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Inventory Control of Steel Materials in Shipyard Company Using the Continuous Review Method

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Abstract

Ship repair activities are characterized by highly uncertain material requirements because the scope of work is often finalized only after on-dock inspection. This uncertainty frequently leads to material shortages, project delays, and increased operational costs, particularly in replating processes where steel is the primary material. This study aims to develop an improved inventory control policy by integrating demand forecasting and continuous review inventory modeling. An ABC classification was first conducted to identify high-value materials requiring strict control, with Category A items selected for further analysis. Demand forecasting was performed using Exponential Smoothing and Long Short-Term Memory (LSTM) models, and forecasting accuracy was evaluated using Mean Absolute Deviation (MAD) and Mean Squared Error (MSE). The method with the lowest error was then incorporated into a Continuous Review (Q) Model with Backorders to determine optimal order quantities, safety stock, and reorder points. A simulation comparing the proposed policy with the company's existing practice shows that the proposed approach reduces total inventory-related costs by IDR 2,671,910,250.20, equivalent to a 7.645% cost saving, while improving material availability and reducing shortage risks. The findings demonstrate that combining machine-learning-based forecasting with probabilistic inventory control can significantly enhance inventory performance in project-based industries with fluctuating demand, such as ship repair.

Keywords: Demand Forecasting; Inventory Control; Ship Repair Industry; LSTM; Continuous Review Model; ABC Classification
JEL Classification: C53, C45, D24, L62, M11

INTRODUCTION

The ship repair industry plays a critical role in supporting maritime transportation by ensuring vessel reliability, safety, and operational continuity. Unlike manufacturing environments with relatively stable production schedules, ship repair activities are project-based and highly dependent on the technical condition of each vessel upon arrival. This characteristic creates significant uncertainty in planning resources, particularly in managing material inventories required for repair operations.

Ship repair activities are highly diverse, one of which is replating. This activity is among the most frequently performed. Steel serves as one of the direct materials in the process, and material shortages are often encountered. Such shortages can disrupt the work. Material deficiency contributes up to 19% to delays in ship repairs (Mahardika, 2023). The impact of these delays can interfere with scheduling, incur penalty payments for late completion, and cause other losses to the company and its partners.

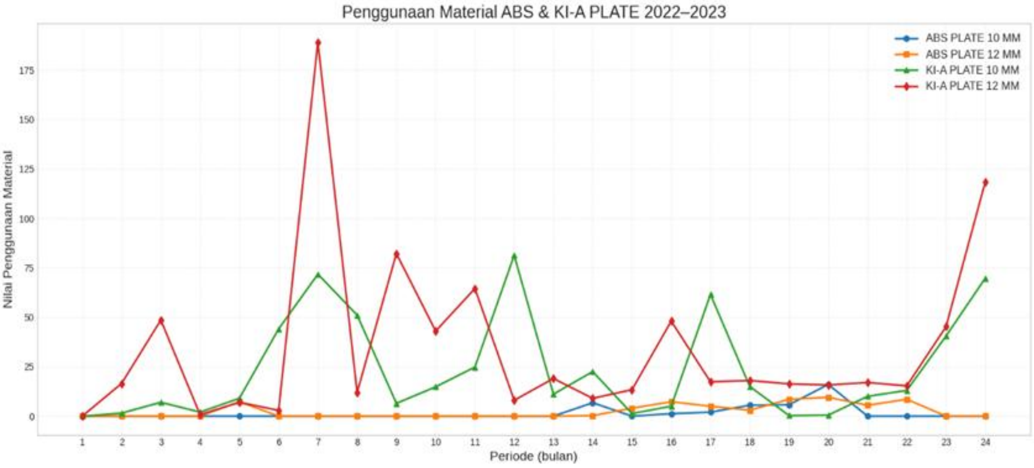

Figure 1 Consumption of Class Plates at a Shipyard in Balikpapan (PT XYZ, 2025)

This industry faces its own challenges in forecasting material requirements. **Figure 1** shows the usage of class plates from 2023 to 2024 at a shipyard in Balikpapan, which fluctuates significantly. The demand varies because the actual material needs are mostly identified after on-dock inspections and agreements between the involved parties. The requirements may increase as more detailed inspections are carried out during the repair process. These materials are used for class items, particularly on the ship's hull.

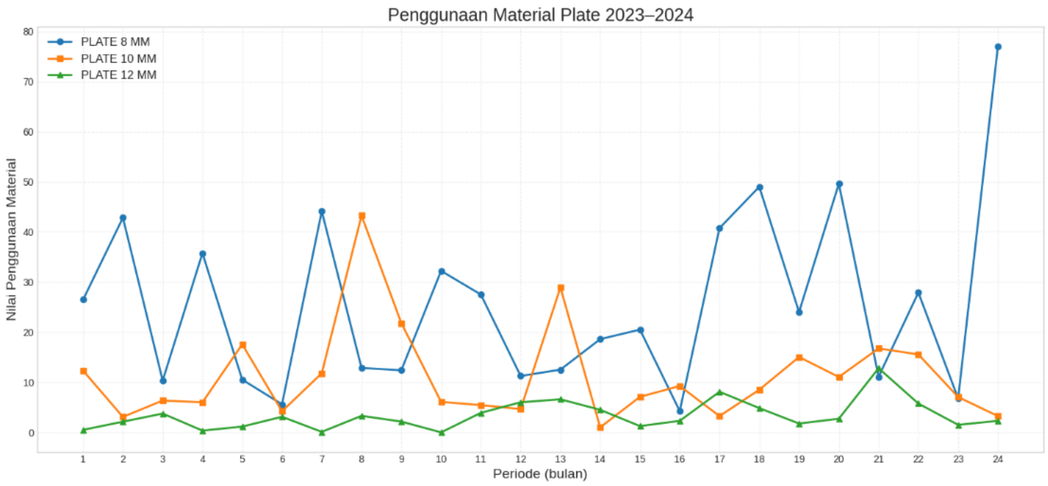

Figure 2 Consumption of Non-Class Plates at a Shipyard in Balikpapan (PT XYZ,2025)

Figure 2 shows the usage of non-class plates from 2023 to 2024 at a shipyard in Balikpapan, which also fluctuates significantly. These materials are used for non-class items such as sideboards, skegs, and other outfitting components on the vessel.

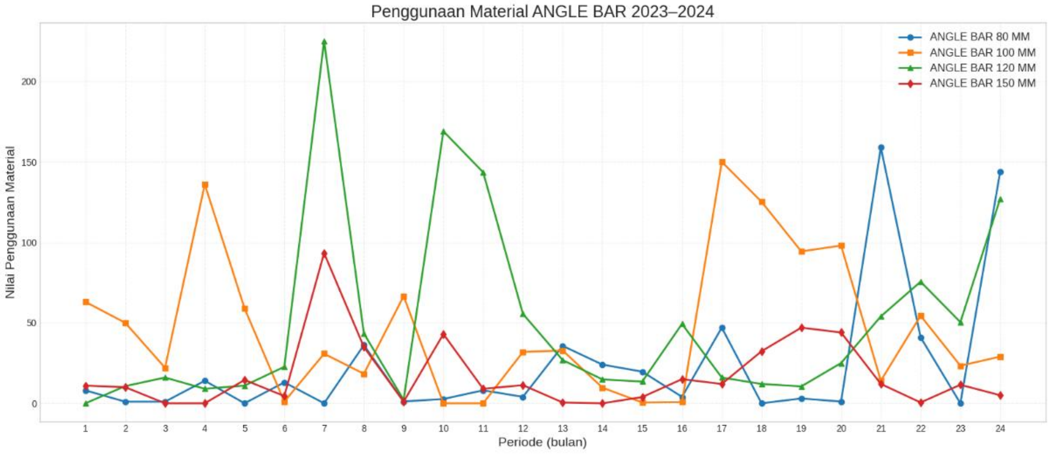

Figure 3 Consumption of Angle Bar at a Shipyard in Balikpapan (PT XYZ, 2025)

Figure 3 shows the usage of angle bar from 2023 to 2024 at a shipyard, which also displays fluctuating trends. These materials are used in the vessel's internal structures, such as bottom longitudinals, deck long chines, longitudinal stiffeners, side longitudinals, sideboard stiffeners, and others.

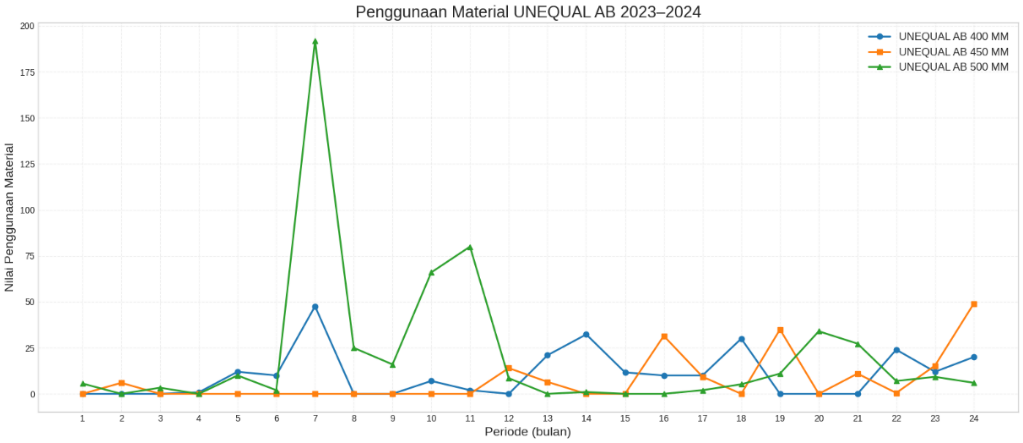

Figure 4 Consumption of Unequal Angle Bar at a Shipyard in Balikpapan (PT XYZ, 2025)

Figure 4 presents the usage data of unequal angle bar from 2023 to 2024 at a shipyard, which also shows fluctuating trends. These materials are used in the ship's internal structure, such as bottom girders, bottom transverses, vertical web frames, deck transverses, deck girders, and others.

The uncertainty in material demand is difficult to predict because the company's current inventory management still relies on a simple replenishment system. This approach has several drawbacks that can negatively impact the company. When demand is high but warehouse stock cannot meet it, the user (production division) submits another material request to cover the shortage. This prevents the company from placing direct orders with its main supplier in Surabaya because the minimum order requirement cannot be met. Consequently, the company becomes highly dependent on its suppliers, leaving it with little bargaining power.

An evaluation of this issue is necessary to mitigate its negative effects. Only a few studies have explored this topic. Research related to inventory management in the ship repair industry was conducted by Mahardika (2023), who used time series forecasting techniques such as Weighted Moving Average and Exponential Smoothing to estimate steel material demand at a shipyard. However, traditional forecasting methods such as Linear Regression and Moving Average struggle to adapt to the complexity of demand patterns, resulting in inaccurate predictions (Sukolkit et al., 2024). Several studies show that machine learning offers higher accuracy compared to traditional methods in forecasting (Mohamed-Amine et al., 2024).

The growth of digitalization has increased the availability of historical supply chain data, facilitating the use of machine learning (ML) and deep learning (DL) models in generating future demand forecasts.. The forecasting capabilities of DL/ML based on historical data can support future demand prediction, enabling companies to set more accurate reorder points and lot sizes (Ahmed et al., 2024). ML-based inventory management also allows businesses to operate at lower costs compared to conventional approaches (Ahmed et al., 2024).

A study by Sukolkit et al. (2024) applied several univariate time series forecasting methods, including Prophet, Support Vector Regression (SVR), 1-Dimensional Convolutional Neural Network (1D-CNN), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM), to accurately forecast demand for steel wire mesh. The study showed that Long Short-Term Memory (LSTM) achieved the lowest error. The forecast results were then used to determine the Economic Order Quantity (EOQ), Safety Stock, and Reorder Point (ROP) through a continuous review model. This optimization resulted in a cost reduction of approximately 4.75% compared to the previously used traditional approach.

Most existing inventory studies focus on manufacturing or retail environments where demand is relatively stable and repetitive. Research in ship repair inventory management remains limited, and prior studies have largely relied on traditional forecasting techniques such as moving averages or linear models. These approaches often fail to capture the irregular and non-linear demand patterns characteristic of repair-based industries, resulting in suboptimal inventory decisions.

In this study, material demand will be forecasted using the LSTM and exponential smoothing methods. The method that produces the lowest error will be used for continuous review calculations. The continuous review Q-model with backorder will be applied to determine the optimal order quantity, safety stock, and reorder point. This proposed policy will then be compared with the current policy used by the company.

LITERATURE REVIEW

Abc Classification

ABC classification aims to focus inventory management efforts on the most critical and high-value items. According to Schroeder & Goldstein (2018), ABC Classification is also referred to as the 80-20 rule, where:

1. A-Items, represent 20% of item volume, but generating about 80% of the total inventory value.
2. B-Items, represent 30% of the item volume, making up 15% of the total inventory value.
3. C-Items, represent 50% of the item volume, but only contributing about 5% of the total inventory value.

Long—Short Term Memory (LSTM)

Demand forecasting is crucial in inventory management. The ability to accurately predict demand helps companies determine the appropriate order quantities when replenishing inventory from suppliers (Giaconia & Chamas, 2023). Long Short-Term Memory (LSTM) is an advanced type of Recurrent Neural Network (RNN) specifically designed to address the challenges of learning long-term dependencies in sequential data (Sukolkit et al., 2024). Its ability to retain and process long sequences of data over time has established LSTM as a foundational model in deep learning for sequential analysis. This capability can significantly optimize supply chain performance by reducing operational costs, improving resource utilization, and providing superior service levels (Rahmatillah et al., 2024). Predictive analytics and machine learning enable supply chain management to become flexible, efficient, and highly adaptive to changing market conditions (Zidu Wang, 2025). LSTM effectively addresses the issues of vanishing and exploding gradients (Mohamed-Amine et al., 2024). Furthermore, LSTM efficiently manages information flow through its unique architecture, which includes cell states and multiple gates (forget, input, and output gates).

Exponential Smoothing

Despite advances in machine learning, classical forecasting techniques such as Exponential Smoothing remain widely applied due to their simplicity, interpretability, and relatively strong performance in short-term forecasting. The method assigns exponentially decreasing weights to past observations, enabling forecasts to adapt to recent demand changes. In many studies, Exponential Smoothing is used as a benchmark model to evaluate whether advanced approaches provide significant predictive improvements. Comparing machine learning models with established statistical methods is therefore necessary to justify methodological adoption in practical inventory systems.

The Exponential Smoothing method is a forecasting procedure that continuously updates predictions by averaging past values of a time series using exponentially decreasing weights (Indrajit & Djokopranoto, 2003). This method employs α as the smoothing constant, which serves as a weighting factor in the forecasting process. When the value of α is close to 0, the new forecast closely follows the previous forecast, indicating minimal adjustment. Conversely, when α approaches 1, the forecast becomes highly responsive, incorporating adjustments for each error in the previous prediction. The forecasting equation for the Exponential Smoothing method is expressed as follows (Chopra & Meindl, 2013):

$$L_{t+1} = \alpha D_{t+1} + (1 - \alpha) L_t$$

Where:
L_{t+1} = Peramalan pada periode t + 1
D_{t+1} = Actual demand in periode t + 1
L_t = Forecast for period t
α = Weighting factor / smoothing constant

Model Evaluation

This study employs two forecasting methods, namely long short-term memory (LSTM) and exponential smoothing. Both methods inevitably produce forecasting errors; therefore, it is necessary to identify which method yields the lowest error. In this study, forecasting accuracy is evaluated using two error metrics: Mean Absolute Deviation (MAD) and Mean Squared Error (MSE).MAD and MSE is calculated using the following formula (Chopra & Meindl, 2013).

Forecasting performance is commonly assessed using error-based metrics such as Mean Absolute Deviation (MAD) and Mean Squared Error (MSE), which measure the magnitude and dispersion of prediction errors. These indicators are widely used in supply chain and inventory research to ensure that forecasting models are evaluated on objective and comparable criteria. Lower MAD and MSE values indicate greater predictive accuracy, which is critical because forecasting errors directly influence safety stock levels, reorder decisions, and total inventory costs.

$$\mathrm{MSE} = \frac{\sum_{t=1}^{n}(Y_t-\widehat{Y_t})^2}{n} \qquad \mathrm{MAD} = \frac{\sum_{t=1}^{n}|Y_t-\widehat{Y_t}|}{n}$$

Where:
Y_t = Actual value in period t
$\widehat{Y}_t$ = Forecast value in period t
n = number of observations

Continuous Review Q Model With Backorder

Steel materials are critical items in the ship repair business. Unlike chains, tires, or zinc anodes, which may be supplied by the ship owner or other parties, steel materials must be procured directly by the company due to the operational policy of a shipyard in Balikpapan. As a result, relevant stakeholders must wait when material shortages occur. The Q-model with backordering assumes that customers are willing to wait for the requested items until they become available in the warehouse, while management places emergency orders to fulfill demand that cannot be immediately satisfied (Bahagia, 2006). Under this policy, inventory is continuously monitored, and replenishment is carried out when the inventory level reaches or falls below the Reorder Point (ROP).The Q-model with backordering is calculated using the Hadley–Within method, with the following formulation (Bahagia, 2006):

$$Q_{01}^{*} = Q_{02}^{*} = \sqrt{\frac{2DS}{h}}$$

Where:
Q = Optimal lot size
D = Annual demand
S = Fixed cost incurred per order
h = Holding cost per year

The probability of an inventory shortage (α) is calculated using the following formula (Bahagia, 2006):

$$\alpha = \frac{hQ_{01}^{*}}{\mathrm{C}u\mathrm{D}}$$

Where:
Cu = Stockout cost per unit

The value of r_1 is calculated after determining z_α using the following formula (Bahagia, 2006):

$$r_1 = dl + z_\alpha \mathrm{S}_{\mathrm{dl}}$$

Where:
d = Average demand per period
l = Average lead time
Sdl = Interaction of the standard deviation of demand per period and lead time

The value of N is calculated after determining r_1 using the following formula (Bahagia, 2006):

$$N = \int_{r'}^{\infty} (x - r')f(x)dx = \mathrm{S_{dl}}[f(z_\alpha) - z_\alpha \psi(z_\alpha)]$$

The value of Q_{02}^* is calculated after determining N using the following formula (Bahagia, 2006):

$$Q_{02}^* = \sqrt{\frac{2\mathrm{D}(\mathrm{S} + \mathrm{C}u\mathrm{N})}{\mathrm{h}}}$$

The value of α is calculated after determining Q_{02}^* using the following formula (Bahagia, 2006).

$$\alpha = \frac{hQ_{02}^*}{\mathrm{C}u\mathrm{D}}$$

The value of r_2 is calculated after determining z_α using the following formula (Bahagia, 2006).

$$r_2 = dl + z_\alpha \mathrm{S_{dl}}$$

The order quantity, safety stock, and reorder point can be determined once $r_1$and r_2 have the same value. If these values are not equal, further iterations must be carried out until both values converge.

METHOD

This study adopts a quantitative decision-support approach aimed at developing an improved inventory control policy for steel materials used in ship repair. The research integrates demand forecasting techniques with a probabilistic inventory model to determine optimal replenishment parameters under uncertain demand conditions.

This study applies ABC classification analysis to historical steel material usage data to categorize materials according to their contribution to total consumption value. This step aims to identify Grade A materials, which represent the most critical items requiring tighter inventory control.

LSTM and exponential smoothing methods are used to forecast the demand of Grade A steel materials. The model with the lowest MAD and MSE values is selected and applied in the continuous review Q model with backorder.

Demand forecasting for Category A materials was performed using two approaches: Exponential Smoothing as a conventional statistical benchmark and Long Short-Term Memory (LSTM) as a machine-learning-based model. The 36-period dataset was divided into training data (24 periods) and testing data (12 periods). For the LSTM model, hyperparameter tuning was conducted using a random search procedure to determine the optimal configuration of units, learning rate, batch size, epochs, and window size. Forecasting accuracy for both methods was evaluated using Mean Absolute Deviation (MAD) and Mean Squared Error (MSE), and the model with the lowest error was selected for inventory analysis.

The order quantity, safety stock, and reorder point obtained from the continuous review method are subsequently simulated using actual material usage data from 2024 and referred to as the proposed (improved) policy. This policy is then compared with the existing inventory policy currently implemented by the company.

RESULTS AND DISCUSSION

Abc Classification

ABC classification will be carried out using the historical usage data of steel materials from a shipyard in Balikpapan. The data required for this process includes the total annual material consumption and the purchase price of each material. The purpose of this classification is to group materials into three categories based on their value. Materials that fall into Category A require special attention. **Table 1** presents the results of the ABC classification, where materials contributing more than 80% of the cumulative value are classified as Category A. These items will be the focus of this study because they carry high value.

Table 1 ABC Classification

No	Material	Cumulative Value	Class
1	KI-A Plate 12mm	28,452%	A
2	Plate 8mm	41,639%	A
3	KI-A Plate 10mm	55,767%	A
4	Plate 10mm	62,066%	A
5	Unequal AB 500	67,128%	A
6	H Beam 200	72,059%	A
7	Angle Bar 120	75,482%	A
8	Angle Bar 100	77,996%	A

Long—Short Term Memory (LSTM)

Forecasting is carried out for the eight materials classified under Category A. The first forecasting process uses the LSTM method. The LSTM model is implemented automatically through the LSTM() layer from the TensorFlow Keras library. The forecasting is performed using 36 periods of historical steel material usage data, which are divided into 24 periods for training and 12 periods for testing. Hyperparameter tuning is added to the LSTM model to find the best combination that produces the lowest error. The model performs a random search across various hyperparameters, including units, learning rate, batch size, epochs, and window size, with 500 trials taken from a total of 2800 possible combinations.

The forecasting is conducted on the 36-periods data for plate 8 mm. The model shows that the optimal combination consists of units set to 16, learning rate set to 0.005, batch size set to 2, epochs set to 250, and window size set to 2. This configuration produces an MAD value of 17.35 and an MSE value of 646.63.

Figure 5 presents a comparison between the LSTM forecasting results and the actual data for the plate 8 mm.

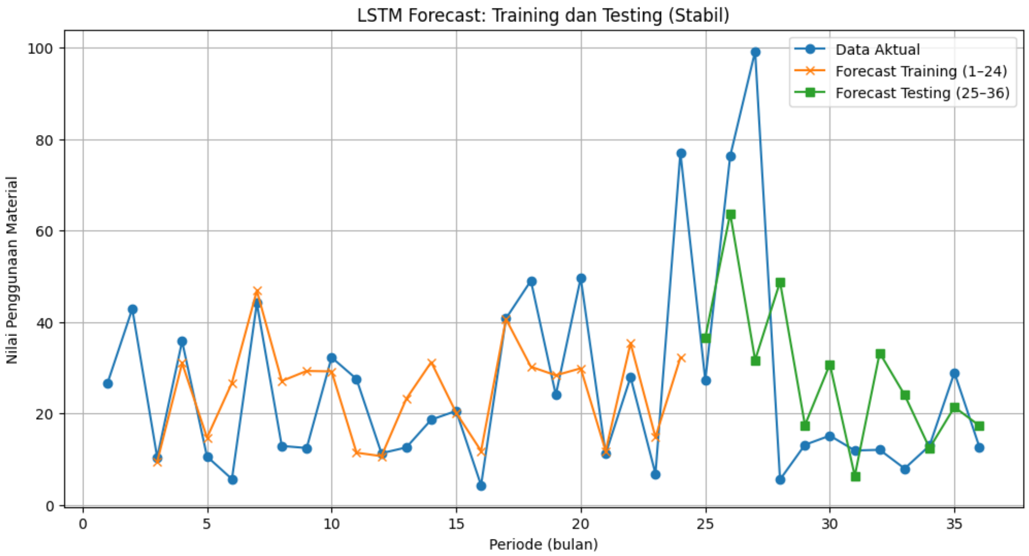

Figure 5 Comparison Between LSTM Forecasting and Actual Data (Plate 8 mm)

Exponential Smoothing

In this study, a solver tool is employed to determine the smoothing parameter (α) that produces the lowest forecasting error. This approach is intended to identify the optimal performance of the exponential smoothing method. The value of α is constrained within the range $0.1 \leq \alpha \leq 0.9$. The forecasting analysis is conducted for the plate 8 mm, with the best performance achieved when $\alpha = 0.8$.

Figure 6 presents a comparison between the exponential smoothing forecasts and the actual usage data of the plate 8 mm over 36 periods. The mean absolute deviation (MAD) and mean squared error (MSE) are calculated based on the last 12 periods, which are used as the testing dataset. This approach ensures that both forecasting methods are evaluated using the same testing period. The results show that the exponential smoothing method produces a MAD of 20.72 and an MSE of 1023.68. Overall, the LSTM method demonstrates superior forecasting performance compared to exponential smoothing for the plate 8 mm.

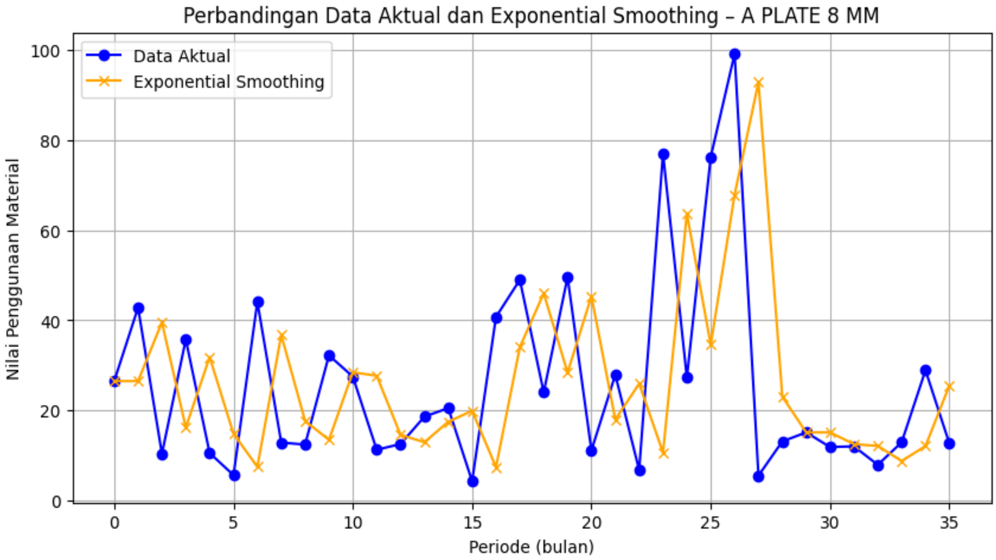

Figure 6 Comparison Between Exponential Smoothing and Actual Data

LSTM Versus Exponential Smoothing

This subsection presents a comparison between the forecasting results obtained using the LSTM and exponential smoothing methods based on the historical steel material usage data from a shipyard in Balikpapan. In this study, the testing results of the LSTM model indicate that it still struggles to capture the highly fluctuating data patterns. As noted by Gauch et al. (2021), the advantages of LSTM models are often less apparent when the available training data are limited. In the present study, only 36 periods of historical data are available, consisting of 24 training periods and 12 testing periods. Although the LSTM model has not yet achieved optimal performance, its forecasting results still exhibit lower error values than those of the exponential smoothing method across the eight tested materials.

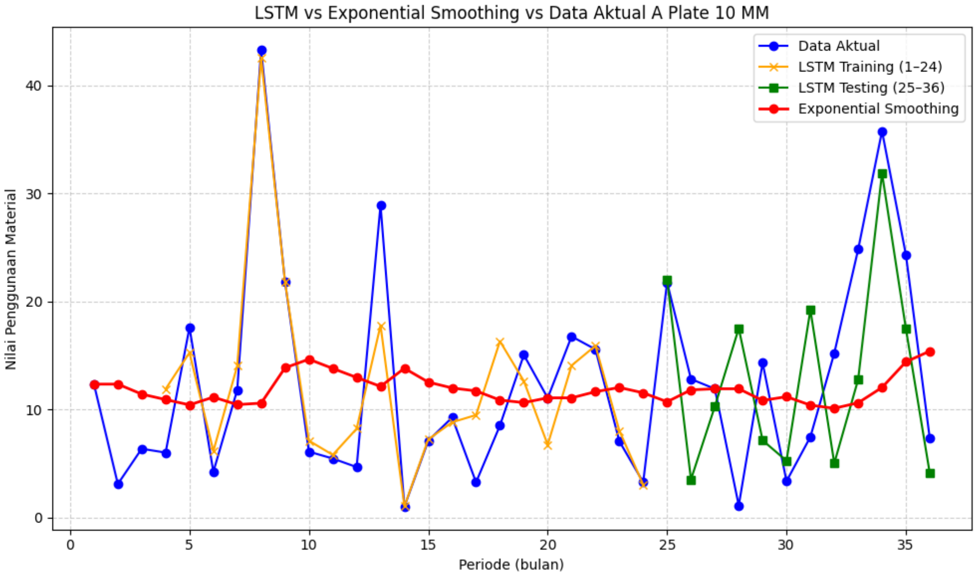

Figure 7 Forecasting Results Versus Actual Data

The random search approach identifies the most suitable set of hyperparameters for the LSTM model applied to the 8 mm plate. The bestperforming configuration consists of 16 units, a learning rate of 0.005, a batch size of 2, 250 training epochs, and a window size of 2. With this configuration, the LSTM model achieves a MAD of 17.35 and an MSE of 646.634. For the exponential smoothing method, the solver is used to determine the optimal value of the smoothing parameter, resulting in α = 0.8. This setting produces a MAD of 20.72 and an MSE of 1023.68. Figure 7 shows a comparison between the forecasting patterns generated by both methods and the actual usage data of the 8 mm plate, highlighting the superior performance of the LSTM model.

Continuous Review Q Model With Backorder

In this study, the inventory replenishment policy is determined using the continuous review (Q) model with backorders. This model uses several key inputs, including inventory cost parameters (unit cost, ordering cost, holding cost, and shortage cost), forecasted demand at monthly and annual levels, and the lead time. These inputs are used to decide how much to order, when to reorder, and how much safety stock is required. The continuous review (Q) model with backorder is calculated using the Hadley–Within method. Table 2 shows the resulting order quantity, safety stock, and reorder point for each material.

Table 2 Quantity Order, Safety Stock, and Reorder Point Each Material

No	Item	Order Quantity	Safety Stock	Reorder Point
1	KI-A Plate 12 mm	38	8	15
2	Plate 8 mm	32	7	10
3	KI-A Plate 10 mm	34	11	14
4	Plate 10 mm	20	4	5
5	Unequal AB 500 mm	29	2	3
6	H Beam 200 mm	37	7	9
7	Angle Bar 120 mm	139	19	28
8	Angle Bar 100 mm	128	14	20

Proposed Policy Versus Existing Policy

The replenishment simulation is carried out for both policies using actual data from 2024. Under the proposed policy (Qr), the continuous review (Q) model is applied, where an order of size Q is placed when the inventory level reaches or falls below the reorder point, as shown in Table 1. Under the existing policy (Ek), materials are ordered only when demand occurs, and the order quantity is adjusted to the required demand.

Table 3 Total Cost Comparison of Both Policies

No	Item	Policy	Total Cost	Stock
1	KI-A Plate 12 mm	Qr	Rp 15.590.232.162,16	24,8
		Ek	Rp 17.430.504.726,40	0
2	Plate 8 mm	Qr	Rp 3.786.539.691,49	31,15
		Ek	Rp 4.003.338.218,65	0
3	KI-A Plate 10 mm	Qr	Rp 5.322.609.181,89	44,8
		Ek	Rp 5.218.686.717,72	1,5
4	Plate 10 mm	Qr	Rp 2.352.466.255,22	22,15
		Ek	Rp 2.445.754.985,85	2
5	Unequal AB 500 mm	Qr	Rp 1.147.322.141,24	29,5
		Ek	Rp 1.191.850.913,70	2

6	H Beam 200 mm	Qr	Rp 1.595.433.073,42	22
		Ek	Rp 1.723.867.784,30	2
7	Angle Bar 120 mm	Qr	Rp 15.590.232.162,16	24,8
		Ek	Rp 17.430.504.726,40	0
8	Angle Bar 100 mm	Qr	Rp 3.786.539.691,49	31,15
		Ek	Rp 4.003.338.218,65	0

The two inventory policies result in different cost trade-offs. Under the existing policy, materials are ordered only when demand occurs. This policy keeps holding costs low, but increases ordering and shortage costs due to frequent orders and material shortages.

The continuous review (Q) model with backorder aims to balance inventory costs while ensuring material availability. By reducing shortages, this policy helps prevent work delays, penalty costs, and quality risks caused by rushed repair activities.

Overall, the proposed policy (Qr) results in a lower total cost than the existing policy (Ek). As shown in Table 3, Qr achieves lower costs for almost all materials, except for the KI-A plate 10 mm. Although the cost is higher for this material, the proposed policy provides an additional inventory of 43,3 plates compared to the existing condition.

CONCLUSION

Demand forecasting is performed using 36 periods of historical steel material usage data, consisting of 24 periods for training and 12 periods for testing. To maximize forecasting performance, optimization techniques are applied to both methods, namely random search hyperparameter optimization for the LSTM model and a solver-based optimization for exponential smoothing. The results indicate that the LSTM model produces lower forecasting errors than the exponential smoothing method across the eight steel materials analyzed.

The continuous review (Q) model with backordering is applied to determine the optimal order quantity, safety stock, and reorder point for each material. The resulting proposed inventory policy is then compared with the existing policy currently implemented by the company. The comparison shows that the proposed policy is able to reduce total inventory costs by IDR 2,671,910,250.20, representing a cost saving of 7.645% relative to the existing policy.

Studies on inventory management in shipyard are still limited. In this industry, material demand is often highly variable, which makes demand forecasting difficult. Therefore, future research is encouraged to apply other machine learning–based forecasting methods to improve material procurement decisions. Better forecasting results are expected to help companies strengthen their bargaining power and competitive advantage in the ship repair industry.

According to Gauch et al. (2021)**,** the advantages of LSTM models are harder to observe when training data are limited. In this study, only 24 training periods are available, which limits the model's ability to learn complex demand patterns. This can be seen in the testing results, where the LSTM model still has difficulty following highly fluctuating demand**.** As a result, the MAD and MSE values of LSTM are not much different from those of exponential smoothing.

Future studies should therefore use longer historical datasets that better represent actual material demand in ship repair activities. Simply increasing data frequency, such as converting monthly data into daily data, does not necessarily reflect real demand conditions. Unlike retail businesses, ship repair yards do not require steel materials every day. As explained by Bandy and Russell (2008)**,** very high-frequency data do not always represent the true underlying variability. Hence, effective LSTM forecasting requires not only more data, but also data that accurately reflect the operational characteristics of the business**,** allowing the model to learn demand patterns more effectively.

REFERENCES

Ahmed, S., Chakrabortty, R., Essam, D., & Ding, W. (2024). A switching based forecasting approach for forecasting sales data in supply. *Applied Soft Computing*.

Al Fatih, M. T. (2020). *Pengendalian Persediaan Material Distribusi Utama (MDU) Pada Pln Unit Induk Distribusi (UID) Jawa Timur Dengan Klasifikasi ABC Dan Pendekatan Continuous Review.* Surabaya: Institut Teknologi Sepuluh Nopember.

Andreasson, E. (1980). *Managing Ship Production.* University of Strathclyde.

Bahagia, S. N. (2006). *Sistem Inventori*. ITB.

Budiarto, D. D., Miftahudin, & Riwurohi, J. E. (2024). *Application Of Exponential Smoothing Method For Forecasting Spare Parts Inventory At Heavy Equipment Distributor Company.* Eduvest – Journal of Universal Studies.

Chopra, S., & Meindl, P. (2013). *Supply Chain Management: Strategy, Planning, and Operation.* Pearson.

Gauch, M., Mai, J., & Lin, J. (2021). The Proper Care and Feeding of CAMELS: How Limited Training Data Affects . *Environmental Modelling and Software*.

Giaconia, C., & Chamas, A. (2023). Innovative Out-of-Stock Prediction System Based on Data History Knowledge Deep Learning Processing. *Computation*.

Indrajit, R. E., & Djokopranoto, R. (2003). *Manajemen persediaan:* . PT Grasindo.

Maddah, B., & Noueihed, N. (2017). EOQ holds under stochastic demand, a technical note. *Applied Mathematical Modelling*.

Mahardika, A. (2023). *Inventory Management Untuk Material Baja Pada Sebuah Perusahaan Galangan Perbaikan Kapal.* Surabaya: Institut Teknologi Sepuluh Nopember .

Mohamed-Amine, N., Abdellatif, M., & Belaid, B. (2024). Artificial intelligence for forecasting sales of agricultural products: A case . *Journal of Open Innovation: Technology, Market, and Complexity 10*.

Pujawan, I. N., & Mahendrawathi. (2017). *Supply Chain Management Edisi 3.* Andi.

Rahmatillah, I., Sudirman, I., Aziz, A. M., & Diryana, I. (2024). BAYESIAN LSTM Neural Network With Bayesian LSTM. *Journal of Theoretical and Applied Information Technology*.

Roslin, E. N., Abdul Razak, S. N., Bahrom, M. Z., & Abd Rahman, M. A. (2015). A Conceptual Model of Inventory Management System using an EOQ Technique - A Case Study in Automotive Service Industry. *Journal of Science & Engineering Technology*.

Schroeder, R., & Goldstein, S. M. (2018). *Operations Management In The Supply Chain Seventh Edition.* New York: McGraw-Hill Education.

Simamora, B. H. (2019). Optimum Inventory Policy at PT. Senahoy Optika Pratama in Indonesia. *International Journal of Mechanical Engineering and Technology*.

Sukhia, K. N., Khan, A. A., & Bano, M. (2014). Introducing Economic Order Quantity Model for Inventory Control in Web Based Point of Sale Applications and Comparative Analysis of Techniques for Demand Forecasting in Inventory Management. *International Journal of Computer Applications*.

Sukolkit, N., Arunyanart, S., & Apichottanakul, A. (2024). An open innovative inventory management based demand forecasting approach for the steel industry . *Journal of Open Innovation: Technology, Market, and Complexity 10*.

Tersine, R. J. (1994). *Principles Of Inventory And Materials Management Fourth Edition.* Prentice-Hall International.

Utama, R. E., Jaharuddin, N. G., & Priharta, A. (2019). *Manajemen Operasi.* UM Jakarta Press.

Wang, Z. (2025). Data-Driven Supply Chain Performance Optimization Through Predictive Analytics and Machine Learning. *Proceedings of the 3rd International Conference on Software Engineering and Machine Learning.* Sydney: EWA Publishing.

Waters, D. (2003). *Inventory Control And Management.* Chichester: John Wiley & Sons Ltd.