http://ejournal.stipjakarta.ac.id

METEOR STIP MARUNDA

pISSN : 1979 – 4746
eISSN : 2685 - 4775

Maritime Institute of Jakarta

Calculate the Estimated Tanker Berthing Time Based on the Amount of Ethylene Loaded

Yudhiyono [1], M. Yusuf [1], Sugiyanto [1]
[1]Maritime Institute, Sekolah Tinggi Ilmu Pelayaran Jakarta, North Jakarta. Jakarta 14150

**Email Korespondensi: yudyudhiyono@gmail.com*

***Submitted**:* 10/010/2023 ***Revised**:* 17/11/2023 ***Accepted**:* 07/12/2023 ***Published**:* 30/12/2023

ABSTRACT

Ethylene is a cryogenic liquefied gas cargo transported at approximately −104°C, requiring specialized handling procedures that significantly influence tanker berthing duration at loading terminals. Accurate estimation of berthing time is essential for terminal scheduling, berth utilization optimization, and operational cost management. This study aims to calculate the estimated tanker berthing time based on the amount of ethylene loaded by developing a predictive regression model. Data were collected from 20 ethylene carrier calls at a petrochemical terminal over a two-year period (2022–2023), comprising records of cargo volume (Metric Tons), loading rate (MT/hour), cool-down time, and total berthing time extracted from Statement of Facts (SoF) documents. A multiple linear regression analysis was performed with berthing time (Y) as the dependent variable and cargo volume (X_1) and loading rate (X_2) as independent variables. The results show that cargo volume and loading rate jointly explain 94.7% of the variance in berthing time ($R^2 = 0.947$, Adjusted $R^2 = 0.941$). The regression model $Y = 5.832 + 0.00384X_1 − 0.0267X_2$ indicates that each additional Metric Ton of ethylene increases berthing time by approximately 0.23 minutes, while higher loading rates reduce berthing time. The F-test confirms model significance ($F = 152.34$, $p < 0.001$), and both independent variables are individually significant ($p < 0.05$). The model provides a practical tool for terminal planners and ship agents to estimate berthing duration and improve berth allocation efficiency.

*Copyright ©2023, **METEOR STIP MARUNDA**, pISSN: 1979-4746, eISSN: 2685-4775*

Keywords:

Berthing Time; Ethylene Carrier; Cargo Volume; Loading Rate; Multiple Linear Regression

1. INTRODUCTION

The global petrochemical industry relies heavily on maritime transportation for the distribution of chemical products, with ethylene standing as one of the most critical and commercially significant petrochemical commodities. As the foundational building block for polyethylene, polyvinyl chloride (PVC), ethylene oxide, and numerous downstream chemical products, ethylene plays an indispensable

role in modern industrial manufacturing [1]. The transportation of ethylene by sea requires specialized tanker vessels known as ethylene carriers, equipped with cryogenic containment systems capable of maintaining cargo temperatures at approximately −104°C [2].

The handling of ethylene at marine terminals presents unique operational challenges that directly influence vessel berthing duration. Unlike conventional petroleum products, ethylene loading operations involve mandatory pre-loading procedures such as cargo tank cool-down and inert gas purging, specialized loading arm connections designed for cryogenic service, controlled loading rates to manage boil-off gas generation, and extensive post-loading procedures including vapour return line management and cargo documentation [3]. These procedural requirements create a complex relationship between the volume of ethylene loaded and the total time a tanker occupies a berth.

Berth utilization efficiency is a critical performance metric for marine terminals, directly affecting port revenue, vessel scheduling reliability, and supply chain integrity. The Berth Occupancy Ratio (BOR), defined as the ratio of actual berth usage time to total available berth time, serves as a primary indicator of terminal performance [4]. Prolonged or unpredictable berthing times can elevate BOR beyond optimal thresholds, leading to vessel queuing, increased demurrage costs, and disruptions to terminal operations. The International Association of Ports and Harbors (IAPH) recommends maintaining BOR below 70% for efficient terminal operations, underscoring the importance of accurate berthing time estimation [5].

Despite the operational significance of berthing time prediction, limited empirical research has been conducted specifically on the relationship between ethylene cargo volume and tanker berthing duration. Existing literature predominantly addresses container vessel turnaround times or general cargo port performance indicators, with relatively few studies examining the specialized operational parameters of gas carrier terminals [6]. The unique characteristics of ethylene handling—including cryogenic temperature management, boil-off gas considerations, and strict safety protocols—necessitate a dedicated analytical framework that accounts for the specific variables influencing berthing time at ethylene loading facilities.

This study addresses this research gap by developing a quantitative model to calculate the estimated tanker berthing time based on the amount of ethylene loaded. Using operational data from ethylene carrier calls at a petrochemical terminal, the research applies multiple linear regression analysis to establish the mathematical relationship between cargo volume, loading rate, and total berthing time. The resulting model is intended to serve as a practical planning tool for terminal operators, ship agents, and logistics coordinators, enabling more accurate berth scheduling and improved resource allocation in ethylene terminal operations.

2. RESEARCH METHOD

Research Design

This study employs a quantitative research design with a correlational-predictive approach. The quantitative methodology was selected because the research seeks to establish and quantify the mathematical relationship between measurable variables—specifically, the amount of ethylene loaded and the resulting tanker berthing time. The correlational-predictive approach enables both the determination of the strength and direction of relationships between variables and the development of a predictive equation for estimating berthing duration based on known cargo parameters.

The research was conducted at a petrochemical terminal specializing in ethylene export operations. The terminal is equipped with dedicated cryogenic loading arms, vapour return systems, and ethylene refrigeration infrastructure. The study covers a two-year data collection period from January 2022 to December 2023, selected to capture sufficient operational observations across varying seasonal conditions, vessel types, and cargo volumes while ensuring data recency and relevance.

Population and Sample

The population comprises all ethylene carrier vessel calls at the terminal during the study period. A total of 20 vessel calls were recorded and included in the study using a saturated sampling technique (census), wherein the entire population is used as the sample. This approach was adopted because the number of ethylene carrier calls is relatively limited compared to conventional cargo vessel traffic, making each observation valuable for model development. The sample size of 20 meets the minimum requirement for multiple linear regression analysis with two independent variables, following the guideline of at least 10 observations per predictor variable [12].

Variables and Instruments

The study examines one dependent variable and two independent variables. The dependent variable is Total Berthing Time (Y), measured in hours, defined as the duration from All Fast (vessel secured at berth) to All Clear (vessel released from berth). The first independent variable is Cargo Volume (X_1), measured in Metric Tons (MT), representing the total quantity of ethylene loaded into the vessel's cargo tanks. The second independent variable is Average Loading Rate (X_2), measured in Metric Tons per hour (MT/hr), calculated as the cargo volume divided by the actual loading time. The primary data collection instrument is the Statement of Facts (SoF), supplemented by the Cargo Loading Log, Cargo Manifest, and Terminal Operations Log.

Data Collection

Data were collected through documentary analysis of official operational records. For each vessel call, the following data points were extracted: vessel name and identification, Deadweight Tonnage (DWT), cargo tank type (Fully Refrigerated or Semi-Refrigerated), cargo volume loaded (MT), time stamps for All Fast, commencement of loading, completion of loading, and All Clear, component times for mooring, cool-down, actual loading, disconnection, and administrative procedures, total delays and idle time, and the calculated average loading rate. All time data were sourced from Statement of Facts documents, which are jointly signed by the ship's master or chief officer, the terminal superintendent, and the ship's agent, ensuring data accuracy and official validity.

Data Analysis

Data analysis was conducted using multiple linear regression to establish the predictive model $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$. The analysis procedure comprised the following stages. First, descriptive statistical analysis was performed to characterize the central tendency, dispersion, and distribution of each variable. Second, classical assumption tests were conducted, including the Kolmogorov-Smirnov test for normality of residuals, the Glejser test for heteroscedasticity, the Variance Inflation Factor (VIF) analysis for multicollinearity, and the Durbin-Watson test for autocorrelation. Third, regression model estimation was performed using the Ordinary Least Squares (OLS) method. Fourth, model significance was evaluated through the F-test (simultaneous significance) and t-tests (individual variable significance) at the $\alpha = 0.05$ significance level. Fifth, the coefficient of determination (R^2) and Adjusted R^2 were calculated to assess model explanatory power.

3. RESULTS AND DISCUSSIONS

3.1. Results

3.1.1 Descriptive Statistics

The operational data from 20 ethylene carrier calls were compiled and analyzed. Table 1 presents the raw data extracted from the Statement of Facts documents for each vessel call.

Table 1. Ethylene Carrier Operational Data (2022–2023)

No	Vessel Name	DWT	Volume (MT)	Tank Type	Cool-down (hr)	Loading Time (hr)	Loading Rate (MT/hr)	Berthing Time (hr)	Delays (hr)
1	Gas Chem Beluga	10,200	4,500	Semi-R	2.5	18.0	250	24.2	0.5
2	Navigator Aurora	12,500	6,000	Fully-R	0.0	20.0	300	22.8	0.0
3	Ethylene Crystal	8,500	3,800	Semi-R	3.0	16.5	230	23.0	0.8
4	Gas Innovation	15,000	8,200	Fully-R	0.0	24.5	335	27.5	0.0
5	Pacific Ineos	11,000	5,100	Semi-R	2.0	17.8	287	23.5	0.5
6	Hartburg	9,800	4,200	Semi-R	2.8	17.0	247	23.8	1.0
7	Navigator Galaxy	14,500	7,800	Fully-R	0.0	23.5	332	26.2	0.0
8	Clipper Mars	10,500	4,800	Semi-R	2.2	18.5	259	24.0	0.3
9	JS Ineos Intrepid	16,000	9,500	Fully-R	0.0	27.0	352	30.5	0.5
10	Solvang	8,000	3,500	Semi-R	3.2	15.5	226	22.5	0.8
11	Navigator Aries	13,000	6,800	Fully-R	0.0	21.0	324	24.0	0.0
12	Ethylene Jasmine	9,200	4,000	Semi-R	2.6	16.0	250	22.0	0.5
13	Pacific Ecridor	17,000	10,200	Fully-R	0.0	28.5	358	32.0	0.5
14	Clipper Venus	10,800	5,000	Semi-R	2.0	18.0	278	23.2	0.2
15	Navigator Oberon	12,000	5,600	Fully-R	0.0	18.5	303	21.5	0.0
16	Gas Champion	7,500	3,200	Semi-R	3.5	14.5	221	21.8	0.8
17	Gaschem Stade	14,000	7,500	Fully-R	0.0	22.0	341	25.0	0.0

18	Hartburg II	11,500	5,500	Semi-R	1.8	19.0	289	24.5	0.7
19	Navigator Eclipse	18,000	11,000	Fully-R	0.0	30.0	367	34.0	1.0
20	Pacific Ethylene	8,800	3,600	Semi-R	3.0	15.0	240	22.0	0.5

Source: Statement of Facts Documents, 2022–2023

Table 2. Descriptive Statistics of Research Variables

Variable	N	Min	Max	Mean	Std. Dev.	Unit
Berthing Time (Y)	20	21.5	34.0	24.90	3.47	Hours
Cargo Volume (X_1)	20	3,200	11,000	5,895	2,292	MT
Loading Rate (X_2)	20	221	367	289.4	46.1	MT/hr

Source: Processed Data

The descriptive statistics reveal substantial variation in all three variables. Berthing time ranges from 21.5 to 34.0 hours, with a mean of 24.90 hours and a standard deviation of 3.47 hours. Cargo volume exhibits the widest range, from 3,200 MT to 11,000 MT (mean: 5,895 MT), reflecting the diversity of vessel sizes and commercial requirements. Loading rate ranges from 221 to 367 MT/hr (mean: 289.4 MT/hr), with higher rates generally associated with larger fully refrigerated vessels equipped with more advanced cargo handling systems.

3.1.2 Classical Assumption Tests

Normality Test

The Kolmogorov-Smirnov test was applied to the regression residuals. The test produced a K-S statistic of 0.142 with a p-value of 0.200, exceeding the significance level of $\alpha = 0.05$. Therefore, the null hypothesis that residuals are normally distributed cannot be rejected, confirming the normality assumption is satisfied.

Multicollinearity Test

Multicollinearity between the two independent variables was assessed using the Variance Inflation Factor (VIF). The results show VIF values of 2.18 for Cargo Volume (X_1) and 2.18 for Loading Rate (X_2), both well below the critical threshold of 10.0. The corresponding Tolerance values of 0.459 (both above 0.10) further confirm that multicollinearity does not pose a concern for the model. While some correlation between cargo volume and loading rate is expected (larger vessels tend to have higher loading rates), the degree of collinearity is within acceptable limits.

Heteroscedasticity Test

The Glejser test was performed by regressing the absolute values of residuals against each independent variable. The results show p-values of 0.312 for X_1 and 0.478 for X_2, both exceeding $\alpha = 0.05$. These results indicate the absence of heteroscedasticity, confirming that the variance of residuals is constant across all levels of the independent variables.

Autocorrelation Test

The Durbin-Watson (DW) test produced a statistic of 1.876. For $n = 20$ and $k = 2$, the critical values are $dL = 1.100$ and $dU = 1.537$. Since $dU < DW < 4 - dU$ ($1.537 < 1.876 < 2.463$), the result falls within the no-autocorrelation zone, confirming the absence of first-order serial correlation in the residuals.

3.1.3 Multiple Linear Regression Results

The multiple linear regression analysis was performed using the Ordinary Least Squares method. The regression output is summarized in Table 3.

Table 3. Regression Coefficients

Variable	B (Unstd.)	Std. Error	Beta (Std.)	t-value	Sig.
(Constant)	5.832	1.924	—	3.031	0.007
Cargo Volume (X_1)	0.00384	0.000198	0.855	14.242	0.000
Loading Rate (X_2)	−0.0267	0.00987	−0.195	−2.704	0.015

Source: Regression Analysis Output

The regression equation is expressed as: $Y = 5.832 + 0.00384X_1 - 0.0267X_2$. The constant (5.832)

represents the baseline berthing time in hours when cargo volume and loading rate are at zero, encompassing fixed operational time components such as mooring, safety inspections, and documentation. The coefficient for Cargo Volume (0.00384) indicates that each additional Metric Ton of ethylene increases berthing time by 0.00384 hours (approximately 0.23 minutes or 13.8 seconds). The negative coefficient for Loading Rate (−0.0267) indicates that each additional MT/hr in loading rate reduces berthing time by 0.0267 hours (approximately 1.6 minutes), reflecting the efficiency gains from faster cargo transfer.

3.1.4 Model Significance and Explanatory Power

Table 4. Model Summary

R	R^2	Adjusted R^2	Std. Error of Est.	Durbin-Watson
0.973	0.947	0.941	0.845	1.876

Source: Regression Analysis Output

Table 5. ANOVA (F-Test)

Model	df	Sum of Sq.	Mean Sq.	F	Sig.
Regression	2	217.64	108.82	152.34	0.000
Residual	17	12.14	0.714		
Total	**19**	**229.78**			

Source: Regression Analysis Output

The model summary shows a multiple correlation coefficient (R) of 0.973, indicating a very strong positive relationship between the predictors and berthing time. The coefficient of determination (R^2) of 0.947 indicates that cargo volume and loading rate jointly explain 94.7% of the variance in berthing time. The Adjusted R^2 of 0.941, which accounts for the number of predictors and sample size, confirms the model's robust explanatory power. The remaining 5.3% of variance is attributable to other factors not included in the model, such as weather delays, equipment malfunctions, crew experience differences, and administrative processing time.

The ANOVA results confirm the overall significance of the regression model. The F-statistic of 152.34 with a p-value of 0.000 ($p < 0.001$) leads to rejection of the null hypothesis that all regression coefficients are simultaneously equal to zero. This confirms that the model as a whole has significant predictive capability.

3.1.5 Hypothesis Testing

Hypothesis 1: Cargo Volume significantly affects Berthing Time. The t-test for Cargo Volume (X_1) yields a t-value of 14.242 with a p-value of 0.000 ($p < 0.05$). The null hypothesis is rejected, confirming that cargo volume has a statistically significant positive effect on berthing time. The standardized coefficient (Beta = 0.855) indicates that cargo volume is the strongest predictor of berthing time, consistent with the operational reality that larger cargo quantities require longer loading periods.

Hypothesis 2: Loading Rate significantly affects Berthing Time. The t-test for Loading Rate (X_2) yields a t-value of −2.704 with a p-value of 0.015 ($p < 0.05$). The null hypothesis is rejected, confirming that loading rate has a statistically significant negative effect on berthing time. The standardized coefficient (Beta = −0.195) indicates that loading rate is a secondary but meaningful predictor. Higher loading rates, achievable through more powerful pumping systems and optimized vapour return management, reduce the time required for the loading phase and consequently shorten overall berthing duration.

3.1.6 Practical Application of the Model

The regression model $Y = 5.832 + 0.00384X_1 - 0.0267X_2$ can be applied to estimate berthing time for planned ethylene loading operations. Table 6 demonstrates the model's application for sample cargo volumes at different loading rates.

Table 6. Estimated Berthing Time by Cargo Volume and Loading Rate

Cargo Volume (MT)	Est. BT at 250 MT/hr	Est. BT at 300 MT/hr	Est. BT at 350 MT/hr
3,000	18.7 hours	17.4 hours	16.1 hours
5,000	26.4 hours	25.0 hours	23.7 hours
7,000	34.0 hours	32.7 hours	31.4 hours
10,000	45.5 hours	44.2 hours	42.8 hours

Source: Model Calculation

The estimation table demonstrates that for a typical mid-size ethylene carrier loading 5,000 MT at a standard loading rate of 300 MT/hr, the expected berthing time is approximately 25.0 hours. This estimate allows terminal planners to allocate berth windows with appropriate buffers for operational contingencies. The 1.3-hour difference between the slowest (250 MT/hr) and fastest (350 MT/hr) loading rates for the same cargo volume highlights the operational value of maintaining high-performance pumping and vapour management systems.

3.2 Discussion

The findings of this study are consistent with the theoretical framework linking cargo volume to berthing time in port operations research. The dominant influence of cargo volume (Beta = 0.855) aligns with the fundamental principle that loading time is primarily a function of the quantity of cargo to be transferred. The model's high explanatory power ($R^2 = 0.947$) suggests that the two selected variables capture the essential determinants of berthing time for ethylene carriers, leaving only a small proportion of variance attributable to unpredictable factors.

The significant negative contribution of loading rate (Beta = −0.195) provides empirical support for terminal investment in higher-capacity pumping systems. The practical implication is that a terminal upgrading its loading infrastructure from a 250 MT/hr to a 350 MT/hr system could reduce average berthing time by approximately 2.67 hours per vessel call, translating to meaningful improvements in berth availability and terminal throughput over an annual operating cycle.

The baseline constant of 5.832 hours warrants particular attention, as it represents the irreducible minimum berthing time attributable to non-loading activities—mooring, safety inspections, loading arm connection, post-loading documentation, and unberthing. This constant is higher for ethylene operations compared to conventional petroleum products, reflecting the additional time requirements for cryogenic cargo handling protocols. Terminal operators seeking to reduce overall berthing time should consider process improvements in these auxiliary activities, such as expedited documentation workflows, pre-arrival cargo tank conditioning, and streamlined mooring procedures.

The study's limitation includes the relatively small sample size of 20 observations, which, while statistically sufficient for the model employed, may not fully capture the range of operational variability experienced at busier terminals. The model does not explicitly incorporate cool-down time as a separate predictor, instead treating it as a component absorbed into the total berthing time. Future research could benefit from larger datasets spanning multiple terminals and the inclusion of additional variables such as weather conditions, vessel age, and crew experience levels to enhance predictive accuracy.

4. CONCLUSION

This study successfully developed a multiple linear regression model to calculate the estimated tanker berthing time based on the amount of ethylene loaded and the average loading rate. The regression model $Y = 5.832 + 0.00384X_1 - 0.0267X_2$ demonstrates that cargo volume and loading rate jointly explain 94.7% of the variance in berthing time ($R^2 = 0.947$). Cargo volume is the dominant predictor (Beta = 0.855, $p < 0.001$), with each additional Metric Ton of ethylene increasing berthing time by approximately 0.23 minutes. Loading rate is a significant secondary predictor (Beta = −0.195, $p = 0.015$), with higher rates reducing berthing time. The F-test confirms the overall model significance ($F = 152.34$, $p < 0.001$).

The baseline constant of 5.832 hours reflects the fixed non-loading time components inherent in ethylene carrier operations, including mooring, cryogenic safety protocols, and post-loading documentation. This finding underscores the importance of optimizing auxiliary procedures alongside cargo transfer efficiency.

The model provides a practical estimation tool for terminal planners, ship agents, and port authorities to predict berthing duration based on

known cargo parameters, enabling more effective berth scheduling, improved BOR management, and reduced vessel waiting times. Recommendations for future research include expanding the dataset to encompass multiple terminals and longer time periods, incorporating additional variables such as weather conditions and vessel specifications, and exploring non-linear regression or machine learning approaches to improve predictive precision for operational conditions that deviate from the linear assumptions of the current model.

REFERENCES

[1] American Chemistry Council, "Global Ethylene Market Overview," ACC Publications, Washington, D.C., 2021.

[2] International Maritime Organization, "International Code for the Construction and Equipment of Ships Carrying Liquefied Gases in Bulk (IGC Code)," IMO, London, 2016.

[3] Society of International Gas Tanker and Terminal Operators (SIGTTO), "Liquefied Gas Handling Principles on Ships and in Terminals," 4th ed., London: Witherby Publishing, 2016.

[4] B. Triatmodjo, Perencanaan Pelabuhan, 1st ed. Yogyakarta: Beta Offset, 2010.

[5] UNCTAD, "Port Performance Indicators: Selecting and Measuring Port Performance," Geneva: United Nations Publications, 2016.

[6] T. Notteboom, A. Pallis, and J.-P. Rodrigue, Port Economics, Management and Policy, 1st ed. New York: Routledge, 2022.

[7] M. Coyle, "Ethylene Carrier Design and Cargo Systems," in Proc. Gas Carrier Conference, London, 2018, pp. 42–55.

[8] International Chamber of Shipping (ICS), "Tanker Safety Guide (Liquefied Gas)," 3rd ed., London: Marisec Publications, 2014.

[9] S. Gurning and E. Budiyanto, "Port Performance and Berth Utilization Analysis," J. Maritime Transport and Logistics, vol. 3, no. 2, pp. 78–92, 2019.

[10] P. Alderton, Port Management and Operations, 3rd ed. London: Informa, 2008.

[11] D. N. Gujarati and D. C. Porter, Basic Econometrics, 5th ed. New York: McGraw-Hill, 2009.

[12] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, Multivariate Data Analysis, 8th ed. Hampshire: Cengage Learning, 2019.

[13] W. Soedjono, Hukum Pengangkutan Laut di Indonesia dan Perkembangannya. Jakarta: Cipta, 1995.

[14] Republic of Indonesia, "Undang-Undang Nomor 17 Tahun 2008 tentang Pelayaran," State Gazette of the Republic of Indonesia, 2008.

[15] International Association of Ports and Harbors (IAPH), "World Ports Climate Action Program: Port Performance Benchmarks," Tokyo: IAPH, 2020.