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Centro Interdisciplinario de Posgrados

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Escuela de Ingeniería

Maestría en Sistemas Integrados de Manufactura y Estrategias de Calidad

**DEVELOPMENT OF THE ENTERPRISE LOGISTIC SYSTEM FOR LLC
«100 TONN MONTAGE»**

Tesis que para obtener el Grado de Maestro
en Sistemas Integrados de Manufactura y Estrategias de Calidad

Presenta

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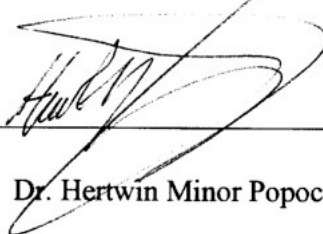
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INTRODUCTION

Nowadays demand management is being incorporated in many companies looking for optimization of their inventories levels and costs. In this research, we study methods for effective controlling the demand inventories. The purpose of the study is to analyze different established forecasting methods and make recommendations for their application to a Russian service company “100 Tonn Montage” who provides services industrial equipment assembly and facility relocation.

Currently, the number of clients has increased and consequently the number of projects, because of the increase in the demand for projects, there is a lack of equipment and tools in their inventories. In other words, they are not efficiently supplying the equipment they need to complete the demand for these projects. As a consequence, the increase of time to finish some projects, the increase in expenses of urgent purchase and the possible loss of clients.

By using forecasting methods, you can predict possible project demand for the coming months through using historical data on the demand for previous year's projects. In this way, to obtain an estimate of the amount of tools and equipment that will be needed to respond to this future demand, thus achieving an efficient supply in their inventories. After analyzing different methods, we suggest the company to apply the method that produces the optimal solution that as a result brings an efficient inventory controlling and better cost benefits.

JUSTIFICATION OF THE PROBLEM

The Russian company 100 Tonn Montage is a service company specialized on equipment assembly and relocation of industrial equipment. The clients of the company have increased year after year in several cities of the country, therefore the demand for work projects has increased as well. For that reason the lifting equipment, tools and personnel are not enough to assist clients and carry out the projects.

To mention some of the consequences for not having enough resources to respond to the increased project demand:

- The company has begun to increase its time to complete new projects.
- Have expenses in urgent purchases of equipment and tools.
- Customer dissatisfaction and possible loss.

OBJECTIVE

The objective of the research is that through the study of the literature in the field of demand management and its different methods of forecasting, find an optimal method that will help to estimate the future demand for the following months. Ensuring that 100 Tonn Montage Company can be able to respond to the increase of customers and work load. Then resulting in a better resource planning, work capacity and cost benefits.

In order to achieve the objective:

- The advantages and limitations of several forecasting methods will be examined.
- The historical data of demand in lifting projects will be analyzed with the different forecasting methods studied.
- The quality of the forecasting result will be proved using the instruments of forecasting accuracy measures.
- The method that provides the best result will be recommended.

BACKGROUND

1 Logistics and the Supply Chain in Non-Manufacturing Areas.

It may be easier to think of logistics and the supply chain regarding moving and storing the physical product of a manufacturing facility. Thus, it is a very limited point of view and can lead to losing business opportunities. The principles and concepts of logistics and the supply chain learned over the years can be applied to areas such as service industries, military industry and even the direction of the environment.

1.1 Service Industry

The services sector of industrialized countries is large and continues to grow. For example in the United States, more than 70% of all jobs are in what the federal government classifies as the service sector. The size of this industry by itself forces us to ask ourselves if the concepts of logistics would not be equally applicable here as they are in the manufacturing sector [2]. If they are, there is a tremendous wasted opportunity that has to be fulfilled. Many companies designated as service companies produce a product. Examples include restaurants, shops, supermarkets, light, and oil companies. These companies carry out all the regular activities of the supply chain of any manufacturing company. However, they are service companies although the operations of the supply chain, especially those related to the physical distribution, are not so obvious. Even though many service-oriented companies may be distributing an intangible, non-physical product, they are engaged in many distribution activities and decisions.

1.2 Difference between Service and Manufacturing Organization

Organizations can be divided into two broad categories: manufacturing organizations and service organizations, each posing unique challenges for the operations function. There are two primary distinctions between these categories. “First, manufacturing organizations produce physical, tangible goods that can be stored in inventory before they are needed. By contrast, service organizations produce intangible products that cannot be produced ahead of time” [17].

Second, in manufacturing organizations most customers have no direct contact with the operation. Customer contact occurs through distributors and retailers. For example, a customer buying a car at a car dealership never comes into contact with the automobile factory. However, in service organizations the customers are typically present during the creation of the service. Hospitals, colleges, theaters, and barbershops are examples of service organizations in which the customer is present during the creation of the service.

The differences between manufacturing and service organizations are not as clear-cut as they might appear, and there is much overlap between them [17]. Most manufacturers provide services as part of their business, and many service firms manufacture physical goods that they deliver to their customers or consume during service delivery. Figure 1.1 shows the differences between manufacturing and services, focusing on the dimensions of product tangibility and the degree of customer contact. It shows the extremes of pure manufacturing and pure service, as well as the overlap between them.

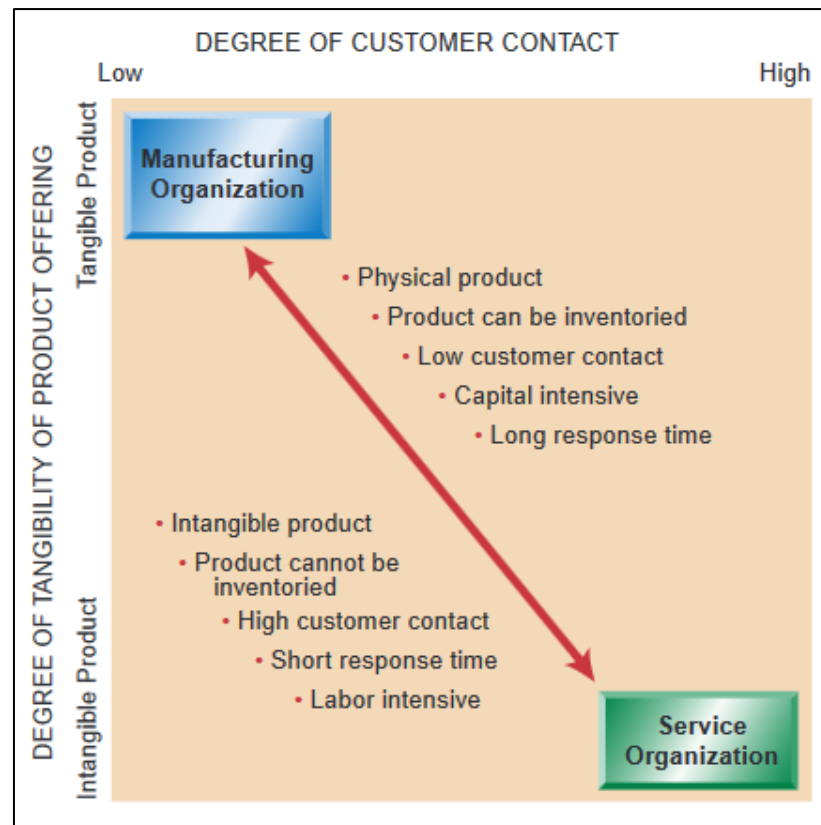


Figure 1.1 Difference between Manufacturing and Services industries [17].

Shown below a Table 1.1 with the mainly differences between manufacturing operations and services are divided into eight categories:

Table 1.1 Categories of difference between manufacturing and service industries

Manufacturing industry	Service industry
Physical, durable product	Intangible product, perishable
Production can be cataloged	Production cannot be inventoried

Little contact with the customer	High customer contact
Long response time	Short response time
Regional, national or international markets	Major national markets
Large installations	Relatively small installations
Intensive capital	Intensive work
Easy to measure quality	Quality is not easy to measure

Of these 8 categories, 5 are the most important to identify and are the ones that we explain in more detail below on Table 1.2:

Table 1.2 The five most significant differences

Manufacturing industry	Service industry
The first difference is due to the material nature of the product. Manufactured goods are physical, durable products.	Services are intangible, perishable (often consisting of ideas, concepts or information).
The second difference is that manufactured goods are resulting from products that can be produced, stored and transported in anticipation of future demand.	On the other hand, services cannot be produced beforehand.
A third difference is customer contact. Most clients of manufactured goods have little or no contact with the production system. The primary contact with the customers is in the hands of distributors and retailers.	However, many service organizations, the customers themselves are Inputs and actively participate in the process (university, hospitals, entertainment centers, etc.)
A related difference is the response time to customer demand. Manufacturers usually have several days or weeks to meet customer demand,	While many services have to be provided within minutes of the client's arrival.

Manufacturing facilities often serve regional, national or even international markets, which often require large installations, a greater degree of automation and more substantial capital investment than service facilities.	In general, services cannot be shipped to distant locations, unless there is good administrative control by area. (Managers, workers, etc.)
--	--

Even in pure service companies, some segments of the operation may have low customer contact while others have high customer contact. The former can be thought of as “back room” or “behind the scenes” segments. In addition to pure manufacturing and pure service, there are companies that have some characteristics of each type of organization. It is difficult to tell whether these companies are actually manufacturing or service organizations. Think of a post office, an automated warehouse, or a mail-order catalog business. They have low customer contact and are capital intensive, yet they provide a service. We call these companies quasi-manufacturing organizations [17].

1.3 Demand Management

We can define demand management as a process that manages material and information flow through internal and external business processes to respond profitably to market demand. The key word in this definition is "profitable", in the past there was an obsession with the service that involved satisfying customers at any cost. However, we all know that this model is not sustainable since a company must maintain sound finances to ensure permanence and, therefore, its ability to serve to his clients [5].

What has made it difficult to adopt demand management is perhaps that we associate the word demand with sales with the commercial functions of the organization and not with a strategic commitment to the business to maintain a dynamic balance between customer satisfaction and profitability for the owners.

If we take the administration of demand as a purely commercial concept, we would think that the essential thing in this process is to know the quantities to sell, the forecast and the creation of plans that allow us to satisfy this demand. However, if we understand its true scope, we will understand that it is much more complex, requiring teamwork between the commercial and operating areas, and extends to collaborative plans with partners in the supply chain business.

Demand satisfaction must be timely and cost-effective. The only way to do things in time is through planning, which requires anticipating what is going to happen and from there to define backward steps and

resources for its achievement. However, for this to happen cost-effectively involves buying, manufacturing and distributing properly and this is only achieved in the same way with proper planning. Demand management is then a fundamental tool to generate adequate planning. Demand management includes different periods for action, the long and medium term for defining product launches, price management, their companies, and promotions, but at the same time the very short term, when deciding on the allocation of lacking material for deliveries on day by day.

If you want to effectively plan the material and capacity of the resources, you must identify all sources of demand. This includes local and foreign customers, other plants of the same corporation, distribution warehouses, parts for maintenance and requirements, promotions, inventory for distribution, and inventory consigned in customer sites [21].

Demand management includes four main activities [21]:

- Forecast
- Processing of orders
- Make delivery commitments.
- Interaction between planning and control of production and the market

1.3.1 Spatial Demand versus Temporal Demand

Time or time refers to the usual demand levels in forecasts, in the context the variation in demand over time is the result of the growth or decline of sales indices, the seasonal variation of the demand pattern, as well as the general fluctuations caused by multiple factors. Most short-term forecasting methods relate to this type of time variation, often referred to as time series [2].

Logistics has both space and time dimensions therefore the person in charge of the logistics must know where the volume of demand will take place and when it will do so. Spatial location of demand needs to plan warehouse location, balance inventory levels across the logistics network, and geographically allocate transportation resources. “Forecasting techniques should be selected to reflect geographical differences that may affect demand patterns” [2].

The techniques may also differ, depending on whether all demand is forecast and then ungrouped by geographic location (top-down forecast), or if each geographic location is predicted individually and then grouped, if necessary (downstream forecast above).

1.3.2 Irregular Demand versus Regular Demand

Logistics managers accommodate the products in groups to differentiate service levels between them or simply to handle them differently. These groups and individual items within them form of different demand patterns over time. When the demand is "regular," some of the general patterns can typically represent it. That is, demand patterns can usually be broken down into a trend, seasonal and random components. As long as the random variations are a small proportion of the remaining variation in the time series, an adequate forecast will generally be obtained from traditional forecasting procedures [8].

When the demand for articles is intermittent, due to a small overall volume and a high degree of uncertainty as to the timing and amount of demand, the time series is said to be disproportionate or irregular. This pattern is often found in products or services being introduced or withdrawn, demanded by relatively few customers, divided among many inventory locations and so that demand at each location is low or is derived from demand for other items or service. Such demand patterns are particularly difficult to forecast using the most popular techniques. However, because such items represent up to 50% of the products that the companies handle, they represent a special demand-forecasting problem for the logistics manager [2].

1.3.3 Derivative Demand versus Independent Demand

The nature of the demand can differ substantially, depending on the operation of the company for which the logistics manager should plan. On the one hand, many customers, most of whom acquire individually only a fraction of the total volume distributed by the company, generate demand. It is said that this demand is independent. On the other hand, demand is derived from the requirements specified in a production program, and it is said that this demand is dependent. For example, the number of new tires ordered from a supplier will be a multiple of the number of new cars the manufacturer will build. This fundamental difference causes alternative forms in which the requirements are predicted [2].

When demand is independent, statistical forecasting procedures work well. Most short-term forecast models are based on conditions of independence or randomness in demand. In contrast, patterns of derived demand are highly skewed and not random. Understanding these biases replaces the need to forecast since demand is known with certainty.

The forecast of the requirements through the derived demand procedure, results in perfect forecasts as the demand for the final product is known with certainty. This type of process is a good example of how the prognosis is improved by the recognition of biases, regularities and systematic patterns that arise in the demand over time. When the causes for variation in demand are unknown and are the result of many factors, randomness occurs. Statistical forecasting procedures deal effectively with the latter.

1.3.4 Irregular Demand

It represents the condition where there is so much random variation in the demand pattern that can overshadow trends and seasonality patterns. The irregular demand situation arises when two or three times the standard deviation of historical information exceeds the forecast of the best model that can be adjusted to the time series [2].

The pattern of irregular demand is often presented for several reasons: the pattern of demand is dominated by large and sporadic customer orders; also, the demand can be derived from the demand for other products or services. The seasonal peak has not been taken into account or the pattern of demand may be the result of exceptional information, outside persons or unusual conditions.

Patterns of irregular demand by nature are difficult to predict accurately by mathematical methods, due to the wide variability in the time series; however, some suggestions can be made about how to treat them. "First, look for obvious reasons for the irregularity and use them to generate the forecast. Separate the forecast of products with irregular demand from those showing a regular pattern and use appropriate forecasting methods for each" [5].

1.3.5 Relation between Demand Management and Forecast

If we define forecasts as probable scenarios, the work of demand management is to turn probable into "possible," to define specific actions that enable the company to achieve its service level objectives and profitability under real market conditions [15].

For improving the demand forecasting process has a direct impact on the improvement of the level of service and profitability of business, but to maximize these contributions, they must be integrated into a superior process that generates a comprehensive demand management with a collaborative approach to Inside and outside the organization[5]. On the other hand, an improvement in the administration of the demand is not conceived without counting on forecasts with an acceptable range of reliability. Thus is why we can assume both management demand and forecast are related, the forecast facilitates the administration of demand, and a good demand management helps to improve the assertiveness of the forecast.

METHODOLOGY

2 Forecast

Forecasting is the art and science of predicting future events that involves the use of historical data and its projection into the future by some mathematical model. Besides can be a subjective or intuitive prediction, or it can be a combination of both, that is, a mathematical model adjusted by the proper judgment of the administrator [16].

The forecasts are the most important for any business industry, as well as for any important business or management decisions because these decisions are based on a projection of the future [13]. Planning and control of logistics and supply chain activities require an accurate forecast of the demand level of product and service that will be monitored by the supply chain. Demand levels and scheduling have a greatly impact on the capacity levels, financial requirements and the whole structure of the business [12].

These estimates are usually presented in the form of forecasts and predictions. Normally in short-term planning, such as inventory control, order size or transport scheduling, the logistics manager often faces the need to carry out the chore of generating this kind of information. The analysis is mainly aimed for forecasting demand. The need for demand projections is a general requirement throughout the planning and control process.

As the different forecasting techniques are analyzed, it can be seen that there is, in fact, no superior method to another. What works best for a company with some conditions may be a complete disaster in other organizations, or for another department of the same company. It has to be understood that there are limits to what can be expected from the forecasts. As a rule, a perfect forecast is impossible. In a business environment, there are many factors that cannot be predicted with certainty.

Therefore, instead of looking for the perfect forecast, it is much more important to establish the practice of a continuous revision of the forecasts and to learn to live with imprecise forecasts. This is not to say that it is not a question of improving the forecasting model or methodology, but what must be done is to try to find and use the best forecast method available, within reason. Following in this chapter, we describe the forecasting techniques that are typically used for demand and to estimate forecast accuracy.

2.1 Forecast Characteristics

There are many types of forecasting models, each model differ in their degree of complexity, the amount of data they use, and the way they generate the forecast[17]. However, some features are common to all forecasting models. They include the following:

1. Forecasts are rarely perfect:

Forecasting the future involves uncertainty. Therefore, it is almost impossible to make a perfect prediction. Forecasters know that they have to live with a certain amount of error, which is the difference between what is forecast and what actually happens. The goal of forecasting is to generate good forecasts on the average over time and to keep forecast errors as low as possible.

2. Forecasts are more accurate for groups or families of items rather than for individual items:

When items are grouped together, their individual high and low values can cancel each other out. The data for a group of items can be stable even when individual items in the group are very unstable. Consequently, one can obtain a higher degree of accuracy when forecasting for a group of items rather than for individual items.

3. Forecasts are more accurate for shorter than longer time horizons:

The shorter the time horizon of the forecast, the lower the degree of uncertainty. Data do not change very much in the short run. As the time horizon increases, however, changes in established patterns and relationships will occur a much greater likelihood. Because of that, forecasters cannot expect the same degree of forecast accuracy for a long-range forecast as for a short-range forecast. For example, it is much harder to predict sales of a product two years from now than to predict sales two weeks from now [17].

2.1.1 Forecasting Time Horizon

A key factor in selecting the most appropriate forecasting method is the time horizon corresponding to the decision that needs to be forecast [10]. A forecast is usually classified by the future time horizon it encompasses. The time horizon is classified into three categories:

1. Short-term forecast:

This forecast has a period of up to 6 months but is almost always less than three months. It is used to plan purchases, schedule work, determine labor levels, assign work, and decide production levels.

2. Medium-term forecast:

A medium-term, or intermediate, forecast ranges from three months to two years. It is useful for planning sales, production, budget and cash flow, as well as for analyzing various business plans.

3. Long-term forecast:

In general, it comprises two years or more; Long-term forecasts are used to plan new products, capital expenditures, location or expansion of facilities and research and development.

Table 2.1 shows examples of demand forecasting applications and indicates the typical planning horizon for each. In addition, this decision sometimes involves a balance between the accuracy of the forecast and the costs, such as software, the time required to prepare the forecast and the training of staff.

Table 2.1 Time Horizon [13].

TIME HORIZON			
Application	Short term (0 to 3 months)	Medium term (3 months to 2 years)	Long term (2 years or more)
Forecast amount	Individual products or services	Total sales groups or families of products or services	Total sales
Decision area	Inventory management, Work schedule, Master production scheduling.	Manpower planning, Staff planning, Production planning, Master production scheduling, Purchases, Distribution.	Location of facilities, Capacity planning, Process management
Forecasting technique	Time series. Causal. Subjective.	Causal. Subjective.	Causal. Subjective.

Also, the difference that makes medium and long-term forecasts to be distinguished from short-term forecasts by three characteristics:

1. First, medium- and long-term forecasts handle more global issues and support management decisions about planning and products, plants and processes. The implementation of some plant decisions, such as open a new manufacturing plant in other country or city, can take from five to eight years from conception to completion.

2. The short-term forecast usually uses different methodologies than the long-term forecast. Mathematical model techniques such as moving averages, exponential smoothing and trend extrapolation are common in short-term projects. Larger and less quantitative methods are useful in predicting, for example, whether a new product should be introduced into a company product line.
3. Finally, as might be expected, short-term forecasts tend to be more accurate than long-term forecasts. The factors influencing the demand change every day, therefore, as the time horizon lengthens, the accuracy of the forecast is more likely to decrease. Needless to say, that demand forecasts must be regularly updated in order to maintain their value and integrity. After each demand period, forecasts must be reviewed and corrected.

2.2 Forecasting Methods

Forecasting methods demand forms the basis for planning activities. Therefore, it is involved in estimating future event by methodically combining past data in some determined way. There are several established forecasting methods, and these methods can be separated into 2 groups as shown in Figure 2.1[17]:

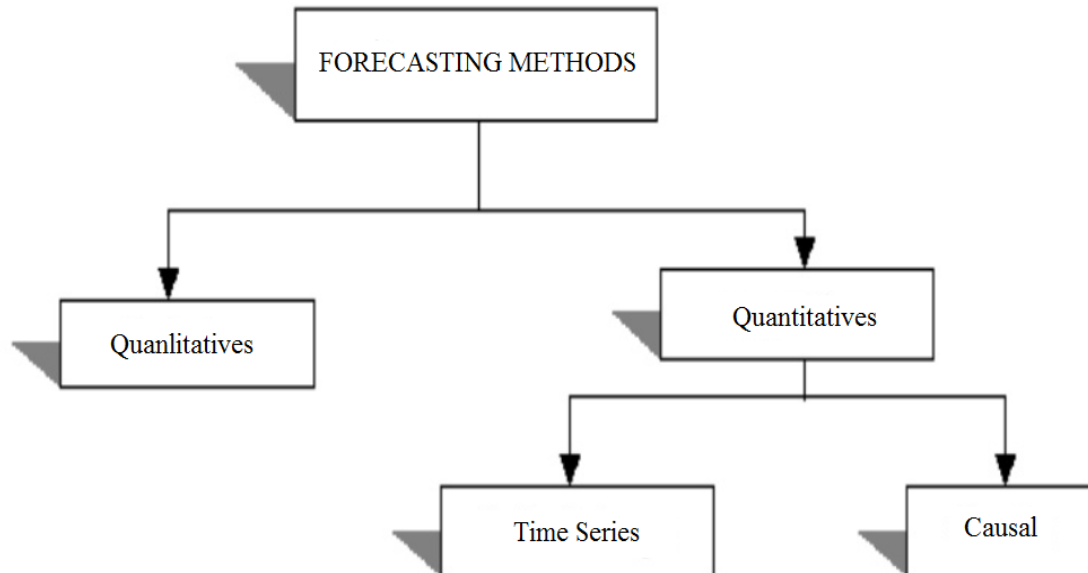


Figure 2.1 Forecasting Methods

In general terms, qualitative methods of forecasting are based on the administrative criterion and do not use specific models; therefore, different individuals can use the same qualitative method and arrive at very different forecasts [17]. However, qualitative methods are useful when there is a lack of data or when historical data are not reliable predictors of the future; In this case, the human decision maker can employ the best available data and a qualitative approach to arrive at a forecast [20].

There are two types of quantitative forecasting methods: time series analysis and causal forecasts. In general, quantitative methods are based on mathematical modeling and make them consistent with their result. It means the same model will produce the same forecast outcome from the same collection of data each time. Time series model consider that all the information needed to produce a forecast is contained in the time series of data, an ordered sequence of observations is taken at regular intervals of time and the past data set presents an identifiable pattern over time. Therefore, the primary assumption of all quantitative forecasting methods is that historical data and data patterns are reliable predictors of the future.

In addition, causal models help in capturing the trend in data, because they consider several independent variables that are related to the dependent variable being predicted. Historical data is then processed through a time series model or a causal model to arrive at a forecast. In Table 2.2 is shown a briefly comparative description of qualitative and quantitative methods.

Table 2.2 Comparative of Qualitative and Quantitative Methods. [17]

	Qualitative	Quantitative
Characteristics	Based on human judgement, opinion; subjective and nonmathematical.	Based on mathematics; quantitative in nature.
Strengths	Can incorporate in the environment and “inside information”	Consistent and objective; able to consider much information and data at one time.
Weakness	Can bias the forecast and reduce the accuracy	Often quantifiable data are not available. Only as good as the data on which they are based.

Both qualitative and quantitative forecasting methods have strengths and weaknesses. Although quantitative methods are objective and consistent, they require data in quantifiable form in order to generate a forecast. Often, we do not have such data, for example, if we are making a strategic forecast or if we are forecasting sales of a new product.

In addition, quantitative methods are only as good as the data on which they are based. Qualitative methods, on the other hand, have the advantage of being able to incorporate last minute inside information in the forecast, such as an advertising campaign by a competitor, a snowstorm delaying a shipment, or a heat wave. Each method has its place, and a good forecaster learns to rely on both.

2.2.1 Qualitative Method

There are several types of qualitative forecasting methods, some informal and some structured. Qualitative methods are mostly subjective and rely on human judgment, intuition, surveys, or related techniques to generate quantitative estimates of the future. These methods are appropriate especially when historical information is few, not so relevant information or the lack of it. The not mathematical nature of the methods makes them difficult to standardize and validate their accuracy. The most used method are shown in Figure 2.2 [20].



Figure 2.2 Qualitative Methods

In addition, qualitative forecasts should be used for introductions of new products, new industries of the impact of new technology for which historical data is not available; as well, qualitative methods can be applied to develop a projection by analogy or by the selective use of market research data. They are rather suitable methods for medium to long-term forecasts. In this case, the forecaster who takes the decision can employ the best available data and a qualitative approach to arrive at a forecast. Some conventional qualitative models are concisely described in Table 2.3;

Table 2.3 Qualitative methods. [3]

Qualitative	Subjective; Judgement. Based on estimates and opinions.
Cumulative techniques.	It derives a forecast by compiling the entries from those at the end of the hierarchy and dealing with what is forecast.
Market research	It is established to collect data in various forms (surveys, interviews, etc.) to test hypotheses about the market. It is usually used to forecast long-term sales and new products.
Consensus groups	Free exchange at meetings. The idea is that group discussion produces better predictions than any individual. Participants can be executives, vendors or customers.
Historical analogy	Match the predicted with a similar article. It is important when planning new products where projections can be derived by using the history of a similar product.
The Delphi model	A group of experts answers a questionnaire. A moderator compiles the results and formulates a new questionnaire that is presented to the panel. Therefore, there is a learning process for the group while receiving new information and there is no influence by the pressure of the dominant group or individuals.

As following the qualitative method mentioned in Table 2.3 are described below:

a) Cumulative techniques:

Creates the forecast adding in succession from the bottom. The assumption here is that the person who is closest to the customer or end user of the product knows their future needs better. Although this is not always true, in many cases this is a valid assumption and forms the basis of this method. The forecasts in this last level are added up and taken to the next highest level. Usually this is a district warehouse, which then adds security inventory and any quantity request effect. Then, this amount is taken to the next level, which can be a regional warehouse. The procedure is repeated until it becomes an input at the highest level; which, in the case of a manufacturing company, would be the input for the production system.

b) Market research:

Often, companies hire outside companies that specialize in market research to perform this type of forecast. Market research is mainly used for product research in order to find new ideas, to know the likes and dislikes related to existing products, the preferred competitive products in a particular class, etc. Again, the methods of data collection are mostly surveys and interviews.

c) Consensus group:

The idea that two heads think more than one is extrapolated with the idea that a group of people occupying different positions may develop a more reliable forecast than a smaller group. Group forecasts are made through open meetings with a free exchange of ideas from all managerial and individual levels. The problem with this open style is that lower-level employees are intimidated by the higher levels of management. When forecasting decisions are taken at a broader and higher level (such as introducing a new product line or making strategic decisions about a product, as in new market areas), the term executive judgment is used. Explains for himself: he participates in a higher level of management.

d) Historical analogy:

When trying to forecast the demand for a new product, an ideal situation would be that an existing or generic product can be used as a model. There are many ways to classify these analogies; for example, complementary products, substitutable or competitive products, and products as a function of income.

e) Delphi method:

As stated in the section on consensus groups, affirmation or opinion of a person of a higher level is likely to weigh more than that of a lower-level person. The worst-case scenario occurs when lower-level people feel threatened and do not contribute what they believe. To avoid this problem, the Delphi method hides the identity of the individuals involved in the study. All have the same weight. As for the procedure, a moderator creates a questionnaire and distributes it among the participants. Your answers are added up and given to the whole group with a new set of questions. RAND Corporation developed the Delphi method in the 1950s. The step-by-step procedure is:

1. Choose experts to participate. There must be a great variety of people with knowledge in different areas.
2. Through a questionnaire (or e-mail) obtain the projections (and any premise or qualification for the forecast) of all the participants.
3. Summarize the results and redistribute them among the participants with the appropriate new questions.
4. Resume, refine the projections and conditions, and once again pose new questions.
5. Repeat step 4, if necessary. Distribute the final results among all the participants.

As a rule, the Delphi technique can achieve satisfactory results in three rounds. The time required is a function of the number of participants, the amount of work to develop their forecasts and their speed to respond.

The need to use judgment forecasts is very clear when there are no quantitative data that allow the application of quantitative forecasting approaches. However, judgment methods can be used in combination with quantitative approaches to improve the quality of prognosis. Among the guidelines applicable to the use of judgment to adjust quantitative forecasts, are the following [3]:

1. Adjust quantitative forecasts when they tend to be inaccurate, and the person who makes the decision has the necessary contextual knowledge [13]. By contextual knowledge is understood the knowledge that is obtained by experience in the exercise of activity, as in the case of cause and effect relationships, environmental cues and information about the organization that can have an effect on the variable that is going to forecast. It is often not possible to incorporate these factors into quantitative-type forecasting approaches.
2. Make adjustments to quantitative forecasts to compensate for specific events [13]. Specific events, such as advertising campaigns, competitor activities or international events, are often

not recognized in quantitative forecasts and must be taken into account when developing a definitive forecast.

2.2.2 Causal Models

The basic premise on which causal methods are constructed for forecasts is that the level of the predicted variable is derived from the level of other related variables. For example, if customer service is known to have a positive effect on sales, then knowing the level of service provided to the customer will be able to project the level of sales. We could say that the service "causes" sales. To the extent that adequate cause-and-effect relationships can be described, causal models may be quite good at anticipating major changes in time series and accurately forecasting over a medium-to-long period [2].

Causal forecasting models, sometimes called associative models, assume that the forecast of demand is highly correlated to other variables in the environment such as the economy, interest rates, etc. There are several forms of causal models: statistical, such as regression and econometric models; And descriptive, as regarding input-output models and life cycle. Each model considers this correlation between demand and environmental factors and draws on estimates of what environmental factors will be to calculate future demand.

Causal models can be very complex, especially if they consider relationships among many variables. The main problem with this category of forecasting models is that it is often difficult to find real causal variables. The causal variables that guide the forecast variable over time are even harder to find. All too often, the time to acquire the information for the conducting variables consumes plenty time, a minimum period from one to six months. Some common causal methods are shown in Table 2.4;

Table 2.4 Causal Methods. [3]

Causal Models		Try to understand the underlying system and surrounding the element to be predicted. For example, sales can be affected by advertising, quality, and competitors.
Regression analysis		Similar to the method of least squares in the time series, but may contain several variables. The basis is that the forecast is developed by the occurrence of other events.
Econometric models		Attempts to describe some sector of the economy through a series of interdependent equations.

Input / output models	It focuses on the sales of each industry to other governments and companies. It indicates changes in sales that a manufacturing industry can expect due to changes in purchases by another industry.
Principal indicators	Statistics that move in the same direction as the series to be forecast, but before it, such as an increase in the price of gasoline that indicates a future decline in the sale of large cars.

2.2.3 Simulation

The methods of forecasting by simulation imitate the customer's choices that give rise to the demand to arrive at a forecast. By employing simulation, the company can combine time series and causal methods to answer many questions. The typical simulation model is shown in Table 2.5;

Table 2.5 Simulation Model. [3]

Simulation Models	Dynamic models, always by the computer that allow the person in charge of the projections to make assumptions about the internal variables and the external environment in the model. Depending on the variables in the model, the forecast manager can ask questions such as: What would happen to my forecast if the price increased 10%? What effect would a mild national recession have in my forecast?
--------------------------	--

2.3 Time Series

Time series forecasting involves making projections or forecasts about future performance based on historical and current data. A Time series is a collection of observations of well - defined data items collected at different points of time but Data collected irregularly or only once are not time series. Specifically forecasting would be helpful in situations where statistical models can account for what might happen in nonspecific time. Therefore, these time series forecasting data helps us in the process of making statements

about the events whose actual outcomes have not yet been observed. There are two main goals of time series analysis:

1. Identify the pattern of the phenomenon represented by the sequence of observations.
2. Forecasting the future values of the time series variable.

Both of these goals involve that the pattern of observed time series data has to be identified and more or less formally described. One of the fundamental assumptions of all methods of time series analysis is that demand can show five basic patterns such as level, trend, seasonality, cycle and random. The easiest way to identify patterns is to plot the data and examine the resulting graphs. Any of these patterns, or a combination of them, can be present in a time series of data, the basic patterns are described below:

- a) **Horizontal:** A level or horizontal pattern appears when data values vary around a constant mean. This one is the simplest pattern and the easiest to predict and is typical for products in the advanced stage of their life cycle, in which demand is stable and foreseeable. As shown in Figure 2.3;

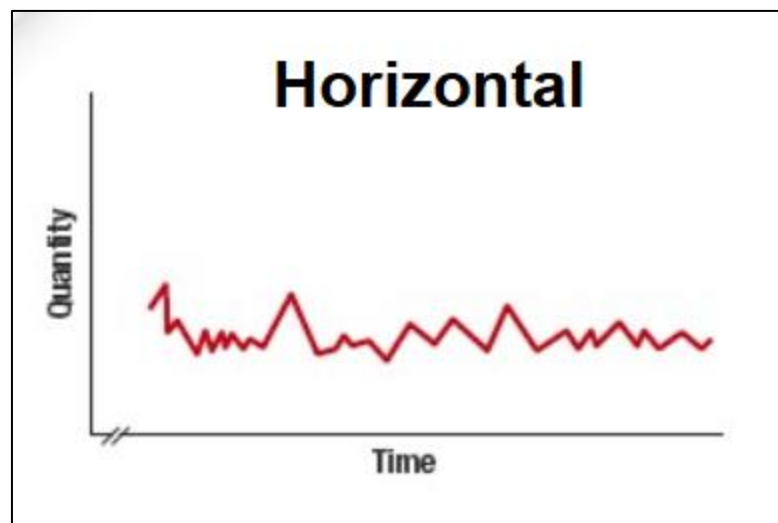


Figure 2.3 Level or Horizontal pattern. [13]

- b) **Trend:** The trend is shown as a long-term pattern in the time series. The pattern can be positive or negative depending on if the time series shows an increasing long-term pattern or a long-term decreasing pattern. The simplest type of trend is a straight line or linear trend. As shown in Figure 2.4;

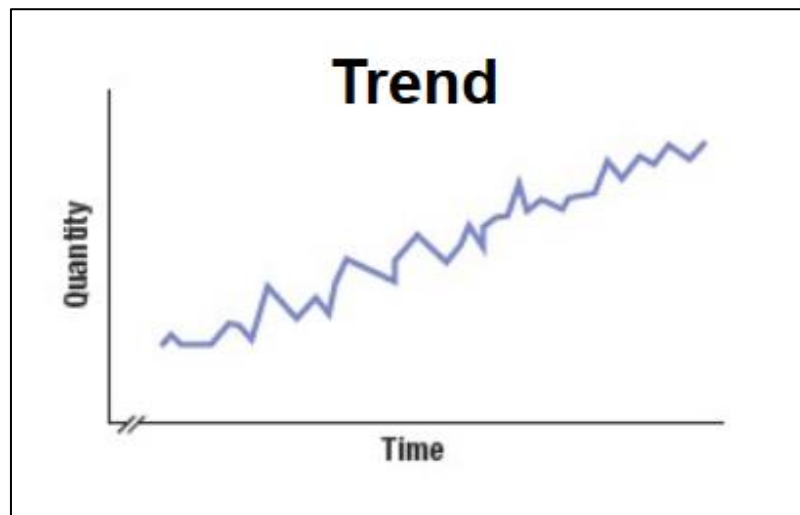
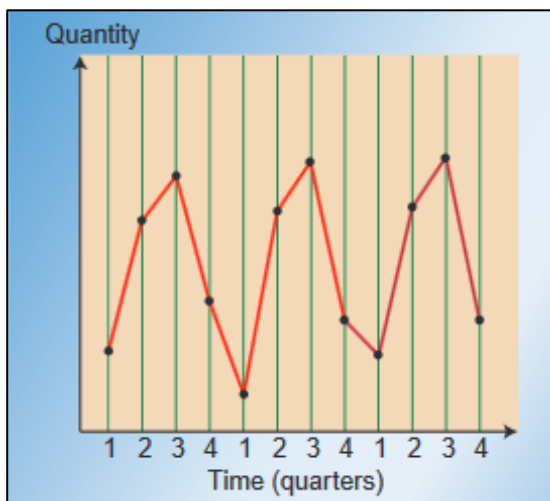
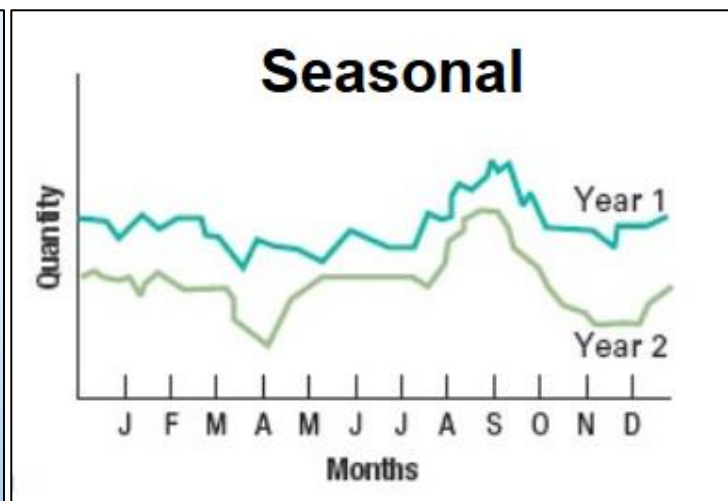


Figure 2.4 Trend pattern [13].

- c) Seasonal: The component of the time series that represents the variability in the data due to seasonal influences is called the seasonal pattern. This variation corresponds to the movements of the series that recur year after year in the same months or the same quarters of the year, the day of the week with more or less with the same intensity. As shown in Figure 2.5;



a)



b)

Figure 2.5 a) Trend pattern quarter [17], b) Trend pattern months [13].

- d) Cycle: The time series often present alternating sequences of points below, and above the trend line that takes for more than a year, this variation is maintained after the seasonal and irregular variations or tendencies have been eliminated. An example of this type of variation

is economic cycles whose recurrent periods depend on prosperity, recession, depression, and recovery, which do not depend on factors such as climate or social mores. As shown in Figure 2.6;

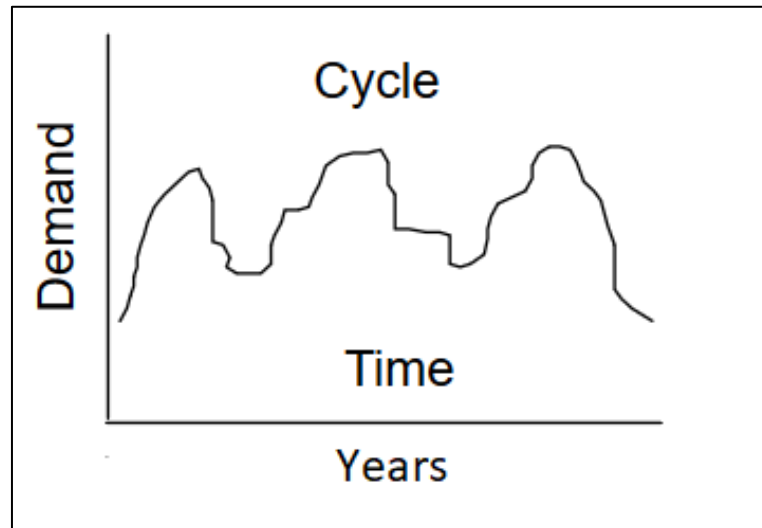


Figure 2.6 Cycle pattern

Cyclic patterns come from two influences. The first is the economic cycle, which includes various factors by which the economy moves from a recession to an expansion over the course of several years. The other influence is the life cycle of the product or service in question, which reflects the stages of demand, from development to decline.

The movement of the economic cycle is difficult to predict because it is affected by national or international events, such as presidential elections or political turmoil in other countries. Making a forecast of the growth rate or decreasing demand in the life cycle is also difficult. Sometimes, companies estimate the demand for a new product from the previous demand history of the product they are going to replace with the new one.

Random Variation: This is due to short-term, unpredictable and non-recurring factors affecting time series. As this component explains the random variability of the series, it is unpredictable, that is, one cannot be expected to predict its impact on the time series. There are two types of Irregular variation:

- a) Variations caused by special, easily identifiable events, such as elections, floods, strikes, earthquakes.
- b) Variations at random or by chance, whose causes cannot be expressed accurately, but tend to be balanced in the long run.

Four of the demand patterns (horizontal, trend, seasonal and cyclical) are combined in varying degrees to define the fundamental pattern of demand time that corresponds to a product or service. The fifth pattern, random variation, is the result of random causes and, therefore, cannot be predicted. Random variation represents an aspect of the demand for which all forecasts are wrong.

Time series models are generally easier to use than causal models. Causal models can be very complex, especially if they consider relationships among many variables. However, time series models can often be just as accurate and have the advantage of simplicity. They are easy to use and can generate a forecast more quickly than causal models, which require model building. Some common Time series methods are shown in Table 2.6;

Table 2.6 Common Time Series Models [17].

Time Series			
Type	Description	Strengths	Weakness
Simple Mean	Uses an average of past data as a forecast	Good for level pattern	Requires carrying a lot of data
Simple Moving Average	A forecasting method in which only n of the most recent observations are averaged	Only good for level pattern	Important to select the proper moving average
Weighted Moving Average	A forecasting method where n of the most recent observations are averaged and past observations may have different weights	Good for level pattern; allow placing different weights on past demands	Selection of weights requires good judgment
Exponential Smoothing	A weighted average procedure with weights declining exponentially as data become older	Provides excellent forecast results for short – medium – length forecast	Choice of alpha is critical
Trend – Adjusted Exponential Smoothing	An exponential smoothing model with separate equation for forecasting the level and trend	Provides good result for trend data	Should only be used for data with trend
Holt Winters	Method is an exponential smoothing approach for handling Seasonal data.	Medium difficulty and logical procedure for computing seasonality	Make sure seasonality is actually present

Time series analysis is the primary focus of this research. The common time series models are used for forecasting demand are fully described in the next subchapters.

2.3.1 Simple Average

Simple average model forecast the demand by using the data or demand occurring in the previous times periods and obtains the average.

$$F_{t+1} = \frac{\sum A_t}{n} = \frac{A_{t-1} + A_{t-2} + \dots + A_{t-n}}{n} \quad (2.1)$$

Where F_{t+1} = forecast of demand for next period $t + 1$

A_t = real demand value for current period t

n = number of periods to be averaged

This model is useful if the process is stable and it is limited to growing process since for long periods there are many changes and makes it inefficient.

2.3.2 Simple Moving Average

The simple moving average is similar to the simple average model, but in this case, we do not use the average of all previous data. The use of this technique assumes that the time series is stable, thus, that the data that compose it are generated without significant variations between one data and another. Therefore, although the behavior of the data shows a growth or a decrease, it does with a constant tendency.

When using the moving averages method, it is assumed that all the observations in the time series are equally important for estimating the parameter to be forecast. In this way, the average of the n values of the most recent data in the time series is used as the forecast for the next period. Using a mathematical expression, we have:

$$F_{t+1} = \frac{\sum A_t}{n} = \frac{A_{t-1} + A_{t-2} + \dots + A_{t-n}}{n} \quad (2.2)$$

Where F_{t+1} = forecast of demand for next period, $t + 1$

A_t = real demand value for current period, t

n = number of periods used in the moving average

The moving term indicates that as we have a new observation of the time series, the oldest observation in the equation is replaced and a new average is calculated. The result is that the average will move, that as new data are available and are replaced in the formula, the value of the average will change. There is not a particular rule that tells us how to select the basis of the moving average n .

The longer n periods we take in the average, the slower the response to changes in demand; therefore, a longer n period has the advantage of providing stability in the forecast, but the disadvantage of responding more slowly to the actual variations in the level of demand. In practice, the values of n range from 2 to 10. Because the model is only useful for forecasting one level data it works best for short-term planning where there is no tendency or seasonality. Another disadvantage is that put equal weight on each of the historical data used.

2.3.3 Weighted Moving Average

As the simple moving average model, we only take the last n periods that are most relevant in the average so when we observe new data, we drop the oldest observation. However, in weighted moving average, different weights are given to the historical demand data while computing simple moving average as the demand estimated for next period. Usually, most recent data is assigned the highest weight factor. The formula is as follows:

$$F_{t+1} = \sum C_t A_t = C_1 A_1 + C_2 A_2 + \dots + C_t A_t \quad (2.3)$$

Where F_{t+1} = forecast of demand for next period, $t + 1$

C_t = weight placed on the actual value of period t

A_t = real demand value in period t

In a weighted moving average, any desired weights can be specified as long as they sum 1. This model is better at responding to a trend because it puts more weight on recent data and less weight on old data. However, if the data are seasonal, for example, the weights should be set accordingly (Schroedr, 2005) [20]. The unpractical procedures of a weighted moving average are that the entire history of the demand for N periods has to be mobilized throughout the calculation; furthermore, the response of a weighted moving average cannot be easily altered without adjusting each of the weights. Here are some advantages and limitations of this model.

Advantages:

- a) Easy to learn and use.
- b) It has a relatively small computational cost.
- c) It can produce accurate forecasts.
- d) It is a faster way to forecasts.
- e) It reacts faster to changes in the pattern.
- f) Provide more accurate forecasts than a Simple Moving Average model if applied to a trended series.

Limitations:

- a) The model cannot produce accurate forecasts when data has cyclical or seasonal variations.
- b) The current data values have to be multiplied by some weights, and this makes calculations more difficult.

2.3.4 Exponential Smoothing (Brown Model)

Another method for making a forecast is the exponential smoothing method. Unlike moving averages, this method predicts a weighting of the data depending on the weight they have within the forecast calculation. This weighting is done by giving value to the smoothing constant, α , which can be greater than zero and less than one.

The exponential smoothing method assumes that the process is constant; it means that the time series does not have an observable cycle, trend or seasonality just as the method of moving averages. This technique is designed to attenuate a disadvantage of the moving average method, where the data for averaging has the same weight. In a particular way, this method considers that the recent observations have more value, reason why it gives greater weight to the average one. (R. Dan Reid, 2011) [17] To make a forecast for the next period, we need three pieces of information:

1. The current period's forecast,
2. The current period's actual value
3. The value of a smoothing coefficient,

As the initial requirement to start exponential smoothing. There are two ways to get that initial forecast: using last-period demand, or if you have historical data, calculate the average of several recent

demand periods. The effect of the initial estimate of the average on the successive estimates of the same decreases over time because, with the exponential smoothing, the weights assigned to the successive historical demands that are used to calculate the average decrease exponentially

The equation for the forecast is: Next period's forecast = α (current period's actual) + (1 - α) (current period's forecast). The formula is as follows:

$$F_{t+1} = \alpha A_t + (1 - \alpha)F_t \quad (2.4)$$

Where F_{t+1} = forecast of demand for next period $t + 1$

α = smoothing coefficient

A_t = real demand value for current period t

F_t = forecast for current period t

t = current period

For choosing the right value for the exponential adjustment, constant requires α degree of discernment. When the value α is higher, the greater is the weight given to the most recent data on demand. With this, the model responds faster to changes in the time series. On the other hand, a value of α too high can make the forecast sensitive and track random variations in the time series instead of the essential changes. When is chosen a smaller value of α , the greater the weight is given to the last of data for the forecast of future demand and the greater the time lag to respond to fundamental changes in the level of demand. Low values of α provide stable forecasts that are not sensitive to strong influences due to randomness in the time series. In most forecast work, α is assigned a value between .01 and .5 to maintain reasonable stability.

One of the practical ways when looking for a value for α is to select one that allows the forecast model to identify the significant changes that occur in time series and the average random variations. By doing this, we will get a α that minimize the forecast error. Here are some advantages and limitations of this model.

Advantages:

- a) Easy to learn and use.
- b) It has a relatively small economic cost.
- c) It can produce forecasts quickly and accurate.

- d) It puts more weight to current observations.
- e) The model needs a less amount of data to be stored than to the methods of moving averages.
- f) The model considers the data as a whole and does not need cut-off points like with the model of moving averages.
- g) It allows changing the value of the smoothing constant to adequate the model properly in any different circumstances.

Limitations:

- a) Normally produce forecasts that lag behind the actual trend.
- b) When the data has cyclical or seasonal variations, the model fails to produce accurate forecasts
- c) The forecasts generated by this model are sensitive to the specification of the smoothing constant.

In general, if large values of α (example > 0.50) are required for an exponential smoothing application, a more complex model is likely to be required because of the presence of a significant seasonal trend or influence in the time series of demand.

2.3.5 Trend-Adjusted Exponential Smoothing (Holt Model)

When there is a significant trend, exponential smoothing methods must be modified. Otherwise, forecasts will always be above or below actual demand. The model Trend Adjusted Exponential Smoothing is used when it is assumed that demand has a level and a trend but not seasonality. For improving the forecast, it is necessary to calculate an estimate of the trend. “The model is a set of equations, the first smooths out the level of the series, the second smooths out the trend, and the third generates a forecast by adding up the findings from the first two equations” (R. Dan Reid, 2011) [17]:

1. Step 1 Smoothing the Level

$$S_{t+1} = \alpha A_t + (1 - \alpha)(S_t + T_t) \quad (2.5)$$

2. Step 2 Smoothing the Trend

$$T_{t+1} = \beta(S_{t+1} - S_t) + (1 - \beta)T_t \quad (2.6)$$

3. Step 3 Forecast Including Trend

$$FIT_{t+1} = S_{t+1} + T_{t+1} \quad (2.7)$$

Where S_t = smoothed level in period t

α = smoothing coefficient of the level

A_t = actual demand value for period t

T_t = smoothed trend in period t

β = smoothing coefficient of the trend

FIT_{t+1} = forecast including trend next period $t + 1$

We begin by calculating the current estimate of this trend, which is only the difference between the level of the series calculated in the current period and the average calculated in the last period. For obtaining an estimate of the long-term trend, the current estimates can be averaged. The method for estimating a trend is similar to that used to estimate the average demand with exponential smoothing. In this approach, the level and trend estimates are smoothed, for which two smoothing constants are required, the smoothing coefficient α , the trend equation uses the smoothing coefficient β . The β reduces the impact of the error that occurs between real data and forecast. If we do not include both of these coefficients, the trend reacts exaggeratedly to errors.

2.3.6 Trend and Seasonality Corrected Exponential Smoothing (Holt – Winters Model)

In addition to the trend, the effects of seasonal fluctuations in time series can also be considered. Before applying this type of model, two conditions must be met.

1. There must be a known reason for periodic peaks and valleys in the pattern of, demand, and these peaks and valleys must be presented at the same time each year.
2. The seasonal variation must be greater than the random variations, or "noise".

If the seasonal demand is not stable, significant or discernible concerning random variations, then it becomes extremely difficult to develop a model that accurately predicts the direction of demand in the next period. If this is the case, a basic form of the exponential leveling model, with a high value for the adjustment constant to reduce the effects of the delay, may generate a smaller forecast error than with the more complicated model. Caution is required in the selection of the model.

The trend-seasonality adjustment model is built around the concept of forecasting the index of the real demand to the trend and then is seasonally adjusted to generate the forecast. The equations for this model are:

a) Step 1 Smoothing the Level

$$S_{t+1} = \alpha(A_t/I_{t-L} + (1 - \alpha)(S_t + T_t)) \quad (2.8)$$

b) Step 2 Smoothing the Trend

$$T_t = \beta(S_{t+1} - S_t) + (1 - \beta)T_t \quad (2.9)$$

c) Step 3 Seasonality index

$$I_t = \gamma(A_t/S_t) + (1 - \gamma)I_{t-L} \quad (2.10)$$

d) Step 4 Forecast Including Trend and Seasonality

$$FIT_{t+1} = (S_{t+1} + T_{t+1})I_{t-L+1}$$

Where S_t = smoothed level in period t

α = smoothing coefficient of the level

A_t = actual demand value for period t

I_t = seasonality index in period t

L = time for a complete season

T_t = smoothed trend in period t

β = smoothing coefficient of the trend

γ = smoothing coefficient of the trend

FIT_{t+1} = Forecast corrected for trend and seasonality for the period $t + 1$

Here are some advantages and limitations of this model:

Advantage:

- a) Used for short term forecast.
- b) Gives interpretable results.
- c) Easy to implement.
- d) Being able to adapt to changes in trends and seasonal patterns

Disadvantages:

- a) Presence of outliers distorts the results.
- b) Cannot generalize to multivariate approach.
- c) Accounts for only single seasonal pattern.

2.4 Error

The term error refers to the difference between forecast value and what actually occurred. In statistics, these errors are known as residuals. As long as the forecast value is within the confidence limits, as will be seen later in “Error Measurement”, this is not really an error. However, common usage refers to difference as an error.

The demand for a product or service is generated by the interaction of too many complex factors to accurately describe them in a model. Therefore, all projections contain some error. When analyzing forecast errors, it is convenient to distinguish between sources of error and measurement of errors.

Errors can come from a variety of sources. A common source that many forecast makers are not aware of is the forecast of past trends in the future. For example, when speaking of statistical errors in regression analysis, reference is made to the deviations of the observations of the regression line. It is common to relate a confidence band (statistical control limits) to the regression line to reduce error without explaining. However, when this regression line is used as the forecast device, it is likely that the error is not defined correctly by the projected confidence band. This is because the confidence interval is based on past data; it may not take into account the projected data points and therefore cannot be used with the same confidence. In fact, experience has shown that actual errors are often greater than those projected by forecasting models.

Errors can be categorized as biased or random. Biased errors occur when a consistent error is made. Sources of bias include failure to include the correct variables; The use of the wrong relationships between variables; The use of the wrong trend line; A wrong change in seasonal demand from the point where it typically occurs; And the existence of some undetected secular tendency. Random errors are defined as those that the forecast model used cannot explain.

2.4.1 Forecast Accuracy Measure

When doing any forecasting process, we need to take into account how much is the error; by doing this, “the forecast methods should produce forecasting that is neither consistently high nor low. Forecasts should not be overly optimistic or pessimistic, but rather should tell it like it is.” (Jacobs, y otros, 2011)[12].

The accuracy of the models can be evaluated by the forecast performance measured over time, as it is well known the forecasting are only an estimation of the future demand. Thus, the forecast of future demand will normally have some degree of error. The forecast error measures the difference between the actual demand value for current demand and the forecast for current period

$$E_t = A_t - F_t \quad (2.11)$$

Where E_t = forecast error for period t

A_t = actual demand value for period t

F_t = forecast for current period t

The objective of measuring forecast accuracy is:

1. Provide a single measure of a model's reliability.
2. Compare the accuracy of forecasting models.
3. Search for an optimal model.

When working with forecasts models, there are different ways of measuring the error of long-term cumulative forecasts over different periods. The following methods will be presented below.

2.4.2 Mean Squared Error

The Mean Squared Error (MSE) measure of forecast error that calculates error as the average of the squared error. Express in another way; the mean squared error uses the square of each error term so that the positive and negative errors do not cancel each other.

$$MSE = \frac{\sum_{t=1}^n E_t^2}{n} \quad (2.12)$$

Where MSE = mean squared error

E_t = forecast error for period t

n = number of periods used

The advantage of the mean squared error: “due to the squaring of the error term, large errors tend to be magnified. Consequently, mean squared error places a higher penalty on large errors. This can be a useful error measure in environments in which large errors are particularly destructive” (R. Dan Reid, 2011) [17].

2.4.3 Mean Absolute Deviation

The Mean Absolute Deviation (MAD) measure the forecast error that calculates error as the average of the sum of the absolute errors. In other words, it expresses the size of the average error irrespective of whether it is positive or negative.

$$MAD = \frac{\sum_{t=1}^n |E_t|}{n} \quad (2.13)$$

Where MAD = mean absolute deviation

n = number of periods used

E_t = forecast error for period t

One of the advantages of mean absolute deviation is that it is based on absolute values. Thus, the errors of opposite signs do not cancel each other out when they are added.

As is known the mainly used measure for deviation or dispersion in statistics is the standard deviation. So the mean absolute deviation can also measure deviation error from an expected result the forecast. (Roberts & Berry, 2011) [12] “When the forecast errors are normally distributed, there is a direct relationship between the two measures that can be used to develop statistical insights and conclusions.” As Figure 1.5 shown;

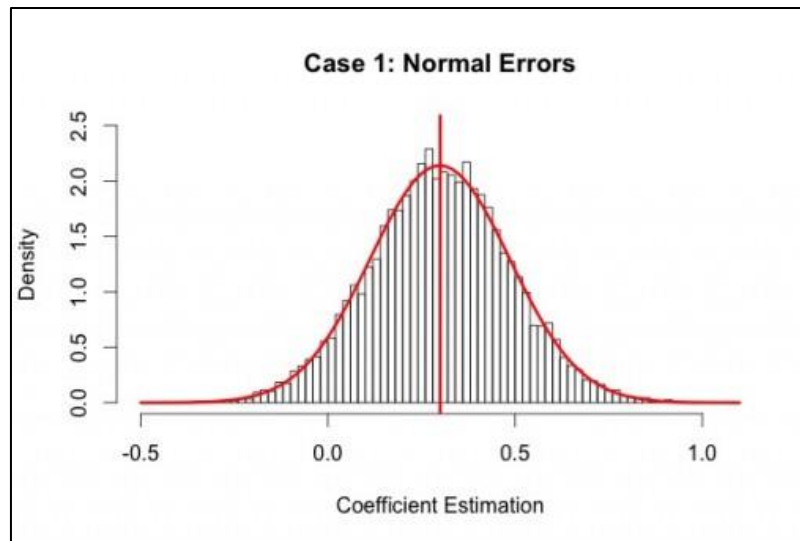


Figure 2.7 Normally distributed error [22].

Then it is related to the standard deviation form as:

- a) 1 standard deviation = 1.25 MAD

b) 1 MAD = 0.8 standard deviations.

In practice, mean absolute deviation has been applied to forecasting jobs because it is easy to understand and use.

2.4.4 Mean Absolute Percentage Error

The Mean Absolute Percentage Error normalizes the error calculations by calculating an error percentage.

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{E_t}{A_t} \right| 100}{n} \quad (2.14)$$

Where $MAPE$ = mean absolute percentage error

n = number of periods used

E_t = forecast error for period t

A_t = actual demand value for period t

Mean absolute percentage error is an accurate way to compare errors between different forecast models. The advantages of the mean absolute percentage error over other tests of forecast accuracy are as follows:

- a) The measure relates each forecast error to its current data value.
- b) Due to gives the result in percentage makes it easier to interpret than the others measures.
- c) Easy to use.

Each forecast accuracy measure should be utilized, as each them have their advantages and limitations. The different measures of forecast error will not necessarily produce the same outcomes, as no single error measure has been shown to provide a clear indication of forecast accuracy. Nevertheless, if a forecasting model is better than the others, then all measure should agree. If the different measures disagree, then that would be an indication that each of the forecasting models is not better than the others.

2.4.5 Tracking Signal

The Tracking Signal is utilized when there is a difference between forecast data and current values because it is necessary to identify whether the difference is caused by a random variation or due to a bias in the estimate. (R. Dan Reid, 2011) [17] “Forecast bias is a persistent tendency for a forecast to be over or

under the actual value of the data. We cannot do anything about random variation, but bias can be corrected”. It serves to monitor how well a forecast is predicting real values if it is keeping pace with a change in demand. So conventional method to measure forecast bias is by using a tracking signal. It is possible to calculate a Tracking Signal (TS) using the arithmetic sum of the forecast errors divided by the Mean Absolute Deviation (MAD):

$$TS = \frac{\sum E_t}{MAD} \quad (2.15)$$

Where TS = tracking signal

E_t = forecast errors

MAD = mean absolute deviation

For verify forecast accuracy, the values of the tracking signal have to be compared against determined limits, if errors fall outside these limits, the forecast needs to be reviewed.

If the Tracking Signal at any time is outside the range of ± 6 , this is a sign that the forecast is biased and is under-performing (Tracking Signal < -6) or over-running (Tracking Signal $> +6$). In this case, the company should choose to choose a new forecasting method. A case in which a large negative Tracking Signal will result is when demand has a growth trend and the manager is employing a forecasting method such as the moving average. Because the trend is not included, the historical average of demand is always lower than future demand. Negative Tracking Signal detects that the forecasting method consistently underestimates demand and alerts the manager.

2.5 Selecting a Forecasting Method

In this subchapter, we present a conceptual framework for selecting between the several methods reviewed. The most important factors in the selection of a model are the following:

1. The sophistication of the user and the system:

How sophisticated are managers, both in and out of operations, who are expected to use forecasting results? It was found that the forecasting method must be coupled with the knowledge and sophistication of the user. Almost always, managers are reluctant to apply results that come from techniques they do not understand. Another related factor is the condition of the forecasting systems that are currently in use. Forecasting systems tend to evolve towards methods with greater mathematical sophistication; they do not change to a considerable extent; therefore, the method chosen should not be too advanced or

sophisticated for its users or so advanced that it is located beyond the current system of forecasts. In addition, simpler models can sometimes perform better, and sophistication is not the ultimate goal.

2. Time and resources available:

The selection of a forecasting method will depend on the time available for data collection and forecasting, which involves the time of users, who prepares forecasts and collects data. Preparing a complicated forecast, in which most of the data needs to be collected can take several months and cost thousands of dollars. In the case of routine forecasts made by computerized systems, both the cost and the amount of time required can be very modest.

3. Application or characteristics of the decision:

As mentioned at the beginning, the forecasting method must relate to the application or decisions that are required. The application, in turn, is closely linked with characteristics such as the accuracy required, the time horizon of the forecast and the number of concepts to be forecast; Inventory scheduling, production scheduling, and pricing decisions, to mention examples, imply highly accurate short-term forecasts for a large number of items. Time series analysis methods are ideally useful for those needs; In contrast, decisions associated with processes, plant planning, and marketing programs are long-term and involve less accuracy on, perhaps, a single estimate of total demand. Qualitative or causal methods tend to be more appropriate for these decisions. In the intermediate term, the category is aggregate planning, capital budgeting, and new product introduction decisions, which often handle time series or causal methods.

4. Availability of data:

Often, the choice of forecasting method is constrained by the available data. An econometric model may require data that is simply not available in the short term; therefore, another must be selected. The quality of the available data is also essential; those of poor quality lead to poor forecasts. Data should be checked for strange factors or unusual points.

5. The pattern of the data:

The pattern contained in the data will affect the type of forecasting method that is selected. If the time series is flat, as we have assumed in most of this chapter, a first order method can be used; however, if the data show seasonal trends or patterns, more advanced methods will be needed. The pattern contained in the data will also determine whether a time series analysis method will be sufficient or whether other models will be required. If the data pattern is unstable over time, a qualitative method can be selected; therefore, the pattern contained in the data is one of the fundamental factors that affect the selection of a

forecasting method. One way to detect the pattern is to represent the data on a graph, which should always be done as the first step of the forecast.

Another aspect related to the selection of a forecast method is the difference between the adjustment and the forecast. When testing different models, it is often thought that the model with the best fit to historical data (the minimum error) is also the best predictor model.

The best predictive model is the one that describes the fundamental time series and that there is no forced data. The correct way to adjust models based on historical data is model fit and model prediction. First, the data set is divided into two parts. Then, several models based on reasonable assumptions about seasonality, trend, and cycles fit the first set of data. These models are used for the values for the second set of data and the one with the lowest error in the second set is the best model. This approach uses the adjustment on the first set of data and the prediction on the second as a basis for the selection of the model.

Once decided the improvement that greater approach achieves to the levels of desired and necessary precision is passed to the practical implementation of it. The application must be linked to a constant monitoring that goes back to the system, to take the necessary measures in the event of any disturbance (undesirable variations than expected).

The methods of the organization must be evaluated against the characteristics of the system; that is why the ultimate key to success is the follow-up during your application. It is necessary to periodically audit the results obtained about the projected ones, to monitor the obstacles to the success, and to re-establish the guidelines. During the monitoring of the behavior of the system plays a fundamental role, in the present work, to determine the existence of errors during the realization of the forecast, which can be obtained by running a prognostic test

ANALYSIS AND RESULT

3 Case of Study

100 Tonn Montage is a company specialized in the industrial equipment assembly since 2002. The company has its own stock of hydraulic equipment from Holland and Germany that is constantly updated to meet the needs of a customer and to perform different rigging and assembly works. Figure 3.1 shows the Company logo.



Figure 3.1 Company Logo [23].

The company have 10-1100 ton gantry systems, shift and lateral displacement systems, turning table, carts and trailers (load capacity up to 120 ton), rails, bars, supports and many other components enable the quick assembly avoiding any problems with moving super heavy equipment parts. 100 Tonn Montage operation centers are located in Moscow, Saint-Petersburg, Tolyatti and Yekaterinburg thus providing assembly service throughout the Russian Federation and near abroad, and cooperating with European partners as well. Figure 3.1.1 shows a map of the main area where company works.

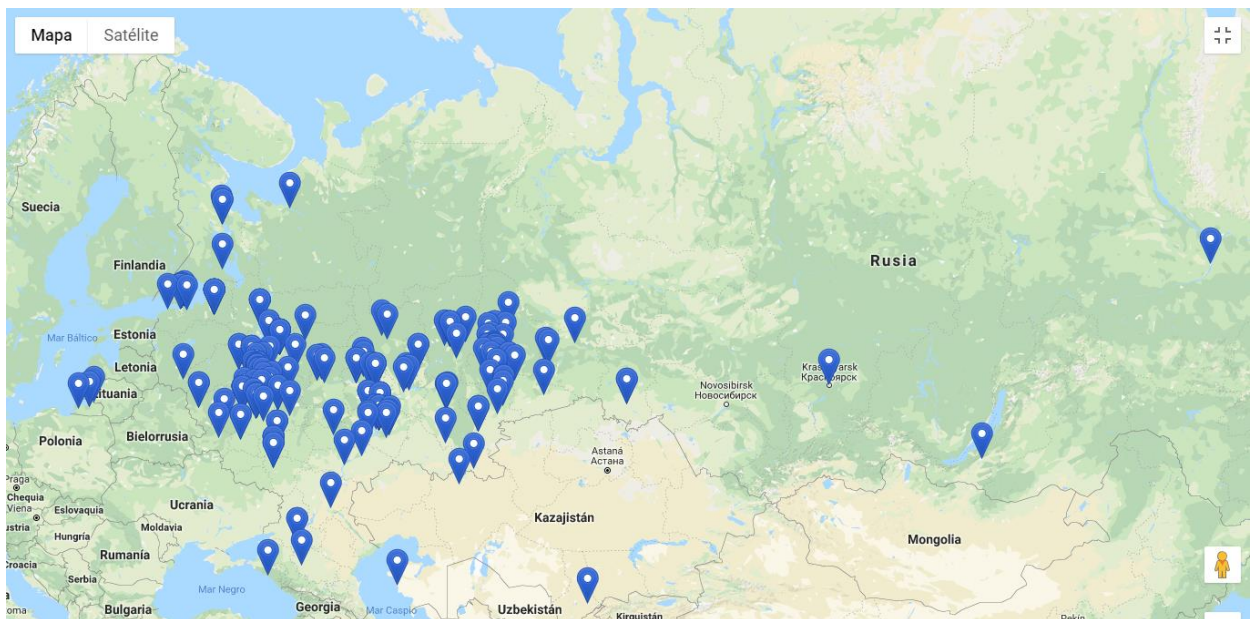


Fig 3.1.1 Coverage area [23].

Due to its experience and technical equipment, the company offers a wide range of assembly services such as: mechanical installation and electric wiring, foundation setting, welding, operational documentation and many others. Heavy equipment whether hydraulic press, metalworking machine, furnace or turbines are safely and carefully moved, installed in its final position and assembled.

Specifically for this research, we will focus on the service that 100 Tonn Montage company provides on equipment assembly and relocation with the use of modern specialized technology and high-qualified personnel. 100 Tonn Montage company constantly invests money in the development of its own stock and is ready to provide its equipment to realize projects for its clients. During the usual work when the client perform assembling with its own efforts, the company can provide its rental services of it equipment. 100 Tonn Montage specialists will choose the best technical solution, check its clients work production plan in terms of company equipment or develop a plan as well as provide well-qualified use of such a complex and expensive equipment during rigging and relocation works. At present, the company is ready to provide rental services of eight 10-1100 ton portal systems as well as other equipment for rigging and assembly works:

- a) Cargo shifting system (load capacity of 450 tons).
- b) Lateral displacement systems (load capacity of 1000 tons).
- c) Jack systems with hydro station (load capacity of 360 and 600 tons).
- d) 40 ton internal trailers.
- e) 120 ton carts.
- f) 3 and 5 ton forklift truck.

The company provides rental services of the required equipment just after the expert assessment of objective of the client. The company will supply it anywhere or dispatch from one of its stocks.

3.1 Data Analysis and Results

As it was mentioned before the present research studies the behavior of the demand in lifting Projects for the Russian Service company 100 Tonn Montage from which the historical data is taken from the month of January of 2015 until the month of April of 2017. In the Table 3.1, it shows the data from the Lifting Projects.

Table 3.1 Data set

<i>Lifting Projects</i>					
<i>t</i>	<i>A_t</i>	<i>t</i>	<i>A_t</i>	<i>t</i>	<i>A_t</i>
<i>Period</i>	Projects	Period	Projects	Period	Projects
<i>Jan-15</i>	6	Jan-16	5	Jan-17	5
<i>Feb-15</i>	1	Feb-16	1	Feb-17	4
<i>Mar-15</i>	5	Mar-16	4	Mar-17	2
<i>Apr-15</i>	5	Apr-16	11	Apr-17	7
<i>May-15</i>	6	May-16	10		
<i>Jun-15</i>	8	Jun-16	10		
<i>Jul-15</i>	6	Jul-16	9		
<i>Aug-15</i>	8	Aug-16	3		
<i>Sep-15</i>	3	Sep-16	2		
<i>Oct-15</i>	3	Oct-16	4		
<i>Nov-15</i>	5	Nov-16	6		
<i>Dec-15</i>	8	Dec-16	8		
<i>Total</i>	64		73		18

In addition, from just observing the data in Table 3.1, it can be noted that there is a growth in the demand for projects. In the year 2015 had 64 projects, and for the year 2016 was 73. It can be inferred that the company is growing year by year. With the data shown in the table 3.1, we test the different Time Series methods, to observe which fits and gives us a better forecast result. As one of the first steps, it is necessary to graph the data to observe its behavior over time and see if one can recognize some of the patterns of demand that usually occur in the time series. By using Excel software, we plotted the data and obtained its trend line. As shown in Figure 3.2.

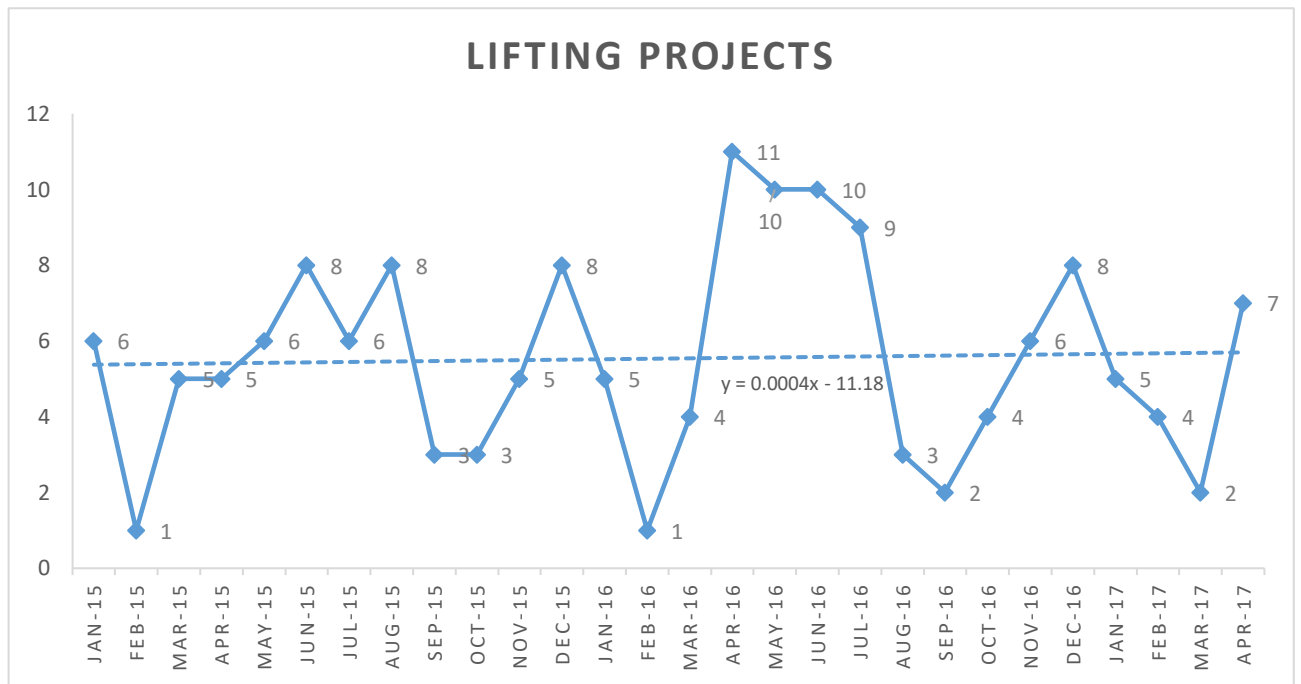


Figure 3.2 Lifting Project chart

With the trend line obtained through Excel helps us to confirm that there is a positive trend. It cannot be clearly appreciated what kind of pattern the demand follows. To ensure that demand is not irregular we must obtain its standard deviation and see that it is not greater than the average demand. The average obtained from the demand is equal to 5.535 and the standard deviation is 2.741, therefore we know that the demand is not irregular.

So we proceed to analyze the data using the first method Simple average. Table 3.2 shows the analysis of the data and the results obtained.

Table 3.2 Simple average

SIMPLE AVERAGE						
<i>t</i>	<i>A_t</i>	<i>F_t</i>	<i>E_t</i>	<i>(E_t)²</i>	<i> E_t </i>	<i> PE_t </i>
<i>Period</i>	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
<i>Jan-15</i>	6					
<i>Feb-15</i>	1					
<i>Mar-15</i>	5	3.500	1.500	2.250	1.500	30.000
<i>Apr-15</i>	5	4.000	1.000	1.000	1.000	20.000
<i>May-15</i>	6	4.250	1.750	3.063	1.750	29.167

<i>Jun-15</i>	8	4.600	3.400	11.560	3.400	42.500
<i>Jul-15</i>	6	5.167	0.833	0.694	0.833	13.889
<i>Aug-15</i>	8	5.286	2.714	7.367	2.714	33.929
<i>Sep-15</i>	3	5.625	-2.625	6.891	2.625	87.500
<i>Oct-15</i>	3	5.333	-2.333	5.444	2.333	77.778
<i>Nov-15</i>	5	5.100	-0.100	0.010	0.100	2.000
<i>Dec-15</i>	8	5.091	2.909	8.463	2.909	36.364
<i>Jan-16</i>	5	5.333	-0.333	0.111	0.333	6.667
<i>Feb-16</i>	1	5.308	-4.308	18.556	4.308	430.769
<i>Mar-16</i>	4	5.000	-1.000	1.000	1.000	25.000
<i>Apr-16</i>	11	4.933	6.067	36.804	6.067	55.152
<i>May-16</i>	10	5.313	4.688	21.973	4.688	46.875
<i>Jun-16</i>	10	5.588	4.412	19.464	4.412	44.118
<i>Jul-16</i>	9	5.833	3.167	10.028	3.167	35.185
<i>Aug-16</i>	3	6.000	-3.000	9.000	3.000	100.000
<i>Sep-16</i>	2	5.850	-3.850	14.823	3.850	192.500
<i>Oct-16</i>	4	5.667	-1.667	2.778	1.667	41.667
<i>Nov-16</i>	6	5.591	0.409	0.167	0.409	6.818
<i>Dec-16</i>	8	5.609	2.391	5.718	2.391	29.891
<i>Jan-17</i>	5	5.708	-0.708	0.502	0.708	14.167
<i>Feb-17</i>	4	5.680	-1.680	2.822	1.680	42.000
<i>Mar-17</i>	2	5.615	-3.615	13.071	3.615	180.769
<i>Apr-17</i>	7	5.481	1.519	2.306	1.519	21.693
<i>May-17</i>		5.536				
			TS	MSE	MAD	MAPE
			4.840	7.918	2.384	63.323

From the results obtained it can be noticed that the values always remain in the average of the demand, therefore, it does not follow the peaks that exist in the real demand. With the help of the methods for error measurement in the forecast, we obtained that the Track Signal is 4,840, this value is very high and indicates that there is a bias in the forecast. In other words is a persistent tendency for a forecast to be over or under the actual value of the data.

To appreciate it better we should look the Figure 3.3, which it is the graph of the result for the simple average. As can be seen in the graph, the orange line that represents the forecast of the demand all the time is in the middle, either below or above when there are high and low peaks. In the case of the other three error measurement like Mean Square Error is 7.918, the Mean Absolute Deviation is 2.384, and the Mean Absolute Percentage Error is 63.323. The first two measurements are not particularly large values, only the

third one that gives us the result in percentage can be noticed that it is high. Therefore, we continue to compare with the other methods that are in the Time Series

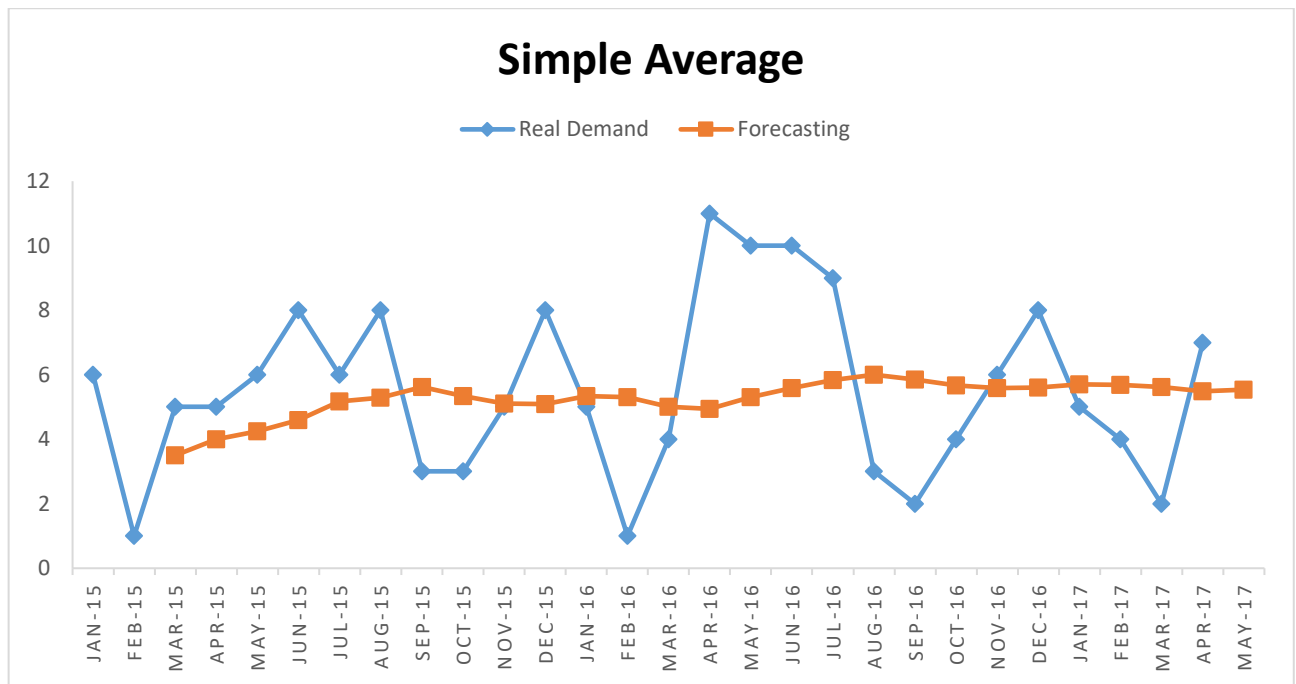


Figure 3.3 Simple average graph

After the Simple Average method, we proceed to analyze the data using the Simple Moving Average method which allows to not take an average of all the data as the previous, for this case we use the last 2 recent data to forecast. Table 3.3 shows the analysis of the data and the results obtained.

Table 3.3 Simple moving average n=2

SIMPLE MOVING AVERAGE <i>n=2</i>						
<i>t</i>	<i>A_t</i>	<i>F_t</i>	<i>E_t</i>	$(E_t)^2$	$ E_t $	$ PE_t $
<i>Period</i>	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5	3.500	1.500	2.250	1.500	30.000
Apr-15	5	3.000	2.000	4.000	2.000	40.000

May-15	6	5.000	1.000	1.000	1.000	16.667
Jun-15	8	5.500	2.500	6.250	2.500	31.250
Jul-15	6	7.000	-1.000	1.000	1.000	16.667
Aug-15	8	7.000	1.000	1.000	1.000	12.500
Sep-15	3	7.000	-4.000	16.000	4.000	133.333
Oct-15	3	5.500	-2.500	6.250	2.500	83.333
Nov-15	5	3.000	2.000	4.000	2.000	40.000
Dec-15	8	4.000	4.000	16.000	4.000	50.000
Jan-16	5	6.500	-1.500	2.250	1.500	30.000
Feb-16	1	6.500	-5.500	30.250	5.500	550.000
Mar-16	4	3.000	1.000	1.000	1.000	25.000
Apr-16	11	2.500	8.500	72.250	8.500	77.273
May-16	10	7.500	2.500	6.250	2.500	25.000
Jun-16	10	10.500	-0.500	0.250	0.500	5.000
Jul-16	9	10.000	-1.000	1.000	1.000	11.111
Aug-16	3	9.500	-6.500	42.250	6.500	216.667
Sep-16	2	6.000	-4.000	16.000	4.000	200.000
Oct-16	4	2.500	1.500	2.250	1.500	37.500
Nov-16	6	3.000	3.000	9.000	3.000	50.000
Dec-16	8	5.000	3.000	9.000	3.000	37.500
Jan-17	5	7.000	-2.000	4.000	2.000	40.000
Feb-17	4	6.500	-2.500	6.250	2.500	62.500
Mar-17	2	4.500	-2.500	6.250	2.500	125.000
Apr-17	7	3.000	4.000	16.000	4.000	57.143
May-17	4.500					
			TS	MSE	MAD	MAPE
			1.465	10.846	2.731	77.056

From the results obtained, it can be noticed that the values begin to follow demand, as shown in Figure 3.4. With the help of the methods for error measurement in the forecast, we obtained that the Track Signal is 1.465, the value is lower compared to the one obtained in Simple Average and indicates that there is still a bias in the forecast but is within the normal limits.

As can be seen in the graph, the orange line that represents the forecast data, it begins to try to follow the demand but it is still too low or too high and also is lagging behind the real demand. The Mean Square Error is 10.846, Mean Absolute Deviation is 2.731, and the Mean Absolute Percentage Error is 77.056. Compared with the values from the Simple Average they increased only Track Signal give us a lower result because now the results do not stay only in the middle and our objective is that the forecast follows as close as it can the demand.

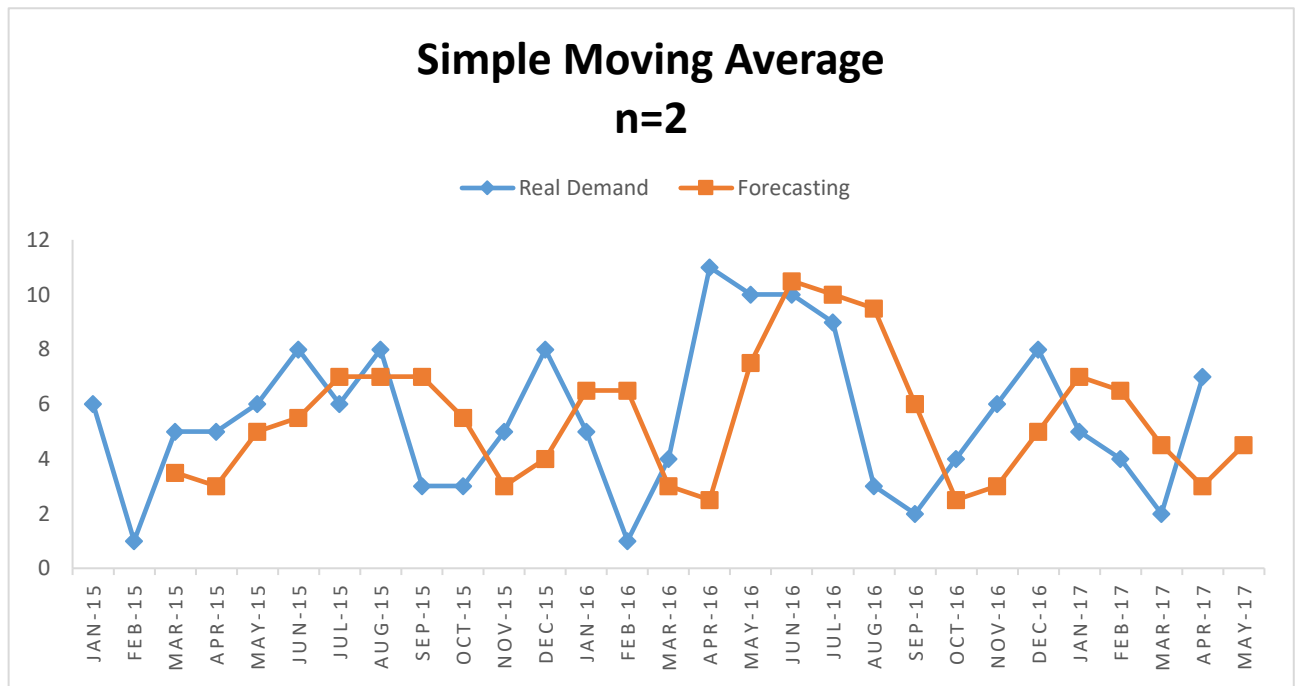


Figure 3.4 Simple moving average n=2 graph

Therefore, we continue to use the Simple Moving Average but for this case we use the last three recent data to forecast. Table 3.4 shows the analysis of the data and the results obtained.

Table 3.4 Simple moving average n=3

SIMPLE MOVING AVERAGE n=3						
t	A _t	F _t	E _t	(E _t) ²	E _t	PE _t
Period	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5					
Apr-15	5	4.000	1.000	1.000	1.000	20.000
May-15	6	3.667	2.333	5.444	2.333	38.889
Jun-15	8	5.333	2.667	7.111	2.667	33.333
Jul-15	6	6.333	-0.333	0.111	0.333	5.556
Aug-15	8	6.667	1.333	1.778	1.333	16.667
Sep-15	3	7.333	-4.333	18.778	4.333	144.444
Oct-15	3	5.667	-2.667	7.111	2.667	88.889
Nov-15	5	4.667	0.333	0.111	0.333	6.667
Dec-15	8	3.667	4.333	18.778	4.333	54.167
Jan-16	5	5.333	-0.333	0.111	0.333	6.667
Feb-16	1	6.000	-5.000	25.000	5.000	500.000
Mar-16	4	4.667	-0.667	0.444	0.667	16.667

<i>Apr-16</i>	11	3.333	7.667	58.778	7.667	69.697
<i>May-16</i>	10	5.333	4.667	21.778	4.667	46.667
<i>Jun-16</i>	10	8.333	1.667	2.778	1.667	16.667
<i>Jul-16</i>	9	10.333	-1.333	1.778	1.333	14.815
<i>Aug-16</i>	3	9.667	-6.667	44.444	6.667	222.222
<i>Sep-16</i>	2	7.333	-5.333	28.444	5.333	266.667
<i>Oct-16</i>	4	4.667	-0.667	0.444	0.667	16.667
<i>Nov-16</i>	6	3.000	3.000	9.000	3.000	50.000
<i>Dec-16</i>	8	4.000	4.000	16.000	4.000	50.000
<i>Jan-17</i>	5	6.000	-1.000	1.000	1.000	20.000
<i>Feb-17</i>	4	6.333	-2.333	5.444	2.333	58.333
<i>Mar-17</i>	2	5.667	-3.667	13.444	3.667	183.333
<i>Apr-17</i>	7	3.667	3.333	11.111	3.333	47.619
<i>May-17</i>		4.333				
			TS	MSE	MAD	MAPE
			0.708	12.009	2.827	79.785

From the results we can note that the Track Signal is 0.708, the value is lower compared to the one obtained in Simple Moving Average $n=2$. As shown in Figure 3.5, the forecast line it is giving a better follow to the demand but is still lagging behind the real demand. The Mean Square Error is 12.009, Mean Absolute Deviation is 2.827, and the Mean Absolute Percentage Error is 79.785. Although this has given a better following to the demand, the values increased compared with the ones from $n=2$.

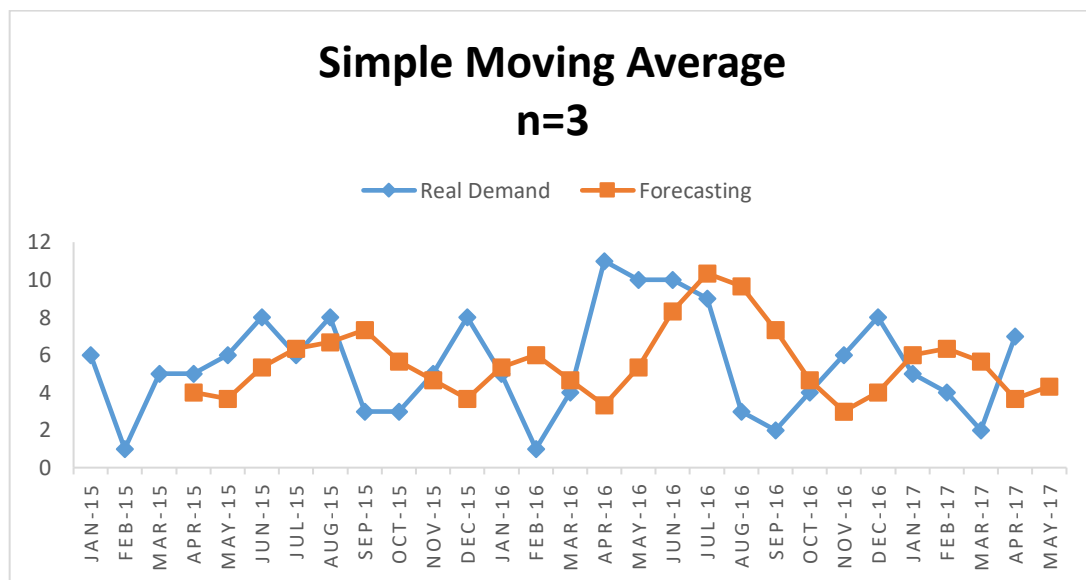


Figure 3.5 Simple moving average $n=3$ graph

So we proceed to continue using the Simple Moving Average, but for this case we use the last four recent data to forecast, just to verify if it gives us a better result than $n=2$ and $n=3$. Table 3.5 shows the analysis of the data and the performance.

Table 3.5 Simple moving average n=4

SIMPLE MOVING AVERAGE						
n=4						
t	A_t	F_t	E_t	(E_t)²	 E_t 	 PE_t
Period	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5					
Apr-15	5					
May-15	6	4.250	1.750	3.063	1.750	29.167
Jun-15	8	4.250	3.750	14.063	3.750	46.875
Jul-15	6	6.000	0.000	0.000	0.000	0.000
Aug-15	8	6.250	1.750	3.063	1.750	21.875
Sep-15	3	7.000	-4.000	16.000	4.000	133.333
Oct-15	3	6.250	-3.250	10.563	3.250	108.333
Nov-15	5	5.000	0.000	0.000	0.000	0.000
Dec-15	8	4.750	3.250	10.563	3.250	40.625
Jan-16	5	4.750	0.250	0.063	0.250	5.000
Feb-16	1	5.250	-4.250	18.063	4.250	425.000
Mar-16	4	4.750	-0.750	0.563	0.750	18.750
Apr-16	11	4.500	6.500	42.250	6.500	59.091
May-16	10	5.250	4.750	22.563	4.750	47.500
Jun-16	10	6.500	3.500	12.250	3.500	35.000
Jul-16	9	8.750	0.250	0.063	0.250	2.778
Aug-16	3	10.000	-7.000	49.000	7.000	233.333
Sep-16	2	8.000	-6.000	36.000	6.000	300.000
Oct-16	4	6.000	-2.000	4.000	2.000	50.000
Nov-16	6	4.500	1.500	2.250	1.500	25.000
Dec-16	8	3.750	4.250	18.063	4.250	53.125
Jan-17	5	5.000	0.000	0.000	0.000	0.000
Feb-17	4	5.750	-1.750	3.063	1.750	43.750
Mar-17	2	5.750	-3.750	14.063	3.750	187.500
Apr-17	7	4.750	2.250	5.063	2.250	32.143
May-17		4.500				
			TS	MSE	MAD	MAPE
			0.361	11.859	2.771	79.091

In this case Tracking Signal get even lower than n=3 and the Mean Square Error is 11.859, Mean Absolute Deviation is 2.771, and the Mean Absolute Percentage Error is 79.091. Even if it give us a better Tracking Signal than the previous cases and a little bit lower values in the measurement errors than n=3,

the forecast is staying really behind the real demand line, as shown in Figure 3.6. So we proceed to test the others methods.

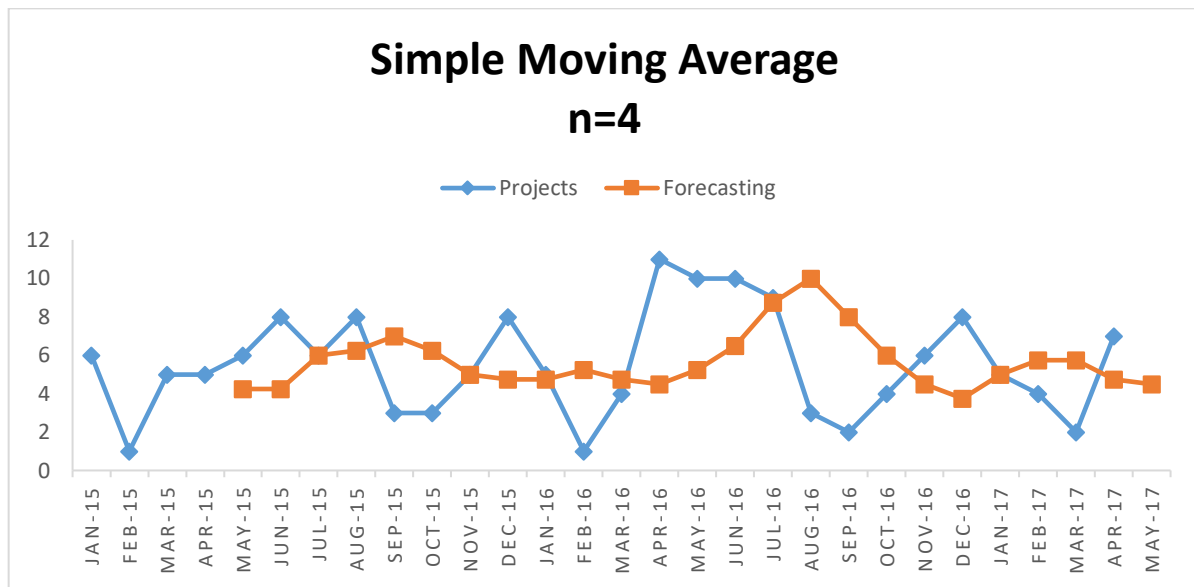


Figure 3.6 Simple moving average n=4 graph

After using the Simple Moving Average method for the cases $n=2$, $n=3$ and $n=4$. We proceed to analyze the data using the Weighted Moving Average method which allows assigning different weights to the last recent observation, for this case we use the last two recent data to forecast $n=2$. Table 3.6 shows the analysis of the data and the results obtained.

Table 3.6 Weighted moving average $n=2$

WEIGHTED MOVING AVERAGE						
$n=2$	W_1	1	W_2	2	Each W is divided by the sum of W_1+W_2	
t	A_t	F_t	E_t	$(E_t)^2$	$ E_t $	$ PE_t $
Period	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5	2.667	2.333	5.444	2.333	46.667
Apr-15	5	3.667	1.333	1.778	1.333	26.667
May-15	6	5.000	1.000	1.000	1.000	16.667
Jun-15	8	5.667	2.333	5.444	2.333	29.167
Jul-15	6	7.333	-1.333	1.778	1.333	22.222
Aug-15	8	6.667	1.333	1.778	1.333	16.667

Sep-15	3	7.333	-4.333	18.778	4.333	144.444
Oct-15	3	4.667	-1.667	2.778	1.667	55.556
Nov-15	5	3.000	2.000	4.000	2.000	40.000
Dec-15	8	4.333	3.667	13.444	3.667	45.833
Jan-16	5	7.000	-2.000	4.000	2.000	40.000
Feb-16	1	6.000	-5.000	25.000	5.000	500.000
Mar-16	4	2.333	1.667	2.778	1.667	41.667
Apr-16	11	3.000	8.000	64.000	8.000	72.727
May-16	10	8.667	1.333	1.778	1.333	13.333
Jun-16	10	10.333	-0.333	0.111	0.333	3.333
Jul-16	9	10.000	-1.000	1.000	1.000	11.111
Aug-16	3	9.333	-6.333	40.111	6.333	211.111
Sep-16	2	5.000	-3.000	9.000	3.000	150.000
Oct-16	4	2.333	1.667	2.778	1.667	41.667
Nov-16	6	3.333	2.667	7.111	2.667	44.444
Dec-16	8	5.333	2.667	7.111	2.667	33.333
Jan-17	5	7.333	-2.333	5.444	2.333	46.667
Feb-17	4	6.000	-2.000	4.000	2.000	50.000
Mar-17	2	4.333	-2.333	5.444	2.333	116.667
Apr-17	7	2.667	4.333	18.778	4.333	61.905
May-17		5.333				
		TS	MSE	MAD	MAPE	
		1.784	9.795	2.615	72.379	

For this method we give lower weight to the second last data $W_1 = 1/3$ and $W_2 = 2/3$ to last data. Tracking Signal get higher than the ones obtained in Simple Moving Averages. The Mean Square Error is 9.795, Mean Absolute Deviation is 2.615, and the Mean Absolute Percentage Error is 72.379.

In contrast to the result from Tracking Signal, the result from the measurement error are lower than the previous method. In addition, from looking at the Figure 3.7 the forecasting line is giving a better response to the real demand line, but is still behind the demand line. It can be noted that this method is even better than the other 2 previous methods

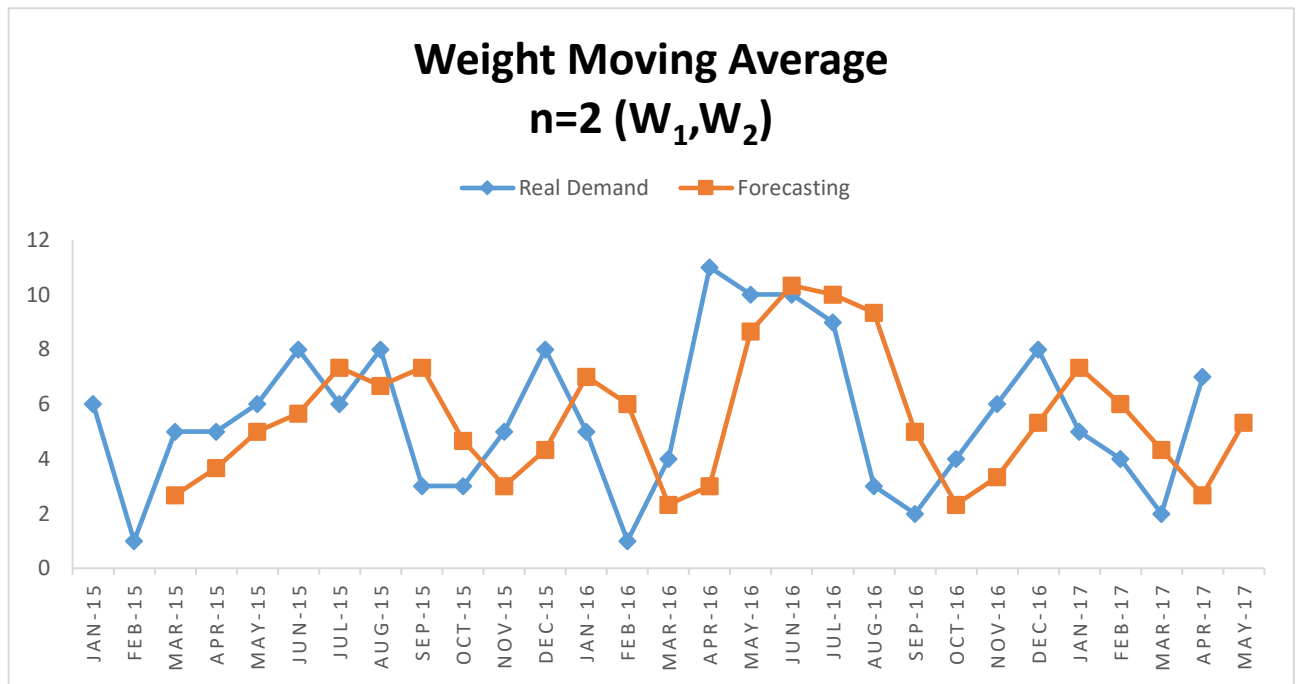


Figure 3.7 Weighted moving average n=2 graph

So we proceed to still use the Weighted Moving Average but for this case we use the last three recent data to forecast n=3. Table 3.7 shows the analysis of the data and the results obtained.

Table 3.7 Weighted moving average n=3

WEIGHTED MOVING AVERAGE						
<i>n=3</i>		W_1	W_2	W_3	Each W is divided by the sum of $W_1+W_2+W_3$	
		1	2	4	7	
<i>t</i>	A_t	F_t	E_t	$(E_t)^2$	$ E_t $	$ PE_t $
Period	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5					
Apr-15	5	4.000	1.000	1.000	1.000	20.000
May-15	6	4.429	1.571	2.469	1.571	26.190
Jun-15	8	5.571	2.429	5.898	2.429	30.357
Jul-15	6	7.000	-1.000	1.000	1.000	16.667
Aug-15	8	6.571	1.429	2.041	1.429	17.857
Sep-15	3	7.429	-4.429	19.612	4.429	147.619
Oct-15	3	4.857	-1.857	3.449	1.857	61.905

<i>Nov-15</i>	5	3.714	1.286	1.653	1.286	25.714
<i>Dec-15</i>	8	4.143	3.857	14.878	3.857	48.214
<i>Jan-16</i>	5	6.429	-1.429	2.041	1.429	28.571
<i>Feb-16</i>	1	5.857	-4.857	23.592	4.857	485.714
<i>Mar-16</i>	4	3.143	0.857	0.735	0.857	21.429
<i>Apr-16</i>	11	3.286	7.714	59.510	7.714	70.130
<i>May-16</i>	10	7.571	2.429	5.898	2.429	24.286
<i>Jun-16</i>	10	9.429	0.571	0.327	0.571	5.714
<i>Jul-16</i>	9	10.143	-1.143	1.306	1.143	12.698
<i>Aug-16</i>	3	9.429	-6.429	41.327	6.429	214.286
<i>Sep-16</i>	2	5.714	-3.714	13.796	3.714	185.714
<i>Oct-16</i>	4	3.286	0.714	0.510	0.714	17.857
<i>Nov-16</i>	6	3.286	2.714	7.367	2.714	45.238
<i>Dec-16</i>	8	4.857	3.143	9.878	3.143	39.286
<i>Jan-17</i>	5	6.857	-1.857	3.449	1.857	37.143
<i>Feb-17</i>	4	6.000	-2.000	4.000	2.000	50.000
<i>Mar-17</i>	2	4.857	-2.857	8.163	2.857	142.857
<i>Apr-17</i>	7	3.000	4.000	16.000	4.000	57.143
<i>May-17</i>		5.143				
			TS	MSE	MAD	MAPE
			0.821	9.996	2.611	73.304

This time we assign the weight to the last 3 data $W_1 = 1/7$, $W_2 = 2/7$ and $W_3 = 4/7$. Tracking Signal give a lower value that the ones obtained from $n=2$. The Mean Square Error is 9.996, Mean Absolute Deviation is 2.611, and the Mean Absolute Percentage Error is 73.304. In contrast to the result from Tracking Signal, the result from the measurement error increased a little compared with $n=2$. Moreover, from looking at Figure 3.8 the forecasting line gives a better response to the real demand than in $n=2$, but the forecasting lines get further behind the real demand line compared with $n=2$.

The Weighted Moving Average method give a less Mean Absolute Percentage Error 73.304 than Simple Moving Average Method 77.056, but if we compared with the Simple Average method is higher because in that case, we obtained 63.323 percentage error. Nevertheless Weighted Moving Average meets its objective of better tracking the peaks of the real demand than the last 2 methods. But it is still not good enough in its results. Therefore, we are going to test the data with more advanced methods that will probably offer better results

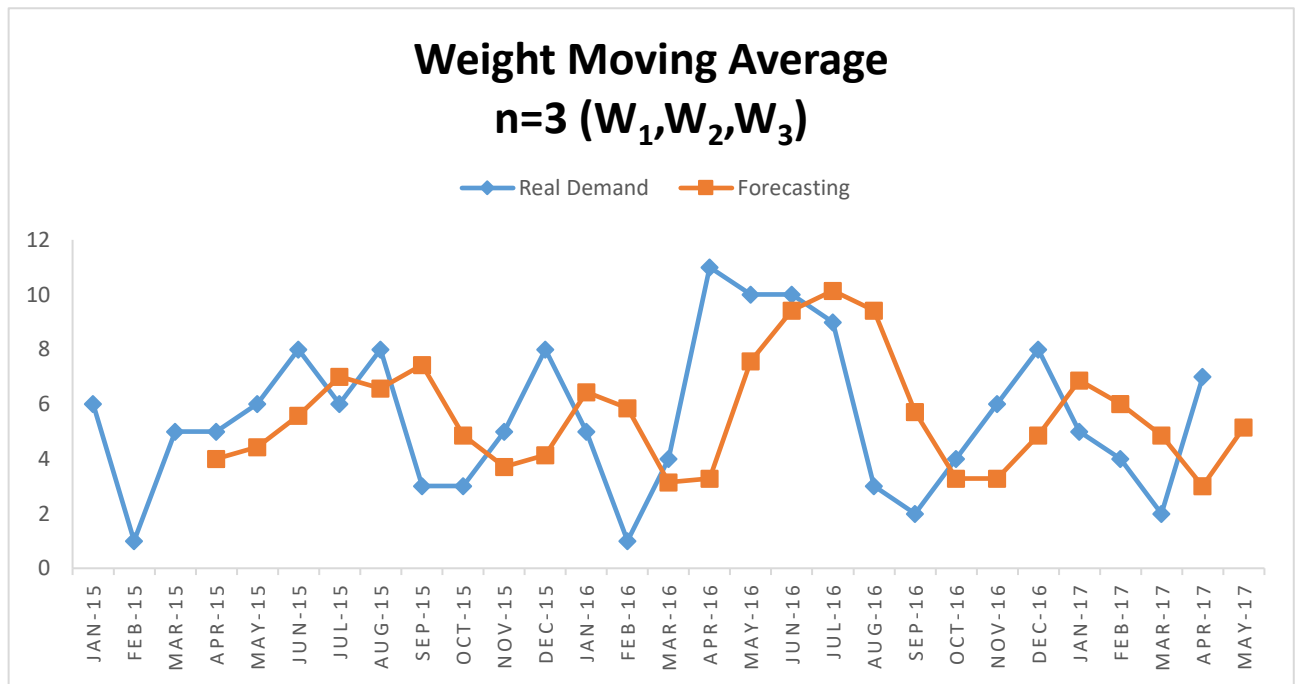


Figure 3.8 Weighted moving average n=3 graph

For this case, we use Exponential Smoothing method, which is more advanced than the previous. This model is widely used, particularly in operations management. It has been shown to produce accurate forecasts under many conditions. The smoothing coefficient who gives us a better result for the data is $\alpha = 0.99$. In Table 3.8 shows the analysis of the data and the results obtained.

Table 3.8 Exponential smoothing

EXPONENTIAL SMOOTHING						
<i>t</i>	A_t	F_t	E_t	$(E_t)^2$	$ E_t $	$ PE_t $
Period	Real Demand	Forecasting	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15	6					
Feb-15	1					
Mar-15	5	5.536	-0.536	0.287	0.536	10.714
Apr-15	5	5.005	-0.005	0.000	0.005	0.107
May-15	6	5.000	1.000	1.000	1.000	16.666
Jun-15	8	5.990	2.010	4.040	2.010	25.125
Jul-15	6	7.980	-1.980	3.920	1.980	32.998
Aug-15	8	6.020	1.980	3.921	1.980	24.753
Sep-15	3	7.980	-4.980	24.802	4.980	166.007
Oct-15	3	3.050	-0.050	0.002	0.050	1.660
Nov-15	5	3.000	2.000	3.998	2.000	39.990
Dec-15	8	4.980	3.020	9.120	3.020	37.750

<i>Jan-16</i>	5	7.970	-2.970	8.820	2.970	59.396
<i>Feb-16</i>	1	5.030	-4.030	16.238	4.030	402.970
<i>Mar-16</i>	4	1.040	2.960	8.760	2.960	73.993
<i>Apr-16</i>	11	3.970	7.030	49.415	7.030	63.905
<i>May-16</i>	10	10.930	-0.930	0.864	0.930	9.297
<i>Jun-16</i>	10	10.009	-0.009	0.000	0.009	0.093
<i>Jul-16</i>	9	10.000	-1.000	1.000	1.000	11.112
<i>Aug-16</i>	3	9.010	-6.010	36.120	6.010	200.333
<i>Sep-16</i>	2	3.060	-1.060	1.124	1.060	53.005
<i>Oct-16</i>	4	2.011	1.989	3.958	1.989	49.735
<i>Nov-16</i>	6	3.980	2.020	4.080	2.020	33.665
<i>Dec-16</i>	8	5.980	2.020	4.081	2.020	25.252
<i>Jan-17</i>	5	7.980	-2.980	8.879	2.980	59.596
<i>Feb-17</i>	4	5.030	-1.030	1.060	1.030	25.745
<i>Mar-17</i>	2	4.010	-2.010	4.041	2.010	100.515
<i>Apr-17</i>	7	2.020	4.980	24.799	4.980	71.141
<i>May-17</i>		6.950				
			TS	MSE	MAD	MAPE
			0.613	8.628	2.330	61.366

As it was expected, the Exponential Smoothing give us a better result than the previous methods tested. We obtained a lower Tracking Signal value 0.613 which tell us that the forecast is getting lower in it tendency to be under or above of the actual value data. The Mean Square Error is 8.628, Mean Absolute Deviation is 2.330, and the Mean Absolute Percentage Error is 61.366. The 3 measurement of error also begins to get lower in contrast with the other methods.

At the beginning, we gave a random value to α , $\alpha = 0.2$. After doing all the procedure for analyzing the data and obtain a result, we began to play with the values of α to see which α adapted better so that the forecast line would give a better follow-up to the real demand line. To find the best value for α we used the Solve complement in Excel that allows searching for the optimal value. From looking at Figure 3.9 the forecasting line, behave even better, the forecasting line it copying the real demand line, but it is still behind it. So this can mean that there is a trend in the pattern and need to be correct, so data can stop lagging behind it.

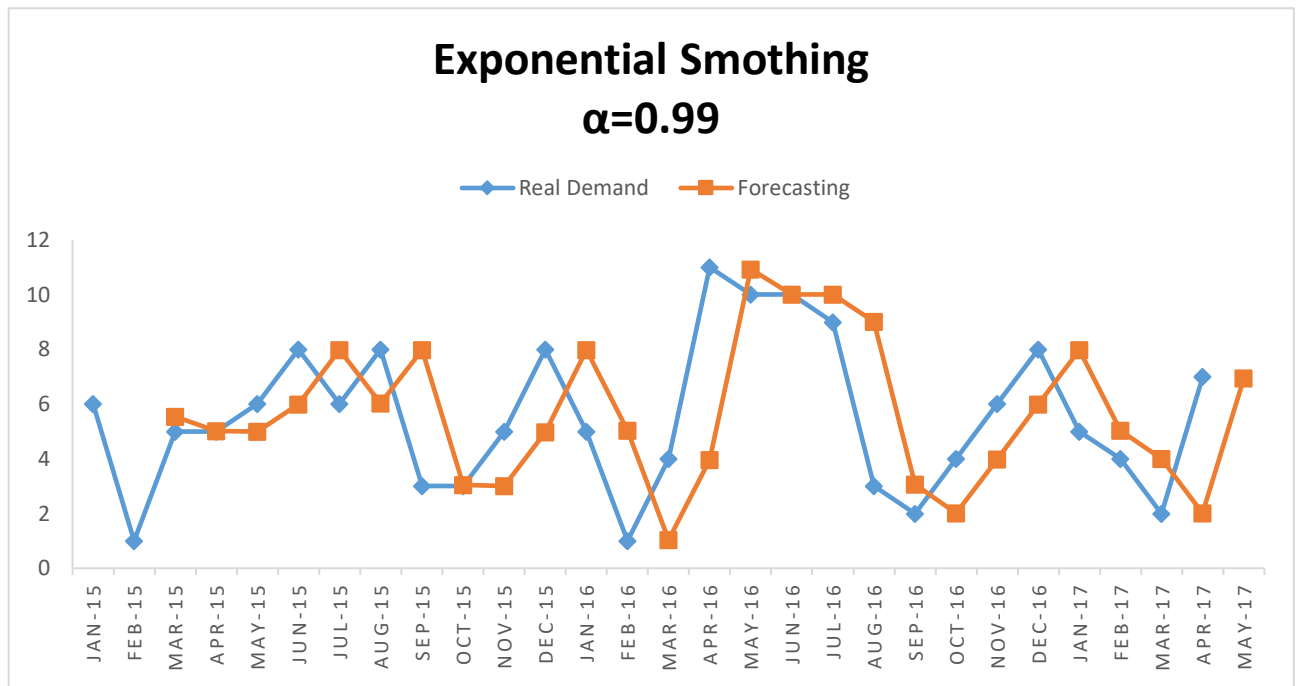


Figure 3.9 Exponential smoothing graph

After observing that even when the exponential smoothing method was used, and the forecast line remains behind the actual demand. We proceed to use a more advanced version of the previous method, The Trend adjusted Exponential Smoothing use an additional feature added to compensate for the lagging that would otherwise keep occurring. For this case, we have two coefficient, the smoothing coefficient α like in the previous method and the trend coefficient β who help us to correct the trend. In Table 3.9 shows, the analysis of the data and the results obtained.

Table 3.9 Trend adjusted exponential smoothing

TREND ADJUSTED EXPONENTIAL SMOOTHING				
<i>t</i>	A_t	S_t	T_t	F_t
<i>Period</i>	Real Demand	Smoothing	Trend	Forecasting
<i>Jan-15</i>	6			
<i>Feb-15</i>	1			
<i>Mar-15</i>	5	5.536	0.0000	
<i>Apr-15</i>	5	5.000	0.0000	5.536
<i>May-15</i>	6	6.000	0.0000	5.000
<i>Jun-15</i>	8	8.000	0.0000	6.000
<i>Jul-15</i>	6	6.000	0.0000	8.000
<i>Aug-15</i>	8	8.000	0.0000	6.000
<i>Sep-15</i>	3	3.000	0.0000	8.000

Oct-15	3	3.000	0.0000	3.000
Nov-15	5	5.000	0.0000	3.000
Dec-15	8	8.000	0.0000	5.000
Jan-16	5	5.000	0.0000	8.000
Feb-16	1	1.000	0.0000	5.000
Mar-16	4	4.000	0.0000	1.000
Apr-16	11	11.000	0.0000	4.000
May-16	10	10.000	0.0000	11.000
Jun-16	10	10.000	0.0000	10.000
Jul-16	9	9.000	0.0000	10.000
Aug-16	3	3.000	0.0000	9.000
Sep-16	2	2.000	0.0000	3.000
Oct-16	4	4.000	0.0000	2.000
Nov-16	6	6.000	0.0000	4.000
Dec-16	8	8.000	0.0000	6.000
Jan-17	5	5.000	0.0000	8.000
Feb-17	4	4.000	0.0000	5.000
Mar-17	2	2.000	0.0000	4.000
Apr-17	7	7.000	0.0000	2.000
May-17				7.000

Continuation Table 3.9 Trend adjusted exponential smoothing

TREND ADJUSTED EXPONENTIAL SMOOTHING				
<i>t</i>	E_t	$(E_t)^2$	E_t	PE_t
<i>Period</i>	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
Jan-15				
Feb-15				
Mar-15				
Apr-15	-0.536	0.287	0.536	10.714
May-15	1.000	1.000	1.000	16.667
Jun-15	2.000	4.000	2.000	25.000
Jul-15	-2.000	4.000	2.000	33.333
Aug-15	2.000	4.000	2.000	25.000
Sep-15	-5.000	25.000	5.000	166.667
Oct-15	0.000	0.000	0.000	0.000
Nov-15	2.000	4.000	2.000	40.000

<i>Dec-15</i>	3.000	9.000	3.000	37.500
<i>Jan-16</i>	-3.000	9.000	3.000	60.000
<i>Feb-16</i>	-4.000	16.000	4.000	400.000
<i>Mar-16</i>	3.000	9.000	3.000	75.000
<i>Apr-16</i>	7.000	49.000	7.000	63.636
<i>May-16</i>	-1.000	1.000	1.000	10.000
<i>Jun-16</i>	0.000	0.000	0.000	0.000
<i>Jul-16</i>	-1.000	1.000	1.000	11.111
<i>Aug-16</i>	-6.000	36.000	6.000	200.000
<i>Sep-16</i>	-1.000	1.000	1.000	50.000
<i>Oct-16</i>	2.000	4.000	2.000	50.000
<i>Nov-16</i>	2.000	4.000	2.000	33.333
<i>Dec-16</i>	2.000	4.000	2.000	25.000
<i>Jan-17</i>	-3.000	9.000	3.000	60.000
<i>Feb-17</i>	-1.000	1.000	1.000	25.000
<i>Mar-17</i>	-2.000	4.000	2.000	100.000
<i>Apr-17</i>	5.000	25.000	5.000	71.429
<i>May-17</i>				
	TS	MSE	MAD	MAPE
	0.605	8.971	2.421	63.576

For the Trend Adjusted Exponential Smoothing give us a little bit better Tracking Signal value 0.605. So the forecast got even lower in its tendency to be under or above of the actual value data. The Mean Square Error is 8.971, Mean Absolute Deviation is 2.421, and the Mean Absolute Percentage Error is 63.576. Nevertheless, the 3 measurement of error gave a little bit higher values compared with the Exponential Smoothing, yet in this case, the trend coefficient helped us to eliminate completely the Trend in the forecast.

In addition, like in the Exponential Smoothing method, at the beginning we gave a random value to α and β , $\alpha = 0.2$, $\beta = 0.2$. After doing all the procedure for analyzing the data and obtain a result, we began to play with the values of α and β to see which values could adapt better so that the forecast line would give a better follow-up to the real demand line. To find the best value for α and β , we also used the Solver complement in Excel which allows to search for the optimal value, in this case the optimal values were $\alpha = 1$, $\beta = 0$.

As shown in Figure 3.10, the forecast line completely imitates the real demand line but remains behind it. It can mean that demand not only has a trend pattern but also has a seasonal pattern and therefore a method to fix the seasonality factor has to be considered. It is also observed that this method decreased,

even more, the values of error measurements compared to the first methods, and that Trend Adjusted Exponential Smoothing accomplish the objective of follow the low and high peaks of the real demand.

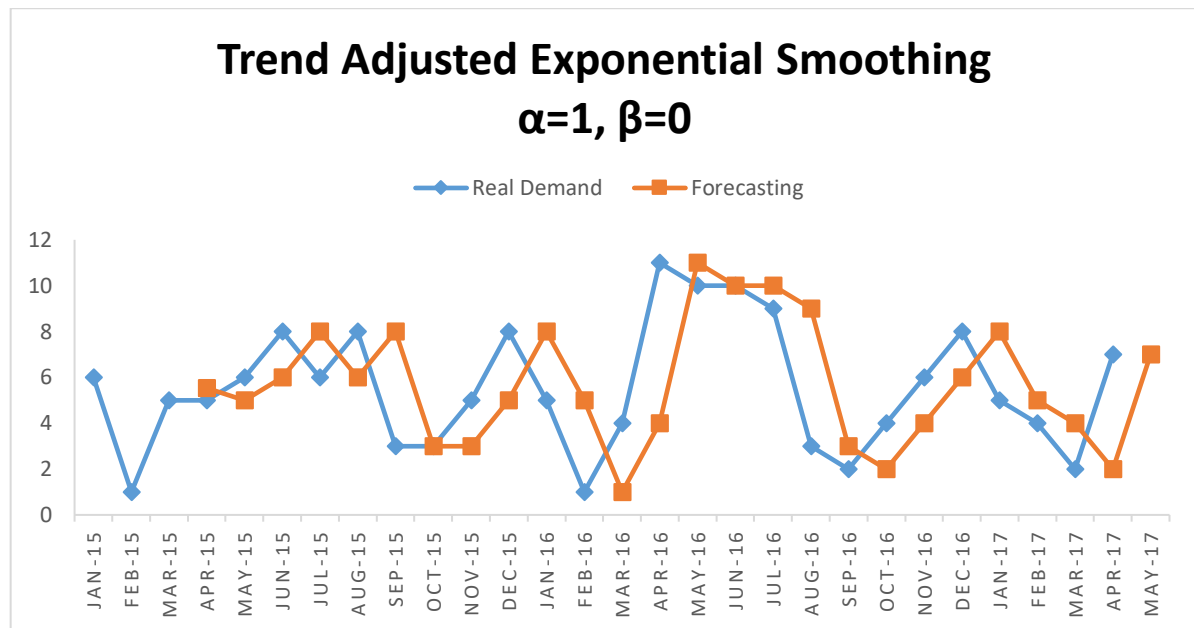


Figure 3.10 Trend adjusted exponential smoothing graph

Finally, we proceed to use a more advanced version of the previous method, the Trend and Seasonality corrected Exponential Smoothing use a third coefficient that takes into consideration the seasonality that the data can present. The seasonality coefficient is γ . The only drawback with this model is that it is usually a little more complicated than all previous models. In Table 3.10 shows, the analysis of the data and the results obtained.

Table 3.10 Trend and seasonality corrected exponential smoothing

HOLT – WINTERS MODEL				
Period	Month	Demand	Deseasonalized Demand	Deseasonalized Demand (After Regression)
May-15	1	6		5.751
Jun-15	2	8		5.752
Jul-15	3	6		5.754
Aug-15	4	8	5.583	5.755
Sep-15	5	3	5.500	5.757
Oct-15	6	3	5.417	5.758
Nov-15	7	5	4.750	5.760

<i>Dec-15</i>	8	8	4.250	5.762
<i>Jan-16</i>	9	5	5.000	5.763
<i>Feb-16</i>	10	1	6.083	5.765
<i>Mar-16</i>	11	4	6.667	5.766
<i>Apr-16</i>	12	11	7.167	5.768
<i>May-16</i>	13	10	7.667	5.769
<i>Jun-16</i>	14	10	7.667	5.771
<i>Jul-16</i>	15	9	6.917	5.772
<i>Aug-16</i>	16	3	6.000	5.774
<i>Sep-16</i>	17	2	5.500	5.775
<i>Oct-16</i>	18	4	5.000	5.777
<i>Nov-16</i>	19	6	4.750	5.779
<i>Dec-16</i>	20	8	4.833	5.780
<i>Jan-17</i>	21	5	5.083	5.782
<i>Feb-17</i>	22	4		5.783
<i>Mar-17</i>	23	2		5.785
<i>Apr-17</i>	24	7		5.786
<i>May-17</i>	25			
<i>Jun-17</i>	26			

Continuation Table 3.10 Trend and seasonality corrected exponential smoothing

<i>HOLT – WINTERS MODEL</i>					
<i>Period</i>	Seasonal Factor (for initialization)	Seasonal Factor	Level	Trend	Forecast
			5.7492	0.001548	
<i>May-15</i>	1.043	1.171	5.751	0.001548	6.733
<i>Jun-15</i>	1.391	1.474	5.752	0.001548	8.479
<i>Jul-15</i>	1.043	1.084	5.754	0.001548	6.235
<i>Aug-15</i>	1.390	0.694	5.755	0.001548	3.992
<i>Sep-15</i>	0.521	0.477	5.757	0.001548	2.744
<i>Oct-15</i>	0.521	1.083	5.758	0.001548	6.234
<i>Nov-15</i>	0.868	1.171	5.760	0.001548	6.744
<i>Dec-15</i>	1.389	1.474	5.762	0.001548	8.493
<i>Jan-16</i>	0.868	1.084	5.763	0.001548	6.245
<i>Feb-16</i>	0.173	0.694	5.765	0.001548	3.999
<i>Mar-16</i>	0.694	0.477	5.766	0.001548	2.749
<i>Apr-16</i>	1.907	1.083	5.768	0.001548	6.244
<i>May-16</i>	1.733	1.171	5.769	0.001548	6.754
<i>Jun-16</i>	1.733	1.474	5.771	0.001548	8.506

<i>Jul-16</i>	1.559	1.084	5.772	0.001548	6.255
<i>Aug-16</i>	0.520	0.694	5.774	0.001548	4.005
<i>Sep-16</i>	0.346	0.477	5.775	0.001548	2.753
<i>Oct-16</i>	0.692	1.083	5.777	0.001548	6.254
<i>Nov-16</i>	1.038	1.171	5.779	0.001548	6.765
<i>Dec-16</i>	1.384	1.474	5.780	0.001548	8.520
<i>Jan-17</i>	0.865	1.084	5.782	0.001548	6.265
<i>Feb-17</i>	0.692	0.694	5.783	0.001548	4.012
<i>Mar-17</i>	0.346	0.477	5.785	0.001548	2.758
<i>Apr-17</i>	1.210	1.083	5.786	0.001548	6.264
<i>May-17</i>					6.776
<i>Jun-17</i>					8.534

Continuation Table 3.10 Trend and seasonality corrected exponential smoothing

<i>HOLT – WINTERS MODEL</i>				
<i>Period</i>	Forecast Error	Squared Error	Absolute Error	Absolute Percentage Error
<i>May-15</i>	-0.733	0.537	0.733	12.212
<i>Jun-15</i>	-0.479	0.230	0.479	5.989
<i>Jul-15</i>	-0.235	0.055	0.235	3.912
<i>Aug-15</i>	4.008	16.061	4.008	50.095
<i>Sep-15</i>	0.256	0.065	0.256	8.521
<i>Oct-15</i>	-3.234	10.458	3.234	107.798
<i>Nov-15</i>	-1.744	3.040	1.744	34.872
<i>Dec-15</i>	-0.493	0.243	0.493	6.160
<i>Jan-16</i>	-1.245	1.549	1.245	24.896
<i>Feb-16</i>	-2.999	8.993	2.999	299.881
<i>Mar-16</i>	1.251	1.566	1.251	31.280
<i>Apr-16</i>	4.756	22.620	4.756	43.237
<i>May-16</i>	3.246	10.534	3.246	32.456
<i>Jun-16</i>	1.494	2.231	1.494	14.935
<i>Jul-16</i>	2.745	7.536	2.745	30.502
<i>Aug-16</i>	-1.005	1.011	1.005	33.508
<i>Sep-16</i>	-0.753	0.567	0.753	37.661
<i>Oct-16</i>	-2.254	5.081	2.254	56.351
<i>Nov-16</i>	-0.765	0.586	0.765	12.755
<i>Dec-16</i>	-0.520	0.271	0.520	6.502
<i>Jan-17</i>	-1.265	1.600	1.265	25.298

<i>Feb-17</i>	-0.012	0.000	0.012	0.292
<i>Mar-17</i>	-0.758	0.574	0.758	37.883
<i>Apr-17</i>	0.736	0.542	0.736	10.513
<i>May-17</i>				
<i>Jun-17</i>				
	TS	MSE	MAD	MAPE
	-0.001	3.998	1.541	38.646

For this case too, as in the two variants of Exponential Smoothing methods, at the beginning we gave a random value to α , β and γ , $\alpha = 0.2$, $\beta=0.2$, $\gamma = 0.2$. After doing all the procedure for analyzing the data and obtain a result, we began to play with the values of α , β and to look for which values could adapt better so that the forecast line would give a better follow-up to the real demand line. To find the best value for the three coefficients, we also used the Solve complement in Excel which allows obtaining the optimal value for each of them. For this case the best values obtained are γ , $\alpha = 0$, $\beta=0.1$, $\gamma = 0$. As shown in Figure 3.11

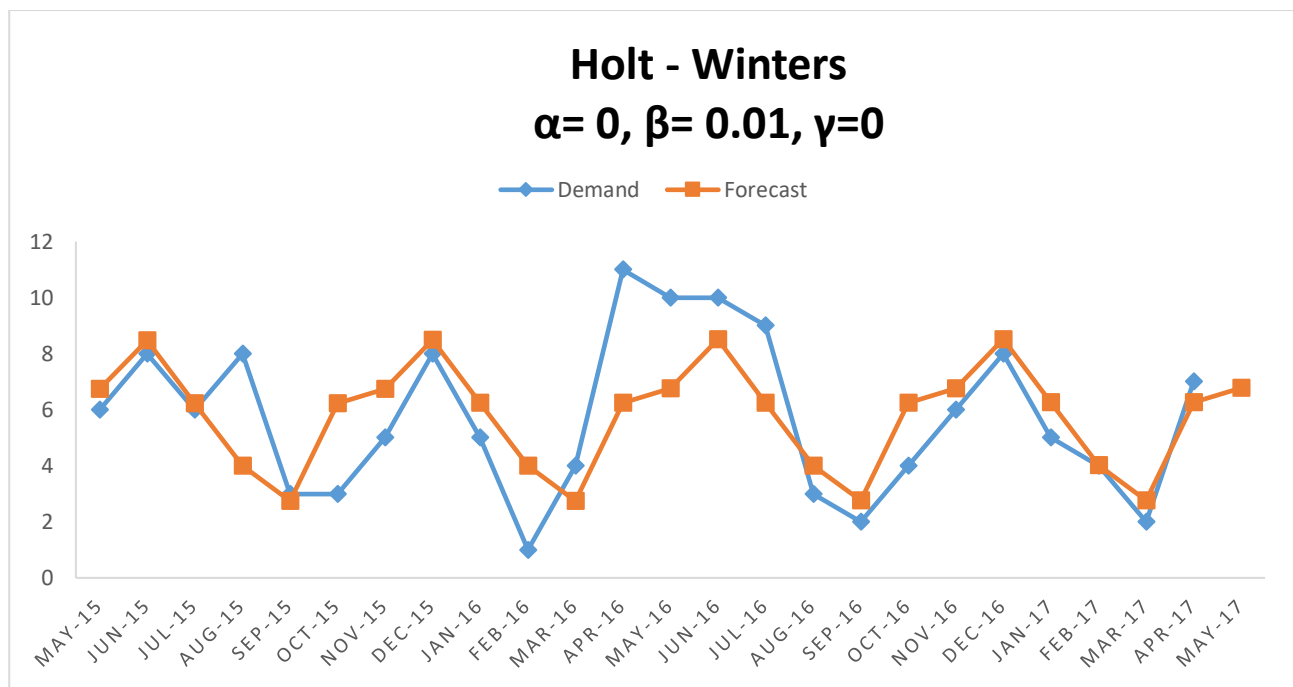


Figure 3.11 Trend and seasonality corrected exponential smoothing graph

For the Trend and Seasonality corrected Exponential Smoothing gave the best Tracking Signal value -0.001. It means the forecast almost doesn't have tendency to stay below the actual value data. The Mean Square Error is 3.998, Mean Absolute Deviation is 1.541, and the Mean Absolute Percentage Error is 38.646. Additionally the three measurements of error gave the lowest results compared with all the previous methods.

In addition, as we can observe the forecast line finally keep up with the real demand. Only in some particular cases does the forecast line remain below or above actual demand. These values can have a particular cause, as in the year 2016 the economy of Russia became stronger than the previous years and therefore there was more growth in the industry and resulting in more demand in certain months than in past years these months did not have this type of demand. This model is best suited to our data because it considers the seasonality factor; the graph can be noted that the data follow a seasonal period of 6 to 7 months.

CONCLUSION

It will always be convenient for the logistics manager the need to provide his demand forecasts, waiting times, prices and costs for use in strategic and operational planning and control. Forecasts are a crucial part of the operations manager's role. Demand forecasts affects directly on the performance of the service, capacity, and scheduling of the company.

Finally, for our case of study, we analyzed the Lifting Project demand historical data by using different forecast models, each of these models have its advantages and limitations (Each model is suitable identifying a particular type of pattern). Therefore we concluded that the data for the demand of Lifting projects for the Russian company service 100 Tonn Montage present a trend and seasonality factor, we found that the data follow a seasonal period of 6 to 7 months. Thus, the Holt-winter models provide the optimal forecasting result for our particular case and the three measurements of error confirm the quality of the result.

However, it would also be convenient to use a qualitative method such as the expert opinion in the area when taking a decision based on the forecasting result provided by the Holt-Winters model. Because as reviewed in the literature a single forecast method, will never be perfect and is always better when complemented with another method for obtain the best result.

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