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Operation Data Analityc of Barge Changeover Process in Coal Loading Jetties: A Case Study with Multi-Size Barges and Variable Jetty Capacities

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Abstract

The barge turnover process at the loading jetty is a crucial factor determining the operational efficiency of bulk commodity terminals. This study presents an analytical approach based on real-world observational data to identify and quantify factors that influence barge change duration in the coal loading process. A total of 156 barge turnover data of four different sizes (240 ft, 250 ft, 270 ft, 300 ft) from two different jetty locations and capacities were collected and analyzed using a combination of descriptive statistics, hypothesis testing, and analysis of variance (ANOVA). The results show there are no significant differences in change duration across barge sizes (p-value 0.069), with the 270 ft barge having the lowest average time (28.4 minutes) compared to other sizes. The cross-jetty analysis reveals no differences in changeover time (p-value 0.829). The novelty of this study lies in the integration of multiple-variable analytical data to analyze the barge size–berth location–change duration relationship in a real-world operational context, which has been previously rarely quantitatively addressed in the maritime literature. These findings not only strengthen the theoretical understanding of barge changeover dynamics but also provide a basis for data-driven decision-making to reduce waiting times, reduce demurrage costs, and increase terminal throughput.

Keywords: Barge, Jetty, Efficiency, Changeover, Berth, Analytical.

1 | Introduction

The ship changeover process at the loading dock is a key determinant of operational efficiency in bulk commodity export terminals [1], [2]. Efficient barge changeover can minimize idle time, reduce vessel queues, and maximize throughput, thus directly impacting port productivity and shipping schedules in the coal,

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mineral, and agricultural sectors. Delays in the barge changeover process can trigger demurrage costs, disrupt supply chains, and reduce competitiveness in the global market [3]. Operational complexity increases when terminals handle multiple barge sizes with varying berthing capacities, necessitating data-driven planning and process optimization to address constraints such as tidal windows, limited loading equipment capacity, and berthing availability [4]. Ineffective management of these variables can lead to prolonged vessel turnaround times, reduced resource utilization, and substantial financial losses.

In regions where fluctuations influence barge size variations in production volumes, contract requirements, barge size availability, water draft, and market demand, optimizing the sequence and timing of barge changeover is crucial. Advanced operational analytics supported by quantitative tools and simulations provide a structured path to improving barge changeover performance in complex environments [5]. Recent research emphasizes the importance of integrating real-time monitoring, predictive analytics, and intelligent scheduling algorithms to predict loading durations, optimize barge arrival patterns, and reduce dwell times [2], [6]. Furthermore, multicriteria decision-making frameworks, including simulation-based optimization and data envelopment analysis, have demonstrated potential in balancing operational efficiency with resource constraints in port logistics [7]. Excessively long barge changeover processes can disrupt dock operations, reduce port productivity, and negatively impact shipping schedules. These delays have the potential to trigger significant demurrage costs due to delayed ship departures or the accumulation of cargo at the port.

Based on this literature, this study conducts an in-depth operational analysis of the barge changeover process at a loading jetty under conditions of varying barge sizes and jetty capacities, with the aim of generating practical insights that can be applied to similar maritime logistics contexts.

2 | Literature Review

Operational analysis of the barge changeover process at loading docks has received increasing attention in maritime logistics research due to its direct impact on port throughput, fleet utilization, and overall supply chain performance. Efficient barge scheduling and changeover are crucial in bulk cargo operations, where delays can result in significant demurrage costs and create bottlenecks in the downstream supply chain. Previous studies have identified key variables that influence this process, including barge size, dock loading speed, tidal constraints, and berth allocation policies [8]. The changeover process itself is multi-stage, encompassing mooring and unmooring activities, berth and cast-off times, vessel type, berth maneuvers, human factors, and environmental influences such as wind and waves, making operational performance highly nonlinear [9–11]. Emphasized that cargo volume, ship deadweight, and weather conditions are essential factors in determining the ship's berth time.

Berthing time is defined as the total duration of a vessel's stay at the dock for loading and unloading activities, calculated from the time the first mooring line is tied until the last mooring line is released from the dock [12], [13]. Meanwhile, the cast-off process is a series of activities to release a vessel from the dock, starting from the release of the mooring line, followed by the ship's departure from the dock, until the dock is empty for the arrival of the next ship. This process is a critical transition phase, spanning the period from the end of one vessel's use of the dock to the preparation for the next vessel's berth. It is a significant determinant of the efficiency of dock changes.

Automatic Identification System (AIS) vessel tracking records and port call logs enable more precise analysis of berthing performance. These data reveal that, in addition to vessel dimensions and cargo profiles, port congestion, berthing occupancy, and simultaneous demand from heterogeneous vessel types are key determinants of berthing duration, particularly in busy mixed-use terminals [11], [14], [15]. An AIS-based congestion index has been developed to detect bottlenecks and support berth planning decisions [7], [15], [16]. In bulk cargo terminals, where multi-sized barges and ocean-going vessels share berthing resources, competition for limited berthing capacity can trigger complex scheduling conflicts and cascade delays. This requires a dynamic berthing allocation strategy that integrates real-time traffic monitoring, environmental forecasts, and operational constraints, such as tugboat availability and tidal windows, to maintain throughput efficiency under varying demand [17].

Infrastructure capacity and operational coordination also play a crucial role. Limited availability of tugboats, slow mooring line handling, and limited onshore loading and unloading equipment can prolong berthing times even when there is no congestion [18]. External environmental factors such as tidal windows, crosscurrents, and limited navigation channels can impose rigid operational schedules, potentially leading to vessel clustering and avoidable delays. Integrating predictive analytics into berth planning, considering environmental forecasts and specific vessel handling requirements, has been proposed as a strategy to minimize unproductive berth times and improve port efficiency.

Empirical evidence from port studies in Indonesia supports these findings. According to [19], berthing throughput positively impacts berth utilization, while prolonged berthing times decrease it. Similarly, research at dry bulk cargo terminals found that shorter berthing times improve loading and unloading performance, throughput, and efficiency, while longer berthing times lead to delays, higher operational costs, and reduced terminal productivity [20] overall, these studies underscore the importance of integrated operational planning, data-driven decision-making, and technology-based process control to optimize barge changeover and berthing performance at bulk commodity terminals.

3 | Research Methodology

This research adopts a quantitative case study approach to evaluate the operational performance of barge changeover processes at a coal loading jetty, focusing on the influence of different barge sizes and loading jetty capacities. The study was conducted at a bulk coal terminal located on the Barito River, Central Kalimantan, Indonesia, utilizing actual operational data. The dataset includes daily records of barge changeover times and total operational cycles within a specified observation period. The coal loading process at this terminal is carried out via a conveyor belt system that flows material directly from the port into barges, allowing consistent control of cargo flow and minimizing reliance on conventional loading equipment such as ship loaders or grab cranes. Observations were made during the barge exchange process at two jetties of varying capacities and locations along the river. Jetty A has a loading capacity of 500 Tons Per Hour (TPH), while Jetty B has a loading capacity of 750 TPH. The two jetties are approximately 500 meters apart.

3.1 | Barge Changeover Process

A barge changeover is defined as a series of operational activities at a loading jetty that begins when a full barge casts off its mooring lines and leaves the jetty, followed by the berthing of the next barge, and ends when all mooring lines have been secured. The barge is ready to begin the next loading operation (*Fig. 1*). This process excludes the actual loading time. It focuses only on the transition interval between barges, which is crucial for assessing the efficiency of a jetty changeover.

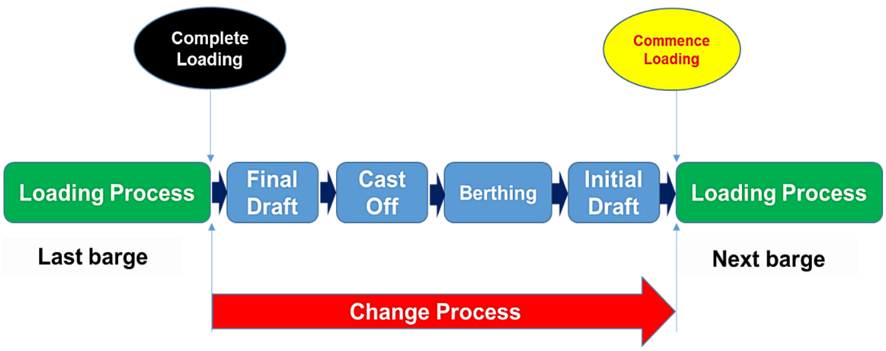

Fig. 1. Barge changeover process time.

3.2 | Data Collection

Operational data was collected directly from jetty operation logs, time sheets, and the terminal management system. The data included barge arrival timestamps, berth times, berth availability, tugboat movements, loading and unloading times, and departure times. Additional variables such as barge size (Deadweight tonnage), berth type (Capacity class), and shift patterns were also extracted. The uploaded dataset consisted of multiple sheets, providing detailed time records for barge changeover operations. All data was validated for completeness, and outliers were checked for accuracy. Prior to analysis, the raw data were cleaned to remove incomplete entries, correct inconsistent time formats, and unify units of measurement. The barge data comprised four different sizes: 240 ft, 250 ft, 270 ft, and 300 ft. The berth capacities included two berths with capacities of 500 TPH and 750 TPH, respectively.

3.3 | Analysis Approach

The analysis was conducted in two stages. First, a descriptive analysis was conducted to determine the average berthing and waiting times for each combination of barge size and berth capacity. Second, a comparative analysis using ANOVA was conducted to assess whether there were significant differences in operational performance among the various barge sizes and berth capacities. This method was chosen based on the methodological consideration that descriptive analysis allows researchers to understand the general pattern and distribution of the data before conducting statistical testing, while ANOVA was chosen because it can compare the means of more than two groups simultaneously with a high level of confidence. This approach aligns with best practices in operational research, which combine initial data exploration with inferential testing to ensure valid and reliable findings.

4 | Results and Discussion

A total of 156 observations of barge changeover processes were analyzed, spanning four different size groups: 240 ft ($n = 4$), 250 ft ($n = 4$), 270 ft ($n = 66$), and 300 ft ($n = 82$). Each observation recorded the variables of barge size, jetty location, Jetty A with a capacity of 500 TPH, Jetty B with a capacity of 750 TPH, and the duration of the changeover (Minutes). Prior to analysis, data cleaning and standardization were performed to ensure format consistency, remove non-representative outliers, and adjust for differences in recording between periods, resulting in more reliable results. The distribution by location showed that Jetty A contributed 101 observations, while Jetty B contributed 55 observations.

The selection of barge size as a categorical variable was based on its potential influence on changeover time due to differences in cargo capacity and maneuvering difficulty. Meanwhile, berth location was retained as a discriminating variable because each berth has a different design, facilities, and loading and unloading capacity, which could theoretically affect operational efficiency. This variable design enables a comparative analysis to identify systematically significant factors affecting barge changeover performance.

4.1 | Descriptive Analysis

Based on the data visualization in *Fig. 2*, the Size factor shows a significant influence. The lowest average change-around time is for the 250 ft barge (~47.5 minutes). After that, as the barge size increases (270 ft and 300 ft), the changeover time increases significantly, even reaching ~57.5 minutes for the 300 ft barge. This pattern indicates that larger barges tend to require longer turnaround times, possibly due to more difficult maneuvers, the need for more mooring line adjustments, or a more complex loading and unloading process. Further statistical analysis is required to determine whether the difference in barge size has a statistically significant effect on changeover time.

Meanwhile, the jetty factor has a small influence. Jetty A and Jetty B have almost the same average changeover time (~56 minutes). This indicates that jetty capacity is not a significant factor in the difference in changeover time in this dataset, so the efficiency between jetties is relatively equal.

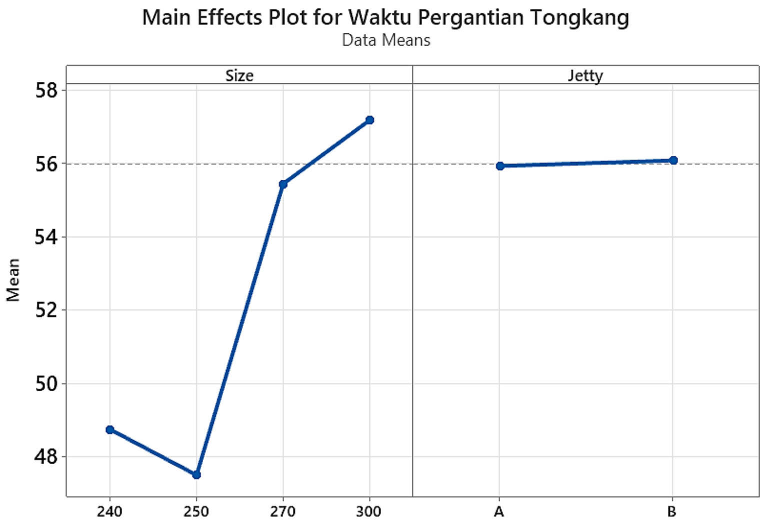

Fig. 2. Main effects plot for barge changeover time.

The boxplot of changeover times by barge size in *Fig. 3* shows that the lowest median is found for the 250 ft barge size (~47 minutes), followed by the 240 ft barge size (~50 minutes), while the 270 ft and 300 ft barge sizes have higher medians (~52 and ~55 minutes, respectively). Variation in changeover times tends to increase for the 300 ft barge size, with a wider interquartile range and extreme outliers above 90 minutes, indicating process instability for large barges. The 270 ft barge size also shows several outliers above 80 minutes, while the 240 ft and 250 ft barge sizes are relatively more consistent. These findings indicate that smaller to medium barge sizes provide shorter and more stable changeover times, while larger barges require procedural optimization to reduce variability and wait times.

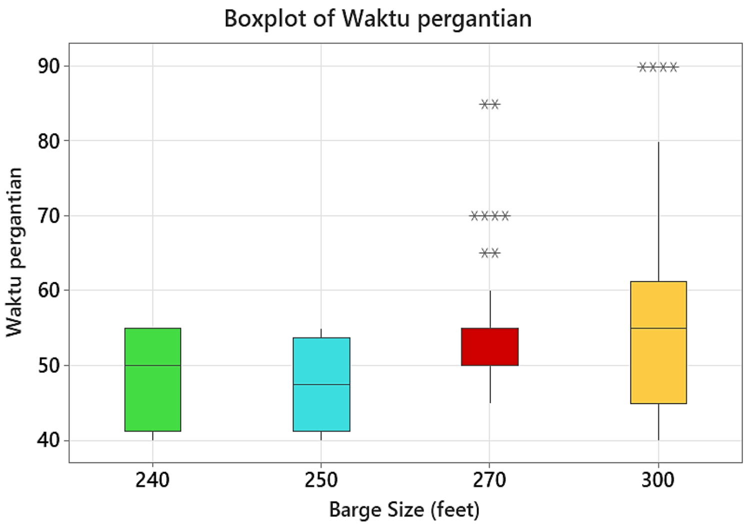

Fig. 3. Boxplot of barge changeover time based on size.

The boxplot of changeover times in *Fig. 4*, shows that the medians of Jetty A and B are almost the same (±54–55 minutes), consistent with the Main Effects Plot results, but Jetty A has a larger variation with a wider IQR and a greater number of extreme outliers (up to >90 minutes) compared to Jetty B which only has a few outliers in the range of 80–85 minutes; this finding indicates that despite similar average performance, Jetty B shows a more stable changeover process, while Jetty A requires investigation and procedural improvements to reduce its extremely long changeover duration.

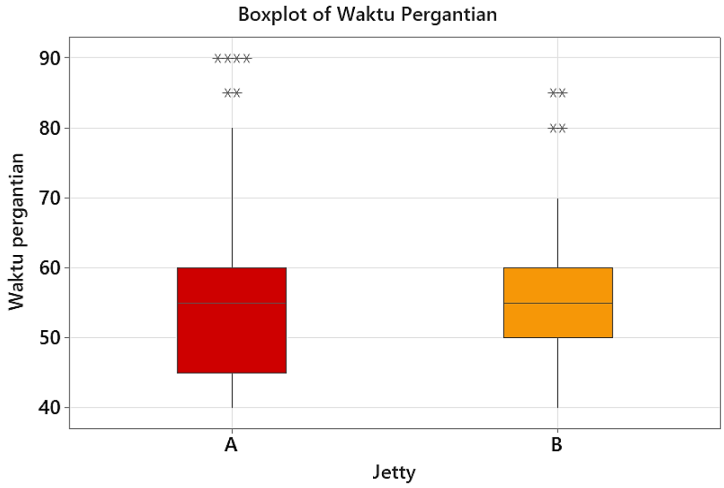

Fig. 4. Boxplot of barge changeover time based on jetty capacity.

4.2 | ANOVA Analysis

The regression analysis results in *Table 1* show that the size variable has a positive coefficient of 0.0982, which indicates that changeover time increases when barge size increases, with a p-value of 0.069 approaching the significance level (0.05), suggesting a trend that larger barges tend to require longer changeover times. In contrast, the Jetty variable (A vs B) does not show a significant effect (p-value = 0.829), confirming that the jetty capacity is not a major determinant of changeover time variability. The low VIF value (1.01) indicates the absence of multicollinearity issues; thus, the coefficient estimates are reliable. This finding aligns with the ANOVA and boxplot results, which show similar time distributions across jetties, as well as an increase in the median and variance for larger barges, although not statistically significant.

Table 1. ANOVA analysis.

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	27.9	15.3	1.82	0.071	
Size	0.0982	0.0536	1.83	0.069	1.01
Jetty	0.42	1.93	0.22	0.829	1.01

This study is consistent with previous literature that emphasizes the dominant role of operational and technical variables in addition to physical infrastructure. For example, research at a South African container port found that approximately 80% of the variation in ship changeover time can be explained by indicators such as crane performance, vessel uptime, and the efficiency of related land modes, rather than by the berth location itself [14]. A machine learning-based predictive approach at the Port of Bordeaux demonstrated that integrating historical operational data with external variables, such as weather and tides, improved the accuracy of changeover time predictions by over 20% compared to manual estimation [2], [21]. This approach is consistent with our finding that operational variables, particularly barge size, need to be managed dynamically and data-driven.

Practically, the research findings suggest more agile operational strategies: instead of major infrastructure investments, procedural improvements —particularly for large barges, such as rescheduling, better tugboat coordination, and optimized workforce and equipment allocation—can reduce changeover time variability. The rare occurrence of high-duration outliers (80–90 minutes) signals that ad-hoc interventions to address extreme delays have the potential to deliver substantial efficiencies without requiring significant capital investment [22].

5 | Conclusion

This study evaluates the effect of barge size and jetty capacity on barge changeover time in coal loading and unloading operations based on real-world operational data. ANOVA and regression analyses indicate that barge size tends to have a positive effect on changeover duration (Coefficient 0.0982; p = 0.069). This p-value, above 0.05, indicates that the effect is statistically not significant. In contrast, differences between jetty are not substantial (p = 0.829). Consistency of results between statistical analysis and boxplot visualization indicates that current operational procedures and infrastructure effectively accommodate variations in vessel size and berth location. However, high-duration outliers still occur and require operational intervention. These findings emphasize that optimization should focus on managing large barges through procedural improvements, tugboat synchronization, and berth crew coordination.

In the future, research can be expanded with higher time-resolution data and additional variables such as port traffic and mooring equipment performance. Machine learning and optimization modeling-based approaches, proven effective in international studies, can be used to develop decision support systems that predict and optimize shift scheduling, thereby increasing efficiency, reducing variability, and strengthening port competitiveness.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability

All data are included in the text.

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