grasp of need for a solution and its nature understanding.

Step III: Develop a model: This step develops a model; a model is a representation of some abstract or real situation. The models are basically mathematical models, which describes systems, processes in the form of equations, formula/relationships. The different activities in this step are variables definition, formulating equations etc. The model is tested in the field under different environmental constraints and modified to work. Sometimes the model is modified to satisfy the management with the results.

Step IV: Select appropriate data input: A model works appropriately when there is appropriate data input. Hence, selecting appropriate input data is important step in the O.R. development stage or process. The activities in this step include internal/external data analysis, fact analysis, and collection of opinions and use of computer data banks. The objective of this step is to provide sufficient data input to operate and test the model developed in Step III.

Step V: Provide a solution and test its reasonableness: This step is to get a solution with the help of model and input data. This solution is not implemented immediately, instead the solution is used to test the model and to find there is any limitations. Suppose if the solution is not reasonable or the behaviour of the model is not proper, the model is updated and modified at this stage. The output of this stage is the solution(s) that supports the current organizational objectives.

Step VI: Implement the solution: This step the solution obtained from the previous step is implemented. The implementation of the solution involves many behavioural issues. Therefore, before implementation the implementation authority must resolve the issues. A properly implemented solution results in quality of work and gains the support from the management.

1.5 - APPLICATION OF OPERATIONAL RESEARCH

Today, almost all fields of business and government utilizing the benefits of Operations Research. There are voluminous of applications of Operations Research. Although it is not feasible to cover all applications of O.R. in brief. The following are the abbreviated set of typical operations research applications to show how widely these techniques are used today:

Accounting:

- Assigning audit teams effectively
- Credit policy analysis
- Cash flow planning
- Developing standard costs
- Establishing costs for by products
- Planning of delinquent account strategy

Construction:

- Project scheduling, monitoring, and control
- Determination of proper work force
- Deployment of work force
- Allocation of resources to projects

Facilities Planning:

- Factory location and size decision
- Estimation of number of facilities required.
- Hospital planning
- International logistic system design
- Transportation loading and unloading
- Warehouse location decision

Finance:

- Building cash management models
- Allocating capital among various alternatives
- Building financial planning models
- Investment analysis
- Portfolio analysis
- Dividend policy making

Manufacturing:

- Inventory control
- Marketing balance projection
- Production scheduling
- Production smoothing

Marketing:

- Advertising budget allocation
- Product introduction timing
- Deciding most effective packaging alternative

Organizational Behaviour / Human Resources:

- Recruitment of employees
- Skill balancing
- Training program scheduling
- Designing organizational structure more effectively

Purchasing:

- Optimal buying
- Optimal reordering
- Materials transfer

Research and Development:

- R & D Projects control
- R & D Budget allocation
- Planning of Product introduction

Chapter 2

Inventory Management

2.1 – About Inventory Management

Simply inventory is a stock of physical assets. The physical assets have some economic value, which can be either in the form of material, men, or money. Inventory is also called as an idle resource if it is not utilized. Inventory may be regarded as those goods which are procured, stored, and used for day-to-day functioning of the organization. Inventory can be in the form of physical resource such as raw materials, semifinished goods used in the process of production, finished goods which are ready for delivery to the consumers, human resources, or financial resources such as working capital etc. Inventories means measures of power and wealth of a nation or of an individual during centuries ago. That is a businessman or a nation's wealth, and power were assessed in terms of grams of gold, heads of cattle, quintals of rice etc.

In recent past, inventories mean measure of business failure. Therefore, businessmen have started to put more emphasis on the liquidity of assets as inventories, until fast turnover has become a goal to be pursues for its own sake. Today inventories are viewed as a large potential risk rather than as a measure of wealth due to the fast developments and changes in product life.

The concept of inventories at present has necessitated the use of scientific techniques in the inventory management called as inventory control. Thus, inventory control is the technique of maintaining stock items at desired levels. In other words, inventory control is how material of the correct quality and quantity is made available as and when it is needed with due regard to economy in the holding cost, ordering costs, setup costs, production costs, purchase costs and working capital.

Two fundamental questions that must be answered in controlling the inventory of any physical goods are, when to replenish the inventory and how much to order for replenishment.

2.2 – Features of Inventory System

The costs incurred in opening an inventory system play the major role in determining what the operating doctrine should be:

Fundamentally, there are five such costs:

Set up cost: This cost originates from expenses of placing a purchases order to an outside supply or from an internal production setup. This cost is usually assumed to vary directly with the number of orders or setups and not in the size of the order. In case of procurement, this cost includes such as making requisition, analysing vendors, writing purchase cost, securing material and transportation cost, inspecting materials, following up orders, and doing the paperwork necessary for making transactions. In case of production, set up cost includes cost of changing over production process; produce the order item, preparing shop orders, scheduling the work, pre-production set up, expediting and quality acceptance.

Unit production cost or unit purchase price: Such a cost is of special interest when "quantity discounts" can be availed for orders above certain quantity or large production runs may result in a decrease in the production cost. Under these conditions, the order quantity must be adjusted to take advantage of these rebates.

Selling price: In some inventory situations, the demand of the commodity may be affected by the quantity stocked. In such case the decisions model is based on a profit maximization criterion, which includes the revenue from selling the commodity. Unit selling price may be constant or variable, depending on various factors, for example, whether quantity discount is allowed or not.

Inventory holding cost: This cost includes real out of pocked cost such as costs of insurance, taxes, breakage and pilferage at the storage side, warehouse rental if the management does not own warehouse, and the cost of operating the warehouse such as light, heat, night watchman etc. It also includes opportunity cost, which is an important component of this cost. This is the incurred by having capital tied up in inventory rather than having it invested elsewhere, and it is equal to the largest rate of return which the system could obtain from alternative investments. By having funds invested in inventory, one forgoes this rate of return and hence, it represents a cost of carrying inventory. The cost is assumed to be varying directly with the level of inventory as well as the length of time the item is held in stock.

Shortage cost: These are the costs, which are incurred by having demand when the system is out of stock. These are inherently extremely difficult to measure since they can include such as loss of customer goodwill and potential loss in income. Other parts include cost of notifying a customer than an item is not in stock and will be back ordered plus the cost of attempting to find out when the customers' orders can be filled and giving him this information. If the system uses the part, the back-order cost may simply be the cost of keeping a machine idle for lack of parts.

In case where unfilled demand for the commodity can be satisfied later (backlog case), these costs are assumed to be usually varying directly with both the shortage quantity and delayed time. On the other hand, if the unfilled demand is lost (lost sale case), the shortage cost becomes proportional to shortage quantity only.

The demand pattern is the next major characteristic of any inventory system. The demand pattern of commodity may be either deterministic or probabilistic. In the deterministic case, it is assumed that the quantity needed over subsequent period is known with certainty. This may be expressed over equal period in term of known constant demand or in term of known variable of demand. The two cases are referred to as static and dynamic demand, respectively.

The probabilistic demand occurs when the demand occurs when the demand over certain period is not known with certainly, but its pattern can be described by a known probability distribution. In this case, probability distribution may be either stationary or non-stationary over time. These two cases are referred to as static and dynamic demand respectively.

The ordering cycle: This is concerned with the measurement of inventory situation. An ordering cycle may be identified by the time between two successive placements of order. The ordering cycle depend on the type of review undertaken.

Continuous review: Where a record of inventory level is updated continuously until a certain lower limit is reached. At the point when new order is placed.

Periodic review: Where orders are placed usually at equally spaced interval of time.

Delivery lag or lead-time: Lead-time for an inventory system is defined as the interval between the time when the stocking point placing an order for replenishment and the time when the order arrives and is on the shelves available to customers. Often the procurement lead-time will not be constant, since the time to fill the order at the source, the shipping time and time required to carry out paperwork etc. can vary from one order to another. Sometimes the variation in the lead-time will be small enough so that the lead-time can be assumed constant. In other cases, it will exhibit sufficient unpredictable variability that it is necessary to assume that the lead-time is a stochastic random variable.

Stock replenishment: They can occur either instantaneously or uniformly over time. Instantaneous replenishment occurs in case the stock is purchased from outside sources. On the other hand, uniform replenishment may occur when the product is manufactured locally within the organization. This means that a system may operate with positive deliver lags and with uniform stock replenishment. This case, however, is not generally considered while developing inventory models.

Time horizon: It defines the time over which the inventory level will be controlled. This horizon may be finite or infinite depending on the nature of the demand for the commodity. Limited floor space: An inventory system may include more than one item or the commodity. This case will be of interest only if some kind of interaction exists between the different items. For example, the item may compete for limited floor space and limited total capital. Such an interaction must lead to a special formulation of the inventory model.

Demand in an Inventory System:

The understanding of nature of demand (i.e., its size and pattern) is very essential to determine the optimal inventory policy for that item.

• **Independent Demand:** An inventory of an item is said to be falling into the category of independent demand when the demand for such an item is not dependent upon the demand for another item. Finished goods Items, which are ordered by External Customers or manufactured for stock and sale, are called independent demand items. Independent demands for inventories are based on confirmed Customer orders, forecasts, estimates and past historical data.

• **Dependent Demand**: If the demand for inventory of an item is dependent upon another item, such demands are categorized as dependant demand. Raw materials and component inventories are dependent on production requirement.

Constraint on inventory system: The stock level of various items depends upon the constraints such as limited warehouse space, limited budget available for inventory, degree of management attention towards individual items of inventory, Customer service level etc.

2.3 – Managing and Controlling Inventory

Inventory models give answers to two questions. When should an order be placed, or a new lot be manufactured? Moreover, how much should be ordered or purchased?

Inventories are held for the following reasons:

- To meet anticipated customer demand with large fluctuations.
- To protect against shortages.
- To take advantage quantity discounts.
- To maintain independence of operations.
- To smooth production requirements.
- To guard against price increases.
- To take advantage of order cycles.
- To overcome the variations in delivery times.
- To guard against uncertain production schedules.
- To count for the possibility of large number of defects.
- To guard against poor forecasts of customer demand.

How to Reduce the Inventory Costs?

- Cycle inventory.
- Streamline ordering/production process.
- Increase repeatability.
- Safety Stock inventory.
- Better timing of orders.
- Improve forecasts.
- Reduce supply uncertainties.
- Use capacity cushions instead.
- Anticipation inventory.
- Match production rate with demand rate.
- Use complementary products.
- Off-season promotions.
- Creative pricing.
- Pipeline inventory.
- Reduce lead-time and decrease lot size when it affects lead times.
- More responsive suppliers.

2.4 – Selective Inventory Control

Every organization consumes several items of store. Since all the items are not of equal importance, a high degree control on inventories of each item in neither applicable nor useful. So is becomes necessary to classify the items in-group depending upon their utility importance. Such type of classification is named as the principal of selective control, which is applied to control the inventories.

In practice when a firm maintains a variety of items that too in large quantities in its inventory, all items obviously cannot and need not be controlled (i.e., keeping record of time interval between successive reviews of demand; order frequencies; expected demand rate; order quantities etc.) with equal attention. All items are not of equal importance to the firm in such terms as sales, profits, availability etc. one way of exercising proper degree of overall control and various types of items held in stocks is to classify them into groups based on the degree of control or intensity of managerial attention. By selectively applying inventory control policies to these different groups, inventory objectives can be achieved with lower inventory levels than with a single policy applied to all items, these techniques are also known as selective multi-item control techniques.

Classification	Basis of classification	Purpose
ABC (Always, Better , Control)	Value of consumption	controlling raw material components & work in progress inventories
VED (Vital, Essential, Dead)	critically of items	determining the inventory level of spare parts.
HML (High, Medium, Low)	Unit price of the material	Mainly to control purchases
XYZ	Value of items in storage	To review the inventories and their uses at scheduled inventories
FSN (Fast, Slow, Non- moving)	Consumption pattern of the Component	To control obsolescence
SDE	Problems faced in procurement	Lead time analysis and purchasing strategies.
GOLF (Government, Ordinary, Local, Foreign sources)	Source of material	Procurement strategies.
SOS (Seasonal, Off seasonal)	Nature of supplies	Procurement/holding strategies of seasonal items

2.4.1 – ABC Analysis

Inventory control can take a lot of effort and so for some items, especially cheap ones, this effort is not worthwhile. ABC Analysis is a comprehensive way of segmenting your customers or products to make sure that you get the most out of your time and your resources when you're servicing them by breaking the items down into three easily distinguishable categories. This technique involves the classification of inventory items into three categories A, B and C in descending order of annual consumption and annual monetary value of each item. In ABC analysis the items are classified in three main categories based on their respective usage value of each item.

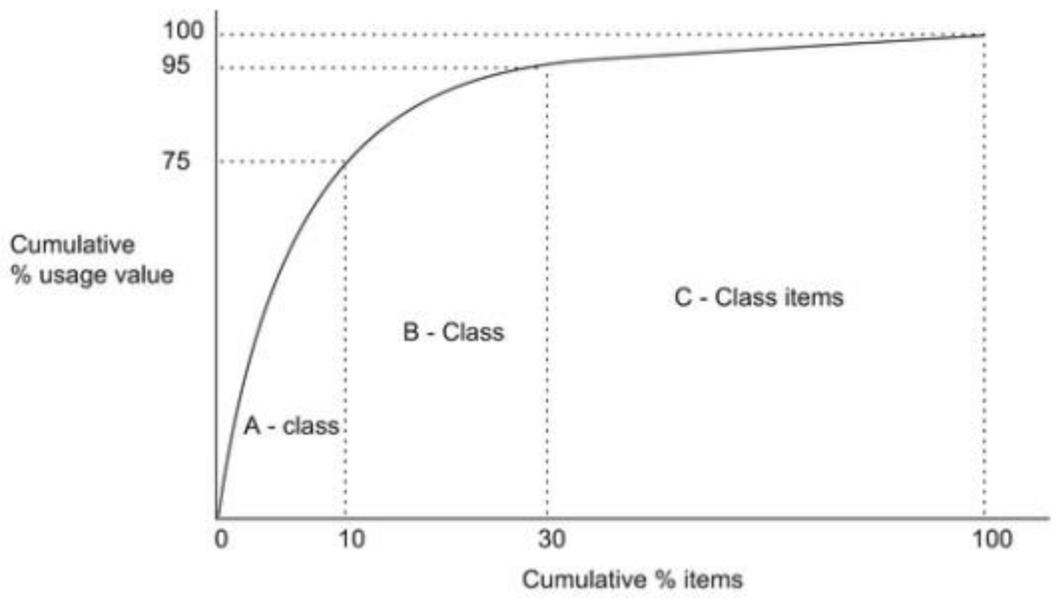
A – Class items: more costly and valuable items are classified as "A". Such items have large investments but not much in number, for example say, 10% of items account for 60%-75% of the total capital invested in inventory. So more careful and closer control is needed for such items. The items of this category should be ordered frequently but in small no. A periodic review policy should be followed to minimize the shortage percentage of such items and top inventory staff should control these items. These items have a high carrying cost and frequent orders of small size for these items can results in enormous savings.

B – Class items: the items having average consumption value are classified as "B". Nearly 15% of items in an inventory account of 20%-25% of the total investment. These items have less importance than a class items but are much costly to pay more attention on their use. These items cannot be overlooked and require less degree of control than those in category A. Statistical sampling is generally useful to control them.

C – Class items: the items having low consumption value are put in class "C". Nearly 75% of the inventory items account only for 10%-15% of the total invested capital. Such items can be stocked at an operative place where people can help themselves with any requisition formality. These items can be charged to an overhead account. In fact, lose control of C class items increase their investment cost and expenditure on itself wear, obsolescence and wasteful use, but this will not be so much offset for the saving n recording costs.

Significant points of ABC-Analysis

- Whenever the items can be substituted for each other, they should be preferably considered as one item.
- More emphasis should be given to the value of consumption and not to the cost per items.
- While classifying as ABC all the items consumed by an organization should be considered together, instead of considering them like spares, raw material, semi-finished, and finished items and then classifying as A, B or C.
- If required, there may be more than three classes and period of consumption need necessarily be one year.



Procedure for ABC – Analysis

The following are the steps of classification of items into A, B and C categories.

Step 1: Determine the no. of unit sold or used in the past one year.

Step 2: Determine the unit cost of each item.

Step 3: Compute the annual usage value (in Rs) of each item constituted by multiplying the annual consumption (of units) by its unit piece. Annual usage value = annual requirement × cost of one unit

Step 4: Arrange the items in descending order according to their respective usage value computed in Step 3.

Step 5: Prepare a table showing unit cost, annual consumption, and annual usage value for each item.

Step 6: Calculate the cumulative sum of the no. of items and the usage value for each item obtained in Step 3.

Step 7: Find the percentage of the value obtained in step 6 with respect to grand total of the corresponding columns.

Step 8: Draw a graph by taking cumulative percentage of items on x-axis and cumulative % age of annual consumption on y-axis. After plotting various points on the graph, we draw smooth curve.

Step 9: Mark the points x and y where the slop of the curve changes sharply. Such points are called points of inflexion.

Step 10: finally, the usage value and the percentage of items corresponding to these points determine the classification of items as A, B or C.

LIMITATION OF “ABC” ANALYSIS

• ABC analysis does not permit precise consideration of all relevant problems inventory control. For example, never ending problem in inventory management is that of adequately handling thousands of low value “C” class items. Low value purchases frequently require more items, and consequently reduce the time allowance available and purchasing personnel for value analysis, vender investigation, and other “B” class items.

• If “ABC” analysis is not updated and reviewed periodically the real purpose of control may be defeated for example, “C” class items like diesel oil in a firm will become most high value items during power crisis and therefore should require more attention.

• The periodic consumption value is the basis for “ABC” classification; hence ABC classification can lead to overlooking the needs of spare parts whose criticality is high, but consumption value is low.

Chapter 3

Forecasting

Forecasting helps a company to set inventory targets to ensure that their inventory allows them to maximize their operations and output. It also aids companies in optimizing the deployment of their inventory, deal with uncertainties, limitations, and difficulties within their supply chain.

3.1- Why Forecasting is needed?

Forecasting has long been associated with processes that impacts on stock. Such process includes production, procurement, and sales. Irrespective of the industry type, whether "make to sell" or "buy to sell", elements of forecasting springs up. This is because the driving phenomenon of "demand" is inevitable.

In a "make to sell" industry, the producer can't wait for orders to be received before the production process is initiated. In like manner, the "buy to sell" entrepreneur can't wait for customers to request for an item before he procures the item. However, these behaviours might be practicable for special order.

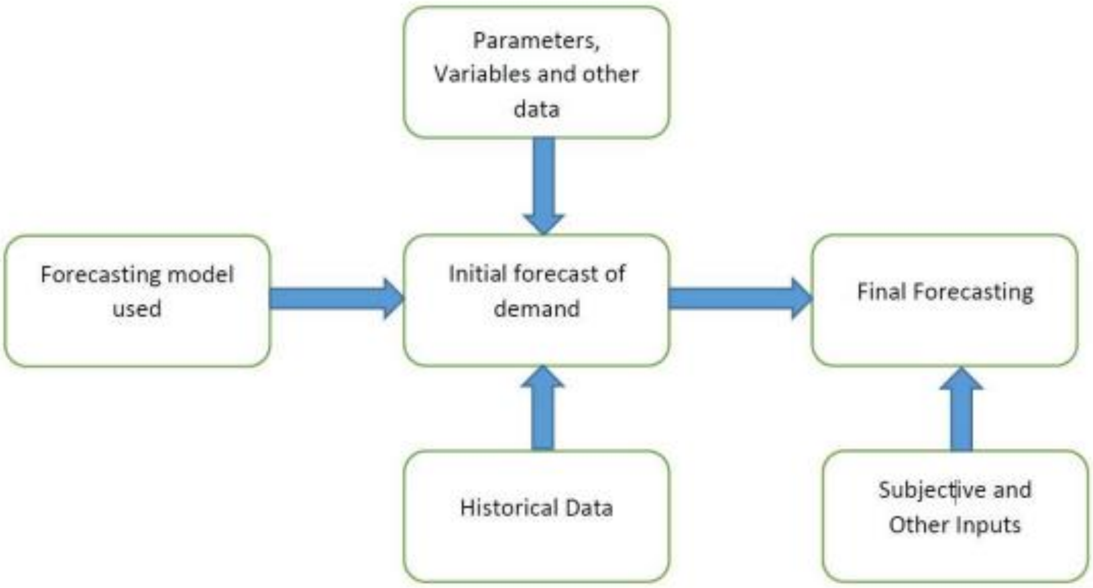
From the foregoing, it is evident that some level of inventory must exist at any point in time. It can be raw materials for production and/or finished goods. The crux of the matter then becomes what should be the relative inventory level at a particular point in time. In objectively answering this question, some form of forecasting must be made.

Inventory forecasting in my opinion is a proactive and futuristic strategy aimed at providing estimated stock level to meet demand at a particular point in time. Proactiveness can be interpreted as a step taken, prelude to a known event. Forecasting involves estimating what will be needed based on certain assumptions. It can also be viewed as projections of some sort.

Several factors can determine the turn of demand for a particular product. They include but not limited to price, availability of close substitutes, market trends, season, and advertising strategy. My concern in this posting is not to emphasize demand as a concept but the perception of inventory forecasting as a tool that can either make or mar an entrepreneur.

In analysing the subject matter, it is worthy to briefly mention two important concepts namely "over stocking" and "under stocking". Inventory forecasting can give rise to the duo especially when it is faulty, and the consequences can be grave as asserted in a prior posting titled: Increasing Profitability through inventory and financial reports.

Another important area to forecast is the lead time. Lead times are generally getting shorter, so we should remember this when looking at the lead time demand. We should also remember that if the lead times become short enough, we may not have to forecast customer demand at all. Forecasts give important inputs to inventory management but, in turn, they need information from other sources. This information includes the best type of forecasting model, values for parameters, historical data, subjective inputs, and so on.



3.2- Methods of forecasts

Qualitative Methods:

Qualitative estimates from informed sources are used when historical data are scarce or non-existent.

Examples

- Sales force composite
- Customer Surveys
- Jury of Executive Opinion
- Delphi Method

Quantitative Methods:

Quantitative estimates use historical data to find patterns in the variable to be forecasted. It is based on the premise that the influenced patterns of activity in the past will continue to do so in future. Quantitative methods are broadly classified into 2 categories:

- **Time Series Models:** In which the forecasts are dependent only on the past data of the variable to be forecasted.
- **Explanatory Models:** In which the values of the variable to be forecasted is dependent on explanatory variables.

TIME SERIES ANALYSIS

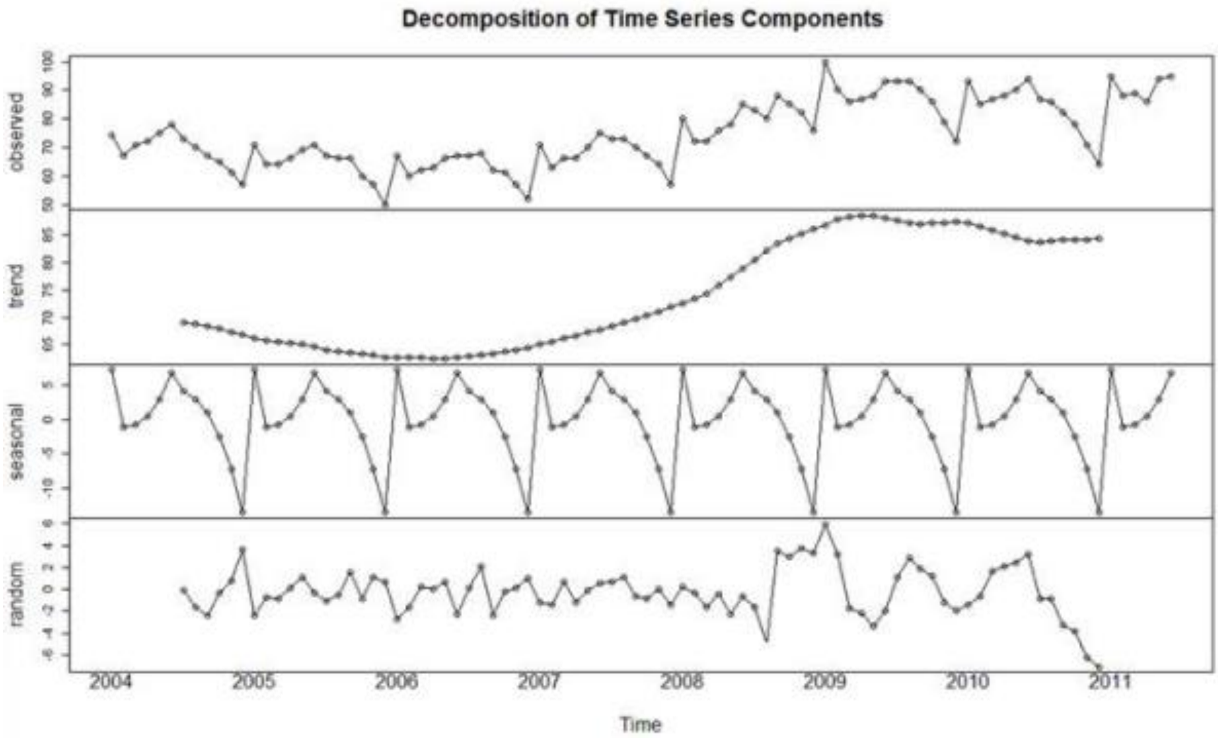
Quantitative forecasts are often based on time series, which are series of observations taken at regular intervals of time. The weekly demand for a product, monthly unemployment figures, daily rainfall and annual population statistics are examples of time series. The best way to start analysing a time series is to draw a graph. The frequent underlying patterns in this, with the three most common are:

• **Constant series:** where demand continues at roughly the same level over time (such as demand for bread or annual rainfall)

• **Trend:** where demand either rises or falls steadily (such as demand for 3G phones or the price of petrol)

• **Seasonality:** where demand has a cyclical component (such as demand for ice cream or electricity).

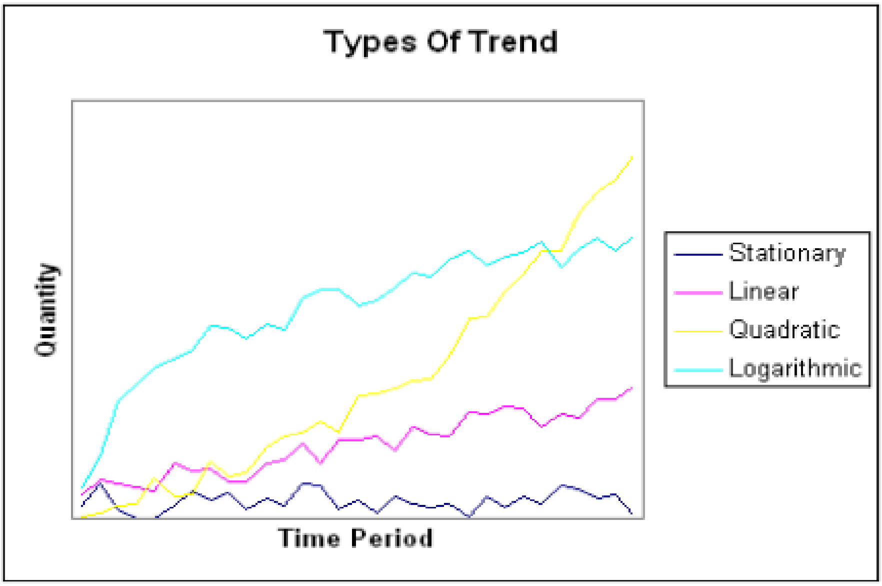
Forecasting would be easy if demand followed such simple patterns. Unfortunately, there are always differences between actual demand and the underlying pattern. These differences form a random noise that is superimposed on the underlying pattern.



COMPONENTS OF A TIME SERIES

The various forces affecting the values of phenomenon in a time series may be broadly classified into the following four categories, commonly known as the components of a time series. These are:

1. **Secular Trend:** Trend is defined as the 'long term' movement in a time series without calendar related and irregular effects and reflects the underlying level. It is the result of influences such as population growth, price inflation and general economic changes.



2. **Seasonal Variations:** These variations in a time series are due to rhythmic forces which operate in a regular and periodic manner over a span of less than a year that is during a period of 12 months and have the same or almost same pattern year after year. Thus, seasonal variations in time series will be there if the data are recorded quarterly (every three months), monthly, and weekly, daily, hourly, and so on. Although to each of the above cases, the amplitudes of the seasonal variations are different, all of them have the same period viz. one year.

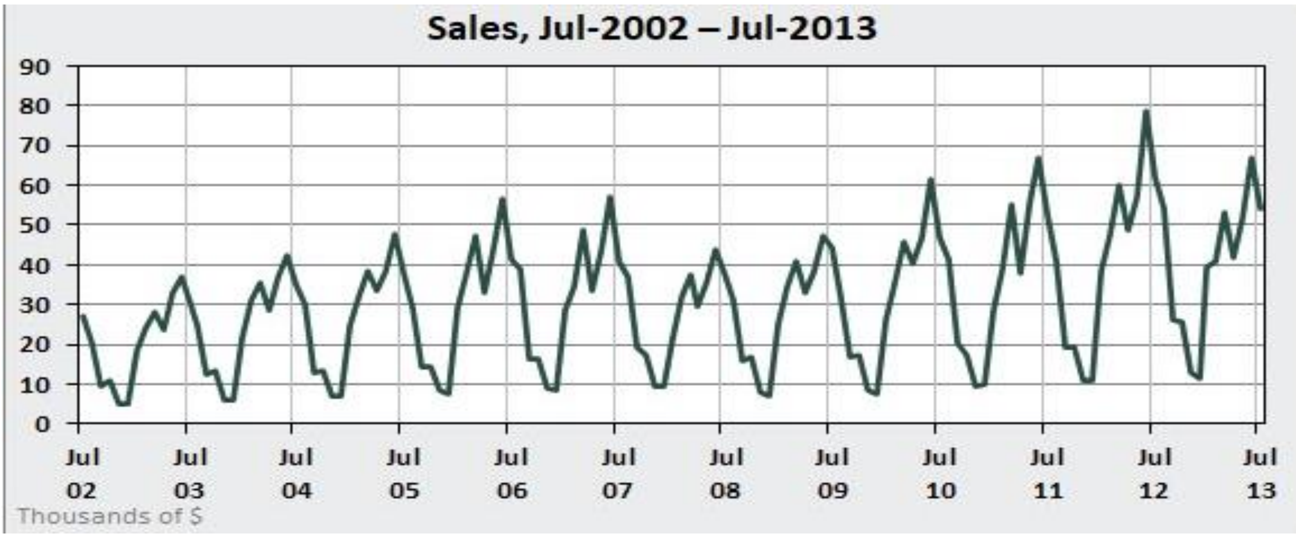
   It also includes calendar related systematic effects that are not stable in their annual timing or are caused by variations in the calendar from year to year, such as:

   Trading Day Effects: The number of occurrences of each of the day of the week in a given month will differ from year to year - There were 4 weekends in March in 2000, but 5 weekends in March of 2002.

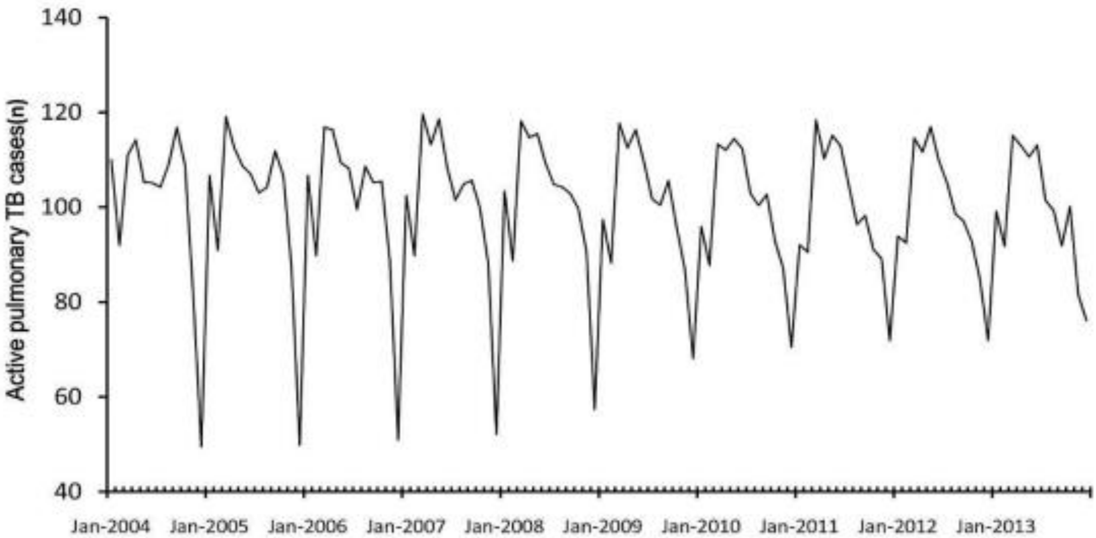
   Moving Holiday Effects: Holidays which occur each year, but whose exact timing shifts - Easter, Chinese New Year.

HOW DO WE IDENTIFY SEASONALITY?

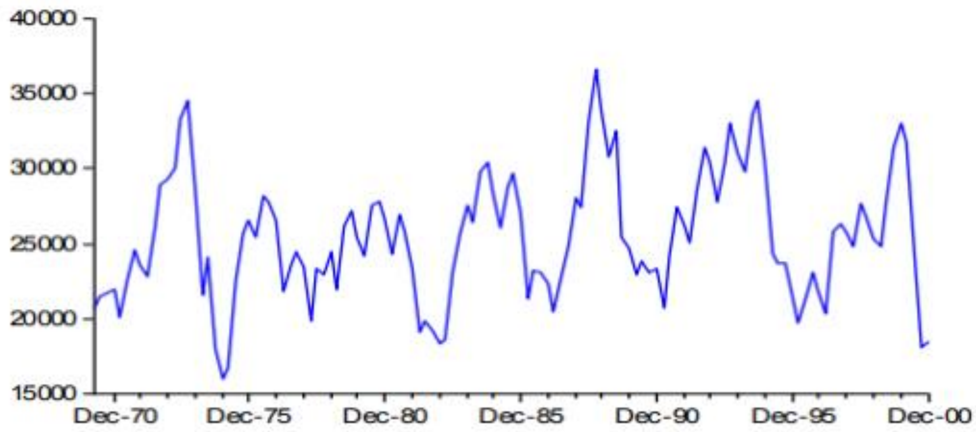
Seasonality in a time series can be identified by regularly spaced peaks and troughs which have a consistent direction and approximately the same magnitude every year, relative to the trend. The following diagram depicts a strongly seasonal series. There is an obvious large seasonal increase in December retail sales in New South Wales due to Christmas ping. In this example, the magnitude of the seasonal component increases over time, as does the trend.



3. **Cyclical Variations:** The oscillatory movements in a time series with period of oscillations greater than one year are termed as cyclical variations. These variations in a time series are due to ups and downs recurring after a period greater than one year. The cyclical fluctuations, though more or less regular, are not necessarily uniformly periodic that is they may or may not follow exactly similar patterns after equal intervals of time. One complete period which normally lasts is from 7 to 9 years is termed as a "cycle". The study of cyclical variations is of great importance to business executives in the formulation of policies aimed at stabilizing the level of business activity.



4. **Random or Irregular Variations**: Mixed up with cyclical and seasonal variations, there is inherent in every time series another factor called random or irregular variations. These fluctuations are purely random and are the result of such unforeseen and unpredictable forces which operate in erratic and irregular manner. Such variations do not exhibit any definite pattern and there is no regular period or time of their occurrence, hence they are named irregular variations.



TIME SERIES MODEL

Two models can be regarded as good approximations to the true relationship that exists amongst the four components.

Multiplicative Model:

This model assumes that as the data increase, so does the seasonal pattern. Most time series plots exhibit such a pattern. In this model, the trend and seasonal components are multiplied and then added to the error component. In a multiplicative model the seasonal, cyclical, and random variation are relative (percentage) deviations from the trend. The higher the trend, the more intensive these variations are.

$$Y_t = T_t * S_t * C_t * I_t$$

where,

Tt: Secular trend value at time

St: Seasonal variation at time t

Ct: Cyclic fluctuation at time t

It: irregular fluctuation at time t

Additive model:

A data model in which the effects of individual factors are differentiated and added together to model the data.

• An additive model is optional for Decomposition procedures and for Winters' method.

• An additive model is optional for two-way ANOVA procedures. Choose this option to omit the interaction term from the model.

• In an additive model the seasonal, cyclical, and random variation are absolute deviations from the trend. They do not depend on the level of the trend.

$$Y_t = T_t + S_t + C_t + I_t$$

where,

Tt: Secular trend value at time

St: Seasonal variation at time t

Ct: Cyclic fluctuation at time t

It: irregular fluctuation at time t

METHODS FOR MEASURING TREND

1. Graphical method/Method of free hand curve fitting
2. Method of semi averages
3. Method of moving averages
4. Method of least squares / least square method.
5. Method of curve fitting
   - i) A straight line: Yt = a+bt
   - ii) Second-degree parabola: Yt = a+bt+ct2
   - iii) Kth degree parabola: Yt = a0+a1t+a2t2+…+aktk
   - iv) Exponential curve: Yt = abt
   - v) Second degree curve fitted to logarithms: Yt = abtct^2

Fitting of these curves are then done as follows:

1. **Fitting Straight line:**

$Y_t = a + bt$

Let curve fit obtained be $\hat{Y}_t = \hat{a} + \hat{b}t$

$S = \sum_{i=1}^{n} (Y_t - \hat{Y}_t)^2 = \sum (Y_t - \hat{a} - \hat{b}t)^2$

The normal equation for estimates $\hat{a}$ and $\hat{b}$

$\frac{\partial S}{\partial \hat{a}} = 0 \Longrightarrow \sum_{t=1}^{n} Y_t = n\hat{a} + \hat{b} \sum_{t=1}^{n} t$

$\frac{\partial S}{\partial \hat{b}} = 0 \Longrightarrow \sum_{t=1}^{n} tY_t = \hat{a} \sum_{t=1}^{n} t + \hat{b} \sum_{t=1}^{n} t^2$

2. **Fitting Second Degree Parabola:**

$Y_t = a + bt + ct^2$

Let the curve fit obtained be $\hat{Y}_t = \hat{a} + \hat{b}t + \hat{c}t^2$

The normal equations for estimation for $\hat{a}$, $\hat{b}$, $\hat{c}$ are

$$\sum_{t=1}^{n} Y_t = n\hat{a} + \hat{b} \sum t + \hat{c} \sum t^2$$

$$\sum_{t=1}^{n} t\, Y_t = \hat{a} \sum t + \hat{b} \sum t^2 + \hat{c} \sum t^3$$

$$\sum_{t=1}^{n} t^2 Y_t = \hat{a} \sum t^2 + \hat{b} \sum t^3 + \hat{c} \sum t^4$$

3. **Fitting Kth Degree Parabola:**

Yt = a0+a1t+a2t2+…+aktk

We can proceed as in the case of 2nd degree parabola 1st degree parabola above to get (k+1) normal equations after minimizing the sum of squares of errors and obtain the estimates of (k+1) parameters of the fit.

4. **Exponential Curve:**

Yt = abt

Taking logarithms of both sides, we have
Log Yt = log a + t log b,

or Ut = a+bt

and now proceed as in (1) to obtain the estimates of A and B which in turn, give us the estimates of 'a' and 'b'.

5. **Second Degree Curve Fitted to the Logarithms:**

$$Y_t = ab^t c^{t^2}$$

Taking logarithms of both sides, we have

$$\text{Log } Y_t = \log a + t \log b + t^2 \log c, \text{ or}$$

$$U_t = a + bt + ct^2$$

And now we can proceed as in case (2) to obtain the estimates of A, B, C and hence those of a, b and c. We can use the principle of least squares only when the Number of Parameters is equal to the Number of Variables. In case of Growth Curves, the number of parameters to be estimated is not equal to the number of variables. So, the method of fitting by least squares fails.

MEASUREMENT OF SEASONAL FLUCTUATIONS

1. Method of Simple Averages
2. Ratio of Trend Method
3. Ratio of Moving Average Method
4. Link Relative Method

1. **Method of Simple (Arithmetic) Averages:**

   This is a simple method of isolating seasonal variations. It assumes that the series contains neither a trend nor cyclical fluctuations, but seasonal & irregular fluctuations. This method consists of following steps:

   Interpretation of Seasonal Indices: The index value or each month shows how for that month's average value relates to the average annual value. Thus, the index for Jan of 142.26 indicates that on the average Jan value will be 42.26% higher than annual average value Similarly, the Feb. seasonal index of 79 indicates that on average the Feb value will be 21% less than annual average value.

   Clearly, having such a seasonal index is helpful to the manager for purpose of control since it tells him what fluctuations to expect simply because of seasonal causes. A study of the seasonal patterns is extremely useful to businessperson, producers, sales managers etc. in planning future operations & in formulation of policy decisions regarding purchase, production inventory control, personal requirements, selling & advertisement programs. In the absence of any knowledge of seasonal variations, a seasonal upswing may be mistaken as indicator of better business conditions whereas a seasonal slump may be interpreted as deteriorating business conditions. Thus, to understand the behaviour of time series properly it must be adjusted for seasonal variations. This is done by isolating them from trend and other components by dividing the time series values by the seasonal variations when multiplicative model ($Yt = Tt*St*Ct*It$) is used and subtracting in case of additive model: $Yt = Tt+ St+ Ct+ It$

2. **Ratio to Trend Method:**

   This is a method which is an improvement over the previous method. It assumes that seasonal variations are a constant factor of trend and cyclicity is absent from the data.

• Compute trend values using method of least squares.
• Express the original data as % of trend values obtained in step 1.
• The preliminary seasonal variations are obtained by averaging the %s obtained in step 2.
• Sum of seasonal variations will not come out to be 1200 or 400 for monthly or quarterly data respectively. to make this sum as 1200 or 400 we find adjusted seasonal variations by multiplying seasonal variations obtained in previous step by a constant factor k, given by: k = 1200(or 400) / sum of seasonal indices.

3. **Method of Moving Averages:**

Moving average consists of a series of arithmetic means calculated from overlapping groups of successive elements of a time series. Each moving average is based on values covering a fixed time interval, called period of moving average, and is shown against the centre of the first. The composition of items is adjusted successively by replacing the first observation of the previously averaged group by the next observation below that group. Thus, the moving average for a period k is a series of successive averages of observations at a time starting with first, 2nd, 3rd, to k terms. Thus, the first average is the mean of the first to k terms, the second is the mean of the k terms from second to (k+1)th terms, the third is the mean of the third to (k+2)th term and so on. Thus, if the time series values are Y1, Y2, Y3 …for different periods, the moving average of period 'k' are given by:

1st value moving average = (Y1 + Y2 + Y3 +…+Yk) / k

2nd value moving average = (Y2 + Y3+ Y4 +…+Yk+1) / k

3rd value moving average = (Y3 + Y4 + Y5 +…...+Yk+2) / k

And so on. The sums in the numerators are called moving totals of order k.

Case 1: When period is odd.

If the period 'k' of the moving average is odd, the successive values of the moving averages are placed against the middle value of concerned group of items. For example, if k=5, the first moving average value is placed against the middle period, i.e., third value and the second moving average value is placed against the period four and so on.

Case 2: When period is even.

If the period ‘m’ of M.A. is even, then there are two middle periods, and the M.A. value is placed in between the two middle terms of the time intervals it covers. Obviously, in this case the M.A. value will not coincide with a period of the given time series, therefore an attempt is made to synchronize them with the original data by taking a two period averages of the moving averages and placing them in between the corresponding periods. This technique is called centering and the corresponding moving average values are called centered moving averages. In particular, if the period k=4, the 1st moving average is placed against the middle of 2nd and 3rd items, the 2nd moving average is place against the middle of 3rd and 4th items and so on.

4. **Link relative method:**

• To Calculate Seasonal Link Relative for each season where Link Relative = Current Season Figure ×100 Previous Season Figure

• Calculate average of the link relatives for each season. Arithmetic mean is generally used but even median could be used.

• Convert their averages into chain relatives based on first season.

• Calculate the Chain relative of the first season on the basis of the last season.

• For correction, the chain relative of the first season calculated by the first method is deducted from the chain relative of the first season calculated by the second method. The difference is divided by the number of seasons. The resulting figure multiplied by 1,2,3, etc. are deducted respectively from the chain relatives of 2nd,3rd ,4th, etc. seasons.

• The seasonal indices are available when we express the corrected chain relatives as percentages of their respective averages.

TIME SERIES DECOMPOSITION METHOD:

1. Find **ratio to moving averages** using the steps given below:

   1.1 Find centred 12 months moving average for the data.

   1.2 Express original values as % of centred moving average values obtained in 1.1.

   1.3 The preliminary seasonal variations are obtained by averaging the %s obtained in 1.2.

1.4 Sum of seasonal variations will not come out to be 1200 or 400 for monthly or quarterly data respectively. to make this sum as 1200 or 400 we find adjusted seasonal variations by multiplying seasonal variations obtained in previous step by a constant factor k, given by:

k = 1200(or 400) / sum of seasonal indices

2. Find **De-seasonalised values** using the formula:

$$\text{De-seasonalised values} = \frac{\text{Original Values}}{\text{Adjusted seasonal variations}}$$

3. Using the de- seasonalised values found in step 2, curve fitting is done using SPSS. Fit values are found corresponding to the best fit curve.

4. Fit values are then multiplied by adjusted seasonal variations to get the predicted values.

5. Find root mean square error using the formula:

Error = Predicted values - Original values

Mean Square Error = 1 Σ(Error)2 N

Root Mean Square = √MSE

SMOOTHING TECHNIQUES:

A time series is a sequence of observations, which are ordered in time. Inherent in the collection of data taken over time is some form of random variation. There exist methods for reducing of cancelling the effect due to random variation. A widely used technique is "smoothing". This technique, when properly applied, reveals more clearly the underlying trend, seasonal and cyclic components. Smoothing techniques are used to reduce irregularities (random fluctuations) in time series data. They provide a clearer view of the true underlying behaviour of the series.

Moving averages rank among the most popular techniques for the pre- processing of time series. They are used to filter random "white noise" from the data, to make the time series smoother or even to emphasize certain informational components contained in the time series. Exponential smoothing is a very popular scheme to produce a smoothed time series. Whereas in moving averages the past observations are weighted equally, Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations. Double exponential smoothing is better at handling trends. Triple Exponential Smoothing is better at handling parabola trends. Exponential smoothing is a widely method used of forecasting based on the time series itself. Unlike regression models, exponential smoothing does not impose any deterministic model to fit the series other than what is inherent in the time series itself.

Exponential Smoothing:

If the focus of interest is forecasting the future rather than reviewing the historical record, the relevant quantities to be estimated are the most recent trend and seasonal terms. These can then be projected forward to derive predictions of future values of the time series. This estimation problem and its solution is the basis of exponential smoothing, an approach to short-term forecasting that is widely used in industry. There is not a unique forecasting algorithm known as exponential smoothing. Rather exponential smoothing is a general approach to the derivation of forecasting algorithms that has led to the development of several alternative procedures, based to some different assumptions about the characteristics of the time series of interest. The algorithms in popular use are typically justified on grounds of intuitive plausibility and successful practical experience in their application. Exponential smoothing is therefore a somewhat Ad-hoc approach to the problem of forecasting a time series based on its own past. Exponential smoothing algorithm is particularly attractive when forecasts of a very large number of time series are needed on a regular basis. Specifically, these procedures were developed for and are currently widely used in, routine sales forecasting for inventory control purposes. Typically, short-term forecasts are required, monthly, for demand for great many mature product lines. In these circumstances, it may not feasible or, given the costs involved, desirable to devote a great deal of time and effort to the tailoring of specific forecasting procedures to the observed properties of each individual sales series. The extra forecast precision and consequent inventory cost savings may fail or compensate for the additional costs incurred. What may be required instead is an expensive algorithm whose application yields adequate short-term forecasts for at least the great majority of series that need to be predicted. In such circumstances, both case of application and a successful track record render exponential smoothing algorithm particularly attractive.

1. **Simple Exponential Smoothing:**
   It calculates the smoothed series as a damping coefficient times the actual series plus 1 minus the damping coefficient times the lagged value of the smoothed series. The extrapolated smoothed series is a constant, equal to the last value of the smoothed series during the period when actual data on the underlying series are available. While the simple Moving Average method is a special case of the ES, the ES is more parsimonious in its data usage.
   $F_{t+1} = \omega D_t + (1 - \omega) F_t$,
   where:
   D_t is the actual value at time t
   F_t is the forecasted value at time t
   ω is the weighting factor, which ranges from 0 to 1
   t is the current time-period.
   Notice that the smoothed value becomes the forecast for period t +1. A small ω provides detectable and visible smoothing. While a large ω provides fast response to the recent changes in the time series but provides a smaller amount of smoothing. Notice that the exponential smoothing and simple moving average techniques will generate forecasts having the same average age of information if moving average of order n is the integer part of $(2-\omega)/ \omega$.
   An exponential smoothing over an already smoothed time series is called double exponential smoothing. In some cases, it might be necessary to extend it even to a triple-exponential smoothing. While simple exponential smoothing requires stationary condition, the double-exponential smoothing can capture linear trends, and triple exponential smoothing can handle almost all other business time series.

2. **Double Exponential Smoothing**:
   It applies the process described above to account for linear trend. The extrapolated series has a constant growth rate, equal to the growth of the smoothed series at the end of the data period.

3. **Triple Double Exponential Smoothing:**
   It applies the process described above to account for nonlinear trend.

Exponentially Weighted Moving Average:

Suppose each day's forecast value is based on the previous day's value so that the weight of each observation drops exponentially the further back (k) in time it is. The weight of any individual is a (1 - a) k, where a is the smoothing constant. An exponentially weighted moving average with a smoothing constant a, corresponds roughly to a simple moving average of length n, where a and n are related by a = 2/(n+1) or n = (2 - a)/a.

Thus, for example, an exponentially weighted moving average with a smoothing constant equal to 0.1 would correspond roughly to a 19- day moving average. And a 40-day simple moving average would correspond roughly to an exponentially weighted moving average with a smoothing constant equal to 0.04878. This approximation is helpful; however, it is harder to update, and may not correspond to 36 | P a g e an optimal forecast. Smoothing techniques, such as the Moving Average, Weighted Moving Average, and Exponential Smoothing, are well suited for one period- ahead forecasting.

4. **Holt's Linear Exponential Smoothing Technique:**
   Suppose that the series {yt} is non-seasonal but does display trend. Now we need to estimate both the current level and the current trend. Here we define the trend Tt at time t as the difference between the current and previous level. The updating equations express ideas like those for exponential smoothing.
   The equations are:
   Lt = a*yt + (1 - a) Ft, for the level
   and
   Tt = b (Lt– Lt-1) + (1 - b) Tt-1, for the trend.

   We have two smoothing parameters a and b; both must be positive and less than one. Then forecasting for k periods into the future is: Fk+n = Ln+kTn

   Given that the level and trend remain unchanged, the initial (starting) values are T2 = y2 – y1, L2 = y2, and F3 = L2 + T2

5. **The Holt-Winters' Forecasting Technique:**

Now in addition to Holt parameters, suppose that the series exhibits multiplicative seasonality and let St be the multiplicative seasonal factor at time t. Suppose also that there are s periods in a year, so s=4 for quarterly data and s=12 for monthly data. St-s is the seasonal factor in the same period last year.

In some time-series, seasonal variation is so strong it obscures any trends or cycles, which are very important for the understanding of the process being observed. Winters' smoothing method can remove seasonality and makes long term fluctuations in the series stand out more clearly. A simple way of detecting trend in seasonal data is to take averages over a certain period. If these averages change with time, we can say that there is evidence of a trend in the series. The updating equations are:

$L_t = a (L_{t-1} + T_{t-1}) + (1 - a)\, y_t / S_{t-s}$, for the level,
$T_t = b (L_t - L_{t-1}) + (1 - b)\, T_{t-1}$, for the trend, and
$S_t = g^* S_{t-s} + (1- g)\, y_t / L_t$, for the seasonal factor.

We now have three smoothing parameters a, b, and g all must be positive and less than one. To obtain starting values, one may use the first a few year data. For example, for quarterly data, to estimate the level, one may use a centered 4-point moving average:

$$L_{10} = (y_8 + 2y_9 + 2y_{10} + 2y_{11} + y_{12}) / 8$$

as the level estimate in period 10. This will extract the seasonal component from a series with 4 measurements over each year.

$$T_{10} = L_{10} - L_9$$

as the trend estimate for period 10.

$$S_7 = (y_7 / L_7 + y_3 / L_3) / 2$$

as the seasonal factor in period 7, Similarly

$$S_8 = (y_8 / L_8 + y_4 / L_4) / 2,$$
$$S_9 = (y_9 / L_9 + y_5 / L_5) / 2,$$
$$S_{10} = (y_{10} / L_{10} + y_6 / L_6) / 2$$

For Monthly Data, the correspondingly we use a centered 12-point moving average:

$$L_{30} = (y_{24} + 2y_{25} + 2y_{26} + \ldots + 2y_{35} + y_{36}) / 24$$

as the level estimate in period 30.

$$T30 = L30 - L29$$

as the trend estimate for period 30.

$$S19 = (y19 / L19 + y7 / L7) / 2$$

as the estimate of the seasonal factor in period 19, and so on, up to 30:

$$S30 = (y30 / L30 + y18 / L18) / 2$$

Then the forecasting k periods into the future is:

$$Fn+k = (Ln+ k. Tn)\ St+k-s, \text{ for } k = 1, 2, ...,s$$

EXPONENTIAL SMOOTHING MODELS GIVEN BY SPSS (EXPERT MODELER) ARE AS FOLLOWS:

Brown's linear trend: This model is appropriate for series in which there is a linear trend and no seasonality. Its smoothing parameters are level and trend, which are assumed to be equal. Brown's model is therefore a special case of Holt's model. Brown's exponential smoothing is most like an ARIMA model with zero orders of auto regression, two orders of differencing, and two orders of moving average, with the coefficient for the second order of moving average equal to the square of one-half of the coefficient for the first order.

Damped trend: This model is appropriate for series with a linear trend that is dying out and with no seasonality. Its smoothing parameters are level, trend, and damping trend. Damped exponential smoothing is most like an ARIMA model with 1 order of auto regression, 1 order of differencing, and 2 orders of moving average.

Simple seasonal: This model is appropriate for series with no trend and a seasonal effect that is constant over time. Its smoothing parameters are level and season. Simple seasonal exponential smoothing is most like an ARIMA model with zero orders of auto regression, one order of differencing, one order of seasonal differencing, and orders 1, p, and p + 1 of moving average, where p is the number of periods in a seasonal interval (for monthly data, p = 12).

Winters' additive: This model is appropriate for series with a linear trend and a seasonal effect that does not depend on the level of the series. Its smoothing parameters are level, trend, and season. Winters' additive exponential smoothing is most like an ARIMA model with zero orders of auto regression, one order of differencing, one order of seasonal differencing, and p + 1 orders of moving average, where p is the number of periods in a seasonal interval (for monthly data, p = 12).

Winters' multiplicative: This model is appropriate for series with a linear trend and a seasonal effect that depends on the level of the series. Its smoothing parameters are level, trend, and season. Winters' multiplicative exponential smoothing is not like any ARIMA model.

3.3- Forecasting Errors

A forecast is never completely accurate; forecasts will always deviate from the actual demand. The objective of forecasting is that it be as slight as possible. There are many measures of forecast error; the more popular ones are: mean absolute deviation (MAD), mean absolute percent deviation (MAPD), cumulative error, and average error or bias (E).

1. **Mean absolute deviation (MAD):**

   Most popular and simplest to use measure of forecasting · MAD is an average of the difference between the forecast and the actual demand.

   Formula:

$$MAD = \frac{Sum|Dt - Ft|}{n}$$

   Where:
   t = the period number
   Dt = the demand in period t
   Ft = the forecast for period t
   n = the total number of periods
   | | = the absolute value

The smaller/lower value of MAD, the more accurate the forecast. One benefit of MAD is to compare the accuracy of several different forecasting techniques.

2. **Mean absolute percent deviation (MAPD):**

Measures the absolute error as a percentage of demand rather than per period. Resulting in elimination of the problem for interpreting the measure of accuracy relative to the magnitude of the demand and forecast values, as MAD does.

3. **Cumulative Error:**

Formula E= Sum (et)

A large positive value indicates the forecast is probably consistently lower than the actual demand or is biased low.

A large negative value implies the forecast is consistently higher than actual demand or is biased high. The cumulative error for exponential smoothing forecast is simply the sum of the values in the error column.

4. **Average error:**

A measure closely related to cumulative error is the average error or bias. It is computed by averaging the cumulative error over the number of time periods.

Formula:

$$E = \frac{Sum(et)}{n}$$

A positive value indicates low bias, and a negative value indicates a high bias. A value close to zero implies a lack of bias.

5. **Coefficient of determination:**

In statistics, the **coefficient of determination**, denoted **R2** and pronounced **R squared**, indicates how well data points fit a statistical model – sometimes simply a line or curve.

$$R^2 = 1 - \left(\frac{ErrorVariance}{TotalVariance}\right)$$

RSS: Sum of squares of residuals

TSS: Total sum of squares

6. **Root Mean squared error:**

   The root mean squared error (RMSE) is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. It is the root of sum (or average) of the squared error values. This is the most used lack-of-fit indicator in statistical fitting procedures.

7. **Mean absolute error:**

   The mean absolute error (MAE) value is computed as the average absolute error value. If this value is 0 (zero), the fit (forecast) is perfect. As compared to the mean squared error value, this measure of fit will "de-emphasize" outliers, that is, unique or rare large error values will affect the MAE less than the MSE value.

8. **Mean absolute percentage error (MAPE):**

   Similar to sum of squared error values, a mean percentage error near 0 (zero) can be produced by large positive and negative percentage errors that cancel each other out. Thus, a better measure of relative overall fit is the mean absolute percentage error. In addition, this measure is usually more meaningful than the mean squared error.

Chapter 4

Procurement

Acquiring goods and/or services from an outside source

4.1- Why Procurement Is Needed?

Procurement is the process of purchasing goods or services and is usually in reference to business spending. Procurement, in the simplest sense, involves a series of activities and processes that are necessary for an organization to acquire necessary products or services. It is very important to business because an organization can end up spending well over half of its revenue on purchasing goods and services, proper procurement management is vital. Even the slightest decrease in purchasing costs can have a significantly direct impact on profits, while a lack of strategic decisions can sink an otherwise financially healthy company. It can make the difference between success and failure. High purchasing costs or a high degree of wastage in the supply chain can affect an organization's bottom line and reputation. Properly managing all procurement activities not only keeps business operations running smoothly; it also saves money, time, and resources. Procurement management ensures that all items and services are properly acquired so that projects and processes can proceed efficiently and successfully. Procurement and inventory management models in the operations management and supply chain management literature usually assume constant or known procurement prices while modelling in detail transaction costs, storage costs and costs associated with fulfilling a stochastic demand. In this research, we explore how exogenously determined random shocks in procurement costs affect operating decisions of a firm. In particular, we explore in detail the procurement process of commodities whose prices are subject to random shocks due to demand and supply fluctuations. Commodity prices exhibit volatility and substantial cyclical behaviour that exacerbates the complexity of procurement for the commodity users. In this study we are suggesting the procurement policy for the management of medicines from different suppliers.

4.2 Procurement Model

Procurement and inventory management models in the operations management and supply chain management literature usually assume constant or known procurement prices while modeling in detail transaction costs, storage costs and costs associated with fulfilling a stochastic demand. In this research, we explore how exogenously determined random shocks in procurement costs affect operating decisions of a firm. In particular, we explore in detail the procurement process of commodities whose prices are subject to random shocks due to demand and supply fluctuations. Commodity prices exhibit volatility and substantial cyclical behaviour that exacerbates the complexity of procurement for the commodity users. In this paper, we develop optimal and approximate procurement policies of a commodity under stochastic prices and random demand. Inventory control is the activity, which organizes the availability. It coordinates the purchasing, manufacturing, and distribution functions to meet marketing needs. This role includes the supply of current sales items, new products, consumables, spare parts, and all other supplies.

Components of Inventory Systems

There are the various components of an inventory system:

1. **Demand:** By this term we mean that a customer requirement occurring at a time point.
2. **Lead Time:** When the demands sufficiently reduce the size of an inventory it becomes necessary to order replenishment stock so as to able to meet the future demands. The time that elapses from the moment a replenishment order is placed until that order is in stock and ready to satisfy demands is called lead time.
3. **Costs:** This includes different types of costs:
   - Inventory Carrying costs.
   - Ordering costs
   - Shortage costs or Penalty costs

The model used here is described below: Here the basic assumptions are:

1. Demand is different in each period.
2. Procurement is done in the beginning of the period and demand is met throughout the period.
3. Shortages are not allowed.

Notations:

Cn = total cost up to and including the nth period.

ri = requirement of the ith period

A = Ordering Cost

I= Inventory Carrying Cost

C= Cost per unit

The total cost for the n-periods is given by:

$$C_n(j) = C_{j-1} + A + C\,(r_j + r_{j-1} + \dots\dots + r_n) + (I*C)\,(r_j/2 + r_{j+1} + \dots\dots + r_n) + (I*C)*(r_{j+1}/2 + r_{j+2} + \dots\dots + r_n) + \dots\dots\dots + (I*C)\,(r_n/2)$$

To minimize cost

$$\mathbf{Min}\ C_n\ (j) = \mathbf{Min}\ \{C_{j-1} + A + C(r_j + \dots\dots\dots + r_n) + (I*C/2)*[r_j + 3*(r_{j+1}) + \dots\dots\dots + (r_n)*\{2(n-j)+1\}\ ]\ \}$$

Chapter 5

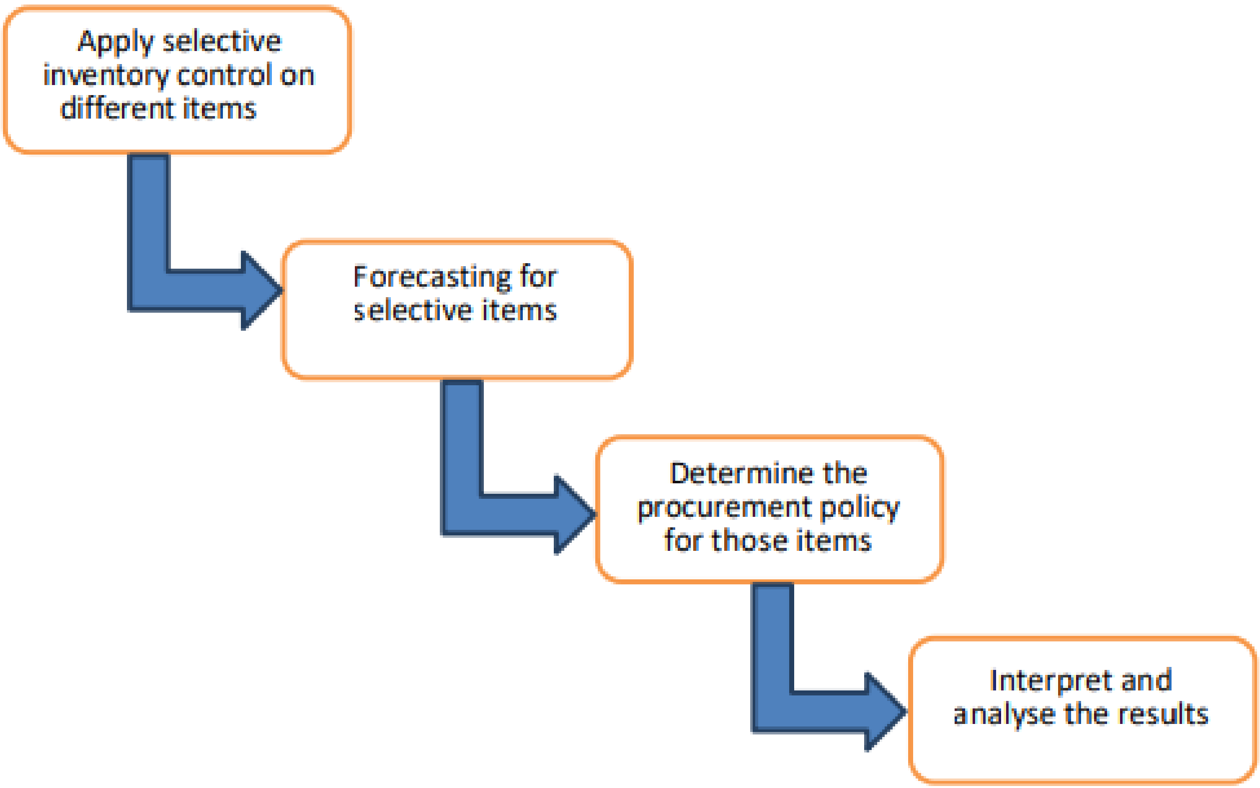
Problem Description & Solution

5.1 - Methodology

OBJECTIVE OF THE STUDY

To forecast the demand for certain FMCG products and to determine the optimum procurement policy for a few products.

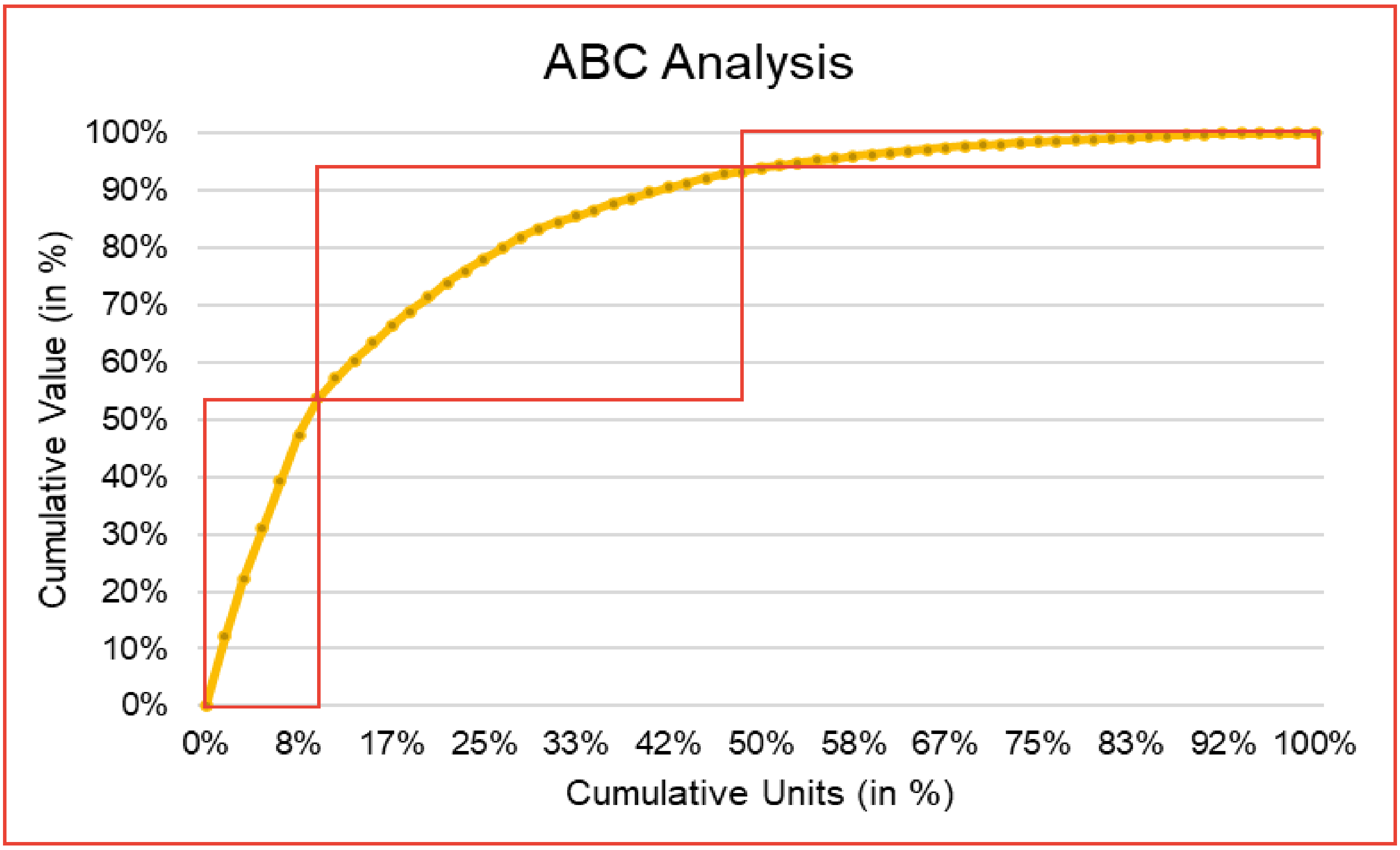
THE STEPS FOLLOWED ARE AS FOLLOWS



5.2 – ABC Analysis

	Product Name	Case Cost (Rs.)	Demand (in cases)	Usage Value (Rs.)	%Value	Cumulative value (in %)	Cumulative items (in %)	Category
						0.00%	0%	
1	MADHUSUDAN DAIRY CREAMER 12GM	2570	4155	₹ 1,06,78,350	12.07%	12.07%	2%	A
2	NIINE DAIPER S-1	1660	5341	₹ 88,66,060	10.02%	22.10%	3%	A
3	ROASTED VERMICILLI 800 GM	1687	4713	₹ 79,50,831	8.99%	31.09%	5%	A
4	WABH BAKRI 250GM CARTON	8662	836	₹ 72,41,432	8.19%	39.28%	7%	A
5	DOUBLE COW DAIRY CREAMER 10 GM	2100	3410	₹ 71,61,000	8.10%	47.37%	8%	A
6	MILI LEAF 1 KG POUCH	6759	830	₹ 56,09,970	6.34%	53.72%	10%	A
7	ROASTED VERMICILLI 400GM	2085	1499	₹ 31,25,415	3.53%	57.25%	12%	B
8	MILI LEAF 250GM POUCH	6903	405	₹ 27,95,715	3.16%	60.41%	13%	B
9	NAVCHETAN LEAF 250GM POUCH	2571	1054	₹ 27,09,834	3.06%	63.48%	15%	B
10	WABH BAKRI 1KG POUCH	8358	312	₹ 26,07,696	2.95%	66.42%	17%	B
11	VERMICILLI 800GM	1191	1893	₹ 22,54,563	2.55%	68.97%	18%	B
12	ARABIAN SEEDED DATES 500 GM	3326	673	₹ 22,38,398	2.53%	71.51%	20%	B
13	MACRONI 800GM	1331	1610	₹ 21,42,910	2.42%	73.93%	22%	B
14	MACRONI 400GM	1794	1045	₹ 18,74,730	2.12%	76.05%	23%	B
15	NIINE SANATARY NAPKEEN RS 32 DRY COMFORT	2402	734	₹ 17,63,068	1.99%	78.04%	25%	B
16	NAVCHETAN LEAF 100GM POUCH	2537	666	₹ 16,89,642	1.91%	79.95%	27%	B
17	VERMICILLI 400GM	1793	942	₹ 16,89,006	1.91%	81.86%	28%	B
18	NIINE SANATARY NAPKEEN RS 30 DRY COMFORT	2180	590	₹ 12,86,200	1.45%	83.32%	30%	B
19	NIINE DAIPER S-42	1656	626	₹ 10,36,656	1.17%	84.49%	32%	B
20	MUSKAT DATES 500 GM	7467	131	₹ 9,78,177	1.11%	85.59%	33%	B
21	NIINE SANATARY NAPKEEN RS 90 DRY COMFORT	2111	461	₹ 9,73,171	1.10%	86.69%	35%	B
22	GOLDEN SHINE MACRONI 20KG	858	1110	₹ 9,52,380	1.08%	87.77%	37%	B
23	WB SPICED 250 GM CARTON	4404	197	₹ 8,67,588	0.98%	88.75%	38%	B
24	NAVCHETAN ELACHI 250GM POUCH	4263	195	₹ 8,31,285	0.94%	89.69%	40%	B
25	WB PREMIUM TEA BAG	1805	417	₹ 7,52,685	0.85%	90.54%	42%	B
26	NIINE DAIPER M-34	1656	446	₹ 7,38,576	0.84%	91.38%	43%	B
27	DESSERT KING DATES 500 GM	7467	96	₹ 7,16,832	0.81%	92.19%	45%	B
28	THIN ROASTED VERMICILLI 140GM	866	770	₹ 6,66,820	0.75%	92.94%	47%	B
29	NIINE DAIPER L-30	1656	287	₹ 4,75,272	0.54%	93.48%	48%	B
30	ARABIAN SEEDED DATES 250 GM	3131	150	₹ 4,69,650	0.53%	94.01%	50%	C
31	KIMIA DATES 500GM CONTAINER	4480	87	₹ 3,89,760	0.44%	94.45%	52%	C
32	DALIA 500GM	672	567	₹ 3,81,024	0.43%	94.88%	53%	C
33	MACRONI 180GM	1518	235	₹ 3,56,730	0.40%	95.29%	55%	C
34	PREMIUM PENNI PASTA 500GM	2000	174	₹ 3,48,000	0.39%	95.68%	57%	C
35	DAIRY CREAMER 500 GM POUCH	5005	65	₹ 3,25,325	0.37%	96.05%	58%	C
36	NAVCHETAN ELACHI RS 10(25+9GM)	2537	114	₹ 2,89,218	0.33%	96.37%	60%	C
37	DELICASY DATES 500 GM	5218	55	₹ 2,86,990	0.32%	96.70%	62%	C
38	GULAB JAMUN 500GM	4672	60	₹ 2,80,320	0.32%	97.02%	63%	C
39	PREMIUM SPIRAL PASTA 500GM	2033	130	₹ 2,64,290	0.30%	97.32%	65%	C
40	ANCHAL MACRONI 400GM	1308	170	₹ 2,22,360	0.25%	97.57%	67%	C

41	KHEER MIX 35GM	1169	161	₹ 1,88,209	0.21%	97.78%	68%	C
42	DALIA ROASTED 500GM	868	209	₹ 1,81,412	0.21%	97.98%	70%	C
43	GOLDEN SHINE PENNI PASTA 1 KG	1007	177	₹ 1,78,239	0.20%	98.19%	72%	C
44	GOLDEN SHINE ROASTED 1 KG	1115	140	₹ 1,56,100	0.18%	98.36%	73%	C
45	GOLDEN SHINE SPIRAL PASTA 1 KG	1007	152	₹ 1,53,064	0.17%	98.54%	75%	C
46	MIXED FRUIT JAM 500 GM	3240	47	₹ 1,52,280	0.17%	98.71%	77%	C
47	PREMIUM PENNI PASTA 250GM	1704	85	₹ 1,44,840	0.16%	98.87%	78%	C
48	GINGER GARLIC PASTE 20GM	1265	114	₹ 1,44,210	0.16%	99.03%	80%	C
49	MACRONI 2KG	1291	110	₹ 1,42,010	0.16%	99.20%	82%	C
50	DALIA 135GM	908	155	₹ 1,40,740	0.16%	99.35%	83%	C
51	PREMIUM SPIRAL PASTA 250GM	1704	82	₹ 1,39,728	0.16%	99.51%	85%	C
52	MIXED FRUIT JAM 250 GM	2916	46	₹ 1,34,136	0.15%	99.66%	87%	C
53	GOLDEN SHINE MACRONI 1KG	935	123	₹ 1,15,005	0.13%	99.79%	88%	C
54	ANCHAL MACRONI 800GM	911	124	₹ 1,12,964	0.13%	99.92%	90%	C
55	HONEY 250GM	3300	21	₹ 69,300	0.08%	100.00%	92%	C
56	ALL SEASON PENNI PASTA 400GM	1067	0	₹ 0	0.00%	100.00%	93%	C
57	ALL SEASON SPIRAL PASTA 400GM	1067	0	₹ 0	0.00%	100.00%	95%	C
58	MADHUSUDAN DESI GHEE 1 LT	8250	0	₹ 0	0.00%	100.00%	97%	C
59	MADHUSUDAN DESI GHEE 500ML	8295	0	₹ 0	0.00%	100.00%	98%	C
60	DESI GHEE 15 KG TIN- YELLOW	8250	0	₹ 0	0.00%	100.00%	100%	C
	TOTAL			**₹ 8,84,40,166**				



	Value %	Products%	Products
A	53.72%	10%	6
B	39.76%	38.33%	23
C	6.52%	51.67%	31

We will be selecting top 5 products from the A category products for the purpose of forecasting and procurement. The products selected are **MADHUSUDAN DAIRY CREAMER 12GM, NIINE DAIPER S-1, ROASTED VERMICILLI 800 GM, WABH BAKRI 250GM CARTON & DOUBLE COW DAIRY CREAMER 10 GM.**

Product Name	QTY/CASE(PIECES)	Product Cost/CASE
ROASTED VERMICILLI 800GM	18	1687
WABH BAKRI 250GM CARTON	72	8662
NIINE DAIPER S-1	240	1660
MADHUSUDAN DAIRY CREAMER 12GM	600 PC	2570
DOUBLE COW DAIRY CREAMER 10GM	600 PC	2100

5.2 – Demand Forecasting

Forecasting for 5 items has been done using 2 different methods:

1. Forecasting through Time Series Decomposition Model in MS Excel

2. Forecasting through Time Series Expert Modeler Criteria in IBM- SPSS 25

For both above Forecasting tools, we check the Root Mean Square Error (RMSE) and use the forecasted values for further analysis of the tool whose RMSE is lesser.

ITEM 1 –WAGH BAKRI 250GM CARTON

Method 1: Forecasting through Time Series Decomposition Model in MS Excel

Ratio to moving average method has been applied. The various steps are:

1. Arrange the Monthly Consumption data horizontally for each year.

2. Plot a Line Graph for each year to check for the seasonality in the data.

3. If Seasonality is Present, eliminate the same using an appropriate deseasonalizing method (Ratio to Moving Average Method applied here) from the given data. Since seasonal variations occur every year i.e., the data has a periodicity of 12 months, hence a centered 12-month moving average is applied to eliminate the fluctuations (In case of quarterly data, a centered4-quarter moving average must be used). The centered 12- month M.A. which aims to eliminate Seasonal and Irregular Fluctuations from the original data, leaving behind the Trend and the Cyclic Variations in the data.

4. Express the original data for each month as a percentage of the centered 12-month moving average corresponding to it. By averaging these percentages, we eliminate the irregular component from the data and the averages itself reflect the seasonal variations alone. The averages so obtained are the preliminary Seasonal Indices. They should total up to 100 percent or total 1,200 for 12 months, by definition. If the total is not equal to 1,200 or 100 percent, an adjustment is made to eliminate the difference. The adjustment consists of multiplying the Index so obtained by the Adjusting Factor, given as K = 1200/the total of the unadjusted Seasonal Indices for 12 months Note: The adjustment is made not only to achieve accuracy, but also because while eliminating the seasonality from the original data we do not wish to raise or lower the level of the data unduly.

3-year Data provided by the company

Demand Data Table				
Month	**2020**	**2021**	**2022**	**2023**
January	74	77	112	80
February	52	73	95	63
March	65	70	47	55
April	15	44	40	
May	50	62	82	
June	75	86	105	
July	23	70	40	
August	45	30	57	
September	55	55	63	
October	42	46	63	
November	62	86	85	
December	26	54	47	

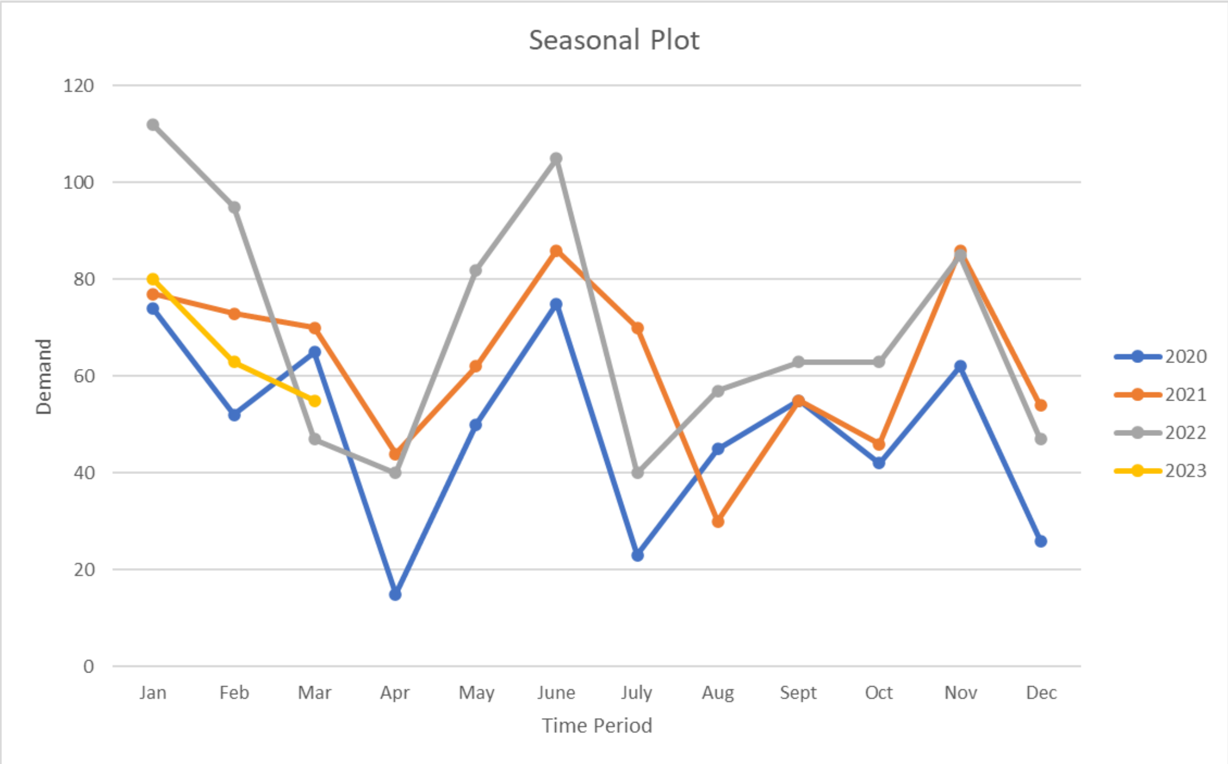
Since seasonality can be observed in the data, we thus use the Time Series Decomposition Model of Ratio to Moving-Averages to decompose the data into the Trend, Seasonal, Cyclic & Irregular components.

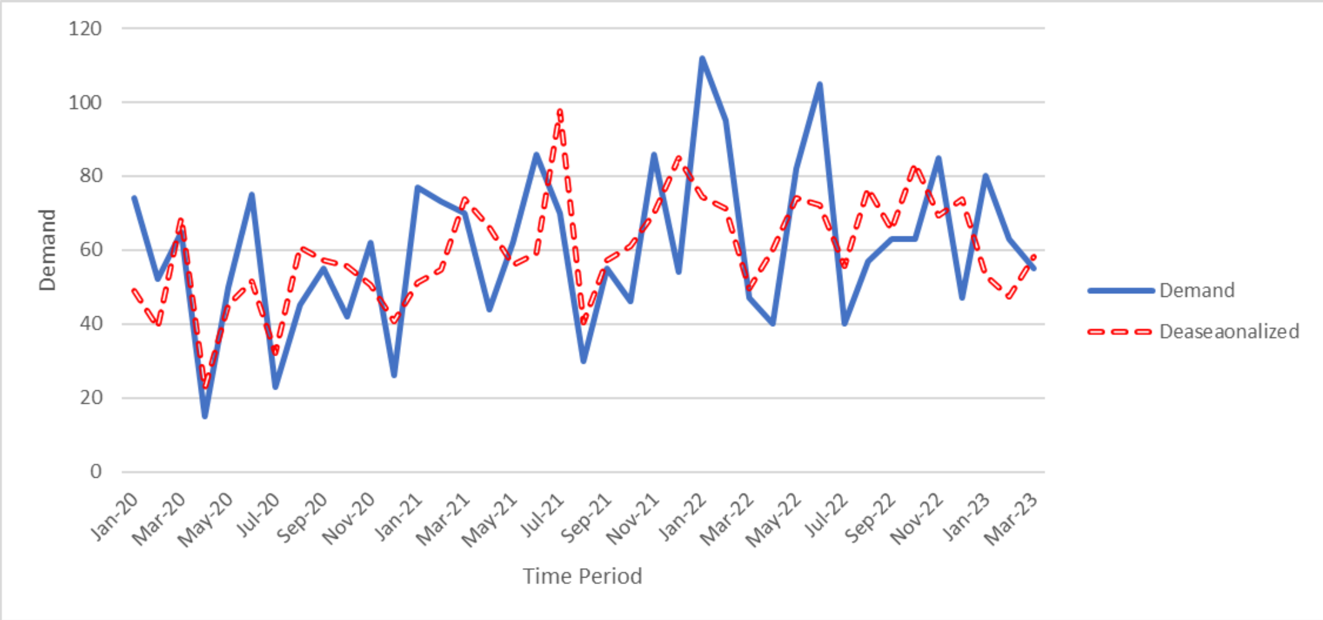
CALCULATIONS:

RATIO TO MOVING AVERAGE METHOD TO DESEASONALISE DATA

Year	Month	Demand	Deseasoanlized
2020	Jan	74	49.10
	Feb	52	39.03
	Mar	65	68.61
	Apr	15	22.51
	May	50	45.15
	June	75	51.65
	July	23	32.07
	Aug	45	60.61
	Sept	55	57.12
	Oct	42	55.64
	Nov	62	50.51
	Dec	26	40.83
2021	Jan	77	51.09
	Feb	73	54.79
	Mar	70	73.89
	Apr	44	66.02
	May	62	55.98
	June	86	59.23

	July	70	97.59
	Aug	30	40.41
	Sept	55	57.12
	Oct	46	60.94
	Nov	86	70.06
	Dec	54	84.80
2022	Jan	112	74.31
	Feb	95	71.30
	Mar	47	49.61
	Apr	40	60.02
	May	82	74.04
	June	105	72.31
	July	40	55.77
	Aug	57	76.77
	Sept	63	65.43
	Oct	63	83.45
	Nov	85	69.24
	Dec	47	73.81
2023	Jan	80	53.08
	Feb	63	47.28
	Mar	55	58.05





1. To fit Trend to the Deseasonalized data, we found the best fit line and it came out to be a linear equation with highest R2 value.
2. Hence, trend values are calculated along with the forecasted values ie forecasting values= Trend+ Adjusted SI.

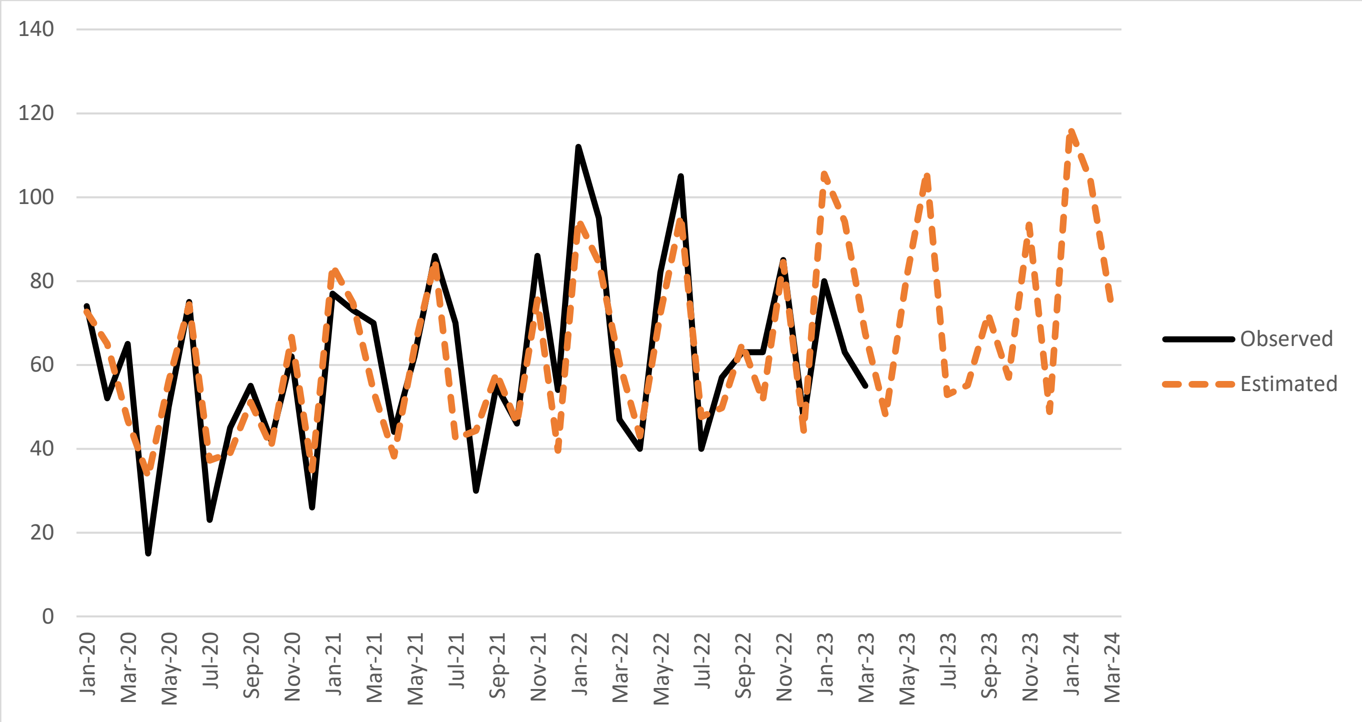
Year	Month	Demand	Deseasoanlize	Trend forecast	Forecast	Error
2020	Jan	74	49.10	48.19	73	1.37
	Feb	52	39.03	48.80	65	-13.02
	Mar	65	68.61	49.41	47	18.19
	Apr	15	22.51	50.01	33	-18.33
	May	50	45.15	50.62	56	-6.06
	June	75	51.65	51.23	74	0.62
	July	23	32.07	51.83	37	-14.18
	Aug	45	60.61	52.44	39	6.06
	Sept	55	57.12	53.05	51	3.93
	Oct	42	55.64	53.65	41	1.50
	Nov	62	50.51	54.26	67	-4.61
	Dec	26	40.83	54.87	35	-8.94
2021	Jan	77	51.09	55.48	84	-6.61
	Feb	73	54.79	56.08	75	-1.72
	Mar	70	73.89	56.69	54	16.29
	Apr	44	66.02	57.30	38	5.82
	May	62	55.98	57.90	64	-2.13
	June	86	59.23	58.51	85	1.04

	July	70	97.59	59.12	42	27.60
	Aug	30	40.41	59.72	44	-14.34
	Sept	55	57.12	60.33	58	-3.09
	Oct	46	60.94	60.94	46	0.00
	Nov	86	70.06	61.54	76	10.45
	Dec	54	84.80	62.15	40	14.42
2022	Jan	112	74.31	62.76	95	17.41
	Feb	95	71.30	63.37	84	10.57
	Mar	47	49.61	63.97	61	-13.61
	Apr	40	60.02	64.58	43	-3.04
	May	82	74.04	65.19	72	9.80
	June	105	72.31	65.79	96	9.47
	July	40	55.77	66.40	48	-7.63
	Aug	57	76.77	67.01	50	7.25
	Sept	63	65.43	67.61	65	-2.10
	Oct	63	83.45	68.22	52	11.50
	Nov	85	69.24	68.83	84	0.51
	Dec	47	73.81	69.44	44	2.79
2023	Jan	80	53.08	70.04	106	-25.56
	Feb	63	47.28	70.65	94	-31.13
	Mar	55	58.05	71.26	68	-12.51
	Apr			71.86	48	
	May			72.47	80	
	June			73.08	106	
	July			73.68	53	
	Aug			74.29	55	
	Sept			74.90	72	
	Oct			75.50	57	
	Nov			76.11	93	
	Dec			76.72	49	
2024	Jan			77.33	117	
	Feb			77.93	104	
	Mar			78.54	74	

Find RMSE using formula:

$$\boldsymbol{RMSE = \sqrt{Mean(Error^{\wedge}2)}}$$

Where ERROR = Original data- Forecasted data



RMSE= 10.44614

Method 2: Forecasting through Time Series Expert Modeler Criteria in IBM-SPSS 25

Step 1: To define a timeseries in the Data Editor, click the Variable View tab and enter a variable name in any blank row.

Step 2: Transformation of data in time series is done using define date procedure. The Define Dates procedure (on the Data menu) generates date variables used to establish periodicity and to distinguish between historical, validation, and forecasting periods.

Step 3: From the menus choose:

Analyze >Forecasting >Create Models..

Step 4: On the Variables tab, select one or more dependent variables to be modelled.

Step 5: From the Method drop-down box, select a modeling method. For automatic modeling, leave the default method of Expert Modeler. This will invoke the Expert Modeler to determine the best fitting model for each of the dependent variables.

Step 6: To produce forecasts: Click the Options Tab. Specify the forecast period. This will produce a chart that includes forecasts and observed values.

Click the Options Tab. Specify the forecast period. This will produce a chart that includes forecasts and observed values.

NOTE: Expert Modeler: The Expert Modeler automatically finds the best fitting model for each dependent series. If independent (predictor) variables are specified, the Expert Modeler selects, for inclusion in ARIMA models, those that have a statistically significant relationship with the dependent series. Model variables are transformed where appropriate using differencing and/or a square root or natural log transformation. By default, the Expert Modeler considers both exponential smoothing and ARIMA models. You can, however, limit the Expert Modeler to only search for ARIMA models or to only search for exponential Smoothing models. You can also specify automatic detection of outliers.

Model Description

			Model Type
Model ID	WAGH_BAKRI_250GM	Model_1	Winters' Additive

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	.798	.	.798	.798	.798	.798	.798	.798	.798	.798	.798
R-squared	.724	.	.724	.724	.724	.724	.724	.724	.724	.724	.724
RMSE	11.691	.	11.691	11.691	11.691	11.691	11.691	11.691	11.691	11.691	11.691
MAPE	18.018	.	18.018	18.018	18.018	18.018	18.018	18.018	18.018	18.018	18.018
MaxAPE	83.474	.	83.474	83.474	83.474	83.474	83.474	83.474	83.474	83.474	83.474
MAE	8.816	.	8.816	8.816	8.816	8.816	8.816	8.816	8.816	8.816	8.816
MaxAE	27.518	.	27.518	27.518	27.518	27.518	27.518	27.518	27.518	27.518	27.518
Normalized BIC	5.200	.	5.200	5.200	5.200	5.200	5.200	5.200	5.200	5.200	5.200

Best-Fitting Models

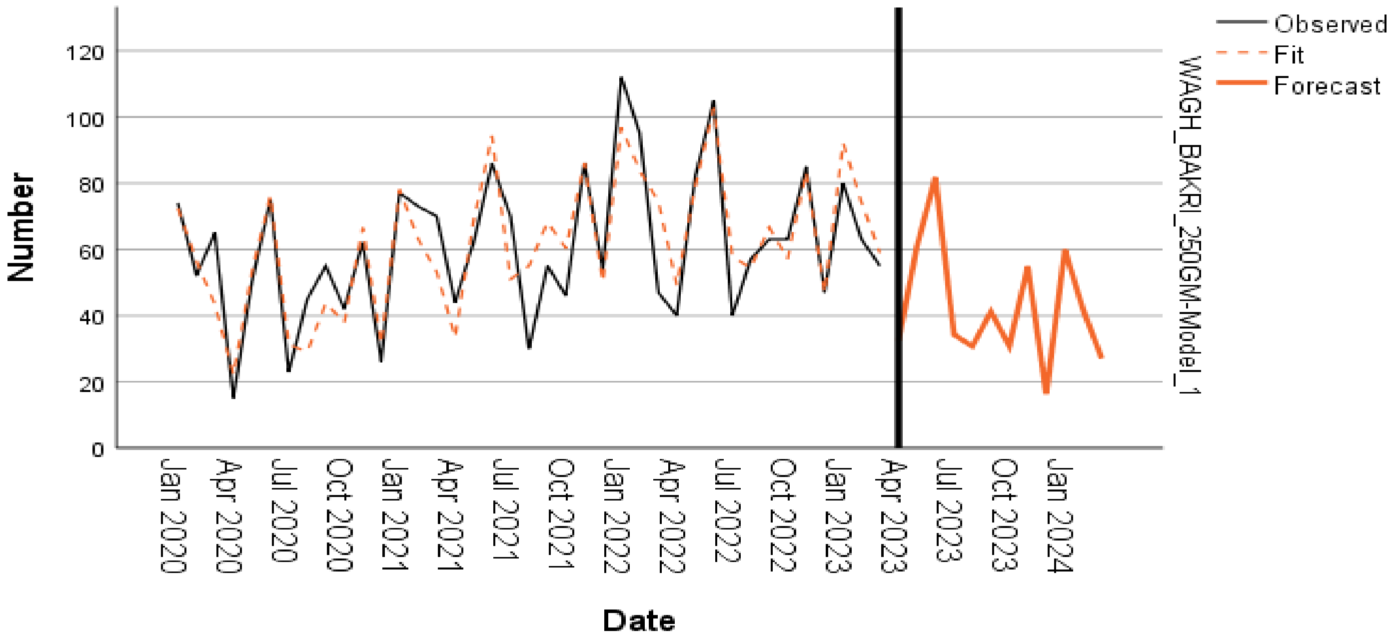
Model Statistics[a]

Model	Number of Predictors	Model Fit statistics: Stationary R-squared	R-squared	RMSE	MAPE	Ljung-Box Q(18): Statistics	DF	Sig.	Number of Outliers
WAGH_BAKRI_250GM-Model_1	0	.798	.724	11.691	18.018	24.707	15	.054	0

a. Best-Fitting Models according to RMSE (smaller values indicate better fit).

Forecast[a]

	Model	Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
WAGH_BAKRI_250GM-Model_1	Forecast	32	61	82	34	31	41	31	55	16	60	42	27
	UCL	56	85	106	60	57	69	61	88	52	99	85	74
	LCL	9	37	57	9	4	13	0	22	-20	21	-1	-20



RMSE= 11.691

RMSE from the Decomposition method is lesser than Winter's Additive model. Hence, the forecasts from Decomposition method are more suitable.

ITEM 2 – MADHUSUDAN DAIRY CREAMER 12GM

Method 1: Forecasting through Time Series Decomposition Model in MS Excel

3-year Data provided by the company

Demand Data Table				
Month	**2019**	**2020**	**2021**	**2022**
January	421	246	272	441
February	312	233	272	225
March	278	290	160	181
April	180	280	285	
May	396	370	515	
June	285	337	265	
July	300	348	455	
August	355	415	441	
September	245	322	402	
October	330	246	310	
November	237	296	493	
December	198	272	285	

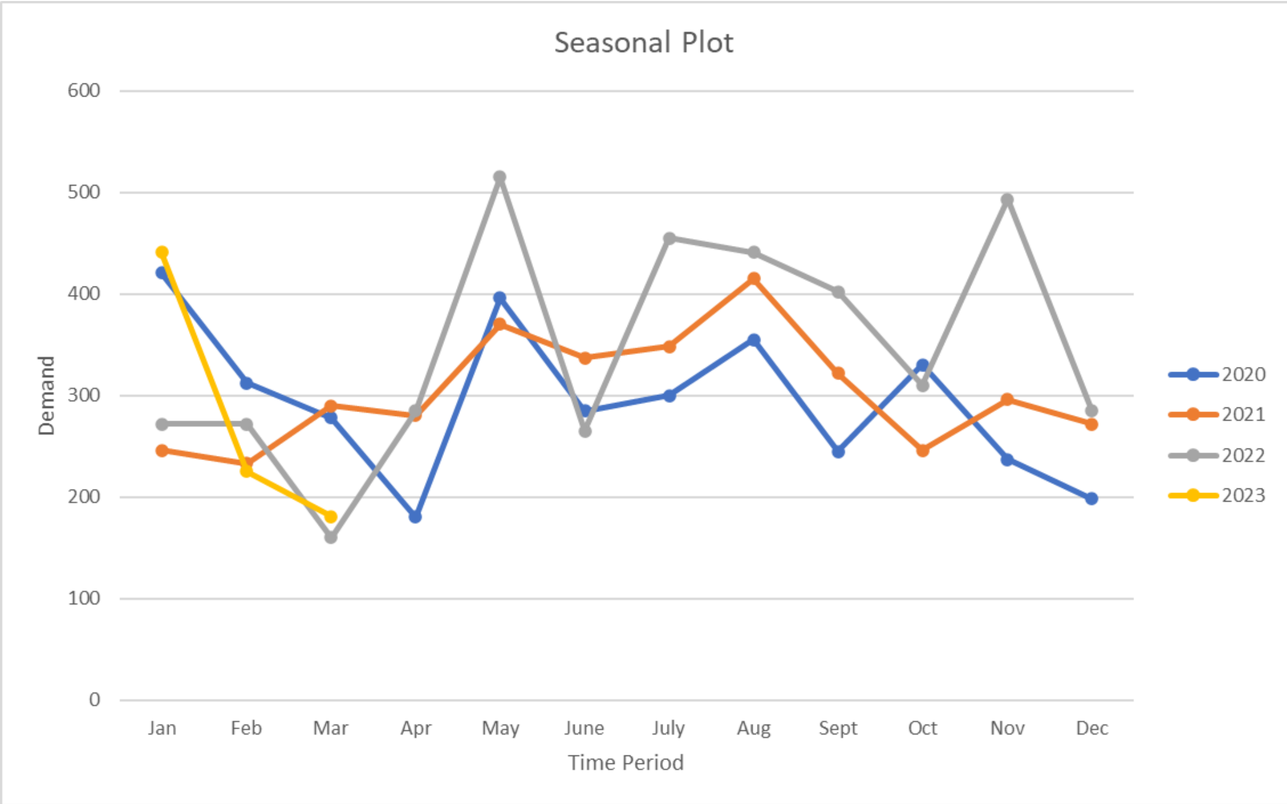
Since seasonality can be observed in the data, we thus use the Time Series Decomposition Model of Ratio to Moving-Averages to decompose the data into the Trend, Seasonal, Cyclic & Irregular components.

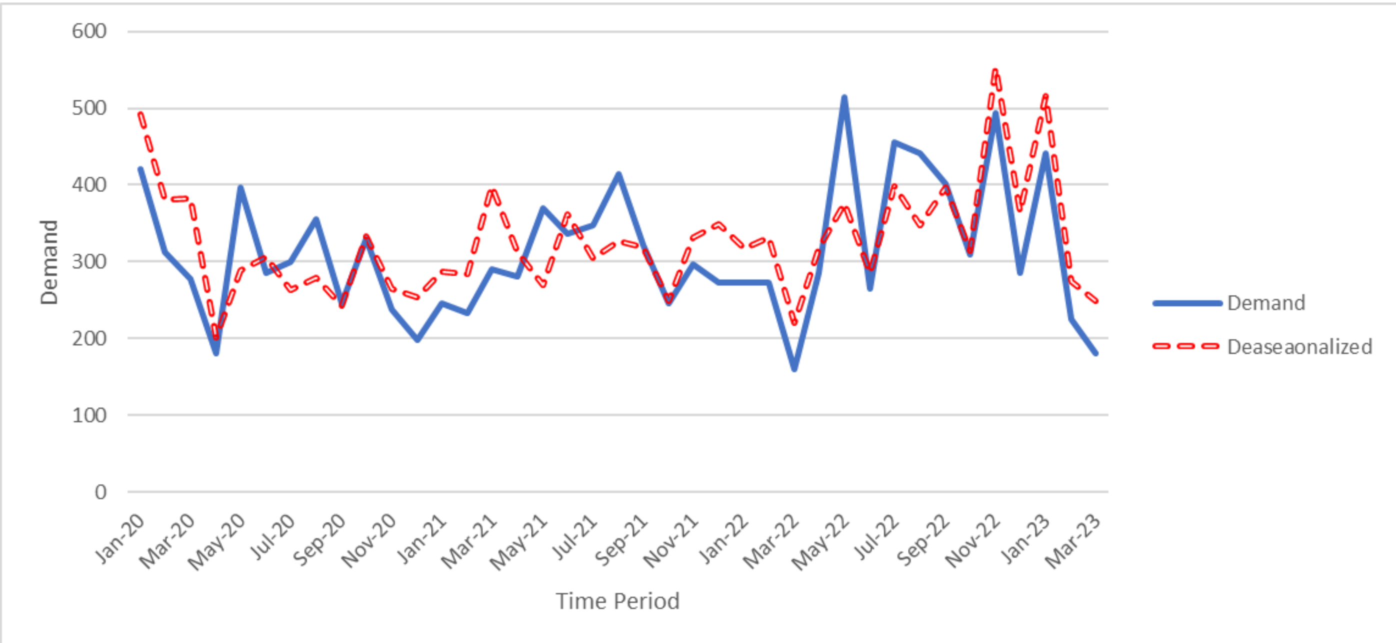
CALCULATIONS:

RATIO TO MOVING AVERAGE METHOD TO DESEASONALISE DATA

Year	Month	Demand	Deseasoanlized
2020	Jan	421	492.11
	Feb	312	380.78
	Mar	278	381.92
	Apr	180	200.81
	May	396	288.87
	June	285	306.56
	July	300	262.85

	Aug	355	279.72
	Sept	245	242.14
	Oct	330	333.50
	Nov	237	265.48
	Dec	198	253.83
2021	Jan	246	287.55
	Feb	233	284.36
	Mar	290	398.40
	Apr	280	312.38
	May	370	269.90
	June	337	362.50
	July	348	304.90
	Aug	415	327.00
	Sept	322	318.24
	Oct	246	248.61
	Nov	296	331.57
	Dec	272	348.69
2022	Jan	272	317.94
	Feb	272	331.96
	Mar	160	219.81
	Apr	285	317.95
	May	515	375.67
	June	265	285.05
	July	455	398.65
	Aug	441	347.48
	Sept	402	397.30
	Oct	310	313.29
	Nov	493	552.24
	Dec	285	365.36
2023	Jan	441	515.49
	Feb	225	274.60
	Mar	181	248.66


Seasonal Plot
600
500
400
300
200
100
0
Demand
Jan
Feb
Mar
Apr
May
June
July
Aug
Sept
Oct
Nov
Dec
Time Period
2020
2021
2022
2023


600
500
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Demand
Jan-20
Mar-20
May-20
Jul-20
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May-21
Jul-21
Sep-21
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Jan-22
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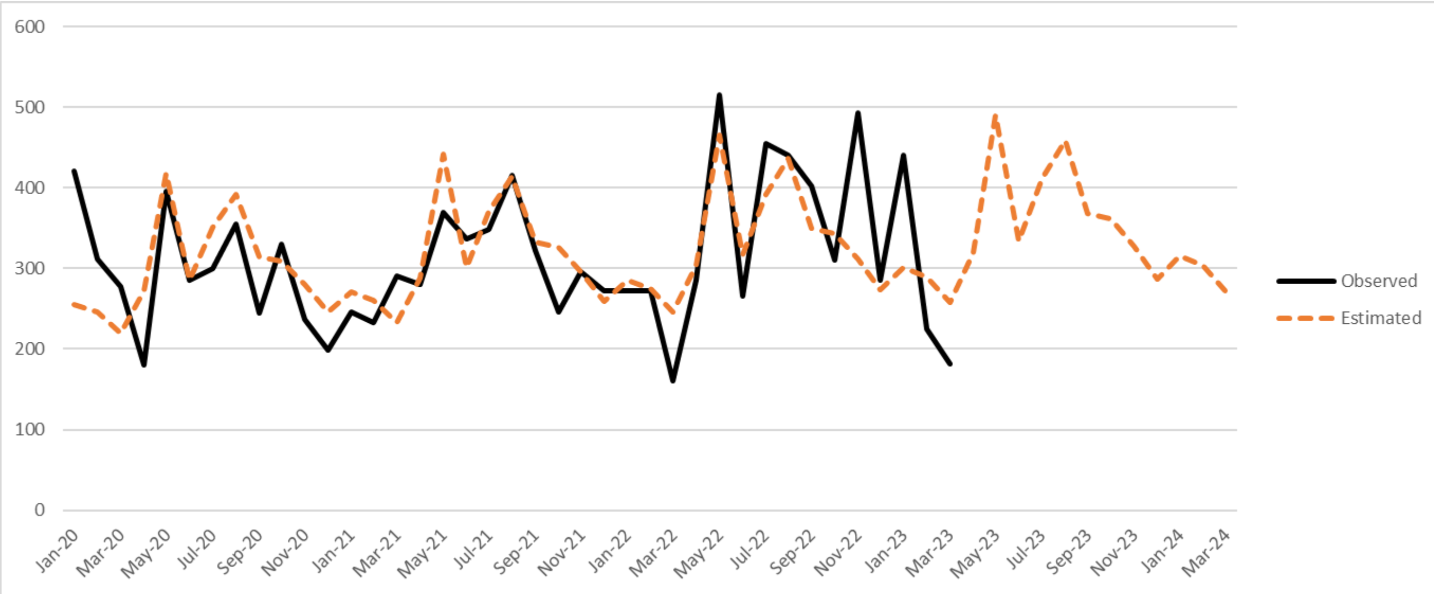
May-22
Jul-22
Sep-22
Nov-22
Jan-23
Mar-23
Time Period
Demand
Deaseaonalized

Year	Month	Deseasoanlize	Trend forecast	forecast	Error
2020	Jan	492.11	298.93	256	165.27
	Feb	380.78	300.39	246	65.86
	Mar	381.92	301.86	220	58.28
	Apr	200.81	303.32	272	-91.89
	May	288.87	304.79	418	-21.83
	June	306.56	306.26	285	0.28
	July	262.85	307.72	351	-51.22
	Aug	279.72	309.19	392	-37.40
	Sept	242.14	310.65	314	-69.32
	Oct	333.50	312.12	309	21.16
	Nov	265.48	313.58	280	-42.95
	Dec	253.83	315.05	246	-47.76
2021	Jan	287.55	316.51	271	-24.78
	Feb	284.36	317.98	261	-27.55
	Mar	398.40	319.44	233	57.48
	Apr	312.38	320.91	288	-7.65
	May	269.90	322.37	442	-71.94
	June	362.50	323.84	301	35.94
	July	304.90	325.31	371	-23.29
	Aug	327.00	326.77	415	0.28
	Sept	318.24	328.24	332	-10.12
	Oct	248.61	329.70	326	-80.24
	Nov	331.57	331.17	296	0.36
	Dec	348.69	332.63	259	12.53
2022	Jan	317.94	334.10	286	-13.82
	Feb	331.96	335.56	275	-2.95
	Mar	219.81	337.03	245	-85.32
	Apr	317.95	338.49	303	-18.41
	May	375.67	339.96	466	48.96
	June	285.05	341.43	317	-52.41
	July	398.65	342.89	391	63.64
	Aug	347.48	344.36	437	3.97
	Sept	397.30	345.82	350	52.09
	Oct	313.29	347.29	344	-33.64
	Nov	552.24	348.75	311	181.66
	Dec	365.36	350.22	273	11.81
2023	Jan	515.49	351.68	301	140.14
	Feb	274.60	353.15	289	-64.36
	Mar	248.66	354.61	258	-77.12
	Apr		356.08	319	
	May		357.55	490	

	June		359.01	334	
	July		360.48	411	
	Aug		361.94	459	
	Sept		363.41	368	
	Oct		364.87	361	
	Nov		366.34	327	
	Dec		367.80	287	
2024	Jan		369.27	316	
	Feb		370.73	304	
	Mar		372.20	271	



RMSE: 60.051

Method 2: Forecasting through Time Series Expert Modeler Criteria in IBM-SPSS 25

Model Description

			Model Type
Model ID	MADHUSUDAN_DAIRY_CREAMER_12GM	Model_1	Winters' Additive

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	.775	.	.775	.775	.775	.775	.775	.775	.775	.775	.775
R-squared	.522	.	.522	.522	.522	.522	.522	.522	.522	.522	.522
RMSE	61.914	.	61.914	61.914	61.914	61.914	61.914	61.914	61.914	61.914	61.914
MAPE	17.750	.	17.750	17.750	17.750	17.750	17.750	17.750	17.750	17.750	17.750
MaxAPE	48.106	.	48.106	48.106	48.106	48.106	48.106	48.106	48.106	48.106	48.106
MAE	51.188	.	51.188	51.188	51.188	51.188	51.188	51.188	51.188	51.188	51.188
MaxAE	129.309	.	129.309	129.309	129.309	129.309	129.309	129.309	129.309	129.309	129.309
Normalized BIC	8.533	.	8.533	8.533	8.533	8.533	8.533	8.533	8.533	8.533	8.533

Best-Fitting Models

Model Statistics[a]

Model	Number of Predictors	Model Fit statistics: Stationary R-squared	R-squared	RMSE	MAPE	Ljung-Box Q(18): Statistics	DF	Sig.	Number of Outliers
MADHUSUDAN_DAIRY_CREAMER_12GM-Model_1	0	.775	.522	61.914	17.750	15.736	15	.400	0

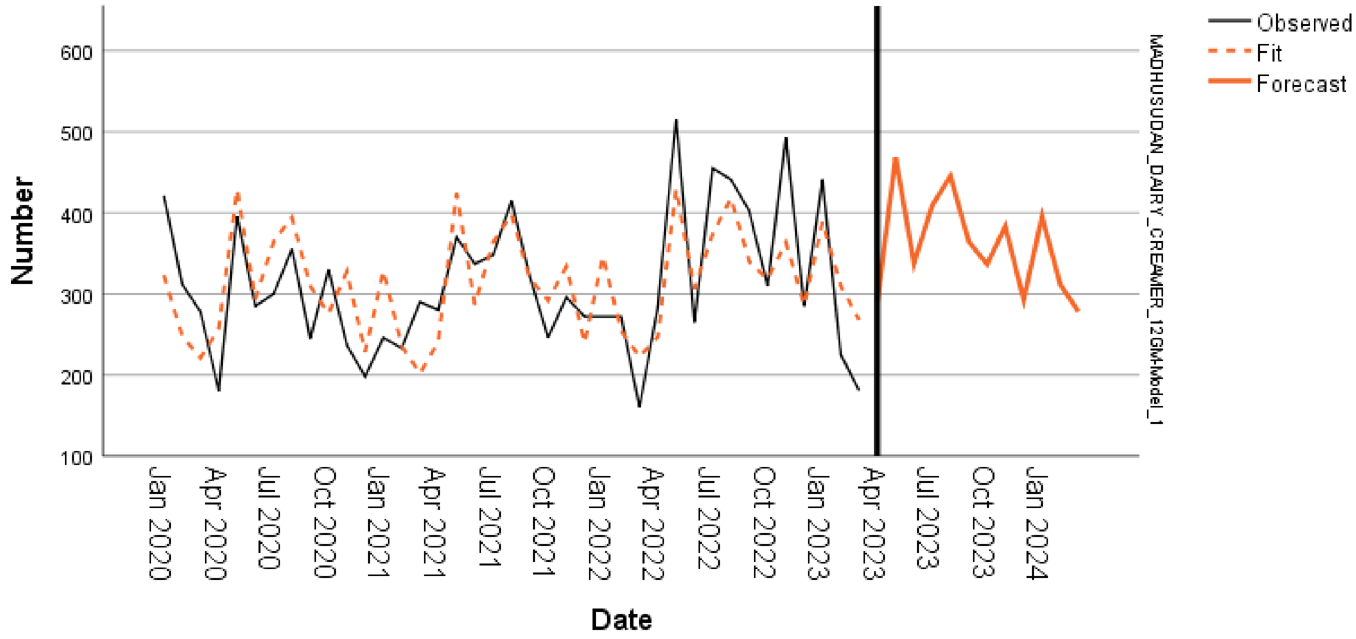
a. Best-Fitting Models according to RMSE (smaller values indicate better fit).

Forecast[a]

Model		Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
MADHUSUDAN_DAIRY_CREAMER_12GM-Model_1	Forecast	290	469	337	409	445	364	337	383	293	396	311	278
	UCL	416	595	464	537	573	493	466	513	423	527	443	410
	LCL	165	343	210	282	317	236	207	253	163	265	180	146

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

a. Best-Fitting Models according to RMSE (smaller values indicate better fit).



RMSE: 61.91

RMSE from the Decomposition method is lesser than Winter's Additive model. Hence, the forecasts from Decomposition method are more suitable.

ITEM 3 – DOUBLE COW DAIRY CREAMER 10GM

Method 1: Forecasting through Time Series Decomposition Model in MS Excel

3-year Data provided by the company

Demand Data Table				
Month	**2019**	**2020**	**2021**	**2022**
January	310	300	250	290
February	254	260	250	200
March	148	175	100	100
April	180	300	250	
May	345	411	455	
June	180	200	300	
July	330	471	401	
August	430	501	504	
September	100	135	200	
October	238	240	250	
November	244	250	220	
December	270	150	280	

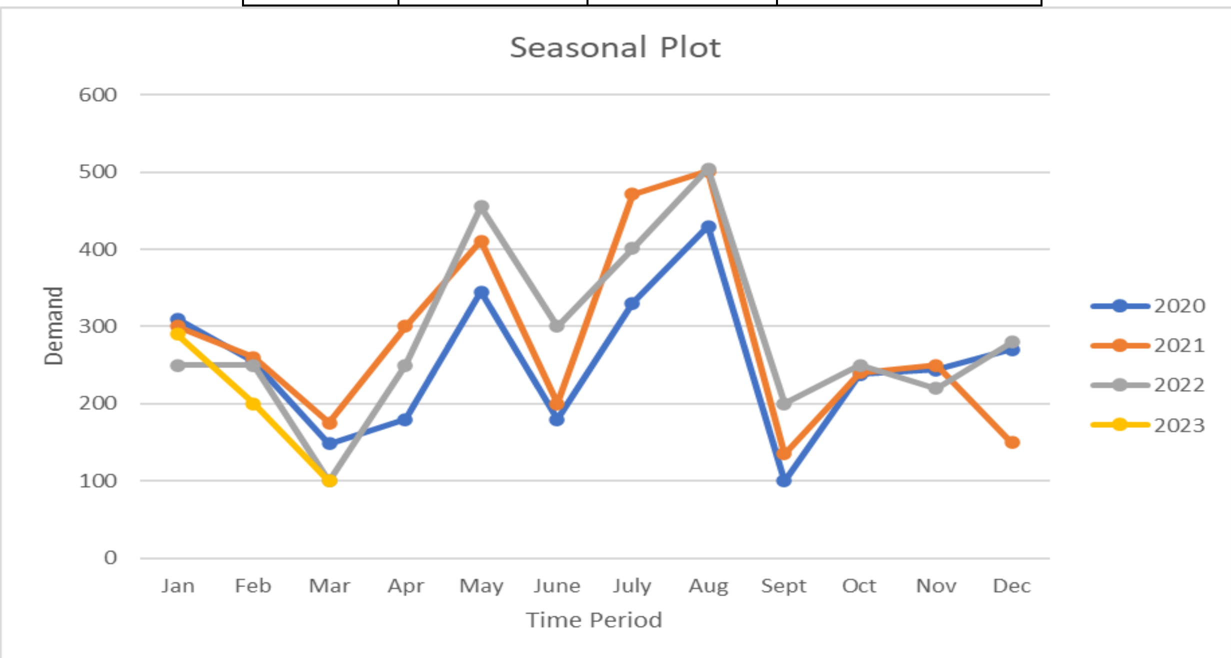
Since seasonality can be observed in the data, we thus use the Time Series Decomposition Model of Ratio to Moving-Averages to decompose the data into the Trend, Seasonal, Cyclic & Irregular components.

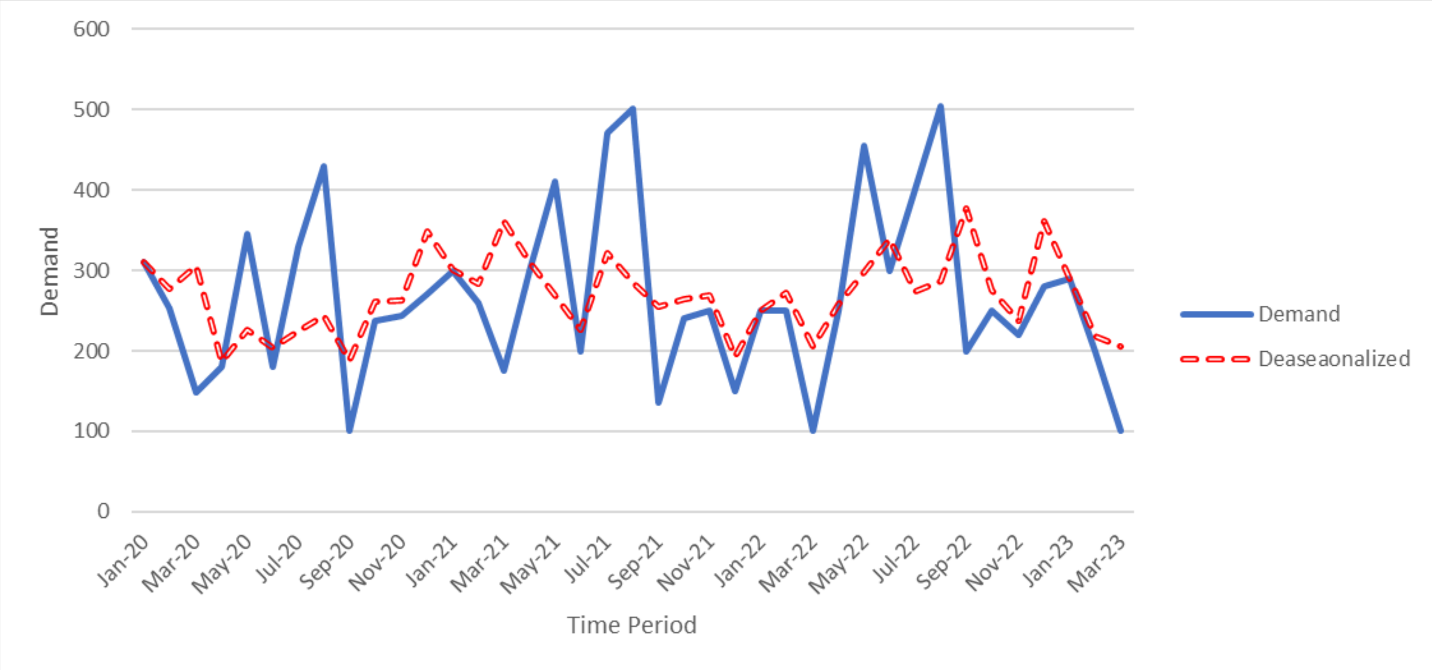
CALCULATIONS:

RATIO TO MOVING AVERAGE METHOD TO DESEASONALISE DATA

Year	Month	Demand	Deseasoanlize
2020	Jan	310	310.28
	Feb	254	277.10
	Mar	148	305.22
	Apr	180	186.26
	May	345	225.78
	June	180	203.83
	July	330	225.14
	Aug	430	244.26
	Sept	100	188.46
	Oct	238	261.59
	Nov	244	263.26

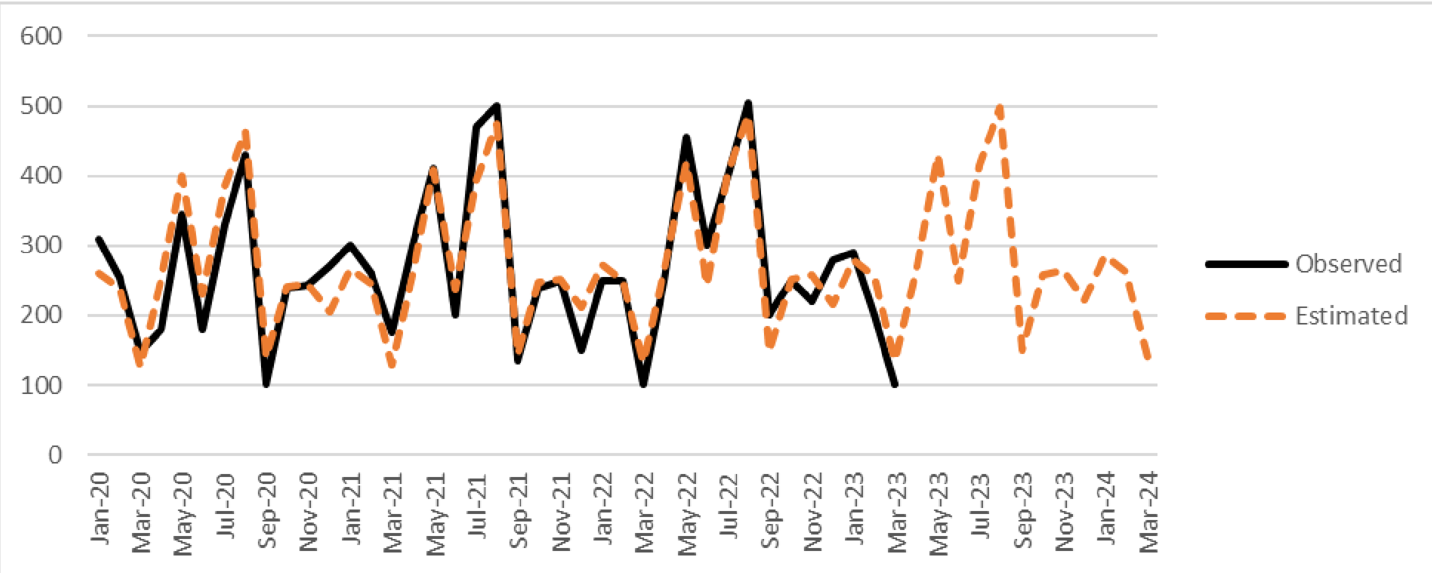
	Dec	270	347.91
2021	Jan	300	300.27
	Feb	260	283.65
	Mar	175	360.91
	Apr	300	310.43
	May	411	268.98
	June	200	226.48
	July	471	321.34
	Aug	501	284.60
	Sept	135	254.42
	Oct	240	263.79
	Nov	250	269.74
	Dec	150	193.28
2022	Jan	250	250.23
	Feb	250	272.74
	Mar	100	206.23
	Apr	250	258.70
	May	455	297.77
	June	300	339.71
	July	401	273.58
	Aug	504	286.30
	Sept	200	376.92
	Oct	250	274.78
	Nov	220	237.37
	Dec	280	360.80
2023	Jan	290	290.27
	Feb	200	218.19
	Mar	100	206.23





Year	Month	Demand	Deseasoanlize	Trend Forecast	Forecast	Error
2020	Jan	310	310.28	259.44	259	50.80
	Feb	254	277.10	259.99	238	15.68
	Mar	148	305.22	260.54	126	21.67
	Apr	180	186.26	261.10	252	-72.32
	May	345	225.78	261.65	400	-54.80
	June	180	203.83	262.20	232	-51.55
	July	330	225.14	262.75	385	-55.12
	Aug	430	244.26	263.30	464	-33.51
	Sept	100	188.46	263.85	140	-40.01
	Oct	238	261.59	264.40	241	-2.56
	Nov	244	263.26	264.96	246	-1.57
	Dec	270	347.91	265.51	206	63.95
2021	Jan	300	300.27	266.06	266	34.18
	Feb	260	283.65	266.61	244	15.62
	Mar	175	360.91	267.16	130	45.46
	Apr	300	310.43	267.71	259	41.29
	May	411	268.98	268.26	410	1.09
	June	200	226.48	268.82	237	-37.39
	July	471	321.34	269.37	395	76.18
	Aug	501	284.60	269.92	475	25.84
	Sept	135	254.42	270.47	144	-8.52
	Oct	240	263.79	271.02	247	-6.58
	Nov	250	269.74	271.57	252	-1.70
	Dec	150	193.28	272.12	211	-61.18
2022	Jan	250	250.23	272.68	272	-22.43

	Feb	250	272.74	273.23	250	-0.45
	Mar	100	206.23	273.78	133	-32.75
	Apr	250	258.70	274.33	265	-15.11
	May	455	297.77	274.88	420	34.98
	June	300	339.71	275.43	243	56.77
	July	401	273.58	275.98	405	-3.52
	Aug	504	286.30	276.54	487	17.19
	Sept	200	376.92	277.09	147	52.97
	Oct	250	274.78	277.64	253	-2.60
	Nov	220	237.37	278.19	258	-37.83
	Dec	280	360.80	278.74	216	63.68
2023	Jan	290	290.27	279.29	279	10.96
	Feb	200	218.19	279.84	257	-56.51
	Mar	100	206.23	280.40	136	-35.96
	Apr			280.95	272	
	May			281.50	430	
	June			282.05	249	
	July			282.60	414	
	Aug			283.15	498	
	Sept			283.70	151	
	Oct			284.26	259	
	Nov			284.81	264	
	Dec			285.36	221	
2024	Jan			285.91	286	
	Feb			286.46	263	
	Mar			287.01	139	



RMSE: 39.37

Method 2: Forecasting through Time Series Expert Modeler Criteria in IBM- SPSS 25

Time Series Modeler

Model Description

			Model Type
Model ID	DOUBLE_COW_DAIRY_CREAMER_10GM	Model_1	Simple Seasonal

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	.745	.	.745	.745	.745	.745	.745	.745	.745	.745	.745
R-squared	.876	.	.876	.876	.876	.876	.876	.876	.876	.876	.876
RMSE	38.510	.	38.510	38.510	38.510	38.510	38.510	38.510	38.510	38.510	38.510
MAPE	13.122	.	13.122	13.122	13.122	13.122	13.122	13.122	13.122	13.122	13.122
MaxAPE	60.406	.	60.406	60.406	60.406	60.406	60.406	60.406	60.406	60.406	60.406
MAE	30.175	.	30.175	30.175	30.175	30.175	30.175	30.175	30.175	30.175	30.175
MaxAE	90.608	.	90.608	90.608	90.608	90.608	90.608	90.608	90.608	90.608	90.608
Normalized BIC	7.490	.	7.490	7.490	7.490	7.490	7.490	7.490	7.490	7.490	7.490

Best-Fitting Models

Model Statistics[a]

Model	Number of Predictors	Model Fit statistics: Stationary R-squared	R-squared	RMSE	MAPE	Ljung-Box Q(18): Statistics	DF	Sig.	Number of Outliers
DOUBLE_COW_DAIRY_CREAMER_10GM-Model_1	0	.745	.876	38.510	13.122	55.955	16	.000	0

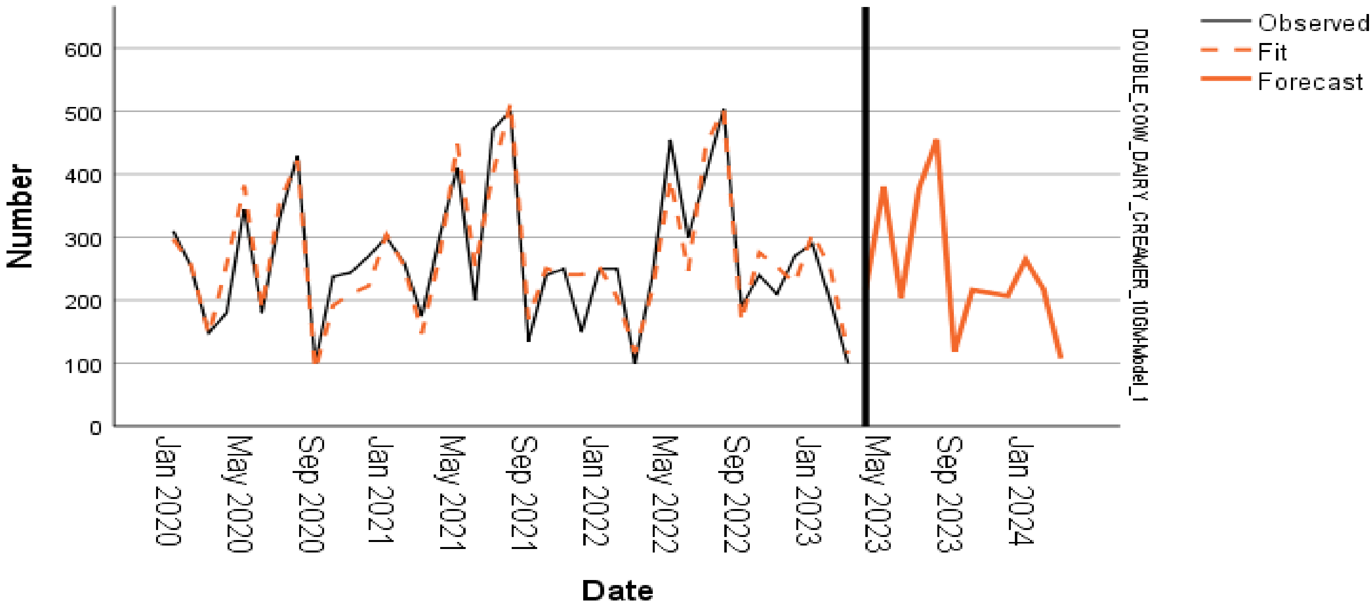
a. Best-Fitting Models according to RMSE (smaller values indicate better fit).

Forecast[a]

Model		Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
DOUBLE_COW_DAIRY_CREAMER_10GM-Model_1	Forecast	217	381	204	378	455	119	216	212	207	264	218	108
	UCL	295	468	299	481	566	236	340	341	342	405	364	259
	LCL	139	293	108	274	345	2	93	82	72	124	72	-43

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

a. Best-Fitting Models according to RMSE (smaller values indicate better fit).



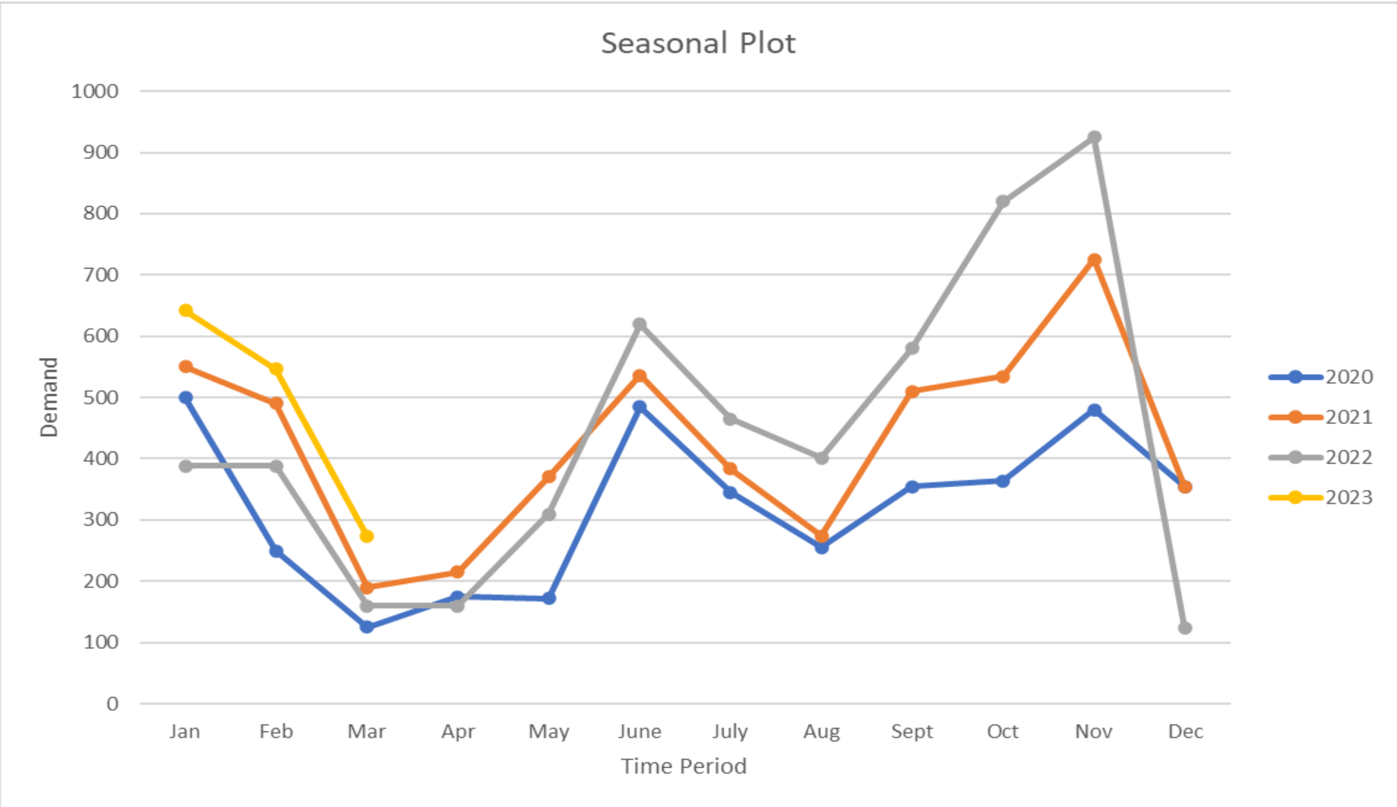
RMSE: 38.51

RMSE from the Simple Seasonal method is lesser than Decomposition model. Hence, the forecasts from Simple Seasonal method are more suitable.

ITEM 4 – NIINE DIAPER S1

3-Year data provided by the company

Demand Data Table				
Month	**2019**	**2020**	**2021**	**2022**
January	500	550	388	642
February	250	490	388	547
March	125	190	160	273
April	175	215	160	
May	172	370	310	
June	485	536	620	
July	345	384	465	
August	255	274	401	
September	355	510	580	
October	364	534	820	
November	480	725	925	
December	355	355	124	



Forecasting through Time Series Expert Modeler Criteria in IBM- SPSS 25

Time Series Modeler

Model Description

			Model Type
Model ID	NIINE_DIAPER_S1	Model_1	Simple Seasonal

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.710	.	.710	.710	.710	.710	.710	.710	.710	.710	.710
R-squared	.787	.	.787	.787	.787	.787	.787	.787	.787	.787	.787
RMSE	88.796	.	88.796	88.796	88.796	88.796	88.796	88.796	88.796	88.796	88.796
MAPE	20.813	.	20.813	20.813	20.813	20.813	20.813	20.813	20.813	20.813	20.813
MaxAPE	183.901	.	183.901	183.901	183.901	183.901	183.901	183.901	183.901	183.901	183.901
MAE	68.853	.	68.853	68.853	68.853	68.853	68.853	68.853	68.853	68.853	68.853
MaxAE	228.037	.	228.037	228.037	228.037	228.037	228.037	228.037	228.037	228.037	228.037
Normalized BIC	9.161	.	9.161	9.161	9.161	9.161	9.161	9.161	9.161	9.161	9.161

Best-Fitting Models

Model Statistics[a]

Model	Number of Predictors	Model Fit statistics				Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	RMSE	MAPE	Statistics	DF	Sig.	
NIINE_DIAPER_S1-Model_1	0	.710	.787	88.796	20.813	12.972	16	.675	0

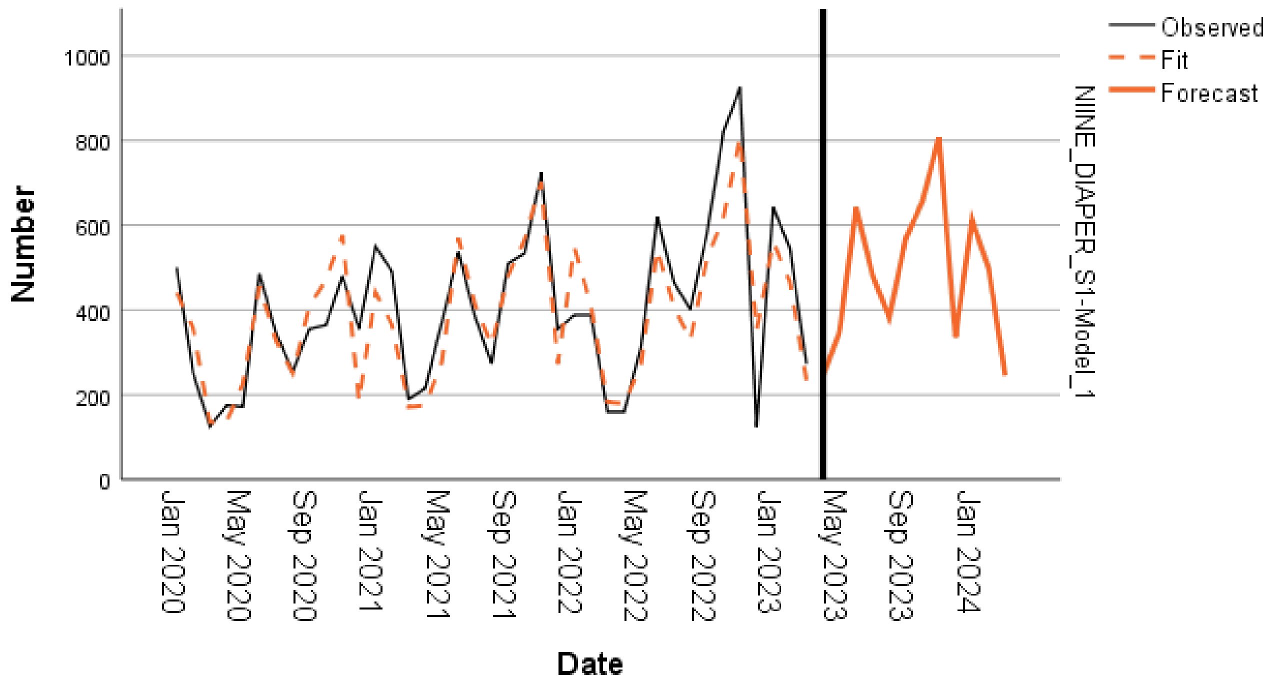
a. Best-Fitting Models according to RMSE (smaller values indicate better fit).

Forecast[a]

Model		Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
NIINE_DIAPE R_S1- Model_1	Forecast	242	349	642	481	382	569	656	807	336	612	497	245
	UCL	408	549	914	722	603	839	951	1137	560	911	774	448
	LCL	112	185	409	278	202	340	405	522	159	360	270	93

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

a. Best-Fitting Models according to RMSE (smaller values indicate better fit).



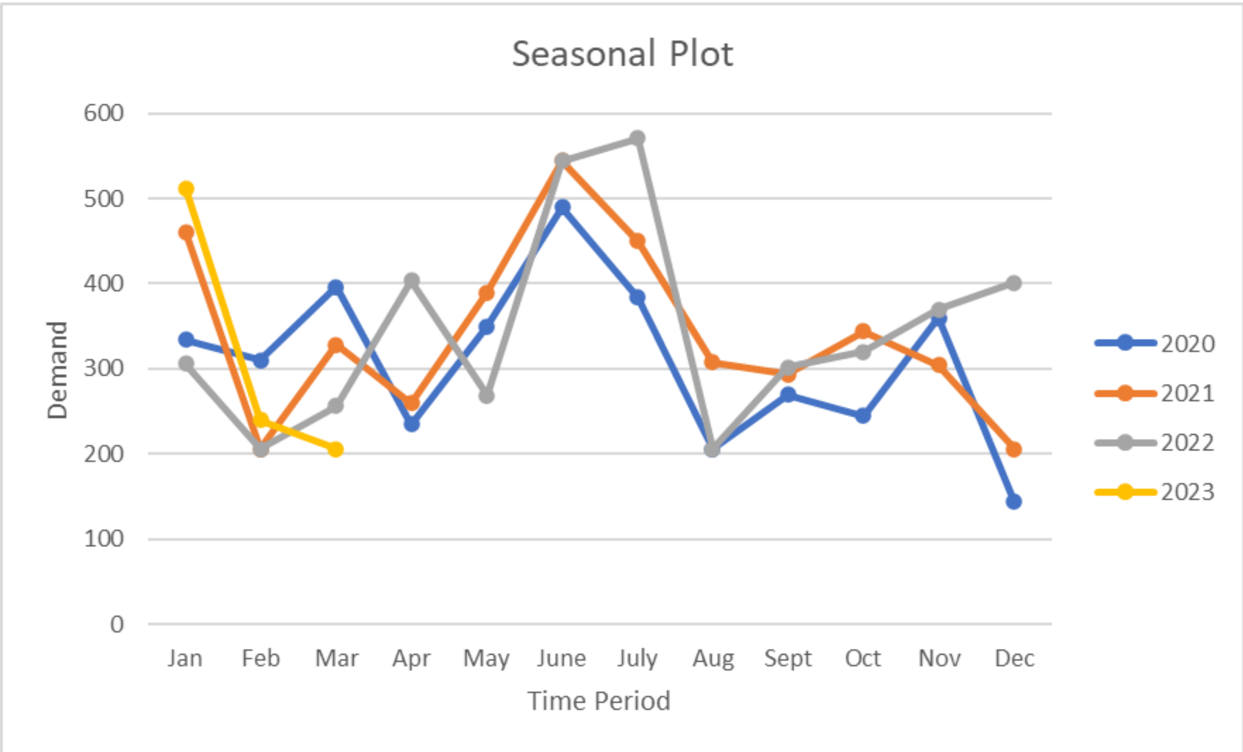
<u>RMSE: 88.79</u>

This method gave the results with least RMSE and MAPE values hence will be used for forecasting.

ITEM 5 – ROASTED VERMICILLI 800GM

3-Year data provided by the company

Demand Data Table				
Month	**2019**	**2020**	**2021**	**2022**
January	334	461	306	512
February	310	206	206	240
March	396	328	256	206
April	235	260	404	
May	350	390	269	
June	490	544	544	
July	384	450	571	
August	206	308	206	
September	270	294	302	
October	245	344	320	
November	360	304	370	
December	144	206	401	



Forecasting through Time Series Expert Modeler Criteria in IBM- SPSS 25

Time Series Modeler

Model Description

			Model Type
Model ID	ROASTED_VERMICILLI_800GM	Model_1	Winters' Additive

Model Summary

Model Fit

Fit Statistic	Mean	SE	Minimum	Maximum	Percentile 5	10	25	50	75	90	95
Stationary R-squared	.776	.	.776	.776	.776	.776	.776	.776	.776	.776	.776
R-squared	.645	.	.645	.645	.645	.645	.645	.645	.645	.645	.645
RMSE	65.656	.	65.656	65.656	65.656	65.656	65.656	65.656	65.656	65.656	65.656
MAPE	16.948	.	16.948	16.948	16.948	16.948	16.948	16.948	16.948	16.948	16.948
MaxAPE	57.928	.	57.928	57.928	57.928	57.928	57.928	57.928	57.928	57.928	57.928
MAE	51.466	.	51.466	51.466	51.466	51.466	51.466	51.466	51.466	51.466	51.466
MaxAE	151.810	.	151.810	151.810	151.810	151.810	151.810	151.810	151.810	151.810	151.810
Normalized BIC	8.651	.	8.651	8.651	8.651	8.651	8.651	8.651	8.651	8.651	8.651

Best-Fitting Models

Model Statistics[a]

Model	Number of Predictors	Model Fit statistics: Stationary R-squared	R-squared	RMSE	MAPE	Ljung-Box Q(18): Statistics	DF	Sig.	Number of Outliers
ROASTED_VERMICILLI_800GM-Model_1	0	.776	.645	65.656	16.948	10.913	15	.759	0

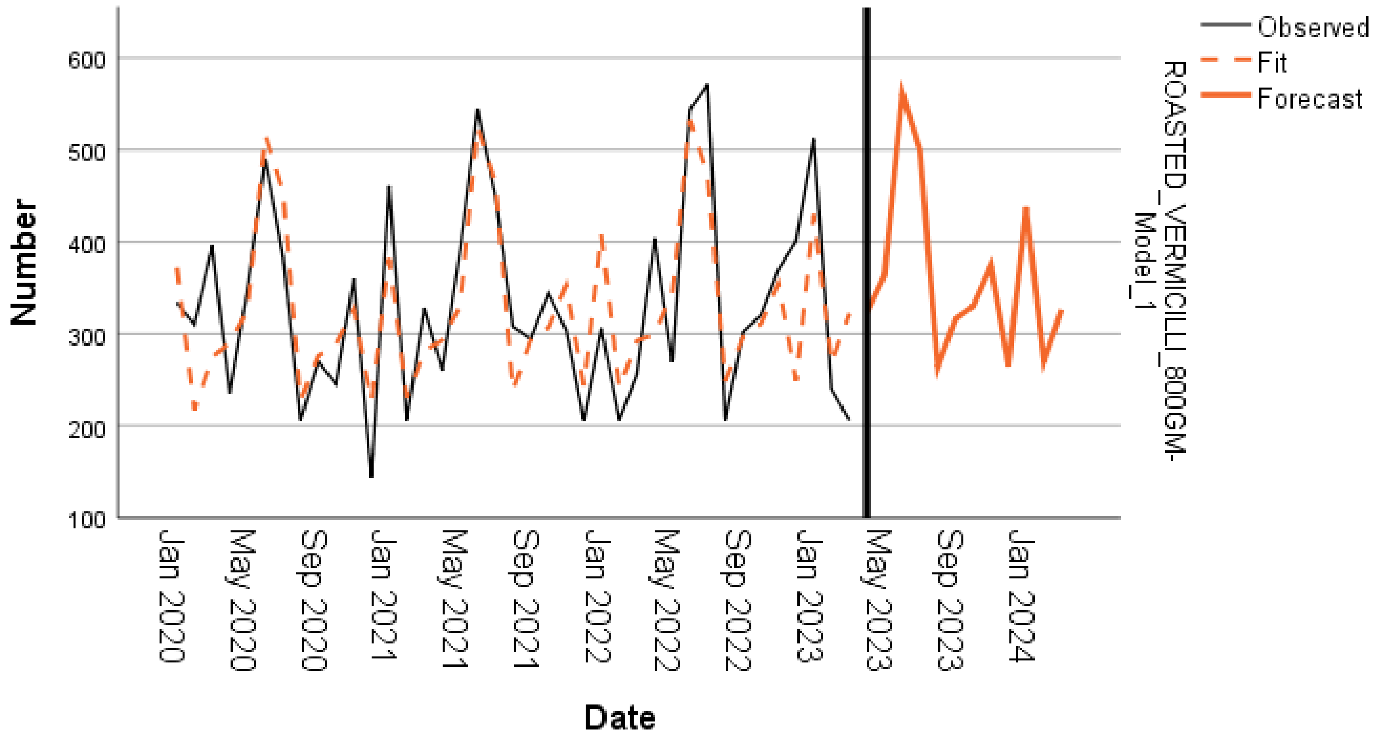
a. Best-Fitting Models according to RMSE (smaller values indicate better fit).

Forecast[a]

Model		Apr 2023	May 2023	Jun 2023	Jul 2023	Aug 2023	Sep 2023	Oct 2023	Nov 2023	Dec 2023	Jan 2024	Feb 2024	Mar 2024
ROASTED_VER MICILLI_800GM-Model_1	Forecast	323	364	562	499	263	316	330	374	265	438	270	326
	UCL	469	518	751	679	397	462	479	532	400	609	407	476
	LCL	199	231	394	341	152	193	203	238	152	289	156	199

For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.

a. Best-Fitting Models according to RMSE (smaller values indicate better fit).



RMSE: 65.66

This method gave the results with least RMSE and MAPE values hence will be used for forecasting.

5.4- Procurement

OBJECTIVE: To determine procurement plan of product that satisfies all demand at minimal total cost.

The total cost up to and including nth period when last procurement/ production is done at the beginning of jth period is given by –

$C_n(j) = C_{j-1} + A + C\,(r_j + r_{j-1} + \ldots + r_n) + (\,IC\,)\,(r_j/2 + r_{j+1} + \ldots + r_n) + (\,IC\,)\,(r_{j+1}/2 + r_{j+2} + \ldots + r_n) + \ldots + (\,IC\,)\,(r_n/2)$

Thus we have, $C_n = \mathrm{Min}\,\{C_{j-1} + A + C\,(r_j + r_{j-1} + \ldots + r_n) + (\,IC/2\,)\,[r_j + 3 * r_{j+1} + \ldots + (2(n-j)+1)r_n]\}$

Let us consider it as **ONE period problem**:
$C1 = C_0 + A + C * r_1 + (IC/2) * r_1$

Let Us consider it as a **TWO period problem**:
$C2(1) = C_0 + A + C * (r_1 + r_2) + (IC/2) *(r_1 + 3r_2)$
$C2(2) = C_1 + A + C * (r_2) + (IC/2) *(r_2)$
$C2 = \min \{C2(1), C2(2)\}$

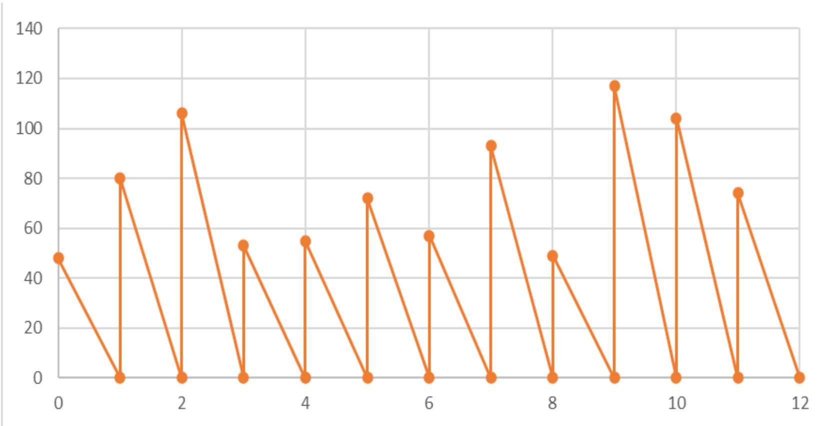
Let Us consider it as a **THREE period problem**:
$C3(1) = C_0 + A + C * (r_1 + r_2 + r_3) + (IC/2) *(r_1 + 3r_2 + 5r_3)$
$C3(2) = C_1 + A + C * (r_2 + r_3) + (IC/2) *(r_2 + 3r_3)$
$C3(3) = C_2 + A + C * (r_3) + (IC/2) *(r_3)$
$C3 = \min \{C3(1), C3(2), C3(3)\}$

Let Us consider it as a **FOUR period problem**:
$C4(1) = C_0 + A + C * (r_1 + r_2 + r_3 + r_4) + (IC/2) *(r_1 + 3r_2 + 5r_3 + 7r_4)$
$C4(2) = C_1 + A + C * (r_2 + r_3 + r_4) + (IC/2) *(r_2 + 3r_3 + 5r_4)$
$C4(3) = C_2 + A + C * (r_3 + r_4) + (IC/2) *(r_3 + 3r_4)$
$C4(4) = C_3 + A + C * (r_4) + (IC/2) *(r_4)$
$C4 = \min \{C4(1), C4(2), C4(3), C4(4)\}$
and so on until twelve period problem

ITEM 1 –WAGH BAKRI 250GM CARTON

Last period with ordering	Planning Horizon											
	1	2	3	4	5	6	7	8	9	10	11	12
1	**418129.18**	1118596.24	2051688.54	2520721.40	3010034.17	3653967.25	4166422.00	5006895.86	5452025.21	6520374.64	7474898.16	8157550.38
2		**1114943.77**	2043062.63	2509608.78	2996340.99	3636895.89	4146676.25	4982786.63	5425616.94	6488476.82	7438120.76	8117300.96
3			**2033369.74**	2502249.69	2986401.35	3623578.07	4130684.03	4962430.93	5402962.20	6460332.54	7405096.88	8080805.06
4				**2495043.52**	2976614.62	3610413.16	4114844.73	4942228.15	5380460.38	6432341.18	7372225.93	8044462.09
5					**2974135.13**	3604555.49	4106312.66	4929332.59	5365265.79	6411657.04	7346662.20	8015426.34
6						**3601278.36**	4100361.15	4919017.60	5352651.75	6393553.46	7323679.02	7964667.02
7							**4097787.81**	4912080.78	5343415.89	6378828.06	7304074.03	7965894.14
8								**4907818.35**	5336854.43	6366777.06	7287143.43	7945491.52
9									**5334656.45**	6359089.53	7274576.31	7929452.39
10										**6353701.05**	7264308.23	7915712.29
11											**7259529.70**	7907461.73
12												**7904090.77**
Ct	418129.18	1114943.77	2033369.74	2495043.52	2974135.13	3601278.36	4097787.81	4907818.35	5334656.45	6353701.05	7259529.70	7904090.77
jt	1	2	3	4	5	6	7	8	9	10	11	12
C(per unit cost	8662											
A	101.057								**Cost of procurement of this model**			
IC/2	46.919								**₹ 79,04,090.77**			

Date	Units to be procured
Apr-23	48
May-23	80
Jun-23	106
Jul-23	53
Aug-23	55
Sep-23	72
Oct-23	57
Nov-23	93
Dec-23	49
Jan-24	117
Feb-24	104
Mar-24	74



Interpretation:

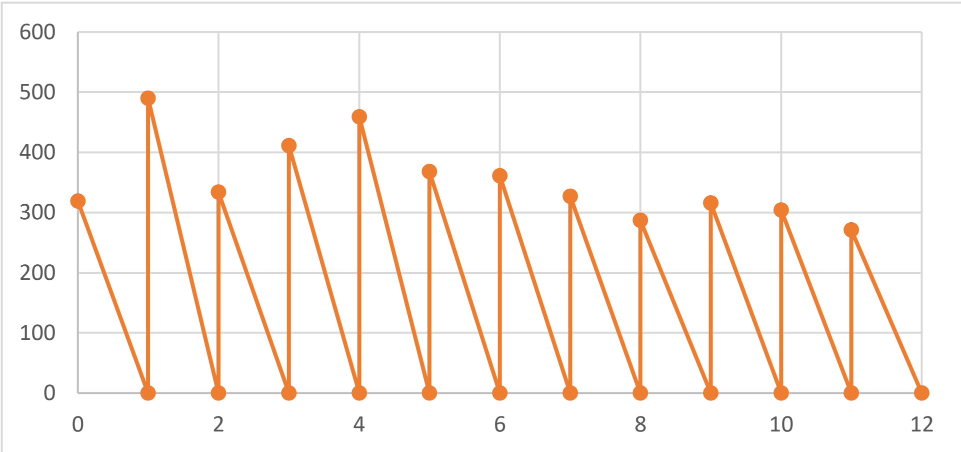
On the basis of the results obtained by applying Wagner Whitin Model (Dynamic Lot Size Model), we here by suggest the timeframes of procuring Wagh Bakri tea. The model is made on the basis of forecasted demand of Wagh Bakri tea for the year 2023-2024. According to this model, the optimum procurement policy for the tea is to acquire the item at the beginning of every month to satisfy the demand of that month.

"The Requirement of Wagh Bakri tea for the month of March 2023 should be procured at the beginning of the month i.e., March 2023. Similarly, the Requirement for the month of April 2023 should be procured at the beginning of the month i.e., April 2023. Likewise, we will proceed further."

ITEM 2 – MADHUSUDAN DAIRY CREAMER 12GM

Last period with ordering	Planning Horizon											
	1	2	3	4	5	6	7	8	9	10	11	12
1	**824300.73**	2097243.1	2969571.8	4048727.7	5260306	6236803.2	7199751.1	8076558	8850105.5	9706215.4	10534047	11275787
2		**2090451.9**	2958131	4031565.4	5236754.1	6208128.4	7166050.9	8038305.7	8807858	9659568.8	10483168	11221136
3			**2949209.8**	4021224.4	5220023.4	6186274.8	7139171.9	8006874.6	8772431.6	9619743.4	10439111	11173306
4				**4011231.3**	5203640.6	6164769.2	7112640.9	7975791.4	8737353.1	9580266	10395401	11125824
5					**5197280.9**	6153286.7	7096132.9	7954731.4	8712297.8	9550811.7	10361715	11088366
6						**6148193.8**	7086014.6	7940060.9	8693632.1	9527747	10334419	11030889
7							**7081019.2**	7930513.4	8680089.2	9509805.2	10312245	11031350
8								**7925991.3**	8671571.8	9496888.8	10295097	11010429
9									**8667606.5**	9488524.5	10282500	10994060
10										**9484155.5**	10273899	10981687
11											**10269697**	10973713
12												**10969970**
:t	824300.73	2090451.9	2949209.8	4011231.3	5197280.9	6148193.8	7081019.2	7925991.3	8667606.5	9484155.5	10269697	10969970
jt	1	2	3	4	5	6	7	8	9	10	11	12
C(per unit co	**2570**											
A	**29.983**								**Cost of procurement of this model=**			
IC/2	**13.921**								**₹ 1,09,69,969.94**			

Date	Units to be procured
Apr-23	319
May-23	490
Jun-23	334
Jul-23	411
Aug-23	459
Sep-23	368
Oct-23	361
Nov-23	327
Dec-23	287
Jan-24	316
Feb-24	304
Mar-24	271



Interpretation:

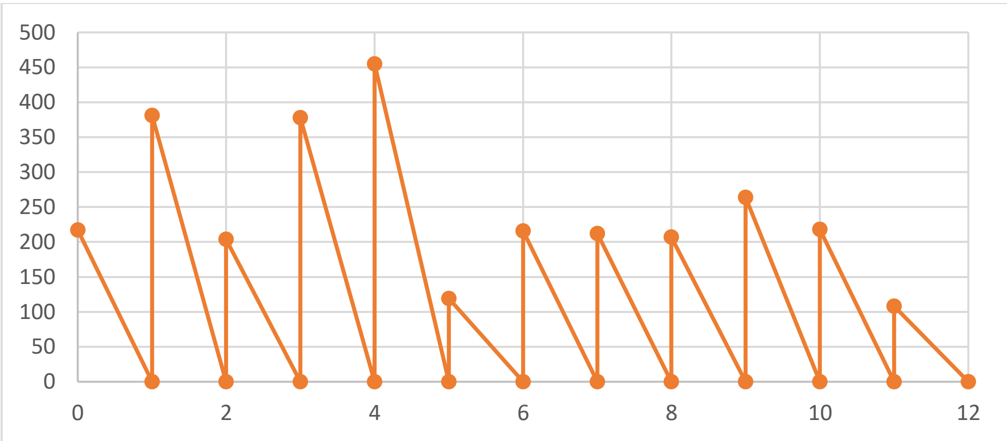
On the basis of the results obtained by applying Wagner Whitin Model (Dynamic Lot Size Model), we here by suggest the timeframes of procuring Madhusudan Dairy Creamer. The model is made on the basis of forecasted demand of Madhusudan Dairy Creamer_for the year 2023-2024. According to this model, the optimum procurement policy for the creamer is to acquire the item at the beginning of every month to satisfy the demand of that month.

"The Requirement of Madhusudan Dairy Creamer_for the month of March 2023 should be procured at the beginning of the month i.e., March 2023. Similarly, the Requirement for the month of April 2023 should be procured at the beginning of the month i.e., April 2023. Likewise, we will proceed further."

ITEM 3 – DOUBLE COW DAIRY CREAMER 10GM

Last period with ordering	Planning Horizon											
	1	2	3	4	5	6	7	8	9	10	11	12
1	**458192.88**	1266960.6	1702322.1	2513321.1	3494699.3	3752721	4223520	4688012	5143903.6	5728333.6	6213410.9	6454952.9
2		**1262651.3**	1695692.3	2502391.5	3478594	3735262.1	4203604.1	4665684.6	5119221.6	5700648.6	6183246.1	6423559.6
3			**1691291.1**	2495795.8	3466822.6	3722137.1	4188022.1	4647691.1	5098873.5	5677297.5	6157415.3	6396500.3
4				**2489415.4**	3455266.6	3709227.5	4172655.5	4629913	5078740.8	5654161.8	6131799.8	6369656.3
5					**3450115.5**	3702722.8	4163693.8	4618539.8	5065012.9	5637430.9	6112589.1	6349217.1
6						**3701393.6**	4159907.6	4612342.1	5056460.6	5625875.6	6098554.1	6325354.1
7							**4157475.1**	4607498.1	5049262	5615674	6085872.8	6320043.8
8								**4605111.1**	5044520.4	5607929.4	6075648.4	6308590.9
9									**5042190.3**	5602596.3	6067835.5	6299549.5
10										**5599617.8**	6062377.3	6292862.8
11											**6059922**	6289179
12												**6287975**
Ct	458192.88	1262651.3	1691291.1	2489415.4	3450115.5	3701393.6	4157475.1	4605111.1	5042190.3	5599617.8	6059922	6287975
jt	1	2	3	4	5	6	7	8	9	10	11	12
C(per unit cos	**2100**											
A	**24.500**								**Cost of procurement of this model**			
IC/2	**11.375**								**₹ 62,87,975.00**			

Date	Units to be procured
Apr-23	217
May-23	381
Jun-23	204
Jul-23	378
Aug-23	455
Sep-23	119
Oct-23	216
Nov-23	212
Dec-23	207
Jan-24	264
Feb-24	218
Mar-24	108



Interpretation:

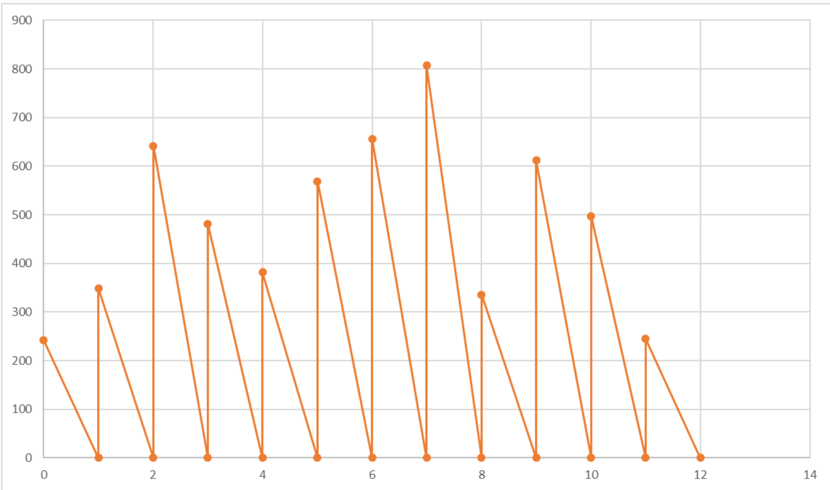
On the basis of the results obtained by applying Wagner Whitin Model (Dynamic Lot Size Model), we here by suggest the timeframes of procuring Double Cow Dairy Creamer. The model is made on the basis of forecasted demand of Double Cow Dairy Creamer for the year 2023-2024. According to this model, the optimum procurement policy for the creamer is to acquire the item at the beginning of every month to satisfy the demand of that month.

“The Requirement of Double Cow Dairy Creamer for the month of March 2023 should be procured at the beginning of the month i.e., March 2023. Similarly, the Requirement for the month of April 2023 should be procured at the beginning of the month i.e., April 2023. Likewise, we will proceed further.”

ITEM 4 – NIINE DIAPER S1

Last period with ordering	Planning Horizon											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	**403915.35**	989531.53	2072569.5	2888329.5	3539623.5	4514861.1	5645110.8	7042781	7627731.8	8698680.8	9572858.3	10005994
2		**986412.81**	2063678.1	2875113.1	3522972.4	4493093.6	5617444.8	7007858.8	7589788.4	8655234.5	9524943.1	9955875.6
3			**2052803.2**	2865034.8	3509459.3	4474464.3	5592917	6976074.6	7554983	8614926.2	9480165.9	9908895.5
4				**2855607.5**	3496597.2	4456485.9	5569040.1	6944941.4	7520828.6	8575268.9	9436039.8	9862566.4
5					**3493181.7**	4447954.2	5554609.8	6923254.9	7496120.9	8545058.3	9401360.3	9825684
6						**4442857.3**	5543614.4	6905003.2	7474848	8518282.5	9370115.7	9776815.7
7							**5537735.2**	6891867.8	7458691.4	8496623	9343987.3	9763905
8								**6884630.9**	7448433.3	8480862	9323757.4	9741472.2
9									**7445431.4**	8472357.2	9310783.8	9726295.7
10										**8466873.7**	9300831.4	9714140.3
11											**9296381.9**	9707487.9
12												**9705304.3**
:t	403915.35	986412.81	2052803.2	2855607.5	3493181.7	4442857.3	5537735.2	6884630.9	7445431.4	8466873.7	9296381.9	9705304.3
jt	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
C(per unit cost)	**1660**											
A	**19.367**								**Cost of procurement of this model**			
IC/2	**8.992**								**₹ 97,05,304.26**			

Date	Units to be procured
Apr-23	242
May-23	349
Jun-23	642
Jul-23	481
Aug-23	382
Sep-23	569
Oct-23	656
Nov-23	807
Dec-23	336
Jan-24	612
Feb-24	497
Mar-24	245



Interpretation:

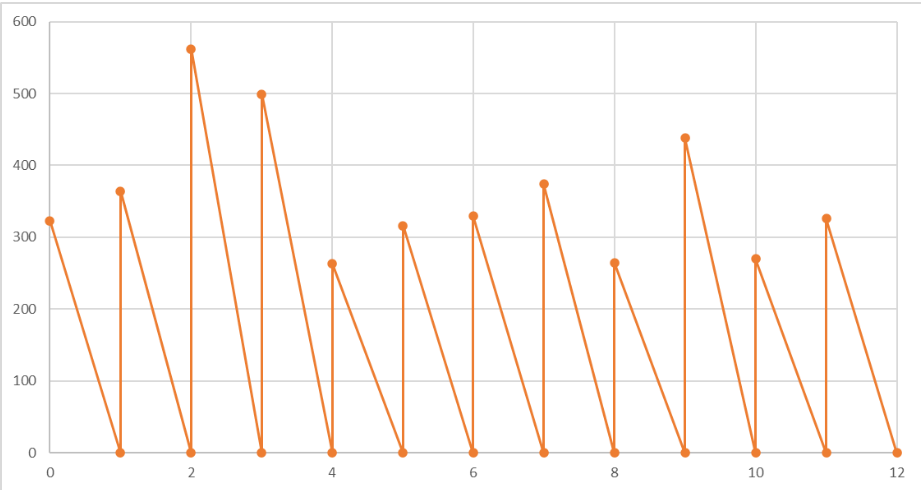
On the basis of the results obtained by applying Wagner Whitin Model (Dynamic Lot Size Model), we here by suggest the timeframes of procuring Niine Diaper_The model is made on the basis of forecasted demand of Niine Diaper_for the year 2023-2024. According to this model, the optimum procurement policy for the diapers is to acquire the item at the beginning of every month to satisfy the demand of that month.

"The Requirement of Niine Diaper_for the month of March 2023 should be procured at the beginning of the month i.e., March 2023. Similarly, the Requirement for the month of April 2023 should be procured at the beginning of the month i.e., April 2023. Likewise, we will proceed further.

ITEM 5 – ROASTED VERMICILLI 800GM

Last period with ordering	Planning Horizon											
	1	2	3	4	5	6	7	8	9	10	11	12
1	**539103.68**	1149889.6	2097969.6	2944256.9	3392661	3934269.2	4502839.9	5150583	5611928.1	6378391.6	6853296.9	7429632.3
2		**1146636**	2089662.6	2931463.2	3377502.4	3916269.2	4481872.7	5126252.9	5585215.3	6347740.4	6820217.9	7393622
3			**2080146.4**	2921942.4	3365616.8	3901542.3	4464178.5	5105195.8	5561775.4	6320362.2	6790411.9	7360884.7
4				**2912992.6**	3354302.2	3887386.3	4447055.3	5084709.7	5538906.5	6293554.9	6761176.9	7328718.5
5					**3351956.8**	3882199.5	4438901.2	5073192.8	5525006.7	6275716.8	6740911.1	7305521.3
6						**3879377.5**	4433112	5064040.6	5513471.8	6260243.6	6723010.1	7264170.1
7							**4430164.1**	5057729.9	5504778.2	6247611.6	6707950.4	7266698.1
8								**5054386.4**	5499051.9	6237947	6695858	7251674.4
9									**5496688.5**	6231645.2	6687128.5	7240013.6
10										**6227726.2**	6680781.7	7230735.6
11											**6678373.3**	7225395.9
12												**7222484**
Ct	539103.68	1146636	2080146.4	2912992.6	3351956.8	3879377.5	4430164.1	5054386.4	5496688.5	6227726.2	6678373.3	7222484
jt	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
C(per unit cost)	**1660**											
A	**19.367**								**Cost of procurement of this model**			
IC/2	**8.992**								**₹ 72,22,483.99**			

Date	Units to be procured
Apr-23	323
May-23	364
Jun-23	562
Jul-23	499
Aug-23	263
Sep-23	316
Oct-23	330
Nov-23	374
Dec-23	265
Jan-24	438
Feb-24	270
Mar-24	326



Interpretation:

On the basis of the results obtained by applying Wagner Whitin Model (Dynamic Lot Size Model), we here by suggest the timeframes of procuring Roasted Vermicilli. The model is made on the basis of forecasted demand of Roasted Vermicilli for the year 2023-2024. According to this model, the optimum procurement policy for the Roasted Vermicilli is to acquire the item at the beginning of every month to satisfy the demand of that month.

"The Requirement of Roasted Vermicilli for the month of March 2023 should be procured at the beginning of the month i.e., March 2023. Similarly, the Requirement for the month of April 2023 should be procured at the beginning of the month i.e., April 2023. Likewise, we will proceed further."

Chapter 6

Results

1. **ABC ANALYSIS:**

Approximately 10% of the items account for 53.72% of annual usage value and 90% of the items account for 46.28% of the annual usage value.

2. **FORECASTING:**

1. For product Wagh Bakri 250 gm carton value for Decomposition method is minimum i.e., 11.691. Hence it will be used for forecasting the demand for next year.

2. For product Madhusudan Dairy Creamer value for Decomposition method is minimum i.e., 60.05. Hence it will be used for forecasting the demand for next year.

3. For product Double Cow Dairy Creamer value for Simple Seasonal method is minimum i.e., 38.51. Hence it will be used for forecasting the demand for next year.

4. For product NIINE Diaper S1 value for Simple Seasonal method is minimum i.e., 88.79. Hence it will be used for forecasting the demand for next year.

5. For product Roasted Vermicelli 800 gm value for Winters' Additive method is minimum i.e., 65.66. Hence it will be used for forecasting the demand for next year.

3. **PROCUREMENT:**

1. For product Wagh Bakri 250 gm units to be procured in the month for Apr-23 is 48 units, for May-23 is 80 units, for Jun-23 is 106 units, for Jul-23 is 53 units, for Aug-23 is 55 units, for Sep-23 is 72 units, for Oct-23 is 57 units, for Nov-23 is 93 units, for Dec-23 is 49 units, For Jan-24 is 117 units, for Feb-24 is 104 units, and for Mar-24 is 74 units.

2. For product wiper Madhusudan Dairy Creamer units to be procured in the month for Apr-23 is 319 units, for May-23 is 490 units, for Jun-23 is 334 units, for Jul-23 is 411 units, for Aug-23 is 459 units, for Sep-23 is 368 units, for Oct-23 is 361 units, for Nov-23 is 327 units, for Dec-23 is 287 units, For Jan-24 is 316 units, for Feb-24 is 304 units, and for Mar-24 is 271 units.

3. For product Double Cow Dairy Creamer units to be procured in the month for Apr-23 is 217 units, for May-23 is 381 units, for Jun-23 is 204 units, for Jul-23 is 378 units, for Aug-23 is 455 units, for Sep-23 is 119 units, for Oct-23 is 216 units, for Nov-23 is 212 units, for Dec-23 is 207 units, For Jan-24 is 264 units, for Feb-24 is 218 units, and for Mar-24 is 108 units.

4. For product NIINE Diaper S1 units to be procured in the month for Apr-23 is 242 units, for May-23 is 349 units, for Jun-23 is 642 units, for Jul-23 is 481 units, for Aug-23 is 382 units, for Sep-23 is 569 units, for Oct-23 is 656 units, for Nov-23 is 807 units, for Dec-23 is 336 units, For Jan-24 is 612 units, for Feb-24 is 497 units, and for Mar-24 is 245 units.

5. For product Roasted Vermicelli 800 gm units to be procured in the month for Apr-23 is 323 units, for May-23 is 364 units, for Jun-23 is 562 units, for Jul-23 is 499 units, for Aug-23 is 263 units, for Sep-23 is 316 units, for Oct-23 is 330 units, for Nov-23 is 374 units, for Dec-23 is 265 units, For Jan-24 is 438 units, for Feb-24 is 270 units, and for Mar-24 is 326 units.

Chapter 7

References

Websites Referred:

- www.wikipedia.org
- www.google.com
- ibm –spss forecasting tutorial: https://www.ibm.com/docs/en/cloud-paks/cp-data/4.5.x?topic=sales-exponential-smoothing
- Brief History of Operations Research (universalteacher.com)
- https://www.google.co.in/search?q=demand+forecasting+techniques&o%20q=demand
- https://www.ibm.com/support/knowledgecenter/en/SSLVMB_sub/statistics_mainhelp_ddita/spss/trends/idh_idd_exp_smooth_crit.html

Software's Used for Analysis:

- Microsoft Excel
- Microsoft Word
- SPSS 25