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Research Article

Optimization of Limestone Inventory System for Safety Stock Control and Reorder Point in The Processing Industry

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ABTRACT

The procurement and management of limestone, the primary raw material, often experience disruptions during production, primarily due to fluctuations in material availability and weather-related constraints at the mining site. The material's rigid characteristics, long processing times, and limited access during the dry season often result in quantities delivered far below required levels, resulting in inventory levels falling below minimum thresholds. This situation highlights the need for a reliable forecasting approach to ensure production continuity. This study aims to determine the optimal quantity of limestone to be supplied by identifying the most accurate forecasting method and establishing recommendations for safety stock and appropriate reorder points. A quantitative time series approach is applied, and several forecasting models are evaluated to determine the most appropriate method for predicting future limestone demand. The analysis shows that the 5-period moving average provides the highest forecasting accuracy, resulting in the lowest error with a MAPE value of 15.81%. Based on this method, the recommended safety stock is 34,719.68 tons for a 90% service level and 53,164.51 tons for a 95% service level. Furthermore, the reorder point should be set at 58,935.03 tons for a 90% service level and 77,379.86 tons for a 95% service level. The results of this study provide practical implications for improving raw material inventory planning. By implementing recommended forecasting methods and inventory control parameters, companies can better anticipate demand fluctuations, reduce the risk of stockouts, and ensure smooth production operations.

1. INTRODUCTION

Limestone inventory management in the manufacturing industry requires an accurate and measurable control system because this material is the primary raw material that determines the continuity of the production process (Ayomide Madamidola et al., 2024). Mining activities, material quality variability, weather conditions, and distribution access from the mining site often cause transmission of material received (Ma et al., 2022). This situation potentially causes inventory fluctuations that do not match production needs, either in the form of shortages or excess stock (Esmail Mohamed, 2024).

The risk of stockouts can hinder or even halt production, ultimately leading to operational losses and reduced production utilization (Gallego-garcía et al., 2021). Conversely, excess inventory increases storage costs, increases the risk of material damage, and reduces the efficiency of storage space. This situation indicates that inaccurate inventory control directly impacts operational costs and production performance (Marc & Berlec, 2023). This inaccuracy is largely related to inaccurate estimates of limestone requirements for the following period.

The accuracy of demand forecasting significantly determines the effectiveness of inventory control (Thompson, 2024). Time series-based forecasting methods such as moving average, exponential smoothing, and Holt-Winters are widely used to predict fluctuating or seasonal material demand patterns (Malik et al., 2023). Selecting the most appropriate method is crucial because forecasting results form the basis for determining inventory control parameters, including safety stock and reorder points (Ridwan & Ahsan, 2024). Safety stock serves as a reserve buffer to anticipate variations in demand and lead times, while reorder points help determine reorder times to prevent inventory from falling below critical limits (Nurcahyawati et al., 2023).

Several previous studies have made important contributions to developing inventory forecasting and control methods. Sulistyo et al., (2024) showed that the Single Moving Average method is capable of determining the most accurate sales forecasts. Yondri et al., (2024) emphasized the importance of selecting a method based on the MAPE value to improve forecasting accuracy in stock management. Fitra et al., (2025) proved that integrating time series methods with safety stock can maintain the availability of chemical raw materials. Agusman, (2023) successfully applied the Holt-Winters method to model seasonal data with high accuracy. Demiray Kırmızı et al., (2024) found that efficient inventory management has a significant impact on the size of safety stock and holding costs. However, most of these studies focus on one aspect, namely forecasting or inventory control separately. Therefore, there are not many studies that comprehensively integrate demand forecasting, safety stock calculations, and reorder point determination simultaneously in the context of limestone inventory in the processing industry.

Optimizing an inventory system that combines the best forecasting methods, safety stock calculations, and reorder point determination is essential for the processing industry to maintain smooth production processes while reducing the risk of inventory shortages or excesses. This need is increasingly pressing because forecasting phenomena in limestone use show fluctuating demand patterns every month and tend to form unstable seasonal patterns. This demand uncertainty is exacerbated by the variability of delivery lead times influenced by weather factors, field conditions, and transportation equipment operational schedules, making it difficult for companies to accurately predict material needs using only experience or conventional approaches. Therefore, this study was conducted to address these challenges by analyzing the most accurate forecasting methods and designing a limestone inventory control system that is more effective, measurable, and able to anticipate future demand uncertainty.

2. METHOD

1. Research Design

This study applies a quantitative approach using time series analysis to predict limestone demand and determine safety stock and reorder point values. This approach was chosen because available historical data shows fluctuating and seasonal patterns, thus making time-based forecasting methods the most relevant. The entire analysis process is carried out systematically, starting from data collection, selecting a forecasting method, measuring accuracy, and validating the model.

2. Data and Number of Observations

The data used in this study consists of historical limestone usage data for one year, from January 2024 to December 2024. Using a monthly recording pattern, 12 observational data points were analyzed. This data was selected because it represents limestone consumption patterns over an annual operational cycle and is relevant for determining the company's needs for the following period. All data was obtained from the company's raw material usage documents.

3. Data collection technique

Data collection was conducted through direct observation in the company's operational areas to observe limestone consumption processes, inventory flows, and raw material storage services. Additionally, structured interviews were conducted with department heads and relevant division employees to gather additional information such as ordering processes, demand variability, delivery times, and factors influencing limestone availability. This approach ensured that the collected data included not only historical figures but also contextual information that helped explain demand patterns.

4. Device and Software Analysis

In the data processing process, this study uses two main software, namely Microsoft Excel and MATLAB. Excel is used to process raw data, compile databases, visualize limestone consumption patterns, calculate moving averages and standard deviations, and calculate error rates using mean absolute percentage error (MAPE). Excel is also used to create moving range diagrams that function as error stability validation tools. Meanwhile, MATLAB is used for more complex computations such as the application of the exponential smoothing and Holt-Winters multiplicative methods. MATLAB is also used to determine smoothing parameters (α, β, and γ) more precisely through an iterative process so that forecasting results become more accurate.

5. Determination of Forecasting Method

The choice of forecasting method is based on the characteristics of historical data, which exhibit fluctuating patterns and seasonality (Shah & Thaker, 2024). Four quantitative methods were used: a 3-period Single Moving Average, a 5-period Single Moving Average, Exponential Smoothing, and Holt-Winters Multiplicative. In addition to quantitative methods, interviews with company representatives also served as a supporting qualitative analysis to understand operational factors that cannot be captured by numerical data. Each forecasting method produces a predicted value, which is then evaluated to determine its accuracy.

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6. Data Analysis Procedures

The schematic diagram of the experiment that will be used in the research is generally explained in Figure 1, namely the concept of the data analysis framework (Abryandoko et al., 2024).

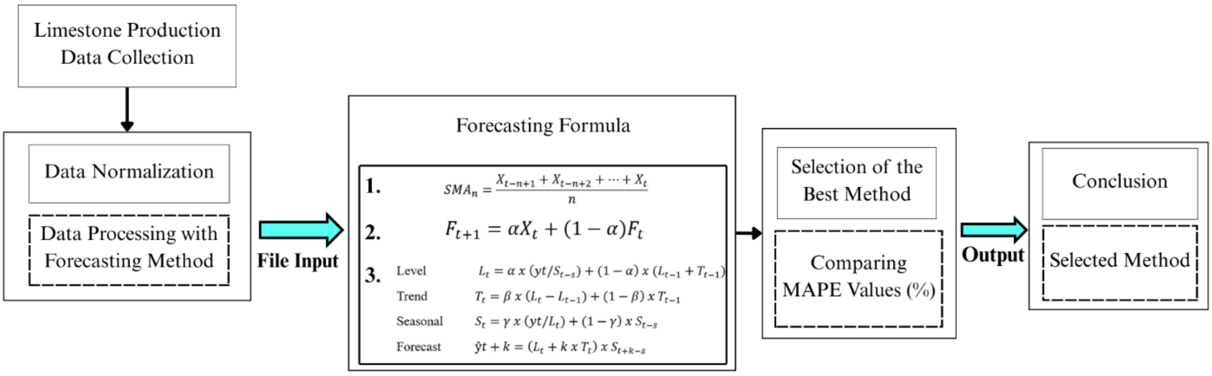

Fig. 1. Schematic Forecasting Diagram

Data visualization using Excel to identify patterns, fluctuations, and seasonal trends in limestone consumption. The next stage is forecasting calculations using four established methods. The forecasting results from each method are then measured for accuracy using MAPE so that the method with the smallest error value can be determined as the best method (Utami et al., 2024). Once the best method is identified, a validation process is carried out using a moving range control chart to ensure that the forecasting model has stable errors and is within the control limits (UCL and LCL). If all error values are within these limits, the model is considered valid and can be applied to determine inventory requirements.

7. Safety Stock Calculation

Once the best forecasting method is obtained, safety stock calculations are performed to anticipate demand and lead times (Babai et al., 2022). To determine the amount of limestone safety stock, the calculation is performed using the following formula:

$$Safety\ Stock = Z \times Std\ Deviasi \times \sqrt{m} \qquad (1)$$

$$Std = \frac{\sqrt{\sum(\mathrm{xi} - \mathrm{x})^2}}{\mathrm{n} - 1} \qquad (2)$$

The safety stock value is calculated using the formula Z × σ × √m, where Z is the service level value (1.28 for 90% service and 1.96 for 95% service), σ is the standard deviation of monthly demand, and m is the lead time converted to months. This calculation is performed using Excel to ensure more accurate results and consistency with historical data.

8. Determining the Reorder Point (ROP)

The final stage in this research method is determining the reorder point to determine the ideal reorder point (Mesina et al., 2022). The formula used is as follows:

$$ROP = D \times LT + SS \qquad (3)$$

ROP = (average demand × lead time) + safety stock. This ROP value serves as a guide for companies in determining when to reorder to avoid stockouts. Thus, the ROP value helps maintain smooth production and ensures that limestone needs are met on time

3. RESULT AND DISCUSSION

1. Limestone Consumption Patterns and Data Characteristics

The following is a plot of limestone material usage data for the last 1 year, from January 2024 to December 2024. As data for forecasting:

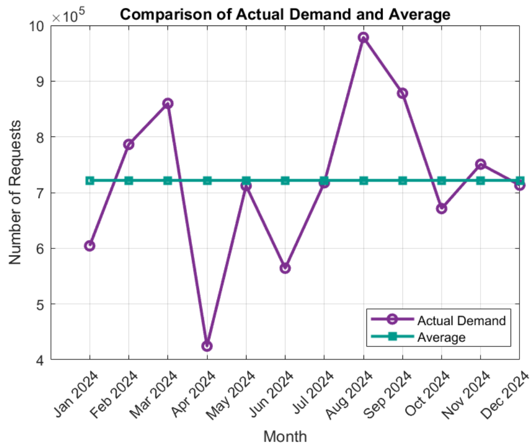

Fig. 2. Graph of Actual Limestone Usage

Figure 2 shows that analysis of historical limestone consumption data shows variations in usage that do not follow a linear trend. Although there are significant shifts between months, the pattern still shows a recurring seasonal trend throughout the observation period. This pattern indicates that limestone demand is influenced by certain operational factors, such as monthly production volume, weather conditions, or machine maintenance schedules, which also influence the intensity of raw material use. The existence of this seasonal pattern is the basis for selecting the time series method as the primary approach in the forecasting process.

2. Comparison of the Accuracy of Four Forecasting Methods

a. Single Moving Average Method 3

The following presents the results of the moving average calculation obtained from the average data in the last three months.

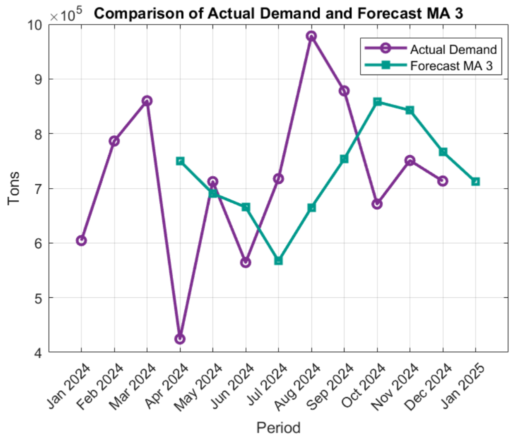

Fig. 3. Moving Average Calculation 3

Figure 3 illustrates the forecast pattern generated using the 3-period moving average method. Evaluation of this model shows that the Mean Absolute Percentage Error (MAPE) obtained from the forecast results is 0.24, equivalent to an error rate of 24%.

b. Single Moving Average Method 5

The following presents the results of the moving average calculation obtained from the average data in the last five months.

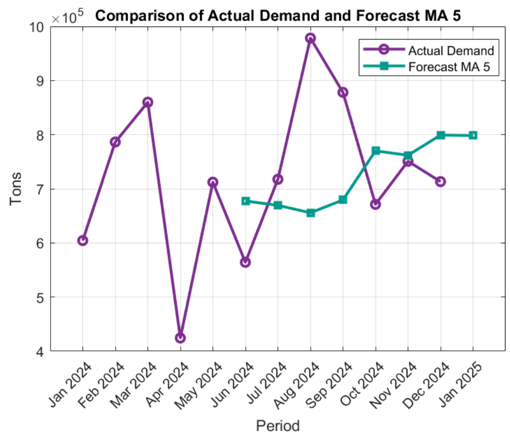

Fig. 4. Calculation of Moving Average 5

Figure 4 illustrates the forecasting pattern generated using the 5-period moving average method. Evaluation of this model shows that the Mean Absolute Percentage Error (MAPE) obtained from the forecasting results is 0.1581, equivalent to an error rate of 15.81%, making it the method with the best accuracy rate among all models.

c. Exponential Smoothing Method

The following presents the results obtained from calculations using the exponential smoothing method.

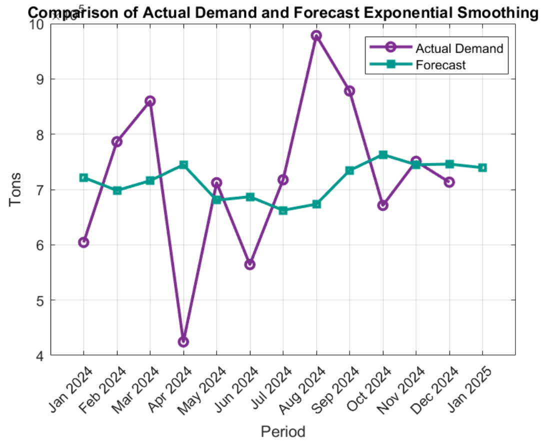

Fig. 5. Exponential Smoothing Calculation

Figure 5 illustrates the forecast output generated using the exponential smoothing method. Using an ES model with an alpha value of 0.154—rounded to 0.2 for calculation purposes—the resulting Mean Absolute Percentage Error (MAPE) is 0.19, which equates to a 19% error rate.

d. Multiplicative Holt-Winter Method

The following presents the results obtained from calculations using the Holt-Winters multiplicative method.

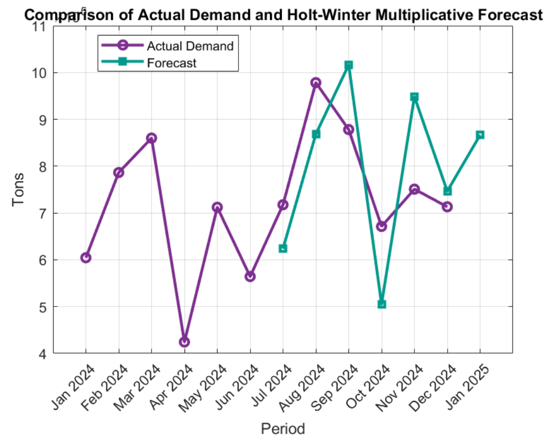

Fig. 6. Multiplicative Holt-Winter Calculation

Figure 6 displays the forecast pattern generated using the Holt–Winter multiplication approach. By applying this method to parameter values $\alpha = 0.2$, $\beta = 0.3$, and $\gamma = 0.5$, the resulting Mean Absolute Percentage Error (MAPE) is 15.97%, indicating the overall accuracy of the model. Although Holt–Winters is designed for seasonal data, the highly variable frictions in the data study make the 5-period moving average remain the most optimal model in this context.

3. Best Model Validation

Validation is performed by plotting the errors generated by the selected forecasting model and observing their movement over time. Figure 7 presents a 5-period moving

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average control chart used to determine whether any error points fall outside the acceptable tolerance range.

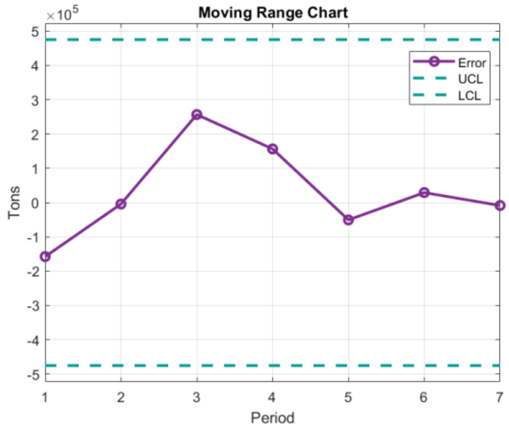

Fig. 7. Moving Range Validation Chart

All error values are within the control limits determined by UCL and LCL, so the 5-period moving average model is declared stable and can be used as a basis for decision making in the limestone inventory planning process.

4. Limestone Demand Forecasting Results

The following table presents the forecast values for the next eight months obtained from the 5-month moving average model.

Table 1. Limestone Forecasting Results

Month	Forecast (Tons)
Jun 2024	677480.40
Jul 2024	669456.40
Aug 2024	655695.20
Sep 24	679387.40
Oct 2024	770122.20
Nov 24	761922.40
Dec 2024	799246.00
Jan 2025	798374.00

The forecast for limestone demand for the next eight months shows variations consistent with the previous year's usage patterns. Estimates range from 655,695 tons to 799,246 tons. These results provide a concrete picture of material needs in the coming period and serve as an important reference for developing supply plans and managing the company's inventory.

5. Safety Stock Analysis

Safety stock calculations are carried out to anticipate demand and potential delivery delays.

Standard Deviation Formula:

$$Std = \frac{\sqrt{\sum(\mathrm{xi} - \mathrm{x})^2}}{\mathrm{n} - 1}$$

$$= \frac{\sqrt{\sum(677480{,}4 - 726460{,}48)^2 \ldots\ldots\ldots (798374 - 726460)^2}}{8 - 1}$$

Std = 148568.37

The lead time of limestone raw material is 1 day.
m = 1 day = 0.033 months

Safety stock of limestone raw materials at service level 90%

1. Safety Stock = 1.28 × 148568.37 × √0.033
 = 34719.68 tons.

Safety stock of limestone raw materials at service level 95%

2. Safety Stock = 1.96 × 148568.37 × √0.033
 = 53164.51 tons.

With a demand standard deviation of 148,568 tons and a lead time of 0.033 months, the safety stock is 34,719.68 tons for a 90% service level and 53,164.51 tons for a 95% service level. The difference between these two values reflects the increased buffer requirements when the company wants to provide a higher level of service to the production process.

6. Determining the Reorder Point (ROP)

Determining the reorder point in the limestone raw material inventory system refers to the following calculation:

- Lead time = 0.033 months
- Safety Stock (service level 90%) = 34719.68 tons
- Safety Stock (service level 95%) = 53164.51 tons
- Average 1-month demand = 726,460.48 tons
- D x LT = 726460.48 tons x 0.033 months = 24215.35 tons
- ROP (service level 90%) = 24215.35 tons + 34719.68 tons = 58935.03 tons.
- ROP (service level 95%) = 24215.35 tons + 53164.51 tons = 77379.86 tons

The ROP calculation results show that limestone reorders should be placed when inventory reaches 58,935.03 tons (90% service level) or 77,379.86 tons (95% service level). This ROP value ensures that the company does not experience stockouts and can maintain a smooth production flow without significant operational disruptions.

7. Industrial Implications of Research Results

The findings of this study emphasize the importance of this approach for industries dependent on volatile raw materials such as limestone. First, selecting the right forecasting method allows companies to minimize the risk of raw material shortages without having to maintain excess inventory. With a low MAPE, the 5-period moving average model can help companies plan production more effectively and optimize storage costs. Second, accurately determining safety stock and ROP allows companies to maintain operational continuity and avoid supply-related downtime. In manufacturing industries sensitive to distribution schedules, the ability to accurately predict demand is a competitive advantage. Third, the approach implemented in this study can be replicated in other industries, particularly mining, cement, logistics, or sectors with seasonal demand patterns. Therefore, this study contributes to the implementation of data-driven inventory control in a broader industrial sector.

8. Research Limitations

Although this study successfully identified the best forecasting method, several limitations warrant consideration. First, the observational data used only covers one year (12), so the resulting seasonal patterns may not fully reflect long-term variations. Studies with longer time periods have the potential to produce more stable and accurate models. Second, this study only used monthly data. If weekly or daily data were available, the forecasting model could capture demand dynamics in more detail and produce more precise results. Third, the lead time calculation uses a fixed value (0.033 months), whereas in actual operational conditions, lead time can fluctuate due to weather factors and logistical disruptions. Lead time variations can be considered in further research to obtain safety stock and ROP analysis results. Fourth, the model used is still limited to conventional methods. The application of advanced models such as ARIMA, SARIMA, or learning algorithms can provide a more comprehensive picture of data patterns.

9. Comparison with Previous Research and Research Gaps

Comparison with previous research shows that this study offers a distinct contribution in the context of forecasting method selection and application in the limestone industry. Several previous studies have shown that the Holt-Winters method is generally more accurate in capturing seasonal patterns (Wongoutong, 2021). However, the results of this study indicate that the 5-period moving average actually produces the lowest MAPE compared to the other three methods, which differs from general findings in previous literature. This suggests that the characteristics of limestone consumption data in this company have fluctuating patterns that cannot be fully captured by models with complex trend and seasonal components.

A research gap is also evident in the limited amount of historical data. Many previous studies used large datasets to strengthen the identification of seasonal patterns (Liu et al., 2021), while this study used 12-month data. This gap opens up opportunities for further research using longer data sets or combining multi-year data to obtain stronger seasonal patterns.

Furthermore, some previous studies have begun to adopt machine learning-based methods (Sai Mani Krishna Sistla, 2024). The following explicit description demonstrates that this research remains within the realm of conventional methods, yet it still offers practical contributions for companies seeking a fast, simple, and easy-to-implement approach without complex computation. Thus, this study strengthens the literature by providing evidence that simple methods like moving averages can still provide superior performance on certain types of data.

4. CONCLUSION

This study concluded that the 5-period moving average method is the most accurate forecasting model for predicting limestone demand, with a MAPE value of 15.81%. This model produces eight-month demand estimates that are consistent with seasonal patterns in historical data. Furthermore, safety stock and reorder point calculations indicate that the company requires safety stock between 34,719.68 tons and 53,164.51 tons and a reorder point between 58,935.03 tons and 77,379.86 tons, depending on the desired service level.

This study has limitations, primarily because the observational data only covers one year and is monthly in nature, preventing in-depth analysis of long-term variations and daily or weekly patterns. Lead times are also assumed to be constant, although they can vary in real-world conditions.

As a follow-up, further research is recommended using longer historical data sets and more detailed data resolution. Furthermore, more sophisticated forecasting methods such as ARIMA, SARIMA, and machine learning-based approaches—including Random Forest, Gradient Boosting, and LSTM—need to be tested to determine whether their accuracy can surpass the conventional methods used in this study.

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