Demand Forecasting for Improved Production Planning; A Time Series Analysis and ARIMA Modeling in case of NEHE Purified Water Bottling Company, Ethiopia

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Declaration

This is to declare that the thesis entitled "Demand Forecasting for Improved Production Planning; a Time Serious Analysis and ARIMA Modeling in case of NEHE Purified Water Bottling Company, Ethiopia", is submitted to Addis Ababa University to the School of Mechanical and Industrial Engineering of Addis Ababa Institute of Technology in Partial Fulfillment of the Requirements for Degree of Masters in Science in Industrial Engineering Stream, is a record of original work carried out by me and has never been submitted to any other institution to get any other degree or certificates. I have properly thanked the support and aid I received throughout this study.

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I hereby certify that I have supervised, read, and evaluated a thesis entitled "Demand Forecasting for Improved Production Planning; a Time Serious Analysis and ARIMA Modeling in case of NEHE Purified Water Bottling Company, Ethiopia" by Tola Kebede is prepared under my guidance. I recommend the thesis be submitted for defense.

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As members of the board of examiners, we examined this thesis entitled "Demand Forecasting for Improved Production Planning; a Time Serious Analysis and ARIMA Modeling in case of NEHE Purified Water Bottling Company, Ethiopia" by Tola Kebede. We hereby certify that the thesis is accepted for fulfilling the requirements for the award of the degree of "Degree of Masters in Science in Industrial Engineering Stream".

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List of Abbreviations

PPC: Production Planning and Controlling

ARIMA: Autoregressive Integrated Moving Average

AR: Autoregressive model

MA: Moving Average model

SARIMA: Seasonal Autoregressive Integrated Moving Average

RMSE: Root Mean Squared Error

APIs: Application programming interface

MAPE: Mean absolute percentage error

LSS: Lean-Six-Sigma

sMAPE: Symmetric mean absolute percentage error.

MAE: Mean absolute error

Abstract

Improving production planning and operational efficiency in the beverage business requires accurate demand forecasts. In order to increase the accuracy of demand forecasting at NEHE Beverage Complex PLC, this study examines the use of time series analysis, namely the ARIMA (AutoRegressive Integrated Moving Average) model. By creating a trustworthy forecasting model using past sales data, the study seeks to address the issues of demand volatility, inventory imbalances, and production inefficiency.

The results show that ARIMA modeling greatly increases demand prediction accuracy, offering a solid foundation for improved inventory control, resource allocation, and production scheduling. This lowers waste and operating expenses by allowing NEHE Beverage Complex PLC to better match its production procedures with consumer demand.

Keywords, forecasting, ARIMA model, time series, production planning

CHAPTER ONE

1. Introduction and Background of the Study

1.1 Introduction

Nowadays, the manufacturing system is under the intensive force from global competition (Nandal et al., 2023). With the product life phases growing shorter, the time desired for marketing, and the diverse consumer needs has enforced manufacturing industries to advance competence and efficiency of manufacturing activities (Bernard;, 2013). In order remain competitive in this extremely unstable industrial setting, and to be able to deliver a quality products at moderate cost the demanded quantity on the right time, industrial systems should have to optimally utilize the accessible and prospective production capabilities (Hochdörffer et al., 2018).

In order to attain the future market demand on right time, product demand forecasts need to be made to enable the industry to effectively plan the quantity of inventory necessary in each level of the supply chain, the amount of product to make, the quantity of material to be purchased from suppliers as well as the sort of transportation needed, warehouses, and distribution centers (Wofuru-nyenke & Briggs, 2022). As a result, production planning activities has long been the vital features of any industrial system (V.M. Sineglazov, 2023; Abbate et al., 2022).

The performance of any manufacturing industry depends not only on the quality of distribution of the system (Bhat, 2008). Rather, it also greatly depends on the efficiency of demand or sale predication practice (Shuang, 2021: Wofuru-nyenke & Briggs, 2022). Hence, production planning requires an effective and precise estimation of the product demanded that should be produced and delivered over a period of time (N. Barbosa & Fluminense, 2015).

In the other regard, the inability to deliver the right quantity of a specific product to a consumer on the right time may effect a serious cost for the industry (Tereshchenko, 2018). Therefore it is very decisive to stride to attain the market need timely. Hence, a realistic allocation of the manufacturing resources and quick response to market demand changes result in reduced cost and to enhance the firm performance (Hasanzadeh et al., 2009). In this regard, an efficient future demand forecasting plays vital role for the industries (Russel, R.S. & Taylor, 2011; Wofuru-nyenke & Briggs, 2022). Therefore, industries should association forecasts to their improvement goals for using past performances to avoid past errors and to attain the market demand efficiently (Baker & Hart, 2016).

1.2 Background of the Study

The most significant element of market demand forecasting is searching for ways to decrease demand variability and advance operational flexibility (Nandal et al., 2023). It helps in assuring reliable production planning process and reduces cost. While, an increasing flexibility assists the manufacturing system to respond quickly to internal and external events (Croxton et al., 2002). Since most consumer centered variability's cannot be removed at full, therefore the purpose of demand forecasting should be to reduce factual errors associated with the planning activity that increases variability (Russel, R.S. & Taylor, 2011). Hence, to establish strategy that promote smooth demand patterns (Maradesa & Akomolafe, 2017). Therefore, accurately forecasting the future market demand plays vital for success of manufacturing industries (Russel, R.S. & Taylor, 2011; Wofuru-nyenke & Briggs, 2022).

According to (Sentia et al., 2022), an efficient and precise demand forecasts play a vital role to perform the planning activity effectively while minimizing costs. Possibly, the estimation to be formulated by the particularly chosen model that should be as close to the reality (N. Barbosa & Fluminense, 2015; G., Junior M.L. M., 2012). Hence, it is vital to properly analyze and establish model that suits the particular manufacturing circumstance (Silva et al. 2014).

Therefore, modeling and pathway analysis on the pattern and trends of product sale, demand or order data over determined period of time is the vital aspect to generate the forecasts (Maradesa & Akomolafe, 2017). It aids to create the assumption that past patterns and trends in data can be used to determine, plane and prepare the planning and management activities accordingly (Maradesa & Akomolafe, 2017). Hence, the appropriate selection of suitable forecasting approach, and the fitting model is vital (Montgomery, 2015; V.M. Sineglazov, 2023).

Indeed, there are different forecasting approaches. They vary from simple qualitative methods method to the emerging data driven sophisticated approaches (Maradesa & Akomolafe, 2017). Quantitative approach's that utilize historical data are much widely utilized for industrial applications to develop predictive models to date (Maradesa & Akomolafe, 2017). Recent scholars (such as., Fattah et al., 2018; Bata et al., 2020; Sentia et al., 2022) have undertaken significant effort in the field of forecasting, he proposed that the two major and most widely used quantitative methods are the generic time series and the Artificial Neural Networking (ANN) approach by scholars yet.

This study is much interested on the most widely used time-series approach. Indeed, the time-series approach consists diverse forecasting models (N. Barbosa & Fluminense, 2015). Despite, according to Fattah et al., (2018), in the history of demand forecasting, the autoregressive integrated moving average (ARIMA) model has proved to perform better than other models because the model can replicate existing conditions. The method is broadly used by scholars in different forecasting domains, for instance (Sim et al., 2019) and Talukdar, (2021) for future electricity demand prediction; El Bahi et al., (2018) future fuel consumption prediction; Gijo, (2011) future tea products demand prediction ; Salami, (2017) future bottled 7-Up demand prediction (Godwin & Fakiyesi, 2016) future bottled Coca-Cola demand prediction, and Fattah et al., (2018) and Abolghasemi et al., (2019) future food products demand prediction.

Despite of such scholarly efforts, (Godwin & Fakiyesi, 2021) have stated that; consistent and precise forecast is crucial for food, beverage, and drinking water industries than in other sectors as long as it will affect the production of fresh goods. Most importantly, in case of drinking water, apart from the fact that water is the primary need of every individual; the growth and changes in community lifestyle have made the drinking water bottling industrial market continue to increase (Nawawi & Riptiono, 2020). As a result, the competition in the drinking water bottling industry is getting tighter and shows a bright prospect going forward to date (Sentia et al., 2022).

However, recently Wofuru-nyenke & Briggs, (2022) has reported that the bottled water supply chain is facing difficulties in fulfilling the market demand at the required quantity on the right time yet. Therefore, according to (Dawei, 2011; Luckyn & Ogra, 2024), these industry should seek to increase supply chain responsiveness, flexibility, and agility by raising forecasting accuracy across the board Moreover according to, (Baker & Hart, 2016), these industry should tie forecasts to their strategy.

Therefore, by determining the preferred time period to be estimated, it is possible to identify and choose the finest method that fits the particular manufacturing system (N. Barbosa &

Fluminense, 2015). Here, based on the time period to be forecasted, time-series forecasting can be classified as; short-term, med-term and long-term methods (Tereshchenko, 2018). In this regard, products in food, beverage, and drinking water industry having steady predictable demand needs an efficient supply chains that shorten lead times and support limited inventory (Godwin & Fakiyesi, 2021).

In particular, Bata et al., (2020) has argued that short-term demand forecasting facilitates water utility to manage the principal operations more efficiently (Bata et al., 2020). In this regard, Sentia et al., (2022) has argued that using historical data for short-term forecasting increases the prediction accuracy than long-term forecasting. Here, in short-term forecasting, conditions that affect demand tend to remain or change slowly (Sentia et al., 2022).

Hence, the above mentioned rationale justifies the relevance of short-term forecasts for in food, beverage, and drinking water products. The ARIMA model is proved to perform better than other time-series models to predict the future short-term demand effectively (Fattah et al., 2018). However, ARIMA model is not well considered by past scholars particularly in the case of drinking water products.

In Ethiopia, several Due to a lack of proper demand forecasting techniques, the water bottling industry has experienced non-conformance in customer demand, inventory shortages in certain situations, and surplus in other situations, all of which have led to financial losses. Therefore, in the present study the sARIMA models are used to estimate the future water demand effectively. A case study has been conducted at NEHE purified water bottling company operating in shaggar, Ethiopia.

The company has been manufacturing three distinct types of DELTA natural purified bottled drinking water products (0.6lt, 1.0lt, and 2.0lt) for the past few years. Indeed, the current real practice is observed at the NEHE beverage complex plc; however these issues are also a common experience in most other beverage industries in Ethiopia. Here, the prime motivation for current research work is the real-world demand forecasting practice that has been affecting the production planning practice exercising at NEHE purified water bottling company, operating in shaggar, Ethiopia. The study problems are identified and formulated by observing the real world planning and predication strategy that evidently practicing actually in the case company.

Hence, in the next sub-section the formulated problems that related to the mentioned practices at case company are presented.

1.3 Statement of the Problem

Bottled water supply chain has been facing difficulties in fulfilling the market demand at the required quantity for product verities on the right time. In Ethiopia, several The water bottling industry, which at the moment lacks sufficient demand forecasting techniques, has had issues with non-conforming client orders, inventory shortages and excesses, and financial losses. Among the industries in Ethiopia, NEHE beverage complex is a Private Limited Company (PLC), operating in Shaggar, Ethiopia. Nowadays, in the company, the practice of future demand estimation has been implemented traditionally by the assembly of authority that the company has considered them with deeper knowledge and several years of experience working in the beverage company.

Demand estimations are made frequently at NEHE beverage complex plc. In the process, the assigned group of people considers the information about recent accessible sale and/or retailed orders, and the previous year products sale or retailed data that exactly matches with the actual time and date of the current year of demand for production planning. They consider the existing marketing scenario along with the inventory on hand and the actually operating capacity of the firm even without taking under consideration the possible capacity of the company.

During demand prediction, the assigned groups of authorized experts only utilize Microsoft Excel software that NEHE beverage complex plc has been using to record all relevant data. Consequently, the entire forecasting practice is implemented by traditional approach which is by group of people who are sensitive to biased decision and to be subjective by a multiplicity of factors. As a result, the current practice can ultimately effect in considerable inaccuracy on the produced forecasts which in turn affects the effectiveness of planning with respect to the production capacity, capabilities, and customer need.

Moreover, the existing conventional practice with the use of Microsoft Excel software that has been exercising in the NEHE beverage complex plc and which is highly subjected to a biased decision due to the use of a group of experts (people) to generate the prediction of future market demand and production plans are identified as a critical problem that needs to be resolved.

Regarding the planning activity, due to the variability in the market demand along with the existence of socio-diversity, socio-cultural, and religious values, multi-street based festivals, and holidays in Ethiopia has effect on the pattern and trends of product sales at varying seasons of shorter horizons. However, the existing forecasting practice, and decision that relay on the authorized groups experts connote effectively estimate the trend and seasonal factors, and the resulting variation.

Moreover, due to the inefficient production planning which is due to inaccurate demand forecasting at different instant of time, it is evidenced from the company that it has not been utilizing its full human and installed machinery capacity. In this regard, according to the marketing survey report of the company for the year 2014 E.C; the sales and marketing department has stated the existence of high customer demand. However, the company has attained only 42.43% on average for the particular kind of product over that year. In this respect, the company production report for the year 2014/2015E.C shows that, the NEHE beverage complex plc had utilized 59.41% over the potential planned capacity.

Table 1: The summary of achieved customer demand, the planed and utilized capacity

Year	The average % of production attained the customer demand	The average capacity (%) planed to utilize	The average capacity(%) utilized by the company
2014/2015 E.C	42.43%	≥ 80% of the potential capacity	59.41%

Hence, an immediate intervention is necessary to attain the existing high market demand by effectively utilizing the optimum capacity of the case company. As the forecasting to be generated by the particularly selected model should be as closed to the reality as possible, therefore, it is vital to analyze and determine the model that fits the particular product manufacturing circumstances.

Therefore, modeling and pathway analysis on the pattern and trends of product sales, demand or order data is imperative for success of the industrial. As a result, it is vital to properly examine and determine forecasting model that well fits to the manufacturing circumstances of the case company in such a way to promote the efficiency of the planning process. In this study, a time-series analysis and modeling is conducted for predicating short-term drinking water demands in such a way to promote an efficient planning activity in an industry. Thus, case study is conducted at NEHE drinking water bottling company.

1.4 Research Questions

1. What is the characteristics nature and pattern of the time-series data of the product over short-time horizon?
2. What are the potential candidate time-series models and their characteristics relevant to estimate the future demand of the product?
3. What is the significance of the identified forecasting model, and its implication on the production planning and related activity?

1.5 Objective of the Study

1.5.1 General Objective

The main objective of this study is to develop and propose short-term ARIMA model for water bottling company in such a way to promote the efficiency of planning activities; a case study will be conducted at NEHE water bottling company operating in Shaggar, Ethiopia

1.5.2 Specific Objectives

2. To examine the characteristics nature and pattern of time-series data of the products;
3. To develop and examine the potential candidate models and their characteristics relevant to estimate the future demand of the product;
4. To identify and validate the model that well fits to the data in such a way to improve the planning and related activity.

1.6 Scope of the Research

The scope of this research work is enclosed by its objective, the theme at which the study focused, and the case company. The main objective of this study is to develop and propose time-series forecasting model for drinking water bottling company in such a way to promote the efficiency of planning activities over a short-term horizon. For this reason, the case study is conducted at NEHE drinking water bottling company that has been operating in Shaggar, Ethiopia.

As short-term forecasting can help a water utility to more efficiently manage many of their principal operations (Bata et al., 2020). In this regard, the ARIMA model is proved to perform better than other time-series models to predict the future short-term demand effectively (Fattah et al., 2018). Moreover, ARIMA is capable of replicating the stochastic process (i.e., having a random probability distribution or pattern that may be analyzed statistically, but may not be predicted) that generate the time series (Godwin & Fakiyesi, 2021). However, the ARIMA model is not considered by past scholars drinking water products.

Therefore through bridging the existing literature gap, in this research, the application of ARIMA model is employed in drinking water bottling company so as to develop models that successfully forecast the future demands of products of the case company. For this purpose, the monthly production and sales quantity record of the products from Apr, 2021 to Sep, 2024. is used for time series analysis, and modeling.

In the effort, Box-Jenkins and Expert Modeler method of ARIMA modeling, forecasts, and evaluation were used, and compared for the effectiveness the two methods on SPSS software package.

1.7 Significances of the Research

The following are the expected significances that will be attained after successfully completing the proposed research plan;

The effective completion of this study will shed light on the substantial challenges as well as the existing opportunities for improving the efficiency of production planning due to the usage of conventional and inaccurate demand forecasting methods, and related problem at the strategic level; the research will also be significant in the following ways; the findings will guide the decision makers and production planners to come-up with an effective demand predication and production decision for bottling water manufacturing sectors over short-term and medium-term time horizons favoring the business as well as the customer side.

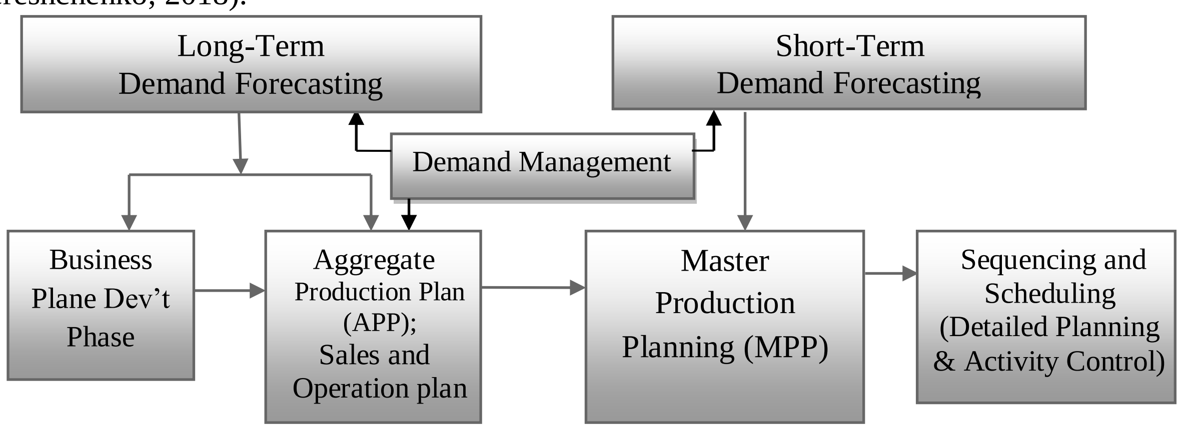
In the other regards, the research will also shed green light to the ordinary considerations over the concepts demand forecasting, tool and practice of demand forecasting in relationships with production planning activities.

Moreover, the finding and achievement of this study will also contribute to the body of knowledge and literatures by providing theoretical formulation (model formulation), and empirical evidence that can help in bridging the existing literature gap in the focus of this study. Hence, by bridging the existing literature gaps the findings of this study can be used as a base line for novice researcher whom might conduct a further study beyond the scope proposed to be addressed by this study.

CHAPTER TWO
2. LITERATURE REVIEW

2.1 Planning and Management in an Industry

According to scholars (for instance.,Wang & Xiao-Bing, 2013; Zhang & Turner, 2016), The main managerial task for businesses that order and guide industries to coordinate their whole operations is planning. Planning has long been one of the fundamental element of the manufacturing industry (Tereshchenko, 2018). Planning is done with different level of detail and time horizons (Kanet & Stößlein, 2010; Baldea & Harjunkoski, 2014). Characteristically, the planning procedure includes a serious of phases that outline a sequence of command (Wofuru-nyenke & Briggs, 2022). Most importantly, the business plan development, aggregate production planning, and master production scheduling (MPS) phase and the sequencing phase are the key (Tereshchenko, 2018).



Adapted from (Starr., 2008; Tereshchenko,2018).

Figure-1: The typical Planning and Management stages in an Industry

As it can be seen in Figure-1, business plan development is the first phase in planning process, and receives long-term forecasts (Hasanzadeh et al., 2009; Tereshchenko,2018). Production planning is a procedure of determining the variety of activities to be implemented by particular manufacturing units that should be performed at pre-specified period of time in the future with the aim of maximizing or minimizing an objective functions(Starr., 2008;Wofuru-nyenke & Briggs, 2022). Here, the aggregate production plane specifies the output levels on monthly basis making certain the planned quantity of product practicable (Tereshchenko, 2018).

While the sales and operation planning is long term planning with aim to balance between available resource capacity and demand (Cui et al., 2019). On the other regard, the master planning represents the expected production and not the expected demand, and specifies number of single products to be produced during a time period with more detailed information (Kanet & Stößlein, 2010). The master planning phase receives short-term demand forecasts by using aggregate production plan as its inputs. While the sequencing and scheduling phase is mainly related with the type of machinery that should be operated at a particular times to meet the plan provided by MPS (Tereshchenko, 2018).

On the other hand, the detailed scheduling is a frame for production activity control and places orders on the detailed scheduling level (Baldea & Harjunkoski, 2014). It decides when an order shall be produced, within the frame of the master planning, and determines time and quantities for each product (Kanet & Stößlein, 2010).

Hence, the entire system performance depends on the quality and effectiveness of the planning system exercised in the planning and controlling phase (Shuang, 2021). Prominently, it also depends on the efficiency of demand predication practice (Wofuru-nyenke & Briggs, 2022). Here, the process of demand management in an industry plays key role in attaining the goal of the planning and controlling activities (Baldea & Harjunkoski, 2014; Wang & Xiao-Bing, 2013),

According to past scholars (for instance., Baldea & Harjunkoski, 2014; Wang & Xiao-Bing, 2013), Forecasting and making plans for the product demands in the market over a specified time frame in the future is known as demand management. In this regard, past study (such as., Croxton et al., 2002) has also argued that, Meeting client demand as effectively and efficiently as possible is the aim of demand management. Hence, the planning and management activity in an industry requires an effective and precise estimation of the product demanded that should be produced and delivered over a period of time (N. Barbosa & Fluminense, 2015).

Nowadays, many manufacturing enterprises often face the problem of mismatch between the production plan of materials and their actual demand in the production operation (Li et al., 2023). Thus, to respond quickly to the rapidly shifting market demand, nowadays, organizations are moving toward a more effective demand-driven supply chain (Wisner et al., 2011). Hence, Product demand management, or forecasting and planning for market demands, has a big impact on a company's profitability, its clients, and suppliers.

2.2 Demand Forecasting and its Implication in Production planning

According to Shuang, (2021) forecasting is a logically designed estimate for determining the future occurrence of an event by forecasting forward past production, market demand or sale data. On the other hand, forecasts are methods to estimate the expected demand in the future (Bottani et al., 2023; Salami, 2017). Moreover, Fattah et al., 2018) has also stated forecasts as a science of estimating the future level of some variables, whereas forecasting is the process of making assumptions about the future values of the studied variables (Fattah et al., 2018). According to Islek, (2017), demand forecasting is the basis for many managerial decisions in the supply chain such as production planning, order fulfillment, and inventory control.

In the process of forecasting, the forecast accuracy is a critical factor in determining the quality of decision making (Abolghasemi et al., 2019). In general, forecasting is vital for the prediction of future events is a critical input into many types of planning and decision-making processes, with wide range of industrial applications; most importantly in production planning, material, and capacity planning (N. Barbosa & Fluminense, 2015), and for quality of distribution of the system (Bhat, 2008). In manufacturing industry, forecasting demands is among the most crucial issues in te supply chain (Vi Phung-thao, 2019); inventory management (Ghobbar & Friend, 2003); for operational and capacity planning; for promotional planning (Ramanathan & Muyldermans, 2010); production panning (N. Barbosa & Fluminense, 2015; Tereshchenko, 2018), production volume planning (Maradesa & Akomolafe, 2017), material demand planning (Li et al., 2023).

For most organizations, managing demand is challenging because of the difficulty in forecasting future consumer needs accurately (Wisner et al., 2011). According to Wofuru-nyenke & Briggs, (2022), inaccurate estimation of future demand can cause significant costs to pay, which proves that the planning and scheduling process is not improved. Consequently, many systems incur large investments in inventories to avoid "stock outs" (Fattah et al., 2018). Inaccurate forecasts may also cause unnecessary costs in procurement and transportation, manpower, service level, and inventory (Abolghasemi et al., 2019).

On the other hand, incapability to deliver the right quantity product to client on the right time effects serious cost for the industry or an organization; these may include severing the entire business connections with the buyer and customer (Tereshchenko, 2018). Thus, the success of the production planning practice greatly depends on the efficiency of future market demand forecasting practice (Tereshchenko, 2018).

In contrast, an improved forecast reduces raw materials and finished goods inventory cost**,** while improving production planning efficiency of the industry (Lindfors, 2021; Nandal et al., 2023). Hence, the company can achieve customer satisfaction optimally. On the other hand, companies that are unable to meet market needs and consumer demand will result reduced opportunities to gain company competitive advantage (Shuang, 2021). In the supply chain, forecasting demand is a part of the demand planning process, supports the decision-making process and determines the performance of different functions within the supply chain (Vi Phung-thao, 2019). Since, pull processes in supply chain are realized with reference to customer demand, while all push processes are realized in anticipation of customer demand (Wofuru-nyenke & Briggs, 2022).

Thus, the supply chain activity planning and control depends on accurate estimates of the volumes of products and services to be processed and the estimates come as forecasts (Ballou, 2007; N. Barbosa & Fluminense, 2015). Here, forecasts are considered as the ground of supply chain's planning for both push and pull systems, and becomes the sign of survival and the language of business in the world (Fattah et al., 2018). The predicted demand enables the supply chain units to react better to changes instead of waiting for orders from the downstream (Vi Phung-thao, 2019).

Therefore, to be competitive in the market, nowadays, industry should tend to improve the supply chain flexibility, agility, and responsiveness through improving forecasting accuracy throughout the long supply chain (Dawei, 2011; Luckyn & Ogra, 2024). Hence, companies must link forecasts to their improvement goals and use past performance to avoid past errors and then reach a high level of planning efficiency (Baker & Hart, 2016). With this, an efficient and precise demand forecasts can play a major role in minimizing costs (Sentia et al., 2022).

Indeed, there are different forecasting methods. They vary from simple qualitative based on an individual or group judgments to highly complex techniques that may involve sophisticated statistical approaches (Maradesa & Akomolafe, 2017). They vary from quantitative as time series methods, to more people-driven (qualitative) (Croxton et al., 2002; Tirkeş et al., 2014; Wofuru-nyenke & Briggs, 2022). However, the appropriate selection of suitable forecasting approach, and the fitting model is vital for the industries success (Montgomery, 2015; V.M. Sineglazov, 2023).

Past scholars (such as., Ballou, (2007); N. Barbosa & Fluminense, 2015) are presents three main approach's of forecasting: qualitative, historical projections and causal. Moreover, according to Fattah et al., (2018), the forecasting approaches are classified as qualitative, time series, causal, and simulation. In broad sense, scholars (such as., Montgomery, 2015; Salami, 2017) categorized the forecasting approach's into two groups: the qualitative approach, and quantitative approach.

When there is no historical data available, the business may subjectively estimate product sales during the new product launch phase of its life cycle by consulting the professional judgment of sales and marketing staff. In this regard, the most formal and widely known qualitative forecasting technique is the Delphi Method (Croxton et al., 2002; Montgomery, 2015; Fattah et al., 2018). In this approach, forecasting is through the administrative experience and customers reviews (N. Barbosa & Fluminense, 2015). Characteristically, qualitative approach is often subjective in nature and requires the expert judgments (Salami, 2017).

On the other regard, quantitative approach uses historical data as an input (Montgomery, 2015). This method predicts the behavior of complex systems simply by looking at past patterns on the input data based on the same phenomenon (Sentia et al., 2022). Here, a demand forecasts is through mathematical models by using historical data (N. Barbosa & Fluminense, 2015). The models summarize patterns in the data and express a statistical relationship between previous and current values of the variable (Montgomery, 2015).

Nowadays, the quantitative approach's that utilize historical data are widely used in the industrial system to develop predictive models (Maradesa & Akomolafe, 2017). The time series analysis in broad, and the forecasting methods in particular has been in use through a broad fields for an industrial application (Tereshchenko, 2018). The method encloses different forecasting models. However, according to (De Oliveira Silva et al., 2014), it is necessary to determine the model that suits the particular application. Therefore, a forecasting model with a high degree of accuracy and minimum error is vital (Sentia et al., 2022).

Hence, prior to selecting the forecasting approach and the desired model for the objective problem, therefore, it is critical to understand and determine the vital aspects and key determinants to be considered (Montgomery, 2015; Sentia et al., 2022). Therefore, in the next sub-sections; first this study reviews the key feature and determining elements of successful demand forecasting problems. Then, the study discusses the forecasting approach, relevant models, and their significant features by focusing on time series analysis and forecasting models relevant to the focus of this study.

2.3 Review of the key feature's and success factors of forecasting

The first and most important factor to be considered is the nature of the input data. Data is the raw material for the modeling and forecasting process (Montgomery, 2015). Nowadays, most forecasting problems involve the use of time series data numerous business forecasting applications make use of daily, weekly, monthly, quarterly, or annual data. However, the way of reporting interval may be vary (Bata et al., 2020).

According to (Wang & Xiao-Bing, 2013), the monthly average, weekly average, and daily average sales data are an important data source for demand estimation**.** Here, the rate variable should be collected at equally spaced time periods, as it is typical in most time series and forecasting applications (Montgomery, 2015). Another important source for product demand data is the received orders which have specified the future delivery time and amount (Wang & Xiao-Bing, 2013).

Scholars, for instance (Arandia et al., 2016; Guo et al., 2018) have used historical demand data as a single data source to develop forecasting models. Their models showed reasonably accurate forecasts (Bata et al., 2020). Other scholars for instance (Rice et al. 2017; Herrera et al. 2010), additional inputs such as seasonality components were considered in the data (this may include time specific order data, besides of sales data) (Bata et al., 2020). Thus, historical data is thoroughly combined in a prearranged way to achieve the approximation of the future market demand (N. Barbosa & Fluminense, 2015; Croxton et al., 2002; Shuang, 2021).

Hence, by assessing the data stripped of its seasonal and trend components facilitates to understand whether the time series is volatile or not (Tereshchenko, 2018). In case, if the demand contains seasonal component, it is vital to select a method that incorporates seasonality (Fattah et al., 2018).

The decision to choose time-series methods that suit the nature of market demand is vital (Croxton et al., 2002; De Oliveira Silva et al., 2014). The other driving factor of the forecasting problem is the forecast horizon (Bata et al., 2020; Montgomery, 2015). The length of the period for which a prediction is implemented is frequently described as forecasting horizon (G. Mahalakshmi, & S. Sridevi, 2016). The forecast horizon is also often called the forecast lead time (Wang & Xiao-Bing, 2013).

Thus, based on the forecasting horizon, forecasting problems are often classified as; short-term, med-term and long-term methods (Tereshchenko, 2018). Short-term forecasting problems involve predicting events only a few time periods (days, weeks, and months) into the future (Arandia et al., 2016). Medium-term forecasts extend from one to two years into the future, and long-term forecasting problems can extend beyond that by many years (Montgomery, 2015).

The short, medium, and long-term forecast horizons have been extensively discussed by scholars; despite the short-term forecasts have received significant attention to date (see Table-2). Hence, through determining the preferred time horizon to be estimated, it is possible to identify and choose the finest model that fits the particular industrial application (N. Barbosa & Fluminense, 2015). Besides, aides the firm for choosing the best technique of forecasting with minimal estimation error or that enable the estimation as close to real as possible (Junior and Filho, 2012).

However, the decision should not be based solely on the time frame required, other factors such as the unit in an industry being forecasted also plays vital role (Fattah et al., 2018; Montgomery, 2015). Thus, the forecast horizon is governed by the model application (Bata et al., 2020), the unit in an industry being considered by the forecast (Croxton et al., 2002), and the nature of the problem (Montgomery, 2015). For instance, short-and Activities ranging from budgeting and operations management to choosing new R&D initiatives require medium-term projections. Scholars such as (for instance., Israel et al., 2019; Sentia et al., 2022; Abbate et al., 2022; Wofuru-nyenke & Briggs, 2022) are among state-of the–art literatures on short term demand forecasting in several domains.

In other instance, when multiple products are involved, the level of aggregation of the forecast (e.g., do we forecast individual products or families consisting of several similar products) can be an important consideration (Bernard;, 2013; Montgomery, 2015). In this regard, scholars (for instance., Barbosa et al., (2015) has proposed short-to-medium term demand predication model for aggregated food products.

Long-term forecasts contact issues such as; strategic planning (Montgomery, 2015), inventory managing, and customer satisfaction (Luckyn & Ogra, 2024), inventory management and product planning (V.M. Sineglazov, 2023). Scholars (for instance., Israel et al., 2019; V.M. Sineglazov, 2023; Luckyn & Ogra, 2024) are among state-of the–art literatures on long-term demand forecasting. According to (Vi Phung-thao, 2019) Because the standard deviation of error is higher for long-term projections than for short-term forecasts, the former are often less accurate.

Indeed, different forecasting approach and models might be used for different products (Bata et al., 2020). However, according to Sentia et al., (2022), the suitability of the method with the real conditions to be modeled and being able to accommodate the factors that influence it (Sentia et al., 2022). For instance, for products with modest demand variability, quantitative approaches based on previous data are employed. In other regard, products with high variability and high volume require more human input, perhaps from the sales force or the customers themselves (Croxton et al., 2002).

A product with high variability and low volume may benefit from make-to-order manufacturing. For instance, for the introduction of a new product, scholars such as (Fattah et al., 2018; Montgomery, 2015) suggests subjective projections since there is little to no previous data to support them. Hence, once management observes the level of demand in the first few weeks, they can begin to generate a reasonably accurate forecast for the future (Croxton et al., 2002; Mahalakshmi et al., 2016).

The other important factor for successful time series analysis and forecasting is that the analyst interaction with computer software (Montgomery, 2015). There are numerous software packages on the market that can handle the forecasting component of demand management (Croxton et al., 2002). Because of their good capability for analyzing time series data and generating forecasts, software packages such as Minitab®, JMP®, and R-software are suggested by Montgomery, (2015). The software package the so called; Statistical Package for Social Science (SPSS) have been widely utilized by scholars (for instance., Ruppert, 2017; Garcia-arismendiz et al., 2023; Sim et al., 2019; Fattah et al., 2018).

Similarly, in the present study, the SPSS software package V.26 is used to make time series analysis and forecasts the short and mid-term bottled water demand in the case company. Here, the key consideration for choosing the software program is based on its ease of use, accessibility, and the variety of statistical techniques the SPSS system employs, as well as its capacity to modify the prediction.

2.4 Structured Literature Review, and Literature Gap Identification

In this section, a structured literature review is done by gathering articles published in academic journals relevant to the thematic area of this research work. For this purpose, published related articles were collected from the Google Scholars search engine. During the process of literature collection, the search words such as Demand forecasting, Time series methods, and ARIMA model, and together with the term production planning were used together related published articles by reading the title, and abstracts. Then, the collected articles are studied in detail structurally and discussed to identify research gap.

2.4.1 Review of Literatures Based on the Forecasting Approach

Nowadays, the quantitative approach's that utilize historical data are much widely utilized for industrial applications to develop predictive models (Maradesa & Akomolafe, 2017). Recently, scholars such as (Fattah et al., 2018; Bata et al., 2020; Sentia et al., 2022) produced a great deal of work in the field of forecasting and proposed a number of forecasting techniques; the two primary and most widely used approaches are the quantitative ones, Artificial Neural Networking (ANN), and time series by the past researches. Similarly, this study has also confirmed that the emerging data driven ANN and the general time series approaches have been gained significant attention by the relevant forecasting literatures.

2.4.1.1 Artificial Neural Networking (ANN) approach

Regarding the former approach, inspired by the architecture of the human brain, ANN have demonstrated extraordinary skills in capturing complicated patterns, nonlinearities, and dynamic interactions. Here, the emergence of big data in varies sector has heightened the importance of ANNs (Luckyn & Ogra, 2024). The ANN models are characterized by intervals with considerable variation of demand, and the approach serves as an alternative approach to capture the nonlinearity in data set (Fattah et al., 2018). The ANN's, with their ability to detect detailed patterns in data, provide a potential route for improving prediction accuracy as compared to traditional forecasting approaches (Luckyn & Ogra, 2024). However, ANN can implicitly detect complex nonlinear relationships between dependent and independent variables. Hence, it is suitable for complex information processing (Anike & Suyoto, 2012; Omar et al., 2016; Sentia et al., 2022).

Having such characteristics, the ANN methods can be used to solve problems related to forecasting, optimization, modeling and simulation, and decision making (Israel et al., 2019). Scholars for instance, (Bata et al., 2020; Israel et al., 2019; Sentia et al., 2022; Abbate et al., 2022; Aci & Yergök, 2023; Bottani et al., 2023; Nandal et al., 2023; Sentia et al., 2022; Tekin & Sar, 2022; V.M. Sineglazov, 2023; Luckyn & Ogra, 2024) are among the relevant up-to-dated empirical literatures that are utilized the ANN methods for an industrial applications to develop forecasting models. Sentia et al., (2022) has also proposed a simulation model of the ANN method using the back-propagation algorithm for future water demand predication.

Since forecasting problems involve the use of time series data (Montgomery, 2015), and many industrial applications of forecasts utilize daily, weekly, monthly, quarterly, or annual data, but the way of reporting interval may be vary (Mahalakshmi et al., 2016). Here, the forecast horizon is the crucial element of forecasting problems. Despite, it is governed by factors such as; the model application (Bata et al., 2020), the unit in an industry being considered by the forecast (Croxton et al., 2002), and the nature of the problem (Montgomery, 2015).

In this regard, in the former approach scholars such as, V.M. Sineglazov, (2023) developed long-term demand forecasting model by using an Ensemble of Neural Networks to improve forecasting accuracy for inventory management and product planning in manufacturing industry; Luckyn & Ogra, (2024) has proposed long-term deep learning model for future diaper sale prediction in retail with aim to improve inventory managing, and customer satisfaction. On the other hand, Aci & Yergök, (2023) developed and compared eighteen Machine Learning-based forecasting models to predict the heavy demand for food without pre-booking.

As a result, an ANN of the Ensemble Decision Tree (EDT) models is proposed with its best performance for short-term food demand prediction with restricted timeframe for instance., lunch time (Aci & Yergök, 2023). Moreover, Nandal et al., (2023) has compared ARIMA, sARIMA and ANN methods, and proposed deep learning methods for effective cement demand predication over short-term horizon by explicitly considering monthly cement sales data.

On the other hand, regarding to the later approach, according to Maradesa & Akomolafe, (2017) the general time-series methods are used in the wide set of industrial application to develop predictive models. In line with the findings of (Fattah et al., 2018 and Bata et al., 2020), this study has also confirmed that along with the ANN approach, the general time series approach's have been widely utilized by recent forecasting literatures. In this regard, scholars for instance (Deshmukh & Paramasivam, 2016; Fattah et al., 2018; Godwin & Fakiyesi, 2016; Barbosa et al., 2015; Lindfors, 2021; Maradesa & Akomolafe, 2017; Ruppert, 2017; Sim et al., 2019; Abolghasemi et al., 2019; Talukdar, 2021; Wofuru-nyenke & Briggs, 2022; Li et al., 2023) are among the up-to-date published scholarly articles in the rising manufacturing industries. Table-2 below presents the detailed summary of relevant state-of-the art literatures collected from the Google Scholars database on the application time series methods.

Table 2: Summary of up-to-dated literatures review on the application time series methods

Author of the Study	Brief Description of the Study	The Proposed Approach/Model	The Forecast Horizon	The Application Area
Abbate et al., (2022)	Developed demand forecasting model for future daily orders prediction in delivery service platform company;	ANN/multilayer perception NN model	- Short term; based on the daily order data	Future online delivery predication in delivery service platform company
V.M. Sineglazov, (2023)	Demand Forecasting by using an Ensemble of Neural Networks to Improve forecasting Accuracy	ANN/ Ensemble of Neural Networking model	- Long-term demand forecasting (implicitly)	- For inventory management and product planning (manufacturing industry)
Aci & Yergök, (2023)	The study developed and compared eighteen Machine Learning-based forecasting models to predict the heavy demand for food without pre-booking.	- ANN/Ensemble Decision Tree (EDT) models is proposed with its best performance	- Short term; with limited timeframe (e.g., lunch time)	- Food products
(Israel et al., 2019)	Proposed a neural networks-based demand forecasting model for a small manufacturer of bottled water in Ecuador	ANN/multilayer perception NN model	-Long-term demand forecasting (implicitly)	Bottled water predication for small manufacturers of bottled water

Sentia et al., (2022)	- Forecasting demand of bottled drinking water by using back propagation algorithm	- ANN/Back propagation algorithm, supervised learning	- Short term; by explicitly considering monthly averages product sale data	- Future bottled water demand predication
(Nandal et al., 2023)	- Effective cement demand forecasting using data-driven approach employing machine learning algorithms; the study also compared ARIMA, SARIMA and ANN	-ANN/proposed deep learning methods	- Short term; by explicitly considering monthly sales data	- Future cement demand predication
(Luckyn & Ogra, 2024)	Proposed a predictive modeling for future diaper sales in retail with aim to improve inventory managing, and customer satisfaction,	ANN/deep learning model is proposed	Long Term (implicitly)	Future diaper demand prediction
(Li et al., 2023)	Material demand analysis and forecasting of manufacturing industry	Time series/ARIMA model is proposed	Short term; on weekly material demand	Future material demand predication (manufacturing industry)
(El Bahi et al., 2018)	Modeling and forecasting of fuel selling price using time series approach	Time series/ARIMA model is proposed	Short term	Fuel selling price prediction
Abolghasemi et al., (2019)	- Demand forecasting in supply chain, the impact of demand volatility in the presence of promotion were studied. - Compared ANN models, Dynamic Linear Regression, Exponential Smoothening, and ARIMA models	-Time-series/ARIMA model is proposed for low and moderately volatile products	- Short term	- Food demand prediction, assessing the impact of demand volatility in planning
Talukdar, (2021)	- Appliance energy prediction using time-series forecasting by identifying trends and appliances involved - A comparative analysis with different Machine Learning Algorithms is made	- Time-series/SARIMA is proposed for best electric energy prediction	- Short term; based on weekday and week number	- Electricity demand prediction
Salami, (2017)	- Time series analysis and modeling for annual sales predication in 7Up Bottling Company PLC, Nigeria	- Time series/ARIMA model is proposed - Box-Jenkins method were used	- Short term; using monthly sales data	- Beverage (7Up sales) predication

(Wofuru-nyenke & Briggs, 2022)	Compared the classical forecasting methods (moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's, and Winter's model), while predicting demand in a bottled water supply chain.	- The classical time series/weighted moving average forecasting model is proposed for predicting demand in a bottled water supply chain	Short term; while demand data were obtained from a number of retailers	- Bottled water supply chain
(Barbosa et al., 2015)	- Proposed demand forecasting model with the aim to enhance production planning efficiency in a food company	-The Holt-Winters Method; the exponential smoothing with trend and seasonal adjustment is proposed -ABC analysis were used	- Short-to-medium term demand predication	- Food demand predication
(Godwin & Fakiyesi, 2016)	- Developed demand forecasting model, and studied with the aim to enhance customer demand of soft drink industry in Nigeria.	- SARIMA model is proposed by the study - Box-Jenkins method were used	- Short term; on monthly and quarterly sales data	- Beverage (Coca-Cola) demand predication
(Sim et al., 2019)	- Modeling and forecasting the future electricity consumption by using time series approach - Box-Jenkins method and Expert Modeler were considered and compared.	- SARIMA model is proposed by the study - Box-Jenkins method and Expert Modeler were used as modeling and evaluation procedure in IBM SPSS tool.	- Short term; on the bases of monthly electricity consumption	- Future electricity demand prediction
(Fattah et al., 2018)	- Modeling and forecasting of demand by using time series approach.	- ARIMA model is proposed -The Box–Jenkins procedure were used	- Short term; on the bases of monthly data	- Food demand predication
(Gijo, 2011)	Time series analysis and demand forecasting of tea by seasonal ARIMA model	- SARIMA model is proposed - Box-Jenkins procedure is used	- Short term; on the bases of monthly tea sales demand.	- Tea demand predication

2.4.1.2 General Time-series Forecasting Methods

According to (Maradesa & Akomolafe, (2017), the general time-series forecasting methods are widely used for industrial application to develop predictive models. The method encloses different forecasting models (Montgomery, 2015). There three basic approaches for generating forecasts are; the regression based methods, heuristic smoothing methods, and general time series models (Mahalakshmi et al., 2016; Montgomery, 2015). Past scholars that have proposed the classical time series methods (regression methods, and heuristic smoothing methods), for instance (Garcia et al., 2005) has proposed the generalized autoregressive conditional heteroskedasticity (GARCH) models; (Barbosa et al., 2015) has proposed the exponential smoothing methods with trend and seasonal adjustment (the Holt-Winters Method). Despite, the classical methods have been missing scholar's attention in the up-to-date.

However, according to (N. Barbosa & Fluminense, 2015), it is necessary to understand the nature of the models, and determine the model that suits the particular application. Here, according to (Fattah et al., 2018) the GARCH models are specifically dedicated to the analysis and forecasting of volatility. Hence, the GARCH models are not relevant to address the scope of the present study. The exponential smoothing is also among the other popular and extensively used forecasting techniques. The model serves fine only for time series data without clear seasonality and trend components (Tereshchenko, 2018).

Indeed, the exponential smoothing method is characterized by its simplicity and accessibility due to the low cost and easiness of application. However, mainly recommended for short time horizon (Mahalakshmi et al., 2016; Montgomery, 2015). The exponential smoothing is not appropriate for the seasonal data that include a cycle or a trend. However, the Holt-Winters Method model uses a modified form of exponential smoothing (Tirkeş et al., 2014). In this regard, (N. D. P. Barbosa et al., 2015) has proposed the exponential smoothing methods with trend and seasonal adjustment for short-term food demand predication.

2.4.1.3 Autoregressive Integrated Moving Average (ARIMA) Model

Recently, (Montgomery, 2015) has pointed out the general time series models such as the ARIMA models among the most widely used time series methods. In this review, it is also found that the autoregressive integrated moving average (ARIMA) models as the most extensively utilized time series forecasting models. Since, time-series represents a combination of its components in two ways as a sum of the trend, seasonality and the remainder, or as a product of the components (Shuang, 2021). In this case, the ARIMA model is capable of replicating the stochastic process that generate the time series, therefore, the model is suitable to predict future demand more effectively (Byung & Yeong, 2010; Godwin & Fakiyesi, 2021).

In fact, the ARIMA model was first introduced by Box and Jenkins, (1976), and since then it is the most accepted models for the predication of univariate time-series data (Godwin & Fakiyesi, 2021). Scholars such as (Abolghasemi et al., 2019; N. D. P. Barbosa et al., 2015; Fattah et al., 2018; Li et al., 2023) have proposed autoregressive integrated moving average (ARIMA) models, (Gijo, 2011; Godwin & Fakiyesi, 2016; Sim et al., 2019; Talukdar, 2021) have proposed the seasonal ARIMA (sARIMA) models in various application domains.

The time series analysis in broad, and the forecasting methods (ARIMA/sARIMA) models in particular has been in use through a broad range of industries and fields of application (Tereshchenko, 2018). Regarding the forecasting methods, scholars for instance; Maradesa & Akomolafe, (2017) conducted a time series analysis and modeling for annual sales predication in 7-Up Bottling Company in Nigeria, and suggested the ARIMA model for predication of the sort-term production volume. Abolghasemi et al., (2019) studied the impact of demand volatility in the presence of promotion in Food Company, and proposed ARIMA model for short term food demand predication. Prominantly, Abolghasemi et al., (2019) has suggested the ARIMA model for low and moderately volatile products.

On thier work, Fattah et al., (2018) have demonstrated the way historical demand data could be utilized to forecast future demand, and how these forecasts affect the supply chain. As a result, Fattah et al., (2018) have found that the ARIMA model could be utilized to model and forecast the future demand in food manufacturing industry. El Bahi et al., (2018) has introduced the modeling and forecasting of fuel selling price using time series approach for short term fuel price predication, and the ARIMA model was proposed by the study (El Bahi et al., 2018).

In case, if seasonal components are needed to consider by the ARIMA model, then the model is referred as seasonal ARIMA (sARIMA) model Godwin & Fakiyesi, (2021). In this regard, scholars such as; (Gijo, 2011) proposed the sARIMA model for future tea demand predication by studding over short-term horizon of time-series sales data on the bases of monthly tea demand. Scholars such as (Talukdar, 2021; Sim et al., 2019) has proposed the sARIMA model for short-term electricity demand prediction, Godwin & Fakiyesi, (2016) has proposed the sARIMA model for short term coca-cola demand predication in Nigeria.

2.4.3 Review of Theoretical Models by Application Domains

As shown in Table 1 below, ANN approaches are now used in demand forecasting studies, and general time series methods have been used in a variety of fields. The earlier approaches focus on demand forecasting for a variety of goods and services, including cement demand prediction

(Nandal et al., 2023), food product sales (Aci & Yergök, 2023), and diaper product sales (Nandal et al., 2023).in the rising manufacturing industry (V.M. Sineglazov, 2023; Abbate et al., 2022).

In the later approach, the ARIMA and sARIMA models are extensively used in different forecasting domains, from different contexts. Regarding the ARIMA model, Fattah et al., (2018) and Abolghasemi et al., (2019) for food products demand prediction, El Bahi et al., (2018) for fuel selling price predication, Salami, (2017) for annual sales predication in 7Up Bottling Company, (Li et al., 2023), material demand analysis and forecasting in the rising manufacturing industry. Regarding the sARIMA model, (Sim et al., 2019) and Talukdar, (2021) for electricity demand prediction, Gijo, (2011) for tea demand predication; (Godwin & Fakiyesi, 2016) for Coca-Cola demand predication, in Nigeria.

In the case of drinking water bottling industry, (Israel et al., 2019) has proposed long-term demand forecasting algorithm based on neural networks for a small bottled water firm in Ecuador, specifically using customer order data from the previous 36 months; Artificial neural network (ANN) models were created by Bata et al. (2020) to predict short-term water demand by subtly using manufacturing costs, sales data, and product sales targets. Moreover, (Sentia et al., 2022) has also proposed a simulation model of the ANN method with the back-propagation algorithm to predict short-term water demand for bottling water industry by explicitly considering monthly averages product sales data.

In the later approach, Wofuru-nyenke & Briggs, (2022) have compared the classical forecasting methods such as the moving average, weighted moving average, exponential smoothing, adjusted exponential smoothing, linear trend line, Holt's, and Winter's model), while predicting demand in a bottled water supply chain, while demand data were obtained from a number of retailers. As a result, the weighted moving average forecasting model is proposed for predicting demand in a bottled water supply chain (Wofuru-nyenke & Briggs, 2022).

Since, historical data used for short-term forecasting will produce less uncertainty (more accurately) than long-term forecasting because in short-term forecasting conditions that affect demand tend to remain or change slowly (Sentia et al., 2022). Moreover, short-term demand forecasting facilitates water utility to manage the principal operations more efficiently (Bata et al., 2020). In this regard, according to Fattah et al., (2018), in the history of demand forecasting, ARIMA model has proved to perform better than other models because the model can replicate existing conditions, and therefore suitable to predict future short-term demand effectively. However, the model is not well exploited by past scholars in the case of water bottling company.

2.4.2 Review of Method of Analysis and Modeling

Regarding the method of time series analysis, prior scholars have discussed and proposed different methods for time series analysis. Past scholar such as (N. D. P. Barbosa et al., 2015) have used the ABC analysis. However, according to (Krajewski et al.2012), it is suggested that The ABC ranking, which establishes the product's significance in relation to demand and sales, is the most widely used technique for aggregating products..

Other scholars, for instance (Godwin & Fakiyesi, 2016; Salami, 2017; Godwin & Fakiyesi, 2016; Fattah et al., 2018) are among recent literatures that have used Three iterative processes make up the Box-Jenkins method: model identification, parameter estimate, and diagnostic testing of model identification, parameter estimation, and diagnostic checking steps. It use the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data as the basic tools to identify the order of the ARIMA model (Fattah et al., 2018). However, recently on their study (Sim et al., 2019), have compared the Box-Jenkins method and the Expert Modeler methods and found that both Box-Jenkins method, and Expert Modeler are eligible to forecast using sARIMA model. Indeed Expert Modeler is more sophisticated than the Box-Jenkins approach, which requires a manual review of the best model among many models found through testing. Expert Modeler uses SPSS to complete the forecast in a few clicks.Three iterative processes make up the Box-Jenkins method: model identification, parameter estimate, and diagnostic testing.

Regarding the procedure of ARIMA modeling and analysis, this review has found that the Box-Jenkins method have been widely used in most forecasting problems, and it has received significant attention by the state-of the art forecasting literatures. The Box and Jenkins was founded on the contributions of Yule and Wold to develop a practical approach in order to perform ARIMA models (Box & Jenkins, 1970). The Box–Jenkins principle consists of three iterative steps of model identification, parameter estimation, and diagnostic checking steps (Fattah et al., 2018).

On the other hand, the Expert Modeler is more advanced as compared to Box-Jenkins method for ARIMA modeling. According to, (Sim et al., 2019) With just a few clicks, the expert modeler, a black box tool in the Statistical Package for Social Science (SPSS), can execute ARIMA.

Recent scholars such as (Ruppert, 2017; Garcia-arismendiz et al., 2023; Sim et al., 2019) have utilized the Statistical Package for Social Science (SPSS) software package to for time series analysis and modeling. However, the Expert Modeler is not much considered by the state-of the art forecasting literature. In case of bottled water, even the method is not fully considered by relevant scholarly literatures.

Particularly, in the case of Ethiopia, almost there is no relevant empirical study was conducted yet. Despite, in Ethiopia Due to their current lack of proper demand forecasting techniques, the water bottling industry has experienced issues with non-conforming client demand, inventory shortages in certain situations, and surplus in other situations, all of which have led to financial losses. Therefore, in the present study the ARIMA model is used to estimate the future water demand in the case drinking water bottling industry. In the effort Box-Jenkins methodology and Expert Modeler procedure of modeling and evaluation were used, and the findings from the two methods is compared for the effectiveness in the SPSS software package.

CHAPTER THREE

3. METHODOLOGY

3.1 The Research Approach

In this research, a quantitative time series analysis and modeling approach is used. As time-series analysis and forecasting methods provide a constructive set of statistical techniques for determining the market demand that most probably to occur in the future. Therefore, in the present research work, time-series analysis and forecasting is employed to model and predict the future demand of bottled drinking water. Hence, a case study is conducted at NEHE drinking water bottling company operating in Shaggar, Ethiopia. The company has been manufacturing three distinct types of DELTA natural purified bottled drinking water products (0.6lt, 1.0lt, and 2.0lt) for the past few years.

Therefore, historical bottled drinking water sales data recorded over the past few years of each product verity is obtained from NEHE drinking water bottling company that has been operating in Addis Ababa, Ethiopia. As a result, the present research work organizes, analyze and utilize the historical data to develop a predictive model. Hence, a quantitative approach, particularly time-serious analysis and modeling have been considered by this research work.

Consequently, two methods for implementing ARIMA have been examined in this study: the Box-Jenkins methodology and Expert Modeler in IBM SPSS.

3.2 Theoretical Framework of the Research Work

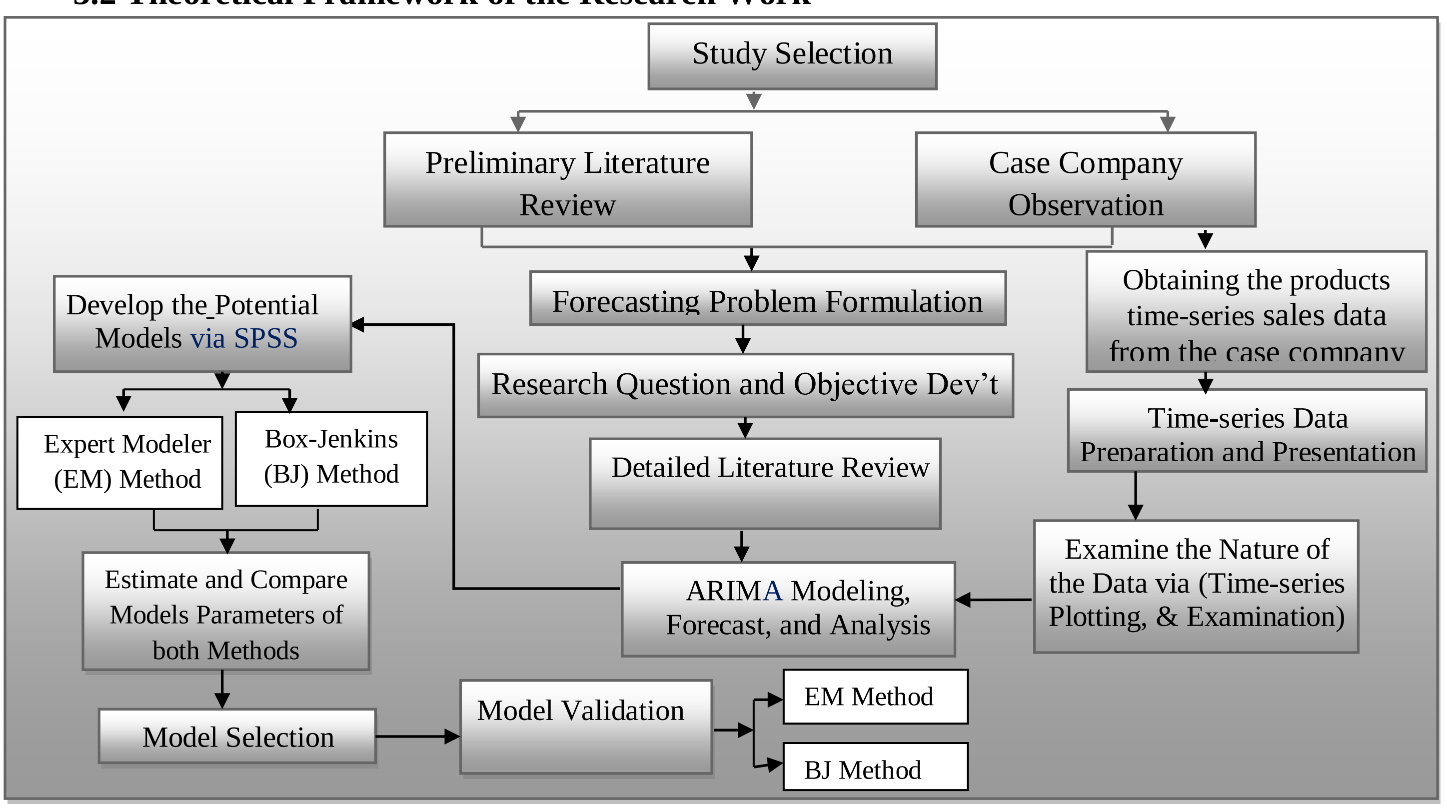


Figure-2: Theoretical framework of the research work

3.2.1 Defining Problems, and Key Elements

Defining the Forecast Problem

According to Vi Phung-thao, (2019), defining the forecasting problem requires understandings about the nature of the available historical data and its reliability, the usage of the forecasts, and the time horizon for which the forecasts will be made. Moreover, according to scholars such as (Hanke and Wichern, 2014; Hyndman and Athanasopoulos, 2018), it is vital to start the forecasting process by defining the reasons for whom the forecast should be made. Therefore in the present study, the aforementioned pieces of information were obtained from the case company through facilitating an interview session with relevant representatives of the case company.

Defining the Forecast Horizon

In this research work, short-term with a horizon of time series data over a period of one month is used to estimate the future demand (estimated sale) of products of the case company. The rationale considered here is that, short-term forecasting helps water utility to more efficiently manage many of their principal operations effectively (Bata et al., 2020). Moreover, the reason for the choosing a time-horizon of one month is primarily based on the need of the case company and the specification for the production planning system. This is in line with the forecast which is conducted manually by the experts of the case company, which is with a horizon of one month yet. Besides, the specification for the planning system requires it to produce a detailed production plan for at least the next one month.

3.2.2 Data Collection, Preparation and Presentation

Preliminary Data Collection (the Early Stage of the Study);

During the initial phase of this study, the researcher (I) wanted to the case company and made preliminary observation on the existing practice of production planning, the forecasting practice, the forecasting tool used in the company, related fundamental activates, and the challenge they have been faced. In this stage, (I) the researcher tried to examine past production, customer orders, and company sales data to the potential market demands which is so far recorded by marketing and sales department of the company. So, a list of interview questions was formulated through preliminary literature review (see Appendix-2: Key Informant Interview Questions). As a result, (I) the researcher identified, and formulated the research problem which is stated in Chapter-one: Section-1.2 of this research.

Actual Data of the Research;

Since, the case company has been manufacturing three distinct types of DELTA natural purified bottled drinking water products (0.6lt, 1.0lt, and 2.0lt) for the past few years. Therefore, because of the existence of somehow complete sate of recorded total quantity of produced data to attain potential customer such as produced to attain customer order, and produced to the market sales data of the products from Apr, 2021 to Sep, 2024. The production planning department head of the case company has advised to secure the recorded data and use effectively for the purpose of this research only. Hence, the total monthly production and the quantity sold out to the wider target market recorded from Apr, 2021 to Sep, 2024 was gathered from the production, and sales and marketing department of the case company. As a result, the obtained time-series data is thoroughly organized and used for further analysis and modeling.

3.2.2 Data Preparation and Presentation Phase

In this stage, the recorded data that constituted the total quantity product produced per month, particular product quantity produced based on customer ordered, and the total sold out quantity of product per month of bottled water products obtained from NEHE water bottling company were processed to the format that suits for the further analysis stages. For instance, the obtained quantity of product sold to the targeted market per each month were coded, tabulated, evaluated with respect to the production quantity per month, and organized on particular total monthly market sales quantity (Qty.) format. These activities were conducted with respect to each of three distinct products of the case company. As a result, the prepared monthly total production and quantity of each product sold to the targeted market per each month that is utilized for time-series analysis and ARIMA modeling is presented in Table-1.

In the Table-1 below, products total production per month that contains of quantity of product produced for customer ordered per month plus quantity remain on stock per month + total sold out quantity to the market per month is presented on the bases of number of package per month (i.e., 1-pack =12-bottles for 0.6litre and 6bottles for 1 and 2litrre). For time analysis, this study considers the products total production per month that contains of quantity of product produced for customer ordered per month + quantity remain on stock per month plus the total sold out quantity to the market per month. However, to develop time series model in such a way to predicate the feature market demand with respect to the potential customer of the company, therefore the present study uses records of sold out quantity to the wider target market per month over the past three years. The Table-2 below presents the data obtained from the case company.

Table 3: Time-serious data; total quantity of BW produced/month, and product sold to the target market/month

S. No	**Time-Series**	**Quantity of product-1** (0.6lt bottled water) / **month**		**Quantity of product-2** (1.0lt bottled water) / **month**		**Quantity of product-3** (2.0lt bottled water) / **month**	
		Production per month	**Qty Sold out to the market**	Total production per Month	**Qty Sold out to the Market**	Production per Month	**Qty Sold out to the market**
1	APR 2021	1280.00	1214.00	8520	7325	10395	9625
2	MAY 2021	1661.00	1541.00	13472	8607	13198	10109
3	JUN 2021	1743.00	1421.00	8501	7418	8005	6746
4	JUL 2021	2674.00	1720.00	20737	10043	11720	11370
5	AUG 2021	2611.00	1980.00	8189	9443	11833	11807
6	SEP 2021	1206.00	1640.00	13179	9851	11122	9944
7	OCT 2021	2649.00	1809.00	14963	9986	18047	11921
8	NOV 2021	1490.00	1490.00	13483	10369	16052	13625
9	DEC 2021	2150.00	1967.00	12772	8759	21581	11509
10	JAN 2022	3074.00	2020.00	19761	10920	29254	14348
11	FEB 2022	2611.00	2680.00	8898	10286	9532	13515
12	MAR 2022	3427.00	2787.00	12458	10279	14266	13507
13	APR 2022	3278.00	1989.00	11058	9478	13272	12454
14	MAY 2022	5547.00	2432.00	9624	11991	9695	10356
15	JUN 2022	4881.00	2781.00	8691	10483	11588	12574
16	JUL 2022	3113.00	3613.00	18258	11299	34236	14847
17	AUG 2022	5936.00	3936.00	39688	11679	46483	17746
18	SEP 2022	2654.00	2954.00	16736	13093	50839	16004
19	OCT 2022	2430.00	3830.00	18422	11719	19123	15399
20	NOV 2022	5576.00	4176.00	21985	12445	17867	16352
21	DEC 2022	3803.00	3803.00	30271	13981	22806	18371
22	JAN 2023	1605.00	3705.00	26104	16368	21397	20307
23	FEB 2023	3570.00	3670.00	34568	20096	28745	21007
24	MAR 2023	3726.00	3611.00	37407	21253	30511	24326
25	APR 2023	4630.00	4093.00	47946	23072	48445	26117
26	MAY 2023	4743.00	4342.00	38746	22669	42407	29786
27	JUN 2023	6514.00	4814.00	33402	22723	42005	29857
28	JUL 2023	2919.00	4919.00	32578	25774	32993	32066
29	AUG 2023	6194.00	5494.00	41089	28985	49845	30287
30	SEP 2023	7798.00	4698.00	43353	23353	52474	28886
31	OCT 2023	4630.00	3930.00	46459	25126	19123	33615

32	NOV 2023	5776.00	5638.00	31084	29259	17867	32446
33	DEC 2023	6810.00	5110.00	37286	23403	22806	30751
34	JAN 2024	6630.00	5330.00	47428	28052	21397	35660
35	FEB 2024	4900.00	5040.00	41622	29857	28745	34432
36	MAR 2024	5689.00	4070.00	48607	30497	30511	37072
37	APR 2024	6440.00	5100.00	33839	32304	48445	35247
38	MAY 2024	6743.00	5541.00	48684	32900	42407	37230
39	JUN 2024	6671.00	5411.00	39495	34322	42005	39100
40	JUL 2024	6190.00	5700.00	45952	34083	32993	38185
41	AUG 2024	6700.00	5362.00	41089	35449	49845	37579
42	SEP 2024	5607.00	5764.00	46760	37445	42353	37202

3.3 Examining the Nature of Time-series Data

In time-series analysis, according to (Fattah et al., 2018), the forecasting accuracies depend on the characteristics of time-series of demand data. Here, the data forecasting ability can be determined based on the existence of data patterns, which can be identified and modeled, and are likely to occur in the future (Vi Phung-thao, 2019). Hence Basic tests like the stationery test are performed in order to find potential patterns, such as trends in the data or seasonality or non-seasonality, by first plotting the pre-prepared time-series data, generated data, and sold out data into a graphical display. Thus, the study measures and assesses the forecasting power of the data Sequence charts and other time-series plots have been employed in this work for this aim.

In order to determine potential patterns, such as the time series' linearity or stationarity, the prese nce of trends or seasonality, and the data's forecasting capabilities, the time-series data is plotted into a graphical presentation at this stage of the research project. The time-series plot of each product's production and quantity sold to the larger target market, together wit h the relevant time periods, is displayed in Figure 3.

3.5 Statistical Tool, Modeling and Analysis Methods

3.5.1 Statistical Tools

In order to develop the conduct time-series analysis of the data sate, develop the ARIMA modeling, estimate the models parameters and verify the forecast findings, therefore the research work uses the Statistical Package for Social Science (SPSS) software package version.26. Here, the rationale for selecting the SPSS software package is that; the software package is easily availability, the knowhow is simple, it’s ability to adjust the forecasts with the wider span of statistical methods associated with the software package.

3.5.2 The Autoregressive Integrated Moving Average (ARIMA) model

Characteristically, the ARIMA model is presented as a combination of; autoregressive models (AR), differencing models, and the moving averages (MA) (Tereshchenko, 2018);

The Autoregressive Process; Autoregressive models assume that Y_t is a linear function of the preceding values and is given by equation-1.

$$Y_t = \alpha_1 Y_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{ Equation} - 1)$$

Were: ε_t is a random component and a linear combination of the previous observations,

α_1 is the self- regression coefficient.

The integrated process; the integrated processes are the archetype ofnonstationary series. A differentiation of order-1 assumes that the difference between two successive values of Y is constant. An integrated process is defined by equation-2;

$$Y_t = Y_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{ Equation} - 2)$$

The moving average process; the moving average order indicates the number of previous periods embedded in the current value. Thus, a moving average is defined by equation-3.

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{ Equation} - 3)$$

The forecasts are expressed as a linear function consisting of the nearest true value and the nearest forecast error (Li et al., 2023). The model is given by equation-4;

$$Y_t = \delta + \alpha_1 Y_{t-1} - \theta_1 \varepsilon_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{ Equation} - 4)$$

Where Y_t, Y_{t-1}: sales of period t and $t-1$, respectively;

$\varepsilon_t, \varepsilon_{t-1}$: residuals of period t and $t-1$, and constitute a white nose;

α_1, θ_1: coefficients of autoregressive and moving average processes respectively.

3.5.2 Modeling and Evaluation Methods

In this research work, both the Box–Jenkins procedure for ARIMA modeling and Expert Modeler method are considered.

3.5.2.1 Box–Jenkins procedure:

The most widely used method for ARIMA modeling is the Box-Jenkins method. The method consists of three iterative steps;

- The data characteristics
- Model identification
- Parameters estimation

- Diagnostics for getting the best model
- Forecasting

3.5.2.2 Expert Modeler procedure:

However, the expert modeler is a black box tool in SPSS that allows you to implement ARIMA with only a few clicks without having to go through the previously outlined Box-Jenkins approach by hand. The novel Expert Modeler is more advanced than the Box-Jenkins method. The method performs the ARIMA modeling and forecasts in a few clicks automatically in the SPSS software packages. However, the Expert Modeler method is scarcely considered by relevant previous scholars.

Therefore, in this research work, both the Box–Jenkins, and Expert Modeler method are considered. As a result, the resulted models and parameters from the both the Box–Jenkins, and Expert Modeler method with respect to each products is tabulated, and statistically analyzed.

3.5.2.1 Methods for Model Evaluation

Regarding the methods of analysis, according to (Fattah et al., 2018) If a time series is derived from an ARIMA process, it should possess some theoretical autocorrelation qualities, according to the usual criterion for identifying the model. In order to determine the order of the possible ARIMA models, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the sample data are regarded as essential tools in this study.

As a result, it is possible to use the ACF and PACF to recognize patterns that characterize moving average (MA), autocorrelation (AR) and mixed (ARIMA) models, when the assumption of stationary has been satisfied. It should be appreciated that the study is focusing on theoretical models, but this does facilitate recognition of similar patterns in actual time series data. By comparing actual ACF's and PACF's to the theoretical patterns, the study shall be able to identify the specific type of ARIMA model that will adequately represent the data.

This study then finds one or more possible models for the provided time series data set by contrasting the theoretical and empirical autocorrelation patterns. Finally, in order to examine the performance of the ARIMA process of SPSS of the Box-Jenkins, and Expert Modeler method, this research work evaluate, tabulate and compare the mean absolute percentage errors (MAPE) of both methods.

3.5.2.2 Assumptions

The following hypotheses are used to identify significant models:

H0: There is a unit root in the series.

H1: there is no a unit root of series. The series does not move.

3.6 Performance Evaluation; the Box-Jenkins Method Vs Expert Modeler

The mean absolute percentage errors (MAPE) of the Box-Jenkins technique and Expert Modeler SPPS will be used to compare their respective performances.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}}{n} \times 100\%, \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\text{Equation} - 5)$$

Where, n is the number of data, y_i and $y_i\hat{}$ are real and predicted values correspondingly.

Chapter Four

4. Result and Discussion

4.1 The Characteristics of Time-series date, and Implications

4.1.1 Preliminary Time-series Analysis

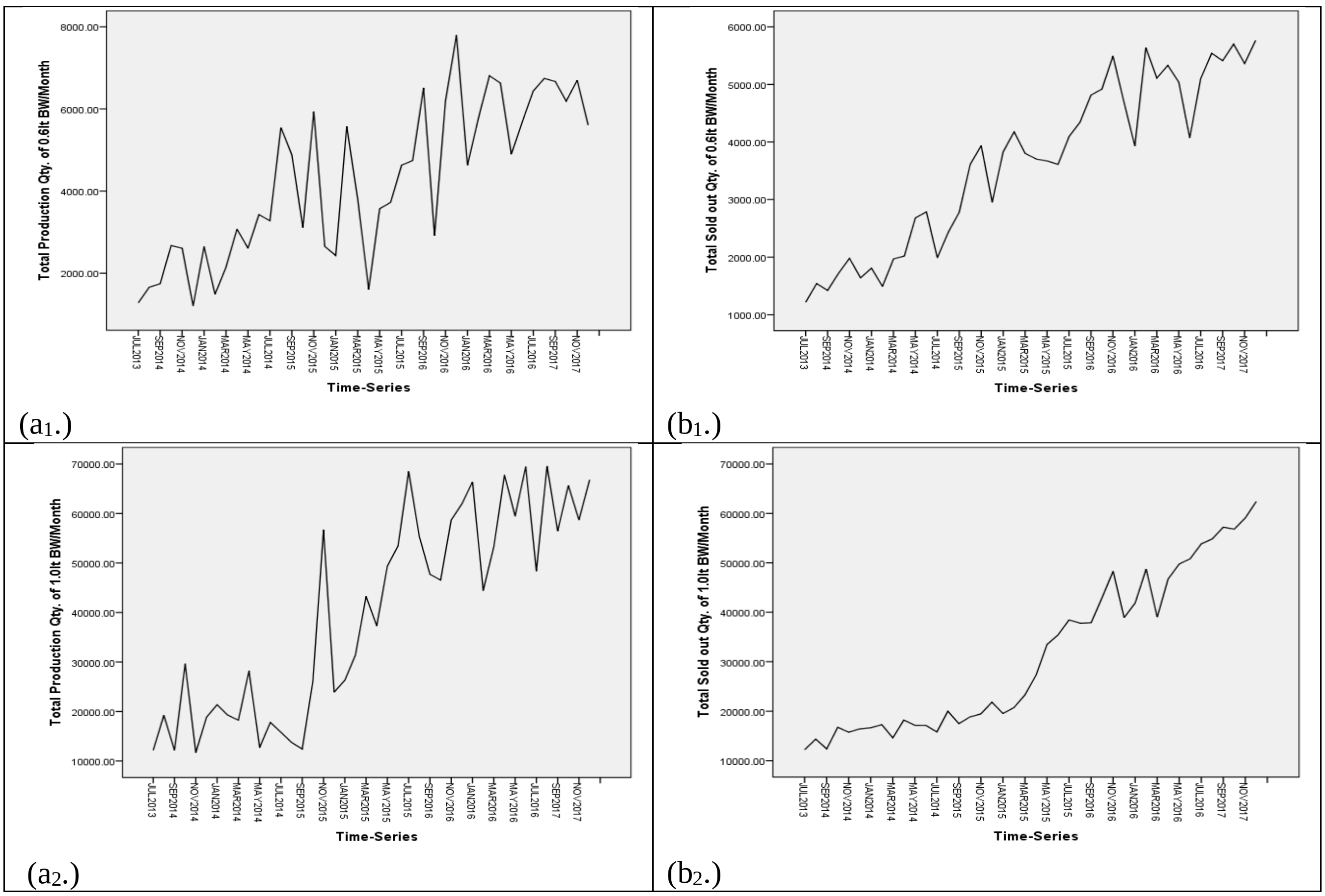
It is obvious that, the case company NEHE drinking water bottling company that has been operating in Shaggar, Ethiopia, and it has been manufacturing three distinct types of DELTA natural purified bottled drinking water products (0.6lt, 1.0lt, and 2.0lt) for the past few years. In this research, due to the existence of well documented data with respect to the total quantity of particular products from Apr, 2021 to Sep, 2024 in such a way to attain potential customer demands.

Generally speaking, product demand planning involves forecasting and making plans for the market's demands for a specific future time frame. Therefore, the market projection is one of its primary resources. Orders that have been received with future delivery dates and quantities indicated are another significant source of product demand.

According to the production planning department head of the case company, such particular products were produced to attain particular customer order, and produced to sell out to the wider customer in the market. In this study, for time series analysis and ARIMA modeling, the researcher (I) have considered the total monthly production and the quantity sold out to the wider target market recorded from Apr, 2021 to Sep, 2024 and the data is obtained from the record of the production, and marketing and sales department of the case company. As a result, the obtained time-series data is thoroughly sorted, organized and used for the purpose of this research only (i.e., time-series analysis and modeling).

The pre-prepared monthly total production and quantity of each product sold to the targeted market per each month that is utilized for time-series analysis and ARIMA modeling is presented in Appendix-2. Thus, the researcher (I) tried to transform the tabulated time series data in to graphical sequence chart plot with the aim to examine the characteristics of the data obtained from the production, and marketing and sales department of the case company. For the purpose of analysis and modeling the time series data, the data was sorted, coded, and tabulated at first stage (see Table-1 in the appendix section). Then, the sorted, coded and tabulated data with respect to 0.6lt, 1.0lt, and 2.0lt Bottled Water (BW) products of the case company is transported in to the SPSS data analysis software package, Version 23.

Figure-3 below presents, the sequence chart is plot developed by using SPSS statistical software package. In the sequence chart plot shown below, the right hand side chart (a1, a2, and a3) represents the plot of bottled water (BW) products of the case company total production quantity, and the left hand side (b1, b2, and b3) represented the plot of total quantity product sold out to the target markets per each moth over the time series considered in this study.



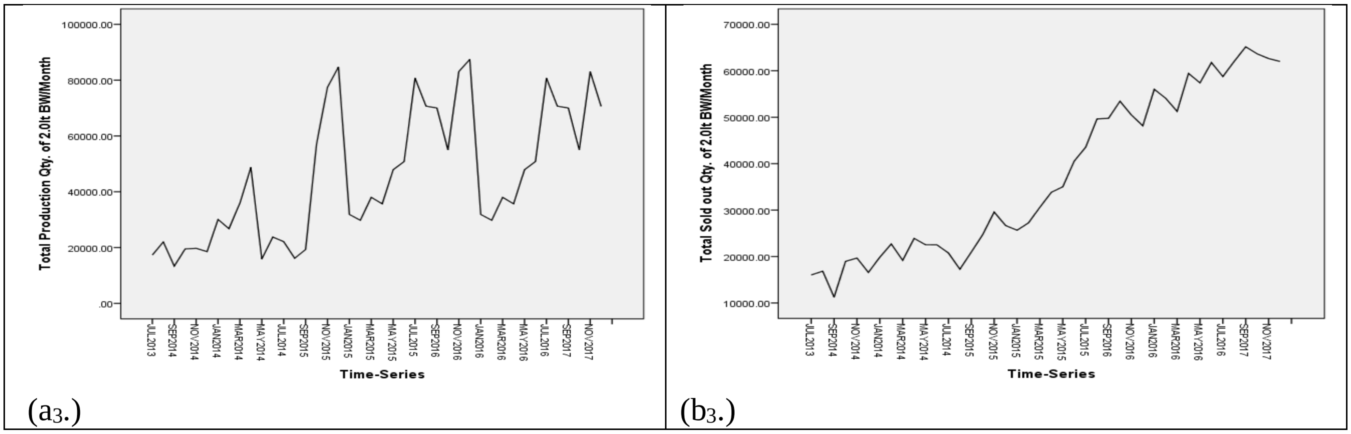


Figure 3: Evolution of the final product's total production quantity (a1, a2, and a3), and sales data (b1, b2, and b3) sequence charts (i.e., time series plot without transformation)

In the Figure-3 shown above, the sequence chart a_1, a_2, and a_3 are the plot of total production quantity of 0.6lt, 1.0lt, and 2.0lt Bottled Water (BW) over the considered time series respectively. In addition, the sequence chart b_1, b_2, and b_3, in the Fgure-3 represent the plot of total product sold out quantity to the potential customer on the market for 0.6lt, 1.0lt, and 2.0lt Bottled Water (BW) over the considered time series respectively.

Indeed, As demonstrated above in the cases of b1, b2, and b3, time-series data frequently exhibits features like distinct trends and patterns, which are easier to explain than cyclical patterns which is shown above in case of a_1, a_2, and a_3. When such clear patterns (as shown in Figure-3; a case of b_1, b_2, and b_3) do not exist in the data, it is almost impossible to forecast (Chase, 2013). From the time-series plot (shown in Figure-3; a case of b_1, b_2, and b_3), such characteristics are observed in the time-series data with respect to each of the three products of the case company.

In line with the with the pattern of the time–series plot seen in this research work, scholars such as (Gijo, 2011; Fattah et al., 2018) has also suggested that most of the real-life time-series data show similar properties. To improve customer happiness, the company will deliver the items based on the intended data, as opposed to the data from the market research. There can be repetition and variance if the orders and market projections are taken into account simultaneously. These repeats will therefore be removed from the dataset since they are the main sources of variances that could affect the forecast accuracy**.**

In this research, the total production data recorded over the time-series considered in this research work with respect to each of the three products of the case company is characteristically not-relevant to generate accurate forecast of the future occurrence of the events. In the Figure-3 above, (a1, a2, and a3) represents the plot of total production quantity of bottled water (BW) products of the case company produced over the considered time series. In this regard, detailed analysis of the recorded data, and further interview was made with the sales and marketing department of the case company has given the following information;

According to the sales and marketing department head of the case company, the total production data of bottled water products constituted; quantity of products produced based on the special customer order at specific period of the series, which is additionally produced quantity from the quantity of product panned and produced to attain the wider market demand of the company which is presented as the total sold out quantity of products. Further examination of the plots a1, a2, and a3 in Figure-2 above also shows greater variability of the production quantity over the study's time series, and it is not consistent with the attained sales to the potential market demand.

In addition, the sales and marketing department head of the case company has also stated that; the greater source of variation for the total production data over the time series is not only the additional quantity produced to attain special customer orders at a particular time, but also the conventional market demand forecasting practice of the company that cannot provide clear information which that is vital for precisely estimating future product demands for the production planners.

The sales and marketing department head of the case company further explained that, the miss alignment of the planned production proposal and the actual production with the actual market need has also resulted excessive stoke of products in some period of time, and shortage of product to attain the wider customer demand in the other periods. This is also clearly observed from the sequence plots presented in Figure-1, by comparing the demand patterns on the right hand side chart (a1, a2, and a3) and the left hand side (b1, b2, and b3).

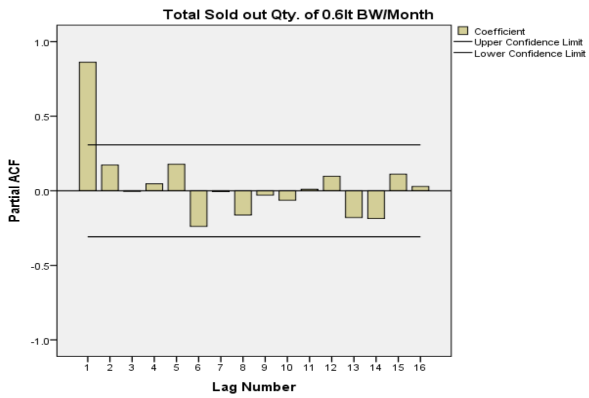
Hence, for each of the three goods of the case company, the sales data set with the sequence plots in b1, b2, and b3 is characteristically important to forecast the future occurrence of the events considered. Thus, according to Vi Phung-thao, (2019), time-series forecasting methods for these kinds of pattern (i.e., with data characteristics constituted trend, seasonality or both patterns) as shown in plot b1, b2, and b3 is believed to deliver better insight into the future, rather than the rapidly changing or untraceable pattern as shown in plots of a1, a2, and a3 or with only flat forecasts generated from stationary models. Yet, such pattern in the dataset is considered as the enemy of stationery which makes the modeling process very difficult. Hence, it is vital to further refine the sales data so as to make it stationer.

Hence, as short-term forecasting can help a water utility to more efficiently manage many of their principal operations (Bata et al., 2020). Therefore, in this research forecast to be generated is used to estimate the future short-term demand of bottled drinking water products of the case company. In this regard, prior scholars have proved the Autoregressive Integrated Moving Average (ARIMA) model is to perform better than other time-series models to predict the future short-term demands effectively (see scholars such as; Fattah et al., 2018; Abolghasemi et al., 2019; Sim et al., 2019).

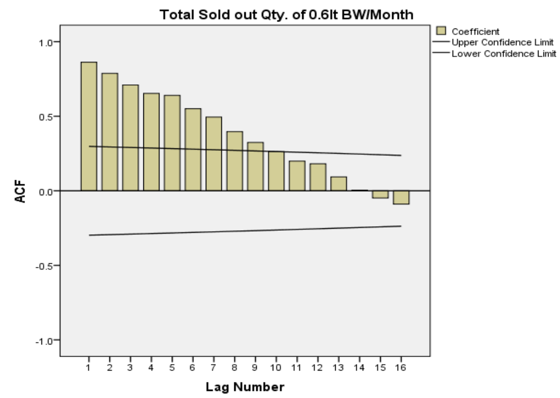
Therefore, in this sub-section, the application of ARIMA model is employed by considering the Box–Jenkins procedure of ARIMA modeling so as to develop and choose a model that can better predict the future bottled water demands of products of the case company.

4.1.2 Stationary Test of the Sales Dataset

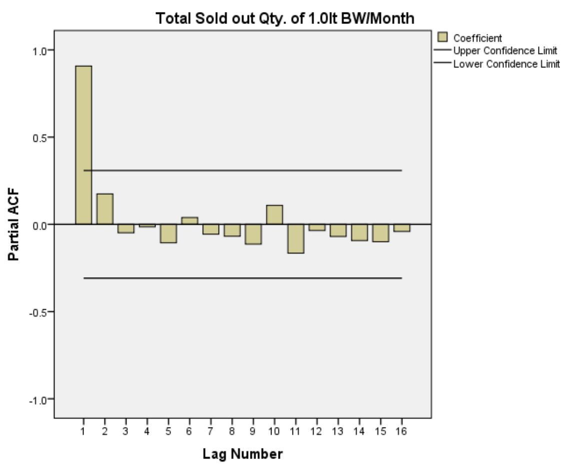
In this stage, the aim of this research is to examine the stationary and normality nature of the sales data set of the three distinct product types of the case company. Therefore, the study first preprocesses the data to make it stationary in this step. Next, it selects potential values for p and q, which can obviously be changed as the model fitting process goes on Hence, the autocorrelation function (ACF) and the partial autocorrelation function (PACF) plots are created as shown below in Figures-4 respectively for each products of the case company so as to examine the stationary and normality nature of bottled water sales dataset.



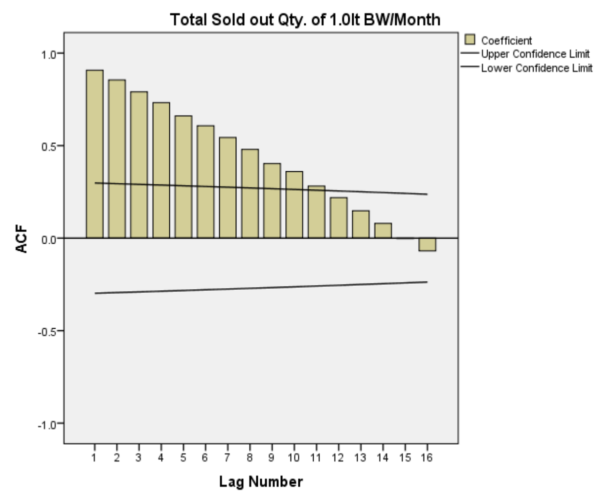
Partial ACF of 0.6lt BW sales data



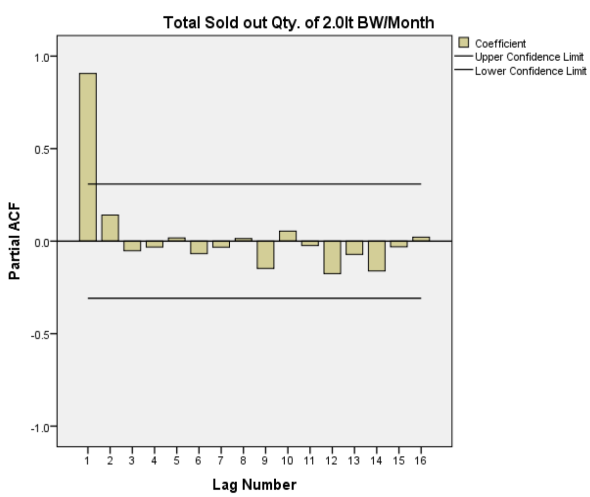
ACF plot of 0.6lt BW sales data



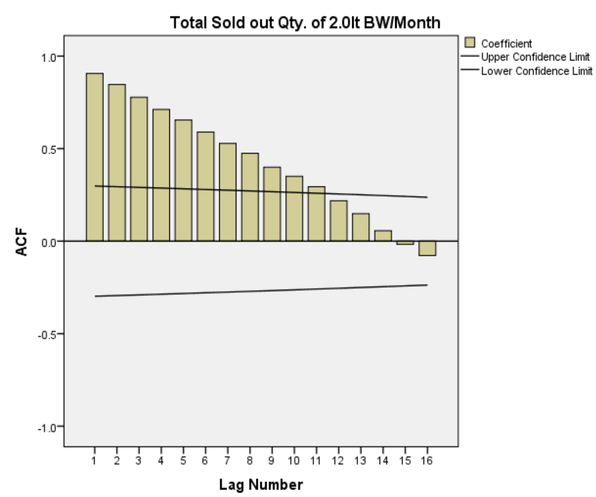
Partial ACF of 1.0lt BW sales data



ACF plot of 1.0lt BW sales data



Partial ACF of 2.0lt BW sales data



ACF plot of 2.0lt BW sales data

Figure 4: The Partial ACF and ACF plots of the sales data i.e., without transformation (d = 0)

As it can be seen from the Figures-4 above in the ACF plot, it is clearly seen that the demand for bottled water over the considered time series is non-stationary. According to This is because, instead of rapidly dropping to zero, the ACF of non-stationary series stays substantial for six or more delays. Hence, first differencing with transformation @ d = 1 shouled be employed to the detaset.

The ARIMA model is labeled as an ARIMA (p,d,q) model, the parameters (p, d, q) are called as the model parameters (Fattah et al., 2018):

Where :- p-reperesent autoregressive term

- d is the differences; and

- q is moving averages.

Since, the ARIMA (p,d,q) model implies that the time series is differenced "d" times and that each observation in the series is represented by a linear combination of the past "p" observations and "q" residuals. The prediction is "error-free" or integrated to achieve the final prediction (Li et al., 2023).

Thus, the parameter "d' in the ARIMA (p,d,q) model takes a value of unity (i.e., with transformation @ d = 1). Then, in order to estimate the appropriate values for the remaining parameters (p and q), it is essencial to plot the ACF and/or the PACF of the sample data for the first order differenced data (Ruppert, 2017). Therefore, the datasate sholed be further processed so as to make it stationary.

Then, this research work chooss's the possible values of "p" and "q" which can be adjusted with the model fitting progresses. Hence, the time-series plot of the sales dataset of bottled water of each products of the case company over the considered time-series @ d = 1 is created. The time-series plot with a difference, d= 1 is shown in Figures-5 below for the three products of the case company distinguished by colors are created.

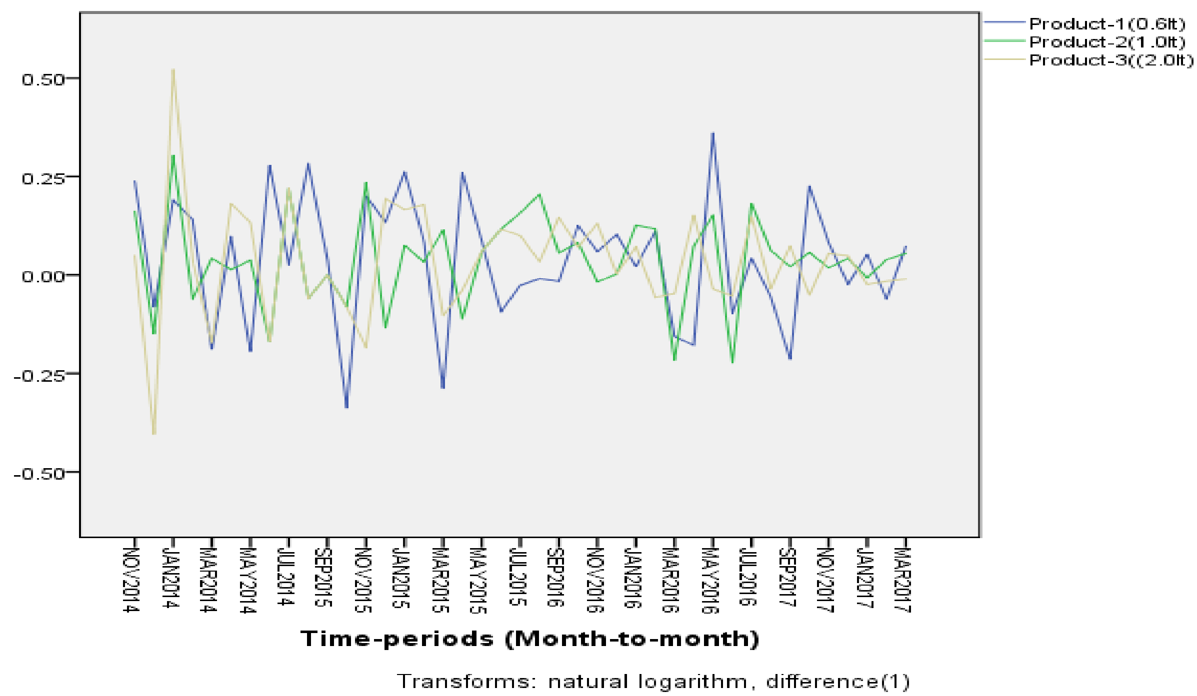
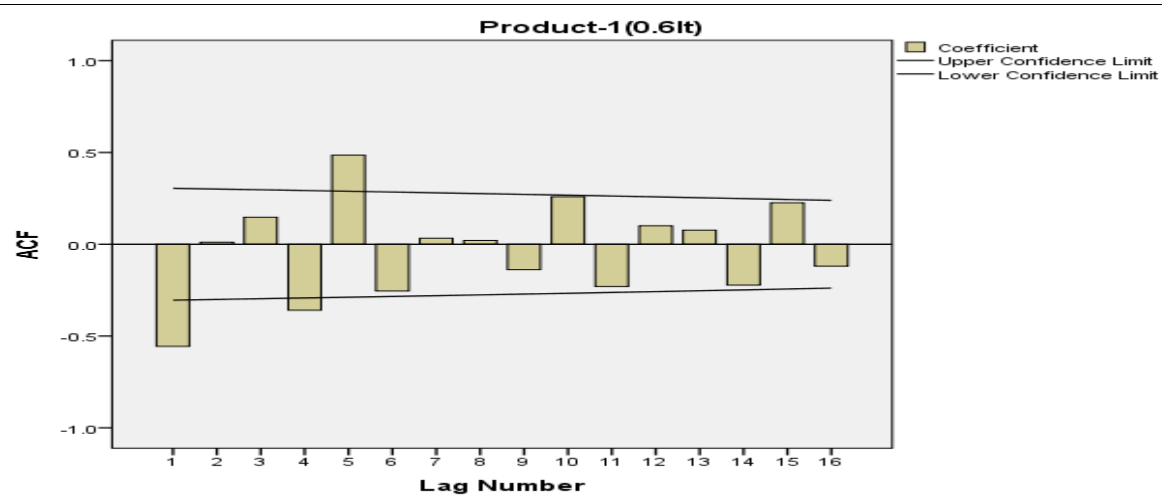


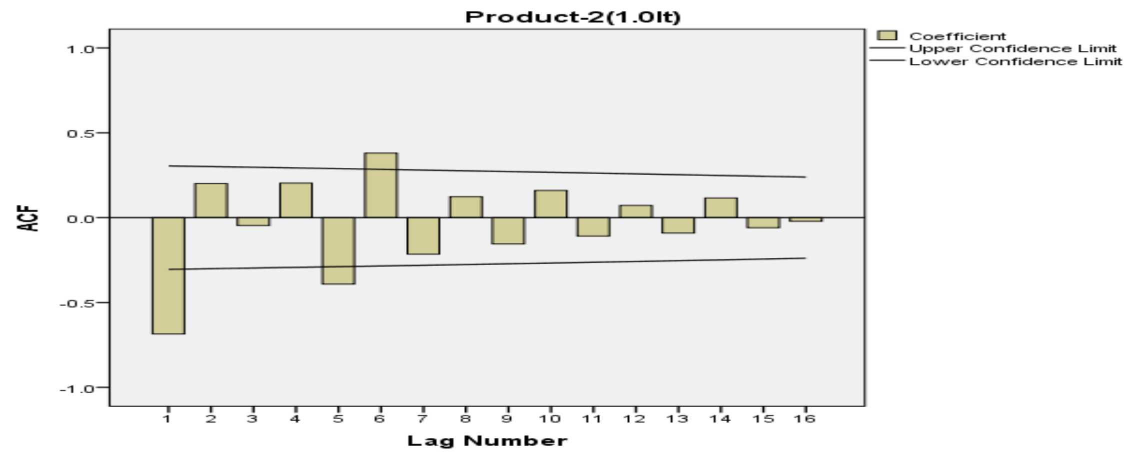
Figure 5: Time-series plot with transformation, **d = 1**

As it can be seen above in Figure-5, the variance of the sales dataset is converged around the constant mean value, and this is evidenced by the enclosed variance between 0.5 and -0.5. Thus, it proves the stationary nature of the time-series data with transformation d=1.

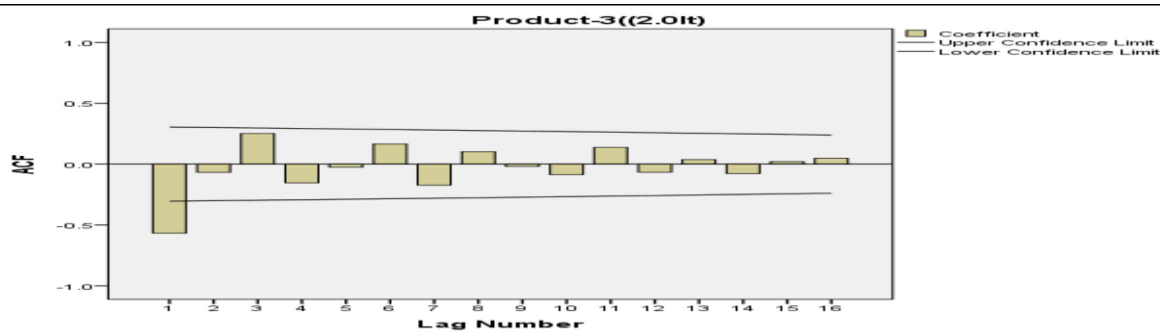
Moreover, the ACF and PACF plot with transformation d = 1 is plotted on SPSS tool is shown below in Figures-6.



ACF plot of 0.6lt BW sales data



ACF plot of 1.0lt BW sales data



ACF plot of 2.0lt BW sales data

Figure 6: The Partial ACF and ACF plots of the sales data (i.e., with transformation @ d = 1)

Figures 5 and 6 above illustrate a stationary and normal time-series plot with a difference of d = 1. The time-series plot seen above in Figure-5 with a difference, d= 1 is evidenced by the enclosed variance between 0.5 and -0.5. Moreover, the ACF plot seen above in Figure-6 is also additional evidence that the ACF decays to zero fairly rapidly, which proves the stationary nature of the time-series with transformation d=1.

Here, after verification of the stationary nature of the series, it is also observed from the ACF and PACF correlograms that the model of the present study is not pure AR or pure MA. Therefore, it is important to test several models and to identify the model that is most suitable one for future sales predication. As a result, in the next sub-section this study has tested several ARIMA models to identify the most suitable one for the sales of 0.6lt bottled water, which is one of the majorly produced products of the case company, and the finding can be customized for the remaining products of the case company.

4.1.3 Identification of the Potential Models

4.1.2.1 Estimation of Model's Coefficients

By supplying the parameters p, q, and d, the SPSS time series module's ARIMA process enables the estimate of the models' coefficients using a quick maximum likelihood estimation algorithm. When the process is carried out, new time series that show the values that have been modified or projected by the model, residuals (adjustment errors), and adjustment confidence intervals at a 95% confidence level are added. The ideal model minimizes a number of criteria and is as straightforward as feasible.

The forecasts are expressed as a linear function consisting of the nearest true value and the nearest forecast error (Li et al., 2023). Accordingly, the chosen model parameters for the sales data of 0.6lt bottled water are presented in Table-5 below.

The table summarizes the values model different parameters for the sales dataset of 0.6lt bottled water (Product-1), and proves the choice of the model on which this study will use as a base for the future demand predictions from the sales quantity of bottled water of the case company, and can be customized for the remaining products of the case company as well as for related manufacturing industries.

Table 4: Summary of the potential ARIMA models parameters (for the sales data of 0.6lt BW)

Models	R^2	Est.	Sig.	Remark
ARIMA(1,1,0) (2,0,0)	0.875	0.19	0.022*	Most other parameters remain not significant.
ARIMA(0,1,1) (0,1,1)	0.61	0.34	0.052	Most other parameters remain not significant.
ARIMA(0,1,0) (2,0,1)	0.875	0.45	0.01*	Other parameters remain significant.
ARIMA(2,1,1)) (1,1,1)	0.619	0.33	0.156	Most other parameters remain not significant.
ARIMA(1,1,1) (1,1,0)	0.66	0.31	0.15	Most other parameters remain not significant.
ARIMA(0,1,1) (1,1,0	0.58	0.28	0.44	Most other parameters remain not significant.

4.1.3. Diagnosis check for the model fitness (Test for the Assumptions)

In this study, the following assumptions are used to identify significant ARIMA model on which this study will use as a base for the future demand predictions from the sales quantity of 0.6lt bottled water of the case company:

H0: There is a unit root in the series.

H1: there is no a unit root of series. The series does not move.

According to (Sim et al., 2019), if α > 0.05, then the model is not significant, therefore accept H0. On the other hand, if α < 0.05, the model is significant, therefore accept H1. Accordingly, from Table-4, above it is clearly shown that, the ARIMA (0, 1, 0) (2, 0, 1) has met the assumptions. Hence, from Table-4, it is clearly shown that only ARIMA (0, 1, 0) (2, 0, 1) has met the assumptions of the model diagnostics.

4.1.4. Forecasting

After determining which demand model is best for our situation, we must forecast. To do this, we used IBM SPSS Forecasting to identify patterns and create a prediction. The results of our sales estimates for the following two months using our model ARIMA (0, 1, 0) (2, 0, 1) are shown in Table 4 and Figure 5. It is evident that the selected model may be used to model and anticipate future demand in the purified water bottling industry. However, in order to improve the new model and forecasting, we must constantly update the historical data with fresh information. The forecasted plot of ARIMA (0, 1, 0) (2, 0, 1) through Box-Jenkins method is shown in Figure-6 and the forecasted results of the next two month were presented in Figure below.

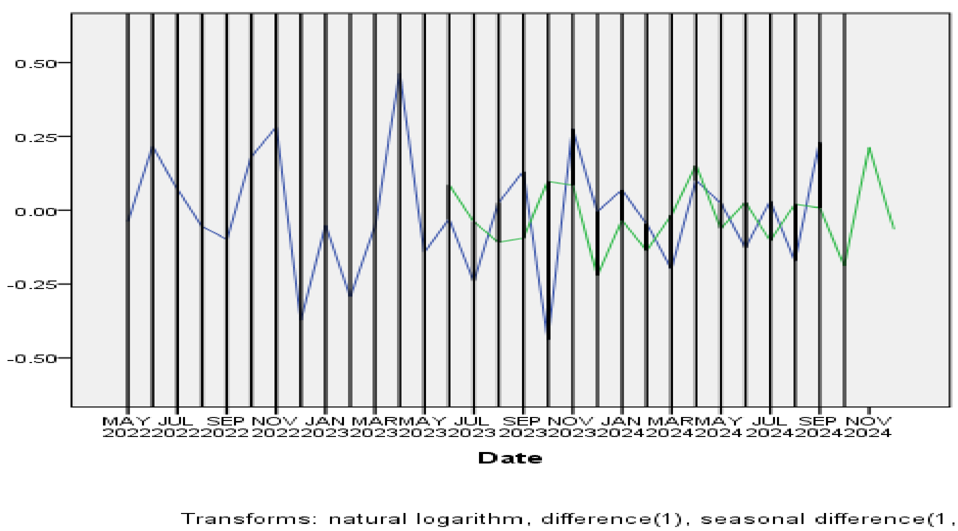


Figure 7: The forecast generated by the significant model (ARIMA (0, 1, 0) (2, 0, 1))

Figure-7 above shows the model is adequate as it shows a random variation from the origin zero (0), the points below and above are all uneven, hence the model fitted is adequate.

4.3. ARIMA Modeling with the Expert Modeler

Table 7 displays the results of the comparison between the Box-Jenkins technique and Expert Modeler SPSS, which comprised parameter estimation, model statistics, and the predicted outcome. It shows that the Expert Modeler's results are roughly superior to those of the Box-Jenkins approach.

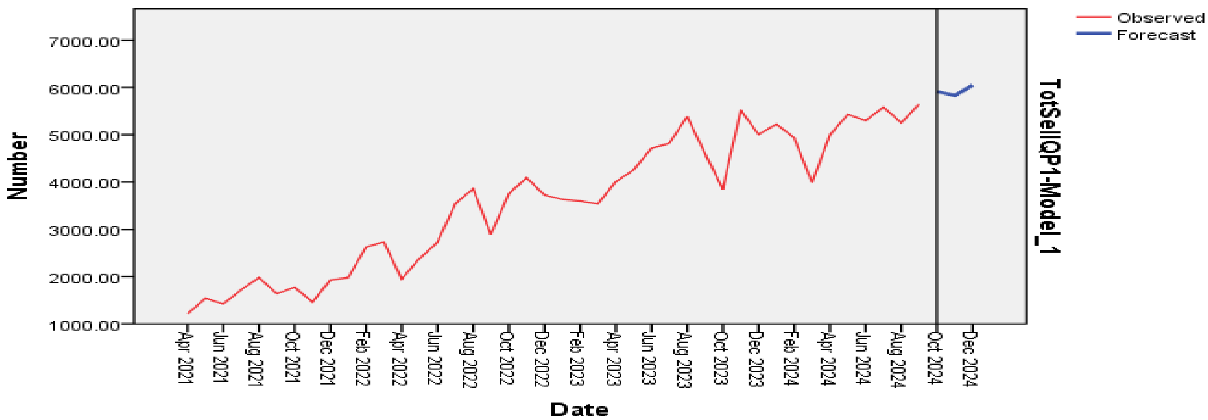


Figure 8: A plot generated through Expert Modeler procedure of ARIMA modeling

4.3 Comparison of Box-Jenkins Method with Expert Modeler futures of in SPSS

Regarding the procedure of ARIMA modeling and analysis, this review has found that the Box-Jenkins method have been widely used in most forecasting problems, and it has received significant attention by the state-of the art forecasting literatures. The Box and Jenkins was founded on the contributions of Yule and Wold to develop a practical approach in order to perform ARIMA models (Box & Jenkins, 1970). The Box–Jenkins principle consists an iterative steps of model identification, parameter estimation, and diagnostic checking steps (Fattah et al., 2018).

On the other hand, the Expert Modeler is more advanced future of Statistical Package for Social Science (SPSS as compared to Box-Jenkins method of ARIMA modeling. According to, (Sim et al., 2019) the expert modeler is a black box tool provided in SPSS to implement ARIMA modeling in a few clicks.

As it can be seen in the prior section, in this study Box-Jenkins methodology and Expert Modeler procedure of ARIMA modeling and evaluation were used, and the findings from the two methods is compared for the effectiveness in the SPSS software package.

Table-7: Comparison of model parameters built via Box-Jenkins and Expert Modeler

Models	R^2	Est.	Sig.	**Remark**
ARIMA(4,1,0) (2,0,0)	0.94	0.70	0.00*	Model identified by Expert Modeler on SPSS
ARIMA(0,1,0) (2,0,1)	0.87	0.45	0.01*	Model identified by Box-Jenkins Method on SPSS

As it can be seen above I Table -7, the finding is in line with the recent study by (Sim et al., 2019), have compared the Box-Jenkins method and the Expert Modeler methods and found that both Box-Jenkins method, and Expert Modeler are eligible to forecast future demand.

Despite, the finding of this study presented in Table-7 indicates that, the result generated from the Expert Modeler procedure of ARIMA modeling in SPSS for ARIMA(4,1,0) (2,0,0) at R^2=0.94 with Sig.= 0.00* and Est.= 0.7 tells that the predictive power of the mode to the sales dataset is approximately 94% which is better than model ARIMA(0,1,0) (2,0,1) generated by the Box-Jenkins method whose prediction power is R^2=0.87 (87%) Sig. = 0.01* and Est. = 0.45.

4.3 Forecast Implications in Production Planning

The forecasts obtained after identifying the best model, in case of this study ARIMA (4, 1, 0) (2, 0, 0) facilitates the decision on the production planning activities in the case company. Thus, the model identified in this study ARIMA (4, 1, 0) (2, 0, 0) is believed enable to forecast the future demand and make accurate predictions in the case company.

It will be much simpler and more obvious to make the proper production planning decisions and prevent significant cost losses once we have a demand forecast. That will assist managers in making the best choices regarding the provision of raw materials and the calculation of daily production, warehouse management, and distribution plan. Moreover, that will also affect the whole production process through directing planners to minimize the diverse sources of variation. Hence, the forecasts obtained after modeling is believed to facilitate managerial decisions on various perspectives of production planning activities of the case company.

Therefore, the projection would be regarded as a valuable information source for the instance company's sales and marketing planning department as well as production planning. Additionally, it is thought that the prediction created by this study would help the logistics and material planning department predict the future estimated quantity of products to be produced. This information can then be communicated with the input suppliers in order to improve the timely delivery of materials.

CHAPTER FIVE
5. Conclusion and Recommendations

5.1 Conclusions

Forecasting is a logically designed estimate for determining the future occurrence of an event by forecasting forward past production, market demand or sale data. Production planning and control, the most important function, is essential to the efficient operation of business and production operations and the management of cost of ventures. So far, different scholars have considered various approaches to develop a predictive model. Among which, the general time-series methods are used in the wide set of industrial application to develop predictive models.

In this effort, past scholars such as (Ruppert, 2017; Sim et al., 2019; Garcia-arismendiz et al., 2023) have utilized the Statistical Package for Social Science (SPSS) software package for time series data analysis and to generate ARIMA models. However, the Expert Modeler is not much considered by the state-of the art forecasting literature. In case of bottled water, even the method is not fully considered by relevant scholarly literatures. Particularly, in the case of Ethiopia, almost there is no relevant empirical study was conducted yet.

Despite, in Ethiopia Due to their current lack of proper demand forecasting techniques, the water bottling industry has experienced issues with non-conforming client demand, inventory shortages in certain situations, and surplus in other situations, all of which have led to financial losses In the present study, the potential ARIMA models were developer to estimate the future water demand in the case of NEEH purified water bottling industry using both Box-Jenkins method and Expert Modeler in SPSS. As a result,

Based on the study's findings, it can be said that the Box-Jenkins approach and SPSS's Expert Modeler are suitable for predicting the sales dataset of the case company's purified bottled waters. The results can also be tailored for the case company's other products. Most significantly, this study discovered that Expert Modeler is a more sophisticated alternative than Box-Jenkins, which requires manually selecting the best model from a large number of models determined through various testing procedures. While, the Expert Modeler can finish the forecast in just few clicks in Statistical Package for Social Science (SPSS).

This study has found that, the model developed by this research work through the Expert Modeler procedure of ARIMA modeling on SPSS (i.e., ARIMA (4,1,0) (2,0,0)) is more accurate, reasonably simply, and can be easily customized in to various manufacturing industrial setups with distinct data sources such as sales datasets, and distinct statement of material demands.

Hence, the forecasts obtained after modeling ARIMA (4, 1, 0) (2, 0, 0) is believed to facilitate managerial decisions even with low IT skill and knowledge on various perspectives of production planning activities of the case company.

5.2 Recommendations

In this study, the forecast developed would be considered as a useful source of information for the production planning, and sales and marketing planning department of the case company.

Moreover, In order to improve on-time material delivery, the prediction provided by this study is also thought to help the material planning and logistics department predict the future estimated product quantity to be produced. This information may then be communicated with the input suppliers.

Thus, a further study can be conducted beyond the scope addressed by the present study. For instance in varies industrial setups from various perspectives of production planning and management objectives so as to enhance the applications of the ARIMA model that the present study has found.

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Appendix-1: Key Informant Interview Questions

1. How the company has been conducting production planning?
2. How do you explained the efficiency of the forecasting practice in the case company
3. What are the major challenges facing the case company, with respect to production planning, and the alignment of the planned production with the market demand and the company capability?
4. What are the possible limitations associated with the actual production panning and demand predication practice in the case company?
5. Do you need an innovative forecasting model for effectively estimate the future market demand?

   If Yes, why forecasting is needed in the industry?

   For which departments the forecasts will be used?
6. What kind of data is available? Since which year the historical production, order demand and market sales data is well recorder (i.e., the most reliable)?
7. On which time-horizon you estimate the forecasts to the be developer is relevant and believed effective for bottled water products?
   A. Short-term: - on weakly bases or, monthly or, quarterly, or semi-annually, or per annual)
   B. Mid-term:- on Yearly Base e.g., the future 1 to 3 rears),
   C. C. Long-term:- two and more years