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Comparative Analysis of Forecasting Methods and Integration with Inventory Models for Efficient Demand Management in the Electronics Sector

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ABSTRACT

Demand fluctuates over time, so forecasting future needs based on the previous data is crucial for proper inventory management. This study aims to showcase the proper way of choosing the perfect forecasting technique for a system and utilize it in the inventory model. In this study, the forecasted demands have been determined based on the sales data obtained from an electrical appliance retailer company using three forecasting techniques: Simple Moving Average, Simple Exponential Smoothing method, and Linear Regression. The forecasting results from these three methods are then examined by several error detection techniques: Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Mean Forecast Error (MFE), and Mean Absolute Percentage Error (MAPE). The Linear regression has fewer errors among the forecasting techniques than the other two. The linear regression has 207.37 for MAD, 74679.50 for MSE, 0 for MAPE, and 25.13% for MAPE. Hence, the data obtained from linear regression was used to build an inventory model. The retailer sells electronic appliances, which are finished goods, and there is no evidence of extreme fluctuation or shortage, so the purchase model with instantaneous replenishment without shortage has been chosen as the inventory model. Sensitivity analysis on this inventory model has been conducted based on different carrying costs and ordering costs, which suggested that small changes in the ordering cost or the carrying cost result in remarkable changes in the total cost, and it indicates that the sensitivity of each type of cost on this inventory model is very high. This sensitivity can be mitigated by keeping the ordering and carrying costs within a fixed range. The findings of the study focuses on the importance of robust demand forecasting for effective inventory management.

Keywords: Simple Moving Average, Simple Exponential Smoothing Method, Linear Regression, Forecast

1. Introduction

Inventory management deals with planning and controlling the inventory level of an industry. It plays a crucial role in production and supply chain. Effective inventory management requires proper synchronization of amount and place to be cost efficient system, satisfy consumer needs & improve supply chain performance [1]. Utilization of forecasting techniques in the operations of an organization is economically justified. Early demand forecasting helps to limit costs by optimizing inventory levels. The forecasting is a method that indicates the prediction of a certain event happening in the future, which is not known at the time of predicting. Forecasting is done through steps like: definition of forecasting event, data collection, prognostic tools selection, preparation and assessment of the forecast [2]. The most common application of quantitative forecasting techniques is within production & inventory systems [3]. Accurate demand forecasting is a critical success factor in inventory management. Demand forecasting includes predicting and estimating the expected product demand over a specified period. Product demand varies because of factors like seasons, trends, and the economy. After the selling season, stocked products are largely devalued, so demand planning can be said as the first step of a supply chain planning process, which connects it to managing the inventory level and demand of product to avoid unnecessary stocking & reduce holding costs. Demand forecasting aims to estimate the number of products or services customers may require in the future in a certain timeframe. Based on the forecasts, management can make decisions about production amount, inventory level & supply to market [4].

2. Literature Review

A study investigated inventory management and logistics performance using ABC-FSN classification and multiple forecasting techniques. The adjusted exponential method was identified as preferable with a smaller MAD. Integrating forecasting outputs with real-time logistics metrics, like On-Time In Full (OTIF) and Vehicle Capacity Utilization, was essential to address fluctuating demand effectively [1]. The significance of demand forecasting in inventory management, primarily focusing on how miscommunication and misalignment between supply and demand across supply chain links lead to high inventory costs, was highlighted in a study [2]. Advanced forecasting techniques, including hybrid models that combine statistical and collaborative methods, were suggested to enhance forecast accuracy. Cross-functional communication and data sharing across supply chain links were essential to minimize errors and optimize inventory levels. The type of products determines the selection of forecasting methods and demand data patterns to achieve high accuracy, as suggested in a paper [3]. The inventory-based forecasting is differentiated from other

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fields of applications of forecasting techniques. Mean Absolute Percentage Error (MAPE) and the Root-Mean Square Error (RMSE) were used in a paper as accuracy measurements for forecasting models like the single moving average method, the Holt-Winters exponential smoothing method, the simple linear regression method, and the combination forecast method [4]l in supply chain operations. Integration of forecasting with inventory management is recognized as the most effective way to significantly improve forecasting accuracy and inventory management performance [5]. A study analyzed the impact of demand forecasting errors on aspects like inventory control strategies, system profits, and supply uncertainties through a mathematical model, empirical data, and numerical simulations and found that demand forecasting errors highly affect profit [6]. A case study on inventory management for a small electronics enterprise recognized irregular demand patterns and the lack of structured inventory management methods for small enterprises that can work with irregular demand patterns [7]. A study proposed a novel data transformation approach called Diagonal Feeding, which works in Build-To-Order (BTO) lean manufacturing supply chains. The study analyzed 13 forecasting methods, and Adaboost achieved the most optimal Symmetric Mean Absolute Percentage Error (SMAPE) [8]. Difficulties in inventory management of the products with stochastic demand using Monte Carlo Simulation (MCS). A study addressed Gaussian Process Regression (GPR) with Bayesian optimization [5]. The continuous review system (r, Q) was identified as more efficient because of reduced safety stock and reorder points, gaining approximately 12.73% higher profits than the periodic review system (p, Q). Lack of high-quality historical data and improper node edge relation were the main limitations identified by a paper discussing the challenges faced in supply chain optimization [10]. Using the LM algorithm, the usage of neural networks for seasonal time series forecasting was addressed by a paper focusing on the importance of forecasting in supply chains. Forecasting depends on cycle trends, seasonal components [11], and irregularities identified as limitations.

MSD, MAPE, MSE, and tracking signals were used to determine errors in a study conducted on the manufacturing industry and found that the trend projection method is the most suitable forecasting method. Hybrid forecasting techniques were avoided [12]. A paper's results indicate the demand data as crucial for accurate forecasting [13]. A paper forecasting the short-term load forecasting of the demand in a power system used the mean absolute percentage error (MAPE) value for error calculation and produced good accuracy [14]. The research analyzed forecast combinations and their effect on inventory performance by considering forecast error distribution. Calculating safety stock is considered difficult because of combined forecast error properties such as bias and normality [15]. For better results, an extended comparison of combination methods should be evaluated.

The paper discussed the electricity consumption forecasting model using a linear regression model, considering different variables (GDP, population, etc.). In long-term forecasting, GDP elasticity is more impactful than price elasticity [16]. Then, the proposed regression model was compared with national forecasts. In the future, energy efficiency, technology, climate data, and other factors should be considered to improve forecasting.

A paper highlighted the application of exponential smoothing methods such as simple exponential smoothing, trend-corrected exponential smoothing, and the seasonal variation theorem for time series forecasting. MAPE was used to evaluate the best solution [17]. IC-based models like AIC were found to be accurate and reliable for selecting the best exponential smoothing method. Overall costs or service levels are affected by forecasting errors or unpredictable demands. The effect is determined by combining the uncertainties of demand and forecasting error with inaccurate model selection with a hundred percent service level in a paper [7]. The unit cost was observed to ascend exponentially with demand uncertainty. The errors increased due to the selection of the wrong forecasting model. In the exponential smoothing method, more emphasis is given to recent data, and less is given to old data, which gives a better result [18]. However, choosing the perfect exponential smoothing constant is considered a crucial issue. A study found that an unsuitable forecasting model produces large smoothing constants, although the survey was simulation-based and thus could not perfectly interpret realistic situations [19].

A paper proposed an advanced method to determine moving averages, the Weighted Exponential Moving Average (WEMA) method, which combines the Exponential Moving Average and the Weighted Moving Average for a better forecasting analysis result. Two error detection methods, the Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE), were used to measure error performance [20]. The Simple Moving Average, the Weighted Moving Average, and the Exponential Moving Average were taken into account in a study to conduct a forecast analysis of the Forex market [8]. Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE) were applied, and it was found that the Exponential Moving Average method is the best one as it resulted in the minimal MSE, MAPE, and MASE. However, some other forecasting methods, like the Adjusted Exponential Smoothing Method or Linear Regression Method, and forecast error detection methods, like Mean Absolute Deviation (MAD) or Mean Forecasting Error (MFE), were ignored in this study. Some properties of simple moving average (SMA) were discussed in a study [9] alongside applying to a steady state model and comparing its accuracy with an exponentially weighted moving average (EWMA). In a steady-state model, the variance of forecasting error for SMA is about 3% higher than the appropriate EWMA, which is significant for a lead time forecast. Traditional models, which use various accuracy metrics like MSE, often fail to lead to better inventory performance because the gap between forecast error and inventory result is not considered linear, as identified in a study [23]. So, a parametrized forecasting model was proposed, which combines the competing multiple inventory objectives. This model resulted in about 9% lower accuracy than traditional models but outperformed traditional methods in real-world settings, particularly in reducing bias and improving stock availability. The quadratic exponential smoothing method was used in a study [11], aiming to solve the problem of subjective forecasting. An ABC classification was done based on demand forecasting to solve the inventory management issues where class A items, being the most important, require accurate forecasting and frequent reviews. In contrast, Class B and C items are managed with less intensity. A systematic, data-driven approach improved inventory control in the case study. Based on the above literature study, an attempt was made to forecast and integrate a demand dataset with an inventory management model.

3. Methods

The method used in this research is illustrated using a systematic framework. Fig. 1 shows a framework with a detailed view of the proposed model. Dotted rectangles indicate each principal step. Rectangles with rounded ends indicate the sub-steps under the principal steps. The diamond shapes indicate the decision to be made.

regression the assessments made are based on a single predictor variable while in multiple regression the assessments are based on two or more predictor variables. Simply regression is expressed in the following way Simple regression is represented by the following equation. In this study, simple regression was calculated by the eq. (3).

$$Y = a + bX \tag{3}$$

In the eq. (3), Y = Dependent variable, X = Independent variable, a = Intercept, and b = Slope (trend).

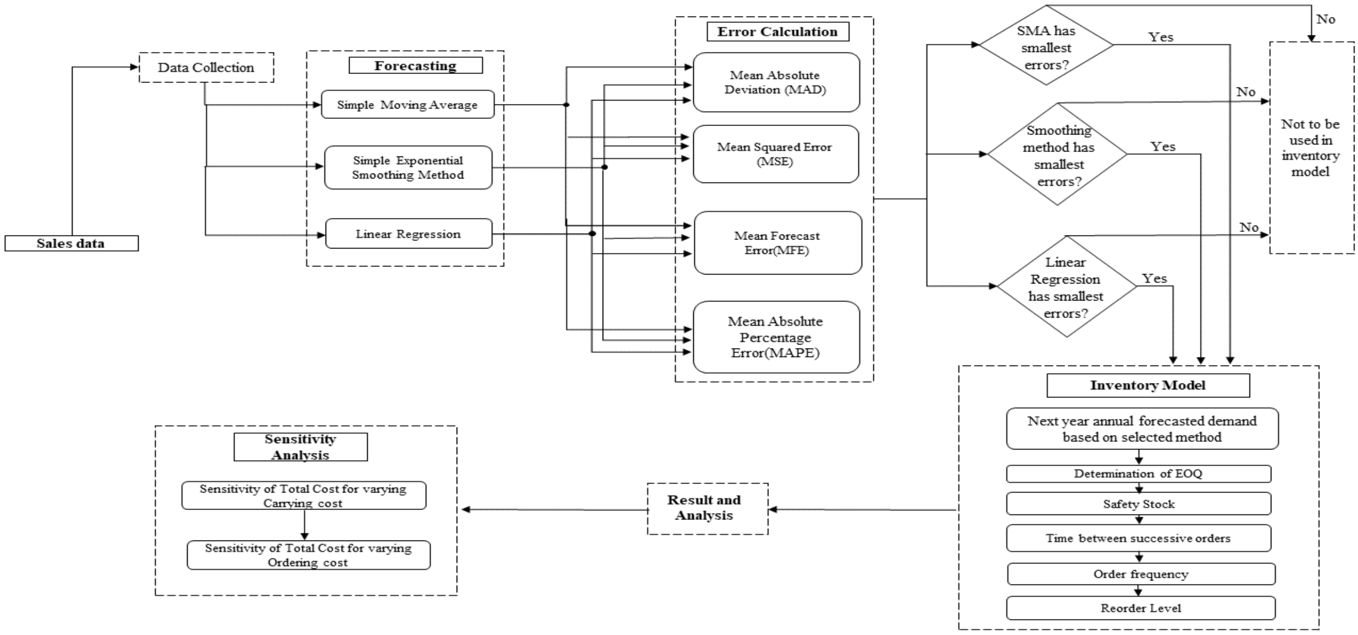

Fig.1 Systematic Framework of Proposed Forecasting Evaluation and Integration with inventory model

3.1Simple Moving Average

A simple moving average is a forecasting method that computes the average of a predetermined number of the most recent demand data. The moving average was calculated by using the eq. (1).

$$MA_n = \frac{\sum_{i=1}^{n} D_i}{n} \tag{1}$$

In the eq. (1), D_i is Demand and n is Period.

3.2 Simple (Single) Exponential Smoothing Method

Exponential smoothing maintains average of demand and with a factor and synthesize each period in ratio to the difference between the latest actual demand value and the latest average value. The smoothing constant reflects the weight given to the most recent demand data. The calculation technique for exponential smoothing can be performed using eq. (2).

$$F_t + 1 = \alpha D_t + (1 - \alpha) F_t \tag{2}$$

In the eq. (2), D_t is Demand,
F_t is Forecast and α is Smoothing constant.

3.3 Linear Regression Method

Regression means dependence and is the process through which the value of a dependent variable, Y, is likely to be estimated from an independent variable, X. In simple

3.4 Error Metrics

After selecting a forecasting model, its characteristics should be confirmed by comparing the forecast it generated to the actual data for the forecasted process. The choice of an error measure plays a fundamental role in the inference made concerning which between a set of forecasting methods is the most accurate. In this study, *MAD* (Mean absolute deviation), *MSE* (Mean square error), *MFE* (Mean Forecast Error), and *MAPE* (Mean absolute percentage error) were utilized, which are represented using eqs. (4)-(7).

$$MAD = \frac{1}{n} \sum_{i=1}^{n} |e_i| \tag{4}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} e_i^2 \tag{5}$$

$$MFE = \frac{1}{n} \sum_{i=1}^{n} e_i \tag{6}$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|e_i|}{y_i} \cdot 100\% \tag{7}$$

3.5 Inventory Model

To implement forecasted data, "Purchase Model with Instantaneous Replenishment and without Shortages" is applied as the inventory management model. In this model, the material is purchased and then sold. The inventory is instantly replenished after finishing without any shortage. Here,

$$\text{Economic Order Quantity, EOQ} = \sqrt{\frac{2C_o D}{C_c}} \qquad (8)$$

Where C_o is Ordering cost/Setup cost, C_c is Carrying cost/Holding cost and D is Demand.

$$\text{Total cost (TC)} = \frac{D}{Q} \times C_o + \frac{Q}{2} \times C_c + D \times P \qquad (9)$$

$$\text{Safety Stock}, SS = K\sigma \qquad (10)$$

Where k is the standard normal statistics value for a service level and σ is standard deviation of demand.

$$\text{Reorder level,ROL} = D_{LT} + SS \qquad (11)$$

4. Results and Analysis

Data analysis using the mentioned methods was done using Python programming language. Fig.2 represents the actual and forecasted data for a simple moving average using three periods. Here, the blue points represent actual demand, and the orange points represent actual demand. Different error metrics were also found by programming, where MAD, MSE, MFE, and MAPE were 202.51, 89162.96, 9.57, and 24.35%, respectively. Fig.3 represents actual and forecasted data by exponential soothing where the value of α was used 0.2. Different error metrics were also found, where MAD, MSE, MFE, and MAPE were 196.72, 77023.39, 11.05, and 23.76%, respectively. Fig.4 represents the same for the linear regression method. Different error metrics were also found, where MAD, MSE, MFE, and MAPE were 207.37, 74679.50, 0, and 25.13%, respectively. Linear regression had less error and was the only method among these three for which more than one demand period could be forecasted. So, by integrating this in the inventory model, different results were obtained: EOQ was 27675 pieces, Safety Stock was 506 units, and Reorder level was 13096 units. The total cost found was $144017618.1. The part of the result is shown by using Table 1, where different methods result forecasts were presented. However, according to a study [18], exponential smoothing method showcased better accuracy while in this study, linear regression method was found to be the most accurate method.

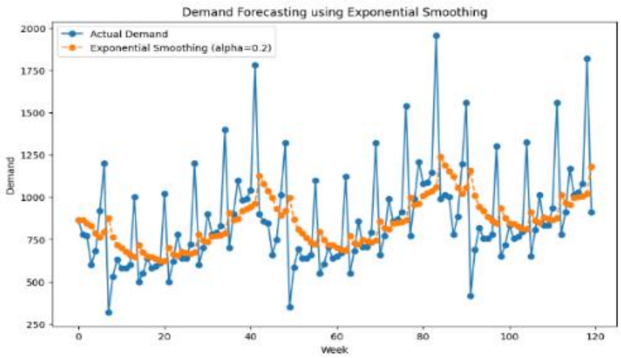

Fig.3 Forecasting by simple exponential smoothing

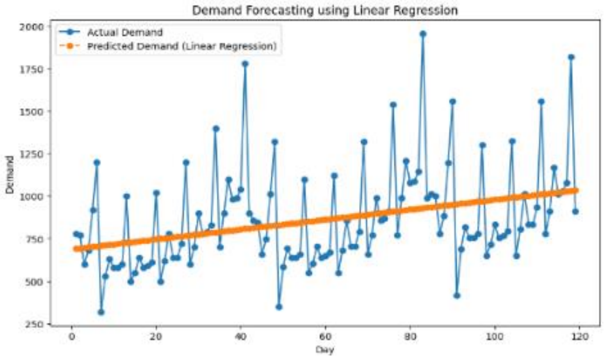

Fig.4 Forecast by Linear Regression

Table 1 Result of different forecasting method

Day	Week	Sales(pieces)	Forecast by Simple Moving Average Method	Forecast by Simple Exponential Smoothing Method	Forecast by Linear Regression
1	1	780	---	864	692.0592
2	1	770	---	847.2	694.9685
4	1	680	716.66666	785.408	700.7870
5	1	920	683.33333	764.3264	703.6963
6	1	1200	733.33333	795.4611	706.6055
7	1	320	933.33333	876.3688	709.5148
8	2	530	813.33333	765.0951	712.4240
9	2	630	683.33333	718.0760	715.3333
10	2	580	493.33333	700.4608	718.2426

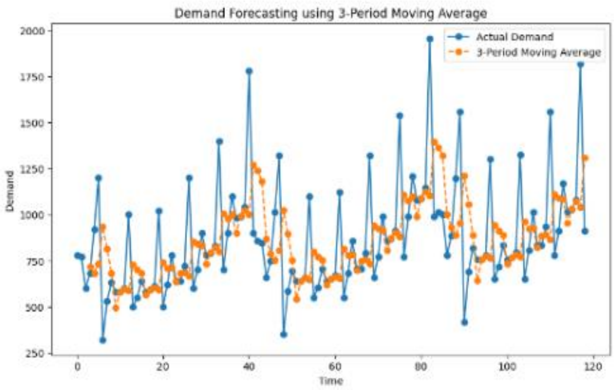

Fig.2 Forecasting by simple moving average

4.1 Sensitivity Analysis

Sensitivity analysis is one way of evaluating financial models which seeks to determine the impact of a change in an independent variable on a dependent variable specified under a given set of conditions. Here, different C_o and C_c sensitivity analyses were performed concerning total cost using equation (9), as shown in Fig.5 and Fig.6.

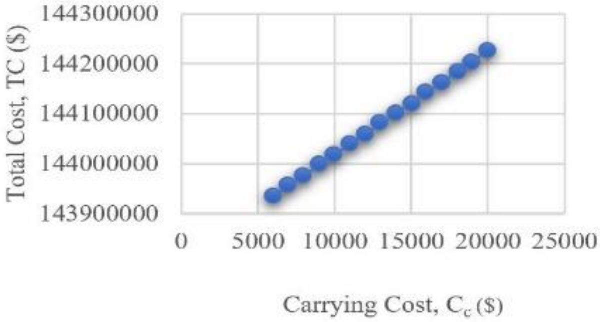

Fig.5 Sensitivity analysis for carrying cost

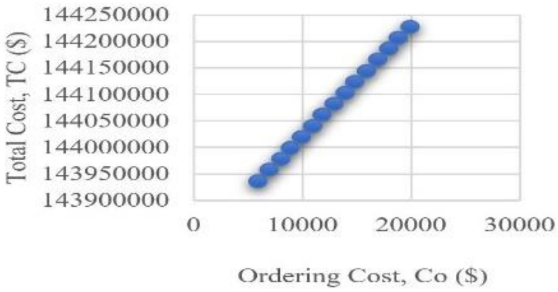

Fig.6 Sensitivity analysis for ordering cost

5. Discussion

Simple Moving Average (SMA) and Simple Exponential Smoothing (SES) methods depend mostly on historical data without capturing complex patterns. So, it struggled to adapt to dynamic trends and variations in demand. In SMA, if there are upward and downward trends, there may be a lag behind actual demand forecasting; that's why this method didn't assign a higher weight for the recent periods. In SES, the smoothing constant controls the weight of the recent observations, but this method cannot capture linear and nonlinear trends. Linear regression acknowledges trends in the model and considers the relation between time and demand. According to that paper, there are no extreme fluctuations in the demand data and no history of stock out or unmet demand due to shortage in that company, so it has been assumed that the purchase model is with instantaneous replenishment and without shortage. This trend awareness enabled linear regression to produce forecasts closer to actual demand, which is why it was more accurate. These methods were selected based on their effectiveness and interpretability. SMA and SES are suitable for scenarios where the data pattern is consistent, while linear regression is known for capturing trends and dataset characteristics. Linear regression is found to be the best fit for the given data, because it minimized the squared errors.

6. Conclusion

This study focuses on the effectiveness of combining forecasting methods for demand prediction and incorporating them with an inventory management model.
Comparison of forecasting methods: Linear Regression was found to be the most accurate while minimizing MFE and MSE.
Choice of Inventory Model: Purchase Model with Instantaneous Replenishment without Shortage was selected.
Sensitivity Analysis: Small changes in carrying or ordering cost significantly impacted on the total cost.

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