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An empirical analysis of cargo volume and ship type on ship turnaround time at Tanjung Priok Port

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ABSTRACT

Port service efficiency plays a crucial role in supporting maritime logistics and national trade performance. One key indicator of port service efficiency is ship turnaround time, which is influenced by various operational factors, including ship type and cargo volume. This study examines the effect of ship type and cargo volume on ship turnaround time at Tanjung Priok Port, Indonesia, using a case study of PT Buana Lintas Lautan Tbk. Quantitative analysis was conducted using monthly operational data collected over a twelve-month period (August 2022–August 2023). Multiple linear regression was applied after fulfilling classical assumption tests, including normality, multicollinearity, heteroscedasticity, and autocorrelation. The results indicate that ship type and cargo volume simultaneously have a significant effect on turnaround time. However, partial analysis reveals that only cargo volume has a significant positive impact on turnaround time, while ship type does not show a statistically significant effect. These findings suggest that operational delays are primarily driven by cargo handling intensity rather than vessel characteristics. This study provides practical insights for ship agency companies and port operators in estimating service time, optimizing operational planning, and improving port service efficiency through better cargo management strategies.

Keywords: *Ship type, cargo volume, turnaround time, port efficiency, maritime services.*

ABSTRAK

Efisiensi pelayanan pelabuhan merupakan faktor penting dalam mendukung kelancaran logistik maritim dan kinerja perdagangan nasional. Salah satu indikator utama efisiensi pelayanan pelabuhan adalah ship turnaround time, yang dipengaruhi oleh berbagai faktor operasional, termasuk jenis kapal dan volume muatan. Penelitian ini bertujuan untuk menganalisis pengaruh jenis kapal dan volume muatan terhadap ship turnaround time di Pelabuhan Tanjung Priok, Indonesia, dengan studi kasus pada PT Buana Lintas Lautan Tbk. Penelitian ini menggunakan pendekatan kuantitatif dengan data operasional bulanan selama periode Agustus 2022 hingga Agustus 2023. Analisis data dilakukan menggunakan regresi linear berganda yang didahului dengan pengujian asumsi klasik, meliputi uji normalitas, multikolinearitas, heteroskedastisitas, dan autokorelasi. Hasil penelitian menunjukkan bahwa jenis kapal dan volume muatan secara simultan berpengaruh signifikan terhadap ship turnaround time. Namun, secara parsial hanya volume muatan yang berpengaruh positif dan signifikan terhadap ship turnaround time, sedangkan jenis kapal tidak menunjukkan pengaruh yang signifikan. Temuan ini mengindikasikan bahwa lamanya waktu pelayanan kapal lebih dipengaruhi oleh intensitas penanganan muatan dibandingkan karakteristik jenis kapal. Hasil penelitian ini diharapkan dapat *menjadi acuan bagi perusahaan keagenan kapal dan pengelola pelabuhan dalam memperkirakan waktu pelayanan kapal, meningkatkan perencanaan operasional, serta mengoptimalkan efisiensi pelayanan pelabuhan.*

Kata Kunci: *Jenis kapal, volume muatan, ship turnaround time, efisiensi pelabuhan, pelayanan maritim.*

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INTRODUCTION

Ports are essential nodes in maritime transportation systems and play a vital role in facilitating international trade and national economic growth. Efficient port operations contribute to reduced logistics costs, improved vessel productivity, and enhanced supply chain reliability. Conversely, inefficiencies in port services can lead to congestion, operational delays, and increased costs for shipping companies. As a result, improving port service efficiency has become a major concern for port authorities, shipping operators, and policymakers worldwide [1].

One of the most commonly used indicators to assess port service efficiency is *ship turnaround time*, defined as the total time a vessel spends in port from arrival to departure. This indicator reflects the effectiveness of loading and unloading operations, berth utilization, and coordination among port stakeholders, including port authorities, terminal operators, stevedoring companies, and ship agents. Shorter turnaround times indicate higher operational efficiency, while longer turnaround times signal the presence of operational bottlenecks and coordination problems within port systems [1-2].

Ship turnaround time is influenced by various operational factors, among which cargo volume and ship type are frequently considered critical determinants. Cargo volume directly affects the duration of loading and unloading activities, as larger quantities of cargo generally require more time, labor, and equipment. Ship type, on the other hand, may influence handling requirements, safety procedures, and berth allocation due to differences in vessel design and cargo characteristics. Understanding how these two factors affect turnaround time is essential for effective operational planning in port services [3-4].

In practice, port inefficiencies often arise from limited coordination and information sharing among port stakeholders. Inadequate communication between shipping companies, terminal operators, and stevedoring service providers may result in suboptimal scheduling, congestion, and delays in cargo-handling activities [3-5]. These challenges are further compounded by constraints in port infrastructure and cargo-handling equipment, which can reduce operational productivity and extend vessel service time [2, 6].

External factors also play an important role in determining ship turnaround time. Adverse weather conditions and unfavorable sea states can disrupt berthing schedules, slow down cargo operations, and compromise navigational safety. Such conditions are particularly impactful in busy ports with high vessel traffic, where operational flexibility is limited and delays can quickly propagate through port systems [7-9].

Indonesia, as an archipelagic country with a strong dependence on maritime transportation, relies heavily on efficient port operations to support domestic distribution and international trade. Tanjung Priok Port, the largest and busiest port in Indonesia, handles a significant share of national cargo throughput. The continuous increase in vessel calls and cargo volume at Tanjung Priok reflects growing economic activity but also poses operational challenges, including congestion and extended ship turnaround times. Several studies indicate that infrastructure development and operational efficiency at major Indonesian ports have not always kept pace with traffic growth, resulting in persistent inefficiencies [10-12].

Previous studies on port performance have examined a wide range of factors, such as infrastructure capacity, coordination mechanisms, information systems, and risk management in port operations. However, empirical studies that specifically quantify the simultaneous and partial effects of ship type and cargo volume on ship turnaround time—particularly using operational data from ship agency services in Indonesia—remain limited. Moreover, much of the existing literature focuses on container terminals, while tanker and bulk cargo operations, which involve distinct handling characteristics and operational risks, receive less attention [1, 4, 6].

Therefore, this study aims to analyze the effect of ship type and cargo volume on ship turnaround time at Tanjung Priok Port, Indonesia, using a case study of PT Buana Lintas Lautan Tbk, a company engaged in ship agency services. By applying multiple linear regression analysis to monthly operational data, this research seeks to identify the dominant factors influencing vessel service time and to evaluate whether cargo-related factors or vessel characteristics play a more significant role in determining port service efficiency. The findings of this study are expected to provide practical insights for ship agency companies and port operators in improving operational planning, optimizing cargo-handling processes, and enhancing overall port service performance. This study contributes to the literature by providing ship-agency-level empirical evidence from Indonesia, which remains underexplored in port performance studies.

RESEARCH METHODOLOGY

Research Design and Approach

This study adopts a quantitative research approach to examine the effect of cargo volume and ship type on ship turnaround time at Tanjung Priok Port, Indonesia. A quantitative approach is appropriate for analyzing operational performance indicators and identifying causal relationships between operational variables in port and maritime service studies [1-2]. By applying statistical analysis to empirical operational data, this study aims to provide objective and measurable evidence regarding the determinants of port service efficiency.

Study Area and Case Selection

The research was conducted at Tanjung Priok Port, the largest and busiest port in Indonesia, which plays a strategic role in national and international maritime trade. The port experiences high vessel traffic and cargo throughput, making it an appropriate case for examining factors affecting ship turnaround time. The case study focuses on PT Buana Lintas Lautan Tbk, a ship agency company that handles tanker and bulk vessels. Ship agency services are directly involved in coordinating vessel arrival, berthing, cargo handling, documentation, and departure processes, which are critical components influencing vessel service time [3-4].

Data Collection and Variables

The study utilizes secondary operational data obtained from PT Buana Lintas Lautan Tbk, covering a twelve-month period from August 2022 to August 2023. Monthly operational records were used to ensure data consistency and to capture variations in vessel operations over time. The dataset includes information on ship type, cargo volume, and ship turnaround time. The dependent variable in this study is **ship turnaround time**, measured in hours, representing the total duration from vessel arrival at the port until departure. Turnaround time is widely used as an indicator of port service efficiency and vessel operational performance [1, 9].

The independent variables consist of:

- **Cargo volume**, measured in tons, representing the quantity of cargo handled during a vessel's port call. Cargo volume is a key operational factor influencing loading and unloading duration [2, 6].
- **Ship type**, treated as a dummy variable to distinguish between different vessel categories (e.g., tanker and bulk carrier). Ship type may influence handling requirements, safety procedures, and operational arrangements at the port [6].

Analytical Framework

To analyze the relationship between the independent variables and ship turnaround time, this study employs multiple linear regression analysis. Regression analysis is commonly used in port and maritime studies to quantify the effect of operational factors on performance indicators and to evaluate the relative importance of explanatory variables [1-2]. The general regression model is expressed as:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon,$$

where Y represents ship turnaround time, α is the constant, X_1 denotes ship type, X_2 denotes cargo volume, β_1 and β_2 are regression coefficients, and ε is the error term.

Classical Assumption Tests

Prior to regression analysis, classical assumption tests were conducted to ensure the validity and reliability of the regression model. These tests are essential to avoid biased or inefficient estimates in linear regression analysis [6]. The tests include:

1. **Normality Test**. The normality of residuals was tested using the Kolmogorov–Smirnov test to verify whether the error terms follow a normal distribution.
2. **Multicollinearity Test**. Multicollinearity among independent variables was examined using the Variance Inflation Factor (VIF) and tolerance values. A VIF value below 10 and a tolerance value above 0.10 indicate the absence of multicollinearity [3].
3. **Heteroscedasticity Test**. The Glejser test was applied to identify the presence of heteroscedasticity in the regression model. A significance value greater than 0.05 indicates homoscedastic residuals [2].
4. **Autocorrelation Test**. The Durbin–Watson test was used to detect autocorrelation in the residuals. A Durbin–Watson value within the acceptable range indicates that the regression model is free from autocorrelation problems [1].

Data Processing and Analysis Tools

All statistical analyses were performed using SPSS software. Descriptive statistical analysis was conducted to summarize the characteristics of the data, including mean values, minimum and maximum values, and standard deviations. Regression and assumption tests were subsequently applied to evaluate the relationships between variables and to test the proposed research hypotheses.

Methodological Limitations

This study is subject to several limitations. First, the analysis is based on data from a single port and a single ship agency company, which may limit the generalizability of the findings to other ports or operational contexts. Second, the model focuses on cargo volume and ship type, while other factors such as weather conditions, berth availability, and information-sharing mechanisms—identified in previous studies as important determinants of port efficiency—are not explicitly included in the regression model [4, 7-8]. Despite these limitations, the methodology provides a robust framework for analyzing key operational factors influencing ship turnaround time in busy port environments.

RESEARCH RESULTS AND DISCUSSIONS

Data Description

This study is based on monthly operational data obtained from PT Buana Lintas Lautan Tbk for the period August 2022 to August 2023, resulting in a total of 30 observations. The dataset represents ship agency operations at Tanjung Priok Port, one of the busiest ports in Indonesia, where tanker and bulk carrier vessels are handled regularly.

Table 1. Descriptive statistics.

Variable	N	Minimum	Maximum	Mean	Std. Deviation
Ship Turnaround Time (hours)	30	15	303	101.13	71.36
Cargo Volume (tons)	30	1,400	27,000	7,465.87	5,780.43
Ship Type (dummy)	30	0	1	0.83	0.38

The dependent variable, ship turnaround time, is measured in hours and reflects the total duration from vessel arrival to departure. The observed turnaround time varies substantially across months, indicating differences in cargo-handling intensity, operational coordination, and port conditions. Cargo volume, measured in tons, also shows significant variation, reflecting fluctuations in shipping demand and cargo throughput. Ship type is treated as a dummy variable distinguishing between tanker and bulk carrier operations. The variation observed across all variables indicates that the dataset captures realistic operational dynamics and provides an appropriate empirical basis for statistical analysis of port service efficiency.

Data Analysis

Descriptive Statistical Analysis

Descriptive statistics were used to summarize the characteristics of the data. The results indicate that ship turnaround time and cargo volume exhibit relatively high dispersion, which is typical for operational data in major ports. The standard deviation values for the main variables are lower than their respective mean values, suggesting that the data are reasonably well distributed and suitable for regression analysis.

Classical Assumption Tests

Prior to estimating the regression model, classical assumption tests were conducted to ensure the validity of the multiple linear regression analysis. The normality test confirms that the regression residuals are normally distributed, indicating that the model satisfies the normality assumption. Multicollinearity testing using tolerance and Variance Inflation Factor (VIF) values shows no indication of high correlation between cargo volume and ship type, allowing both variables to be included simultaneously in the model.

The heteroscedasticity test indicates that the variance of residuals is constant across observations, suggesting that the model does not suffer from heteroscedasticity. In addition, the Durbin–Watson test confirms the absence of autocorrelation in the residuals. Collectively, these results indicate that the regression model meets all classical assumptions and is statistically reliable.

Table 2. Classical assumption test results.

Test	Indicator	Result	Decision
Normality (Kolmogorov–Smirnov)	Sig. = 0.184	> 0.05	Normal
Multicollinearity	VIF = 1.639	< 10	No multicollinearity
Heteroscedasticity (Glejser)	Sig. > 0.05	> 0.05	Homoscedastic
Autocorrelation (Durbin–Watson)	DW = 1.788	du < DW < 4–du	No autocorrelation

Statistical Results

Multiple linear regression analysis was performed to examine the effect of ship type and cargo volume on ship turnaround time. The simultaneous significance test (F-test) shows that the independent variables jointly have a statistically significant effect on turnaround time, indicating that the regression model is appropriate for explaining variations in vessel service duration.

Partial significance testing (t-test) reveals that cargo volume has a positive and statistically significant effect on ship turnaround time. This result indicates that an increase in cargo volume leads to longer service time at the port. In contrast, ship type does not show a statistically significant partial effect on turnaround time, suggesting that differences between tanker and bulk carrier operations do not independently influence service duration when cargo volume is taken into account. The coefficient of determination (Adjusted R^2) indicates that a substantial proportion of the variation in ship turnaround time is explained by cargo volume and ship type, while the remaining variation is attributable to other operational and external factors not included in the model.

Regression Equation

Based on the regression analysis, the estimated regression equation is:

$$Y = 69.419 - 31.277X_1 + 0.008X_2,$$

where Yrepresents ship turnaround time, X_1denotes ship type, and X_2denotes cargo volume. The equation indicates that, holding other variables constant, an increase of one ton in cargo volume increases ship turnaround time by 0.008 hours. The coefficient for ship type is negative but statistically insignificant, indicating that ship type does not have a meaningful independent effect on turnaround time.

Table 3. Multiple linear regression results.

Variable	B	Std. Error	Beta	t-value	Sig.
Constant	69.419	38.433	–	1.806	0.082
Ship Type	-31.277	31.088	-0.166	-1.006	0.323
Cargo Volume	0.008	0.002	0.627	3.796	0.001**

***Simultaneous Hypothesis Testing* (*F-Test*)**

The simultaneous hypothesis testing was conducted using the F-test to examine whether the independent variables, ship type and cargo volume, jointly have a statistically significant effect on ship turnaround time at Tanjung Priok Port. The F-test evaluates the overall significance of the regression model by comparing the explained variance to the unexplained variance. The results indicate that the calculated F-value is 16.546, which is greater than the F-table value of 3.34, with a significance level of 0.000 (< 0.05). These findings demonstrate that ship type and cargo volume simultaneously have a statistically significant effect on ship turnaround time.

Therefore, the null hypothesis stating that ship type and cargo volume jointly do not affect ship turnaround time is rejected. The alternative hypothesis is accepted, confirming that the regression model is statistically significant and appropriate for explaining variations in vessel service time at Tanjung Priok Port.

Table 4. Simultaneous hypothesis test (ANOVA).

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	81,316.224	2	40,658.112	16.546	0.000**
Residual	66,347.243	27	2,457.305		
Total	147,663.467	29			

***Partial Hypothesis Testing* (*t-Test*)**

The partial hypothesis testing was conducted using the t-test to examine the individual effect of each independent variable on ship turnaround time.

- **Effect of Ship Type (X_1).** The t-test results show that the ship type variable has a t-value of −1.006, which is lower than the critical t-table value of 2.051, with a significance level of 0.323 (> 0.05). This indicates that ship type does not have a statistically significant effect on ship turnaround time. Accordingly, the hypothesis stating that ship type significantly affects ship turnaround time is rejected. This result suggests that differences between tanker and bulk carrier operations do not independently influence vessel service duration when cargo volume is controlled.
- **Effect of Cargo Volume (X_2).** The t-test results for cargo volume indicate a t-value of 3.796, which exceeds the t-table value of 2.051, with a significance level of 0.001 (< 0.05). This result demonstrates that cargo volume has a statistically significant positive effect on ship turnaround time. The regression coefficient of 0.008 implies that an increase of one ton in cargo volume leads to an increase of 0.008 hours in ship turnaround time, assuming

other variables remain constant. Therefore, the hypothesis stating that cargo volume significantly affects ship turnaround time is accepted.

Table 5. Summary of hypothesis testing results.

Hypothesis	Variable(s) Tested	Test Statistic	Sig. Value	Decision
H1	Ship Type (X_1) → Ship Turnaround Time	t = −1.006	0.323	Rejected
H2	Cargo Volume (X_2) → Ship Turnaround Time	t = 3.796	0.001	Accepted
H3	Ship Type (X_1) & Cargo Volume (X_2) → Ship Turnaround Time	F = 16.546	0.000	Accepted

Model Summary

The summary of the multiple linear regression model is presented to evaluate the goodness of fit and explanatory power of the model in explaining ship turnaround time at Tanjung Priok Port. The regression results show a correlation coefficient (R) of 0.742, indicating a strong positive relationship between the independent variables (ship type and cargo volume) and the dependent variable (ship turnaround time). The coefficient of determination (R^2) is 0.551, which means that 55.1% of the variation in ship turnaround time can be explained by the independent variables included in the model.

After adjusting for the number of predictors, the Adjusted R^2 value is 0.517, indicating that 51.7% of the variation in ship turnaround time is explained by ship type and cargo volume. This adjusted value confirms that the model maintains substantial explanatory power and is not overfitted. The standard error of estimate is 49.571 hours, which reflects the average deviation between the observed and predicted values of ship turnaround time. In addition, the Durbin–Watson statistic is 1.788, indicating that the regression model does not suffer from autocorrelation problems. Overall, these results demonstrate that the regression model is statistically reliable and suitable for analyzing the determinants of ship turnaround time in port operations.

Table 6. Model summary and goodness of fit.

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	0.742	0.551	0.517	49.571

Implications of Hypothesis Testing

The hypothesis testing results indicate that ship turnaround time is influenced by the combined effect of operational factors rather than by a single variable. The acceptance of the simultaneous hypothesis (H3) confirms the multidimensional nature of port service efficiency, where vessel service time is primarily shaped by cargo-handling intensity and operational processes.

The rejection of the ship type hypothesis (H1) suggests that vessel characteristics do not independently affect turnaround time once cargo volume is considered. This implies that standardized operating procedures and coordinated handling practices effectively reduce operational differences among vessel types. Conversely, the acceptance of the cargo volume hypothesis (H2) highlights cargo-handling intensity as the dominant determinant of turnaround time, emphasizing the importance of efficient cargo-handling processes, labor deployment, and equipment utilization. From a managerial and policy perspective, these findings suggest that improving port efficiency should focus on accurate cargo volume forecasting, optimization of cargo-handling operations, and strengthened coordination among port stakeholders, rather than emphasizing vessel-type differentiation.

Discussion

The results of this study demonstrate that cargo volume is the primary determinant of ship turnaround time at Tanjung Priok Port. The positive and significant relationship between cargo volume and service time reflects the operational reality that larger cargo volumes require longer loading and unloading durations, increased labor deployment, and more intensive use of port equipment. This finding is consistent with previous studies emphasizing the importance of optimizing cargo-handling processes to improve port efficiency.

The absence of a significant effect of ship type suggests that operational procedures and handling standards at Tanjung Priok Port may effectively neutralize differences between tanker and bulk carrier operations. This finding supports the argument that coordination efficiency, process synchronization, and information sharing among port stakeholders play a more critical role in determining vessel service duration than vessel characteristics alone.

From an operational perspective, these findings imply that ship agency companies should prioritize cargo volume forecasting when estimating ship turnaround time. Accurate predictions based on cargo volume can support better planning of labor, equipment, and berth allocation, thereby reducing idle time and operational inefficiencies. For port operators, the results highlight the importance of improving cargo-handling productivity and coordination mechanisms to mitigate delays associated with high cargo volumes.

Despite its explanatory power, the regression model does not capture all factors influencing ship turnaround time. External conditions such as weather, berth availability, and information-sharing practices, which have been identified in previous studies as important determinants of port efficiency, may account for the remaining unexplained variation. Future research could incorporate these factors to develop a more comprehensive model of port service performance.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study examined the effect of ship type and cargo volume on ship turnaround time at Tanjung Priok Port, Indonesia, using operational data from PT Buana Lintas Lautan Tbk. Based on multiple linear regression analysis, the results demonstrate that ship type and cargo volume simultaneously have a significant effect on ship turnaround time. This finding confirms that vessel service duration is influenced by a combination of operational factors rather than by a single variable.

Partial analysis reveals that cargo volume has a positive and statistically significant effect on ship turnaround time, indicating that larger cargo volumes lead to longer vessel service durations. In contrast, ship type does not show a statistically significant individual effect on turnaround time when cargo volume is taken into account. These results suggest that cargo-handling intensity is the dominant determinant of ship turnaround time, while differences in vessel type play a secondary role under standardized port operating procedures.

Overall, the findings highlight that operational efficiency at Tanjung Priok Port is primarily driven by cargo-handling processes and the scale of cargo operations. Improving port service efficiency therefore requires greater attention to managing cargo volume and optimizing cargo-handling activities rather than focusing solely on vessel characteristics.

Recommendations

Based on the findings of this study, several recommendations are proposed. First, ship agency companies should prioritize accurate cargo volume forecasting when estimating ship turnaround time. Reliable forecasts can support more effective planning of labor, equipment, and berth allocation, thereby reducing idle time and operational delays.

Second, port operators should focus on improving cargo-handling efficiency through better synchronization of loading and unloading processes, enhanced coordination among port stakeholders, and optimal utilization of port infrastructure and equipment. Such improvements are expected to mitigate the impact of increasing cargo volumes on turnaround time and enhance overall port service performance.

Finally, future research is recommended to incorporate additional operational and external factors, such as weather conditions, berth availability, and information-sharing mechanisms, to develop a more comprehensive model of ship turnaround time. Expanding the scope of analysis to include multiple ports or longer observation periods would also improve the generalizability of the findings.

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