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Forecasting Loading and Unloading Volume in Port of Surabaya Using Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES)

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Abstract. Maritime transportation plays a vital role in supporting global trade, particularly in archipelagic countries such as Indonesia, where sea transport dominates logistics activities. This study aims to forecast cargo loading and unloading volumes at the Port of Tanjung Perak, Surabaya, using Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) methods. Monthly data from January 2021 to December 2025 were analyzed using a quantitative time series approach, with model performance evaluated based on Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE). The result of this study is SES demonstrates superior accuracy for both loading and unloading activities, although DES produces slightly higher forecasts. The SES model forecasts the next-period loading and unloading volumes at 918,441 tons and 1,934,159 tons, respectively. These findings suggest that SES is more suitable for short-term forecasting, as the data do not strongly require a trend-adjusted model. The study recommends the adoption of SES to support operational planning, along with improved capacity management to accommodate increasing cargo volumes.

Keywords: Double Exponential Smoothing (DES); Forecasting; Port Logistic; Single Exponential Smoothing (SES)

1. Introduction

Maritime transportation is the backbone of global trade, serving as the primary facility for distributing products between countries through sea routes (Cartel et al., 2024). The increasing utilization of this mode of transportation has been driven by growing demand and by shipping companies that continue to enhance service quality, thereby making maritime transport increasingly attractive. Ports play a crucial role in accommodating these conditions by anticipating and responding to changes in demand, as well as by improving service performance and customer satisfaction (Morales-ramírez et al., 2025).

As the world's largest archipelagic country, Indonesia is highly dependent on maritime transportation. Sea transport has long dominated Indonesia's export volume and serves as the main mode of international trade, contributing approximately 99.22 percent of the country's total export volume (Kebijakan, 2024). In addition, demand for maritime transportation has continued to increase. In 2024, domestic shipping cargo handling volumes increased by 10.79 percent for unloading activities and 12.56 percent for loading activities compared to 2023. Meanwhile, in international shipping, unloading and loading volumes increased by 12.48 percent and 16.56 percent, respectively (Statistik, 2026).

Despite the significant growth of maritime transportation, Indonesia faces complex challenges related to inter-island product distribution. These challenges include limited port infrastructure, unequal distribution between western and eastern regions of Indonesia, and distribution routes that remain concentrated in major cities (Humang & Hadiwardoyo, 2019). National logistics costs reach approximately 24 percent of Indonesia's Gross Domestic Product (GDP), which is considerably higher than those of other Southeast Asian countries (Humang & Hadiwardoyo, 2019). These high logistics costs are not only attributable to Indonesia's archipelagic geography, but also to the lack of an integrated logistics system and inadequate infrastructure.

Such high logistics costs can be reduced through the implementation of a more integrated and coordinated logistics system. One approach that can be applied is the prediction of cargo loading and unloading volumes. Accurate forecasting of cargo handling activities is essential for improving port operational efficiency and supporting strategic planning (Lee & Bang, 2024). Precise predictions of loading and unloading volumes not only facilitate optimal resource allocation but also enhance the overall performance of container terminals and the global supply chain.

One effort to optimize port resources is the application of forecasting methods. In this study, the forecasting techniques employed are exponential. The exponential smoothing is selected for its ability to handle data with fluctuating patterns and trends (Budiarto et al., 2024). Several studies have applied these methods, including Budiarto et al. (2024) on spare parts inventory forecasting for heavy equipment distributors; Annabil et al. (2025), who compared SARIMA and exponential smoothing models for predicting the farmer exchange rate in Central Java; and Permana et al. (2024), who predicted stock market trends using the moving average method combined with the LSTM algorithm.

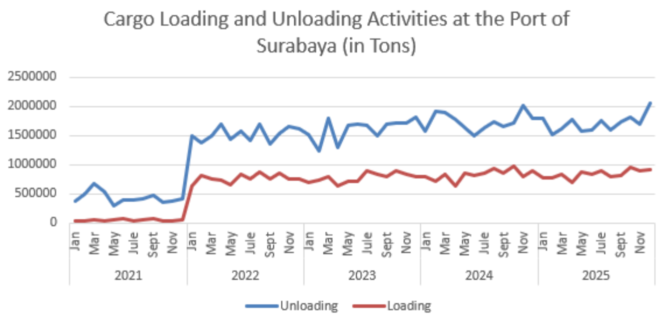

Figure 1 Volume of cargo loading and unloading activities at the Port of Surabaya

The Port of Tanjung Perak in Surabaya is the second busiest seaport in Indonesia, serving as a major logistics hub and an inter-island connectivity center. Based on the data presented in Figure 1, there has been a noticeable increase in cargo handling activities over the past two years, and this upward trend is likely to continue in the coming years. If not properly managed, such growth may lead to increased port operational costs.

This study employs both single exponential smoothing (SES) and double exponential smoothing (DES) forecasting approach to predict cargo loading and unloading volumes at the Port of Tanjung Perak, Indonesia. In addition to forecasting future volume trends, this research aims to determine the most optimal exponential smoothing model to achieve accurate forecasting results. The forecasting outcomes are expected to serve as a guideline for resource allocation at the Port of Tanjung Perak, thereby contributing to the minimization of logistics costs incurred.

2. Literature Review

a. Port Logistics

Port logistics is an integrated system that encompasses the flow of goods, information, and labor, serving as a critical link in the maritime supply chain. This system involves not only the physical activities of loading and unloading, but also the planning, control, and coordination among various components such as terminals, warehouses, transportation equipment, supporting facilities, and information systems (Notteboom &

Rodrigue, 2000). As logistics nodes, ports constitute strategic spaces that contribute significantly to the efficiency of national and international goods distribution.

Port logistics is closely associated with the concept of supply chain management (SCM), in which ports function as major transit points that ensure the smooth flow of goods from their point of origin to the final destination. In this context, ports are required to provide efficient facilities and services in order to minimize costs, processing time, and the risk of delays. With the increasing volume of cargo traffic, port operational challenges have become more complex, necessitating adaptive and optimized logistics management strategies.

According to Song & Panayides (2012) port logistics enhances port competitiveness through operational efficiency, the utilization of information technology, and intermodal transport integration. This can be observed in the implementation of warehouse automation systems, real-time cargo tracking, and coordination between port authorities and stakeholders such as shipping lines and terminal operators. The success of ports in managing logistics not only affects internal performance but also strengthens regional and national competitiveness.

b. Forecasting

Forecasting is a systematic process used to estimate the future values of a variable based on historical data and patterns observed in previous periods. In the context of logistics systems, forecasting serves as a fundamental basis for capacity planning, operational control, and strategic decision-making in order to reduce demand uncertainty (Makridakis et al., 1998). Accurate forecasting plays a crucial role in improving operational efficiency and reducing logistics costs.

In port logistics, forecasting cargo flow volumes is particularly critical, as it is directly related to planning the allocation of resources such as berths, cargo handling equipment, warehouses, and labors. According to Port Economics, Management and Policy, inaccuracies in predicting port traffic volumes may lead to capacity imbalances, manifested either as underutilization or congestion, both of which ultimately increase port operational costs.

Within the context of port logistics experiencing an upward trend in cargo flow volumes, forecasting functions as a decision-support tool for medium- and long-term planning. Accurate forecasting results enable port authorities and operators to formulate optimal resource allocation strategies and minimize the risk of escalating logistics costs arising from mismatches between capacity and actual demand.

c. Exponential Smoothing

One of the forecasting methods widely used in time series analysis is exponential smoothing. This method is a forecasting technique that assigns greater weight to more recent data compared to older data, using an exponential weighting scheme (Hyndman & Athanasopoulos, 2018).

The main advantage of this method lies in its computational simplicity and its ability to produce fairly accurate predictions, especially for short-term forecasting (Gardner, 1985). In this method, there is a parameter known as the smoothing constant, denoted by α (alpha), which takes a value between 0 and 1. This parameter determines the extent to which recent data influence the forecasting results.

Single Exponential Smoothing is applied to time series data that do not exhibit trend or seasonal patterns. This method focuses only on the level component of the data, where the forecast is updated based on the previous forecast and the most recent actual value.

According to Heizer et al. (2017), the basic exponential smoothing formula is as follows:

$$New\ forecast = Last\ period's\ forecast + \alpha(Last\ period's\ actual\ demand - Last\ period's\ forecast) \quad (1)$$

This equation can also be expressed mathematically as:

$$F_t = F_{t-1} + \alpha\,(A_{t-1} - F_{t-1}) \quad (2)$$

where:
F_t = new forecast
F_{t-1} = previous period's forecast
α = smoothing (or weighting) constant ($0 \leq \alpha \leq 1$)
A_{t-1} = previous period's actual demand

Double Exponential Smoothing, also known as Holt's method, is used when the data exhibit a trend pattern. This method extends Single Exponential Smoothing by incorporating an additional component, namely the trend, so that both level and trend are updated at each period.

The level represents the smoothed estimate of the data value at the end of each period, while the trend represents the smoothed estimate of the average change over time (Nazim & Afthanorhan, 2014). In this method, two parameters are used, namely α (alpha) for the level and β (beta) for the trend

The formulas used in the Double Exponential Smoothing method are as follows (Asmaradana & Widodo, 2023).

Level smoothing:

$$L_t = \alpha y_t + (1 - \alpha)(L_{t-1} + b_{t-1}) \quad (3)$$

Trend smoothing:

$$b_t = \beta(L_t - L_{t-1}) + (1 - \beta)b_{t-1} \quad (4)$$

Forecast for m periods ahead:

$$F_{t+m} = L_t + b_t m \quad (5)$$

Where:
L_t = estimated level at period t
α = smoothing constant for the level
y_t = actual data at period t
β = smoothing constant for the trend
b_t = estimated trend at period t
m = number of periods to be forecasted

Compared to SES, DES is more suitable for data with a clear upward or downward trend, as it is able to capture both the current level and the rate of change over time.

Despite its advantages, exponential smoothing methods also have several limitations, including their sensitivity to parameter selection and their inability to effectively model highly complex patterns. In some cases, these methods may be less accurate compared to more advanced approaches, such as machine learning-based forecasting models.

d. Forecasting Error Measurement

Forecasting performance measurement is an essential step in evaluating the accuracy and reliability of predictive models. It involves quantifying the deviation between actual observed values and forecasted results. According to Wallstrom & Segerstedt (2010) the use of error metrics enables researchers to compare alternative forecasting methods and select the most appropriate model for a given dataset.

Several error measures are commonly used in time series forecasting, including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics provide different perspectives on forecast accuracy and are often used together to ensure a comprehensive evaluation.

According to Amalia et al., 2020 Mean Absolute Deviation (MAD) measures the average of absolute errors between actual values and forecasted values. It is expressed as:

$$MAD = \frac{1}{n}\sum_{t=1}^{n} | A_t - F_t | \tag{6}$$

where $A_t$represents the actual value, $F_t$the forecasted value, and $n$the number of observations. MAD is easy to interpret and provides a direct measure of average forecasting error without considering the direction of the error.

Mean Squared Error (MSE) calculates the average of squared differences between actual and forecasted values, giving more weight to larger errors. The formula is:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2 \tag{7}$$

Because errors are squared, MSE is particularly useful when large deviations are undesirable, although it is sensitive to outliers.

Mean Absolute Percentage Error (MAPE) expresses forecast error as a percentage, allowing for comparison across different scales of data. It is defined as:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n} | \frac{A_t - F_t}{A_t} | \tag{8}$$

MAPE is widely used due to its intuitive interpretation; however, it has limitations when actual values are close to zero, which may lead to inflated or undefined results (Hyndman & Athanasopoulos, 2018).

In practice, no single error metric is sufficient to fully evaluate forecasting performance. Therefore, combining MAD, MSE, and MAPE provides a more robust assessment by capturing different characteristics of forecast errors. This multi-criteria evaluation approach helps ensure that the selected forecasting model is both accurate and reliable for decision-making purposes.

3. Methods

This study employs a quantitative approach using time series analysis to forecast loading and unloading activities at a port in Surabaya. The data used in this research consist of monthly loading and unloading volumes measured in tons, covering the period from January 2021 to December 2025, resulting in a total of 60 observations. The dataset was obtained from the official website of the Badan Pusat Statistik, ensuring the reliability and validity of the data.

The research applies a comparative method between Single Exponential Smoothing (SES) and Double Exponential Smoothing (DES) to determine the most appropriate forecasting model. SES is utilized for data without a trend component, while DES is applied to data exhibiting a trend pattern by incorporating both level and trend parameters. The forecasting process is conducted using Minitab 22, where the smoothing constant (α) and the trend parameter (γ in Minitab, equivalent to β in theoretical models) are optimized automatically. Each dataset, namely loading and unloading, is analyzed separately using both methods, and forecasts are generated for the next period.

In addition, trend analysis is performed to identify the underlying pattern of the data, whether increasing, decreasing, or stable over time. This analysis supports the selection of the appropriate forecasting method. To evaluate the performance of each model, several accuracy measures are employed, including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics are used to assess the forecasting errors and to compare the effectiveness of the SES and DES models.

The research procedure is carried out systematically, starting from problem identification, followed by a literature review, data collection, forecasting using SES and DES, evaluation of forecasting accuracy using MAD, MSE, and MAPE, and finally the selection of the most suitable model for each case, namely loading and unloading. The outcome of this study is the determination of the best forecasting model along with forecast results for the next month, which are expected to support decision-making in port operations and planning.

4. Result and Discussion

Based on the forecasting result which applied into each cases (loading and unloading), it can be analyzed which method is optimal that can be forecast volume of loading and unloading accurately. This selection for the best method are presented belows:

a. Loading

In this stage, the researcher analyzes the trend of loading activity at the Port of Surabaya to identify the linear trend from January 2021 to December 2025. Based on Figure 2, the first 12 periods show significantly lower values compared to the subsequent periods. This condition reflects the negative impact of the COVID-19 pandemic, which caused a substantial decline in port activities during the early observation period.

A significant shift is clearly observed starting from period 13, where loading activity increases sharply. This indicates a recovery phase in port operations, likely driven by the normalization of economic activities and supply chain improvements post-pandemic.

The estimated linear trend model $Y_t = 237689 + 13562t$ suggests a positive upward trend, where loading volume increases by approximately 13,562 tons per period. This indicates a steady growth pattern in port activity over time. However, despite the upward trend, the actual data exhibit considerable fluctuations around the trend line, suggesting the presence of short-term variability that is not fully captured by the linear model.

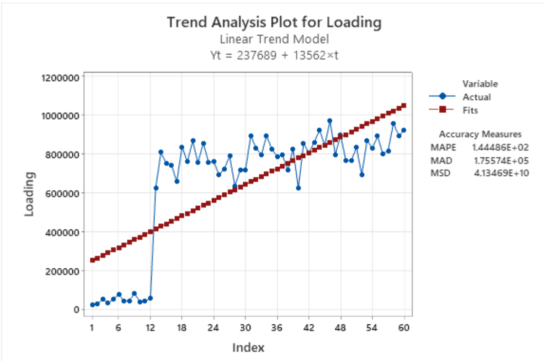

Figure 2. Trend Analysis Plot for Loading Activity at the Port of Surabaya

Based on the trend analysis, loading data exhibit a clear increasing trend, the variability and structural changes in the data highlight the need for more robust forecasting approaches, such as exponential smoothing methods, which can better accommodate dynamic patterns in time series data

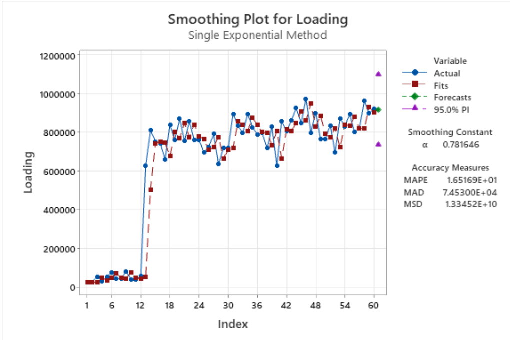

Figure 3. SES Forecasting for Loading Activity at the Port of Surabaya

The first model employed in this study is the Single Exponential Smoothing (SES) model. The forecasting results are based on Equation (2) and were optimized using Minitab. Based on Figure 3, the forecast for the next period is estimated at 918,441 tons, with an upper bound of 1,101,036 tons and a lower bound of 735,846 tons, obtained using a smoothing parameter (α) of 0.781646. The model's accuracy measures indicate a Mean Absolute Percentage Error (MAPE) of 16.51%, a Mean Absolute Deviation (MAD) of 74,530, and a Mean Squared Error (MSE), referred to as Mean Squared Deviation (MSD) in Minitab, of 1.3×10^{10}.

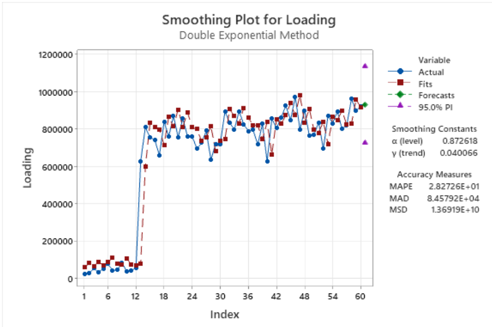

Figure 4. DES Forecasting for Loading Activity at the Port of Surabaya

The second model utilized is the Double Exponential Smoothing (DES) model. The forecasting results are derived from Equation (5) and were also optimized using Minitab. Based on Figure 4, the forecast for the next period is 933,434 tons, with an upper bound of 1,140,649 tons and a lower bound of 726,219 tons. These results are obtained using a smoothing parameter (α) of 0.872618 and a trend smoothing parameter (β), which is denoted as γ in Minitab, of 0.040066. The model performance yields a MAPE of 28.83%, a MAD of 84,579, and an MSE (MSD in Minitab) of 1.4×10^{10}.

Table 1. Comparison between SES and DES for Loading Activity

No	Model	Forecast			Error		
		Next Period	Lower	Upper	MAPE	MAD	MSE
1	SES	1,934,159	1,557,076	2,311,243	12.44%	153,914	4.9×10^{10}
2	DES	2,051,806	1,652,467	2,451,145	13,98%	162,999	5.3×10^{10}

Based on Table 1, the results show that although DES produces a slightly higher forecast than SES, the SES model is more accurate, as indicated by its lower MAPE, MAD, and MSE values. This suggests that SES is more suitable for this dataset, and incorporating a trend component in DES does not improve forecasting performance.

b. Unloading

The same procedure is applied to the unloading activity. Based on Figure 5, a similar pattern is observed as in the loading activity. The first 12 periods exhibit relatively lower values, which can be attributed to the negative impact of the COVID-19 pandemic on port operations.

A significant shift is clearly observed starting from period 13, where unloading activity increases sharply, that exceed more than 1 million tons. This indicates a recovery phase in port operations, likely driven by the normalization of economic activities and improvements in supply chain performance in the post-pandemic period.

The estimated linear trend model, $Y_t = 717327 + 22483t$, suggests a positive upward trend, indicating that unloading volume increases by approximately 22,483 tons per period. This reflects a consistent growth pattern in port activity over time. However, despite the overall upward trend, the actual data show considerable fluctuations around the trend line. This suggests the presence of short-term variability that is not fully captured by the linear trend model.

Overall, this pattern is highly similar to the loading activity, indicating that both loading and unloading operations experienced comparable impacts and recovery dynamics during and after the pandemic period.

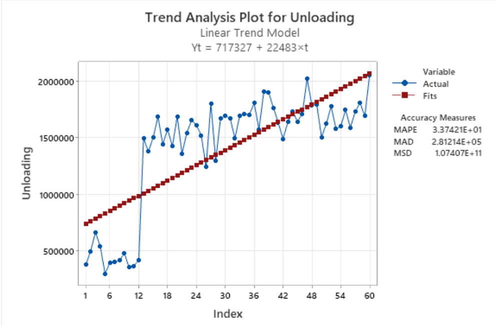

Figure 5. Trend Analysis Plot for Unoading Activity at the Port of Surabaya

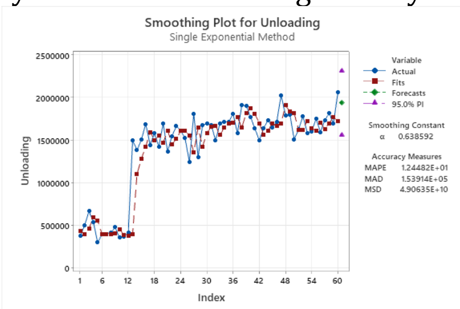

Figure 6. SES Forecasting for Unloading Activity at the Port of Surabaya

The first model is the Single Exponential Smoothing (SES) model. The forecasting results are based on Equation (2) and were optimized using Minitab. Based on Figure 6, the unloading activity forecast for the next period is estimated at 1,934,159 tons, with an upper bound of 2,311,243 tons and a lower bound of 1,557,076 tons, obtained using a smoothing parameter (α) of 0.638592. The model's accuracy measures indicate a Mean Absolute Percentage Error (MAPE) of 12.44%, a Mean Absolute Deviation (MAD) of 153,914, and a Mean Squared Error (MSE), referred to as Mean Squared Deviation (MSD) in Minitab, of 4.9×10^{10}.

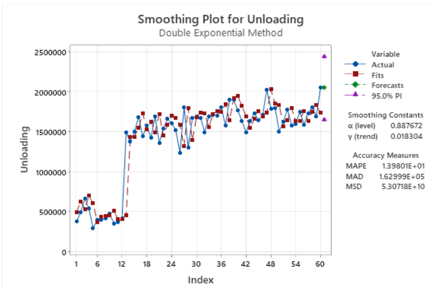

Figure 7. DES Forecasting for Unloading Activity at the Port of Surabaya

The second model utilized is the Double Exponential Smoothing (DES) model. The forecasting results are derived from Equation (5) and were also optimized using Minitab. Based on Figure 7, the forecast for the next period is 2,051,806 tons, with an upper bound of 2,451,145 tons and a lower bound of 1,652,467 tons. These results are obtained using a smoothing parameter (α) of 0.887672 and a trend smoothing parameter (β), which is denoted as γ in Minitab, of 0.018304. The model performance yields a MAPE of 13.98%, a MAD of 162,999, and an MSE (MSD in Minitab) of 5.3×10^{10}.

Table 2. Comparison between SES and DES for Unloading Activity

No	Model	Forecast			Error		
		Next Period	Lower	Upper	MAPE	MAD	MSE
1	SES	1,934,159	1,557,076	2,311,243	12.44%	153,914	4.9×10^{10}
2	DES	2,051,806	1,652,467	2,451,145	13,98%	162,999	5.3×10^{10}

Based on Table 2, the same results are same as the loading activity, that DES produces a slightly higher forecast than SES. This suggests that SES is more suitable for this dataset, both for loading and unloading activity.

5. Conclusion

This study demonstrates that both loading and unloading activities at the Port of Surabaya. The trend analysis reveals a recovery phase beginning around period 13, indicating the gradual normalization of port operations and improvements in supply chain performance. Although linear trend models confirm consistent growth in both activities, the presence of considerable fluctuations suggests that the data contain short-term variability and structural changes that cannot be fully captured by simple trend models.

The forecasting results reveal that, while the Double Exponential Smoothing (DES) model produces slightly higher forecasts, the Single Exponential Smoothing (SES) model provides better accuracy, as indicated by lower MAPE, MAD, and MSE values. The SES model estimates the next-period loading and unloading volumes at 918,441 tons and 1,934,159 tons, respectively, compared to DES forecasts of 933,434 tons and 2,051,806 tons with higher errors. This suggests that SES is more suitable, as the data do not strongly require a trend-adjusted model. Based on these findings, it is recommended that port management adopt SES for short-term forecasting. Additionally, the port should enhance capacity planning and resource allocation to accommodate approximately 0.9 million tons of loading and 1.9 million tons of unloading in the upcoming period, while periodically evaluating forecasting models to improve adaptability to future demand fluctuations.

To better handle data variability, periodic model evaluation is also recommended, along with the potential adoption of more advanced or hybrid forecasting models if future fluctuations become more pronounced. These measures will support more effective decision-making and enhance operational performance in response to growing logistics demand.

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