

Design and development of a forecasting interface and dynamic sales dashboard for enhanced inventory management

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ABSTRACT

Effective inventory management primarily relies on precise demand forecasting, an essential yet challenging aspect for companies pursuing operational excellence. This paper outlines the design and implementation of a forecasting interface integrated with a sales dashboard to enhance demand prediction accuracy and inventory decision-making. The interface incorporates four established forecasting techniques—Naïve, Moving Average, Weighted Moving Average, and Exponential Smoothing—to systematically address demand fluctuations. Created in Excel and automated with VBA, it provides reorder points, safety stock levels, and forecasted demand, along with other distinctly user-friendly inputs and outputs. In addition, a dynamic sales dashboard has been developed with visual features representing historical and projected demand, sales distribution by products and regions which further facilitate detailed analysis and informed inventory management decisions. This study outlines the interface and dashboard development process along with important codes. It also highlights the practical implications of integrating technical forecasting methods with intuitive visualization tools to enhance inventory management substantially. The forecasting interface and sales dashboard were further verified and validated through different scenarios including: high demand in season peaks, managing with variation in lead time issues, and forecasting in case of launching new product.

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1. Introduction

Effective inventory control depends on accurate demand forecasts since it directly affects a company's capacity to satisfy consumer needs and preserve ideal stock levels. Inefficient forecasts might cause problems including stock outs, extra inventory, higher holding costs, and supply chain interruptions. These problems lower general company performance and customer satisfaction. Thus, companies trying to improve inventory control must create a trustworthy forecasting system. The development of a forecasting interface linked with a dynamic sales dashboard is presented in this work. Four known techniques—Naïve Method, Moving Average, Weighted Moving Average, and Exponential Smoothing—are used by the forecasting interface to raise demand +prediction accuracy. The interface provides a simple way for entering forecast parameters and creating actionable outputs including safety stock, reorder points, and demand forecast. The Power BI-based sales dashboard balances the interface to help with data visualization and informed decision-making. This dashboard lets users examine trends properly by including interactive graphics of historical and projected data. The system greatly enhances inventory management techniques by aggregating forecasting techniques with real-time visualization.

2. Literature Review

This section provides an overview of the research done in enhancing the accuracy of conventional forecasting approaches. Why and when a particular forecasting method is suitable and should be preferred is a fundamental point of concern in forecasting (Pinçe et al., 2021). When several forecasts are made, their overall effectiveness is normally higher than the

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effectiveness of one single model. Moreover, by combining different algorithms, companies can improve predictive accuracy while minimizing the risk of errors associated with using a single forecasting technique. Classical forecasting methods with machine learning models are compared (Wahedi et al., 2023) and the researchers concluded that specific economic conditions might benefit from reinforcement learning approaches. They suggested that leveraging machine learning techniques, combined with insights from previous experiences, could enhance forecast accuracy. The study highlights the value of integrating reinforcement learning into existing forecasting models to improve organizational decision-making. A new forecasting structure using the integration of BiLSTM networks and the NARX model are presented in a study (Cocianu et al., 2022) where evolutionary search is utilized for the forecasting purpose. This approach demonstrated the capability of deep learning strategies in identifying patterns within time-series data.

The amount of data availability also influences the selection of forecasting. In a study (Amin et al., 2023) data from 192 databases were used to investigate how concrete age and cement quantity influence compressive strength. Their research focused on factors such as data quality and the need for comprehensive databases to build predictive models. Logistic regression and gradient boosting techniques improved the accuracy of insolvency forecasts (Abdul-Kareem et al., 2024). Their research emphasized the importance of selecting appropriate forecasting models, as errors in financial prediction can be costly. The authors provided a comparative analysis, showing how different techniques can offer advantages depending on economic conditions.

The growing use of big data for sales forecasting emphasize the shift towards machine learning and deep learning techniques. As more organizations adopt these advanced methods, forecasting accuracy improves, and the ability to detect complex patterns increases (Ahaggach et al., 2024). Machine learning methods are particularly useful in handling large volumes of data common in e-commerce, helping to match inventory levels more closely with customer demand. This results in minimized costs associated with overstocking or understocking. Mean absolute percentage error (MAPE) is one of the common measures of forecasting techniques. XGBoost model have shown significant improvement in error reduction (Tightiz et al., 2025).

Forecasting accuracy can be enhanced by integrating nonlinear models into retail settings, particularly where consumer behavior varies significantly (Chu & Zhang, 2003). However, selecting appropriate models for retail forecasting is essential, given the diverse factors influencing consumer decisions. The efficient forecasting results leads to have optimized utilization and optimization of warehouse management (Duque-Jaramillo et al., 2024).

Over the years, forecasting methods have evolved from traditional approaches to incorporating machine learning models. However, the importance and usefulness of old and well-established forecasting methods cannot be denied. Such methods include the Nieve method, moving average, weighted moving average, and exponential smoothing. For instance, the moving average model of forecasting has been applied by (Ejder & Özel, 2024) on time-series data and discussed the accuracy of the model. Othe well-established forecasting methods (moving average and exponential smoothing has been employed by (Restyana et al., 2021) to analysis the forecasting of medicine distributions. Mean absolute prediction error (MAPE) has been taken as a measure of comparison between the two methods. Similarly, (Sulandari & Yudhanto, 2015) used simple moving average integrated with weighted fuzzy time series to predict the enrollment in education sector. In another study (Kahraman & Akay, 2023) exponential smoothing method is used to predict the forecasting of global prices of metals. It is also discussed by (Lawrence et al., 2000) that simple method can be a good solution to forecasting. They challenged the notion that complex models are always superior to simple models. They demonstrated that sometimes, even the basic form of unadjusted naïve forecasts may outperform corporate forecasts, particularly in specific scenarios. The authors strongly recommend that an analytical approach should be taken cautiously, noting that basic techniques may be sufficient under stable conditions or when data availability is limited.

The concept of designing user interfaces and dashboards is not that much common as compared to other research areas of forecasting. However, some studies present the design of dashboards and interfaces in the area of manufacturing. For instance, a dashboard user interface has been designed by (Shamsuzzoha et al., 2014). Their dashboard serves for the factory business process. Likewise, a manufacturing industry related dashboard is presented by (Tokola et al., 2016) to visually reflect the industry's main KPIs and their related statistics. Virtual assistant based interactive interface for smart manufacturing applications has also been designed by (Jwo et al., 2021). In a similar direction, an interface and dashboard is designed for an automotive industry to visually represent the industry's KPIs and their status. With reference to designing a dashboard and interface for the forecasting, a limited research has been found which is the main motivation and contribution of our presented study.

This study intends to solve inventory related challenges as well as sales data management and its user-friendly visual requirements and difficulties by means of an automated forecasting interface connected with a dynamic sales dashboard. Four often used techniques—Naïve Method, Moving Average, Weighted Moving Average, and Exponential Smoothing—are used by the forecasting interface to fit changing demand patterns. The system guarantees that the most accurate method is selected for every forecasting situation by automating the computation and comparison of several techniques, so minimizing human error. A dynamic sales dashboard meant to offer clear and interactive data visualization balances the interface. Designed with Power BI, the dashboard creates aesthetically pleasing graphs and charts from forecast outputs and raw data. This integration not only supports real-time monitoring but also helps to spot trends, so enabling decision-makers to respond quickly to demand variations.

3. Problem Definition and objectives

Effective inventory control depends on accurate demand forecasting since it directly affects a company's capacity to keep ideal stock levels, lower expenses, and guarantee timely product availability. Many companies, especially those in the consumer goods industry, find operational difficulties resulting from forecasting errors. Usually presenting themselves as stock outs, extra inventory, higher holding costs, and disrupted supply chain continuity are among these difficulties. Inadequate forecasting thus not only compromises operational efficiency but also customer satisfaction and profitability. One of the main difficulties is the inconsistent and manual application of forecasting techniques. Often based just on historical data, conventional methods fall short in capturing the complexity of changing demand patterns. This restriction becomes especially more noticeable when considering goods influenced by seasonal fluctuations or erratic market changes. Companies sometimes find themselves either overproducing, which results in extra inventory, or under producing, which causes lost sales possibilities without the capacity to dynamically change forecasts.

Decision-makers are left without the tools to evaluate which approach suits their data patterns, producing inconsistent forecasting results. Furthermore, the lack of clear visualization makes it challenging for decision-makers to properly analyze the data and implement quick responses even in cases of accurate forecasts. Inventory managers, especially in new companies and startup businesses, could find it difficult to make quick decisions without a user-friendly dashboard highlighting trends and contrasting forecast accuracy. Hence following objectives were set to conduct this study.

1. To create a thorough forecasting interface capable of automating several forecasting approaches' computation and comparison.
2. To integrate forecasting methods with visual outputs in a single platform to reduce errors and strengthen inventory control.
3. To develop a dynamic sales dashboard that shows forecast results together with historical data, facilitating more informed study.
4. To help companies, especially the startups and new businesses, to keep ideal stock levels, cut inventory-related expenses, and react dynamically to evolving market conditions.

4. Design Methodology

The study is carried out in three sequential phases. Phase 1 mainly consists of developing the forecasting interface, phase 2 deals with the designing of the sales dashboard, and phase 3 addresses the validation of both the interface and the sales dashboard. A structured design methodology for developing a forecasting interface and dashboard aimed at optimizing inventory management processes is presented. The methodology integrates various forecasting techniques and data visualization within a single, user-friendly interface. The primary objective is to enhance forecasting accuracy through systematic analysis and model evaluation. The methodology follows a series of stages as depicted in the flowcharts shown below in Fig. 1.

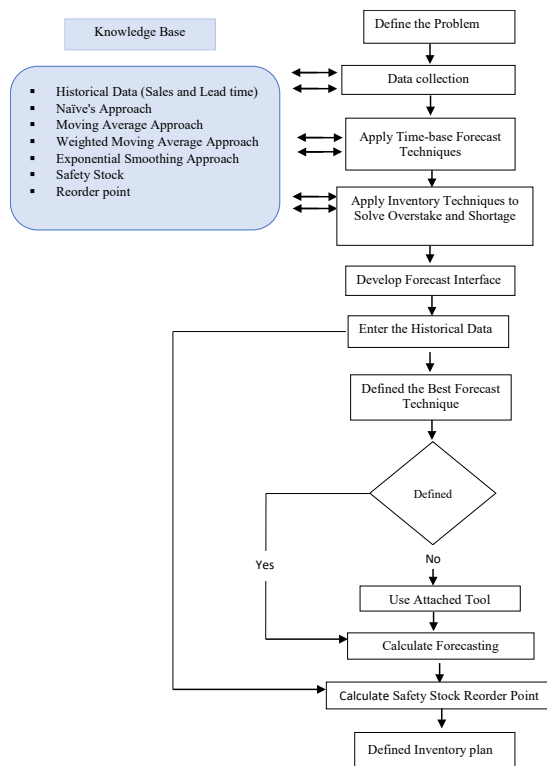


Fig. 1. Flowchart of design methodology

4.1 Mathematical Formulation

This section outlines the mathematical foundation upon which the forecasting interface and sales dashboard are developed. The goal is to apply quantitative methods that improve demand prediction, reduce uncertainty, and ensure timely inventory replenishment. Then the selection of forecasting models and forecasting generation were opted to make the forecast of sales expected in the future periods. Forecasting affirms on the right stocks that should be put in the market satisfying the expected demand to avoid excessive stock keeping or inadequate stocks. In this context, the critical measures include safety stock and the reorder point (ROP) which can be calculated from Eq. (1) and Eq. (2), respectively.

$$\text{Safety Stock} = Z \times \sigma d \times \sqrt{L} \quad (1)$$

$$\text{ROP} = [(\text{Average Daily Usage} \times \text{LeadTime}) + \text{SafetyStock}] \quad (2)$$

where, Z is the Z -score (based on desired service level), σd is the standard deviation of demand, and L is the lead time.

Four different forecasting models are applied to result into future periods estimates in terms of safety stocks, reorder point, and the expected sales. It includes the commonly practiced models such as Naïve, moving average, weighted moving average, and exponential smoothing. The model resulting in minimum amount of prediction error has been considered as the selection criterion of the most appropriate solution. To evaluate forecasting accuracy, three common metrics are usually used. Mean absolute deviation is an index of merit based on the average of the absolute differences between forecasted and actual values. Mean absolute deviation (MAD), in general, can be found by Eq. (3) and the MAD in the context of forecasting can be calculated by Eq. (4). Like the MAD, the mean absolute percentage error (MAPE) and mean squared error (MSE) are also considered other measures in forecasting computed by the use of Eq. (5) and Eq. (5). MAPE is beneficial for comparing the level of forecast error between goods and services, or between different time periods because errors are measured in percentages. MAPE is the most common measure in forecasting methods and it is used in designing the interface.

$$\text{MAD}_{\text{General}} = \frac{1}{n} \sum_{i=1}^n |x_i - m(X)| \quad (3)$$

$$\text{MAD}_{\text{Forecasting}} = \frac{[\sum |A_t - F_t|]}{n} \quad (4)$$

$$\text{MAPE}_{\text{Forecasting}} = \frac{1}{q} \left[\sum_{t=1}^q \left| \frac{A_t - F_t}{A_t} \right| \right] \times 100 \quad (5)$$

$$\text{MSE}_{\text{Forecasting}} = \sum [A_t - F_t]^2 \times n \quad (6)$$

where, $m(X)$ is the average value of dataset, x_i is the specific value of the dataset, n is the count of values, q is the number of summation iterations, A_t is the actual value, and F_t is the forecast value.

4.1.1 Naïve Method

By optimizing resource allocation and stock control, accurate demand forecasting makes it easier to make decisions about supply chain and inventory management. Using the most recent observation as the forecast for the next period is a simple but effective way to use the Naïve Method. Because it does not require an extensive amount of calculations, it's a good choice for businesses that want quick and easy-to-understand predictions. This method works best when demand patterns are stable and don't change much. It is also often used as a standard to compare more advanced forecasting models. As it is simple to use, it is a useful reference point in many forecasting situations. Mathematically, the Naive Method is represented by the following formula:

$$F_t = A_{t-1} \quad (7)$$

where:

F_t represents the forecast for the current period.

A_{t-1} represents the actual demand from the previous period.

While the Naive Method offers a simple forecasting approach, it does not consider trends, seasonality, or external factors that may impact demand fluctuations. As a result, it is most effective in situations where demand remains relatively stable over time.

4.1.2 Moving Average (MA)

Accurate demand forecasting is essential for inventory management, enabling businesses to maintain optimal stock levels, improve procurement decisions, and reduce excess inventory. The 3-Month Moving Average (MA) method offers a simple

yet effective approach by smoothing short-term demand fluctuations through the average of the three most recent periods. It is especially useful for stable demand patterns, as it minimizes variability while highlighting trends. This section examines the 3-Month Moving Average method, covering its theoretical foundation, implementation steps, and practical applications. Understanding its assumptions, strengths, and limitations helps users apply it effectively before progressing to more advanced forecasting models. Mathematically, the 3-Month Moving Average is represented by the following formula:

$$F_t = \frac{A_t}{n} = \frac{A_{t-1} + A_{t-2} + A_{t-3}}{3} \quad (8)$$

where:

F_t is the forecast for the current period.

A_t is the actual demand from the last three months.

By averaging past values, this method reduces random fluctuations and produces a more stable forecast. However, it does not consider trends or seasonality, making it most effective in environments with relatively stable demand.

4.1.3 Weighted Moving Average (WMA)

Effective forecasting plays a vital role in supply chain and inventory management, helping businesses anticipate demand and optimize stock levels, procurement, and resource allocation. The Weighted Moving Average (WMA) method improves predictive accuracy by assigning different weights to past observations, making it a valuable tool for demand forecasting. This section explores the WMA method, covering its theoretical basis, step-by-step implementation, and real-world applications. Understanding its assumptions, advantages, and limitations allows users to apply it effectively before advancing to more complex forecasting techniques. Mathematically, the Weighted Moving Average is represented by the following formula:

$$F_t = (W_1 \times A_{t-1}) + (W_2 \times A_{t-2}) + (W_3 \times A_{t-3}) + \dots + (W_n \times A_{t-n}) \quad (9)$$

where:

F_t represents the forecast for the current period.

A_{t-n} represents the actual demand from previous periods.

W_n represents the assigned weight for each period, where the sum of all weights equals 1.

The selection of weights is critical to ensuring forecast accuracy. A common approach is to prioritize recent data while still considering older observations. One effective method is the linearly decreasing weight formula, which assigns higher weights to recent periods and gradually reduces them for older periods. The weights are calculated as follows: Mathematically, the Linearly Decreasing Weighted Moving Average (LDWMA) is represented by the following formula:

$$W_i = \frac{n - i + 1}{\frac{n(n+1)}{2}} \quad (10)$$

where:

W_i is the weight assigned to the i of the most recent data point.

n is the total number of periods (e.g., 3 for a 3-month WMA) with 1 being the oldest and n being the most recent.

This approach ensures that the total weight distribution sums to 1. By gradually reducing the influence of older data instead of abruptly excluding past values, the linearly decreasing weighting method balances sensitivity to recent trends with forecast stability. This makes it particularly effective for demand patterns with moderate fluctuations.

4.1.4 Exponential Smoothing (ES)

Accurate forecasting is essential for inventory and supply chain management, helping businesses anticipate demand shifts and make informed decisions on stock levels, procurement, and resource allocation. Exponential Smoothing (ES) is a forecasting technique that prioritizes recent data points while gradually reducing the influence of older values, making it highly effective for capturing demand patterns while minimizing short-term fluctuations. This section details the implementation of Exponential Smoothing in the forecasting interface, covering its core principles, step-by-step execution, and practical benefits. Understanding its functionality, advantages, and limitations enables users to apply it effectively before advancing to more complex forecasting methods.

Mathematically, Exponential Smoothing is defined as:

$$F_t = \alpha A_{t-1} + (1 - \alpha)F_{t-1} \tag{11}$$

where:

F_t represents the forecast for the current period.

A_{t-1} is the actual demand from the previous period.

F_{t-1} is the previous forecasted value.

α (alpha) is the smoothing constant, a value between 0 and 1, determining how much weight is given to recent observations.

A higher alpha value (closer to 1) places more emphasis on recent observations, making the forecast more responsive to demand changes. A lower alpha value (closer to 0) smooths the forecast further, reducing its sensitivity to short-term fluctuations.

5. Results and Discussion

The forecasting interface and sales dashboard streamlined the inventory forecasting process and facilitated data access. The forecasting tool facilitated the selection and application of various methods in an organized manner. It also autonomously identified the most precise option based on MAPE values. It enhanced inventory management by integrating safety stock and reorder point computations. The sales dashboard served as a real-time visualization layer that transformed raw data into valuable information. These tools expedited the decision-making process and enhanced data-driven approaches, thereby reducing manual labor and facilitating inventory optimization strategies.

5.1 Design and Development of Interface

The interface implementation phase is when a forecasting tool that is easy to use and uses different forecasting methods and error metrics is developed. Users can enter data, choose forecasting methods, and see the results of their forecasts in a visually appealing manner. By automating complicated calculations and showing the results in a clear, organized way, it is meant to make decisions easier. This makes sure that even users who don't know much about technology can use accurate forecasting, which makes the tool both useful and easy to use in real-world business settings. The methodology consisting of numerous steps of developing the forecasting interface is presented in Fig. 2.

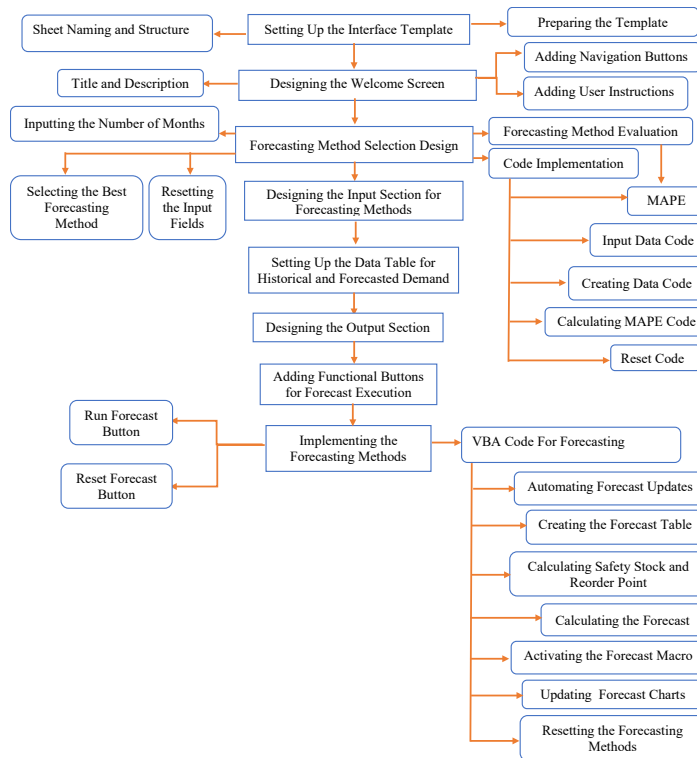


Fig. 2. Flowchart exhibiting different steps to develop the forecasting interface

The first step is to design a customized interface template and the sales dashboard. It ensures that the dashboard looks professional and consistent with the company's brand identity. The interface begins with a welcome screen as shown in Fig. 3. In this screen the user inserts the number of months (input) over which the historical data is available. A historic demand table is generated according to the number months defined earlier (the input). The screen shows up all the pre-defined forecasting methods, i.e. Naïve, moving average, weighted moving average, and exponential smoothing.

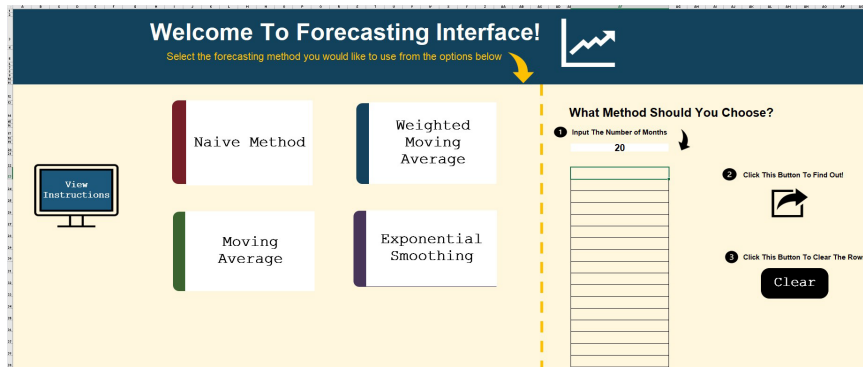


Fig. 3. Welcome screen of the interface

The interface performs computations over the input historical data and calculates mean absolute errors (MAPEs) against each of the listed methods and makes recommendations of the most appropriate method of forecasting based on the lowest amount of MAPE. It guides the user to move on further for precise and detailed forecasting results. It offers four options to select the most appropriate one based on the MAPE computations. A screenshot of the four forecasting methods is shown in Fig. 4. Then, the user can go to the sheet for the chosen method to look at the data in more detail.

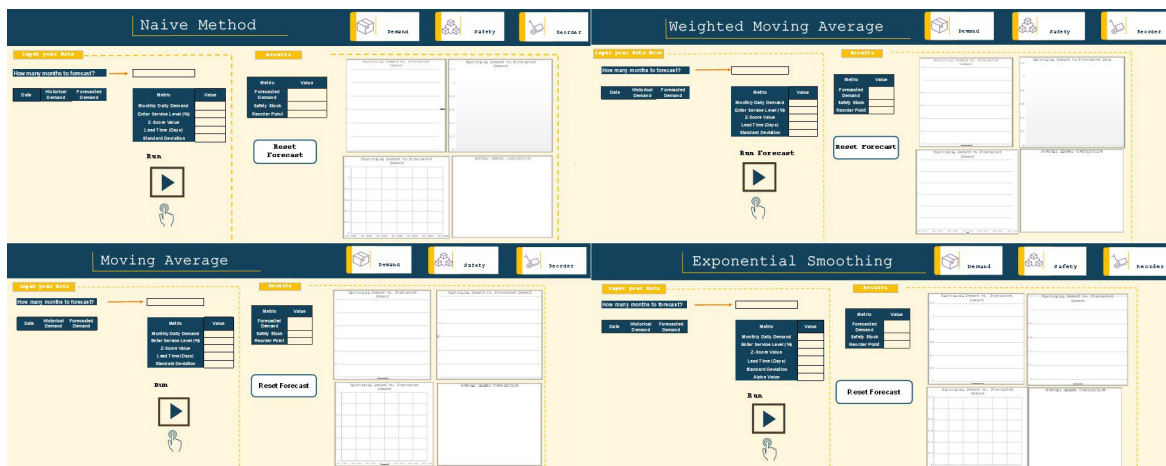


Fig. 4. Screenshot of individual forecasting methods taken from different parts of the interface

Next is to create settings in the data sheet. In the “Data sheet” users can input key settings based on their specific forecasting needs. These settings allow flexibility in calculations for safety stock and reorder points. Users should adjust the following inputs:

- Input the desired service level percentage (e.g., 95%).
- Enter the Z-score that corresponds to the chosen service level (e.g., 1.64 for 95%).
- Specify the lead time in days (e.g., 45 days).
- Input the standard deviation of demand (e.g., 60).

These settings can be customized by the user to reflect changes in supply chain conditions or business requirements, providing flexibility in inventory control calculations. Afterwards the output table appears as shown in Fig. 5. Selecting a method directs the user to its dedicated page, in this case the Naïve Method page. This screen contains sections for users to input data regarding service level, lead time, and standard deviation. It independently displays calculations for safety stock, projected demand, and reorder points. The layout is consistent across all methods to ensure a uniform user experience. The only difference between sheets is the forecasting methodology. Next, the development of the interface consists of adding different charts and graphs. Visualizations help users interpret the data more effectively by highlighting trends and relationships. Thus the interface contains four charts including: 1) the chart of historical demand v/s forecasted demand, 2) Demand Trend chart,

2. Historical and Daily Demand

' Calculate Daily Demand based on user inputs

Dim i As Integer

historicalTotal = 0

For i = 13 To 23

historicalTotal = historicalTotal + wsDashboard.Cells(i, 3).Value ' Sum of demand

Next i

dailyDemand = historicalTotal / 30 ' Assume monthly demand (adjust as needed)

3. Safety Stock and Reorder Point

' Calculate Safety Stock and Reorder Point

Dim safetyStock As Double

Dim reorderPoint As Double

safetyStock = zScore * stdDev * Sqr(leadTime)

reorderPoint = (dailyDemand * leadTime) + safetyStock

4. Output Table

' Update Safety Stock and Reorder Point on the Dashboard

wsDashboard.Cells(14, 7).Value = safetyStock ' G14 for Safety Stock

wsDashboard.Cells(15, 7).Value = reorderPoint ' G15 for Reorder Point

5. Forecasted Demand

' Calculate Forecasted Demand using 3-month moving average

Dim forecastedDemand As Double

Dim totalForecastedDemand As Double

totalForecastedDemand = 0 ' Initialize total forecast

For i = 13 To 23

If i >= 15 Then

' Calculate moving average from the third month onwards

forecastedDemand = Application.WorksheetFunction.Average(wsDashboard.Cells(i - 2, 3), wsDashboard.Cells(i - 1, 3), wsDashboard.Cells(i, 3))

Else

' Use actual historical data for the first two months

forecastedDemand = wsDashboard.Cells(i, 3).Value

End If

' Update forecasted demand in the 'Data' sheet (F17:F27)

wsData.Cells(i + 4, 6).Value = forecastedDemand

' Accumulate total forecasted demand

totalForecastedDemand = totalForecastedDemand + forecastedDemand

Next i

6. Demand output and completion message

' Update total forecasted demand in G13 on the Dashboard

wsDashboard.Cells(13, 7).Value = totalForecastedDemand

MsgBox "Calculation Complete!"

End Sub

Finally, user instructions are added in the interface to provide useful instructions for a new user of the interface as shown in Fig. 7. These instructions help users understand how to interact with the dashboard effectively.

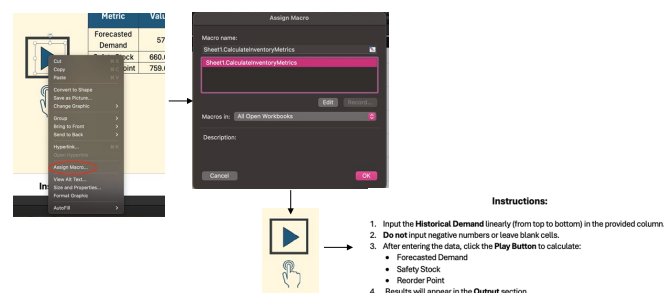


Fig. 7. User instructions part of the interface

5.2 Development of Sales Dashboard

The second phase of the study was to design and develop a sales dashboard. Designing a sales dashboard is all about transforming raw data into actionable insights through dynamic and visually engaging reports. Power BI's powerful data modeling and visualization tools make it easy to highlight key sales metrics, track performance, and uncover trends. With its interactive features, users can explore data from multiple angles, making it a valuable tool for decision-making. The platform supports seamless integration with various data sources, ensuring real-time accuracy and efficiency in monitoring sales activity.

Using interactive elements like charts, slicers, and trend lines, the sales dashboard shows a visual summary of past sales data as shown in Fig. 8. The dashboard, which was made with Power BI, lets users look at how well products do over time and in different categories. It makes it easier to filter, compare, and find trends in real time, which helps users find seasonal changes, best-selling items, and times when demand is low.

Similar to the interface, the sales dashboard consists of different sectional windows. Each section addresses detailed views and stats of different points of interest for the company. For instance, the section belonging to the sum total by city pops up the detailed information on the sales data belonging to different cities. Each city represents the proportion of total sales (% sales) along with the total sales quantity of each product. Likewise, the section associated with the sum of total by product helps users to gain insights about the sales statistics with respect to types of different products and their sub-categories. Hence, the dashboard makes it easier to make decisions about procurement of new items and planning inventory by giving a clear and concise overview. It is an important addition to the forecasting interface as designed in the previous phase.



Fig. 8. Sales Dashboard Output Screen

6. Multi-Scenario Validation

To ensure the Forecasting Interface operates effectively and reliably, a multi-scenario validation has been carried out. This process includes an experiment designed to evaluate the system's forecasting accuracy by comparing its outputs against historical sales data and actual real-world outcomes. Mean Absolute Percentage Error (MAPE) is employed to quantitatively assess the system's accuracy. This comprehensive validation approach is intended to demonstrate the system's reliability and value, providing a sound basis for its recommendation and subsequent implementation.

6.1 Scenario 1: Preparing for High Demand During Seasonal Peaks

In companies usually there is a certain period over which the demand abruptly goes up. Such cases are called seasonal peaks. In one of such months the XYZ company has a pivotal season in April with a surge in demand. In preparation for the April spike, the company must balance inventory management by ensuring sufficient stock to meet increased demand while avoiding overproduction. To achieve this, the company leverages its dashboard to analyze historical demand patterns, allowing them to adjust inventory levels strategically and minimize the risk of stock outs or excess inventory. The company used the interface by following three simple steps as given below:

1. **Input Historical Demand:** The company gathered data from the past 11 months to predict April 2023 demand. They input the demand values in under the "*Historical Demand*" column.
2. **Adjust Settings:** Although the default settings in the Data sheet include predefined values, users can customize them as needed. The company, for example, reduced the service level from 95% to 90%, which lowered the Z-Score to

1.28. This adjustment reflects the company's increased confidence in supplier reliability. By reducing the service level, the company was able to decrease safety stock, balancing inventory costs with an acceptable level of risk while maintaining efficient operations.

3. **Run the Macro:** After running the macro of the interface, it calculated the following:

- **Forecasted Demand:** 2,081.67 units
- **Safety Stock:** 515.19 units
- **Reorder Point:** 3,792.69 units

The interface response over the scenarios of high demand during seasonal peaks is shown in Fig. 9. The interface has shown a noticeable strategic impact on the company. By leveraging the dashboard, the company enhanced its demand forecasting for the April season, enabling precise identification of inventory needs to meet customer expectations. The safety stock and reorder point calculations offered critical insights for planning order placements. This approach allowed companies to minimize the risk of stock outs, which could have led to missed sales opportunities, while also avoiding excess inventory that might have resulted in increased storage costs.

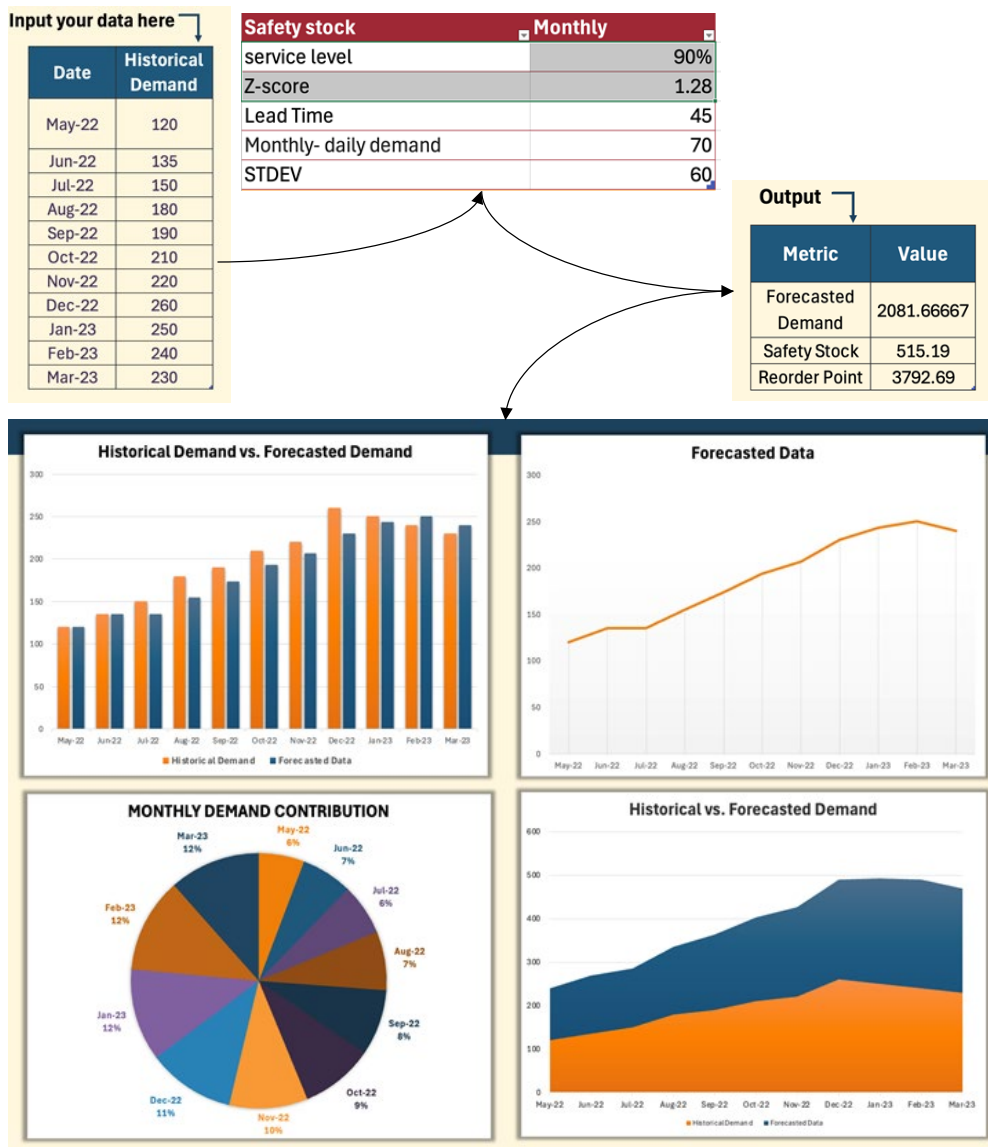


Fig. 9. Validation for scenario one (high demand for seasonal peaks)

6.2 Scenario 2: Managing Supplier Lead Time Issues

The company faces challenges in maintaining inventory levels due to long and unpredictable lead times from foreign suppliers. Recently, the lead time increased from 45 days to 70 days, disrupting the company’s inventory management. To address this, the company used this dashboard to adjust inventory forecasts and reorder points based on the extended lead time, helping to mitigate the risk of inventory shortages and ensure a steady supply during high-demand periods.

1. **Update Lead Time:** The company user enters the new lead time of 70 days in the 'Data' sheet under B20. This reflects the latest supplier performance data.
2. **Input Historical Demand:** The company enters actual demand data from the past 11 months, covering the period of interest.
3. **Run the Macro:** The dashboard provides the following results:
 - **Forecasted Demand:** 3156.67 units
 - **Safety Stock:** 823.27units
 - **Reorder Point:** 8336.61 units

The interface response over the scenarios of managing supplier lead time issues is shown in Fig. 10. The interface has shown a noticeable strategic impact on the company in this case as well. The dashboard enabled the company to make data-driven adjustments to inventory planning following the increase in lead times to 70 days. By recalculating the reorder point, the company was better positioned to place orders early enough to prevent potential stock outs. Additionally, the increased safety stock provided a buffer to maintain demand fulfillment in the event of further supplier delays. These measures offered the company a greater control over their inventory amidst supply chain uncertainties, ensuring more reliable product availability for customers.

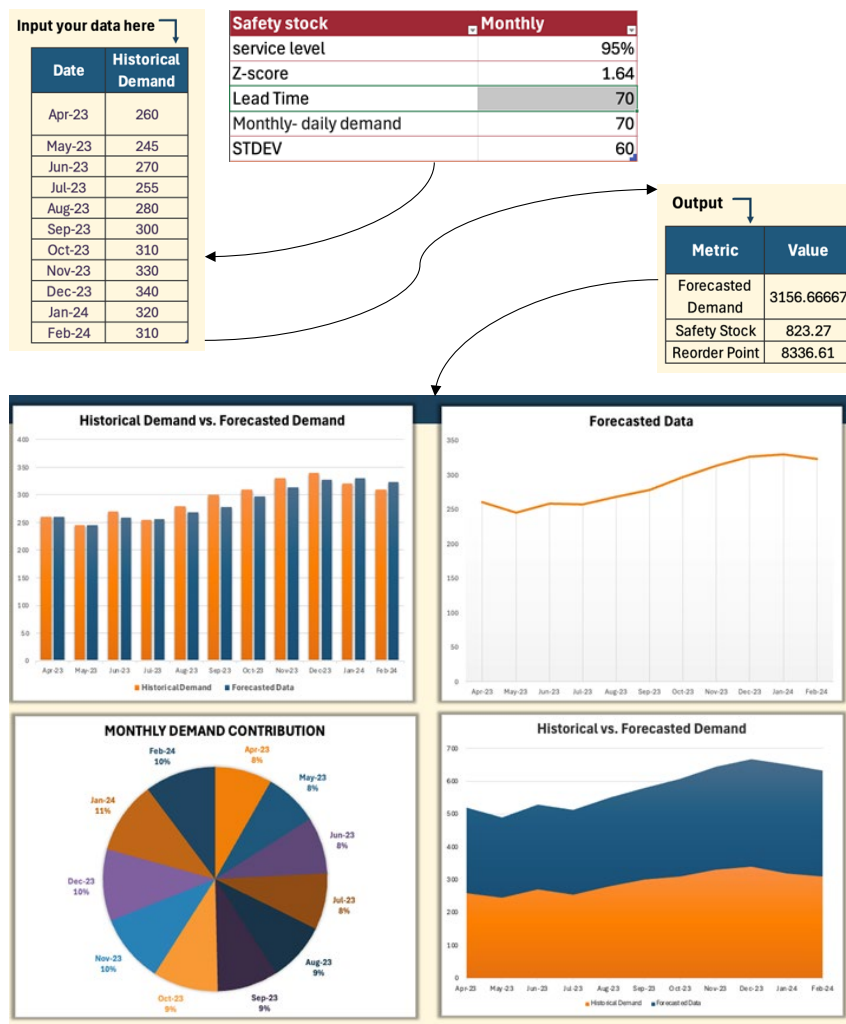


Fig. 10. Validation for scenario two (lead time issues)

6.2 Scenario 3: Launching a New Product

The company is gearing up to launch a new product in the upcoming period. Without historical sales data, the company relies on marketing projections to guide inventory planning. Accurate forecasting is essential to ensure the product remains available throughout the launch phase, preventing stock outs that could hinder momentum or customer interest. By integrating projections into their planning process, the company aims to strike a balance between maintaining sufficient stock and avoiding overproduction. The interface has been tested and validated through following steps:

1. **Input Projected Demand:** The user inputs projected demand for the next 11 months using the following formula to calculate the projected demand in their dashboard steps:

$$D_{Projected} = \frac{D_{n-1} + D_{n-2} + D_{n-3}}{3} \tag{11}$$

where

$D_{Projected}$ = Projected is the projected demand for the current month.

$D_{n-1} + D_{n-2} + D_{n-3}$ = The historical demands for the three preceding months.

2. **Set a High Service Level:** To avoid stock outs during the launch period, the user sets a high service level of 98%.
3. **Run the Macro:** After running the macro, the dashboard displays:
 - **Forecasted Demand:** 3498.33 units
 - **Safety Stock:** 660.09 units
 - **Reorder Point:** 6217.59 units

The interface response over the scenario of launching a new product is shown in Fig. 11. For the launch of their new product, the company utilized the dashboard to manage inventory using projected demand. By setting a high service level, the company minimized the risk of stock outs, which could have been detrimental during the critical launch phase. The dashboard provided a clear view of required inventory levels, allowing us to plan effectively. As actual sales data began to roll in, the company was able to update demand inputs and refine forecasts, enabling them to quickly respond to shifts in demand. This adaptability ensured a smooth and successful product launch.

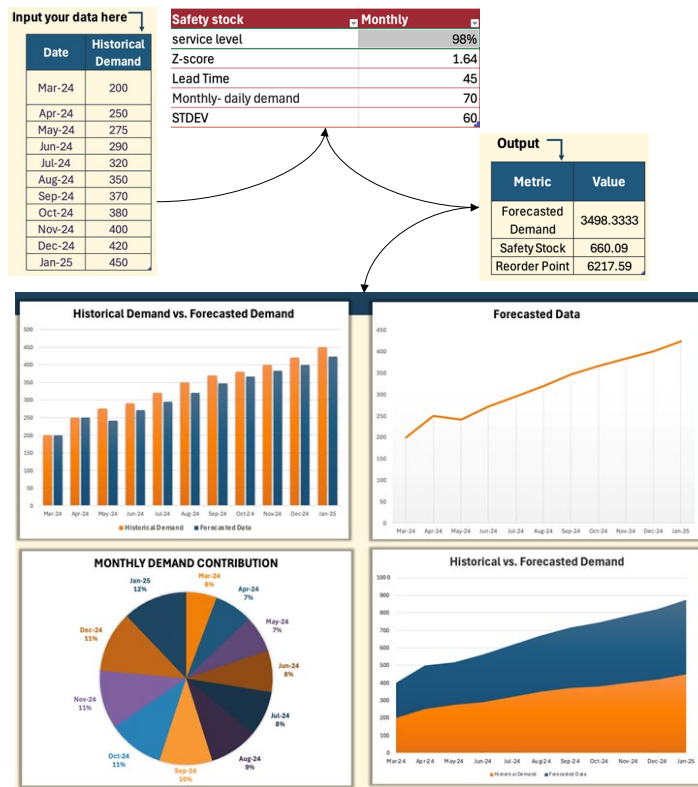


Fig. 11. Validation for scenario three (launch of new product)

7. Conclusions

This study developed a forecasting interface and an interactive sales dashboard to enhance precise demand forecasting and effective inventory management. The forecasting interface is user-friendly, allowing for the selection of forecasting methods, the application of MAPE to assess forecast accuracy, and the generation of critical inventory metrics such as safety stock and reorder points. The tool facilitates accessibility for individuals with different levels of technical expertise by decomposing forecasting procedures into user-friendly and guided steps. It additionally promotes users to consistently adhere to the same forecasting methodologies.

The sales dashboard transforms raw sales data into informative graphs and charts, enabling users to observe fluctuations in demand, assess product performance, and track different activities over a desired time period. The interactive features, such as dynamic filters and graphical insights facilitate the identification of peak demand periods, underperforming items, and seasonal trends. This enables users to make better informed selling and purchasing decisions. The forecasting interface and

dashboard collaborate to address issues related to demand variability and inventory management. They reduce the volume of manual computations, reduce the likelihood of excess or insufficient inventory, and enable data-driven decision-making that enhances operational efficiency.

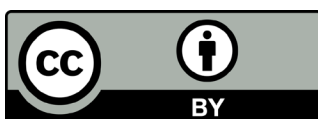
Integrating forecasting models with data visualization tools facilitates users' transition from historical analysis to actionable planning. It demonstrates how user-friendly tools can assist individuals in making data-driven decisions. In the future, the system may be enhanced by incorporating additional forecasting models, utilizing machine learning, or linking it to databases for continuous monitoring and automatic updates.

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References

- Abdul-Kareem, A. A., Fayed, Z. T., Rady, S., El-Regaily, S. A., & Nema, B. M. (2024). Forecasting Financial Investment Firms' Insolvencies Empowered with Enhanced Predictive Modeling. *Journal of Risk and Financial Management*, 17(9), Article 9. <https://doi.org/10.3390/jrfm17090424>
- Ahaggach, H., Abrouk, L., & Lebon, E. (2024). Systematic Mapping Study of Sales Forecasting: Methods, Trends, and Future Directions. *Forecasting*, 6(3), Article 3. <https://doi.org/10.3390/forecast6030028>
- Amin, M. N., Ahmad, W., Khan, K., & Deifalla, A. F. (2023). Optimizing compressive strength prediction models for rice husk ash concrete with evolutionary machine intelligence techniques. *Case Studies in Construction Materials*, 18, e02102. <https://doi.org/10.1016/j.cscm.2023.e02102>
- Chu, C.-W., & Zhang, G. P. (2003). A comparative study of linear and nonlinear models for aggregate retail sales forecasting. *International Journal of Production Economics*, 86(3), 217–231. [https://doi.org/10.1016/S0925-5273\(03\)00068-9](https://doi.org/10.1016/S0925-5273(03)00068-9)
- Cocianu, C. L., Uscatu, C. R., & Avramescu, M. (2022). Improvement of LSTM-Based Forecasting with NARX Model through Use of an Evolutionary Algorithm. *Electronics*, 11(18), Article 18. <https://doi.org/10.3390/electronics11182935>
- Duque-Jaramillo, J. C., Cogollo-Flórez, J. M., Gómez-Marín, C. G., & Correa-Espinal, A. A. (2024). Warehouse management optimization using a sorting-based slotting approach. *Journal of Industrial Engineering and Management*, 17(1), Article 1. <https://doi.org/10.3926/jiem.5661>
- Ejder, U., & Özel, S. A. (2024). A novel distance-based moving average model for improvement in the predictive accuracy of financial time series. *Borsa Istanbul Review*, 24(2), 376–397. <https://doi.org/10.1016/j.bir.2024.01.011>
- Jwo, J.-S., Lin, C.-S., & Lee, C.-H. (2021). An Interactive Dashboard Using a Virtual Assistant for Visualizing Smart Manufacturing. *Mobile Information Systems*, 2021(1), 5578239. <https://doi.org/10.1155/2021/5578239>
- Kahraman, E., & Akay, O. (2023). Comparison of exponential smoothing methods in forecasting global prices of main metals. *Mineral Economics*, 36(3), 427–435. <https://doi.org/10.1007/s13563-022-00354-y>
- Lawrence, M., O'Connor, M., & Edmundson, B. (2000). A field study of sales forecasting accuracy and processes. *European Journal of Operational Research*, 122(1), 151–160. [https://doi.org/10.1016/S0377-2217\(99\)00085-5](https://doi.org/10.1016/S0377-2217(99)00085-5)
- Pınç, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A Critical review. *Omega*, 105, 102513. <https://doi.org/10.1016/j.omega.2021.102513>
- Restyana, A., Savitri, L., Laili, N. F., & Probosiwi, N. (2021). Analysis of Drug Forecasting with Single Moving Average and Single Exponential Smoothing Approach (Case Study in Jombang Regency 2017-2019). *Journal of Physics: Conference Series*, 1899(1), 012100. <https://doi.org/10.1088/1742-6596/1899/1/012100>
- Shamsuzzoha, A., Hao, Y., Helo, P., & Khadem, M. K. (2014). *Dashboard User Interface for Measuring Performance Metrics: Concept from Virtual Factory Approach*. <https://www.semanticscholar.org/paper/Dashboard-User-Interface-for-Measuring-Performance-Shamsuzzoha-Hao/ced5f756d1b37b43744392e67ae10154a0aad5b0>
- Sulandari, W., & Yudhanto, Y. (2015). Forecasting trend data using a hybrid simple moving average-weighted fuzzy time series model. *2015 International Conference on Science in Information Technology (ICSITech)*, 303–308. <https://doi.org/10.1109/ICSITech.2015.7407822>
- Tightiz, L., Yoo, J., & Al-Shibli, W. K. (2025). Strategic enhancements in electricity price forecasting: The role of XGBoost and error correction features. *Results in Engineering*, 26, 105609. <https://doi.org/10.1016/j.rineng.2025.105609>
- Tokola, H., Gröger, C., Järvenpää, E., & Niemi, E. (2016). Designing Manufacturing Dashboards on the Basis of a Key Performance Indicator Survey. *Procedia CIRP*, 57, 619–624. <https://doi.org/10.1016/j.procir.2016.11.107>
- Wahedi, H. J., Heltoft, M., Christophersen, G. J., Severinsen, T., Saha, S., & Nielsen, I. E. (2023). Forecasting and Inventory Planning: An Empirical Investigation of Classical and Machine Learning Approaches for Svanehøj's Future Software Consolidation. *Applied Sciences*, 13(15), Article 15. <https://doi.org/10.3390/app13158581>



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