



Journal of

TANMIYAT AL-RAFIDAIN

(TANRA)

A scientific, quarterly, international, open access, and peer-reviewed journal

Vol. 44 , No.148

Dec. 2025

© University of Mosul |
College of Administration
and Economics, Mosul, Iraq.



TANRA retain the copyright of published articles, which is released under a “Creative Commons Attribution License for CC-BY-4.0” enabling the unrestricted use, distribution, and reproduction of an article in any medium, provided that the original work is properly cited.

Citation: Gharib, Awin S.,
Ghafour, Karzan M. (2025).
Optimizing Company
Performance in Water
Manufacturing: The Synergistic
Impact of Inventory Turnover
and Demand Forecasting.
TANMIYAT AL-RAFIDAIN, 44
(148), 331-358.

<https://doi.org/10.33899/tanra.v4i148.54156>

P-ISSN: 1609-591X
e-ISSN: 2664-276X
tanmiyat.uomosul.edu.iq

Research Paper

Optimizing Company Performance in Water Manufacturing: The Synergistic Impact of Inventory Turnover and Demand Forecasting

Awin Sabah Gharib ¹, Karzan Mahdi Ghafour ² 

^{1,2} Department of Project Management, College of Commerce, University of Sulaimani, Sulaimani, Iraq.

Corresponding author: Karzan Mahdi Ghafour

Karzan.sharif@univsul.edu.iq

DOI: <https://doi.org/10.33899/tanra.v44i148.54156>

Article History: Received: 2/9/2025, Revised: 20/10/2025,
Accepted: 13/11/2025, Published: 1/12/2025.

Abstract

Inventory turnover and demand forecasting, two specialized disciplines in inventory management, are considered highly critical to business success, particularly in the water production sector. However, much research remains to be done on these factors and their joint effect on project success. This study examines the under-researched dilemma of inventory turnover demand forecasting and its impact on organizational performance in the water manufacturing industry. A study spanning 14 months on operational data from a bottled water company reveals that various operational dynamics are more pronounced in small plastic bottles than in glass bottles and large gallon containers. The main results show that inventory turnover has striking differences, with the glass bottle outperforming by far (ratio: 96.35) given the low outgoings associated with carrying it, whereas small plastic bottles were markedly lower in turnover (20.50), influenced by demand fluctuations. This investigation shows that ARIMA outperforms DES in forecasting accuracy, with MAPE values ranging from 10.5 to 23.53% and R² values ranging from 0.717 to 0.833. The EOQ optimization indicated that large orders for glass bottles (22,112 units) are now optimal, even with setup costs of \$5,933.44. In contrast, safety stock settings (e.g., 9,557 units of glass bottles at a 95% service level) have effectively reduced stockouts. This study is theoretically valuable because it connects inventory turnover measures to forecast algorithms within established performance frameworks, and it shows, practically, how ARIMA-informed, size-specific EOQs and reorder points can improve delivery reliability, cost efficiency, and resource utilization. The study then concludes by encouraging the adoption of real-time forecasting systems and by changing inventory policies to operate more effectively in an exceptionally volatile marketplace.

Keywords:

Demand forecasting, inventory turnover, water manufacturing, optimization of EOQ, ARIMA, project performance

ورقة بحثية

تحسين أداء الشركة في تصنيع المياه: التأثير التآزري لدوران المخزون وتوقعات الطلب

نهمين صباح غريب¹، كارزان مهدي غفور²

^{1,2} قسم إدارة المشاريع، كلية التجارة، جامعة السليمانية، السليمانية، العراق.

المؤلف المراسل: كارزان مهدي غفور (Karzan.sharif@univsul.edu.iq)

DOI: <https://doi.org/10.33899/tanra.v44i148.54156>

تاريخ المقالة: الاستلام: 2025/9/2، التعديل والتقيق: 2025/10/20، القبول: 2025/11/13،
النشر: 2025/12/1.

المسخلص

يُعدّ دوران المخزون والتنبؤ بالطلب، عاملين مهمين في إدارة المخزون ونجاح الأعمال، ولا سيما في قطاع إنتاج المياه. ومع ذلك، لا يزال هناك الكثير من البحث الذي يتعين القيام به حول هذه العوامل وتأثيرها المشترك على نجاح المشاريع. تتناول هذه الدراسة مشكلة لم تُبحث بشكل كافٍ والمتعلقة بتنبؤ الطلب على دوران المخزون وتأثيره على الأداء التنظيمي في صناعة تصنيع المياه. تكشف دراسة امتدت 14 شهرًا على البيانات التشغيلية لشركة مياه معبأة أن ديناميكيات التشغيل المختلفة تكون أكثر وضوحًا في الزجاجات البلاستيكية الصغيرة منها في العبوات الزجاجية وحوايات الجالون الكبيرة. تُظهر النتائج الرئيسية وجود اختلافات ملحوظة في دوران المخزون، إذ تفوقت الزجاجة الزجاجية بفارق كبير (النسبة: 96.35) نظرًا لانخفاض النفقات المرتبطة بحملها، في حين كانت العبوات البلاستيكية الصغيرة أقل بشكل ملحوظ في الدوران (20.50)، متأثرة بتقلبات الطلب. ويُظهر هذا البحث أن ARIMA يتفوق على DES في دقة التنبؤ، إذ تتراوح قيم MAPE من 10.5 إلى 23.53% وقيم R^2 من 0.717 إلى 0.833. وأشار تحسين EOQ إلى أن الطلبات الكبيرة على الزججاجات الزجاجية (22,112 وحدة) أصبحت الآن مثالية، حتى مع تكاليف إعداد تبلغ 5,933.44 دولارًا. في المقابل، أدت إعدادات المخزون الاحتياطي (كمثال، 9,557 وحدة من العبوات الزجاجية بمستوى خدمة 95%) إلى تقليل نفاد المخزون بشكل فعال. تُعد هذه الدراسة قيمة من الناحية النظرية؛ لأنها تربط مقاييس دوران المخزون بخوارزميات التنبؤ ضمن أطر الأداء المعمول بها، كما تُظهر، عمليًا، كيف يمكن لـ EOQS ونقاط إعادة الطلب المستندة إلى ARIMA والمحددة بالحجم أن تحسّن موثوقية التسليم وكفاءة التكلفة واستخدام الموارد. ثم تُختتم الدراسة بتشجيع اعتماد أنظمة التنبؤ في الوقت الفعلي وتغيير سياسات المخزون للعمل بشكل أكثر فعالية في سوق متقلبة للغاية.

الكلمات المفتاحية:

التنبؤ بالطلب، دوران المخزون، تصنيع المياه، تحسين كمية الطلب الاقتصادية، ARIMA، أداء المشروع

مجلة

تنمية الرافدين

(TANRA): مجلة علمية، فصلية،

دولية، مفتوحة الوصول، محكمة.

المجلد (44)، العدد (148)،

كانون الاول 2025

© جامعة الموصل |

كلية الإدارة والاقتصاد، الموصل، العراق.



تحتفظ (TANRA) بحقوق الطبع والنشر للمقالات المنشورة، والتي يتم إصدارها بموجب ترخيص (Creative Commons Attribution) (CC-BY-4.0) الذي يتيح الاستخدام، والتوزيع، والاستنساخ غير المقيد وتوزيع للمقالة في أي وسيط نقل، بشرط اقتباس العمل الأصلي بشكل صحيح.

الاقتباس: غريب، نهمين صباح، غفور، كارزان مهدي. (2025). تحسين أداء الشركة في تصنيع المياه: التأثير التآزري لدوران المخزون وتوقعات الطلب. تنمية الرافدين، 44 (148)، 330-358.

<https://doi.org/10.33899/tanra.v44i148.54156>

P-ISSN: 1609-591X

e-ISSN: 2664-276X

tanmiyat.uomosul.edu.iq

1. Introduction

The use of effective performance measures is essential for optimizing operational efficiency; however, the ongoing changes in the business world make achieving successful inventory management increasingly complex, particularly when balancing production with customer demands. This is especially true in the manufacturing sector, where inventory turnover rate (IT) and demand forecasting are crucial. Effectively managing inventory and accurately forecasting demand are now essential strategies for meeting customer needs and achieving organizational objectives. In this context, accurate demand forecasting has become a critical tool, enabling organizations to anticipate market needs and streamline inventory processes. Inventory turnover and demand forecasting are vital to maintaining optimal stock levels, reducing expenses, and improving customer satisfaction. This research analyzes the relevance and influence of these two performance indicators within the industry, emphasizing their use in enhancing overall production performance. (Arnaiz et al., 2023;Thompson, 2024).

The optimal inventory turnover sustains organizational efficiency through minimizing the risk of overstocking, optimizing cash flow, and accelerating the conversion of goods to revenue. This operational efficiency gives organizations a competitive edge and makes them more agile in a dynamic market. A sound inventory management system thus helps in balancing supply and demand to avoid shortages and surpluses. This balance minimizes waste and ensures continuous customer satisfaction. (Deni & Puji, 2023; Hasanah, 2022; Sahoo et al., 2021). Currently, both inventory management and demand forecasting are becoming increasingly important for operational efficiency and customer satisfaction. De Menezes et al., (2023) Corroborated the same. According to Abolghasemi et al. (2020) Inaccuracies in demand forecasting typically lead to significant operational inefficiencies, such as overstocking or stockouts, thereby adversely affecting overall business performance. When strategically integrated, these two functions allow organizations to reduce operational costs, increase sales, and enhance profitability. Thus, stock turnover and demand forecasting have become the most essential tools for enhancing project performance. These allow the company to synchronize supply chain capabilities with actual customer demand, thereby managing market complexity, eliminating waste, and achieving sustainable competitive advantage. To gain a clearer understanding of the factors that influence project performance and outcomes, this study seeks to address the following research questions:

- What is the impact of inventory turnover on company performance?
- How does demand forecasting influence company outcomes?
- How do key inventory metrics such as Economic Order Quantity (EOQ), safety stock, and reorder point affect project performance?
- How do inventory turnover and demand forecasting interact to affect project performance?

2. Theoretical background

2.1 Inventory Management and Project Performance

Project performance has been recognized as one of the most important factors affecting organizational performance in project-proficient settings. Initial methodologies for evaluating project success were often based on the "Iron Triangle" framework, which posits that successful delivery depends on adherence to predetermined cost, time, and quality objectives (Maqsoom et al., 2020). Such characteristics are essential at every stage of a project, from planning through execution to delivery. However, as projects have become increasingly complex and dynamic, renewed inquiry has arisen into whether these three factors are sufficient indicators of real project success. Therefore, the shift is now towards including broader measures of project success, such as the value it produces, stakeholder trust, organizational reputation, and customer satisfaction (Kabirifar & Mojtahedi, 2019; Zhu et al., 2021). From the dawn of humanity, inventory management has existed and has transformed tremendously over the last century due to technological advances. The Greeks and Egyptians enhanced the manual system of product recording that traders used before the advent of record-keeping. These continual improvements to inventory operations have led to cost reduction and enhanced customer satisfaction (Munyaka & Yadavalli, 2022). The first use of the term "inventory" was recorded in 1601, derived from the French word "inventaires," which means "detailed list of goods," used as early as 1415 (Yunusa, 2021). Trading has been part of human life for many centuries. Throughout history, literature has invested heavily in presenting various perspectives on inventory management. Inventory management is the process of maintaining optimal stock levels, along with demand forecasting, stock supervision, and order scheduling. As a subtopic of management science, inventory is approached from various angles, which leads some researchers to define it as a strategy and others as a collection of key activities. Vrat (2014), for example, considers inventory management a strategic process of maintaining an adequate level of stock to meet demand, avoiding stockouts, and maximizing cost efficiency by minimizing excess stock and storage costs. As described in the literature review, there are two primary goals in inventory planning. These aims include purchasing the correct quantity and quality of a given supply at the right time while minimizing inventory holding costs. This method ensures that these items are present at the right places and at the correct times, thereby enabling the execution of operations/services (Ajayi et al., 2021). The secondary objective is to achieve the desired service level at the lowest possible values. Achieving set objectives presents a challenge to optimal spending.

2.2 Concept and Measurement of Inventory Turnover

Inventory is a crucial aspect of strategic management in every organization. It is the stock of items held by a company for future use; the makeup of that stock is contingent upon specific requirements in its operations. (Shukaili et al., 2023). The most important index for measuring the effectiveness of inventory management is the inventory turnover ratio. (Silver et al., 2017). Academics regard this measure as one of the most important financial variables for assessing inventory management

effectiveness. This turnover ratio is regarded as a composite indicator of inventory quality, particularly with respect to obsolescence, and of the proficiency of procurement and inventory management processes and personnel. (Hill & Zhang, 2010). Hence, it can be regarded as reflecting managerial competence in using organizational resources maximally efficiently. Holding stock incurs costs, and a shortage can lead to lost sales. Consequently, organizations must control inventory at the optimum levels to minimize overall costs. (Akbar, 2023). The benefits of holding an inventory include predictability, protection against demand fluctuations, protection against unreliable supply, price protection, quantity discounts, and low ordering costs. With adequate inventory turnover, organizations can manage production levels effectively to avoid overstocking. (Nuraini, 2021). Inventory turnover is calculated using the following steps, with the standard formula. (Vista et al., 2023):

$$\text{Inventory Turnover, IT} = \frac{\text{Cost of Goods Sold (COGS)}}{\text{Average Inventory (AI)}} \quad (1)$$

COGS refers to the total cost incurred in producing the water sold within a specific period. At the same time, average inventory is defined as the average value of stock held over a period.

Step 1: Determine COGS

$$\text{COGS} = \text{Beginning of Inventory} + \text{Purchases} - \text{Ending of Inventory} \quad (2)$$

Step 2: Calculate Average Inventory, AI

$$\text{AI} = \frac{\text{Beginning Inventory} + \text{Ending Inventory}}{2} \quad (3)$$

For highly volatile inventory, averaging monthly or quarterly turnover works fine (13 months may be appropriate as a year).

Step 3: Calculate Inventory Turnover from equation (1)

On the other hand, there is an alternative formulation to extract inventory turnover (IT) using sales revenue, which is a less common method (Vista et al., 2023).

$$\text{Inventory Turnover, IT} = \frac{\text{Net Sales}}{\text{Average Inventory (AI)}} \quad (4)$$

Limitation: Efficiency will be overstated if sales are recorded with a markup (cost of goods sold is preferred). The days of sales of inventory (DSI) can be calculated by considering the average duration inventory is retained prior to sale.

$$\text{DSI} = \frac{365}{\text{Inventory Turnover Ratio}} \quad (5)$$

By analyzing inventory turnover, organizations can enhance operations and maintain a balance between supply and demand. Pratama et al. (2020) Defined it as the ratio of

the cost of products produced to the average inventory over a specific period. According to (Sunaryo & Lestari, 2023). The inventory turnover ratio is calculated by dividing the cost of products sold by the average inventory.

2.3 Concept and Importance of Demand Forecasting

Demand forecasting is the systematic process of projecting future demand for a given product, typically by analyzing historical demand patterns and current market intelligence. This essentially assists in inventory-buying decisions by anticipating consumption trends to help optimize stock levels and working capital. These methods use historical sales data to build a predictive model of current customer demand. (Karwankar et al., 2021).

Demand forecasting can be conducted over various time periods, such as days, weeks, months, or quarters. After selecting a specific time frame, historical demand data for those periods is utilized to anticipate future requirements for similar intervals. (Thomopoulos, 2015). A forecast presents the anticipated future events through meticulous analysis. However, forecasting plays a crucial role in identifying future uncertainties early and mitigating potential risks. It details what suppliers must do to implement their production plans or fulfill orders from partners further along the supply chain. (Yücer, 2006).

2.4 Gaps in Existing Literature

The literature currently has several significant gaps that this work intends to fill. There is voluminous literature on inventory management and demand forecasting. However, few studies have examined the combined effect of the two on project performance, much less in the water manufacturing sector. Most past studies have treated inventory turnover and demand forecasting separately, rather than investigating their interrelationships. Additionally, most studies focus on general manufacturing or retail settings and do not account for the specific challenges faced in the water manufacturing industry, such as regulatory requirements, reliance on infrastructure, and the potential for water products to spoil. In standard literature, project performance is considered primarily in terms of time and cost efficiency. This limited view excludes other important areas, such as social and environmental sustainability impacts, stakeholder satisfaction, and long-term operational resilience. Such a restricted interpretation is extremely unfortunate because it poses significant difficulties for developing economies, where limited infrastructure and resource availability often create severe operational constraints that are seldom accounted for in typical inventory management paradigms. Despite growing stakeholder recognition of corporate governance, the literature does not address ethics and sustainability considerations associated with inventory management in the water-producing industry. The above research gaps provide sufficient justification for theoretical and applied research to foster more evidence-based improvements in inventory systems within this vital sector.

3. Research Methodology

This section describes a comprehensive methodological framework for analyzing the impact of inventory turnover and demand forecasting on project success. There are several practically important roles that a research design might embrace, including stating the research design itself, recognizing and describing the sources of data, establishing protocols for data collection and types of variables, examining forecasting techniques, measuring inventory using a developed model, and then analyzing data to evaluate the aforementioned analytical framework.

3.1 Data Source

The Sulaimani bottled drinking water production, considered one of the largest branches of the regional consumer goods market in the Kurdistan Region of Iraq, has consistently grown due to urbanization, population growth, and enhanced public awareness of water safety and health. The industry comprises small and medium-sized companies with varying technological capacities and production levels. Due to its favorable geographic location, both for uninterrupted access to clean water and for an industrial environment conducive to peace, Sulaimani became a hub for bottled water production. The ineffectiveness of municipal water networks also drove industry development, increased dependence on bottled water, and enhanced government incentives to attract private investment into manufacturing (KRG, 2023). In this case, one bottled water company in Sulaimani was selected based on its product range, available data, and willingness to cooperate. The research uses secondary data for 14 months (January 2024-February 2025) from the company's internal records.

3.2 Data types and collection

Secondary data were used in this study since they were extracted from operational records maintained by a bottled-water manufacturing firm. This dataset covers the period from January 1, 2024, to February 21, 2025, and includes multiple quantitative variables relevant to demand forecasting, inventory turnover, and project performance.

3.2.1 Demand Data

The demand data would provide end-of-day sales volumes in three product categories: small plastic bottles, glass bottles, and large gallon containers. Such data reflect real market demand, which is essential for evaluating the accuracy of the models' forecasts. The sales records give historical demand patterns necessary to test and validate predictive models such as ARIMA and DES.

3.2.2 Lead-time Data

Lead-time data represents the time intervals between order placement, production, and inventory replenishment. It includes both internal processing time and external procurement duration. These data points help determine the responsiveness of the production and inventory systems to fluctuating demand and are essential for modeling just-in-time inventory practices and service-level analysis.

3.2.3 Holding Cost and Setup Cost (Incorporating COGS)

The study can be divided into two basic cost components: holding cost (h) and setup cost (A), where the holding cost represents the total cost incurred by a company or project for storing materials in warehouses or the manufacturer's costs incurred for holding finished goods in inventory and on the other hand setup cost which indicates the expenditure incurred for preparing equipment for processing a new batch of items, thus classifying it as a batch-level cost in activity-based costing (ABC).

The derivation of holding cost (h) is calculated as follows:

$$h = (I)(C) + (COGS * r) \quad (6)$$

In this context, there is I , which is the holding cost as a percentage of inventory value. This cost includes capital investment, insurance, and opportunity costs. C is the price per unit for holding the item, whereas COGS is the cost of goods sold per unit (\$), and (r) is the annual capital opportunity rate and equal to (% 8) (Chopra & Meindi, 2010; Nahmiasn & Olsen, 2015) I can be evaluated as the result of dividing investment cost per item (IC) by expected demand per day (D_L):

$$I = \frac{IC}{D_L} \quad (7)$$

The setup cost (A) can be derived through the following calculation, utilizing the predetermined holding cost (h), projected daily demand (D_L), and unit price per metric item.

$$A + h = \frac{(D_L)(SP)}{IC}$$

Where SP is the selling price per item (bottle). Therefore,

$$A = \frac{(D_L)(SP)}{IC} - h \quad (8)$$

3.3 Inventory Turnover

The study investigates inventory management practices in the bottled water manufacturing sector, which are highly dependent on shelf life, warehouse costs, and changing market demand. This study is concerned with size-specific inventory turnover (bottles are classified as small, medium, and large), with the purpose of (i) profiling the classification with the most effective sales conversion and (ii) establishing the relationship between inventory flow dynamics and some of the key operational variables: production planning and distribution logistics, as well as overall project cost-effectiveness. (Nuraini, 2021).

It will calculate the inventory turnover for each bottle size using the following formula:

$$\text{Inventory Turnover, IT (item size)} = \frac{(\text{COGS})_{\text{for (item size)}}}{\text{Average Inventory (AI)}_{\text{for (item size)}}} \quad (9)$$

For each type of water bottle, COGS refers to the direct production cost of the specific bottle size, including raw materials (bottles, water, labels), labor, and overheads.

Thus, Aggregate Turnover (Company-Wide)

$$\text{Overall IT} = \frac{(\text{COGS})_{\text{for (all sizes)}}}{\text{Average Inventory (AI)}_{\text{for (all sizes)}}} \quad (10)$$

Where, $\text{Average Inventory Value} = \frac{EOQ}{2} + \text{Safety Stock} * \text{COGS}$

3.3.1 COGS Data

Primary data will be collected by gathering the cost of goods sold (COGS) and inventory metrics from three primary organizational sources: (i) internal production records, (ii) inventory management systems, and (iii) corporate financial statements over a longitudinal timeframe of 14 months. Methodologically, the framework under which this research operates will include weekly inventory counts and monthly computation of the Cost of Goods Sold (COGS). For analysis, an analytical methodology will be applied to each product type: small plastic bottles, glass bottles, and large gallon containers. To enhance methodological accuracy, the study will implement strategies to control for important temporal covariates, such as production batch cycles and seasonal consumption patterns, especially around planning for the peak demand period, the summer months when most sales transactions occur.

$$\text{COGS} = \text{Beginning of Inventory} + \text{Purchases} - \text{Ending of Inventory} \quad (11)$$

$\text{COGS} \approx 70\%$ The selling price unit (industry average for water manufacturing) is an industry-specific assumption. (Nahmiasn & Olsen, 2015). The traditional cost structure in bottled water manufacture is indicated by Rodwan (2023), which estimates COGS upwards of 70% of the selling price per unit. These consist of three main components: (i) raw materials (bottles, caps, labels), constituting 40-50% of the total unit costs; (ii) direct labor costs, 15%-20%; and (iii) overheads, which constitute about 10%-15%. A 70% parameter falls within the conservative mid-level of this set of aggregate cost parameters.

3.3.2 Average Inventory

To compute inventory turnover accurately, one needs to determine the Average Inventory for each bottle type: small, medium, and large. In this study, average inventory refers to the mean stock level maintained over a specified period and is placed in the denominator of the inventory turnover ratio.

$$\text{AI} = \frac{\text{Beginning Inventory} + \text{Ending Inventory}}{2} \quad (12)$$

3.4 Double Exponential Smoothing

Here we are now in the Double Exponential Smoothing (DES) method, intended for data forecasting without a strong seasonal effect, provided a trend is present. It builds on its simpler predecessor by adding a smoothing component to account for the trend. The following equation calculates DES. (Moiseev, 2021):

$$S_t = \alpha Y_t + (1 - \alpha)(S_{t-1} + T_{t-1}) \quad (13)$$

$$T_t = \gamma[L_t - L_{t-1}] + (1 - \gamma)T_{t-1} \quad (14)$$

$$\hat{Y}_t = S_{t-1} + T_{t-1} \quad (15)$$

where,

S_t : Time t of the Level

α : Level Weight

T_t : Time t Trend

γ : Trend Weight

Y_t : Time st Data value

$\hat{Y}_t$: Time t Forecasted value

The actual current value of a series is substituted with an estimated smoothed value.

There are different methods of determining the original value of T_1 :

$$T_1 = Y_2 - Y_1 \quad (16)$$

$$T_1 = \frac{[(Y_2 - Y_1) + (Y_3 - Y_2) + (Y_4 - Y_3)]}{3} \quad (17)$$

$$T_1 = (Y_3 - Y_1)(n - 1) \quad (18)$$

Mean Absolute Deviation (MAD) is the measure of accuracy of the model for customized time series values. Accuracy is expressed in the same units as the amount of error is estimated (Leung et al., 2009). The calculation formula of MAD can be represented as follows:

$$MAD = \frac{1}{n} \sum_{t=1}^n |Y_t - \hat{Y}_t| \quad (19)$$

where n represents the number

3.5 ARIMA Model

The ARIMA model is used to forecast time series data that may exhibit autocorrelation and non-stationarity. It is well-suited to model the underlying structure of demand data, including trends and lags. The autoregressive model of order p is practically displayed in the following equation:

$$Y_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \varepsilon_t \quad (20)$$

there $\phi_1, \dots, \phi_p$ Are the corresponding coefficients of observations Y_t to be estimated in historical time, and ε_t Is an error term of white noise. The MA in ARIMA stands for moving average, which is denoted by q in the model. While the AR model

is based on previous observations, the MA model is based solely on previous forecast errors. The following is the most commonly written set of MA equations of order q (Swaraj et al., 2021):

$$Y_t = C + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (21)$$

where $\theta_1, \dots, \theta_q$ The estimated coefficients ensure that the time series is stationary. The "I" in ARIMA stands for "integration," which is indicated by the parameter d in the model. A non-seasonal ARIMA model is formed by differencing the time series at least once (rendering it stationary) and joining it with AR and MA models. The difference thus becomes the reverse operation of integration. The ARIMA equation can be given as follows:

$$Y_t' = C + \phi_1 Y_{t-1}' + \dots + \phi_p Y_{t-p}' - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (22)$$

where Y_t' Signifies a group of differentiations compared with several occasions, and on the right side of the equation consists of both the lagged observations of the AR model and the lagged errors of the MA model (Selvaraj et al., 2020).

3.6 Optimizing order quantity and cost

An order quantity that is more likely to reduce the total inventory cost, including holding and setup costs, is called the optimal order quantity. Blackburn and Scudder (2009) Developed a cost function in context, which should minimize the expenditure under the inventory model and is expressed in the subsequent equation.

$$\left(\begin{array}{c} \text{Total} \\ \text{inventory} \\ \text{cost. } TC \end{array} \right) = \left(\begin{array}{c} \text{Purchasing} \\ \text{cost, } c \end{array} \right) + \left(\begin{array}{c} \text{Holding} \\ \text{cost, } h \end{array} \right) + \left(\begin{array}{c} \text{Setup} \\ \text{cost, } k \end{array} \right) + \left(\begin{array}{c} \text{Shortage} \\ \text{cost, } p \end{array} \right)$$

Shortage costs are not considered in this study because this was assumed in the model. Taha (2017) Further suggested that the purchase cost can be ignored in the following equation.

$$\left(\begin{array}{c} \text{Total} \\ \text{inventory} \\ \text{cost. } TC \end{array} \right) = \left(\begin{array}{c} \text{Holding} \\ \text{cost, } h \end{array} \right) + \left(\begin{array}{c} \text{Setup} \\ \text{cost, } k \end{array} \right)$$

This study examines three items (small plastic bottles, glass bottles, and large gallon containers). The holding cost for each item is denoted h_i (where $i = 1, 2, 3$), whereas the setup cost is constant per item and unaffected by the order quantity. Furthermore, the demand lead time (DLTL) for each item is independent, represented as D_{Li} , (where $i = 1, 2, \dots, n$). Consequently, both the total inventory cost (TC) and the order quantity (q) vary based on h_i and D_{Li} , and can thus be expressed as TC_i and q_i , respectively.

According to inventory theory, the average inventory level during a cycle is $\frac{q}{2}$, and the cycle length is $\frac{q}{D_L}$ (Hillier & Lieberman, 2010). Hence

$$\text{holding cost, } h_i / \text{cycle} = \frac{h_i q_i^2}{2D_{Li}} \quad (23)$$

The demand lead time (D_{Li}) is derived from Equation (23) using the Double Exponential Smoothing (DES) method for one-period-ahead predictions (daily forecasts). Consequently,

$$TC_i \text{ per cycle} = A + cq_i + \frac{h_i q_i^2}{2D_{Li}} \quad (24)$$

The TC per unit time is:

$$TC_i = \frac{A + cq_i + \frac{h_i q_i^2}{2D_{Li}}}{\frac{q_i}{D_{Li}}} = \frac{D_{Li}A}{q_i} + D_{Li}c + \frac{h_i q_i}{2} \quad (25)$$

By taking the derivative, we obtain

$$\frac{dTC_i}{dq_i} = -\frac{AD_{Li}}{q_i^2} + \frac{h_i}{2} \quad (26)$$

By setting Equation (26) equal to zero,

$$q_i^* = \sqrt{\frac{2A_i D_{Li}}{h_i}}, i = 1, 2, 3 \quad (27)$$

Equation (27) provides the mathematical formulation for determining the optimal order quantity. The total cost per unit time can subsequently be calculated by substituting Equation (27) into Equation (25), yielding the following expression. (Chopra & Meindi, 2010; Nahmiasn & Olsen, 2015).

$$TC_i = \sqrt{2A_i h_i D_{Li}} + (SS * SOGS * 0.08), \quad i = 1, 2, 3 \quad (28)$$

3.7 Safety Stock Optimization

In inventory management systems employing continuous review with constant demand models, service level (SL) is typically measured as the probability of avoiding stockouts per order cycle. This calculation ensures that the specified service level probability is achieved, where the demand during lead time (D_L) does not exceed the reorder point (R) (Saliji, 2021). Thus,

$$P(D_L \leq R) = SL = \phi\left(\frac{R - \mu_L}{\sigma_L}\right) = \phi\left(\frac{SS}{\sigma_L}\right) \quad (29)$$

Given the relationship $SS = R - \mu_L$, where SS represents safety stock, R is the reorder point, and μ_L Denotes the mean demand during the lead time; the standardized ratio, $\frac{SS}{\sigma_L}$ Corresponds to the safety factor K for a specified service level (SL). It is evident, from the perspective of K as a safety factor, that the overall probability distribution representing lead-time demand is a condition. In other words, if lead-time demand were normally distributed, one could directly obtain K from standard regular distribution tables for the desired service level. (Maqsoom, et al., 2020). Consequently,

$$SS = K\sigma_L \quad (30)$$

Safety stock is an important factor in inventory management regarding both the setting of the reorder point and the mitigation of delays in order preparation or replenishment. Safety stock fulfills customer demand during the period between the time the reorder point is reached and the time a new order quantity (Q) is released. Thus, carrying too high a level of safety stock increases holding costs, leading to poor stock conditions and stock-outs. Hence, the optimal safety stock quantity is given in Equation (30).

3.8 Establishment of the reorder point

A fundamental parameter in inventory management systems is the reorder point (R) when implementing any inventory policy. The determination of R follows a consistent methodological approach across various inventory policies, where it is derived as the sum of safety stock (SS) and the mean demand during lead time (μ_L), expressed as $R = SS + \mu_L$. This formulation serves as the foundational calculation for single echelon inventory systems. (Maqsoom et al., 2020).

Equations (29) and (30) demonstrate that the reorder level R is functionally dependent on two key components: the safety stock S and the mean demand during lead time, irrespective of the specific inventory policy being implemented. Consequently,

$$R = SS + D_L \quad (31)$$

4. Results and Discussion

Demand data fluctuations are presented in Figure 1 for the Small Plastic Type, Figure 2 for the Glass Bottles, and Figure 3 for the Large Gallon Containers. Overall, demand fluctuations exhibit distinct daily patterns across the three product types: small plastic containers, large gallon containers, and glass bottles. Among the three, the highest volatility is observed in the small plastic containers, ranging from about 1,000 to 10,000 units, with numerous sudden spikes indicating erratic or reactive consumer behavior. Demand for large gallon containers, on the contrary, tends to remain stable with moderate fluctuations between 500 and 4,500, which would indicate that customers have more predictable purchase behavior. Glass bottles when compared on

a larger scale provided a range of 10,000 to 70,000 units, yet generally indicate an upward slope through these spikes, which could imply growth in popularity and variability either incidental to bulk ordering or market shifts. Therefore, the demand data exhibit a trend, either increasing or decreasing. The double Exponential smoothing is considered by (Moiseev, 2021). To be the best forecasting procedure for deriving the mean and the standard deviation in this situation.

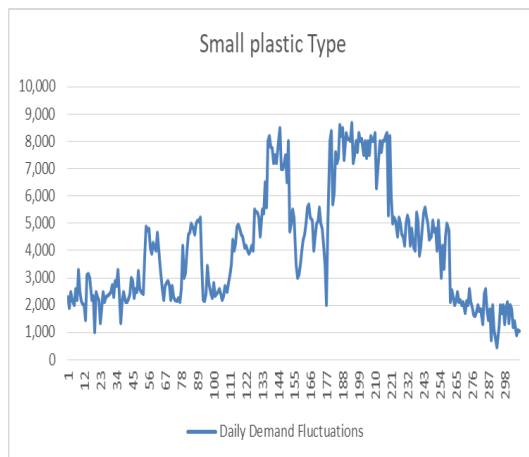


Figure (1). The Daily Demand of Small Plastic Type

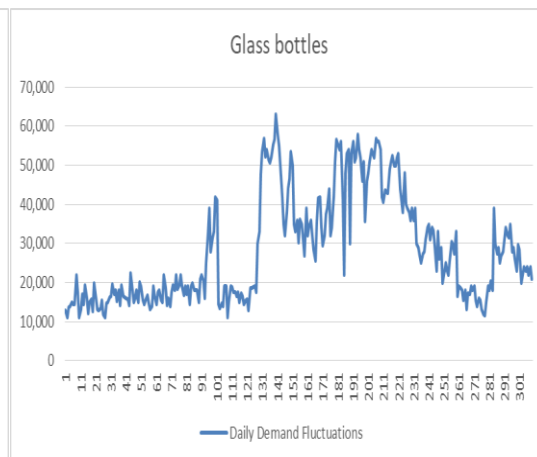


Figure (2). The Daily Demand of Glass bottles Type

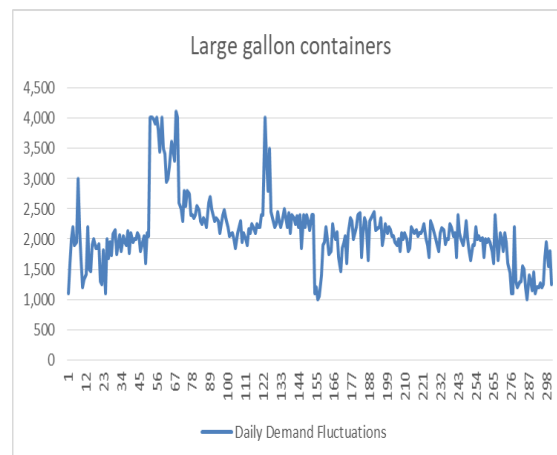


Figure (3). The Daily Demand of Large gallon containers Type

4.1 Lead Time Data Analysis

Lead time is a time interval between placing an order and the replenishment of inventory and is thus an important determinant of supply chain responsiveness. The operational data analysis from the bottled water manufacturer in Sulaimani confirms a

fixed one-day lead time for all product types (small plastic bottles, glass bottles, and large gallon containers). This stroke period includes internal work (production scheduling, quality checks) as well as external procurement (raw material delivery), enabling just-in-time inventory practices.

The consistent one-day lead time greatly simplifies the demand and inventory modeling process.

- D_L : Demand during lead time is equal to daily demand since replenishment occurs within 24 hours.
- Safety Stock, SS Calculations: Sharpens the variability risk calculation since $CapSigma\sigma_L$ (standard deviation of lead time demand) is equal to daily demand variability.
- Reorder Points: Directly related to daily sales averages (Table 11), because $R = SS + \mu_L$ (Equation 31) uses $\mu_L = D_L$ (daily demand).

4.2 Double Exponential Smoothing (DES)

Given its ability to capture trends in time series data, the Double Exponential (DES) model was applied to predict demand for three classes of water products (small plastic bottles, glass bottles, and large gallon containers). Initializing involved defining the level component (S_0) as equal to the first observed demand value (Y_1) and setting the initial trend (T_0) to the difference between the second and first observations (Equation 16). After this setting, the model updated the level and trend iteratively for each subsequent period: level (S_t) was smoothed by a weighted average of the current observation and the past level trend combination (Equation 15), whereas trend (T_t) was adjusted by the difference between the two last levels and the previous trend (Equation 14). Smoothing parameters (α) for level and γ for trend were optimized by grid search to minimize the Mean Absolute Deviation (MAD, Equation 19) using a training subset of the data. Forecasts ($\hat{Y}_{t+1}$) were made by adding together the most recent estimates of level and trend (Equation 15). One-period-ahead demand forecasts were generated using Double Exponential Smoothing (DES), which were significant contributors to lead-time inventory calculations. The first-period trend T_1 was obtained from Equation (18), where Y_1 and Y_3 represent the first and third historical demand observations, respectively, and n is the adjustment period. This provides a stabilized estimate of the trend, reducing the volatility of the single-interval differences. For the following periods, the model updated the level (S_t) and trend (T_t) components using Equations (13) and (14), where the smoothing parameters (α and γ) were chosen to minimize MAD using Equation (19). The one-period forecast ($\hat{Y}_{t+1}$) was calculated as $S_t + T_t$ (Equation 15) and was used as demand during lead-time (D_L) for inventory optimization. This one-period forecast value was directly fed into calculations for safety stock (SS) (Equation 30) and the reorder point (R) (Equation 31), ensuring the forecast aligned with the company's operational replenishment cycles. These procedures have been applied to each individual water product item considered. Table 1 presents the DES-determined values of the mean, DL , and standard deviation (sigma sub cap L) of demand.

Table (1). Determined values of mean, D_L , and standard deviation, σ_L of the demand by using DES

Measures	Water Products Items		
	Small Plastic Box	Glass Bottles Type	Large Gallon Containers
D_L	615	4662	269
σ_L	769	5827	336

4.3 ARIMA Model

Before implementing the ARIMA model, a preliminary seasonal analysis was conducted to examine fluctuations in the demand data. The three water product groups, namely Small Plastic Bottles, Glass Bottles, and Large Gallon Containers, show quite different, distinct seasonal trends in Figures 2 through 4. Since seasonality is evident, the ARIMA model acts as a linear forecasting tool using the Business Forecasting Solution for Business software (GMDH-SHELL, 2018). The forecasted and actual demand data in Figures 4 through 6 align and show the model's linear trend approximation. Forecasting began in the third data period, or Lag 3 (post-peak), and linear forecasting continued for the next 60 days, a duration ratified by empirical studies (Satrio et al., 2021; Swaraj et al., 2021). The exclusion of pre-Lag 1 data from the model is well justified, as seasonal peaks characterize the summer months. Performance evaluation was conducted using RMSE, MAE, and MAPE, as well as goodness-of-fit (R^2), and the results are shown in Table 2. It is found that ARIMA can achieve high forecasting accuracy, as evidenced by its lowest MAPE, indicating low error. The R^2 values of 0.784, 0.833, and 0.717 for the products indicate how well the linear regressions fit; higher R^2 values indicate how closely the observed data match their predicted values (Satrio et al., 2021).

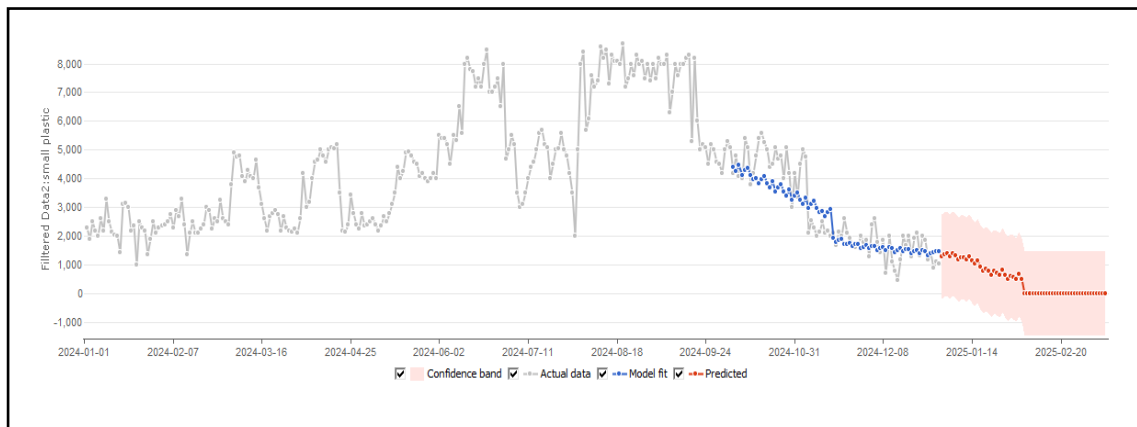


Figure (4). ARIMA model for Small Plastic Bottles type

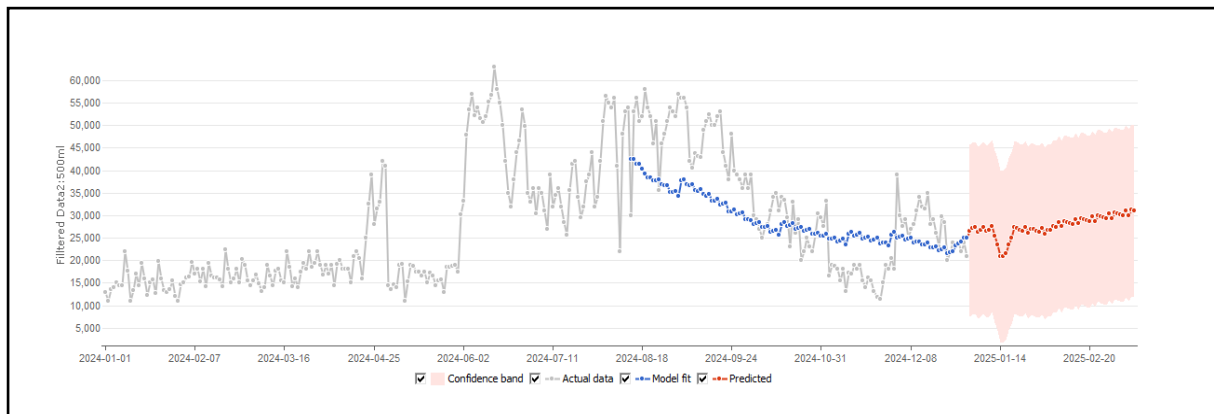


Figure (5). ARIMA Model for Glass Bottles type

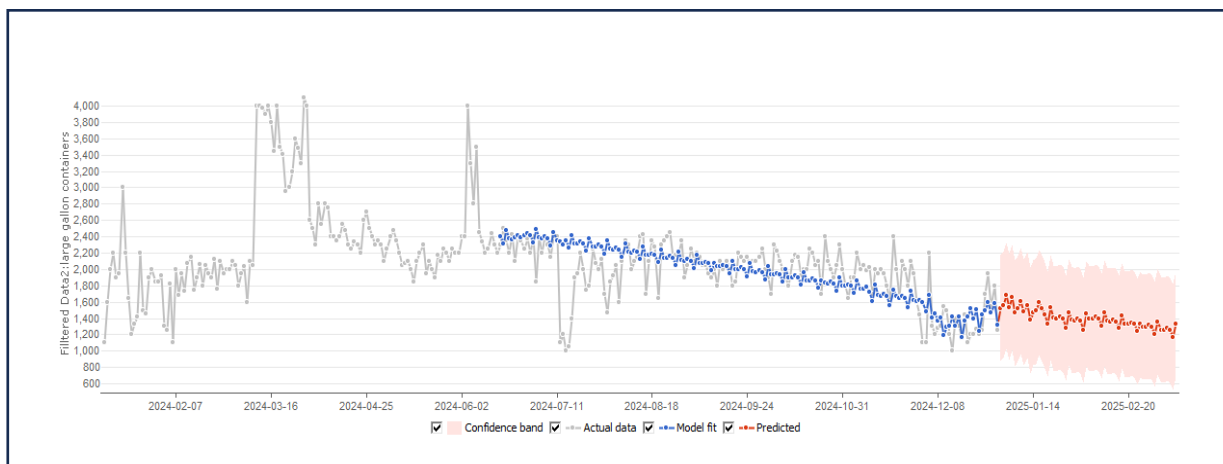


Figure (6). ARIMA model for Large Gallon Containers type

Table (2). Evaluating ARIMA models' performance

Water Products Items	ARIMA set			
	RMSE	MAE	MAPE	R^2
Small Plastic Type	1001.09	760.372	% 21.13	0.781
Glass Bottles Type	7575	6018	% 23.53	0.833
Large Gallon Containers	292.37	230.92	% 10.5	0.717

4.4.Holding Cost Values

Holding costs, h , entail costs supported by the firm, factory, or the project when materials are stored in the depot. It consists of the following elements: interest on capital, rent of the storage site (including electricity, water, cooling, etc.), insurance costs for natural hazards, losses due to product damage, and investment costs. In some instances, holding costs may not be obtained directly, since they depend on the

inventory level (I) and the cost per unit (C). Thus, according to Equation (7), Table 3 presents the I values for the three items.

Table (3). The values of Inventory level, I , for the products

Items	D_L	IC	The result of I
Small Plastic Type	615	0.758621	0.0012335
Glass Bottles	4662	0.37931	0.0000234
Large Gallon Containers	269	0.862069	0.0032047

The unit cost (C) and COGS for each product are presented in Table 4. Using Equation (6), the holding costs (h) for the three products were calculated, as shown in Table 5.

Table (4). The unit cost, C , for each product

Products	Unit Cost, C (\$)	$COGS \approx \%70$ of C
Small Plastic Type	0.733	0.513
Glass Bottles	0.367	0.257
Large Gallon Containers	0.833	0.583

Table (5). Extracting the holding cost, h for the three products

Products	The holding cost, h (\$)
Small Plastic Type	0.0419
Glass Bottles	0.0206
Large Gallon Containers	0.0493

The holding costs (h) in Table 5 reflect the per-unit storage cost. For instance, the holding cost of Small Plastic Type amounts to \$0.0419 per unit meaning it has low storage costs because of probably good warehousing and light packaging. Glass Bottles, on the contrary, appear to be extremely low with a holding cost of \$0.0206 for every unit, implying that such materials would really not require much storage, perhaps on account of quick turnover or small storage methods. On the high side, Large Gallon Containers have a holding cost of \$0.0493 per unit, likely because their storage needs are bulkier or require special conditions (e.g., temperature controls). The low figures across all products provide evidence that the company manages its stock efficiently and thus does not incur a substantial storage cost burden. However, the near-zero cost of glass bottles raises questions about potential underestimation or unique operational advantages, such as high demand velocity and reduced dwell time.

4.5 Setup Cost Values

The setup cost is a fixed cost that does not depend on order quantities for producing and purchasing items. It consists of the amount spent on audit requests and follow-up, the cost incurred per item stored in a depot, the cost incurred in setting up

production, costs incurred as a function of the environment, depreciation or demolition of buildings, and inspection costs for flawed or shoddy items or for inspection quality. The extracted value of A from the setup cost is determined by the equation given in (8). However, Table 6 presents the A values for the three products.

Table (6). The extracted values of A for the three product categories

Products	D_L	SP	IC	h (\$)	A (\$)
Small Plastic Type	615	0.965517	0.758621	0.0419	782.68
Glass Bottles	4662	0.482759	0.37931	0.0206	5933.44
Large Gallon Containers	269	1	0.862069	0.0493	312

Table 6 details the fixed expenses for setting up production batches (A). Moderate setup costs are incurred by Small Plastic Type, amounting to \$782.68, with the small setup associated with mass production forms. Glass bottles, however, have an extremely high setup cost of \$5933.44, an enormous amount that most probably owes its exorbitance to either specialized equipment, labor-intensive processes, or quality control measures unique to glass manufacturing. Large Gallon Containers typically have setup costs of only \$312, which are lower than those for other types, indicating a much simpler production setup than for glass bottles. The vast difference in setup costs demonstrates the complexity of glass bottle production, which often requires frequent equipment recalibration and stringent inspection procedures. These also refer to the need for strategic batch scheduling to minimize frequent setups, especially when glass bottles with high (A) values could eat into potential profits if careful management is not followed.

4.6 Extracting the optimal EOQ

The optimal order quantity (q_i^*) is determined along with the total cost function TC_i From Equations (28). The extracted demand lead time (D_L) from Equation (15) of the DES model for one period ahead, as presented in Table 1, was also coupled with the holding cost (h) and setup cost (A), as previously extracted (Tables 5 and 6). Table 7 represents the optimal (q_i^*) for each water product type.

Table (7). The optimal order quantity for the product categories

Product categories	q_i^*
Small plastic bottle	23068
Glass bottle	22112
Large gallon container	5606

The values for EOQ in Table 7 indicate the ideal volumes of procurement to minimize total inventory cost for each product category. Glass bottles have an extremely high EOQ of 22,112 units, which results from their disproportionately high setup cost (\$5,933.44, Table 6) and negligible holding cost (\$0.0206/unit, Table 5). This implies that ordering in bulk reduces frequent setups, even at massive quantities, because setup costs are minimal. The lower EOQs for small plastic bottles (EOQ = 23,068 units) and

large gallon containers (EOQ = 5,606 units) are reflected in their moderate setup costs (\$782.68 and \$312, respectively) and slightly higher holding costs (\$0.0419 and \$0.0493/unit). By ensuring operational efficiency without overstocking, these quantities strike a balance between setup and holding costs.

4.7 Total Cost Analysis

Having determined the optimal order quantities as presented in Table 4.7, the total cost function can subsequently be derived using Equation (31) for all three product categories. The resulting minimum total costs for each product category are presented in Table 8.

Table (8). the minimum TC_i for product categories

Product categories	TC_i (\$)
Small plastic bottle	70.89
Glass bottle	272.10
Large gallon container	41.96

Minimum total inventory costs obtained from (31) are presented in Table 8. Although the EOQ for glass bottles is huge, the total cost is \$272.10, which seems counterintuitive but mathematically fits the ultralow holding cost revealed here. The holding cost of \$0.0206 per unit is completely insignificant compared to the high setup cost over thousands of units. The smaller proportion of the costs for small plastic bottles (\$70.89) and large gallon containers (\$41.96) can be attributed to the lower order quantities and an equally balanced cost structure.

4.8 Optimizing Safety Stock

Safety stock (SS) is the fundamental ingredient of a stock management system for minimizing the uncertainty of stockout events while avoiding surplus accumulation. The optimal level of SS establishes a balance between overstocking and understocking, aiming to keep shortages to a minimum. As defined by Equation (30), safety stock determination includes a safety factor (K), which corresponds to some particular service level (or confidence interval) in the context of the normal distribution. The K values as presented in Table 9 were obtained through statistical analyses conducted on SPSS software (StatSoft.Inc., 2007). Related to various service-level scenario cases.

Table (9). Values of Safety Factor, k , Based on Normal Distribution

Service levels	K -values	Service levels	k -values
0.90	1.28	0.95	1.64
0.91	1.34	0.96	1.75
0.92	1.41	0.97	1.88
0.93	1.48	0.98	2.05
0.94	1.55	0.99	2.33

Table 9 shows that a high level of service and a high safety factor (k) are associated. Based on that, the extracted (SS) for product categories is presented in Table 10.

Table (10). Values of Safety Stock, SS , under Different Service Levels for product categories

product categories	Service levels	Value of SS	Service levels	Value of SS
Small plastic bottle	0.90	984	0.95	1261
	0.91	1030	0.96	1346
	0.92	1084	0.97	1446
	0.93	1138	0.98	1576
	0.94	1192	0.99	1792
Glass bottle	0.90	7459	0.95	9557
	0.91	7809	0.96	10198
	0.92	8217	0.97	10956
	0.93	8625	0.98	11946
	0.94	9033	0.99	13578
Large gallon container	0.90	430	0.95	556
	0.91	454	0.96	593
	0.92	478	0.97	637
	0.93	502	0.98	695
	0.94	525	0.99	790

The highest service level most similar to cases or literature adopted is 95% confidence and 0.05% errors, which is more realistic (Graves & Willems, 2000; Humair et al., 2013).

4.9 Reorder Point Establishment

In finding the reorder points (R) for each product category, Equation (31), which factors in the safety stock (SS) and the mean demand during lead time (D_L) was implemented. This crucial inventory parameter establishes the replenishment point within the safety stock limits. For the three product categories of small plastic bottles, glass bottles, and large gallon containers, the resultant values for reorder points are as follows:

To begin with, safety stock (SS) values were computed via Equation (30), where $SS = K\sigma_L$. The safety factor (K) was based on a target service level of 95% ($K = 1.64$), while σ_L (standard deviation of lead-time demand) was derived from DES forecasting results (Table 1). The lead-time demand (D_L) was sourced from historical data, reflecting daily sales averages over replenishment cycles. The reorder point for each product was then calculated, as shown in Table 11.

Table (11). The established Reorder Point for each product category

product categories	SS	D_L	R
Small plastic bottle	1261	615	1876
Glass bottle	9557	4662	14617
Large gallon container	556	269	825

The results incorporated in Table 11 show how product-specific demand volatility (σ_L) and lead time variability affect reorder levels. For example, glass bottles are given a very high reorder point, as much for the volume of demand as for demand variability. In contrast, the R for large containers is low, indicating stable demand patterns. The method assumes that lead-time demand follows a normal distribution.

4.10 Inventory Turnover by Product Category

The inventory turnover ratios were computed utilizing Equation (10). Furthermore, the cost of goods sold (COGS) was derived from Equation (11). However, COGS approximates 70% of the unit cost Rodwan (2023). Consequently, the inventory turnover ratios categorized by product type are displayed in Table 12. Where Average Inventory = $\frac{EOQ}{2} + \text{Safety Stock} * COGS$ (Chopra & Meindl, 2016). The sales data were extrapolated from daily demand (D_L ; Table 1) over 426 days (14 months). These results are summarized in Table 12.

Table (12). Inventory Turnover rates (14 months period)

Products	COGS (\$)	Annual COGS	Average Inventory cost (\$)	Inventory Turnover
Small Plastic Type	0.513	131145	6398	20.50
Glass Bottles	0.257	595804	6184	96.35
Large Gallon Containers	0.583	68756	2015	34.12

An inventory turnover ratio of 96.35 suggests that glass bottles are highly efficient in terms of asset utilization, given their very rapid sales and low holding costs of \$0.0206 per unit. This very high turnover figure is in keeping with the volatile demand pattern and the upward trend of sales for the product as outlined in Section 4.1. It indicates healthy inventory utilization but carries the risk of stockouts when demand spikes unexpectedly; thus, closely monitoring safety stock levels is necessary. It goes without saying that at this level of stock utilization, one should monitor turnover carefully. In contrast, large-gallon containers maintained a movement ratio of 34.12, corresponding to a demand range of 500 to 4,500 units per day. Keeping holding costs at moderate levels (\$0.0493 per unit) will substantiate this turn method and imply that inventory levels closely match sales patterns, with little risk of overstocking or shortages. In other words, an inferior inventory turnover ratio for small plastic bottles: 20.50, indicating inefficiency in inventory management. Refinement in this area is compounded by highly variable daily demand, ranging from 1,000 to 10,000 units, and by maintaining a very high safety stock of 1,261 units. Low turnover ratios are usually indicative of an ever-increasing inventory, immobilizing working capital, and higher

holding costs. Improvement in this area would probably require updated demand forecasting methodologies, coupled with appropriate policy adjustments to align them with the high variability in actual sales.

5. Discussion

This empirical study identifies a synergistic relationship between inventory turnover and demand forecasting as a predictor of project performance in the water manufacturing industry. Wide variations in inventory turnover were observed across products. Glass bottle turnover reached an impressively high rate of 96.35, given the very low holding cost (\$0.0206 per unit) and sustained demand. This supports the observation by Hasanah (2022) that turnover is a valid measure of sales efficiency. Conversely, small plastic bottles had a very low turnover ratio (20.50), reflecting poor inventory management due to demand volatility (1,000-10,000 units per day) and high safety stock levels (1,261 units). This correlates with Elsayed (2015) Findings that link poor inventory management to poor financial performance. The analysis further stated that, in demand forecasting, ARIMA was more accurate than Double Exponential Smoothing, yielding lower MAPE values (10.5-23.53%), underscoring the need for advanced forecasting techniques to enhance operational excellence. As per the cost optimization-oriented principles by Mohite & Hankare (2024), setup costs for glass bottles (\$5,933.44) warranted higher economic order quantity levels (22,112 units). Keeping the 95% service level, however, required heavy investments in safety stock (e.g., 9,557 units for glass bottles), illustrating the trade-off between preventing stockouts and incurring holding costs, as examined by (Grubor et al., 2013).

6. Conclusion

The current study empirically validates that the synergistic integration of demand forecasting and inventory management is a key performance-driving initiative in the world's water manufacturing industry, which, in turn, directly affects several critical financial and operational metrics. This study shows how optimal cost efficiency is achieved by using explicit ARIMA forecasts to calculate size-specific Economic Order Quantity (EOQ) and safety stock, thereby optimizing the trade-off between prohibitive setup costs and carrying expenses. This integrated process also ensures product availability through strategic reorder point setting, which strongly boosts service levels and on-time deliveries while increasing operational resilience against demand variability. The wide disparity in inventory turnover ratios across product categories indicates that this strategic alignment is necessary to maximize resource utilization and sales efficiency. Greatly, therefore, this research presents a strong case for achieving above-par cost-effectiveness, operational agility, and customer satisfaction. However, it will be better for manufacturers to incorporate advanced forecasting models into their dynamic inventory policies, thereby improving their competitive advantage. Future research should empirically analyze performance improvements by incorporating machine learning techniques and broadening the set of sustainability indicators within this performance-optimization paradigm.

Acknowledgment:

The authors have no one to acknowledge.

Funding:

No funding was received for this research.

Author Disclosures:

All authors declare that they have no conflicts of interest.

Author Contributions:

Awin Sabah Gharib contributed to data collection, development of the theoretical framework, and a portion of the methodology. The second author, Karzan Mahdi Ghafoor, was responsible for data analysis, practical implementation, data interpretation, and the remaining methodological development.

References

- Abolghasemi, M., Beh, E., Tarr, G., & Gerlach, R. (2020). Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion. *Computers & Industrial Engineering*, 142, 106380. <https://doi.org/10.1016/j.cie.2020.106380>
- Ajayi, E. O., Olutokunbo, T., Obafemi, F., & Araoye, E. (2021). Effective inventory management practice and firms performance: Evidence from Nigerian consumable goods firms. *American International Journal of Business Management*, 4(5), 65-76. <https://www.aijbm.com/wp-content//1456576>
- Akbar, A. (2023). Pengaruh Inventory Turnover dan Working Capital Turnover Dengan Current Ratio Sebagai Mediasi terhadap Harga Saham Pada Sub Sektor Industri Kabel di Bursa Efek Indonesia. *Eksis: Jurnal Ilmiah Ekonomi dan Bisnis*, 14(1), 112-116. <http://dx.doi.org/10.33087/eksis.v14i1.366>
- Arnaiz, L., Cristal, A. F., Gubaton, M., Tanael, D., & Centeno, C. (2023). Optimizing inventory management and demand forecasting system using time series algorithm. *World Journal of Advanced Research and Reviews*, 20, 021-027. <https://doi.org/10.30574/wjarr.2023.20.3.2456>
- Blackburn, J., & Scudder, G. (2009). Supply chain strategies for perishable products: The case of fresh produce. *Production and Operations Management Society*, 18(2), 129–137. <https://doi.org/10.1111/j.1937-5956.2009.01016.x>
- Chopra, S., & Meindi, P. (2010). *Supply Chain Management strategy, Planning and Operation* (Fourth). Springer.
- Chopra, S., & Meindl, P. (2016). *Supply Chain Management: Strategy, Planning, and Operation*. In *Pearson Education Limited* (Sixth Edit).
- De Menezes, A. D., De Barros, J. G. M., Da Fonseca, B. B., Aguilera, M. V. C., & Sampaio, N. A. de S. (2023). Demand forecasting and inventory management

- as requirements for quality assurance in a bakery company. *Revista de Gestão e Secretariado (Management and Administrative Professional Review)*, 14(9), 15680–15694.
<https://doi.org/10.7769/gesec.v14i9.2832>
- Deni, S., & Puji, L. E. (2023). Effect of Cash, Receivables, and Inventory Turnover on Net Profit Margin (NPM) in Food & Beverage Subsector Manufacturing Companies. *Studies in Business and Economics*, 18(1), 298–313.
<https://doi.org/10.2478/sbe-2023-0016>
- Elsayed, K. (2015). Exploring the relationship between efficiency of inventory management and firm performance: An empirical research. *International Journal of Services and Operations Management*, 21(1), 73–86.
<https://doi.org/10.1504/IJSOM.2015.068704>
- GMDH-SHELL. (2018). *Business Forecasting Solution for Business*. (v3.8.9).
<https://www.gmdhshell.com/>
- Graves, S. C., & Willems, S. P. (2000). Optimizing strategic safety stock placement in supply chains. *Manufacturing and Service Operations Management*, 2(1), 68–83.
<https://doi.org/10.1287/msom.2.1.68.23267>
- Grubor, A., Milicevic, N., & Mijic, K. (2013). Empirical Analysis of Inventory Turnover Ratio in FMCG Retail Sector - Evidence from the Republic of Serbia. *Inzinerine Ekonomika-Engineering Economics*, 24(5), 401–407.
<https://doi.org/10.5755/j01.ee.24.5.3546>
- Hasanah, A. S. (2022). The Effect of Inventory Turnover on Return on Investment (ROI) in Pg. Rajawali II Cirebon. *Return : Study of Management, Economic and Bussines*, 1(01), 7–11. <https://doi.org/10.57096/return.v1i01.6>
- Hill, A. V., & Zhang, W. (2010). Six Common Misuses of the Inventory Turnover and Days On Hand Metrics. *Production and Inventory Management Journal*, 46(1), 36–46.
- Hillier, F. S., & Lieberman, G. J. (2010). Introduction to the Ninth Edition. In *Writing Empirical Research Reports* (Ninth Edit).
<https://doi.org/10.4324/9781003230410-1>
- Humair, S., Ruark, J. D., Tomlin, B., & Willems, S. P. (2013). Incorporating Stochastic Lead Times Into the Guaranteed Service Model of Safety Stock Optimization Salal. *Institute for Operations Research and the Management Sciences*, 43(5), 421–434.
<https://doi.org/10.1287/inte.2013.0699>
- Ikechukwu, F., Christopher, O., & Okonkwo, A. O. (2023). Inventory Management Strategy and Performance of Brewery Companies in South East, Nigeria. *Advance Journal of Management and Social Sciences*, 7(02), 44–79.
<https://aspjournals.org/Journals/index.php/ajmss/index>
- Kabirifar, K., & Mojtahedi, M. (2019). The impact of Engineering, Procurement and Construction (EPC) phases on project performance: A case of large-scale residential construction project. *Buildings*, 9(1), 1–15.
<https://doi.org/10.3390/buildings9010015>

- Karwankar, R., Jaiswal, R. C., Potdar, G. P., & Khodaskar, M. R. (2021). Demand Forecasting for Inventory Optimization. *Journal of Emerging Technologies and Innovative Research (JETIR)*, 8(12), 121–131.
- KRG, I. R. (2023). *invest in kurdistan overview of priority sectors*.
- Leung, M., Quintana, R., & Chen, A. (2009). Make-To-Order Product Demand Forecasting: Exponential Smoothing Models With Neural Network Correction. *Advances in Business and Management Forecasting*, 6, 249–266. [https://doi.org/10.1108/S1477-4070\(2009\)0000006015](https://doi.org/10.1108/S1477-4070(2009)0000006015)
- Maqsoom, A., Hamad, M., Ashraf, H., Thaheem, M. J., & Umer, M. (2020). Managerial control mechanisms and their influence on project performance: an investigation of the moderating role of complexity risk. In *Engineering, Construction and Architectural Management* (Vol. 27, Issue 9). <https://doi.org/10.1108/ECAM-05-2019-0244>
- Mohite, S., & Hankare, A. V. (2024). "An Investigation of JIT (Just in time) Approach in Inventory Control of Ongoing Construction Project ". *International Research Journal of Engineering and Technology*, 11(7), 49–52. www.irjet.net
- Moiseev, G. (2021). Forecasting oil tanker shipping market in crisis periods: Exponential smoothing model application. *The Asian Journal of Shipping and Logistics*, 37(3), 239–244. <https://doi.org/10.1016/j.ajsl.2021.06.002>
- Munyaka, J. B., & Yadavalli, V. S. S. (2022). Inventory Management Concepts and Implementations: a Systematic Review. *South African Journal of Industrial Engineering*, 33(2), 15–36. <https://doi.org/10.7166/33-2-2527>
- Nahmiasn, S., & Olsen, T. L. (2015). *Production and Operations Analysis* (Seventh).
- Nuraini, A. I. (2021). The Effect of Cash Turnover and Inventory Turnover on Return on Assets (ROA). *Almana : Jurnal Manajemen Dan Bisnis*, 5(2), 259–270. <https://doi.org/10.36555/almana.v5i2.1659>
- Pratama, A. E., Dimiyati, M., & Pratiwi, Y. E. (2020). Working Capital Turnover, Operational Cost Ratio, and Inventory Turnover on Company Performance. *Assets : Jurnal Ilmiah Ilmu Akuntansi, Keuangan Dan Pajak*, 4(1), 42–49. <https://doi.org/10.30741/assets.v4i1.566>
- Rodwan, J. G. J. (2023). *Bottled water reaches new peaks in revenue and volume*. International Bottled Water Association.
- Sahoo, A., Tandon, D., Jena, D., Mishra, P. C., Meher, J. R., & Panigrahi, R. R. (2021). Inventory Management and Performance of Manufacturing Firms. *International Journal of Value Chain Management*, 12(2), 149–170. <https://doi.org/10.1504/ijvcm.2021.10033598>
- Saliji, M. (2021). *Effective inventory management in the automotive industry* [Malardalen University Sweden]. <https://www.diva-portal.org/smash/get/diva2:1563549/FULLTEXT01.pdf>
- Satrio, C. B. A., Darmawan, W., Nadia, B. U., & Hanafiah, N. (2021). Time series analysis and forecasting of coronavirus disease in Indonesia using ARIMA model and PROPHET. *Procedia Computer Science*, 179(2020), 524–532. <https://doi.org/10.1016/j.procs.2021.01.036>
- Selvaraj, J., Arunachalam, V., Coronado-franco, K., Romero-orjuela, L. V., &

- Ramirez-Yara, Y. (2020). Time-series modeling of fishery landings in the Colombian Pacific Ocean using an ARIMA model. *Regional Studies in Marine Science*, 39, 101477. <https://doi.org/10.1016/j.rsma.2020.101477>
- Shukaili, S. M. S. Al, Jamaluddin, Z., & Zulkifli, N. (2023). The Impact of Strategic Inventory Management on Logistics Organization's Performance. *International Journal of Business and Technology Management*, 5(3), 288–298. <https://doi.org/10.55057/ijbtm.2023.5.3.24>
- Silver, E. A., Pyke, D., & Thomas, D. J. (2017). Inventory and Production Management in Supply Chains. In *Taylor & Francis Group* (Fourth Edi).
- StatSoft.Inc. (2007). *Statistica dta analysis software system*. Retrieved from www.statsoft.com
- Sunaryo, D., & Lestari, E. P. (2023). Effect of Cash, Receivables, and Inventory Turnover on Net Profit Margin (NPM) in Food & Beverage Subsector Manufacturing Companies. *Studies in Business and Economics*, 18(1), 298–313. <https://doi.org/10.2478/sbe-2023-0016>
- Swaraj, A., Verma, K., Kaur, A., Singh, G., Kumar, A., & Melo de Sales, L. (2021). Implementation of stacking based ARIMA model for prediction of Covid-19 cases in India. *Journal of Biomedical Informatics*, 121(August), 103887. <https://doi.org/10.1016/j.jbi.2021.103887>
- Taha, H. A. (2017). Operation Research: An Introduction. In *Sustainability (Switzerland)* (Tenth Edit). Pearson Education. an_Terpusat_Strategi_Melestari
- Thomopoulos, N. T. (2015). Demand Forecasting for Inventory Control. In *Springer* (first). https://doi.org/10.1007/978-3-319-11976-2_1
- Thompson, S. (2024). The Impact of Demand Forecasting Accuracy on Customer Satisfaction. *International Journal of Supply Chain Management*, 9(5), 55–64. <https://doi.org/10.2139/ssrn.4256115>
- Vista, V., Leandra, W. A., Katharina, N., & Seliamang, Y. M. (2023). the Effect of Cash Turnover, Receivables Turnover, Inventory Turnover and Company Growth on Profitability in Manufacturing Companies in the Multiple Industrial Sectors Listed on the Indonesia Stock Exchange in 2018-2020. *SULTANIST: Jurnal Manajemen Dan Keuangan*, 11(1), 89–96. <https://doi.org/10.37403/sultanist.v11i1.498>
- Vrat, P. (2014). Basic Concepts in Inventory Management. In *Basic Concepts in Inventory Management* (127th ed., pp. 21–36). https://doi.org/10.1007/978-81-322-1970-5_2
- Yücer, C. T. (2006). Modelling the evolution of demand forecasts in a production-distribution system (Master's thesis, Middle East Technical University (Turkey)).
- Yunusa, A. (2021). Inventory Management Practices and Performance of Manufacturing Firms in Kogi State. *Journal of Good Governance and Sustainable Development in Africa*, 6(3), 54–63. <http://journals.rcmss.com/index.php/jggsda/article/view/134>

Zhu, F., Wang, X., Wang, L., & Yu, M. (2021). Project manager's emotional intelligence and project performance: The mediating role of project commitment. *International Journal of Project Management*, 39(7), 788-798.
<https://doi.org/10.1016/j.ijproman.2021.08.002>

Authors Biography

Awin Sabah Gharib is a master student in the Project management Department at the University of Sulaimani.

Dr. Karzan Mahdi Ghafour is an Assistant Professor in the Project management Department at the

University of Sulaimani. His research interests include Supply Chain, Inventory System, Queueing Theory, Forecasting Simulation and with multiple publications in international journals.