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IMPROVING OPERATIONAL EFFICIENCY OF NICKEL ORE PORT IN NORTH KONAWE WITH VSM AND OPTIMIZATION APPROACH

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ABSTRACT

Indonesia, the world's largest nickel producer, has enforced a nickel ore export ban since 2020 to promote domestic downstream processing. This policy surge has intensified port activities, especially in nickel ore logistics, leading to operational inefficiencies such as prolonged barge waiting times, demurrage penalties, and logistics delays at key ports like Lameruru, Southeast Sulawesi. This study applies Lean principles and Value Stream Mapping (VSM) to identify waste and bottlenecks in nickel ore port operations. The research further develops a Genetic Algorithm (GA)-based optimization model to improve barge scheduling and minimize waiting times. Data collected from port operations, stakeholder interviews, and secondary sources reveal that waiting times at the jetty constitute the primary inefficiency, causing nearly half of shipments to incur demurrage. The GA optimization reduced total barge waiting time by 55%, increased immediate docking by 71%, and significantly decreased maximum waiting times, boosting port productivity and reducing costs. The Future State VSM reflects a 79.7% Process Cycle Efficiency, an improvement over the current 69.97%. Despite limitations such as reliance on static historical data and exclusion of real-time dynamic factors, this integrated Lean-VSM-GA approach demonstrates significant potential to enhance Indonesia's nickel ore logistics, offering actionable strategies for port operators and policymakers to increase competitiveness in the global nickel industry.

Keywords: Port Scheduling, Lean Manufacturing, Value Stream Mapping, Genetic Algorithm (GA), Optimization, Nickel Ore

INTRODUCTION

Indonesia was the world's largest producer of nickel in 2022, with total reserves reaching 21 million metric tons (mt), surpassing Australia's 19 million mt (USGS, 2022). With such substantial reserves, Indonesia plays a vital role in the global nickel supply chain, as nickel is widely utilized in various industries, including stainless steel, metal manufacturing, battery production, and construction. Since January 1, 2020, Indonesia has enforced a ban on nickel ore exports under the Ministry of Energy and Mineral Resources (ESDM) Regulation No. 11 of 2019, to promote downstream processing and increase the added value of nickel through the construction of ore refining plants (smelters).

The implementation of the export ban has centralized the nickel ore supply chain in Sulawesi, where logistics and trade are conducted between miners (nickel ore sellers) and smelters (end-buyers of nickel ore). Refined nickel ore can be processed into Nickel Pig Iron (NPI), Ferronickel (FeNi), or nickel matte, which are then used as raw materials in other industries or exported.

This downstream policy has led to a surge in domestic demand for nickel ore and an increase in the number of industry players, including miners, traders, and smelters. According to the Indonesian Nickel Miners Association (APNI), as of 2024, there are 365 issued mining business permits (IUP), covering a total area of 3,158,067.75 hectares, predominantly concentrated in Southeast Sulawesi (171 permits) and Central Sulawesi (123 permits). Meanwhile, based on data from the Advisory Board of the Indonesian Metallurgical Professional Association (Prometindo), as of 2022, there were 135 NPI and FeNi smelter lines operated by 65 companies in Indonesia.

The rise in domestic nickel ore trading has increased the demand for barge sets and tugboats (hereafter referred to as barges), which serve as the primary transportation mode for moving ore from mines to smelters, thereby increasing port traffic. This surge has introduced several operational challenges at ports, including a limited number of available ports and inefficiencies in the logistics process—particularly during loading, transportation, and unloading activities. These inefficiencies are evidenced by prolonged berthing times, slow loading and unloading processes, which can lead to penalties such as demurrage or deadfreight. Additionally, weather conditions such as rainfall can disrupt loading activities due to the risk of ore liquefaction, exacerbated by inadequate infrastructure. These inefficiencies not only escalate logistics costs but also reduce the competitiveness of Indonesia's nickel industry in the global market.

As port activities increase, improving port services becomes essential to ensure smooth operations and boost productivity (Chairunnisa & Sunarto, 2019; Firmansyah M. R. et al., 2016; Hadi, 2021; Juwarlan, 2020). Productivity can be enhanced by reducing waste, increasing value-added processes, and shortening lead time (Ferdiansyah et al., 2013; Suprana et al., 2020; Sutarman, 2020). The implementation of Lean principles in supply chain management enables the identification of waste and its root causes (Boonsthonsatit S., 2015; Kihel et al., 2022; Kumar et al., 2020; Vasanth Kumar et al., 2020). Lean approaches can be employed to identify inefficiencies in port logistics and design solutions to improve operational efficiency.

While many studies on Lean application focus on manufacturing processes, there is a growing body of research applying Lean principles to port operations and container terminals. However, these studies primarily address container-based logistics. Research by Tumbol identified common types of waste in container port operations, such as excessive transportation, waiting time, and motion.

The objectives of Lean principles align with the challenges encountered in nickel ore logistics, such as reducing waiting time/demurrage, eliminating underutilized labor or excessive motion, and streamlining material flow. Lean is widely used to improve efficiency in port environments. Value Stream Mapping (VSM) is also commonly used to map and analyze logistics processes, identify value-added and non-value-added activities, and eliminate waste. Although most existing Lean applications are concentrated in manufacturing, several studies have begun to adapt these concepts to container port operations. Bulk material logistics, such as for nickel ore, present unique challenges that differ from container logistics, including ore's susceptibility to liquefaction, reliance on heavy equipment, and variable weather conditions that impact scheduling. VSM can help identify waste in nickel ore loading processes at ports and reveal the primary sources of operational inefficiency.

Although Lean and VSM provide a strong framework for identifying and reducing inefficiencies in port operations, the unique challenges of bulk material logistics often require additional approaches to enhance efficiency—one of which is developing adaptive operational scheduling through optimization models such as Genetic Algorithms (GA).

GA is a metaheuristic optimization technique inspired by the principles of biological evolution and natural selection. GA operates by generating a population of potential solutions, which evolve over successive iterations through processes such as selection, crossover, and mutation (Holland, 1975). The main objective is to discover optimal or near-optimal solutions for complex problems that are difficult to solve using conventional methods. GA has been widely adopted in various fields for solving optimization problems, such as scheduling and resource allocation, including in bulk logistics transport, as demonstrated in the study by Zhao Z.; Chen L. (2024).

The waste identification results from VSM can be used as a foundation to develop a GA-based optimization model aimed at minimizing barge waiting times and improving operational efficiency at nickel ports in Indonesia. GA serves as a solution to this minimization problem by searching for optimal solutions (rather than merely the best local solution). It is suitable for handling non-linear data, can explore multiple possibilities simultaneously, and simplifies computation in models with numerous variables by modifying solution chromosomes to search for optimal outcomes. This allows for faster computation and avoids local optima traps.

By integrating Lean, VSM, and GA, this study aims to provide practical solutions to reduce loading waiting times and improve the operational efficiency of nickel ports. The outcomes are expected to contribute significantly to enhancing the efficiency of Indonesia's nickel ore supply chain and serve as a reference for future research in mining logistics, as well as the application of Lean principles to other bulk commodity logistics.

METHOD

This research will be conducted through several systematic stages. The initial stage involves identifying the main problems in nickel ore logistics in Indonesia through preliminary observations, reviews of previous studies, and case studies. During this phase, the research objectives, scope, framework, and methodology are also established. The next stage is the literature review, which outlines the theoretical foundations and concepts used in the study, including Lean principles and approaches, Value Stream Mapping (VSM), Linear Programming, Genetic Algorithms (GA), and mineral logistics. In the data collection stage, both primary and secondary data are obtained from credible sources, covering operational port data (such as number of barges, berthing time, and loading time), geographic and weather data, as well as information on heavy equipment allocation, load capacities, and logistics costs. Interviews or surveys with stakeholders—including miners, port operators, and barge users—are also conducted to enrich the dataset. The data processing stage includes validation, cleaning, visualization, and mapping using current-state VSM to identify waste. Following waste identification, optimization is performed using GA, which generates scheduling scenarios, evaluates solutions based on barge waiting time minimization, and applies selection, crossover, and mutation mechanisms to find optimal results. This GA approach is designed to account for constraints such as berth slot availability, loading time, and weather impacts in order to improve port operational efficiency. The final stage of the research involves drawing conclusions from the analysis and providing practical recommendations to enhance nickel ore logistics efficiency in Indonesia. The findings will be compiled in a final report and are expected to serve as a foundation for further research in mining logistics, contributing significantly to the development of the national nickel industry.

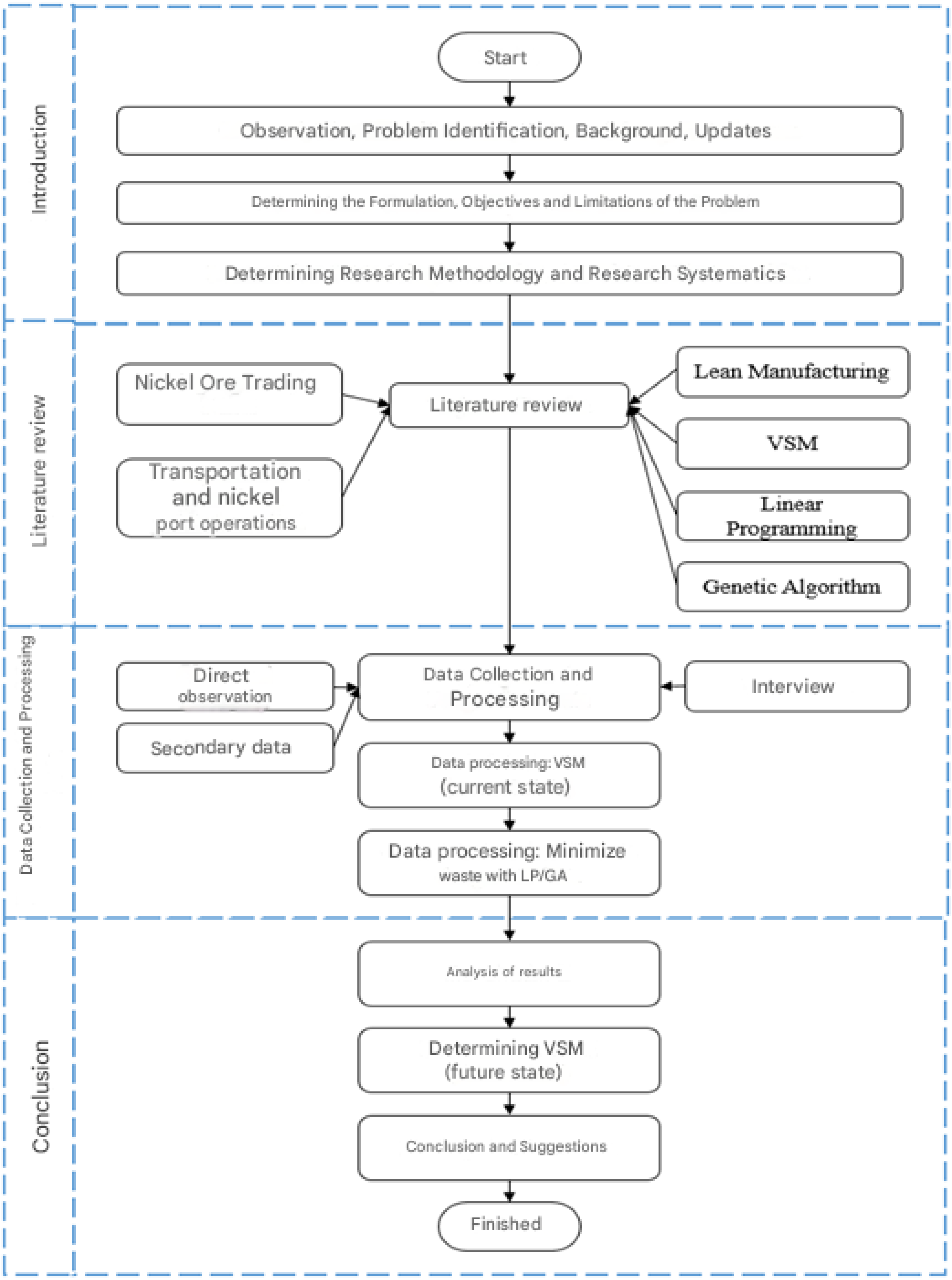

Figure 1. Research Methodology Flowchart

Research Method with the Research Object Being the Operational Activities of the Nickel Ore Port Located in Lameruru, North Konawe, Southeast Sulawesi, Indonesia. The primary focus is to understand and analyze the operational processes of the nickel ore port in order to identify potential waste using a Lean Manufacturing approach, as well as explore optimization opportunities using a metaheuristic method, namely Genetic Algorithm (GA), to reduce barge waiting time during shipment.

The nickel ore loading operation follows a series of stages beginning with mining activities and ending with barge loading. First, nickel ore is extracted from the mining site by contractors appointed by the mine owner. The ore is then temporarily stored in a stockpile pit near the mining area before being hauled by dump trucks either to a jetty stockpile or directly to the barge at the port. At the jetty, the ore is temporarily stockpiled before being loaded onto the barge using dump trucks or excavators. The barge flow begins with its arrival at the loading port, where it anchors and submits a Notice of Readiness (NOR) to indicate its readiness for loading. Upon NOR acceptance, the barge berths at the port, and an independent surveyor conducts an initial draft survey. The loading process then commences, with nickel ore transferred from the jetty stockpile into the barge. After loading, a final draft survey is performed, and the barge crew covers the cargo with tarpaulin. The mining company then processes the necessary documents, including the Bill of Lading, Manifest, Draft Survey, Verification Report, proof of PNBP payment, and other cargo-related certificates. Once documentation is complete, the harbor master issues a sailing clearance, allowing the barge to depart for its destination port.

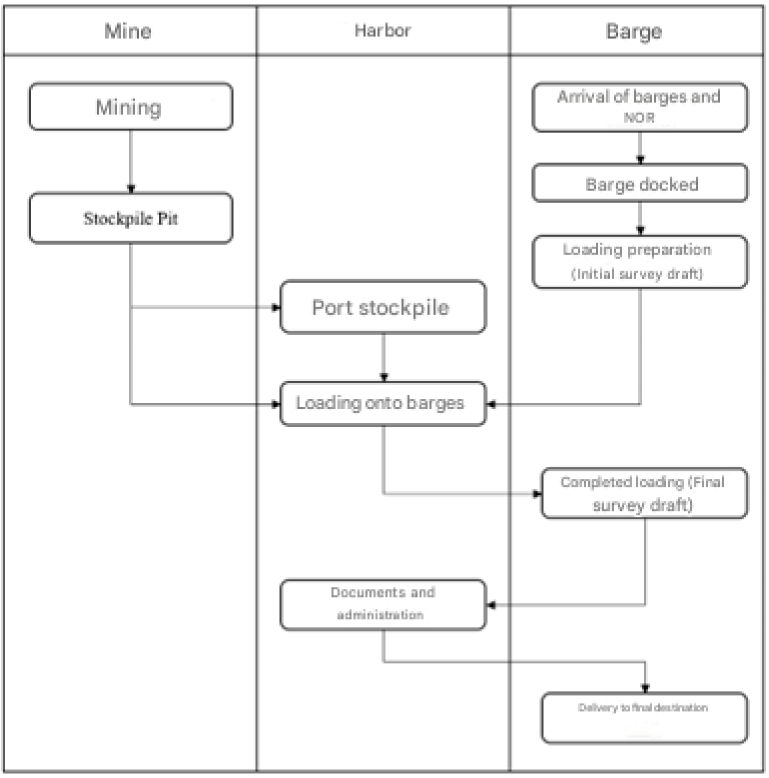

Figure 2. Nickel Ore Loading Operational Flowchart

This study employs both primary and secondary data sources. Primary data was gathered through direct observation and interviews with relevant stakeholders involved in the nickel ore loading operations. Secondary data was collected from historical operational and financial records provided by a mining company and its associated loading port located in Lameruru, North Konawe, Southeast Sulawesi. The data covers various aspects of port operations, including the sequence of loading activities, time required for each operational step, equipment availability and usage, and jetty capacity. It also includes performance indicators such as loading efficiency, barge waiting times, equipment utilization, and cost-related data. Supporting information like weather conditions and barge availability was also considered. The data was collected using multiple methods, including field observation, interviews with key personnel such as loading supervisors and logistics coordinators, as well as a review of historical documents, operational logs, and financial reports.

Value Stream Mapping (VSM) is utilized to map the flow of operational processes at the port, starting from barge arrival, loading, to departure. This method helps identify Non-Value Added (NVA) activities that contribute to operational delays. Based on the stages proposed by Rother J. (1999), the process includes identifying key operational steps—such as barge arrival, berthing queue, loading, and departure—to detect issues like waiting time and deadfreight. It also involves measuring cycle times at each stage, identifying waste using Lean Manufacturing principles (TIMWOOD), and developing a Current State VSM using standard VSM symbols to visualize the existing conditions. The insights gained from the Current State VSM serve as the foundation for identifying scheduling problems and applying optimization approaches to reduce inefficiencies. Ultimately, the output can be used to design a Future State VSM that is more efficient and less wasteful. To evaluate the current loading process, Process Cycle Efficiency (PCE) is calculated as a key metric, focusing on the ratio of value-added time to total cycle time. A higher PCE indicates a more efficient process, where most of the time is spent on productive rather than wasteful activities.

To address inefficiencies in barge operations, a Genetic Algorithm (GA) is applied to optimize scheduling with the objective of minimizing total barge waiting time, referring to the model developed by Li S.; Mingjun R.; Tao J.; Yuanbo Z. (2012). The optimization model defines sets, parameters, and decision variables to represent port operations, including barge arrival times, berth slot capacities, loading durations, and weather effects. The objective function aims to minimize the total port time, calculated as the difference between actual departure and expected arrival times, while considering constraints such as berth allocation, loading sequence, weather delays, and queuing effects. Chromosomes represent feasible barge schedules encoded with loading start times and weather delays. The GA process involves generating an initial random population, evaluating fitness based on total time at port, and applying tournament selection, one-point crossover, and random mutation to evolve better solutions. Constraint handling ensures realistic schedules by adjusting infeasible genes. The algorithm iterates until convergence, producing an optimized schedule expected to significantly reduce waiting times. The implementation is conducted in Python using libraries like NumPy, Matplotlib, and PrettyTable, developed in PyCharm IDE on a system with a 13th Gen Intel Core i5-13500H processor and 16 GB RAM.

RESULTS AND DISCUSSION

Data Analysis

Data collected from January to December 2024 depicts the operational performance of the nickel ore loading port in Lameruru, North Konawe, Indonesia. Over the course of one year, 270 shipments were recorded, with an average of 25 shipments per month. However, fluctuations in shipment volume can be observed in Table 1 below, with the lowest number of shipments occurring in February (8 shipments) and the highest in November (54 shipments). This variation indicates potential congestion in port capacity, operational inefficiency, or external constraints such as weather conditions and barge availability.

Table 1. Shipments and Demurrage

Month	Number of Shipments	Average Loading Time (days/barge)	Shipments with Demurrage	% Shipments with Demurrage	Average Demurrage Days (days)	Total Demurrage Days (days)	Total Demurrage Penalty (Rp)
Jan							
Feb	8	1.66	1	13%	2.15	2.15	96,616,502
Mar	24	2.42	5	21%	0.53	2.64	120,831,983
Apr	19	2.70	9	47%	0.68	6.15	284,899,248
May	12	6.34	9	75%	2.89	26.05	1,370,716,008
Jun	10	7.89	10	100%	4.22	42.16	2,206,648,036
Jul	9	6.20	7	78%	4.19	29.32	1,319,188,452
Aug	21	4.12	14	67%	2.89	40.49	1,564,641,993
Sep	43	2.29	12	28%	2.75	32.97	1,162,393,077
Oct	36	2.63	14	39%	1.00	13.97	738,059,032
Nov	54	2.58	16	30%	1.34	21.42	1,007,538,736
Dec	34	3.65	14	41%	3.53	49.45	2,160,174,295

Month	Number of Shipments	Average Loading Time (days/barge)	Shipments with Demurrage	% Shipments with Demurrage	Average Demurrage Days (days)	Total Demurrage Days (days)	Total Demurrage Penalty (Rp)
Total	**270**		**111**			**266.78**	**12,031,707,363**
Average	**25**	**3.86**	**10.09**	**49%**	**2.38**	**24.25**	**1,093,791,578**

Source: Data processed

One of the issues identified from the data is demurrage, which refers to the penalties imposed when barges experience delays beyond the allocated loading time. The average loading time per barge is 3.86 days per shipment, but significant deviations occur in certain months. In June, the loading time peaked at 7.89 days per shipment, indicating a high level of inefficiency. This prolonged loading duration correlates with higher instances of demurrage.

A total of 111 shipments (49%) experienced demurrage, resulting in a cumulative delay of 266.78 days and fines amounting to Rp12.03 billion. The highest demurrage penalties were recorded in June (Rp2.2 billion) and December (Rp2.16 billion), consistent with the months of highest loading inefficiency. This trend suggests that congestion in the loading process, possibly caused by operational issues, rain, scheduling errors, or inefficient resource allocation, significantly contributed to longer waiting times.

The months with the highest demurrage occurrences were June (100% of shipments affected), July (78%), and May (75%). In contrast, months like February and March had lower demurrage levels (13% and 21%, respectively), indicating more efficient port operations during these periods. These differences may be due to lower shipment volumes during these months, allowing for smoother operations.

However, shipment volume and demurrage rates are not always correlated, as the data shows that an increase in shipments does not always lead to better operational efficiency. For example, while November had the highest number of shipments (54), the demurrage rate was only 30%, whereas June, with only 10 shipments, had a 100% demurrage rate. This indicates that factors beyond shipment volume, such as operational scheduling, weather conditions, and equipment availability, play significant roles in efficiency.

Another important factor influencing demurrage is the average delay per affected shipment, which reached 2.38 days per impacted barge. However, in certain months, such as June and July, delays extended beyond four days per barge, exacerbating port congestion. These long waiting times may be linked to factors like insufficient docking space, slow cargo loading processes, and inefficient equipment utilization.

In addition to demurrage, deadfreight is another significant inefficiency in port operations. Deadfreight occurs when barges fail to reach full loading capacity, resulting in financial losses due to unused space. In 2024, four shipments recorded deadfreight, totaling 5,223 wet metric tons (wmt) of nickel ore, with a penalty of Rp887.8 million.

Table 2. Deadfreight Amounts

Month	Number of Shipments	Shipments with Deadfreight	Deadfreight (wmt)	Deadfreight Penalty (Rp)
Jan				
Feb	8			
Mar	24	1	662.30	122,524,575
Apr	19			
May	12			
Jun	10	1	747.95	59,836,240
Jul	9			
Aug	21			
Sep	43			
Oct	36			

Month	Number of Shipments	Shipments with Deadfreight	Deadfreight (wmt)	Deadfreight Penalty (Rp)
Nov	54	1	1,363.93	252,327,790
Dec	34	1	2,449.26	453,113,100
Total	**270**	**4**	**5,223**	**887,801,705**
Average	**25**	**1**	**1,306**	**221,950,426**

Source: Data processed

From Table 2, the highest deadfreight occurrence occurred in December, where 2,449 wmt of nickel ore went unshipped, resulting in a penalty of Rp453.1 million. Similarly, November recorded 1,363.93 wmt of deadfreight, leading to a penalty of Rp252.3 million. Other months impacted included March (662.3 wmt) and June (747.95 wmt), though the penalties were relatively lower, at Rp122.5 million and Rp59.8 million, respectively.

The relatively low frequency of deadfreight events (4 out of 270 shipments, or 1.48%) may suggest that cargo allocation is generally well-managed. However, the financial impact of each deadfreight event is significant, with an average penalty of Rp221.95 million per affected shipment. This highlights the importance of accurate load forecasting, optimal barge allocation, and efficient cargo consolidation to minimize waste.

A key observation from the deadfreight data is that months with high demurrage occurrences do not always coincide with high deadfreight events. For instance, while June had the highest demurrage rate, it did not report significant deadfreight. This indicates that although loading delays are a major issue, capacity planning remains a secondary concern, although it still contributes to inefficiency.

Heavy to very heavy rainfall occurred from January to July 2024. Compared to the number of shipments, this correlates positively, as seen in Table 4.3, where during these months, the number of shipments was lower compared to the following months. This is because heavy rain can disrupt outdoor activities such as transporting nickel ore from storage to the dock and operating heavy equipment like excavators.

Table 3. Rainfall in 2024

Month	Rainfall	Rainfall (mm)
Jan	High	300 – 500
Feb	High	300 – 500
Mar	Medium	200 – 300
Apr	High	300 – 500
May	Very High	>500
Jun	High	300 – 400
Jul	Very High	>500
Aug	Medium	200 – 300
Sep	Medium	200 – 300
Oct	Low	50 – 100
Nov	Low	50 – 100
Dec	High	300 – 400

Source: BMKG, reprocessed

Additionally, excessively wet nickel ore can become heavier and more difficult to handle, which can reduce loading efficiency. Furthermore, high humidity can trigger corrosion on heavy equipment and port infrastructure. Severe weather conditions, such as heavy rain and strong winds, may also endanger worker safety at the port, leading to temporary halts in loading activities to ensure worker safety. From August to November, rainfall was lower, providing an opportunity to maximize loading productivity, as seen in the increased number of shipments.

Current State VSM

Before visualizing the value stream of the nickel ore barge loading process as a whole, key elements were first identified using a SIPOC diagram (Supplier, Input, Process, Output, Customer).

Table 4. SIPOC

Category	Description
Supplier	Mining contractors, hauling operators, shipping companies
Input	Nickel ore, dump trucks, excavators, barges
Process	Hauling → Jetty Stockpile → Loading onto barge
Output	Barge fully loaded according to its capacity
Customer	Nickel ore smelting factories (smelters)

Source: Data processed

Next, cycle time calculations were conducted for each stage of the process to understand the duration and potential bottlenecks, and to identify which activities add value (VA) and which do not (NVA).

Table 5 Cycle Time of the Current State VSM Process

Process	C/T Dump Truck (min)	C/T Barge (min)	L/T (min)	VA/NVA
Stockpiling at jetty	4	2,000	4,320	VA
Hauling (3 km)	12	6,000	6,000	VA
Queueing at jetty	-		2,160	NVA
Loading onto barge	6	3,000	3,000	VA
Administration & survey	-		180	NVA
Clearance & sail out	-		60	NVA

Source: Data processed

Based on the cycle time calculations in Table 5, it is identified that certain stages are categorized as value-adding (VA) activities, while others are non-value-adding (NVA). Processes such as stockpiling, hauling, and barge loading are classified as VA because they directly contribute to material transfer. Meanwhile, queueing at the jetty, administration & survey, and clearance & sail out are categorized as NVA because they do not directly add value to the processed material.

To support further analysis and process optimization, a list of assumptions used in the cycle time calculation is presented in Table 6.

Table 6 List of Assumptions

Category	Assumption	Unit
Dump Truck Capacity	20	Tons
Barge Volume	10000	WMT/barge
Number of truck trips per barge	500	Trips
Loading Rate	2500	WMT/day
Number of Dump Trucks	8	Units
Loading Days	4	days

Source: Data processed

Based on the SIPOC analysis and obtained cycle time data, a VSM model can be developed. This VSM model will visually map the material and information flow from the beginning to the end of the loading process, enabling the identification of waste and opportunities for efficiency improvements more comprehensively.

In the nickel ore barge loading logistics process, the current VSM mapping shows that the material flow consists of several key stages: Stockpile → Hauling → Queueing at Jetty → Loading onto Barge → Survey & Documentation → Clearance & Departure. Based on the process time analysis, the total Cycle Time (C/T) is 11,000 minutes, while the total Lead Time (L/T) is 15,720 minutes, resulting in a Process Cycle Efficiency (PCE) of 69.97%.

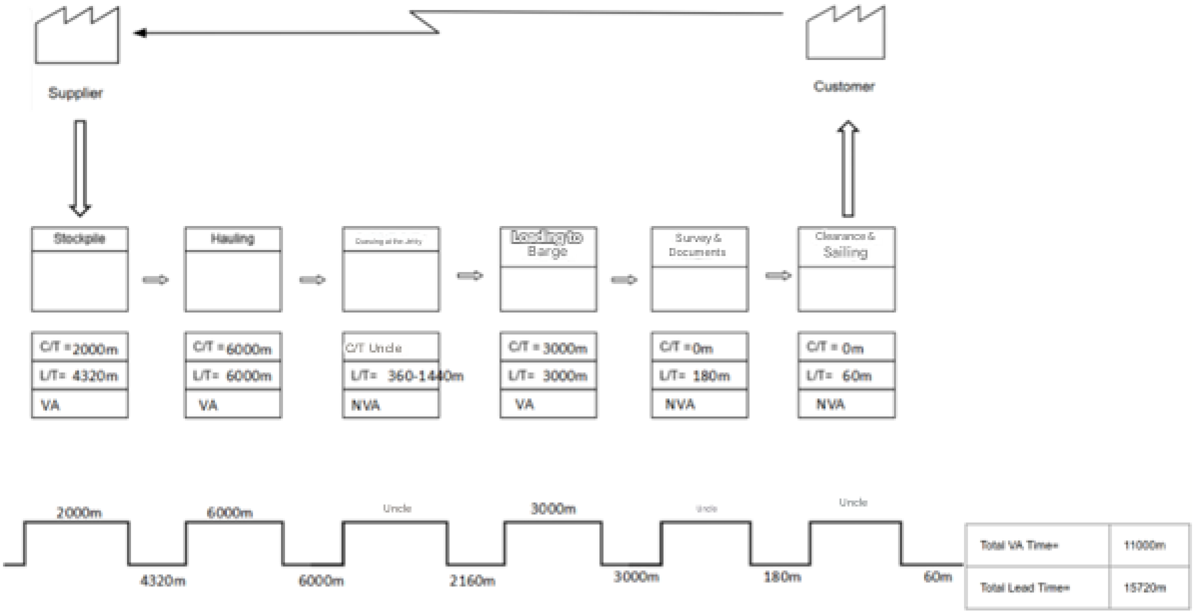

Figure 3. ***Current State VSM***

Process Cycle Efficiency (PCE) is calculated as:

PCE = (11,000 minutes) / (15,720 minutes) × 100% = 69.97%

From this mapping result, the most significant bottleneck occurs at the jetty queuing stage, where barges must wait between 6 to 24 hours (360–1440 minutes) before the loading process can begin. This waiting time does not add value (Non-Value Added/NVA) to the supply chain, making it a major source of inefficiency that needs to be reduced.

Using the 7 Wastes (Muda) method in Lean Manufacturing, several key forms of waste in the nickel ore loading logistics process can be identified:

1. **Waiting**: The primary bottleneck is at the jetty queue, with waiting times of up to 1,440 minutes, resulting in significant inefficiency.
2. **Overproduction**: The absence of an optimal buffer between hauling and loading creates an imbalance in material flow.
3. **Transportation**: Unclear prioritization in jetty queuing causes misalignment between hauling activity and jetty capacity.
4. **Inventory**: The jetty's capacity is often underutilized, leading to prolonged waiting times.
5. **Motion**: The lack of a First In, First Out (FIFO) system causes inefficiencies during the loading process.
6. **Overprocessing**: Administrative and survey processes taking up to 180 minutes could be optimized through digitalization.
7. **Defects**: Although not explicitly stated, delays due to incomplete documents or administrative errors are likely.

Among these, the most impactful waste affecting operational efficiency is the waiting time at the jetty. This waiting period directly extends the overall lead time, reduces operational throughput, and increases operational costs.

Optimization Results Using GA

After identifying the current condition and the factors causing inefficiencies, a solution is needed that can optimize jetty queuing and balance the material flow. The Genetic Algorithm (GA) explores various possible solutions with the aim of reducing barge waiting time at the jetty.

The optimization in this study aims to minimize barge waiting time using the GA approach. By performing iterations over a number of generations, an optimal solution can be found to reduce inefficiencies in the loading process. This section discusses the optimization results, sensitivity analysis, and the implications of these findings on the operational efficiency of the port.

1. Best Fitness Search Process

The GA iteration graph, as shown in Figure 4.2, indicates that during the early generations (0–50), there is a significant decrease in total waiting time, signaling a rapid search for an optimal solution. After generation 100, the rate of decrease begins to slow down, and from generation 300 to 500, the values reach a point of convergence. This demonstrates that the algorithm has successfully identified an optimal solution that is significantly better than the initial condition.

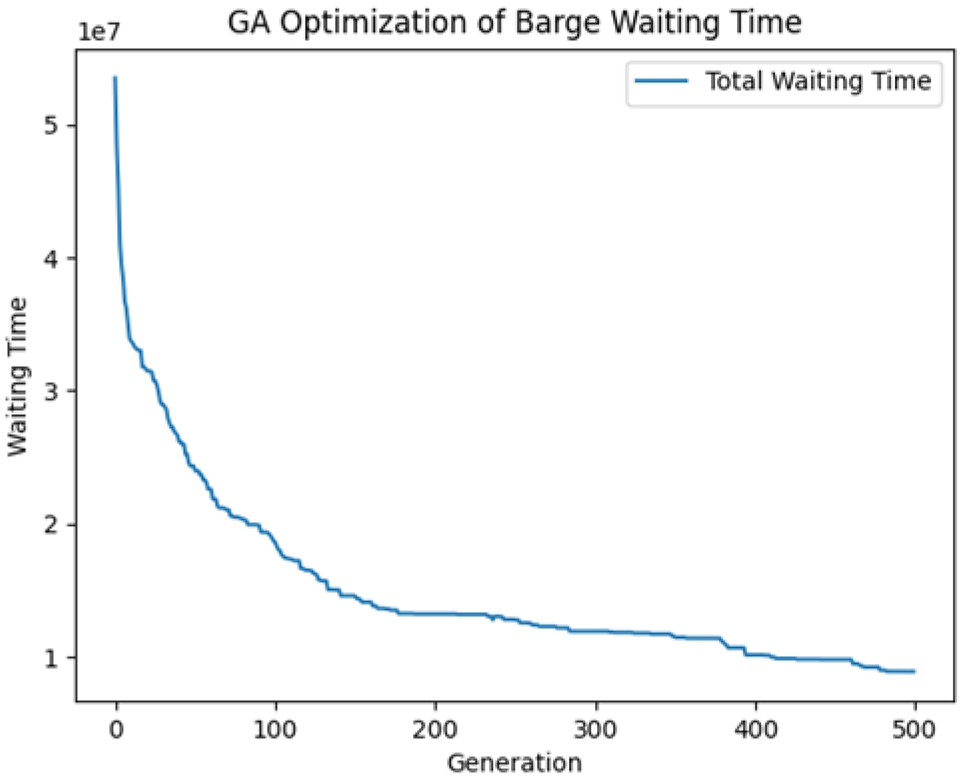

Figure 4. GA Iteration Graph

In the first generation, the fitness value was still very high, reaching approximately 48,451,731 minutes. This indicates that the initial schedule contained many inefficiencies, with numerous barges experiencing long waiting times. As generations progressed, the algorithm selected individuals with the best fitness, performed crossover operations (information exchange between solutions), and mutations (small changes in solutions) to create more optimal schedules. By generation 165, the fitness value had significantly decreased to around 13.8 million, showing that the algorithm successfully reduced waiting times.

After approximately 200 generations, the curve began to flatten, indicating that the algorithm had likely reached a near-optimal solution and no significant improvements were occurring. At this point, the total waiting time was 13.2 million minutes, representing a reduction of nearly 73% from the initial condition. By generation 500, the fitness value dropped further to 8,912,931 minutes—an 81% reduction from the initial state—demonstrating that the GA approach effectively reduced inefficiencies in barge scheduling and optimized the loading process.

Although there were gradual improvements, some generations showed stagnant fitness values over several iterations (e.g., Generations 22–25, 64–65, 131–134). This may indicate that the algorithm was temporarily stuck in a local optimum, where the solutions found were satisfactory but not necessarily the best overall.

Additionally, there were several points where significant drops in fitness values occurred (e.g., Generations 20, 29, 39, 75, 119). These drops may have resulted from crossover or mutation steps that successfully generated better solution combinations. In the context of barge schedule optimization, this suggests that even small changes in arrival sequences or docking times can have a major impact on reducing delays.

2. Results

After running the optimization model, a comparison between the initial method and the GA-based optimization can be made, as shown in Table 7.

Table 7. Optimization Results Using GA and Comparison

Metric	Initial Method	GA Optimization	Improvement (%)
Total Waiting Time	227 days 13 hours 58 mins	102 days 4 hours 37 mins	55.10%
Average Waiting Time per Barge	0 days 20 hours 9 mins	0 days 9 hours 5 mins	54.93%
Maximum Waiting Time	6 days 9 hours 5 mins	3 days 18 hours 42 mins	40.75%

Source: Data processed

From the optimization results, the total waiting time was significantly reduced from 227 days 13 hours 58 minutes to 102 days 4 hours 37 minutes, representing an efficiency improvement of 55.10%. The average waiting time per barge also decreased from 20 hours 9 minutes to 9 hours 5 minutes, an improvement of 54.93%.

Additionally, the number of barges experiencing any waiting time dropped sharply from 218 to 86 barges, a reduction of 60.55%. Meanwhile, the number of barges able to dock immediately without waiting increased significantly from 52 to 184 barges, reflecting a 71.74% improvement. Moreover, the maximum waiting time, previously 6 days 9 hours 5 minutes, was reduced to 3 days 18 hours 42 minutes, an efficiency gain of 40.75%.

By reducing the total waiting time by 55.10%, port utilization efficiency was significantly improved. The 60.55% decrease in delayed barges demonstrates the model’s effectiveness in reducing congestion and improving operational throughput. A more detailed look at barge waiting times can be seen in Table 8.

Table 8. Comparison of Waiting Time Categories

Waiting Time Category	Initial Shipments	Optimized Shipments	Improvement (%)
No Waiting Time (Direct Docking)	52	184	71,74%
Short Waiting Time (< 6 hrs)	53	22	58,49%
Medium Waiting Time (6–12 hrs)	47	10	78,72%
Long Waiting Time (> 12 hrs)	118	54	54,24%

Source: Data processed

The number of barges able to dock immediately without any waiting time increased from 52 to 184 barges, an improvement of 71.74%. This is a highly positive outcome, showing that the optimized scheduling system drastically reduced port queueing. More barges docking immediately means more efficient operations, reduced delay-related costs, and increased shipping throughput. Barges with short waiting times (< 6 hours) also dropped from 53 to 22, and medium waiting time barges (6–12 hours) dropped from 47 to 10. This shows that the new system better allocates docking slots, minimizing the number of barges that need to wait, though a few still face minor delays.

The number of barges with long waiting times (> 12 hours) also decreased significantly, from 118 to 54 barges. Although some barges still experienced extended delays, the number has been nearly halved, indicating room for further improvement to reduce extreme waiting times.

The maximum waiting time before docking decreased from 6 days 9 hours 5 minutes to 3 days 18 hours 42 minutes—about 40.75% faster. This is a very significant improvement, indicating the optimization effectively reduced the longest queue times, which are typically major sources of inefficiency in logistics chains.

However, some barges still experienced longer wait times, especially when arrivals were close together and docking slots were still occupied. For example, barge no. 155, which arrived on October 4, 2025, at 03:00:00, had to wait 5 hours 13 minutes 4 seconds because berth no. 4 was still occupied by barge no. 153, which departed at 08:13:04 on the same day.

The optimization model also demonstrated efficient berth slot distribution, where a departing barge immediately freed the slot for the next incoming barge. This reflects effective rotation of berth usage. Under the traditional First In First Out (FIFO) method, many barges had to wait longer because berth allocation didn't consider system-wide optimization. The GA model allows for more flexible and efficient scheduling, reducing overall waiting time while still respecting FIFO principles.

Overall, the optimized scheduling had a positive impact on port operational efficiency. The increase in the number of barges that could dock immediately, along with the significant reduction in maximum waiting times, demonstrates that the new system successfully reduced loading process bottlenecks. However, as some barges still experience delays over 12 hours, there is potential to further improve the system, perhaps through refinement of the optimization method or implementation of real-time scheduling strategies. Continued improvements could help the nickel ore logistics industry reduce cost-related waste from deadfreight, increase operational capacity, and enhance overall competitiveness.

3. Findings Analysis

Based on the GA modeling results, several key findings were identified, including:

a. Reduced Waiting Time

The simulation results show that the majority of barges were able to dock immediately without experiencing significant delays. For instance, barges 0, 1, and 2, which arrived on specific dates, were able to dock immediately without waiting. The minimized waiting times indicate the model's effectiveness in optimally allocating docking slots. Compared to the current manual scheduling method, this model demonstrates improved efficiency by significantly reducing the average waiting time for barges.

b. More Effective Utilization of Berth Slots

The model ensures that each slot is used by only one barge at a time, preventing overlaps that could cause delays. For example, a particular barge that arrived on a specific date and time could only dock after the previous barge vacated the slot. Compared to conventional scheduling systems that often face long queues due to a lack of optimization, this model is more effective in managing berth slot rotation.

c. Impact of External Factors on Scheduling

The model also incorporates factors such as loading time and weather delays, which contribute to more realistic schedule planning. For instance, a particular barge experienced prolonged loading time and weather-related delays, which affected its final departure time. By considering these factors, the model produces a more adaptive schedule than the current scheduling method, which does not account well for operational variability.

4. Model Limitations

Although the model has demonstrated improved results compared to the initial measurements, several limitations should be noted:

a. **Static Data Assumptions**

1. The model operates based on historical and estimated data, and thus does not update the schedule in real-time in the event of sudden changes.
2. In real-world implementation, integration with live monitoring systems is necessary so that the model can adapt to changing field conditions.

b. **Limitations in Handling Capacity Surges**

If the number of arriving barges exceeds the port's handling capacity, the model still has limitations in scheduling without causing long queues.

c. **Dependence on GA Parameters**

Optimization results are highly influenced by the choice of parameters such as the number of generations, population size, mutation rate, and selection method. Poorly chosen parameters can cause the algorithm to take longer to reach the best solution.

d. **Computational Complexity**

GA requires longer computation times compared to simple heuristic methods, especially when scheduling a large number of barges. In this study, the model took 1,933.365 seconds or approximately 32–33 minutes to complete 500 generations. At a larger scale, the model may require further optimization or a hybrid approach with other methods to remain time-efficient.

e. **Scheduling Prioritization**

The model still adheres to the First In First Out (FIFO) principle, but in real-world scenarios, there may be barges with higher priority that require more flexible berth scheduling.

Future State VSM

Based on the optimization results using GA, the Future State VSM shows several significant improvements in terms of time efficiency and the reduction of Non-Value-Added (NVA) activities. These changes aim to minimize barge waiting time and improve the efficiency of the nickel ore logistics process, as shown in Table 4.9.

Table 9. Process Cycle Time of Future State VSM

Process	c/T dump truck (minutes)	C/T barge (minutes)	L/T (minutes)	VA/NVA
Stockpile loading	4	2,000	4,320	VA
Hauling (3 km)	12	6,000	6,000	VA
Queueing at jetty	-		360 (↓83%)	NVA
Loading to barge	6	3,000	3,000	VA
Administration & survey	-		90 (↓50%)	NVA
Clearance & sail out	-		30 (↓50%)	NVA

Source: Data processed

From this mapping, it is evident that there is increased efficiency through the reduction of waiting time at the jetty, as well as improvements in the administrative and clearance processes. For the queueing process at the jetty, the time previously consumed was 2,160 minutes (NVA). After optimization, this has been reduced to just 360 minutes. This improvement results from optimized barge docking schedules, allowing barges to start loading/unloading immediately without long delays. Time spent on administration and survey, which was initially 180 minutes, has been reduced to 90 minutes. Additionally, the clearance & sail-out process, previously requiring 60 minutes, is now completed in just 30 minutes. This has been achieved through better coordination between port authorities and barge operators, preventing delays in departures.

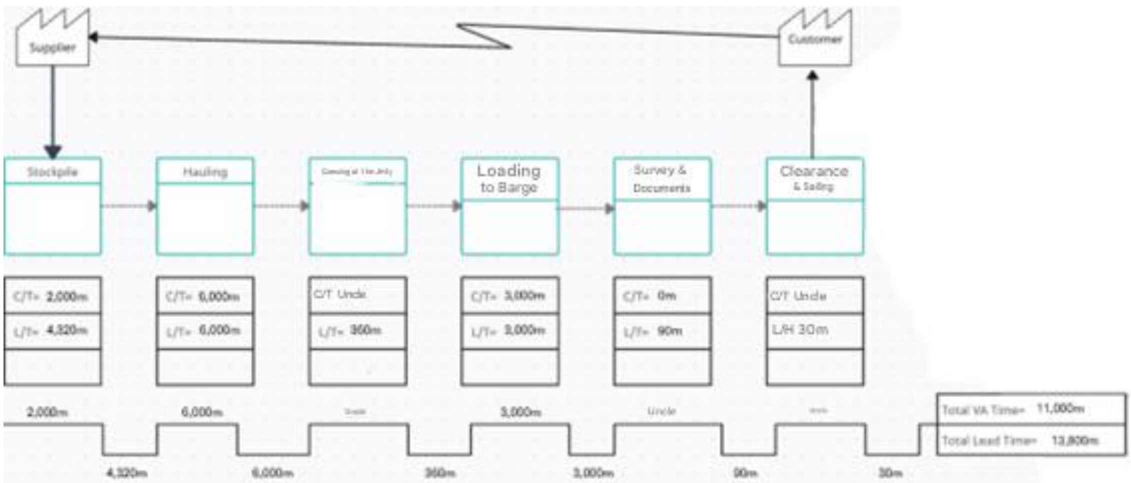

Figure 5. Future State VSM

Process Cycle Efficiency (PCE):

PCE = (11,000 minutes) / (13,800 minutes) × 100% = 79.71%

With the reduction of total lead time, PCE has increased from 69.97% to 79.71% in the Future State VSM. This increase reflects a reduction in waste throughout the logistics process, particularly in terms of waiting time.

Through the implementation of GA, the nickel ore logistics process has undergone significant operational efficiency improvements. The reduction of waiting time at the jetty and the acceleration of administrative and clearance processes directly impact lower operational costs and increased productivity. With this Future State VSM, the logistics system becomes more Lean, in line with Lean Logistics principles that focus on eliminating waste and enhancing value-added activities at each process stage.

CONCLUSION

This study aims to improve the logistics efficiency of nickel ore shipping at Indonesian ports by applying the Lean approach, Value Stream Mapping (VSM) analysis, and Genetic Algorithm (GA) optimization. The research identifies key inefficiencies, particularly excessive waiting times during barge queueing at the jetty and inefficiencies in documentation and clearance procedures, which are categorized as non-value-added (NVA) activities in the VSM. The current state VSM reveals that only 69.97% of the process contributes value, while the rest consists of NVA activities that can be minimized. By designing a future state VSM optimized through GA, these NVA activities are significantly reduced, resulting in an increase in direct barge dockings from 52 to 184, indicating a 71.74% improvement. The application of GA effectively optimizes barge docking schedules, reducing total waiting time from 227 days to approximately 103 days, achieving a nearly 54% improvement in efficiency. These findings offer practical recommendations for enhancing the nickel ore port logistics system, including better management of jetty slots and streamlining of administrative procedures, with the adoption of digital systems and algorithm-based scheduling as key strategies. Nonetheless, the study is limited by its reliance on historical data and several randomized assumptions, such as weather conditions, documentation time, and operational delays. It also does not consider dynamic factors like equipment failures or shipment priorities, focuses solely on port and docking processes without encompassing the entire supply chain, and lacks real-world validation due to time and access constraints.

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