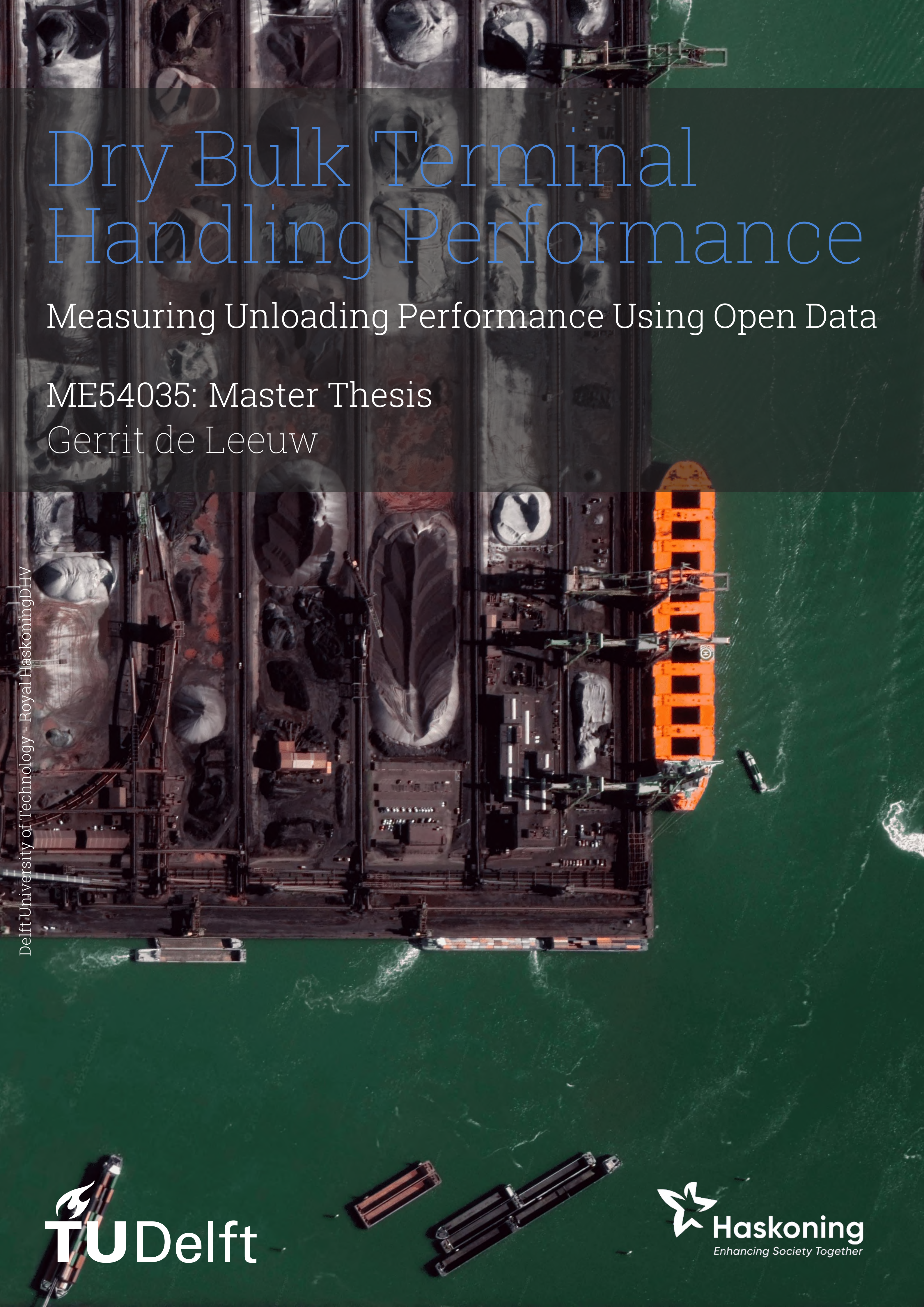

Dry Bulk Terminal Handling Performance

Measuring Unloading Performance Using Open Data

ME54035: Master Thesis

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Haskoning
Enhancing Society Together

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by

Gerrit de Leeuw

Master Thesis

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Cover: Google Earth, HBTR terminal, 10 March 2022

Preface

This thesis marks the final part of my studies in Delft. A time in which I not only learned to be an engineer but also explored the many things life has to offer. I look back with gratitude for all the great memories and the people I met along the way.

During the thesis, I explored the challenging logistics of dry bulk handling. I really enjoyed the erratic nature of it. I've always found the combination of typical engineering skills with a bit of boerenverstand very compelling.

First of all, I want to thank all my supervisors. Mark always kept me grounded and provided direct and effective feedback. Dingena challenged my ideas while maintaining a positive and motivational tone. Reinier ensured I stayed connected with the people at Haskoning. Thank you all for helping me through this project.

I'm thankful to all my friends in Delft who made my time here so memorable, especially my roommates, who were always there for me these past few months. You were a comforting place to come home to and a listening ear for all my complaining and doubting. I honestly don't think I could have survived the past year without you guys.

I'd also like to thank my colleagues at Haskoning for giving me the opportunity to explore the port design sector through the CoE. I really enjoyed our interesting conversations during lunch. Specifically, I want to thank Sander for motivating me and taking the time to discuss the HBTR terminal with me. Your positive energy really helped me keep going. I also want to thank Ekke for his endless enthusiasm and expertise. Your excitement truly validated my research.

Lastly, I want to thank my family, especially my parents. You always gave me the space to explore what I wanted to do, while providing an unconditionally loving place to fall back on. That gives me so much certainty in life and really helps me to grow and learn. You taught me to be confident, but also to never go somewhere without reason.

Gerrit de Leeuw
Delft, September 2025

Summary

This thesis investigates whether the handling performance of dry bulk terminals can be assessed using open data sources. Traditional performance analysis in port logistics often relies on proprietary operational data, which is difficult to access and inconsistent across terminals. To address this limitation, the study proposes a method that uses publicly available data, specifically AIS vessel tracking logs and satellite imagery, to estimate key performance indicators and benchmark terminal operations.

The method is structured around the Overall Equipment Effectiveness (OEE) framework, adapted for dry bulk unloading. Terminal performance is decomposed into three measurable components: quay occupancy, crane utilization, and crane productivity. These are quantified using a set of performance indicators that separate endogenous factors (controlled by the terminal) from exogenous influences (such as access channel transit times and weather conditions). A discrete-time model is developed to estimate crane operational hours, incorporating downtime events and throughput calculations based on vessel DWT and cargo type.

The model is validated using data from two terminals, HBTR and Tata Steel IJmuiden, showing good alignment with reported crane hours and cargo volumes. The method is then applied to four major dry bulk terminals: HBTR, EECV, Tata Steel, and Hansaport. Results show consistent OEE values between 21–36%, with notable differences in crane usage, berth commitment, and crane productivity. HBTR demonstrates high berth commitment and low waiting times, while Hansaport achieves the highest crane productivity. EECV showed long waiting times and berth commitment, while crane performance was similar to other terminals. Tata Steel's showed long waiting times and lower performance. Tata Steel's performance is shaped by its integration with the steel production process.

While the method provides reliable average estimates, uncertainties remain due to assumptions about crane ratings, internal logistics, and equipment allocation. These limitations highlight the importance of contextual interpretation when comparing terminals. Nonetheless, the study confirms that open data can be used to assess dry bulk terminal performance in a structured and scalable way. The approach offers a valuable tool for benchmarking, design validation, and strategic planning in port logistics, and opens the door for broader applications across terminal types and cargo categories.

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Nomenclature

- AIS: Automatic Identification System
- OEE: Overall Equipment Efficiency
- DWT: Deadweight Tonnage
- TEU: Twenty-Foot Equivalent Unit
- UNCTAD: United Nations Conference on Trade and Development
- PIANC: Permanent International Association of Navigational Congresses

1 Introduction

1.1. Motivation

Sustained economic growth is impossible without trade growth. Trade has been an important driver of economic prosperity, and over 80% of the volume of international trade in goods is carried by sea. (UNCTAD, 2024). Therefore, ports form very important components in the economies of many countries. *To a great extent, the economic development of countries depends on the existence of efficient ports and their competitiveness* (PIANC, 2014, p. 17).

Dry bulk goods are unpackaged raw or partly processed materials that are transported in large quantities, typically by bulk carriers. The three major dry bulk types, coal, iron ore, and grain, account for 29.2% of the global maritime trade (UNCTAD, 2020). Dry bulk forms an important basis for many industries. In the short term, coal still forms an important energy source, especially in developing countries.

The dry bulk solids handling industry is mainly concerned with transporting products from locations with large mineral reserves or production facilities, but with little local demand, to regions requiring inputs for processing, distribution, or manufacturing (PIANC, 2018, p. 28). Major bulks include coal (28%), iron ore (34%), and grain (12%) based on their percentage of global tonnage in 2017. Minor bulks, which account for the other 27%, mainly consist of cement, bauxite (for aluminum production), scrap iron, agribulks, and fertilizers. (PIANC, 2018, p. 29, based on data from Clarkson Research Services Limited)

A terminal operator typically has limited control of the global supply chain. Terminals compete with each other for servicing vessels. Therefore, the objective is to provide the least cost per handled tonne of dry bulk and to offer a competitive service and waiting time.

The performance of a dry bulk terminal consists of its effectiveness and productivity. Port operators collect data to analyze and monitor their terminals. This can be used to plan expansion, measure performance, or optimize the allocation of resources during operation. One form of analysis is the creation of a set of Port Performance Indicators (PPIs). Port Performance indicators are measures of different aspects of the port's operation.

The most important performance indicator of a dry bulk terminal is its productivity. Productivity can be classified as peak, optimum, and annual. The peak productivity is the absolute maximum loading/unloading capacity that can be obtained for a short time. The optimum productivity is when the terminal operates comfortably and has enough resilience for unforeseen conditions and equipment breakage. To decide on the port capacity during port planning, the balance between shortages and overcapacity should be appropriately balanced (Dekker & Verhaeghe, 2006).

1.1.1. Port Planning

Port planning refers to the strategic process of designing, developing, and managing port facilities. Often, port planning is concerned with increasing productivity. To increase productivity, terminal operators generally face a decision between enhancing efficiency and expanding capacity. However, port construction or expansion involves big investments, making increasing capacity or efficiency often a high-stakes endeavor. Quality analysis of the port operation is therefore crucial for terminal operators, as it facilitates informed decisions.

When designing the capacity for new greenfield terminals or expanding existing ones, scaling of various components is often based on rules-of-thumb. These rules help determine achievable metrics, such as tonnage per meter of quay or the utilization factor for a crane. However, some guidelines are outdated, and research has shown that actual operational values can differ significantly from these rules-of-thumb (van Vianen et al., 2011). Consequently, there is uncertainty regarding how the designed capacity relates to the actual operational productivity. While the eventual throughput might be adequate, it may be achieved differently than initially planned, causing this issue to remain unnoticed.

Currently, it is difficult for terminals to benchmark equipment performance on a broader scale. Most rely on internal monitoring systems to track performance over time. While basic metrics such as tons handled per hour or total utilization hours are commonly used, more detailed benchmarking remains limited. This is mainly due to the lack of accessible data and the complexity of comparing terminals with different layouts and external conditions.

1.1.2. Open Data

Open data, which is widely available and accessible, plays a key role in this research by utilizing AIS and aerial imaging to analyze terminal performance. By leveraging open data, research can be conducted efficiently and systematically without requiring compliance from terminal operators, enabling quick and organized performance analysis.

However, open data presents limitations in accuracy, particularly regarding operations within the terminal. Without direct communication with terminal operators, internal processes associated with loading and unloading must be estimated.

Since 2004, vessels over 300 Gross Tonnage have been required to be equipped with an Automatic Identification System (AIS) (De Boer, 2010). It automatically and periodically transmits the vessel's position. This data is publicly available and a great data resource for researchers. The positional data of the vessels is transmitted automatically from the vessel's navigational instruments and is therefore reliable. AIS also includes voyage information such as destination, estimated arrival time, draught, and navigational status. These are changed manually by the crew of the vessel and are, therefore, much more prone to error.

Similarly, aerial images from sources like earth.google.com offer insights into terminal layouts and used equipment. Combining images from multiple sources and different dates can improve the accuracy of terminal layout assessments, providing a more detailed perspective.

Combining different open data sources to assess the productivity of a terminal could allow for assessing port performance quickly, systematically, and efficiently, allowing for new insights is dry bulk port design.

1.1.3. Haskoning

This research is done in collaboration with Haskoning. Haskoning is an independent consulting engineering company that is dedicated to creating a positive impact on people and the planet. (Royal HaskoningDHV, 2025) The mission statement of Haskoning is *Enhancing Society Together*. The company is dedicated to creating resilient, adaptive systems that ensure the well-being of our communities and the planet.

Engineers at Haskoning are involved in the planning and design of dry bulk ports. A recurring challenge in this field is the uncertainty surrounding terminal capacity and productivity. Comparing actual operational capacities with the theoretical guidelines used in design methods could enhance their effectiveness. Additionally, data provided by clients, often port operators, to Haskoning is often unstructured, low quality and delayed, which complicates the process. Using open data to quickly assess dry bulk port performance could provide a useful first step to accelerate this process, making it more efficient and organized.

1.2. Problem Definition

Port planning consists of long-term strategic decision-making and short-term operational resource allocation. Port planning involves high-stakes investments and strategic decisions. Making quality analysis crucial for making informed decisions. Increasing productivity is the most common reason for port reforms. Thus, effective port planning requires assessing the capacity and productivity of a terminal.

Gathering the necessary information presents significant challenges, particularly as cost- and time-intensive data collection is impractical during the early design phases. Furthermore, port operators play a key role in providing data, but compliance is not guaranteed. They may be unwilling to cooperate, cause delays due to prolonged response times, or supply data of questionable quality. This creates a gap in accessible and reliable data sources for evaluating terminal performance.

The use of open data for analyzing the internal processes of a terminal remains largely unexplored. However, it presents an opportunity to efficiently and systematically assess dry bulk handling performance.

AIS has been widely utilized for analyzing seaside operations, offering reliable information about vessel locations and movements. However, research linking AIS data to landside handling operations remains sparse. Assessing the terminal layout from aerial imaging allows for understanding the context of AIS data, which allows for a more comprehensive assessment of dry bulk terminal performance.

1.3. Scope of the Research

While the aim of this research is to develop a method that can be applied across various terminals and dry bulk types, the current study focuses specifically on import terminals handling iron ore and coal. These terminals were selected based on their proximity to the university, the availability of relevant data, and established contacts with terminal operators.

The scope further provides some boundaries to ensure clarity and feasibility for the study. This research focuses on four import terminals in Northwestern Europe that handle iron ore and coal. The selected terminals represent a diverse yet comparable set of operations, enabling the development of a performance evaluation method that is both grounded in real-world data and scalable to other dry bulk facilities. To validate the research, the terminals of HBTR and Tata Steel are contacted to verify assumptions and address identified anomalies, enhancing the study's credibility.

This project focuses on assessing the performance of dry bulk terminals specializing in handling coal and iron ore. The scope is limited to terminals that operate year-round, to ensure results apply to facilities with substantial operational capacity. Additionally, the study emphasizes unloading operations of sea-going vessels rather than loading processes, narrowing the analysis to the incoming flow of bulk materials. To maintain consistency in environmental and operational conditions, the research focuses exclusively on terminals located in northwestern Europe. This area experiences good coverage of AIS data and ensures the analyzed terminals operate in shared geographical factors.

The proposed terminals for analysis:

- HBTR, Rotterdam, The Netherlands
- EECV, Rotterdam, The Netherlands
- Tata Steel, IJmuiden, The Netherlands
- Hansaport, Hamburg, Germany

1.4. Research Objective

This research aims to explore how open data can be used to assess the handling performance of dry bulk terminals. Accurate evaluation of terminal capacity and productivity is essential for effective port planning and decision-making, but this is often limited by difficulties in accessing reliable operational data. The use of open data sources, such as AIS and aerial imagery, may offer a way to perform structured analyses without requiring cooperation from terminal operators.

The research also aims to develop a method for assessing unloading performance and capacity utilization. By defining a set of performance indicators that separate controllable and uncontrollable factors, the study seeks to enable clearer comparisons between terminals and improve benchmarking practices.

In addition, the research aims to propose techniques for processing open data to analyze port operations. It will also address the uncertainty introduced by missing data and the assumptions required to apply the method.

1.4.1. Main Research Question

From the research objective, the following research question emerged:

How can open data be used to assess the handling performance of a dry bulk terminal?

1.4.2. Sub-questions

To answer the research question, the study addresses a set of sub-questions. Each sub-question is addressed in a separate chapter. Lastly, the main research question is addressed in Chapter 8. This gives the following structure to the report:

1. What are the key processes and components that determine the handling performance of a dry bulk terminal? -> **Chapter 2**
2. Which open-data sources are available for terminal operations, and what limitations arise from data gaps? -> **Chapter 3**
3. How can open data be processed to evaluate terminal performance, and how can unloading productivity be effectively modeled using such data? -> **Chapter 4**
4. To what extent does the proposed method reflect the actual performance of dry bulk terminal operations? -> **Chapter 5**
5. What can be concluded from the performance assessment results, and what difference between the terminals can be observed? -> **Chapter 6**
6. How do the results align with dry bulk terminal design guidelines, and what improvements to design methodologies can be derived from observed differences? -> **Chapter 7**

1.5. Structure Report

To further clarify the method and structure of the report, the following diagram is given below:

Chapter 2	System analysis	SQ1
Chapter 3	Open data sources	SQ2
Chapter 4	Method	SQ3
Chapter 5	Calibration & validation	SQ4
Chapter 6	Results	SQ5
Chapter 7	Discussion of results	SQ6
Chapter 8	Conclusions	**MRQ**
Chapter 9	Discussion of research & Recommendations	

Figure 1.1: Overview of the report structure and corresponding sub-questions addressed in each chapter

2 System Analysis

Chapter Sub-question: 1. What are the key processes and components that determine the handling performance of a dry bulk terminal?

This chapter analyses the different components and processes occurring at a dry bulk terminal. It explores Overall Equipment Effectiveness and how it can be used to assess terminal performance.

Deep-sea dry bulk terminals across the globe are designed to manage large volumes of bulk materials, such as coal and iron ore. Dry bulk terminals are generally either export- or import-oriented. Services provided by an import dry-bulk terminal consist of unloading cargo from ship to shore, temporarily storing the material, limited processing of the material, and loading and unloading into the through-transport means (Ligteringen, 2022, p. 137).

A terminal consists of one or multiple berths where a vessel can moor. The terminal might consist of clearly separated berths or a continuous quay where multiple vessels can moor simultaneously. Increasing net berth productivity is the most important reason for port reforms. However, net berth productivity is determined by numerous factors of very different natures and intensities of influence (Deda Đelović, 2020).

This research focuses on the unloading performance of large sea-going dry bulk vessels at import-oriented terminals. From the unloading perspective, seaside operations are the most critical. The internal logistics of the stockyard must prevent equipment blockage to avoid delaying these operations, while the landside must ensure sufficient material outflow to maintain stockyard availability.

2.1. Dry bulk terminal system

An import-oriented dry bulk terminal can be separated into three distinct parts: the seaside unloading system, the stockyard system, and the landside loading system, as can be seen below in Figure 2.1. The three systems are usually connected by a conveyor system. In some cases, the stockyard system is bypassed when loading occurs from vessel to vessel directly. This is challenging to achieve due to all kinds of disruptions of the supply chain, and therefore occurs rarely (Vianen, 2015).

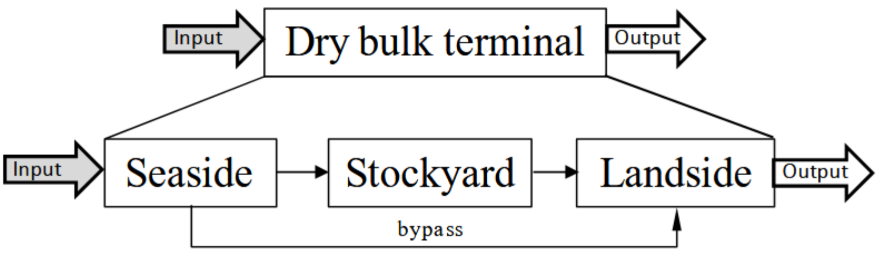


Figure 2.1: The dry bulk import terminal system (Vianen, 2015, p. 6).

2.2. Terminal components

The import terminal system consists of three subsystems: seaside, stockyard, and landside. These subsystems contain various components and work together to manage the flow of bulk materials through the terminal. The system also interacts with external components to move goods into and out of the terminal.

- **Seaside**
  - **Berths** - Needs to be available for a vessel to moor. Limited by length and depth, restricting vessel size.
  - **Port access channels** - Takes time to navigate through, and availability might be influenced by locks or tidal movements.
  - **Unloaders** - Includes cranes, used to move material out of the vessel.
  - **Auxiliary equipment** - Supporting machinery like front-end loaders used during the last phases of unloading.
- **Stockyard**
  - **Stacker/Reclaimers** - Used for moving material in and out of storage
  - **Storage** - Open yards or silos for bulk material storage.
  - **Conveyor system** - The conveyor system connects all components of the terminal.
- **Landside**
  - **Barge loaders** - Used to load barges.
  - **Train loaders** - Used to load trains.
- **External components**
  - **Vessels** - With different bulk types and dimensions.
  - **Barges** - Used for exporting material via inland waterways.
  - **Trains** - used for exporting material via rail.

The seaside system is concerned with unloading seagoing vessels. The stockyard system concerns the internal logistics of the terminal. The landside operation is concerned with moving material out of the terminal. A typical layout for a dry bulk import terminal can be seen below in Figure 2.2. Vessels moor at the berths and are emptied by cranes. The cranes are connected to stacker/reclaimers via a belt conveyor system. The stacker/reclaimers are used to stack the material in stockpiles in the stockyard. The stacker/reclaimers are also used to retrieve material and transport it via the belt conveyor system to train or barge loaders.

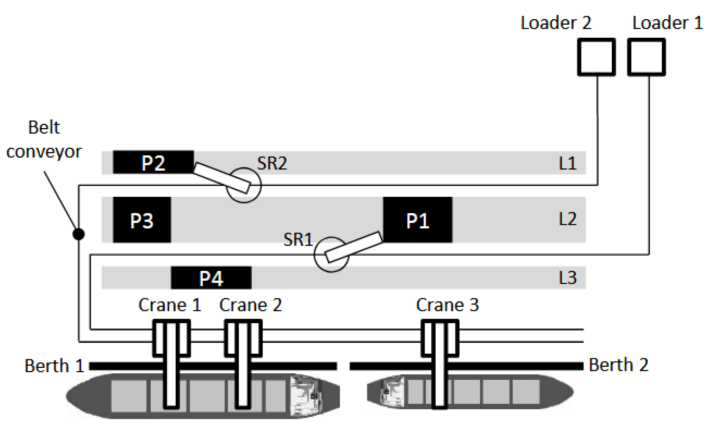


Figure 2.2: A typical layout for a dry bulk import terminal (Vianen, 2015, p. 136).

The seaside operation is typically the most critical component influencing the unloading performance of the terminal. Meanwhile, the stockyard must maintain sufficient availability to support continuous seaside activity, and the landside operation must ensure adequate material outflow. Consequently, the assessment of unloading performance emphasizes the seaside processes. The IDEF0 diagram of the flow of material through the system is shown in Figure 2.3 below. The seaside operation consists of the first three functions in this diagram: arriving at port, docking, and unloading. These activities are fundamental in defining overall port performance and determining the terminal's unloading productivity.

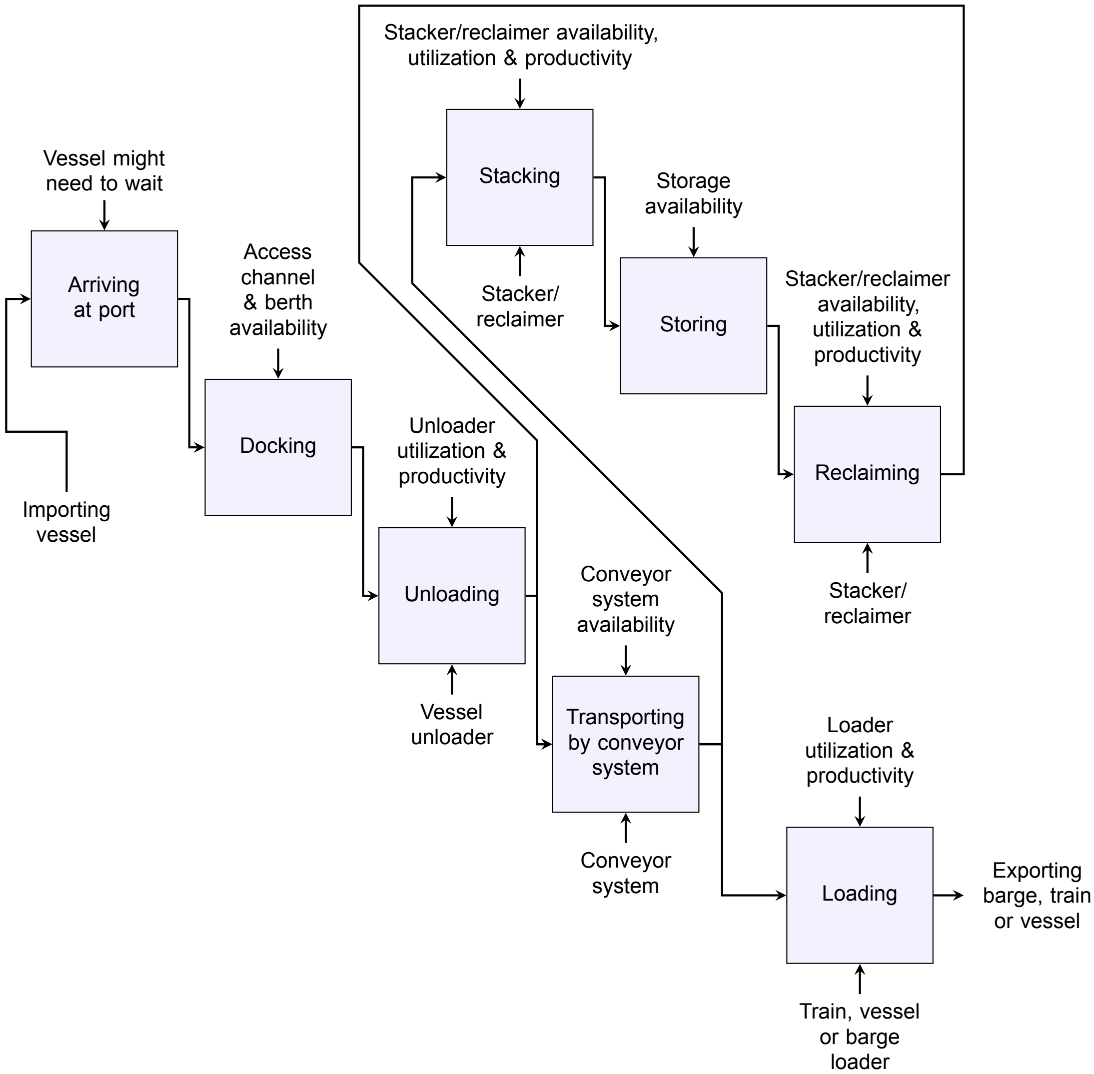


Figure 2.3: General IDEF0 diagram of an import-oriented dry bulk terminal system

The different components operating in or interacting with the system are further discussed below.

2.2.1. Vessels

The vessel is transporting the dry bulk cargo to and from the terminal. Its main characteristics are its cargo type and Deadweight Tonnage (DWT). Vessel size classes used in dry bulk shipping can be seen below in Table 2.1. Especially iron ore carriers can become very big. These vessels can only be received by a limited number of terminals.

Vessel type	Dead-weight tons (dwt)	Notes
Handysize bulk carrier	10 000 - 39 999	Can access shallow ports and are often multi-purpose, often geared. Often used to carry perishable goods such as grain. 65% of all dry bulk carriers fall into these two classes.
Handymax bulk carrier	40 000 - 64 999	
Panamax bulk carrier	65 000 - 99 999	Can still navigate through the Panama Canal.
Capesize bulk carrier	100 000 - 199 999	Often used for coal and iron ore. Since the recent deepening, they can go through the Suez Canal.
Very large ore carrier (VLOC)	200 000+	Almost exclusively for iron ore. Often exporting from South America to Europe or Asia.

Table 2.1: Dry bulk vessel size classes(UNCTAD, 2024, p. vi)

More detailed characteristics include overall length, ship gear, draft, and ballast. A vessel must take in ballast to control the draft and ensure stability. Typical arrival ballast is 35-45% of DWT. (PIANC, 2018, p. 41) During loading, the vessel will pump out ballast water to control its draft and stability. This process, known as the ship's de-ballasting capacity, may limit the loading speed if the crane's loading speed exceeds the vessel's de-ballasting capacity.

A dry bulk vessel contains multiple cargo holds, with the number varying by vessel size class, as shown in Table 2.2. For larger vessels, the number of cargo holds remains relatively similar to smaller-sized vessels, meaning individual holds are significantly larger. Larger cargo holds allow for more efficient unloading since the crane can operate in optimal conditions for longer. This is further explained in subsection 2.2.3. During unloading, unloaders move between cargo holds, typically visiting each cargo hold at least twice to prevent excessive stress on the vessel structure.

Ship Category	# Holds [-]
Handysize	3-6
Handymax	5-7
Panamax	5-9
Small Capesize	7-9
Large Capesize	7-10

Table 2.2: The number of cargo holds for different vessel size classes (Vianen, 2015, p. 26).

2.2.2. Berth and Port Channel

The berth provides space for the vessels to interact with the terminal. Its main characteristics are its length and water depth. Depending on the berth's location, weather, tides, and other external influences might cause it to be unavailable.

The size and depth of the port channel are other limiting factors for the size of the vessels. The access channel might have limited space, which means vessels might need to wait before they can traverse it. Furthermore, if there are locks in the port channel, this causes more congestion. The access channel can be under the influence of tides, resulting in a change in the permissible draught of the vessels. As a result, certain vessel sizes may be temporarily restricted from entering or exiting the terminal.

2.2.3. Unloading equipment

Dry bulk ships might unload cargo themselves with gear mounted on the ship. For larger terminals, however, it is more common for equipment on the quayside to do this. Unloading equipment can be either fixed or mobile, meaning it can operate in multiple berths.

Frankel et al. (1985) categorizes the following unloading equipment:

- Level luffing grab cranes

- Trolley-type grab cranes
- Continuous Unloaders
- Pneumatic unloaders
- Vessel-mounted equipment

Vessel unloaders use grabs, continuous bucket chains, or pneumatics to lift cargo out of the cargo hold. The most important characteristics of unloading equipment are whether the unloading is continuous or non-continuous, capacity, both in volume and tonnage, cycle time (if non-continuous), and reach. The operational performance of the crane has a big influence on vessel turnaround time. This depends on its capacity, reliability, flexibility, and precision. During the unloading of a vessel, the productivity also decreases, as can be seen in Figure 2.4. As the vessel becomes emptier, it becomes increasingly difficult to fully load the grab, leading to a decrease in tonnage per hour. In the final stage, known as the trimming phase, auxiliary equipment such as front-end loaders is loaded into the cargo hold to consolidate the dry bulk into more easily grabbable stacks for the grab.

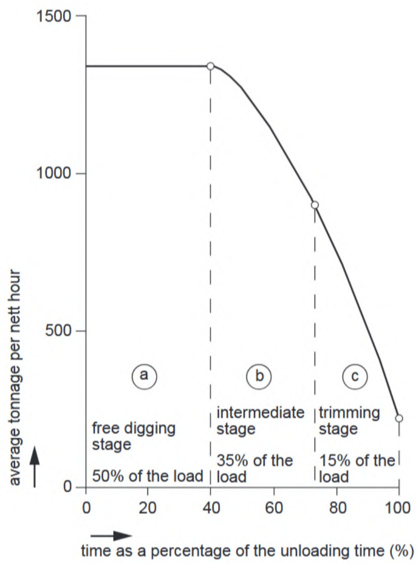


Figure 2.4: Unloading stages (Ligteringen, 2022)

To minimize stress on the vessel, unloading must be conducted in a distributed manner. This process involves partially unloading or loading a hold, typically around 50%, before shifting operations to a hold on the opposite side of the ship. As a result, each cargo hold is generally visited twice (PIANC, 2018).

Unloading is typically performed using two cranes. The terminal operator aims to maintain high productivity with one crane during the initial hold visit, while the second crane operates at a lower productivity during the second visit. This approach helps regulate material throughput, preventing excessive peaks in the conveyor system and ensuring the availability of auxiliary equipment.

Besides the skill of the crane operator and the different stages of unloading, the characteristics of the handled material also influence the productivity of the unloading process. Iron ore, being much denser than coal, requires smaller and more robust grabs to manage the heavier load.

Coal experiences more fluctuations in moisture levels. High moisture levels might cause the material to stick together and form lumps, which is undesirable. Materials come in different grain sizes or forms. Iron ore can, for example, be transported in pellets, concentrate or lumps. All of which influence the effective use of the unloading equipment.

Some examples of other material characteristics that contribute to decreased productivity at the HBTR terminal in Rotterdam are given below (R. Slikkerveer, personal communication, May 16, 2025):

- Coal transported from warmer regions, such as Indonesia, tends to retain heat and is prone to self-heating. As a result, condensation forms within the compartments, creating mist that obstructs the crane operator's view.
- Coal from colder regions may contain large ice blocks, which can damage the conveyor system and increase coal humidity. To mitigate this, the coal must be handled twice—first removed from the vessel and placed on the quay, then reloaded onto the conveyor system after the ice has melted.

2.2.4. Auxiliary equipment and Harbor support

Next to the main equipment in the port, there are many supporting components. Auxiliary handling equipment, such as front-end loaders, is used to support loading and unloading. Similarly, they can move bulk, which is out of reach of stacker-reclaimers. Tugboats assist larger vessels during berthing and de-berthing. Dust suppression systems might be required to reduce the dust. For example, dry bulk stacks can be sprayed with water. Also, dry bulk material is often weighed prior to loading or after unloading for payment purposes. Material can be either weighted per batch or continuously. Lastly, customers might require samples of the bulk material to be taken to ensure quality and correct composition and blending. This can also be done automatically.

2.2.5. Stockyard components

The stockyard typically includes a conveyor system, stacker/reclaimers, and storage space. Conveyors link unloaders, loaders, and stacker/reclaimers, transferring dry bulk via hoppers. A key limitation is their restricted vertical angle (Ligteringen, 2022, p. 287), which can be mitigated using pipe conveyors. These enable tighter curves and gradients while minimizing dust emissions. The main characteristic of a conveyor belt system is the capacity per hour, which should be typically be higher than the unloading or loading system it supports, so unloading peaks in the first stages of unloading can be supported.

Iron ore and coal are most often stored in open-air stockpiles. These allow for the storage and blending of the material. Blending is the mixing of different batches so that a uniform quality is obtained. Stacker-reclaimers are concerned with loading and retrieving the dry bulk from the storage. Covered storage might be used if the material is prone to weather damage or if dust emission is a concern. Silos can also be used for storage. This minimizes the footprint and allows for protection against the outside environment. The most important characteristic is the overall capacity of the storage. If multiple dry bulks are handled or if there is a difference in quality, the terminal must be able to store these separately, which will limit the terminal's operational flexibility.

For unloading operations, the stockyard system needs to be available. The conveyor system might be blocked when it is occupied with other operations, such as loading a train. The right stacker/reclaimer must also be available and have access to enough storage space for the dry bulk material. Moreover, both the conveyor system and the stacker/reclaimer might experience downtime caused by breakage, which will generally halt the entire operation.

2.2.6. Landside components

The landside system is concerned with moving material outside of the terminal. Material is moved out of the terminal via barges, trucks, trains, or small sea-going vessels, which are loaded by dedicated loaders. The barges, trucks, trains, or vessels might experience random arrival patterns. Most loading equipment is of the continuous type, whereby product is discharged from the end of a conveyor. A continuous loading process requires interruptions when switching between transport units, such as railcars or cargo holds. The quantity of material loaded must be accurately measured, controlled, and logged, which can be done through weighing either before, during, or after the loading operation (PIANC, 2018, p. 147).

Ship loading occurs at an export terminal or at a transfer terminal, which might transfer dry bulk to smaller barges for inland shipping. Most often, the loading of bulk cargo is a continuous process in which the ship loaders are fed by a belt conveyor system from the stockpile and drop the cargo in the different holds of the ship (Ligteringen, 2022, p. 275). Loading also has a trimming phase in which the load is spread more evenly in the hold. Modern dry bulk carriers have holds designed so that necessary trimming during loading can be kept to a minimum. This step ensures the remaining empty voids are filled with cargo. This ensures more capacity is used and the cargo will not shift and damage the ship. Often, trimming is done by auxiliary equipment (Frankel et al., 1985, p. 133).

An example of productivity losses during loading at the HBTR terminal in Rotterdam includes the limited height reach of the loader used for sea-going vessels. Larger vessels are required to fill one or two holds with water during initial loading. This is necessary because the bunkering compartments do not provide enough capacity to lower the vessel sufficiently (R. Slikkerveer, personal communication, May 16, 2025).

2.3. Crane states

A terminal may have several individual berths with dedicated equipment or a continuous quay setup where equipment can move between berths as needed. The primary components of the seaside unloading system are the cranes. The seaside system can operate in the following states (PIANC, 2018):

- Unscheduled downtime
- Scheduled downtime
- Operational time
- Set time
- Idle time

Examples of unscheduled downtime are weather delays and equipment breakdowns. Scheduled downtime mostly consists of maintenance and shift changes. Set time refers to the time during which a vessel is moving through the access channel, mooring or unmooring at the quay, and the equipment is being prepared for operation. Lastly, idle time refers to periods when the terminal is not engaged in any activities. Idle time is still required to supply sufficient flexibility and redundancy for the other processes.

In a discrete berth system, the states of the berth usually match the states of the cranes. For a continuous quay, cranes can be in different states simultaneously. One crane might be operating while another is under maintenance. On longer continuous quays, it is unlikely that all cranes operate on the same vessel simultaneously. Since this research uses open data, all states are calculated as an average across all cranes. The exact location and activity of each crane are unknown. As a result, the average crane state is used to represent the average terminal state.

The terminal throughput is determined by three key factors: the nominal capacity of the components, the utilization of components, and the productivity of the components. Utilization is limited by downtime, which can result from maintenance, mechanical failures, or equipment unavailability.

To better investigate the performance of a dry bulk terminal, operational events can be divided into controlled and uncontrolled events (Pinto et al., 2017):

Exogenous influences Uncontrolled by the port operator.

Endogenous influences In control of the port operator.

A lack of productivity, which is caused by exogenous downtime, should not be interpreted as bad port performance. Different terminals might experience different exogenous influences. Acknowledging these differences allows for better comparison between different terminals and better assessment of the dry bulk terminal's performance. Assessing performance based only on endogenous influences allows for benchmarking port performance. With this definition in mind, events at the terminal can be categorized as either exogenous or endogenous, as shown in Table 2.3. All symbols in this table are expressed in hours. The sum of all these events is equal to the total time TT.

Symbol	State	Influence
	Unscheduled downtime	
WC	Stops due to adverse weather conditions	Exogenous
CM	Corrective maintenance	Endogenous
ED	Exogenous downtime	Exogenous
	Scheduled downtime	
UNV	Unavailability	Exogenous
PM	Preventive maintenance	Exogenous
	Operational time	
OS	Operational stops	Endogenous
BE	Blockage of equipment	Endogenous
OT	Operating time	Endogenous
	Set time	
TR	Transit time	Exogenous
PO	Pre- and post-operational time	Endogenous
	Idle time	
IDL	Idle time	Exogenous

Table 2.3: Endogenous and exogenous states in a dry bulk terminal system (Pinto et al., 2017).

Most crane states require a vessel to be present at the terminal. However, idle time (IDL), preventive maintenance (PM), and transit time (TR) can occur with or without a vessel present at the terminal. Other cranes are then already operational on the vessel, while another crane is idle, undergoing maintenance, or is expecting a vessel to more soon once it finishes its transit through the access channel. Therefore, a distinction is made, as can be seen in Table 2.4.

Preventive maintenance and transit time are considered exogenous factors. With a vessel present or without, their duration is not in control of the terminal operator. In contrast, idle time while a vessel is present is an endogenous loss factor. It reflects inefficiencies within the terminal, such as poor logistical coordination or suboptimal layout.

Adverse weather conditions and unavailability can also occur outside quay occupancy hours. These are usually not considered operational losses and are therefore not categorized differently.

Symbol	State	Influence
PM_v	Preventive maintenance (vessel present)	Exogenous
PM_{nv}	Preventive maintenance (no vessel present)	Exogenous
TR_v	Transit time (vessel present)	Exogenous
TR_{nv}	Transit time (no vessel present)	Exogenous
IDL_v	Idle time (vessel present)	**Endogenous**
IDL_{nv}	Idle time (no vessel present)	Exogenous

Table 2.4: States that can occur during quay occupancy and outside of occupancy hours.

Stops due to adverse weather conditions

Weather conditions can hinder the operation of the terminal. Cranes cannot be operated above 8 Beaufort (van Vianen et al., 2012). Heavy rain, storm, thunder, or fog are other conditions in which operations need to be halted. Coal and iron ore, opposed to grain, can be handled in the rain.

High wave conditions can disrupt unloading by causing excessive vessel movement, limiting the safe operation of unloaders. Acceptable wave height limits are shown in Table 2.5. Terminals located upriver or behind locks are typically not affected by wave action. In exposed locations, breakwaters can be used to reduce wave impact.

	Limiting Wave height in m	
Process	**0° (head or stern)**	**45° or 90° (beam)**
Loading	1.5	1.0
Unloading	1.0	0.8-1.0

Table 2.5: Limiting wave height on terminal operations for dry bulk carriers (30 000-100 000 tons) (Ligteringen, 2022, p. 128).

Corrective maintenance

Corrective maintenance refers to unplanned maintenance triggered by equipment failure, breakage, or blockage. The timing and duration of such events are uncertain. In some cases, failure of a single component can halt the entire operation, though the availability of alternative cranes, conveyors, or stacker/reclaimers may allow operations to continue. The amount and timing of corrective maintenance are a result of the terminal's policies. Therefore, this is an endogenous factor.

Exogenous downtime

Exogenous downtime refers to downtime caused by other exogenous influences or external parties. Examples include a power outage, labor strikes, or a stoppage due to the vessel captains' demand.

Unavailability

Unavailability refers to the time the terminal is not available for operation, such as holidays or a closed access channel. Tide restrictions and harbor navigational safety measures also limit the available time windows for vessel entry into the port. In Rotterdam, for instance, very large vessels can only move in or out of the terminal once per day when conditions permit (R. Slikkerveer, personal communication, May 16, 2025). Unavailability is out of the port operator's control.

Preventive maintenance

Preventive maintenance is the planned maintenance of the terminal equipment. Typically, maintenance is done during a maintenance shift of 8 hours, after which the equipment can resume operations. Sometimes it will be possible to perform "opportunity maintenance" of the system between vessel calls (PIANC, 2018). Often, equipment undergoes large-scale maintenance yearly. Preventive maintenance is considered an event controlled by the terminal operator, but since its timing and duration are often prescribed by regulations or manufacturer guidelines, it offers limited insight into a terminal's handling performance. Therefore, preventative maintenance is assumed to be exogenous.

Operational stops

Operational stops refer to routine pauses during unloading, including tasks like moving the crane between cargo holds, opening cargo hold doors, or changing grabs. Operational stops also include meal breaks or shift changes. As shown in Table 2.2, the number of cargo holds does not significantly increase with vessel size. Therefore, the duration of operational stops is generally consistent across vessel classes, with larger vessels gaining efficiency through economies of scale.

Blockage of equipment

Blockage of equipment refers to the time lost when the unavailability of other equipment prevents operations. For example, this can occur when the conveyor system is already operating at peak capacity due to activity at another berth.

Blockage of equipment is a challenging aspect of a terminal's operation. Internal logistics frequently present significant bottlenecks within the system. Unloading operations must be halted if a stacker reclaimer is unavailable or if the conveyor route to the required equipment is obstructed, despite capacity being available. Since stacker reclaimers handle both importing and exporting, these processes can interfere with one another, particularly when a high volume of trains and vessels arrive simultaneously. This limits the availability of the stacker reclaimers and conveyor systems for each operational component.

In terminals where material blending is required, three stacker reclaimers are typically involved: two reclaiming materials of different qualities and one stacking the blended mix. By adjusting the reclaiming speeds, the desired material composition can be achieved. Processes like these further contribute to equipment unavailability due to blockages, making quantification difficult, as they do not directly generate productivity, typically measured in tons of material imported or exported by the terminal. Additionally, transfer terminals manage a wide range of materials with varying qualities and characteristics. Each pile in the stockyard is assigned both an owner and a destination, meaning that only a limited number of stacker reclaimers may be available to reach certain stockpiles. If these reclaimers are occupied with other tasks, loading operations must be paused.

Therefore, stockyard planning is crucial to ensuring operational efficiency, yet uncertainties in terminal activities pose ongoing challenges. Another logistical concern is the availability of the conveyor system. Even when stacker reclaimers are operational, an uninterrupted conveyor route is essential for continued loading and unloading operations.

These operations and stockyard scheduling are typically managed by planners who rely on experience and technical know-how. However, quantifying the flexibility and resilience of the internal logistics remains difficult, making it challenging to assess stockyard performance accurately. Even terminal operators often have limited data on time lost due to equipment blockages. (R. Slikkerveer, personal communication, May 16, 2025)

Operational time

Operational time represents the duration during which the unloaders are actively working. Within this period, productivity varies depending on the unloading stage, as previously seen in Figure 2.4. Additionally, material characteristics, such as type (coal or iron ore), stickiness, and moisture content, can significantly impact unloading efficiency.

Transit time

Transit time refers to the time the vessel takes to move through the access channel and moor or unmoor to the quay. Transit time starts when the vessel leaves the anchorage waiting area and moves towards the berth. This will vary between ports depending on the location of the waiting area, the length of the access channel, transit speed limits set by the pilots and/or port authority, and weather conditions during transit. This could include waiting for tides to transit the access channel.

Transit time also includes the time it takes for a ship to clear the berth and transit channel before the next ship can make its way in. Docking and undocking are considered exogenous events, as they are determined by the length of the access channel and do not reflect the terminal's operational performance (PIANC, 2018, p. 72).

Pre- and post-operational time

Pre-operational time is defined as the period between the mooring of the vessel and the commencement of unloading activities. Post-operational time refers to the duration between the completion of unloading and the vessel's departure. Processes typically carried out during these intervals include draught surveys and customs inspections. These timeframes are considered endogenous, as they depend on the terminal's protocols and operational organization.

Idle time

Idle time refers to the time the terminal is not engaged in any processes or events. A terminal needs idle time to ensure redundancy and flexibility for other processes. Otherwise, congestion and vessel waiting times will increase, which indicates the terminal is operating above its optimum capacity. This is further discussed in section 2.8.

The distribution of the time committed to these processes and events defines the effective use of the terminal. An overview can be seen in Figure 2.5. Available time, occupancy time, utilized time, and committed time are all fractions of the total calendar time. Occupancy refers to the time a vessel is moored along the quay. The utilized time is the time cranes are actively moving cargo in or out of the vessel.

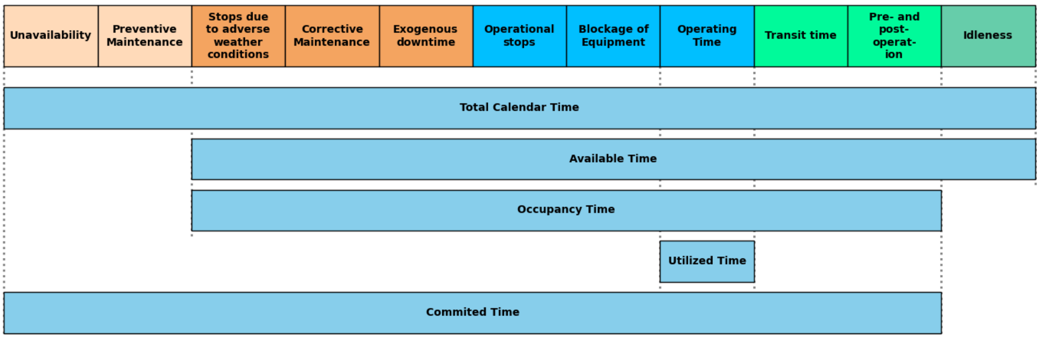


Figure 2.5: Berth commitment

With these different processes and events at the terminal in mind, the following performance indicators can be determined, as can be seen in Table 2.6. Idle time, unavailability, and preventative maintenance are fractions of total time (TT). Weather downtime, waiting for dockage/un-dockage, and pre- and post-operational time are calculated as an average per vessel call. Corrective maintenance, operational stops, blockage of equipment, and exogenous downtime are calculated as a fraction of operational time OT.

Indicator	Indicator name	Driver	Formula
$ID1_v$	Idle time (vessel)	Operational time	$\frac{IDL_v}{OT}$
$ID1_{nv}$	Idle time (no vessel)	Total time	$\frac{IDL_{nv}}{TT}$
$ID2$	Unavailability	Total time	$\frac{UNV}{TT}$
$ID3_v$	Preventive maintenance (vessel)	Operational time	$\frac{PM_v}{OT}$
$ID3_{nv}$	Preventive maintenance (no vessel)	Total time	$\frac{PM_{nv}}{TT}$
$ID4$	Weather downtime	Number of vessel calls	$\frac{WC}{\#Calls}$
$ID5_v$	Waiting for transit (vessel)	Number of vessel calls	$\frac{TR_v}{\#Calls}$
$ID5_{nv}$	Waiting for transit (no vessel)	Total time	$\frac{TR_{nv}}{TT}$
$ID6$	Pre- and post-operational time	Number of vessel calls	$\frac{PO}{\#Calls}$
$ID7$	Corrective maintenance	Operational time	$\frac{CM}{OT}$
$ID8$	Operational stops	Operational time	$\frac{OS}{OT}$
$ID9$	Blockage of equipment	Operational time	$\frac{BE}{OT}$
$ID10$	Exogenous downtime	Operational time	$\frac{ED}{OT}$

Table 2.6: Performance indicators for different terminal processes and events (Pinto et al., 2017)

2.4. Capacity factor & Overall Equipment Effectiveness

Equipment cannot operate at maximum capacity continuously. There will be periods when the equipment is completely idle, and even during operational times, it will experience inefficiencies. The capacity factor, as defined by (van Vianen et al., 2011), represents the ratio between the installed capacity and the minimum required capacity. The minimum required capacity refers to the theoretical equipment capacity if it were operating continuously (24 hours, 365 days a year) and without any losses during its operational time.

$$Capacity\ Factor = \frac{Installed\ Capacity}{Theoretical\ Minimal\ Required\ Capacity} \tag{2.1}$$

Determining the right capacity factors for the different terminal components is a big aspect of terminal design. Measured capacity factors by van Vianen et al. (2011) can be seen in Table 2.7 below. For import dry bulk terminals, 3 to 4.5 times more maximal unloading capacity is installed than what is used on average.

Unit	Import Terminals	Export Terminals
Seaside (un)loading	3 - 4.5	1.5 - 2.5
Stacking	5.5 - 9	3 - 4.5
Reclaiming	4 - 8	2 - 3
Hinterland (un)loading	2 - 5	1.1 - 3

Table 2.7: Capacity factors for equipment observed by van Vianen et al. (2011).

The capacity factor can serve as a good guideline for the initial stages of port planning. A capacity factor above the range indicated in Table 2.7 likely indicates a lack of performance. Which may result from operational inefficiencies, excessive downtime, or too many idle periods.

2.4.1. Overall Equipment Effectiveness

To further investigate the origin of operational inefficiencies, Overall Equipment Effectiveness (OEE) can be utilized. The OEE was introduced in 1971 by Seiichi Nakajima, who classified the inefficiencies of a factory and created this indicator to help monitor overall efficiency (Nakajima, 1988). OEE is typically used to measure a manufacturing system's performance. It splits performance into three separate parts:

$$OEE = \text{Availability} \times \text{Performance} \times \text{Quality} \tag{2.2}$$

Availability Availability represents the percentage of actual operating time relative to the planned operating time. Losses in this category are referred to as availability losses.

Performance Performance represents the percentage of actual process speed compared to the theoretical maximum speed. Losses in this category are referred to as speed losses.

Quality Quality represents the percentage of useful end product relative to the total product produced. Losses in this category are referred to as quality losses.

As shown by van Vianen et al. (2012), OEE can also be applied to the unloading process at a dry bulk terminal. The planned operational time is defined as any period during which at least one vessel is moored along the quay. Availability refers to the proportion of this time during which the cranes are operational. Performance is measured by the effective unloading rate in tons per hour, compared to the nominal rating of the equipment.

The quality factor is typically negligible in dry bulk unloading operations, since nearly all material unloaded from the vessel is used. Unlike in manufacturing, there is no rejection of end-products. However, terminals may experience minor losses due to spillage or, in rare cases, double handling. Double handling might occur when material is temporarily placed on the quay and then reloaded onto the conveyor. These instances are considered quality losses, but due to their infrequency, quality losses are generally assumed to be 0%.

Therefore, the OEE of a dry bulk crane can be simplified and described as the product of availability and performance as follows:

$$OEE = \text{Crane Utilization} \times \text{Crane Productivity} \tag{2.3}$$

A visual representation of the stacking of the different losses of the unloading operations is given below in Figure 2.6.

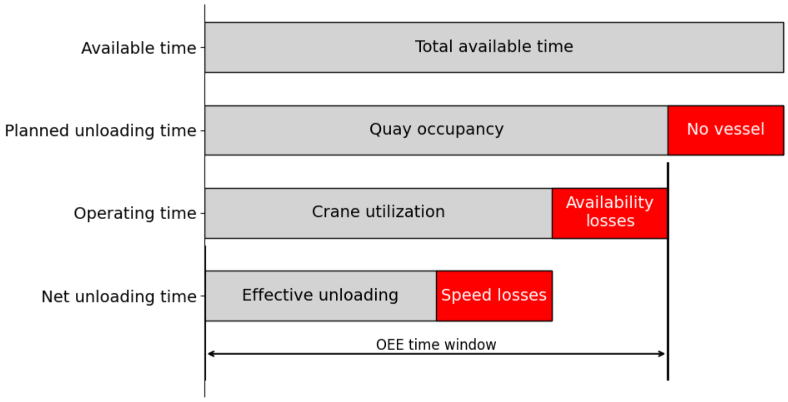


Figure 2.6: Overall Equipment Effectiveness losses (van Vianen et al., 2012)

Quay occupancy represents the fraction of time during which at least one vessel is present at the terminal. For continuous quays, multiple vessels may be moored simultaneously. Within the OEE framework, the presence of a single vessel is considered to provide planned operational time to all cranes at the terminal.

Crane utilization shows the percentage of time cranes are active during quay occupancy. Effective unloading time is the number of hours needed to reach the actual throughput if the crane worked at nominal capacity.

The OEE metric is effective for measuring unloading performance because it excludes periods when no vessel is present. During such times, cranes cannot operate regardless of their readiness, and including this time would distort the performance evaluation.

However, to assess berth commitment and how much of the total time is used, berth occupancy must be included as a loss. Berth commitment is defined as the total time minus the time cranes are idle.

$$\text{Berth Commitment} = \frac{TT - IDL_v - IDL_{nv}}{TT} \tag{2.4}$$

2.4.2. Crane productivity

Within the operational time, the unloaders achieve a certain productivity. Besides the ability of the crane operator, standard losses as the vessel empties occur, as previously seen in Figure 2.4.

Material properties directly affect unloader productivity. Factors such as density, stickiness, and moisture content influence how easily a material can be handled. The most significant difference is observed between iron ore and coal.

Iron ore has a higher density than coal. This requires the use of stronger and smaller grabs, which limits the amount of material moved per lift. Despite this, iron ore is unloaded more efficiently. As shown in Appendix D, 31.9% to 88.0% more tons of iron ore are unloaded per hour of service time compared to coal. Similarly van Vianen et al. (2012), reports slightly faster unloading rates for iron ore at Tata Steel.

At the Koper terminal in Slovenia, gantry cranes are rated for 1300 tons per hour for iron ore and 1000 tons per hour for coal (Port of Koper, 2021). The conveyor system at the same terminal can handle 2000 tons per hour of iron ore, but only 1600 tons per hour of coal. This is likely due to coal's lower density and higher volume, which increases the risk of overflow.

These differences in handling and equipment capacity mean that iron ore is typically unloaded at a higher rate than coal. When evaluating crane productivity, it is necessary to account for the distinct nominal ratings assigned to each material type.

Since the port operator has no direct influence over the cargo being handled, losses caused by hard-to-handle cargoes are exogenous. Therefore, crane productivity can be divided into two distinct performance indicators, as can be seen in Table 2.8 below. An exogenous material indicator and an endogenous performance indicator.

Indicator	Indicator name	Formula	Influence
$ID11$	Variation in effective rate	$\frac{ER}{NR_{CT}}$	Endogenous
$ID12$	Cargo type nominal rate variation	$\frac{NR_{CT}}{NR}$	Exogenous

Table 2.8: Performance indicators for crane productivity. Based on Pinto et al. (2017).

The parameters found in functions for the different performance indicators can be seen in Table 2.9 below. The effective rate (ER) is the achieved productivity per operational hour. The nominal rate variation per cargo type (NR_{CT}) is the nominal rate over the total operational time OT, relative to the cargo mix handled. Since coal and iron ore have different nominal rates, this needs to be accounted for. The nominal rate relative to the amount of operational time each cargo was handled then becomes:

$$NR_{CT} = \frac{OT_{coal} \times NR_{coal} + OT_{iron\ ore} \times NR_{iron\ ore}}{OT} \tag{2.5}$$

The mix of cargo received by the terminal is beyond the control of the terminal operator and is therefore considered exogenous. In contrast, the effective rate achieved is indicative of the terminal's unloading performance and is classified as endogenous.

Symbol	Parameter	Unit
ER	Effective Rate	ton/h
NR_{CT}	Nominal rate variation per cargo type	-
NR	Nominal rate for standard cargo	ton/h

Table 2.9: Crane productivity parameter definitions.

2.5. Benchmarking

For benchmarking the performance of different terminals or different months, exogenous indicators should be excluded from the OEE assessment. The OEE metrics of quay occupancy, crane utilization and crane productivity can be defined as functions of the performance indicators in Table 2.6 and Table 2.8.

2.5.1. Quay Occupancy

Quay occupancy can be expressed in the previously defined performance indicators as seen below:

$$Quay\ Occupancy = 1 - ID1_{nv} - ID2 - ID3_{nv} - ID5_{nv} \tag{2.6}$$

Since $ID1_{nv}$, $ID2$, $ID3_{nv}$, and $ID5_{nv}$ are all exogenous, quay occupancy is perceived as out of the control of the terminal operator. Quay occupancy is an effect of the wider global market and the provided service level of the terminal in the long term. It is not influenced by the short-term unloading performance of the terminal system.

2.5.2. Crane utilization

Crane utilization is the fraction of operational time (OT) within the quay occupied time (Pinto et al., 2017):

$$Crane\ Utilization = \frac{OT}{TT - IDL_{nv} - UNV - PM_{nv} - TR_{nv}} \tag{2.7}$$

Which is equal to:

$$Crane\ Utilization = \frac{OT}{OT + WC + CM + ED + PM_v + OS + BE + TR_v + PO + IDL_v} \tag{2.8}$$

And therefore can be expressed in the performance indicators as follows:

$$Crane\ Utilization = \frac{1}{\frac{\#Calls}{OT}(ID4 + ID5_v + ID6) + ID1_v + ID3_v + ID7 + ID8 + ID9 + ID10 + 1} \quad (2.9)$$

In which $\#Calls$ is the number of vessel calls. Which can be expressed in performance indicators $ID11$ and $ID12$ as follows:

$$\#Calls = \frac{THR}{LOAD} = \frac{OT \times NR \times ID11 \times ID12}{LOAD} \quad (2.10)$$

In which THR is the total throughput and $LOAD$ is the average vessel load. Therefore, crane utilization can be defined as:

$$Crane\ Utilization = \frac{1}{\frac{NR}{LOAD}(ID11 \times ID12) \times (ID4 + ID5_v + ID6) + ID1_v + ID3_v + ID7 + ID8 + ID9 + ID10 + 1} \quad (2.11)$$

2.5.3. Crane Productivity

Crane productivity is the ratio of effective rate ER and nominal rate NR and can be expressed in $ID11$ and $ID12$:

$$Crane\ productivity = \frac{ER}{NR} = ID11 \times ID12 \quad (2.12)$$

2.6. Port performance

By combining, Equation 2.11, and Equation 2.12, the OEE can be expressed in performance indicators as follows:

$$OEE = \frac{ID11 \times ID12}{\frac{NR}{LOAD}(ID11 \times ID12) \times (ID4 + ID5_v + ID6) + ID1_v + ID3_v + ID7 + ID8 + ID9 + ID10 + 1} \quad (2.13)$$

To neutralize the influence of exogenous influences, the performance indicators related to exogenous events should be replaced by average values of the sample. Such as over the entire year for one terminal, or the average value between different terminals. This way, an informative conclusion about the performance can be made. The new parameter $OEE_{benchmark}$ is then defined as:

$$OEE_{benchmark} = \frac{ID11 \times ID12_{avg}}{\frac{NR}{LOAD}(ID11 \times ID12_{avg}) \times (ID4_{avg} + ID5_{v-avg} + ID6)} \times \frac{ID11 \times ID12_{avg}}{ID1_{v-avg} + ID3_{v-avg} + ID7 + ID8 + ID9 + ID10_{avg} + 1} \quad (2.14)$$

2.7. Data requirements

To determine the unloading performance of a dry bulk terminal, data is required on its operation. The combination of this data can be used to determine quay occupancy, crane utilization, and crane productivity. Which, thereafter, can be used to determine the berth commitment, OEE, and $OEE_{benchmark}$. Data is required on the crane's time spent in the following states seen in Table 2.10.

Symbol	Parameter	Unit
TT	Total time	h
$IDL_{v/nv}$	Idle time	h
UNV	Unavailability	h
$PM_{v/nv}$	Preventive maintenance	h
WC	Stops due to adverse weather conditions	h
$TR_{v/nv}$	Transit time	h
PO	Pre- and post-operational time	h
CM	Corrective maintenance	h
OS	Operational stops	h
BE	Blockage of equipment	h
ED	Exogenous downtime	h
OT	Operational time	h
OT_{coal}	Operational time coal	h
$OT_{iron\ ore}$	Operational time iron ore	h
$LOAD$	Average vessel load	ton
ER	Effective rate	ton/h
NR_{coal}	Nominal rate coal	ton/h
$NR_{iron\ ore}$	Nominal rate iron ore	ton/h
NR	Nominal rate	ton/h
THR	Throughput	kiloton
$\#Calls$	Number of vessel calls	

Table 2.10: Times and processes used to determine the performance indicators.

2.7.1. Quay occupancy

Determining quay occupancy requires knowing when vessels arrive and depart from the terminal.

The data requirements for the quay occupancy can be seen in Table 2.11 below.

Parameter		Data requirement
Idle time	IDL	Vessel identity
Idle time	IDL	Vessel berth arrival time
Idle time	IDL	Vessel berth departure time
Unavailable time	UNV	Terminal unavailable hours
Preventive maintenance time	PM	Preventive maintenance hours

Table 2.11: Data requirements for performance indicators included in the quay occupancy formula.

2.7.2. Crane utilization

As seen in Equation 2.11, $ID4$ to $ID12$ and nominal rate NR and average vessel load $LOAD$ are required to determine the crane utilization. To determine $ID11$ and $ID12$, the effective rate ER, and operational time OT need to be determined. To determine the effective rate the cargo type, cargo direction

Therefore, the following data requirements can be established, as seen below in

Parameter		Data requirement
Weather downtime	WC	Hours with high wind (≥ 8 Bf)
Weather downtime	WC	Hours with low visibility
Weather downtime	WC	Hours with high waves (≥ 1 meter)
Transit time	TR	Vessel berth arrival time
Transit time	TR	Vessel berth departure time
Transit time	TR	Vessel departure from anchorage area time
Transit time	TR	Vessel entering/leaving access channel time
Pre- & post-operational time	PO	Pre-operational hours per vessel
Pre- & post-operational time	PO	Post-operational hours per vessel
Corrective maintenance time	CM	Corrective maintenance hours
Operational stop time	OS	Operational stop hours
Blockage of equipment time	BE	Blockage of equipment hours
Exogenous downtime	ED	Exogenous downtime hours
	NR	Nominal rating of equipment
	NR	Number of unloaders
	NR_{coal}	Nominal rate coal
	$NR_{iron\ ore}$	Nominal rate iron ore
	$LOAD$	Average vessel load
Number of vessel calls	$\#Calls$	Number of vessel calls
Operational time coal/iron ore	OT_{coal} & $OT_{ironore}$	Vessel cargo type
Effective rate, throughput	ER, THR	Vessel cargo direction
Effective rate, throughput	ER, THR	Vessel DWT
Operational time	OT	Max number of cranes operating per vessel

Table 2.12: Data requirements for performance indicators included in crane utilization.

2.7.3. Crane productivity

Crane productivity is determined from $ID11$ and $ID12$. The performance indicators require the following parameters: NR, ER, NR_{coal}, $NR_{iron\ ore}$, OT_{coal}, $OT_{ironore}$. The data requirements for these parameters are already discussed in Table 2.12.

2.8. Port capacity planning

During port planning, expected berth commitment is used to determine a port's capacity. First, an estimation is made for the time spent on all the different processes seen in Figure 2.5. Based on the operational environment in which the terminal operates, a maximal berth commitment is determined, as can be seen in Table 2.13. When the required throughput is known from market analysis, the terminal can be designed to handle this throughput in the expected operational time. For example, the number of unloaders and their capacity can be determined. When operational, good port performance should result in obtaining the anticipated throughput.

Berth commitment is defined as the total time, excluding idle time:

$$Berth\ Commitment = TT - IDL_v - IDL_{nv} \tag{2.15}$$

Berth Commitment Thresholds	Conditions (one or more apply)
75%	- Single berth terminal, with high variability on ship arrivals and service times - Single berth with limited advanced notice on product demands, such as in the case of a multi-user or multi-cargo public berth at a public terminal - High weather downtime
85%	- Single berth terminal with more controlled ship arrival patterns and advanced warning regarding product demands and supply, such as in the case of a single product or privately owned terminal - Dual berth and/or dual shiploader terminal where one berth can be used as a lay-by-berth and the second shiploader can provide redundancy
90%	- Multi-berth terminal where the product owner has extended control over the logistics chain from the production source(s) to the final customer, such as in the case of mining companies that act as rail operators, terminal operators, and shippers.

Table 2.13: Berth Commitment Thresholds vs. Conditions (PIANC, 2018, p. 75)

The following unloading capacities can be distinguished (Ligteringen, 2022, p. 148):

- Maximum instantaneous capacity
- Maximum annual capacity
- Optimum annual capacity

Maximum instantaneous capacity refers to the peak or rated output of equipment or the entire terminal system, but this level cannot be maintained over extended periods. While maximal annual capacity can be sustained longer, it often leads to long vessel waiting times, high operational pressure, and reduced economic efficiency. The optimum annual capacity represents the ideal balance between performance and sustainability, and it is the level a terminal should be designed for. As a result, good port performance does not mean achieving the highest possible throughput, but rather operating efficiently within optimal capacity limits.

The following methods for determining capacity, with increasing level of detail: (Ligteringen, 2022, p. 150):

1. An estimate using capacity factors. Empirical values of tonne cargo per m quay length, or per m2 storage area.
2. A calculation of the berth productivity/storage capacity taking into account the specific type of handling equipment and their numbers, but estimated occupancy values.
3. A detailed calculation as per (2), but also accounting for variations in arrival- and service times of vessels and applying queuing theory or simulation models to determine the proper quay length and storage area.

Capacity is determined by the berth commitment, which reflects the total time vessels occupy the berth due to various operational events, as outlined in Table 2.3. These events are influenced by both exogenous and endogenous factors. Exogenous factors, such as weather or tidal conditions, are outside the terminal's control, while endogenous factors, like crane allocation or internal logistics, are manageable. Effective control over endogenous events indicates strong port performance. In that case, the terminal should be able to achieve its target capacity and operate in line with the envisioned berth commitment.

2.9. Conclusion

Terminals are composed of berths, loading and unloading equipment, storage facilities, stacker/reclaimers, conveyor systems, and auxiliary machinery. Terminals interact with vessels, barges, trains, or trucks to move material in and out of the system.

Operations or states at a terminal can be categorized into unscheduled downtime (e.g., equipment breakdown or weather delays), scheduled downtime (e.g., maintenance and shift changes), operational time (active handling of cargo), set time (e.g., mooring and equipment setup), and idle time. The distribution of time among these processes defines terminal utilization. Higher berth productivity depends on minimizing downtime and improving operational efficiency.

Productivity is the most important performance indicator of a dry bulk terminal and plays a central role in assessing terminal unloading performance. It is determined by the nominal capacity, utilization, and efficiency of the system's components.

Overall Equipment Effectiveness (OEE) is introduced as a method to quantify performance by combining crane utilization and crane productivity. This metric can be expressed in performance indicators defined by both external (exogenous) and operator-controlled (endogenous) factors. By averaging out the influence of exogenous conditions, $OEE_{benchmark}$ can be calculated. This enables meaningful benchmarking across different months or terminals, even when external conditions vary.

An overview of the data required to calculate the performance indicators included in OEE is presented in Table 2.14 below. This chapter, therefore, establishes the foundation for using open data to evaluate the unloading performance of dry bulk terminals.

Parameter		Data requirement
Idle time	IDL	Vessel identity
Idle time, transit time	IDL, TR	Vessel berth arrival time
Idle time, transit time	IDL, TR	Vessel berth departure time
Unavailable time	UNV	Terminal unavailable hours
Preventive maintenance time	PM	Preventive maintenance hours
Weather downtime	WC	Hours with high wind (≥ 8 Bf)
Weather downtime	WC	Hours with low visibility
Weather downtime	WC	Hours with high waves (≥ 1 meter)
Idle time	IDL	Vessel departure from anchorage area time
Idle time	IDL	Vessel entering/leaving access channel time
Pre- & post-operational time	PO	Pre-operational hours per vessel
Pre- & post-operational time	PO	Post-operational hours per vessel
Corrective maintenance time	CM	Corrective maintenance hours
Operational stop time	OS	Operational stop hours
Blockage of equipment time	BE	Blockage of equipment hours
Exogenous downtime	ED	Exogenous downtime hours
	NR	Nominal rating of equipment
	NR	Number of unloaders
	NR_{coal}	Nominal rate coal
	$NR_{iron\ ore}$	Nominal rate iron ore
	$LOAD$	Average vessel load
Number of vessel calls	$\#Calls$	Number of vessel calls
Operational time coal/iron ore	OT_{coal} & $OT_{ironore}$	Vessel cargo type
Effective rate, throughput	ER, THR	Vessel cargo direction
Effective rate, throughput	ER, THR	Vessel DWT
Operational time	OT	Max number of cranes operating per vessel

Table 2.14: Data requirements for performance indicators included in OEE estimation.

3
Open Data Sources

Chapter Sub-question: 2. Which open-data sources are available for terminal operations, and what limitations arise from data gaps?

In this chapter, the available open data sources for assessing dry bulk handling performance are explored. Open data refers to data that is freely available for access and use. It allows for assessing the port's performance without the compliance of the terminal operator. The research mostly makes use of Sea-web data and aerial images.

3.1. Required data

The data requirements outlined in the previous chapter must be retrieved as accurately as possible using open data sources. Due to limitations inherent to open data, certain information will be unavailable. As a result, applying standard values from literature or relying on estimations and assumptions becomes necessary. Moreover, open data sources may be affected by gaps or inaccuracies.

Open data is explored from Sea-web, the Haskoning AIS platform, Google Earth, literature, and publicly available web resources. Sea-web is a database developed by S&P Global that utilizes AIS data to provide details on vessel movements and characteristics. The Haskoning AIS platform also uses AIS data, but it outputs raw datapoints, which increases the complexity of data processing due to the added time and computing power required. However, this approach offers greater flexibility when analyzing vessel trajectories.

Google Earth serves as an open source of aerial imagery, enabling the examination of terminal layouts across multiple years. Literature is employed to estimate unknown aspects of the terminal's internal operations. Public web resources include websites, databases, and informal sources that provide additional information, such as weather conditions or specific terminal characteristics.

An overview of the required data and its corresponding possible sources is presented below in Table 3.1, with each source rated according to its data quality. Following this, Sea-web and aerial imagery are examined in more detail in section 3.2 and section 3.3, respectively.

Required data	Sea-web	AIS platform	Google Earth	Literature	Public web resources
Vessel identity	++	++			
Vessel berth arrival time	++	++			
Vessel berth departure time	++	++			
Terminal unavailable hours				-	-
Preventive maintenance hours				+	
Hours with high wind (≥ 8 Bf)				+	++
Hours with low visibility				+	++
Hours with high waves (≥ 1 meter)				+	++
Vessel departure from anchorage area time	+	-			
Vessel entering/leaving access channel time		+		-	
Pre-operational hours per vessel				+	
Post-operational hours per vessel				+	
Corrective maintenance hours				-	
Operational stop hours				-	-
Blockage of equipment hours				- -	
Exogenous downtime hours				-	-
Nominal rating of equipment				-	-
Number of unloaders			+		
Nominal rate coal				-	
Nominal rate iron ore				-	
Average vessel load				+	
Number of vessel calls	++	++			
Vessel cargo type					-
Vessel cargo direction	++	+			
Vessel DWT	++				++
Maximum number of cranes operating per vessel			+	+	

Data quality				
++	+	-	- -	
Very good	Good	Poor	Very poor	No data

Table 3.1: Required data and its possible open data sources. The quality of the data sources reflects the presence of data gaps, the reliability of the information, and the accuracy of the data.

Vessel identity

Most parameters are determined per vessel, so it is essential to link the different data points using the MMSI number. Both Sea-web and AIS data from the AIS platform include an MMSI number, which allows for consistent identification and integration of vessel-specific information across datasets.

Vessel departure from waiting/anchorage area time

Sea-web provides arrival and departure times from the anchorage area, which can be used to estimate the time a vessel spends moving through the access channel. During this transit, the vessel is already effectively claiming the berth it is approaching. In theory, the AIS platform could offer the same insight by defining a polygon over the anchorage area. However, anchorage zones are often extensive, and the AIS platform does not perform efficiently when processing such large polygons, making this approach impractical for timely analysis.

Vessel leaving access channel time

Sea-web does not provide information on when a vessel exits the access channel, as it only records arrival and departure times at the anchorage area, and vessels typically do not return there after unloading. However, since the access channel is relatively narrow, it is feasible to define a polygon at its mouth using the AIS platform. This allows the moment a vessel leaves the access channel to be determined based on AIS data.

Terminal unavailable hours

Unavailable time refers to periods when a vessel is unable to moor due to external factors, such as a closed access channel. These instances typically represent a minimal portion of total time and can be neglected in most analyses. However, if publicly available web sources report that the terminal has been unavailable for longer periods of time, this should be incorporated into the assessment.

Preventive maintenance hours

Preventive maintenance refers to scheduled periods of equipment downtime intended for upkeep. This typically includes an extended annual maintenance window, supplemented by smaller maintenance activities distributed throughout the year. The exact timing of these events cannot be identified from open data sources. However, estimates derived from literature are considered reliable, as maintenance durations often follow manufacturer recommendations or regulatory requirements.

In certain cases, opportunistic unscheduled maintenance may be performed when the terminal becomes unexpectedly idle. These activities fall under corrective maintenance and would reduce the preventive maintenance hours, as some maintenance tasks are completed outside the planned schedule.

Weather data

To determine the number of hours with high wind (≥ 8 Bf), low visibility, and high waves (≥ 1 meter), publicly available web resources or literature can be used. Various open-access weather data platforms provide historical data, which makes it possible to identify the specific moments when these weather conditions occur. A simplified approach is to use typical yearly lost hours due to weather conditions as reported in the literature. These values tend to show limited variation over longer time periods and can provide a reasonable estimate for long-term performance assessments.

Vessel berth arrival & departure time

Sea-web provides vessel arrival and departure times, while the AIS platform offers location-based data points around a berth. However, to extract actual arrival and departure times from AIS data, the vessel's speed and position must be analyzed. Since Sea-web and the AIS platform demonstrate similar performance, as shown in Appendix C, Sea-web offers a more efficient workflow for this purpose. Its arrival and departure times are accurate to within one minute, which is considered sufficient for the analysis.

Pre- and post-operational hours per vessel

Since open data does not provide insight into the internal operations of the terminal, there is limited information available on the duration of pre- and post-operational activities. As a result, standard values from literature can be applied. These procedures are expected to have relatively consistent durations, as they typically involve routine tasks such as paperwork, draught surveys, and the review and approval of the unloading plan.

Corrective maintenance hours

The time between equipment failures and the duration of repairs is uncertain. Open data sources do not offer sufficient detail to identify the exact timing or frequency of corrective maintenance. Therefore, to estimate the time lost due to these events, standardized values from the literature must be used.

However, since the layout of the terminal can be observed using aerial imagery, the vulnerability of the unloading system can be assessed. Terminals with limited availability of critical components—such as stacker/reclaimers, unloaders, or conveyors—are more susceptible to corrective maintenance downtime. A simplified model based on equipment redundancy and layout can help estimate this risk and provide a more informed approximation of expected delays.

Operational stop hours

Operational stops refer to routine operational activities such as changing grabs and repositioning cranes between cargo holds. The duration of these stops typically shows limited variation due to the standardized nature of the procedures involved.

However, the total duration is influenced by the number of cargo holds on a vessel. Since this number can be retrieved from web sources or platforms like Sea-web, a more refined estimation of operational stop duration becomes possible by scaling these activities per cargo hold. This vessel-specific approach improves accuracy in estimating operational stop time.

Blockage of equipment hours

The internal logistics of the terminal determine the time lost due to equipment blockage. Since the terminal layout is known, it is possible to develop a basic model to estimate equipment blockage losses. These estimates can be further refined if train and barge arrival times are available, as they significantly affect the timing and coordination of cargo flow.

However, this approach remains an estimation. Several factors that contribute to equipment blockage—such as specific client requirements, blending operations, or contractual deadlines, are typically unknown and cannot be captured through open data. For this reason, using standard values reported in literature or gathered through personal communication with terminal operators offers a practical alternative for assessing time lost due to equipment blockage.

Exogenous downtime hours

Exogenous downtimes, such as power outages, are infrequent and may therefore be excluded from the assessment. However, if publicly available online sources report incidents, such as power outage, at the terminal, these should be considered.

Nominal rating of equipment

The nominal rating, also referred to as the free digging rate, of unloading equipment is typically not publicly available, and there is often no clear consensus on its exact value. Equipment suppliers tend to overstate nominal ratings, which adds to the uncertainty (Frankel et al., 1985, p. 135). However, an estimate can be made by combining information from multiple online sources. To make valuable benchmarks between terminals, a standard definition of the nominal rating of equipment is required.

The nominal rate refers to the maximal sustainable load handled under ideal conditions. While this value is typically known from experience by terminal operators, it can be approximated by calculating productivity based on the single lift load. Using a grab-to-lift ratio of one-third (i.e. the grab weight is one-third of the total lifted weight), and assuming a minimal cycle time of one minute, a reasonable estimate of the crane's nominal rate can be derived (Haoyo Machinery, 2025).

The single lift capacity of unloaders is often listed on the terminal's website or other publicly accessible web sources.

Number of unloaders

The number of unloaders can be identified using aerial imagery, such as satellite views from platforms like Google Earth. However, it should be noted that this method introduces several uncertainties. It does not confirm whether the observed equipment is operational or currently out of service. Additionally, some machinery may be designated for specific cargo types or may have restricted mobility—factors that cannot be assessed from aerial images alone. Moreover, certain unloaders, such as floating cranes, may not be visible if they were not present at the terminal at the time the imagery was captured.

Nominal rate coal & iron ore

The difference in nominal rate between coal and iron ore can be estimated using values found in literature. Generally, iron ore is unloaded at a higher rate than coal. The nominal or free digging rate is influenced by various equipment and material characteristics. Iron ore, being denser than coal, requires more reinforced and smaller grabs. For coal, volume is typically the limiting factor, whereas for iron ore, the constraint is weight. As a result, coal grabs tend to be larger and heavier. According to manufacturers such as Haoyo Machinery (2025), coal grabs represent approximately 40% of the total lifting weight, while iron ore grabs account for around 34%. Due to the higher density of iron ore, vessels with equivalent DWT are smaller compared to those carrying coal, which leads to shorter crane movements and reduced cycle times.

Average vessel load

The deadweight tonnage (DWT) of a vessel, which represents its total carrying capacity, can be obtained from Sea-web or other publicly available sources. The parcel size refers to the actual tonnage of cargo delivered to the terminal. For estimation, a DWT utilization rate of 90% for cargo is assumed, based on literature values. For example, Adland et al. (2018) found an average capacity utilization of 92% for iron ore carriers departing from Brazil. Although some vessels may discharge only part of their cargo at the terminal and continue to other ports, such partial deliveries cannot be reliably identified from open data and are therefore excluded from the analysis due to their infrequent occurrence.

Number of vessel calls

If vessel arrival and departure times are known through either Sea-web or the AIS platform, the number of vessel calls can be determined.

Vessel cargo type

Whether a vessel is carrying iron ore or coal is typically not publicly disclosed. However, an estimate can be made based on the vessel's previous port of call. Most export-oriented ports specialize in either coal or iron ore exports. The primary cargo type associated with a port can be identified using publicly available sources such as https://www.gem.wiki/ or other websites. Alternatively, aerial images of the port can be examined for coal or iron ore stockpiles. Based on this information, a vessel departing from such a port can be classified as either coal-importing, iron ore-importing, or unknown if the port's export activities are not clearly defined.

Vessel cargo direction

To determine the effective operating rate of unloading equipment, it is crucial to assess whether a vessel is importing, exporting, or not engaged in cargo transfer. This can be established by analyzing changes in draught along with the vessel's previous and next ports of call. Draught variation data is available through both Sea-web and the AIS platform, with Sea-web offering more detail. Additionally, Sea-web provides historic vessel voyage information, which is not accessible through the AIS platform. The method used to classify cargo direction—import, export, or none, is further detailed in Appendix E.

Vessel DWT

To estimate the parcel size of a vessel, and thereby the average vessel load ($LOAD$), the DWT must be known. This information can be retrieved from Sea-web or other publicly accessible web resources that provide basic vessel specifications, provided the vessel's MMSI number is available for reference.

Maximum number of cranes operating per vessel

It is important to know how many cranes are operating in relation to the number of vessels at the terminal. To do this, the maximum number of cranes that can work on one vessel must be defined. Literature shows that dry bulk vessels are usually unloaded by two cranes. This allows for maintaining vessel balance and a steady flow of material onto the conveyor system.

Aerial images from Google Earth help identify how cranes are used at different terminals. Since images from different years are available, multiple operational situations can be observed. In some cases, three cranes are seen unloading the same vessel. This is only possible for larger vessels with enough cargo holds.

For this research, the maximum number of cranes per vessel is set at two. For terminals where three cranes are seen working on one vessel, the limit is set at three, but only for vessels with a deadweight tonnage (DWT) above 100,000. These are capesize vessels or larger, which typically have nine cargo holds.

3.2. Sea-web & AIS data

Since 2004, vessels over 300 Gross Tonnage have been required to be equipped with an Automatic Identification System (AIS) (De Boer, 2010). It automatically and periodically transmits the vessel's position. The main goal is to improve maritime safety. This data is publicly available and a great data resource for researchers. The positional data of the vessels is transmitted automatically from the vessel's navigational instruments and is therefore reliable. AIS also includes voyage information such as destination, estimated arrival time, draught, and navigational status. These are changed manually by the crew of the vessel and are, therefore, much more prone to error.

AIS data is retrieved via an AIS platform developed by Haskoning. The AIS data utilized on the Haskoning-developed platform is sourced from publicly available AIS data via AIShub, which provides coverage from approximately 700 stations worldwide. Figure 3.1 shows the global AIS coverage as of April 2025. Europe, the East Coast of the United States, and China exhibit the highest coverage. Consequently, the research prioritizes terminals located within these regions.

AISHub works on a reciprocal data exchange system. This means AISHub provides data of all 700 stations, given that one operates at least one station and provides its information in exchange. Haskoning has operated one antenna in Scheveningen since December 2018 and consequently has had AIS data availability since April 2019. Therefore, the is no AIS data available from before this period (den Brave, 2023).

The AIS platform developed by Haskoning enables effective filtering of data supplied by AISHub. The platform gives the ability to define a polygon on the map and specify a time window, facilitating the analysis of all vessel movements within the designated area. This serves as an initial step in processing AIS data to evaluate vessel movements and service times.

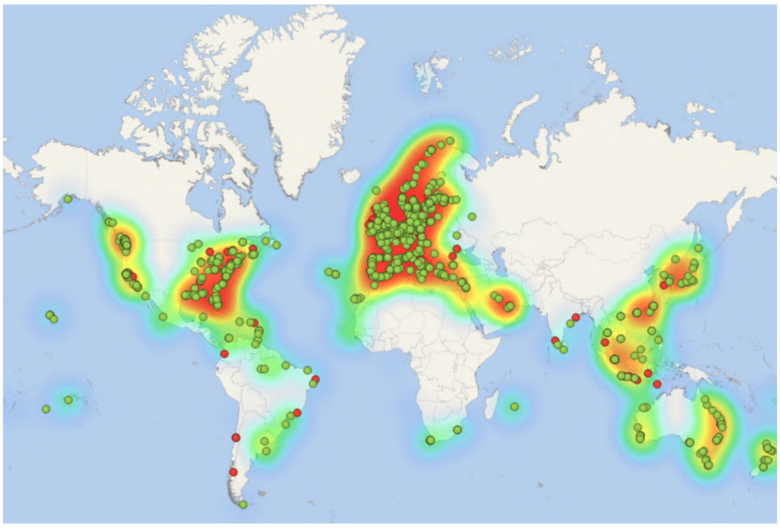


Figure 3.1: Coverage of AIS data (AISHub, 2025)

In addition to vessel location, AIS data provides various other types of information. While the positional data is highly reliable, certain other details may be incomplete or inaccurate (De Boer, 2010). Dynamic data on vessel movements is transmitted automatically, ensuring consistency. However, draught is manually logged by the crew onboard. This manual entry process introduces potential inaccuracies. A detailed overview of the data fields is provided below (den Brave, 2023).

Static Data

- MMSI Number: A unique 9-digit Maritime Mobile Service Identity number
- Vessel Call Sign: Unique sequence of letters and numbers
- IMO Number: International Maritime Organization number
- Vessel Name
- Vessel Length
- Vessel width
- Vessel type

Dynamic Data

- Vessel position
- Timestamp: Time and date of data point
- Course over ground: Direction of movement of the vessel
- Speed over ground
- Heading: Direction of the bow of the vessel
- Draught: Depth of the vessel in the water (manual input)

3.2.1. Limitations of AIS data

All vessels equipped with an AIS unit are also fitted with a Global Navigation Satellite System (GNSS), relying on GPS for location tracking. Latitude and longitude data can theoretically achieve precision up to 1/10,000 of a minute, equivalent to 0.18 meters. However, the accuracy of transmitted data depends on the quality of onboard sensors, and due to inherent GPS limitations, the IMO considers an accuracy of 10 meters for latitude and longitude to be representative (van Zwieteren, 2020).

Vessels may switch off their AIS transmitters, particularly in regions prone to piracy or when involved in illegal activities. However, in the studied area of Northwestern Europe, such issues are not prevalent, and it can be assumed that all large vessels reliably transmit AIS data.

Research by den Brave (2023) showed some data fields remain empty in AIS messages. While MMSI number and vessel position are reliably available, other data fields such as gross tonnage, net weight tonnage, TEU capacity, length overall, and vessel type are often missing. Using the MMSI number, the vessel type, vessel length, and gross tonnage can still be collected from other internet sources since this is static information.

3.2.2. Sea-web

Sea-web, offered by S&P Global, is a maritime intelligence platform designed for tracking and analyzing global vessel movements and port activities based on AIS data (S&P Global, 2025). Sea-web performs the first step in the processing of AIS data.

Raw AIS data consists of unstructured, timestamped positional data points. Vessel tracks and service times still need to be extracted from this information. Therefore, AIS data still requires processing to associate movements with individual vessels. Sea-web addresses this by linking AIS signals to vessel identities, performing the crucial first step in the processing of data. Sea-web allows construction of port call list, with every vessel that visited a certain terminal within a certain timeframe. For individual vessels, it can also show the travel history and information on the vessel's DWT and dimensions.

Moreover, Sea-web provides insights into which berth in the terminal a vessel visits, the arrival and departure times, and the draught changes during port visits.

The data is based on AIS information collected by S&P Global. By structuring and processing AIS data efficiently, Sea-web enables faster and more detailed insights. For example, vessel travel history is determined by analyzing historical AIS records of every port globally. And thereafter, trace the route of every vessel. Therefore, Sea-web streamlines the research by handling large-scale data processing, which otherwise would require significant computational resources.

Sea-web was found to be accurate in providing arrival times, departure times and draught changes of vessels. For allocating which berth was visited, AIS data from the Haskoning AIS-platform proved more reliable. A detailed analysis of the accuracy of Sea-web data can be found in Appendix C.

3.3. Aerial Imaging

Nowadays, global satellite and aerial images are widely available. This can provide insight into the terminal layout. From aerial images, berth locations, quay lengths, stockyards, and cranes can be identified (Vianen, 2015).

While a single satellite image can already provide reliable estimations of stockyard sizes and quay lengths, using images from multiple years allows for analysis of the operation of equipment. As can be seen in Figure 3.2, HBTR seems to operate four berths along the continuous quay at the Mississippihaven. Also, no more than two cranes can be seen operational on one vessel at the same time. It can also be seen that the cranes are movable along the entire quay. Furthermore, multiple vessels are handled simultaneously, as can be seen for September 2016 or March 2020, confirming that the supporting conveyor system can handle this capacity. Although limited, the combination of these images gives an insight into the operational procedures of the dry bulk terminal.

Figure 3.2: Aerial Images from HBTR from different years (Google Earth, 2025)

It can also be seen that the aerial images from August 2014 and November 2015 are the same. This is caused by the method used by Google Earth to stitch images together. The image appears different in the top right corner. However, for the purposes of this research, inaccuracies regarding the exact dates of the images or the occurrence of duplicate images do not pose any issues.

Another consideration is the changes in terminal layout or procedures over the years. For HBTR there seem to be no changes in the number of operated cranes. However, these images do not provide information on used grabs, auxiliary equipment, or changes in operational policies. This should be taken into account when analyzing images that are several years old.

3.3.1. Image Recognition

To speed up the analysis of multiple images and terminals, image recognition technology can be used. This could recognize cranes and assess the number available at every berth automatically. This is done using the YOLOv8 object detection model, which is trained on aerial images of gantry cranes.

YOLOv8

YOLOv8 is a pre-trained deep learning model based on a convolutional neural network (CNN) architecture. It is very fast and accurate in object detection. Where image classification only recognizes what is in the image, object detection also specifies the location of the object. This makes YOLOv8 a versatile tool for analyzing images, capable of identifying and categorizing objects efficiently. Pre-training refers to the model being trained on large datasets beforehand, allowing it to quickly adapt to specific use cases with minimal additional training.

Training Process

To train the YOLOv8 model, labeled data is required for recognizing cranes and vessels. While manual labeling is time-consuming, existing datasets provide a valuable foundation for training.

For crane recognition, a dataset with 314 images featuring multiple cranes is used as a starting point, classifying them as either ”crane,” ”gantry_crane,” or ”standby_gantry_crane” (Miyazaki, 2022). These images have a resolution scale of 0.5 meters per pixel and dimensions of approximately 645 × 1114 pixels, both portrait and landscape orientations. Since non-gantry cranes are not relevant to dry bulk terminals, the ”crane” class is removed, and the remaining classifications are merged. This improves detection accuracy by focusing only on gantry cranes while disregarding their operational status. The primary goal is to estimate the total number of cranes at the terminal.

While the dataset mainly consists of container gantry cranes, dry bulk gantry cranes share similar structural characteristics. To further enhance accuracy, additional images were collected manually. A total of 26 images, featuring 53 cranes from bulk terminals, were gathered via Google Earth from locations such as Eemshaven (Netherlands), Dunkirk (France), and Gijón (Spain). These images were manually labeled and integrated into the dataset, contributing to 9.7% of the total data.

3.3.2. Data Augmentation

Data augmentation can be used to further increase the size of the dataset. Given the model’s application to aerial imagery, orientation adjustments were introduced to prevent directional bias in crane detection. Each image was rotated by 90°, 180°, and 270°, and flipped both horizontally and vertically, increasing the dataset size fivefold. An example can be seen in Figure 3.3. The resulting size of the dataset can be seen below in Table 3.2.

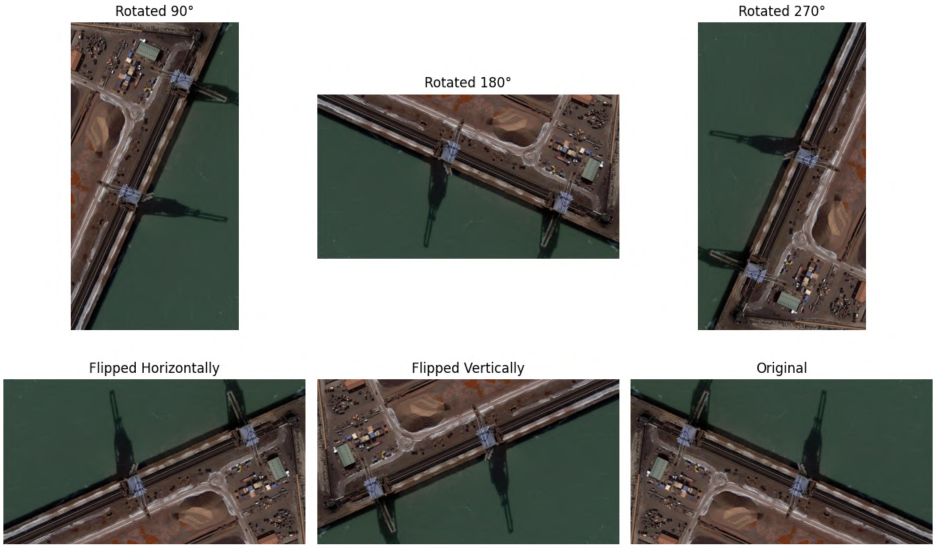


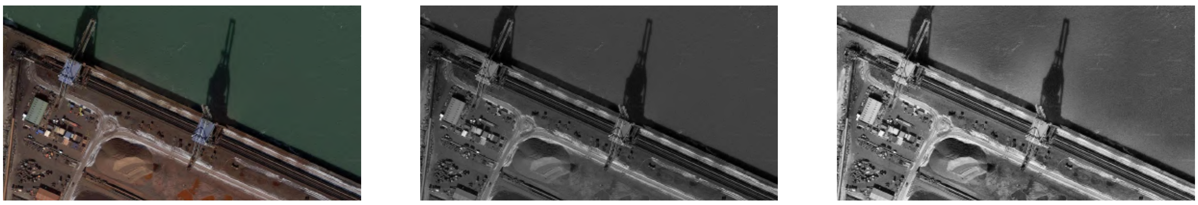
Figure 3.3: The different transformations applied on the dataset

	Training dataset	Validation dataset
Images	1294	322
Cranes	3967	1386
Average cranes per image	3.07	4.30

Table 3.2: Number of cranes and images of the complete dataset

Lighting conditions vary significantly across aerial images, so additional preprocessing was applied to enhance model accuracy. First, all images were converted to grayscale, as color holds little relevance for crane detection, while structural edges are critical. Training the YOLOv8 model on grayscale images ensures better focus on shape recognition.

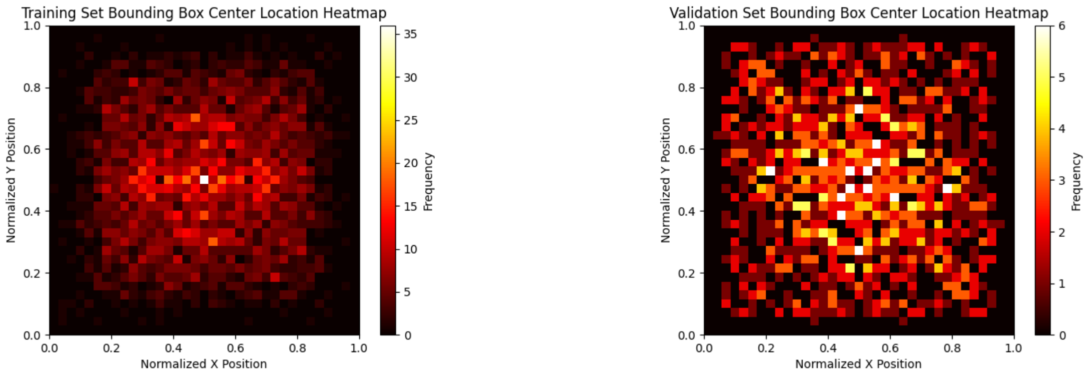
Furthermore, contrast enhancement was applied dynamically using Contrast Limited Adaptive Histogram Equalization (CLAHE). Unlike global contrast adjustments, CLAHE enhances contrast locally, reducing sensitivity to lighting conditions while minimizing noise amplification. The result of these alterations can be seen in Figure 3.4.



(a) The original image. **(b)** The grayscale image. **(c)** The high contrast image.

Figure 3.4: The alterations made to the images in the dataset.

To further evaluate dataset quality, the average positions of the center location of the bounding boxes are plotted below in Figure 3.5. The peak at the exact center is a result of the manually added extra images, since these were centered around the first manually drawn bounding box automatically.

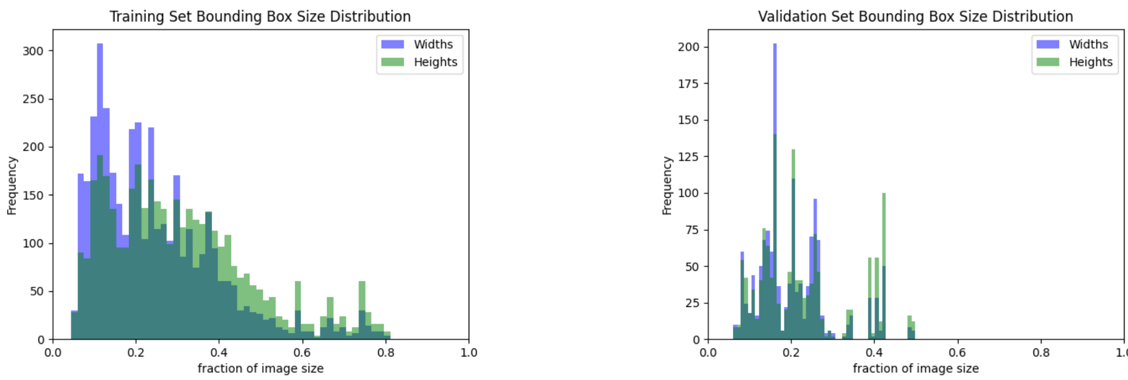


(a) The heatmap of the center location of the bounding boxes in the training dataset.

(b) The heatmap of the center location of the bounding boxes in the validation dataset.

Figure 3.5: The heatmap of the center location of the bounding boxes.

The length and width distribution of bounding boxes in the dataset are plotted in Figure 3.6. Given that cranes typically have an elongated structure and are similar in size, a wider bounding box suggests that the crane is captured at an angle rather than fully horizontal or vertical.



(a) The size distribution of the training dataset

(b) The size distribution of the validation dataset

Figure 3.6: The sizes of bounding boxes of cranes in the data set

3.3.3. Hyperparameter tuning

The model undergoes training over multiple epochs, where each epoch represents a complete cycle through the training dataset, forward and backward, within the learning algorithm. During these iterations, the model continuously adjusts its internal parameters, refining predictions based on observed errors or loss values. Multiple epochs are necessary for the model to gradually converge to the best possible performance.

Throughout training, the model is influenced by various hyperparameters, including batch size, dropout rate, L2 regularization, and layer freezing. The batch size determines the number of instances processed simultaneously. Larger batch sizes offer stability, while smaller batch sizes enhance flexibility. To prevent overfitting, some neurons are deliberately disabled during training. Overfitting occurs when a model memorizes training data instead of identifying underlying patterns. The dropout rate specifies the percentage of neurons excluded in each epoch, ensuring the model does not overly depend on particular neurons. The L2 regularization parameter introduces a penalty for large weights. A higher value promotes weight minimization for better generalization, whereas a lower value allows greater flexibility but increases overfitting risk. Additionally, the freeze parameter controls the number of layers frozen during training. Since the YOLO model is pre-trained for object detection, freezing early layers while fine-tuning later ones may be beneficial.

To assess model accuracy, the F1-score is employed. This metric balances precision and recall, both of which are crucial for determining the number of cranes in a dry bulk terminal. Precision measures the fraction of correctly identified objects among all predicted instances, while recall quantifies the proportion of actual objects successfully detected. The F1-score is computed as follows:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3.1}$$

The training process is optimized using Optuna, an automated hyperparameter tuning framework that efficiently explores parameter combinations. In each trial, a set of hyperparameters is selected and tested over several epochs. The number of epochs is kept low to keep computational time low. But a few epochs are required to allow the model to show its potential performance. The F1-score of each trial is evaluated to measure accuracy. Across different trials, Optuna systematically adjusts hyperparameters, streamlining the selection process.

For this research, the model was trained over 20 trials, with each trial spanning five epochs. This resulted in a final F1-score of 0.899, with the optimal hyperparameters detailed in Table 3.3.

Hyperparameter	**Value**
Batch size	24
Dropout	0.2855666303220892
l2 regularization	2.6975704234084122e-05
freeze	5

Table 3.3: Hyperparameters found during the Optuna study

3.3.4. Performance

With these optimized hyperparameters, the model was trained over 100 epochs, providing the F1 curve shown in Figure 3.7. The high F1-score at low confidence levels suggests strong overall performance. However, signs of overfitting may be present, as the model's performance on new data did not fully align with the expectations set by the F1 curve.

This difference in performance could be attributed to variations in the dataset, particularly the inclusion of satellite images from sources other than Google Earth. Differences in resolution, lighting conditions, and imaging characteristics across sources may have affected the model's ability to generalize effectively. Further adjustments, such as additional data normalization or expanding the training dataset with more diverse imagery, could help improve robustness.

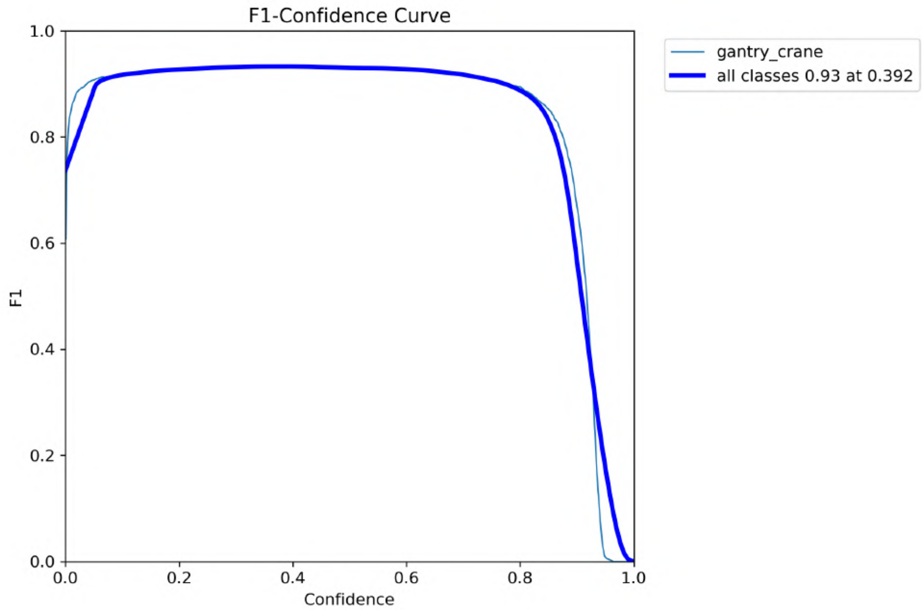


Figure 3.7: F1 score at different confidence levels

The confusion matrix can be seen below in Figure 3.8. This indicates that 1309 cranes in the training dataset were successfully identified. 92 cranes were falsely detected, while 77 cranes were not detected by the model. Since the training dataset is the dataset on which the model is trained, these results might be sensitive to bias of the model. Therefore, the confusion matrix of the YOLOv8 models' performance on the actual terminal images used in the results is displayed below in Figure 3.9. It can be seen that 117 cranes were correctly identified, 26 cranes were not identified, and 14 cranes were falsely detected. The model thus has more false negatives than false positives. Therefore, the number of cranes detected is more likely to be lower than higher than the actual number of cranes.

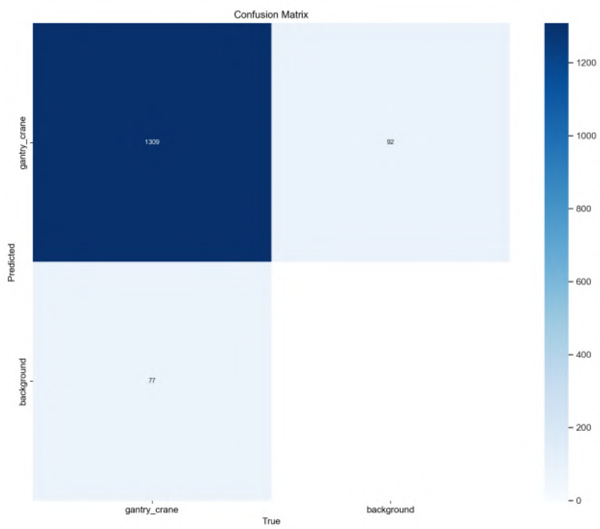


Figure 3.8: The confusion matrix of the trained YOLOv8 model's results on the training dataset.

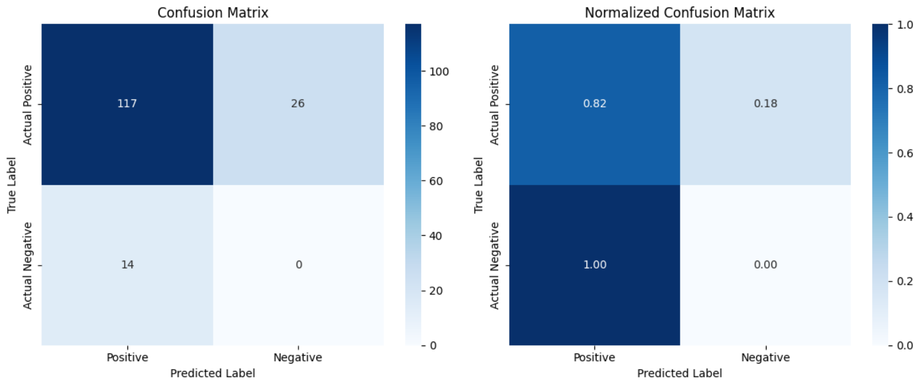


Figure 3.9: The confusion matrix of the trained YOLOv8 model's results on the analysed terminals.

3.4. Required data

As seen in the sections before, Sea-web, AIS data and aerial images form a good basis to asses terminal performance. However, more information on the terminal's operation is required. An overview is given below in Table 3.1, a more detailed overview of all data fields in the call log is given later in Table 4.2.

3.5. Data sources

Following the analysis of the accessible open data sources, the most suitable data sources were selected to meet each specific data requirement, as can be seen in Table 3.4 below. In addition to measurements retrieved from Sea-web, the AIS platform, and Google Earth aerial imagery, standard values found in literature are incorporated to estimate the terminal's operational performance.

Parameter	Data requirement	Chosen data source
IDL	Vessel identity	Sea-web
IDL, TR	Vessel berth arrival time	Sea-web
IDL, TR	Vessel berth departure time	Sea-web
UNV	Terminal unavailable hours	Literature
PM	Preventive maintenance hours	Literature
WC	Hours with high wind (≥ 8 Bf)	Literature
WC	Hours with low visibility	Literature
WC	Hours with high waves (≥ 1 meter)	Literature
TR	Vessel departure from waiting/anchorage area time	Sea-web
TR	Vessel leaving access channel time	AIS platform
PO	Pre-operational hours per vessel	Literature
PO	Post-operational hours per vessel	Literature
CM	Corrective maintenance hours	Literature
OS	Operational stop hours	Literature
BE	Blockage of equipment hours	Literature
ED	Exogenous downtime hours	Literature
NR	Nominal rating of equipment	Public Web Resources
NR	Number of unloaders	Google Earth
NR_{coal}	Nominal rate coal	Literature
$NR_{iron\ ore}$	Nominal rate iron ore	Literature
$LOAD$	Average vessel load	Literature
$\#Calls$	Number of vessel calls	Sea-web
$OT_{coal}, OT_{iron\ ore}$	Vessel cargo type	Public Web Resources, Sea-web
ER, THR	Vessel cargo direction	Sea-web
ER, THR	Vessel DWT	Sea-web
OT	Max number of cranes operating per vessel	Literature, Google Earth

Table 3.4: Data requirements for performance indicators included in OEE estimation.

3.6. Conclusion

This chapter reviewed the available open data sources, Sea-web, AIS data, and aerial images, public web resources, combined with values found in the literature. and how they support the analysis of terminal operations. Sea-web provides static vessel data, arrival and departure times, draught changes, waiting times, and voyage histories. AIS data, via the Haskoning platform, can determine which berth is visited. Aerial images from Google Maps, processed with a YOLOv8 model, help estimate crane numbers. An overview of chosen data sources can be seen in Table 3.4.

Due to reliance on open data, details on internal terminal operations are missing. Some standard values from literature, like pre-operational and operational stoppage times, are used to fill gaps. Less influential elements, such as unavailability during holidays or auxiliary equipment availability, are omitted. The most important remaining data gaps include:

- Timing and duration of corrective maintenance
- Equipment blockage and internal terminal logistics
- Vessel parcel size
- Crane operational stops

- Market context of terminal operation

These gaps limit both the accuracy and contextual depth of performance assessments. Internal logistics influence the availability and downtime of key systems like conveyors and stacker/reclaimers. The exact losses on blockage of equipment or corrective maintenance are therefore unknown. Uncertainty in crane allocation strategies, operational stops and vessel parcel sizes impacts crane productivity estimation.

Even though gaps in data are present, the available information, including vessel service times, makes it possible to form a realistic estimation of terminal unloading performance. This chapter provided a dependable method for data collection, serving as a solid foundation for analyzing port unloading performance.

4 Method

Chapter Sub-question: 3. How can open data be processed to evaluate terminal performance, and how can unloading productivity be effectively modeled using such data?

This chapter explains how data from various sources is processed and how the operational time at the terminal is modeled.

Determining the overall equipment effectiveness (OEE) of a dry bulk terminal requires multiple steps, as shown in Figure 4.1 on the following page. Several inputs are used in this process. Sea-Web serves as the basis for constructing a call log and analyzing the origin and destination ports of vessels before and after visiting the terminal. AIS data from the Haskoning AIS-Platform is used to determine when a vessel enters or leaves the access channel.

From these data sources, the call log is constructed. This includes determining whether a vessel is importing cargo, the waiting time, the service time, and the estimated parcel size. The call log is filtered to focus only on large, sea-going vessels engaged in importing. The filtered call log eventually allows for determining the quay occupancy from the perspective of the unloading equipment.

Object detection is applied to determine the number of cranes, and aerial images provide the basis for analyzing the terminal layout. The number of cranes and the call log enable the setup of the crane utilization model, which also uses operational parameters found in literature that account for lost hours due to factors such as maintenance, system downtime, and equipment blockage. Thereafter, the crane utilization model evaluates operational crane hours per month.

In the fourth step, the operational parameters are calculated. These parameters are used to derive the performance indicators $ID1$ to $ID12$. In the fifth step, the calculated performance indicators are used to determine quay occupancy, crane utilization, and crane productivity. These elements are then combined to assess Overall Equipment Effectiveness (OEE).

To enable benchmarking across different months or terminals, $OEE_{benchmark}$ is determined by averaging the performance indicators that are influenced by exogenous factors. This allows for consistent comparison while accounting for differences in external conditions that affect terminal operations.

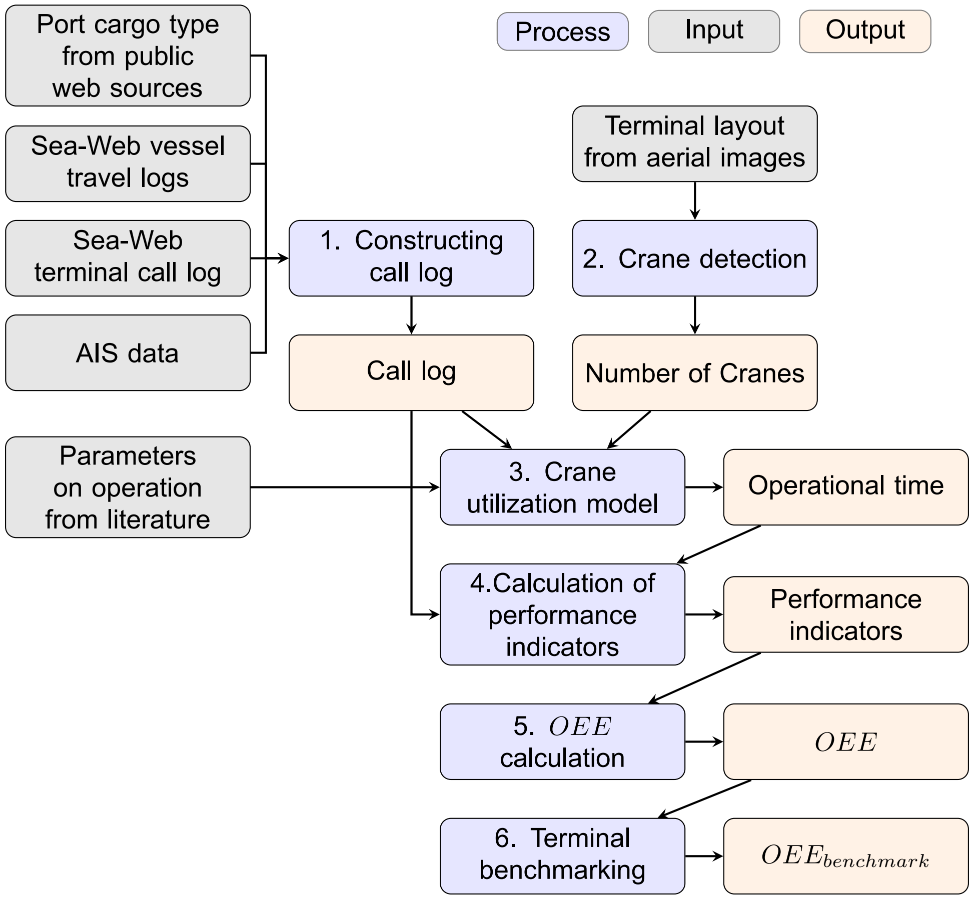


Figure 4.1: Flowchart for the method of determining OEE

4.1. Construction of call log

A call log contains all vessels that visited a terminal during a certain period. For constructing the call log for OEE assessment, multiple data fields need to be added to the dataset. The call log is filtered to only assess large sea-going importing material to the terminal. An overview of the process can be seen in Figure 4.2. The data fields of the resulting call log can be seen in Table 4.2.

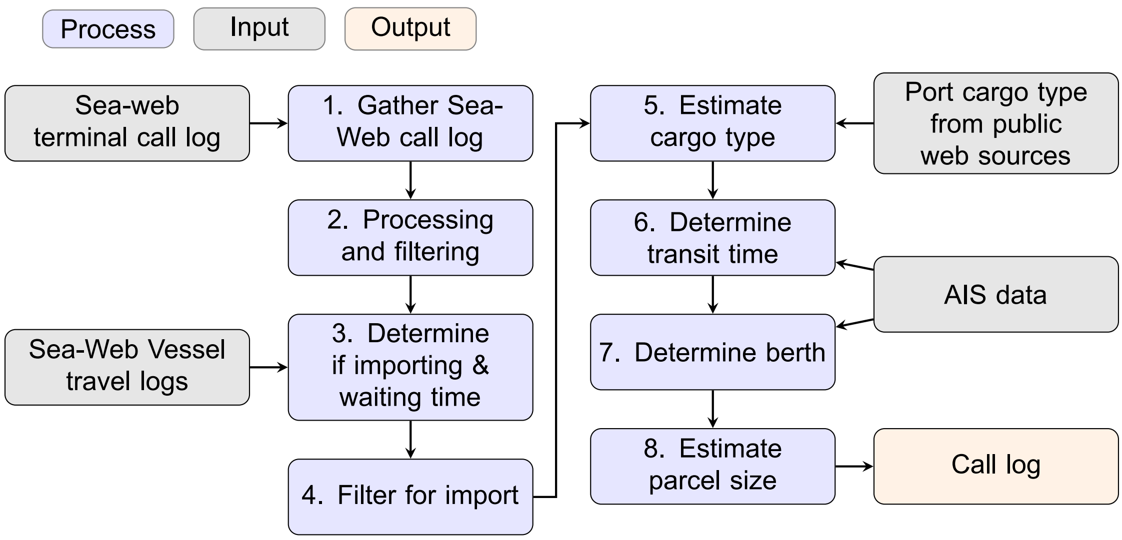


Figure 4.2: Flowchart for construction of the call log.

1. Gathering Sea-web call log
As discussed before in subsection 3.2.2, Sea-web Movements is used as a basis for the call log. The analyzed terminal and time window can be selected. This research assesses vessels that arrived at the terminals in 2024. The following data fields are selected in Sea-web, whereafter the results are exported as an Excel file: Schip Name, Arrival Draught, Arrival Time, Class, Departure Draught, DWT, FLAG, Sailed Time, TEU, Terminal, Vessel Type, MMSI.

2. Processing and filtering
Firstly, the Sea-web call log's unnecessary columns are removed. The list is filtered by 'Vessel Type' containing either 'BULK CARRIER', 'ORE CARRIER', 'OPEN HATCH CARGO SHIP'. Afterwards, 'Arrival Time' is checked to not be within 24 hours after 'Sailed Time' for the same vessel. This occurs sometimes when contact is lost for a while or an inaccurate AIS data point is found far enough away from the terminal. If an arrival is found within 24 hours, the two lines are merged into one port visit.

The draught change and service time are calculated. Draught change is calculated by subtracting the 'Arrival Draught' from the 'Departure Draught'. Service time is calculated by subtracting 'Sailed Time' from 'Arrival Time'.

3. Determine if importing & waiting time
For the assessment of handling performance, it is required to determine if a vessel is importing, exporting, or not exchanging material at the terminal. Also, to determine transit time later on, it must be known when the vessel leaves the anchorage area. Although not required for the OEE estimation, the waiting time of the vessel is also determined since it is a common performance indicator and can provide insight into the terminal's operation later on.

The process of estimating whether a vessel is importing varies by terminal. In some cases, the distinction is straightforward, as certain terminals handle exclusively imports or exports for sea-going vessels. Others have designated berths specifically for import or export activities. However, relying solely on these assumptions is insufficient for a versatile method, since this type of information might not be available for every terminal.

To improve accuracy, a probability-based Naïve Bayes classification is applied. This method calculates the likelihood of a vessel importing or exporting based on historical data, including the origin port continent, DWT, and draught changes. For example, large vessels and those arriving from outside Europe are predominantly involved in importing dry bulk at coal and iron ore terminals.

The HBTR terminal specified that in 2024, berths 1, 2, 3, and 4 were exclusively used for importing, while berths 5 and 6 were designated for exporting, as the sea-going vessel loader is located at these berths. Using this information, each call log entry was classified accordingly. By combining this classification with data such as origin port, draught change, and DWT, Naïve Bayes conditional probabilities were computed. These probabilities allow for estimating cargo flow direction, even when berth assignments for importing and exporting are unknown. A more detailed explanation of the cargo flow direction estimation method is provided in Appendix E.

Since the cargo flow direction estimation method relies on knowing both the vessel's continent of origin and its next destination after the terminal visit, each vessel's voyage is first determined by identifying its port of origin and the next destination. For every unique IMO number in the port call list, the travel history is retrieved from Sea-Web Ships. This history includes visited ports, anchorage locations, and bunkering (fueling) events, as well as draught changes during port visits, as shown in an example in Table 4.1.

To determine the origin port, the entry in the travel history closest to the 'Arrival Time' in the port call list is identified. The first Port Call below this entry is then selected as the origin port. Draught changes during this port visit are calculated by combining all relevant lines in the travel history, as port visits sometimes include duplicate arrivals, as discussed in Appendix C. The same process is used to identify the next port.

	Operations	Location	Country	Start	End	Duration	± Draught
1	STS - Bunkering	Bremen	Germany	10 Apr 2025 13:23	10 Apr 2025 14:58	1 h 35 min	0 m
2	Port Call	Bremen	Germany	10 Apr 2025 12:47	12 Apr 2025 06:02	1 day 17 h 15 min	-3.3 m
3	Anchorage	Bremen	Germany	09 Apr 2025 23:01	10 Apr 2025 05:32	6 h 31 min	0 m
4	Anchorage	Bremen	Germany	08 Apr 2025 12:42	09 Apr 2025 17:27	1 day 4 h 45 min	0 m
5	Port Call	Rotterdam	Netherlands	06 Apr 2025 04:01	07 Apr 2025 12:47	1 day 8 h 46 min	+2.4 m
6	Port Call	Bremen	Germany	03 Apr 2025 18:39	04 Apr 2025 20:32	1 day 1 h 53 min	-3.5 m

Table 4.1: Sample of lines from a Sea-Web Ships export

After the origin port and next port are determined, the cargo flow direction model can estimate whether the vessel is importing or exporting. Three new columns are added to the call log: 'Probability Import', 'Probability Export', and 'Cargo Direction'. Where 'Cargo Direction' contains either 'Importing', 'Exporting', or 'Unknown'. The cargo direction is classified as 'Unknown' when the probabilities of importing and exporting are between 0.4 and 0.6.

Sea-web Ships provides insight into vessel movement to and from the anchorage area, as illustrated in the third and fourth row of Table 4.1. This area is typically visited when terminal space is unavailable, requiring vessels to wait. As seen in the third and fourth row of Table 4.1, the data may contain duplicate entries, such as a brief departure and return to anchorage that seems unlikely. To accurately estimate waiting time, the durations of all anchorage records preceding a port call are combined. In the example given, the vessel remained in anchorage from 8 April at 12:42 until 10 April at 05:32. This found duration is then entered into a new column in the call log named 'Waiting Time'.

Not every vessel visits the anchorage area, as some may proceed directly to the terminal without delay. For those that do, the transit time into the terminal can be calculated as the difference between the end of the anchorage period and the arrival time at berth, which was established during step one. This transit duration is recorded in a separate column called 'Transit Time In'.

4. Filter for import
The call log is filtered to include only vessels importing material into the terminal.

5. Estimate cargo type
To estimate the cargo type imported into the terminal, the voyage history of each vessel, which was determined in step 3, is used. A database is created containing all vessels' previously visited ports. For each terminal, public web sources such as websites and satellite images are used to determine whether coal or iron ore is primarily exported. If reliable information is not available or if both materials are handled, the second previous port is also analyzed. This can be done since vessels do not frequently switch cargo types, and the first previous port may be an import terminal where cargo was only partially discharged. In rare cases where both ports remain unclear, the cargo type is marked as unknown. A new column in the call log, 'Cargo Type', is then assigned one of three values: iron ore, coal, or unknown.

6. Determine transit time
For vessels that visited the anchorage area, the transit time can be determined as the time difference between leaving the anchorage area and arriving at the terminal. For vessels that do not have to wait, this needs to be determined from AIS data. A polygon is defined at the entrance of the access channel, and all AIS data within this boundary during the specified period, in this case 2024, is retrieved. The time difference between the vessel's last recorded appearance within the polygon and its arrival at the

berth defines the 'Transit Time In'. If this value has not yet been determined for a given vessel, it is now added to the corresponding column.

Outbound transit time is calculated for all vessels by measuring the interval between the recorded 'Sailed Time' and the first AIS detection at the polygon near the access channel's mouth. This is stored in the column 'Transit Time Out'.

In cases where a vessel listed in the call log is missing from the AIS dataset, transit times cannot be computed directly. These entries are marked as 'N/A' in the call log. Additionally, a maximum threshold of 24 hours is set for transit times. Any appearance in the AIS polygon with a time difference exceeding this threshold is likely associated with a separate port visit and is excluded from consideration. These cases are also marked as 'N/A'. Later, during the performance indicator calculation phase, average transit durations from the rest of the dataset are used to estimate these missing values.

7. Determine berth

AIS data from the Haskoning AIS platform is used to determine which berth a vessel visited. The AIS data is retrieved for the same timeframe as the Sea-web call log and filtered for each vessel using its IMO number. It is further filtered to include only positions recorded between 'Arrival Time' and 'Sailed Time'. The average latitude and longitude from the remaining AIS messages are then calculated. Polygons representing berths designated for importing and exporting are mapped, and if the vessel's average position falls within one of these polygons, the corresponding berth is assigned to the data field 'Berth'. The case for Tata Steel Ijmuiden can be seen in Figure 4.3 below.

Figure 4.3: The average positions of vessels and the two polygons determining the berth of each vessel at Tata Steel IJmuiden.

A small number of vessels in the Sea-web call log do not have a matching IMO number in the AIS dataset. To assign these vessels to a berth, their service time is compared with other vessels. If one berth is already occupied during that time, the vessel without AIS data is assigned to the other berth. If multiple berths are available, the vessel is assigned to the default berth, defined as the most frequently visited berth at the terminal.

For continuous quay terminals, the berth is still determined, although this information is not used directly in the OEE assessment.

The call log is expanded with three extra columns: 'Average Lat', 'Average Long', and 'Berth'.

8. Estimate parcel size

The parcel represents the total delivered load. In large dry bulk terminals, vessels typically arrive fully loaded and are completely emptied. Although rare, some vessels may only unload half of their cargo, with the remaining portion discharged at another terminal. For simplicity, this analysis assumes that all importing vessels fully unload their cargo at the terminal.

Cargo load is defined by the parameter $Cl = 90\%$, which represents the percentage of the DWT utilized for transporting cargo. The capacity utilization generally falls between 90% and 95%, with the remaining portion allocated for fuel, water, and personnel. For example, Adland et al. (2018) found an average capacity utilization of 92% for iron ore carriers departing from Brazil.

By multiplying the DWT by 0.9, the parcel size for each importing vessel is determined, enabling the calculation of monthly throughput. Since crane utilization is calculated on a monthly basis, throughput must also be assessed per month. The payload of vessels that are present at the terminal during the change of the month is divided over the two months proportionately to the service time of the vessel within each month. The found parcel size is added to a new column in the call log named 'Parcel Size'.

The call log is now completed. All data fields included in the resulting call log can be seen in Table 4.2 below.

Data field	Source	Note
IMO	Sea-web Movements	
Ship Name	Sea-web Movements	
Arrival Draught	Sea-web Movements	Removed after draught calculation
Arrival Time	Sea-web Movements	
Departure Draught	Sea-web Movements	Removed after draught calculation
DWT	Sea-web Movements	
Sailed Time	Sea-web Movements	
Vessel Type	Sea-web Movements	
MMSI	Sea-web Movements	
Draught Change	Calculated	Departure Draught - Arrival Draught
Service Time	Calculated	Sailed Time - Arrival Time
Waiting Time	Sea-web Ships	
Transit Time In	Sea-web Ships or AIS	
Transit Time Out	AIS	
Second Previous Port Continent	Determined	From Second Previous country
Second Previous Port Country	Sea-web Ships	
Second Previous Port City	Sea-web Ships	
Second Previous Port Draught Change	Sea-web Ships	
Previous Port Continent	Determined	From Previous country
Previous Port Country	Sea-web Ships	
Previous Port City	Sea-web Ships	
Previous Port Draught Change	Sea-web Ships	
Next Port Continent	Determined	From Next country
Next Port Country	Sea-web Ships	
Next Port City	Sea-web Ships	
Next Port Draught Change	Sea-web Ships	
Parcel Size	Calculated	$DWT \times Cl$ $(Cl = 0.9)$
Probability Import	Calculated	
Probability Export	Calculated	
Cargo Direction	Determined	Contains either 'Importing', 'Exporting', or 'Unknown', based on probability Import/Export
Cargo Type	Sea-web Ships, Public web sources	
Average Lat	AIS	
Average Long	AIS	
Berth	Determined	From average Lat/long

Table 4.2: The data fields in the constructed call log.

4.2. Crane detection

To detect the number of cranes from aerial images, the trained YOLOv8 model is used. An overview of the workflow can be seen in Figure 4.4 below.

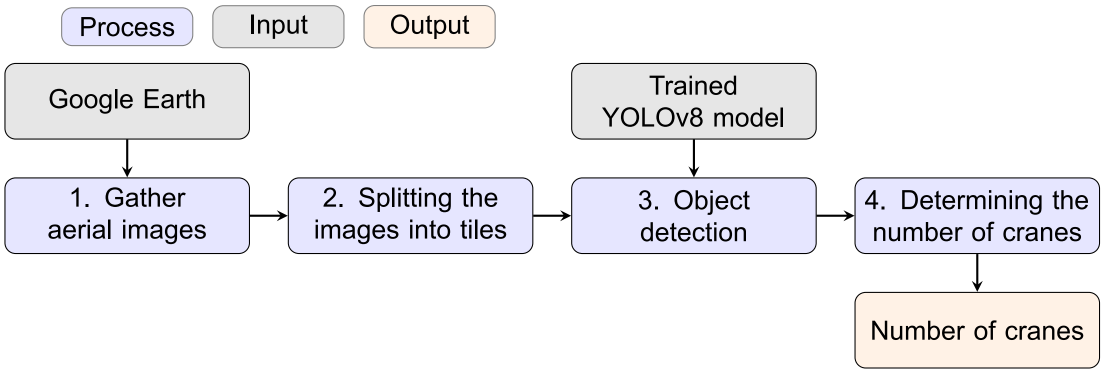


Figure 4.4: Flowchart for determining the number of cranes.

1. Gather aerial images

The dataset on which the YOLOv8 model is trained has a resolution of 0.5 meters per pixel. Therefore, the aerial images of the terminal need to be in the same resolution. When using Google Earth, the coordinates, date of the aerial image, and total meters across the screen can be retrieved from the URL. An example can be seen below:

https://earth.google.com/web/@51.94329864,4.05368691,10.30396578a,3962.26141585d,35y,-20.05639271h,0.31465942t,0r/data=ChYqEAgBEgoyMDI0LTEyLTAxGAFCAggBOgMKATBCAgg ASg0I____________ARAA

In red, the coordinates of the current screen are displayed. In green, the distance from the left side to the right side of the screen is displayed in meters. Lastly, in orange, a Base64-encoded string which, among other things, contains the date in a YYYY-MM-DD format.

A Python script is developed that opens a browser and lets the user navigate to the desired port. Multiple screenshots from different years can be captured using Google Earth's Historical Imagery tool. When pressing 's' on the keyboard, the Python script automatically rescales the browser window to ensure the correct resolution and captures a screenshot, whereafter it rescales back to the regular browser window size. This allows taking large Google Earth screenshots from large terminals, while ensuring a high resolution. The Python script ensures the image is saved while saving the location and date of the image in the filename.

2. Splitting the images into tiles

Since the images on which the YOLOv8 model is trained are typically around 675 by 1140 pixels, they only cover an area of roughly 300 by 550 meters. Many terminals are larger. Therefore, the collected images are split up into different tiles, which can be run through the object detection model separately. To ensure cranes are not cut off on the edge of images, the tiles are processed by a rolling window approach. Where every tile overlaps for 50% with the last tile, both horizontally and vertically. An example is given below in Figure 4.5, where the image is split up into two lines vertically and 11 horizontally, resulting in 22 unique tiles. As can be seen, the tiles only move half of their width or height in every instance.

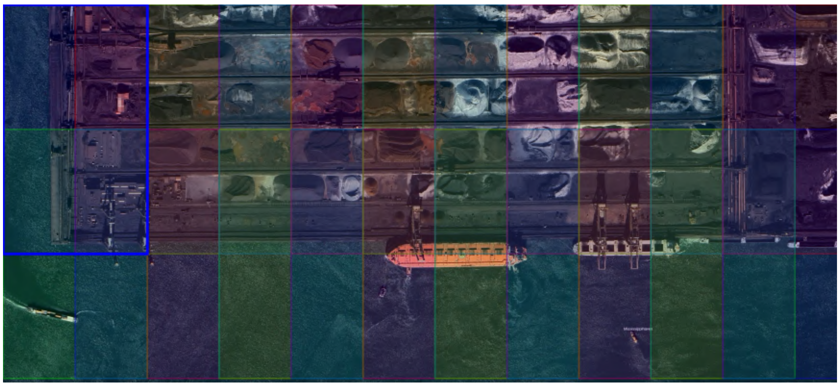


Figure 4.5: A visualization of splitting the aerial image into multiple tiles. The first tile is encircled in blue for clarity.

3. Object detection

Afterwards, all individual tiles are processed by the trained YOLOv8 model. Since the tiles have an overlap, most areas are processed twice. Afterwards, overlapping detections are merged with Non-Maximum Suppression. This selects the bounding box with the highest confidence. It calculates the intersection over union, which is the fraction of the bounding box that is overlapping. If this exceeds the threshold (which is set at 0.25), the bounding box with the lowest confidence is removed.

After this, the resulting bounding boxes are converted to the coordinates of the full image and plotted on the original full-color image.

4. Determining the number of cranes

After processing aerial images from multiple years, the results are analyzed to determine the number of cranes present at the terminal. To determine the number of cranes at the terminal, the mode, the most frequently occurring value, is used as the representative number of cranes present.

4.3. Crane utilization model

After the call log is constructed and the number of cranes is known, the crane utilization model can estimate how the service time of vessels is utilized. During the vessel's service time, downtime, transit time, and pre- and post-operational time will limit the operational time OT. Many factors influence the service time and operational crane hours for each vessel, which is further discussed in Appendix D.

Based on the call log and operational parameters, a discrete-time model assigns an operational state to each crane for every hour in the analyzed period. The model does not track individual crane locations or tasks. It only records how many cranes are in each operational state at a given hour.

After assigning the states, the results are averaged per month. Additional states such as weather downtime and planned maintenance are then calculated using fixed percentages from literature. An overview of this process is shown in Figure 4.6.

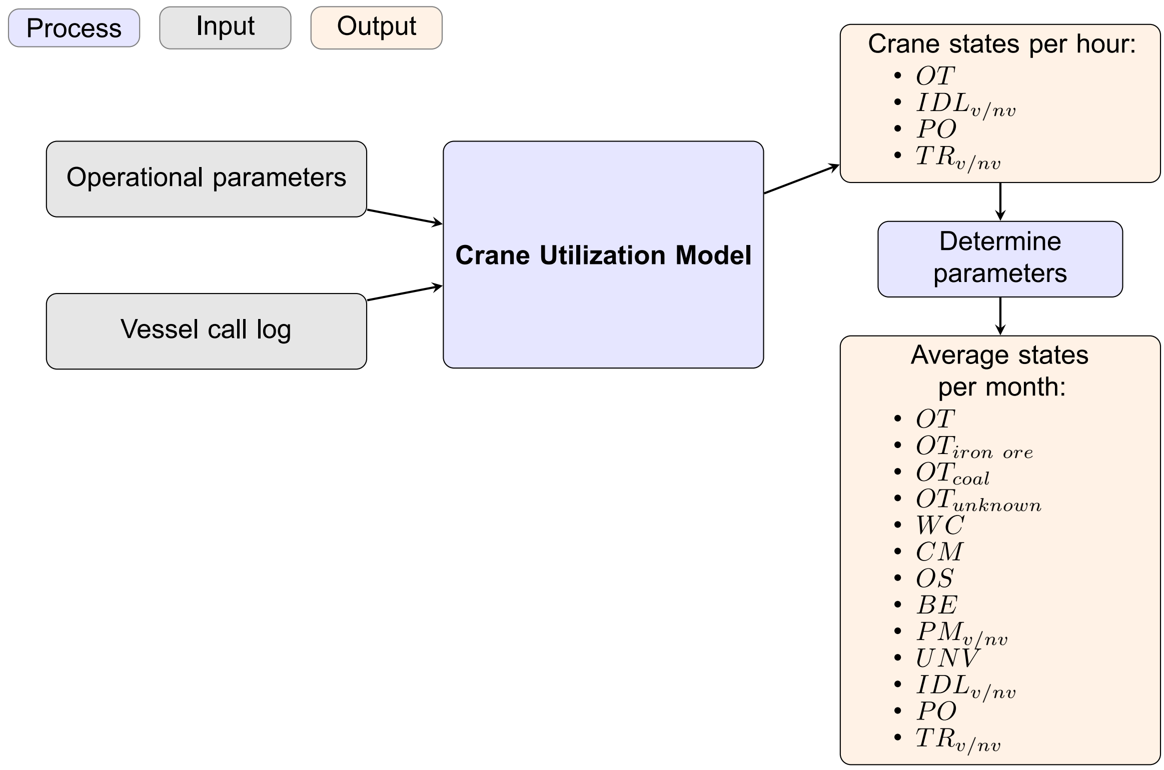


Figure 4.6: Blackbox model of the crane utilization model.

4.3.1. Discrete time model

A discrete-time model determines the operational state of each berth for every hour of the analyzed period. The possible states have been previously defined in Table 2.10. This model relies on a set of input parameters. Some are tailored to specific terminal configurations, and others are drawn from standard values found in the literature. An overview of these input parameters is provided in Table 4.3.

4.3.2. Operational parameters

The operational parameters can be seen in Table 4.3. The number of cranes NoC is determined using aerial images and the object detection model. Po_{pre}, PO_{post}, $OS_{per/vessel}$, $WC_{per\ vessel}$, $CM_{per\ vessel}$, $BE_{per\ vessel}$, and PM_year are retrieved from values found in literature.

Parameter	Name	value	Source
NoC	Number of cranes	Terminal specific	Aerial Images
$MCpV$	Max cranes per vessel	Terminal specific	Aerial Images
NR_{crane}	Nominal rating	Terminal specific	Public web sources
$NR_{iron\ crane}$	Nominal rate iron ore of one crane	Terminal specific	Public web sources
$NR_{coal\ crane}$	Nominal rate coal of one crane	Terminal specific	Public web sources
PO_{pre}	Pre-operational time	1 hour	(PIANC, 2018, p. 73)
PO_{post}	Post-operational time	2 hour	(PIANC, 2018, p. 73)
$OS_{per\ vessel}$	Operational stop time	5 hours per vessel	(PIANC, 2018, p. 73)
$WC_{per\ vessel}$	Weather downtime	5% of operational time	(PIANC, 2018, p. 73)
$CM_{per\ vessel}$	Corrective maintenance time	8.86% of operational time	(Vianen, 2015, p. 139)
$BE_{per\ vessel}$	Blockage of equipment	5% of vessel operational time	(R. Slikkerveer, personal communication, May 16, 2025)
PM_{year}	Preventive maintenance hours per year	500 hours per year	(PIANC, 2018, p. 73)

Table 4.3: Values for the operational parameters in the crane utilization model.

Pre-operational PO_{pre} and post-operational PO_{post} times are standard values derived from literature. Operational stop time $OS_{per/vessel}$ accounts for routine interruptions, such as repositioning the crane, attaching grabs, or opening hold doors. The time used for operational is assumed to remain constant across vessel size classes, as larger vessels benefit from economies of scale and typically feature a similar number of cargo holds, even at increased sizes.

The terminals within the scope of the research are not influenced by wave heights since they operate inside protected harbors. For the handling of coal and iron ore, rain has no impact on operations. Wind is the biggest factor in weather downtime. Generally, Weather downtime $WC_{per\ vessel}$, for terminals in the scope of this research, accounts for 5% of operational time (R. Slikkerveer, personal communication, May 16, 2025; PIANC, 2018, p. 73).

Corrective maintenance $CM_{per\ vessel}$ is required when equipment breaks, fails, or gets blocked. There is an uncertainty in the time between failures and the duration of the repair. Every crane depends on a conveyor and a stacker/reclaimer to also function properly. Failures in the supporting components will halt operations of loading/unloading process if no alternative conveyors or stacker reclaimers are available. A simplified schematic of the unloading process is seen in Figure 4.7.

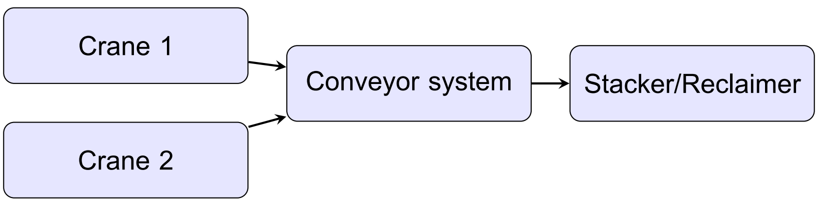


Figure 4.7: A simplified schematic of the components of the unloading chain. A failure in one of the two cranes only halts half the operation. It is assumed that a failure in any other component halts the complete unloading process.

To simulate system downtime caused by corrective maintenance, Vianen (2015) used standard values, which can be seen below in Table 4.4. The values presented here account for the individual stockyard machines, such as conveyors, stacker-reclaimers, and cranes, which can all break down independently. Since little information about the exact terminal's internal logistics is unknown, a simplified calculation is made based on this data. If every component breaks independently for 0.5 hours every 16.5 hours on average, it will experience $0.5/16.5 = 3.03\%$ downtime. The unloading chain for one crane consists of three components in series: the crane, conveyor, and stacker reclaimer, which break independently. Assuming no alternative conveyor routes or stacker/reclaimers are available for use, the downtime one crane experiences can be combined as follows:

$$\begin{aligned}\mathbb{P}(Crane\ downtime) = 1 - (1 - \mathbb{P}(Crane\ breakage) \times (1 - \mathbb{P}(Conveyor\ breakage) \times \\ (1 - \mathbb{P}(StackerReclaimer\ breakage) = 1 - 0.96997^3 = 0.0886 = 8.86\%\end{aligned} \quad (4.1)$$

Since both cranes share the same conveyor system and stacker/reclaimer, any malfunction in these shared components requires both cranes to cease operation. Nevertheless, it can be concluded that each crane's activity is interrupted 8.86% of the time.

Parameter	**Value**
Mean time between failures (MTBF)	16 hours
Mean time to Repair (MTTR)	0.5 hours
MTBF & MTTR distributions	Not Explicitly Defined

Table 4.4: Equipment breakdown modeling parameters for cranes, conveyors, and stacker/reclaimers (Vianen, 2015, p. 139).

Available time lost due to equipment blockage $BE_{per\ vessel}$ refers to instances where equipment cannot operate because it is obstructed by unavailability of other equipment. This might be caused by unfavorable terminal layouts, or poor planning of the stockpiles. Or it might be caused by congestion in other parts of the terminal, such as train or barge loading. Examples include:

- The conveyor system lacks the capacity to unload at full capacity
- The stockyard has no space available for unloading
- The required route through the conveyor system is not available since it is occupied with other operations.
- The required stacker/reclaimer is occupied with other operations.

Assessing the capacity of conveyor systems is challenging with aerial imaging, and since these systems are typically scaled to match the capacity of the cranes, this is generally not a significant issue.

Congestion in internal logistics varies by terminal, influenced by factors such as terminal size, the types of materials handled, and overall planability. Terminals operated by entities that also own other parts of the supply chain, such as vessels or trains, tend to have more efficient logistics planning. While time lost due to internal logistics could be quantified through detailed simulations or operational logging, this falls outside the scope of this research. Based on consultation with HBTR, time lost due to conveyor or stacker/reclaimer unavailability is estimated at approximately 5% (R. Slikkerveer, personal communication, May 16, 2025).

Preventive maintenance PM_{year} is often a fixed number of hours set by manufacturers' instructions or government policy.

To determine the nominal rating NR and nominal rates NR_{iron}, NR_{coal} of the unloaders, the safe working load of the cranes is retrieved from terminal websites or other public web sources. The safe working load refers to the maximum weight the crane can lift at once, which includes the dry bulk material and the grab. The estimated nominal rate for either coal or iron ore can be determined with the following formula:

$$NR_{material} = \frac{3600}{cycle\ time_{material}} \times (1 - grab\ to\ weight\ ratio_{material}) \times safe\ working\ load \quad (4.2)$$

As discussed in Appendix D, iron ore is typically unloaded at a higher rate than coal. Since iron ore is a denser material, the grabs are smaller and therefore lighter, which reduces the grab-to-weight ratio and allows unloading more material per cycle (Haoyo Machinery, 2025). The peak cycle time for iron ore is also lower since iron ore vessels are smaller for the same tonnage, which causes material to be closer to the shore on average. The used parameters can be seen in Table 4.5 below. These parameters result in a nominal rate of iron ore which is 18% higher than the nominal rate for coal. The overall nominal rating NR is set at the same value as the highest cargo-specific nominal rate, which is the one calculated for iron ore.

Material	$cycle\ time$	$grab\ to\ weight\ ratio$
Iron ore	55 seconds	0.35
Coal	60 seconds	0.4

Table 4.5: Parameters used to calculate the nominal rate for coal and iron ore

A sensitivity analysis of these operational parameters can be found in **??**. This indicates that the number of operational cranes and the number of cranes operational per vessel have the largest impact on the average utilized crane hours.

4.3.3. Model process

Due to limited insight into the terminal's internal operations, crane utilization must be modeled. Each crane is assigned a status on an hourly basis using the crane utilization model. These crane identifiers do not represent specific physical cranes but indicate the number of active cranes. For each hour, crane 1 is assigned first, followed by crane 2, and so on.

At the outset, all cranes are initialized with the status idle (IDL) across the entire time range. The vessel call log is sorted by arrival time to ensure chronological processing. When a vessel begins its transit toward the terminal, it is assigned transit time (TR) if a crane is available. Upon arrival, pre-operational time (PO) is recorded. This is followed by operational time (OT), and then post-operational time (PO) before departure. After departure, outbound transit time (TR) is assigned. An overview can be seen in Figure 4.8.

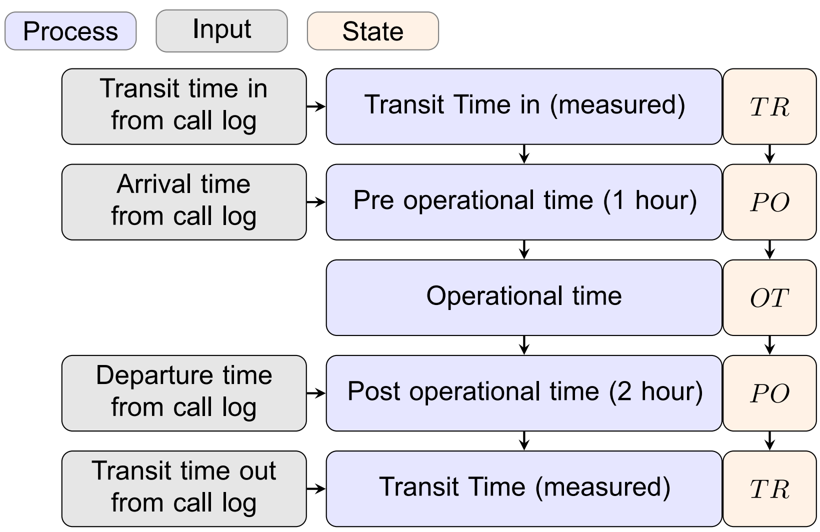


Figure 4.8: Chronological order of a vessel serviced and assigned berth states.

The discrete-time model does not assign specific vessels to specific cranes. Its purpose is to estimate the average number of operational hours (OT) across all cranes. Vessels arriving later may overwrite transit and pre-operational time. This is accepted because these activities can take place at other berths along the quay where no cranes are located. The model assumes that cranes are used as much as possible when vessels are present.

4.3.4. Determine parameters

After assigning crane states, idle time (IDL) and transit time (TR) are set to IDL_v, IDL_{nv}, TR_v, or TR_{nv} based on whether a vessel is present. The monthly sums of TR, PO, OT, and IDL are calculated and averaged across all available cranes. Other parameters are then calculated. Operational stops (OS) are based on the number of vessel calls ($\#CALLS$) during the month. Weather conditions (WC), corrective maintenance (CM), and blockage of equipment (BE) are assigned as fixed percentages of the remaining operational time (OT). These values are subtracted from OT to complete the model.

After processing all vessels, the total hours per state for each month are calculated. Preventive maintenance PM is then distributed across months in proportion to idle IDL_{nv} hours, based on the assumption that maintenance is scheduled during periods that no vessel is moored along the quay. If there is to little IDL_nv in the year to account for the preventive maintenance, the preventive maintenance is assingned during IDL_v and thereafter OT.

After all parameters are determined, the operational time OT is adjusted by subtracting the durations assigned to other crane statuses. The remaining time represents the active crane usage. This operational time is then split into OT_{coal}, $OT_{iron\ ore}$, and OT_{unk}, based on the total cargo tonnage handled during the month. Data from the vessel call log and estimated parcel sizes are used for this calculation. If a vessel is unloaded across multiple months, its cargo is distributed proportionally. The share assigned to each month depends on the amount of service time that occurred within that month.

4.4. Calculation of performance indicators

After determining the hours spent in different states per month, additional parameters and the performance indicators are calculated.

The nominal rating NR and nominal rates NR_{coal} and NR_{iron} of the berth are determined by multiplying NR_{crane}, $NR_{iron\ crane}$, $NR_{coal\ crane}$ with the number of cranes NoC.

For a small fraction of vessels, the cargo type could not be determined. The operational time OT_{unk} of these vessels is assumed to have the standard nominal rating NR. Therefore, the nominal rate variation per cargo type NR_{CT} can be determined as:

$$NR_{CT} = \frac{OT_{coal} \times NR_{coal} + OT_{iron\ ore} \times NR_{iron\ ore} + OT_{unkown} \times NR}{OT} \tag{4.3}$$

The number of calls $\#Calls$ is the count of vessels arriving each month. If a vessel was present during two months 0.5 call is added to both months to improve the accuracy of the performance indicators which use $\#Calls$ as the driver. The average vessel load $LOAD$ is computed by averaging the parcel size of these vessels.

The throughput THR is obtained by summing the parcel sizes of all vessels at the terminal during the month. Parcel sizes are proportionally divided for vessels present across multiple months. The effective rate ER is thereafter calculated as follows:

$$ER = \frac{THR}{OT \times \text{number of cranes}} \tag{4.4}$$

With these values defined, the performance indicators $ID1$ through $ID12$ are calculated using the formulas provided in Table 2.6 and Table 2.8.

4.5. OEE calculation

Once all parameters and performance indicators have been determined, the quay occupancy OCC, crane utilization $UTIL$, crane productivity $PROD$, and OEE can be calculated. These KPI's are calculated according to Equation 2.6, Equation 2.11, Equation 2.12, and Equation 2.13.

Hourly versions of these indicators provide more informative insight. OCC_{hours} and $UTIL_{hours}$, can be determined with the following formulas (Pinto et al., 2017):

$$OCC_{hours} = TT - IDL_{nv} - UNV - PM_{nv} - TR_{nv} \tag{4.5}$$

$$UTIL_{hours} = OT \tag{4.6}$$

$PROD_{hours}$ can be determined with the following formula:

$$PROD_{hours} = \frac{THR}{NR \times \text{number of cranes}} \tag{4.7}$$

The berth commitment COM is determined via Equation 2.15. Its hourly form is calculated as follows:

$$COM_{hour} = TT - IDL_v - IDL_{nv} \tag{4.8}$$

4.6. Terminal benchmarking

Benchmark values for OEE can be calculated either for one terminal over the course of a year or between multiple terminals. According to Equation 2.14, specific indicators ($ID1_v$, $ID1_{nv}$, $ID2$, $ID3_v$, $ID3_{nv}$, $ID4$, $ID5_v$, $ID5_{nv}$, $ID10$, and $ID11$) must be averaged across all months, and terminals in the sample. These averages are then used to compute $OCC_{benchmark}$, $UTIL_{benchmark}$, $PROD_{benchmark}$, and $OEE_{benchmark}$.$OCC_{benchmark}$ remains constant across months, berths, and terminals because it is influenced only by external factors. For this reason, it is irrelevant for comparing operational performance. The benchmarks are intended solely for comparative purposes. This comparison can reveal whether one terminal demonstrates higher performance in crane utilization or greater crane productivity while suppressing the influence of exogenous factors.

4.7. Conclusion

This chapter demonstrated how open data can be processed to evaluate the performance of dry bulk terminals. AIS vessel tracking data is used to reconstruct vessel call logs, estimate service times, and identify unloading events. Aerial imagery is used to determine the number of cranes and the maximum number of operational cranes per vessel. Missing information is substituted with literature-based assumptions. The combination of these open data sources enables a structured port call list with detailed vessel information and a set of operational parameters of the terminal.

With the created dataset, unloading productivity is modeled using a discrete-time approach that divides vessel service time into operational states, including active unloading and different types of downtime. Throughput was estimated from vessel DWT, while crane activity was inferred based on the vessel call log and operational parameters. This method allows for the calculation of crane utilization and productivity, which together form the basis of the adapted OEE metric.

Despite limitations caused by missing information on internal logistics and crane allocation strategies, the model provides reliable average estimates of terminal performance. The approach proves that open data, when carefully processed and interpreted, can be used to assess unloading productivity in a scalable and repeatable way.

5
Calibration & Validation

Chapter Sub-question: 4. To what extent does the proposed method reflect the actual performance of dry bulk terminal operations?

This chapter uses measured data from HBTR to compare the model results with actual operational performance. The comparison shows whether the model accurately represents terminal handling operations. Calibration based on HBTR data was performed.

Initial data was acquired from HBTR and compared to the model output. Based on this comparison, the input parameters were adjusted to improve accuracy. Subsequently, data from Tata Steel IJmuiden was obtained to further validate the model results, which did not result in further parameter tuning.

5.1. Calibration based on HBTR data

To optimize the method for terminals within the scope of the research, the standard operational parameters have to be calibrated. This was done using data provided by HBTR.

5.1.1. Throughput per cargo type

Estimating the correct throughput is important for reliable productivity results. In this method, throughput is estimated by checking if vessels are importing, identifying the type of cargo, and estimating the parcel size as 90 percent of the deadweight tonnage. The accuracy of estimating if a vessel is importing or exporting is discussed in Appendix E. Monthly throughput is calculated by summing parcel sizes per cargo type.

HBTR provided monthly records of total cargo handled in 2024. A comparison is shown in Figure 5.1. The total throughput is shown in Table 5.8. The model overestimates yearly throughput by 11%. This can be explained since all vessels are assumed to be fully loaded on arrival and completely unloaded. In practice, this is not always the case. However, April and May show underestimated throughput values, which suggests the model does not consistently overestimate.

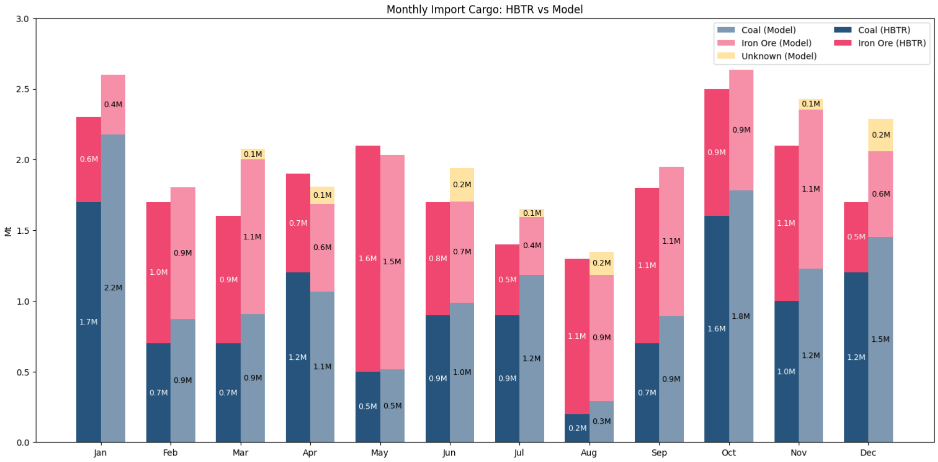


Figure 5.1: Comparison of model results and values supplied by HBTR for overall imported cargo volume per cargo type.

As shown in Table 5.8, the model performs well for iron ore but overestimates coal throughput. This is likely due to coal vessels being partly filled or partly unloaded. The model could therefore be improved by providing a separate cargo utilization rate per cargo type. The cargo load utilization rate for coal could be reduced to 80 percent and treated separately from iron ore.

	Model	**HBTR**
Coal	13.35 Mt	11.30 Mt
Iron Ore	10.25 Mt	10.80 Mt
Unknown	0.95 Mt	-
Total	24.55 Mt	22.1 Mt

Table 5.1: Yearly totals per cargo type.

Table 5.2 shows the root mean square error across all months in 2024. These results confirm the model's accuracy, as the RMSE is 23% of the average monthly value for coal and 13% of the monthly value for iron ore. Iron ore predictions are more reliable than those for coal. For cargo categorized as unknown, the effective rate is based on the system's nominal rating. This rating equals the highest nominal rate, which corresponds to iron ore. As a result, unknown cargo is treated as iron ore when calculating performance indicators $ID11$ and $ID12$, which are in turn used to calculate crane productivity.

Parameter	**Coal**	**Iron Ore**
Root mean square error	0.22 Mt	0.12 Mt
Mean error	0.18 Mt	-0.05 Mt
Standard deviation	0.15 Mt	0.12 Mt
Mean error 95% confidence interval	$\pm$ 0.086 Mt	$\pm$ 0.066 Mt

Table 5.2: The root mean square error of the predicted throughput per cargo type.

5.1.2. Crane utilization

Crane utilization refers to the number of hours a crane is operational. Accurately estimating monthly crane hours depends on identifying both the causes of downtime and the duration of these downtimes. The objective is to reliably estimate the operational time OT, which is the average number of hours a crane is operating, and to provide context by accurately identifying the sources of downtime. Data is retrieved from HBTR on the hours lost on different events at the terminal. These measured values are then compared to the estimates produced by the model to assess its accuracy.

The data below shows average downtimes across all four operational unloaders during the first seven months of operation, as provided by HBTR. The relevant model state parameter associated with the downtime event is indicated in the last column of Table 5.3. The reported values may contain errors due to changes in the logging system that the current setup does not fully support.

Event	Fraction	Model state
Crane operating with delay	3.5%	Operational time OT
Cranes operating	67.1%	Operational time OT
Waiting for (multiple causes)	7.8%	Corrective maintenance CM, Operational stops OS
Hatch change	2.7%	Operational stops OS
Planned maintenance	2.9%	Preventive maintenance PM
Waiting	2.2%	Blockage of equipment BE
Cleaning	0.3%	Operational stops OS
Grab change	0.3%	Operational stops OS
Hoist in/out of equipment	6.4%	Operational stops OS
Breakdown	3.0%	Corrective maintenance CM
Personnel problems	1.0%	Blockage of equipment BE
Weather	0.6%	Weather downtime WC
Other	1.5%	-

Table 5.3: All events occurring at HBTR during the first seven months of 2025.

By combining all events from Table 5.3 per model state and comparing them to the values predicted by the model, we obtain the results shown in Table 5.4. The event 'Waiting for (multiple causes)' includes both corrective maintenance CM and operational stops OS. The time associated with this event is therefore split evenly, with 50 percent allocated to each of the two model states. Although the HBTR data covers the first seven months of 2025, while the model output is based on 2024, the resulting fractions are expected to be comparable. HBTR excludes berth states like transit time and pre/post-operation, interpreting them as outside crane operational time. Consequently, hours spent on transit time and pre- and post-operational time are subtracted from the quay occupancy time to calculate the percentages for the model output in Table 5.4.

Model state	HBTR	Model
Operational time OT	71.2%	66.3%
Weather downtime WC	0.6%	5.0%
Corrective maintenance CM	6.9%	8.8%
Operational stops OS	13.6%	13.9%
Blockage of equipment BE	3.3%	5.0%
Preventive maintenance PM_v	2.9%	-
Other	1.5%	-

Table 5.4: Comparison between berth states of HBTR and the model output

The accuracy of operational time OT is the most important factor, since it defines crane utilization and crane productivity. As can be seen, the model underestimates operational time by 5%. Weather downtime is significantly overestimated. HBTR reported that only high wind speeds halt operations, while the model uses a literature value that assumes rain also stops operations. This is true for some bulk materials but not for coal and iron ore. Therefore, the weather downtime for the terminals in the scope of this research should be reduced to 1 percent of operational time.

The model overestimates the time spent on corrective maintenance. As can be seen in Table 5.3, crane breakdown is indeed 3.0% of the operational time. Which is similar to the downtime of 3.03% used in Equation 4.1. However, the dependency and breakdown time of the stacker/reclaimers and conveyor system is overestimated. HBTR indicated that often an alternative stacker/reclaimer or conveyor route can be used. In this case, the overall corrective maintenance downtime should therefore be changed from 8.86% of the service time to 7% of the service time.

The hours for operational stops and equipment blockage are close to the values predicted by the model. Although equipment blockage is overestimated, it is likely that this category is underreported in the logging system. As a result, a portion of the time recorded under other events can reasonably be attributed to equipment blockage.

The model is based on the assumption that, if possible, preventive maintenance is scheduled when no vessels are present at the berth. In reality, minor planned maintenance often occurs during vessel operations. This highlights the uncertainty in how maintenance time is categorized, particularly when distinguishing between planned maintenance, unplanned maintenance, and equipment failure. Which might be interpreted differently at different terminals.

Despite this overlap, the effect on the overall performance assessment is minimal. The frequency and duration of such maintenance activities are limited, and their influence on key metrics is considered negligible.

5.1.3. Additional validated values

HBTR indicated that cranes achieve an average productivity of approximately 1200 tons per hour during operational hours. The model estimates an average effective rate of 1325 tons per hour. Thus, the effective rate calculated by the model is too high. This is caused by a combination of overestimating throughput and underestimating utilized crane hours.

Planned maintenance is often carried out on cranes that are not operational at the time. HBTR confirmed that this still accounts for roughly 500 hours per year, with a major maintenance session of about two weeks contributing significantly to this total. This aligns with the values used in the model.

While the average operational hours and effective rates are estimated accurately, HBTR noted that there is considerable variation between individual cranes and vessels. Factors such as the quality of the vessel load can significantly affect unloading speed. Crane allocation strategies are also more complex than the simplified assumption of two cranes per vessel. However, these factors have a limited impact on the average values produced by the model and can therefore be excluded without compromising overall accuracy. It should be noted, however, that the model does not capture detailed performance at the level of individual cranes.

5.2. Calibration

After the validation based on data supplied by HBTR, the following changes to the model and its input parameters were made:

- Separate cargo utilization rate for coal, which is set at 80%.
- Change weather downtime percentage from 5% to 1% of service time.
- Change corrective maintenance downtime percentage from 8.86% to 7% of service time.

With the updated parameters, new values were obtained and are presented in Table 5.5. These revised values show improved accuracy in estimating weather downtime WC and corrective maintenance time CM, which in turn leads to a more reliable representation of overall operational time OT.

Model state	HBTR	Model
Operational time OT	71.2%	72.8%
Weather downtime WC	0.6%	1%
Corrective maintenance CM	6.9%	7.0%
Operational stops OS	13.6%	14.1%
Blockage of equipment BE	3.3%	5.0%
Preventive maintenance PM	2.9%	-
Other	1.5%	-

Table 5.5: Comparison between berth states of HBTR and the new model output

By using a cargo load utilization of 80% for coal the following yearly totals were obtained, which can be seen in Table 5.6. As can be seen, the estimated total cargo volume for coal is now closer to the actual value. As can be seen in Table 5.9, the root mean square error for coal was reduced from 0.22 Mt to 0.13 Mt.

	Model	HBTR
Coal	11.87 Mt	11.3 Mt
Iron Ore	10.25 Mt	10.8 Mt
Unknown	0.95 Mt	-
Total	23.07 Mt	22.1 Mt

Table 5.6: Yearly totals per cargo type with the new model parameters.

Parameter	Coal	Iron Ore
Root mean square error	0.13 Mt	0.12 Mt
Mean error	0.06 Mt	-0.05 Mt
Standard deviation	0.13 Mt	0.12 Mt
Mean error 95% confidence interval	$\pm$ 0.074 Mt	$\pm$ 0.066 Mt

Table 5.7: The new error statistics of throughput per cargo type at HBTR with the calibrated model parameters.

5.3. Validation based on Tata Steel IJmuiden data

After tuning the model parameters, additional data was obtained from Tata Steel to further validate the results.

5.3.1. Throughput

Tata Steel provided total monthly throughput but did not specify how much of this was coal or iron ore. A comparison between the model estimates and the reported throughput is shown in Figure 5.2. As can be seen in Table 5.9, the 95% confidence interval is above zero. This indicates the model has a bias to slightly overestimate the throughput.

Figure 5.2 also indicates that the model overestimates throughput in most months. This could be explained by the limiting depth of the terminal. Tata Steel explained that the largest dry bulk carriers often cannot enter the port fully loaded due to depth restrictions. This limitation does not apply to the HBTR terminal, which may explain why the model performs better for that location. Despite the overestimation, the cargo volume estimation is considered sufficiently accurate for the current analysis.

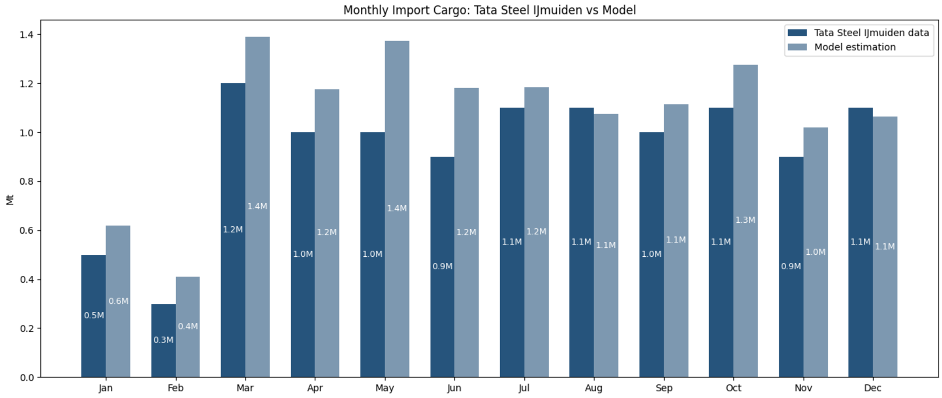


Figure 5.2: Comparison of model results and values supplied by Tata Steel IJmuiden for overall imported cargo volume during 2024.

Tata Steel IJmuiden did not provide throughput data per cargo type. However, they indicated that the ratio of iron ore to coal is expected to follow the chemical requirements for steel production, which is approximately 2 tons of iron ore for every ton of coal. As shown in Table 5.8, the model produced a ratio of 1:1.72, which is close to the expected value of 1:2.

	Model	**Tata Steel IJmuiden**
Coal	4.7 Mt	-
Iron Ore	8.1 Mt	-
Unknown	0.07 Mt	-
Total	12.89 Mt	11.20 Mt

Table 5.8: Yearly totals per cargo type.

Parameter	**Value**
Root mean square error	0.13 Mt
Mean error	0.14 Mt
Standard deviation	0.11 Mt
Mean error 95% confidence interval	$\pm$ 0.064 Mt

Table 5.9: The error statistics of total throughput at Tata Steel IJmuiden.

5.3.2. Quay occupancy

The accuracy of vessel arrival and departure times is discussed in Appendix C. Quay occupancy data from Tata Steel IJmuiden was also compared to the model output, as shown in Figure 5.3. The model results are generally close to the data provided. Some differences may be due to the specific logging of vessel arrivals and departures.

In February, the model significantly overestimates quay occupancy. This month had relatively low actual occupancy. One possible explanation is that vessels remained at the quay longer than recorded, even after being cleared for departure. This could lead to discrepancies between the model and reported data.

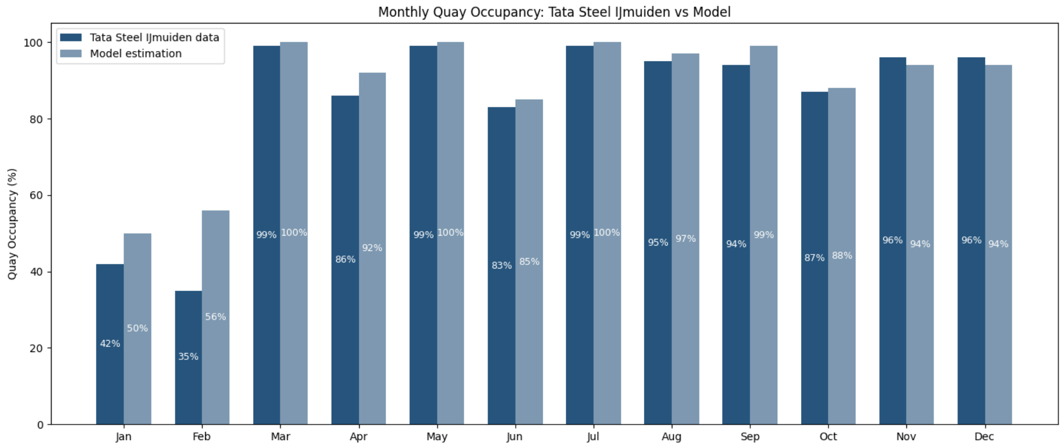


Figure 5.3: Comparison of model results and values supplied by Tata Steel IJmuiden for quay occupancy in 2024.

5.3.3. Crane Utilization

Tata Steel IJmuiden provided crane utilization data for the years 2008 and 2010. Although this period does not align with the time range used in the model, Tata Steel stated that operational performance has remained relatively stable. Nonetheless, the use of older data reduces the reliability of the validation, particularly since a fourth crane was added in 2019.

A comparison between the model and Tata Steel data is shown in Table 5.10. The model overestimates crane utilization. Corrective maintenance at Tata Steel is significantly higher than at HBTR, which was used to calibrate the model parameters. This indicates that maintenance duration and equipment blockage differ substantially between terminals.

Model state	**Tata Steel (2008/2010)**	**Model (2024)**
Operational time OT	62.8%	67.85%
Corrective maintenance CM	12.4%	6.29%
Blockage of equipment BE	10.1%	4.51%
Human/Weather/Other	14.8%	21.36%

Table 5.10: Comparison between average berth states of Tata Steel in 2008 and 2010 and the new model output for 2024

More recent data from Tata Steel shows an average monthly stoppage time of 1,889 minutes due to crane-related technical issues in early 2025, equivalent to 31.5 hours. The model estimates 38.7 hours of monthly stoppage time attributed to corrective maintenance. These recent values for corrective maintenance are thus considerably lower than those from 2008 and 2010.

The model assigns a larger portion of stoppage time to other categories. This may be due to differences in how downtime causes are defined. Despite these variations, the model's estimate of overall crane utilization is 5% higher than the actual value.

Due to the age of the validation data, no further parameter adjustments were made. The analysis shows that identifying specific causes of downtime using open data sources is difficult and subject to uncertainty. Maintenance duration and equipment blockage, in particular, appear to vary significantly between terminals.

5.3.4. OEE

Tata Steel provided monthly OEE data, which was compared to the model output as shown in Figure 5.4. The model results are reasonably accurate but tend to underestimate OEE. This is unexpected, since earlier results showed that cargo throughput was overestimated. Overestimated throughput should normally lead to an overestimation of OEE.

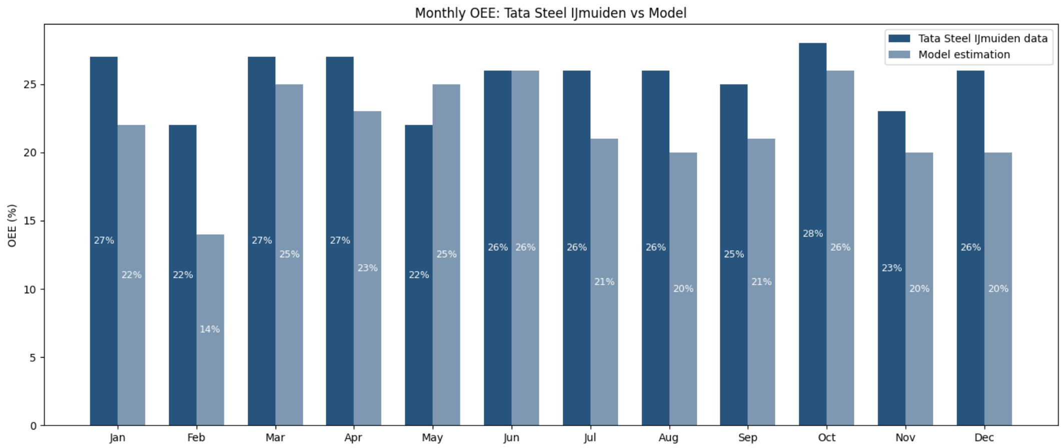


Figure 5.4: Comparison of model results and values supplied by Tata Steel IJmuiden for overall Equipment Effectiveness in 2024.

Crane utilization and crane productivity rely on accurate estimates of utilized hours. However, OEE depends only on quay occupancy, throughput, and nominal rating as can be seen in Equation 5.1.

Inaccuracies in OEE are therefore caused by errors in estimating throughput, quay occupancy, and nominal rating. Tata Steel IJmuiden uses a nominal rating of 6000 tons per hour, based on three cranes rated at 2000 tons per hour each. The model uses a nominal rating of 7872 tons per hour, based on four cranes present at the terminal. This difference alone results in an underestimation of OEE of about 30%.

It can be concluded that the definitions used for nominal rating, number of active cranes, and the exact timing of quay occupancy have a direct impact on the calculated OEE. Clear and consistent definitions are necessary to ensure reliable comparisons.

5.4. Throughput of Hansaport and EECV

No direct contact was made with Hansaport or EECV, but publicly available sources report their total annual throughput. The results for Hansaport are shown in Table 5.11. This table indicates that the model provides a reasonably accurate estimate of overall cargo throughput. For EECV, no specific data was found for the year 2024. The terminal information book mentions an annual throughput of approximately 24 Mt, although the exact year is not specified (Ertsoverslagbedrijf Europoort c.v., 2024). The model estimates a total throughput of 20.1 Mt for EECV, which is reasonably close to the reported average figure since yearly differences are expected.

	Model	**Hansaport**
Coal	3.9 Mt	3.8 Mt
Iron Ore	8.8 Mt	9.1 Mt
Unknown	0.5 Mt	-
Total	13.2 Mt	12.9 Mt

Table 5.11: Yearly totals per cargo type at Hansaport, Hamburg in 2024 (Hafen Hamburg, 2025).

5.5. Confidence interval of Overall Equipment Effectiveness

To further investigate the sensitivity of the OEE assessment, the OEE formula can be defined with as few parameters as possible:

$$OEE = \frac{\text{Throughput}}{\text{Quay Occupancy} \times \text{Total Time} \times \text{Nominal Rating} \times \text{Number of Cranes}} \tag{5.1}$$

This formulation captures the core relationship between quay occupancy, nominal rating, throughput, and OEE. It allows for a focused analysis of how uncertainties in quay occupancy, crane capacity, or throughput affect the accuracy of the overall equipment effectiveness assessment. Therefore, it is required to assess the standard deviation for these factors.

The uncertainty in the number of cranes is addressed in chapter 9. For this analysis, the number of cranes is assumed to be known with certainty. The nominal rating is estimated using cycle time, grab-to-weight ratio, and the safe working load of the crane. These input values are based on assumptions and may vary between terminals. Equipment may operate with different cycle times or use different types of grabs. On the other hand, nominal ratings provided by manufacturers can differ across crane models.

Safe working load data was available for all terminals. Some terminals also reported nominal ratings directly. This allows for a comparison between the estimated and reported values. The results of this comparison are shown in Table 5.12. The predicted nominal rating shows an average error of −25.6 tons per hour and a standard deviation of 276.6 tons per hour.

EECV (Ertsoverslagbedrijf Europoort c.v., 2024)				
Equipment	**Safe working load**	**NR rating model**	**NR rating reported**	**Error**
3 cranes	60 tons	2553 ton/h	2300 ton/h	253 ton/h
1 crane	65 tons	2765 ton/h	2600 ton/h	165 ton/h
Tata Steel IJmuiden (Tata Steel Nederland, 2020)				
Equipment	**Safe working load**	**NR rating model**	**NR rating reported**	**Error**
3 cranes	40 tons	1702 ton/h	2000 ton/h	-298 ton/h
1 crane	65 tons	2765 ton/h	3000 ton/h	-253 ton/h

Table 5.12: Nominal ratings used in the model based on the safe working load and terminal reported nominal ratings. The standard deviation of the prediction error is found at 276.6 ton/h.

Based on the earlier comparison between predicted values and terminal-supplied data, the standard deviation of the error was calculated for throughput and quay occupancy. These values are presented in Table 5.13. Using this information, a Monte Carlo simulation was performed. The simulation applies random sampling to the input parameters, assuming that errors follow a normal distribution and that all parameters are independent (Harrison, 2010).

Parameter	**Mean error**	**Std dev.**	**Sample size**	**Sample**
Throughput (Mt)	-0.1105	0.1537	24	12 months for both HBTR and Tata Steel IJmuiden
Quay occupancy	-3.70%	6.31%	12	12 months at Tata Steel IJmuiden
Nominal rate (ton/h)	-25.6250	276.6214	8	4 cranes at both EECV and Tata Steel IJmuiden

Table 5.13: The mean error and standard deviation of the error found for the three parameters that define the OEE assessment.

The model was run 10,000 times using average values from Tata Steel IJmuiden to produce interpretable results. The output is a normal distribution that reflects the model's accuracy and allows for the estimation of a confidence interval for the OEE assessment. The distribution is shown in Figure 5.5, and the resulting confidence interval is provided in Table 5.14.

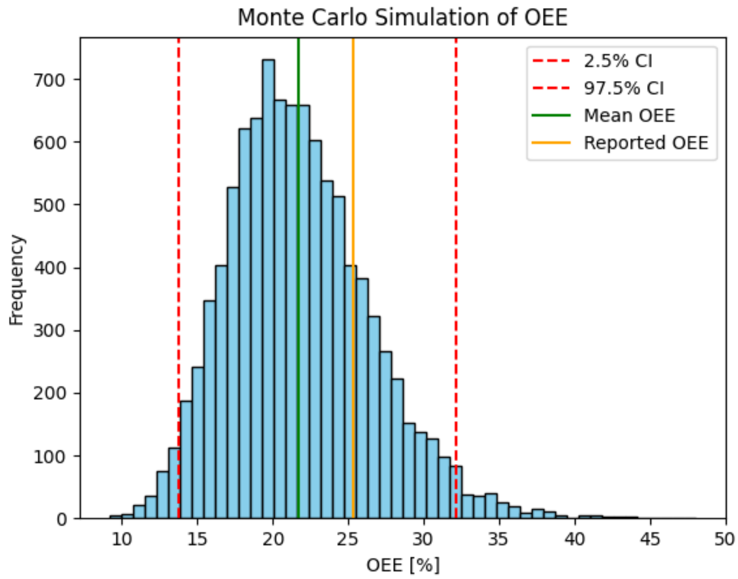


Figure 5.5: The results of the Monte Carlo simulation of the OEE assessment based on Equation 5.1, standard deviations found in Table 5.13, and mean values found for Tata Steel IJmuiden. The yellow line indicates the value reported by Tata Steel.

Estimated OEE mean	21.7%
Estimated OEE Std Dev	4.7
95% Confidence Interval	13.8%, 32.1%

Table 5.14: The values found for the Monte Carlo Simulation of the OEE assessment.

As shown in Table 5.14, the 95% confidence interval is 18.3%, indicating a relatively wide range. To identify which input contributes most to this uncertainty, a sensitivity analysis was performed. The results are presented in Figure 5.6. In this analysis, each input parameter was individually set to its 2.5th and 97.5th percentile, while all other parameters were held constant. The results show that uncertainty in the nominal rating has the largest impact on the OEE outcome. In contrast, quay occupancy has the smallest effect, as it's measured via AIS data and its uncertainty is relatively low.

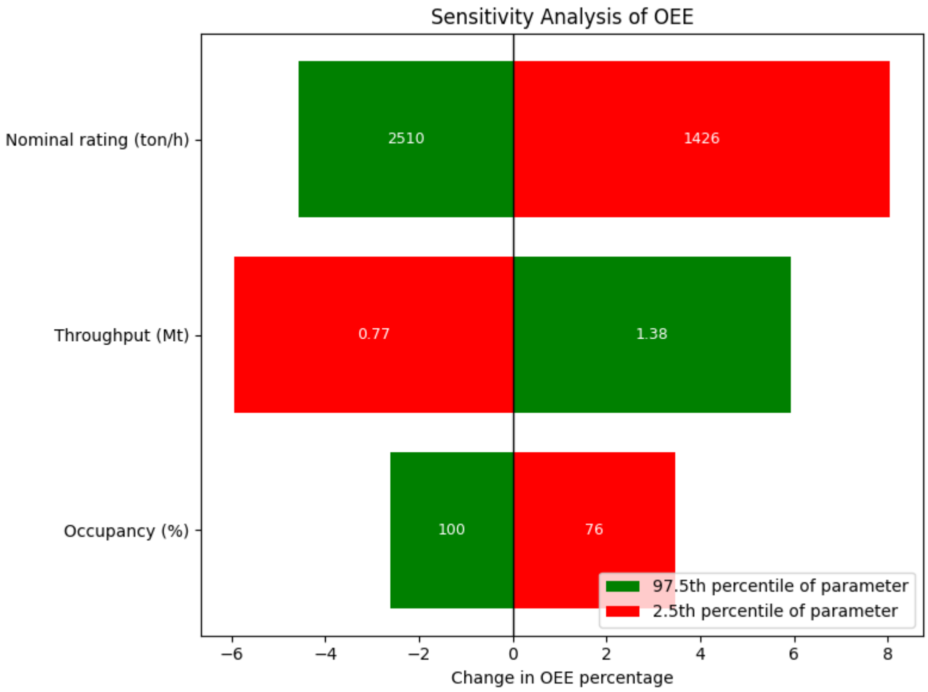


Figure 5.6: Sensitivity analysis of the OEE assessment based on the 2.5th and 97.5th percentile of each input parameter, based on the standard deviations found in Table 5.13 and mean values found for Tata Steel IJmuiden.

5.6. Operational parameters sensitivity analysis

In addition to observations on quay occupancy, throughput, and nominal equipment ratings, a set of operational parameters was defined for each terminal. These parameters include both measured values and estimates derived from literature. Together, these inputs determine the outcomes for key performance indicators: OEE, crane utilization, and crane productivity. The analysis was based on the operational data from Tata Steel IJmuiden. Each input parameter was varied by +50% and −50% to assess its impact. The results of this analysis are presented and discussed in the following sections.

5.6.1. Sensitivity analysis of OEE

Although the sensitivity of OEE is discussed in Figure 5.6, other operational parameters also affect the nominal rating and throughput indirectly. These include the number of cranes and the cargo load utilization factor. Their influence is shown below. A different nominal rating for coal or iron ore does not affect the overall OEE or crane productivity. It only changes the ratio between $ID11$ and $ID12$, which is further explained in subsection 5.6.3.

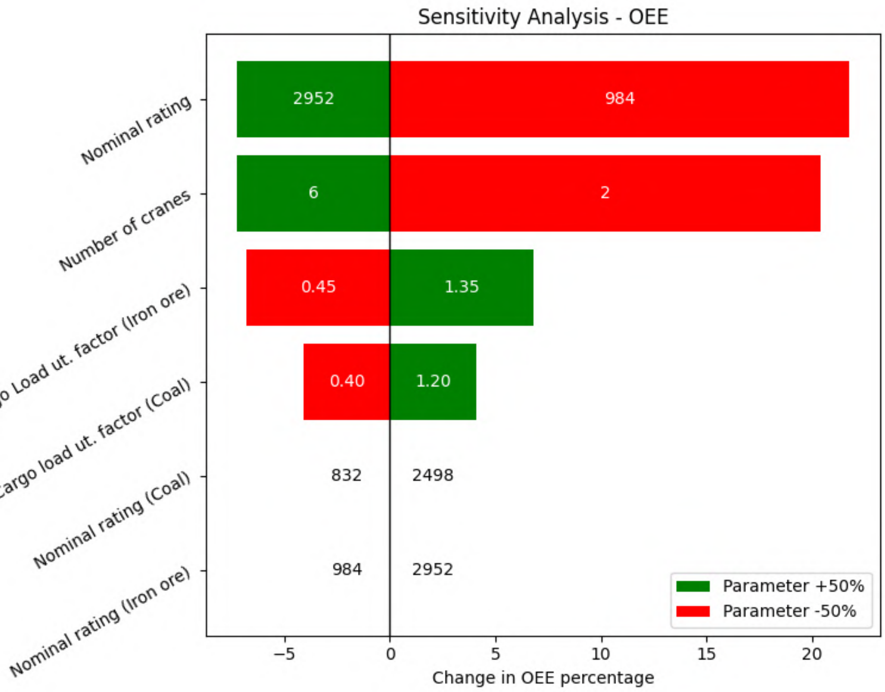


Figure 5.7: Sensitivity analysis of the OEE assessment with respect to different operational parameters. Each input parameter was decreased and increased by 50%. The values shown in the bars indicate the parameter value used in each model run.

5.6.2. Sensitivity analysis of crane utilization

Crane utilization is influenced by several operational parameters. Their individual effects are shown in Figure 5.8. The number of cranes has the largest impact on average operational time per crane, as expected. Other parameters show similar relative levels of influence. Preventive maintenance at Tata Steel IJmuiden is assumed to take place only when no vessels are present. As a result, changes to this parameter do not affect crane utilization in the current model setup.

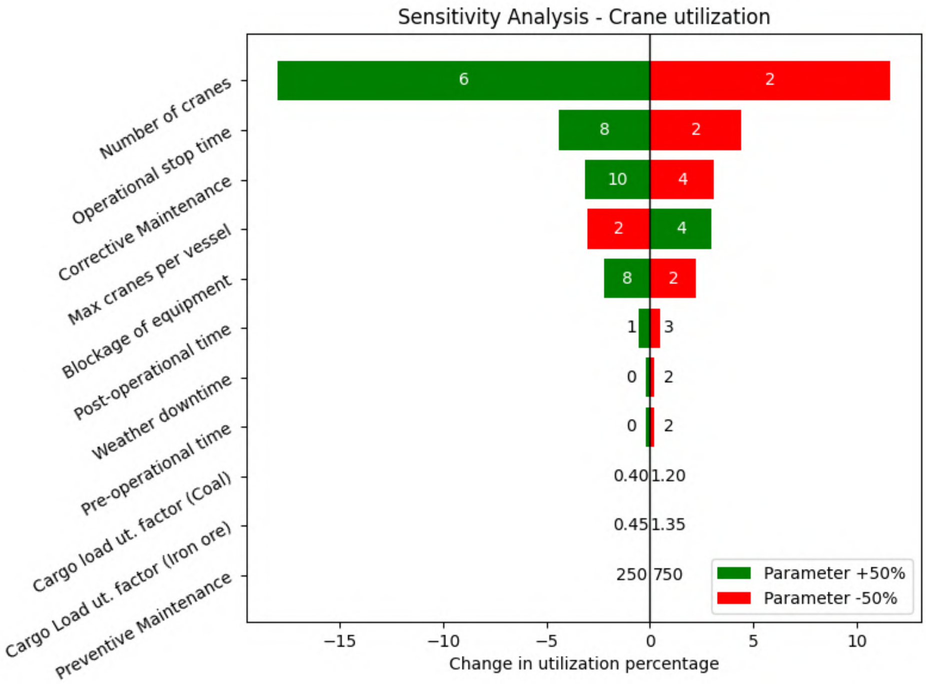


Figure 5.8: Sensitivity analysis of the crane utilization assessment with respect to different operational parameters. Each input parameter was decreased and increased by 50%. The values shown in the bars indicate the parameter value used in each model run.

5.6.3. Sensitivity analysis of crane productivity

Crane productivity is defined by Equation 2.12 and depends on the effective rate (ER) and the nominal rating (NR). It is expressed as a percentage relative to crane utilization. Therefore, any parameter that affects crane utilization also influences crane productivity.

The cargo-specific nominal rating for coal or iron ore does not affect overall crane productivity. It only changes the ratio between $ID11$ and $ID12$. In this context, $ID11$ represents endogenous variation in the effective rate, while $ID12$ reflects exogenous variation due to cargo type. The ratio between these two components is determined by the operational time and the nominal rating for each cargo type.

Terminals that handle more coal show a greater influence from $ID12$, as coal is typically associated with lower handling speeds compared to iron ore. These differences are considered exogenous losses. This effect is illustrated in Figure 5.10.

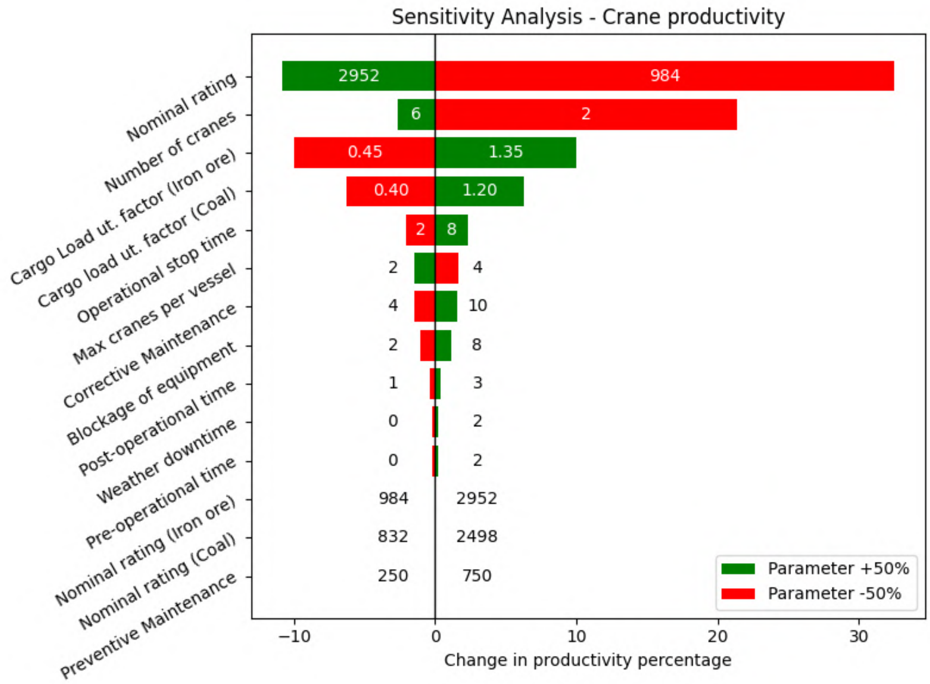


Figure 5.9: Sensitivity analysis of the crane productivity assessment with respect to different operational parameters. Each input parameter was decreased and increased by 50%. The values shown in the bars indicate the parameter value used in each model run.

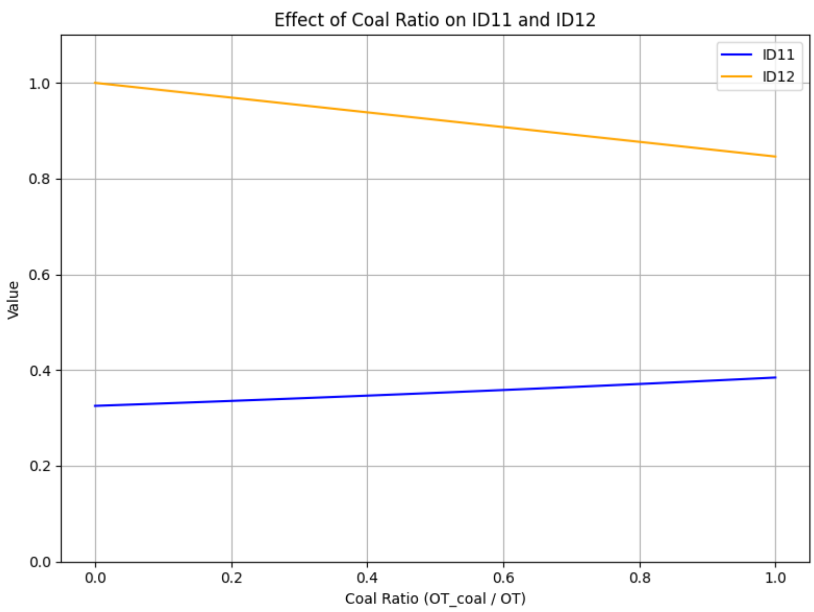


Figure 5.10: The sensitivity of $ID11$ and $ID12$ on the fraction of the operational time spent on unloading coal vs iron ore. $ID11$ represents the endogenous variation in the effective rate, while $ID12$ represents the exogenous Cargo type nominal rate variation.

5.7. Conclusion

The measured data from HBTR showed accurate results for both cargo throughput per cargo type and utilized crane hours. Further calibration of the operational parameters was performed. The tonnage of coal was overestimated. To address this, the cargo load utilization rate for coal-carrying vessels was reduced from 90% to 80%.

Weather-related downtime was also overestimated. The model initially assumed that rainfall also caused operational delays, whereas in reality, only high wind speeds halt operations. Consequently, the weather downtime percentage was adjusted from 5% to 1% of service time.

Corrective maintenance time was similarly overestimated. Although the duration of crane repairs was accurate, the model overstated the dependency on the conveyor system and stacker/reclaimers. As a result, the overall downtime attributed to corrective maintenance was reduced from 8.86% to 7% of service time.

To summarize, the following three changes were made to the model and its input parameters:

- Separate cargo utilization rate for coal, which is set at 80%.
- Change weather downtime percentage from 5% to 1% of service time.
- Change corrective maintenance downtime percentage from 8.86% to 7% of service time.

After implementing these changes, the model showed improved accuracy for this type of terminal in estimating both the tonnage of coal handled and the number of operational crane hours. While it became clear that operations for individual cranes and vessels can vary significantly on continuous quays, the model provides reliable average estimates over longer periods and across multiple cranes.

Additional validation of crane utilization, cargo throughput, quay occupancy, and overall equipment effectiveness (OEE) was performed using data from Tata Steel IJmuiden. The model showed acceptable accuracy for these metrics. However, the results revealed notable differences between terminals in corrective maintenance and equipment blockage. These differences are likely related to variations in terminal layout and equipment age.

The sensitivity of the different inputs and operational parameters was discussed. The model is most sensitive to inaccuracies in the nominal rating of equipment and the estimated number of cranes at the terminal.

The analysis also showed that the accuracy of the model is influenced by how downtimes and quay occupancy are defined. These definitions directly affect the calculation of OEE and can cause inconsistencies if not clearly aligned between the model and the operational data.

A Monte Carlo simulation was used to evaluate the accuracy of the OEE assessment, based on the standard deviation of nominal rating, quay occupancy, and throughput. The resulting 95% confidence interval for the OEE was 18.3%. The largest source of uncertainty was the nominal rating of the unloaders. Uncertainty in identifying the cargo type of incoming vessels affects the ratio between ID11 and ID12, which influences benchmarking across terminals but does not impact the individual OEE calculation. Overall, accurate estimation of nominal rating, including cargo-specific values, is essential for reliable results.

In conclusion, the model now accurately reflects the performance of dry bulk operations and serves as a robust indicator of overall terminal productivity.

6 Results

Chapter Sub-question: 5. What can be concluded from the performance assessment results, and what difference between the terminals can be observed?

In this chapter, the methodology developed in this research is applied to the chosen terminals in chapter 1.

The assessment of performance indicators such as waiting times, OEE, and berth commitment provides a general overview of terminal performance. OEE reflects crane efficiency, while berth commitment indicates the extent to which available berth time is utilized, representing the terminal's capacity usage. Individual performance indicators help identify specific sources of inefficiency. Waiting times reflect the terminal's service level and, when considered alongside berth commitment, can indicate whether the terminal is operating above or below its sustainable capacity. Together, these parameters offer insight into the terminal's handling performance and operational conditions.

6.1. Analyzed terminals

The following four terminals are analyzed. The HBTR terminal is discussed completely in this chapter. The other three terminals are discussed briefly, but the complete results can be found in Appendix B.

- HBTR, Rotterdam -> section 6.2
- EECV, Rotterdam -> section B.1
- Tata Steel, IJmuiden -> section B.2
- Hansaport, Hamburg -> section B.3

All terminals discussed are large, import-oriented terminals that receive seagoing vessels carrying coal and iron ore. The HBTR and EECV terminals feature continuous quays, where multiple vessels can moor simultaneously. The cranes at these terminals can move along the quay to service different berths.

All terminal feature four cranes that can move allong the quay. Tata Steel and Hansaport have two berths along the quay, EECV has three, and HBTR has four berths for vessel to moor.

While the terminals share some operational characteristics, each has unique features. HBTR is a large transfer terminal that operates for various clients. EECV, on the other hand, is owned by German steel manufacturers and functions more as an extension of their supply chain. This ownership structure gives EECV greater control over logistics and reduces the impact of long vessel waiting times.

The terminal at Tata Steel IJmuiden is part of the steel plant located on site, meaning its operations are directly influenced by the production processes of the plant. Lastly, the Hansaport terminal in Hamburg is situated, unlike the other three terminals, 110 kilometers upstream on the river Elbe. As a result, vessels calling at Hansaport experience longer travel times from the anchorage area to the terminal.

6.2. HBRT, Rotterdam

Located at the Maasvlakte in Rotterdam, the Netherlands, Hes Bulk Terminal Rotterdam (HBTR) is the biggest dry bulk terminal in Europe. Formally named EMO, HBTR was taken over by HES International in 2015. HBTR is a transshipment terminal that focuses on handling iron ore, coking coal, and steam coal. Coking coal is used for steel production, whereas steam coal is used for energy production. These materials are imported from overseas, stored at the facility, and then sent off to barges, trains, and ships for delivery to other countries or nearby power plants for immediate use. There are two coal-powered power plants next to the terminal. There are two sets of mixing silos on the terrain of HBTR, one for each power plant, which are thereafter directly connected to the power plant via conveyor systems. Most of the coal and iron ore stored at HBTR is later transported to Germany. The terminal can store up to 7 million tonnes of dry bulk and also has cleaning and blending capabilities.

The terminal operates 4 gantry cranes for the unloading of seagoing vessels. The oldest one has just been taken out of operation. Moreover, it operates two barge loaders and one sea-vessel shiploader. On the terrain are 7 stacker/reclaimers, connected by a conveyor system. The terminal operates 3 train loaders, one for iron ore and two for coal. As mentioned before, two outgoing conveyors are directly connected to two coal-powered power plants.

The layout of the terminal can be seen in Figure 6.1. The locations of the polygons used to determine which berth was visited can be found in Appendix G.

Figure 6.1: Aerial image of the HBTR terminal quay along the Mississippi haven with berth 1,2,3, and 4. Berths 5 and 6 are located more to the right and are used for exporting material. (Google Earth, 2025)

6.2.1. Call log

The original Sea-Web call log has 1547 vessels. After filtering, the following vessels per category were found:

Vessel Type	Number found
BULK CARRIER	253
ORE CARRIER	8
OPEN HATCH CARGO SHIP	3

Table 6.1: Vessels found at HBTR for 2024

For these 264 vessels, 5 duplicate arrivals were found, leaving 259 unique vessel arrivals.

After estimation of the cargo direction, 209 vessels were found to be importing material:

Classification	Number found	Percentage
Importing	209	80.7%
Exporting	47	18.1%
Unknown	3	1.2 %

Table 6.2: Number of vessels categorized as importing/exporting or unknown for HBTR in 2024.

The HBTR terminal has four berths, which are used for unloading material. Berth 1 is westmost and 2,3,4 follow east from that in order. The percentage of time a vessel was present at each of the berths can be seen in Figure 6.2 below. As can be seen berths 3 and 4 are used the most, since the cranes located here are the newest and largest. These are preferred since they will experience the least amount of downtime and archieve the highest productivity. Berth 1 is used rarely since here is the oldest and smallest crane located. It must be noted that the berth occupancy displayed here is different from the quay occupancy in the OEE assessment, as this is just the percentage of time a vessel is present at the specific berth, excluding transit times.

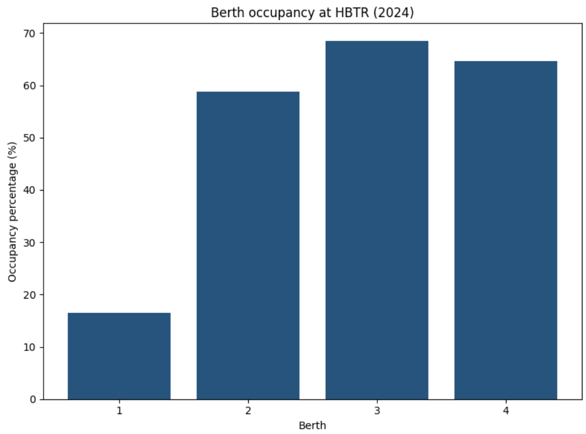


Figure 6.2: The observed percentage of time a vessel was present at each berth at HBTR in 2024.

The distribution of deadweight tonnage (DWT) and cargo types of importing vessels is shown in Figure 6.3. The terminal receives some of the largest dry bulk vessels in the world, including those in the Capesize class (100,000 to 199,000 tons) and the VLOC class (200,000+ tons). Most vessels are around 80,000 tons or 180,000 tons, corresponding to Panamax and Capesize vessels, respectively. HBTR is the only analysed terminal that receives more vessels carrying coal than iron ore. This is likely since it not only serves the steel industry but also the nearby coal power plants.

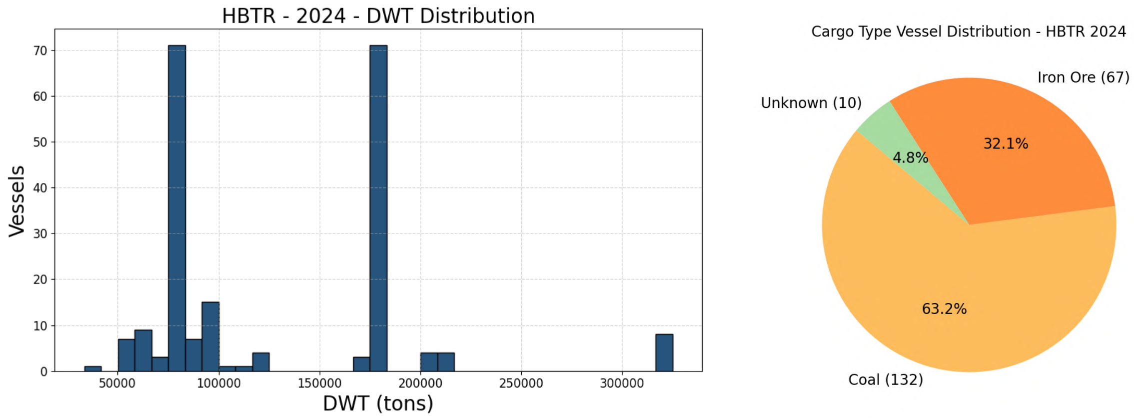


Figure 6.3: The distribution of DWT and the number of vessels per cargo type of importing vessels at HBTR in 2024

The service time and waiting time distributions are shown in Figure 6.4. The average service time is 87.98 hours, while the average waiting time is 37.82 hours, yielding a waiting-to-service time ratio of 0.43. The distribution reveals a few high outliers in waiting time. By filtering out the top 3% of waiting times, which corresponds to any waiting time exceeding 172 hours, the average waiting time decreases to 28.46 hours. This may offer a more representative estimate of typical waiting conditions. The revised waiting-to-service time ratio then becomes 0.32.

Of the 209 arriving vessels, 98 were observed waiting in the anchorage area. This low number of waiting vessels is likely because of the terminal's long quay, which can accommodate up to four vessels moored simultaneously. Instead of waiting offshore, these vessels berth along the quay early and wait until they can be unloaded.

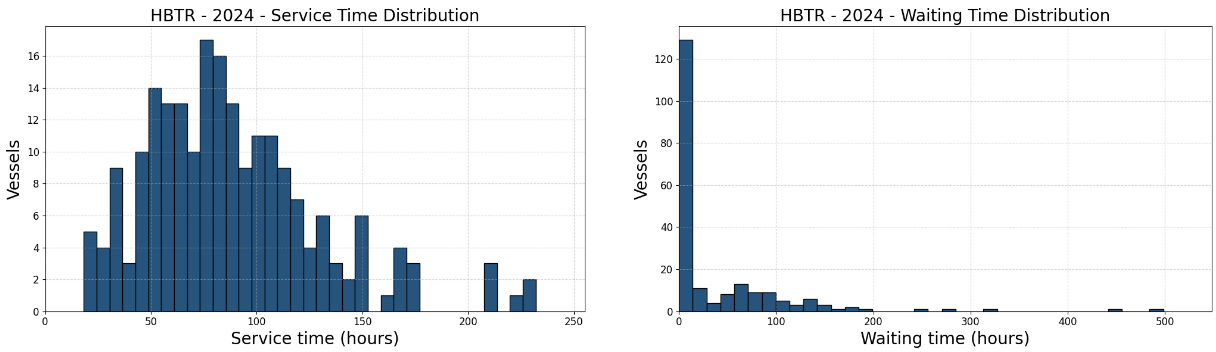


Figure 6.4: The distribution of service time and waiting time of importing vessels at HBTR during 2024

The transit time into the harbor and toward the terminal, as well as the transit time when leaving the harbor, are shown in Figure 6.5. The overall average inbound transit time is 5.56 hours, while the average outbound transit time is 1.17 hours.

The definition of inbound transit time differs depending on whether a vessel waits in the anchorage area. For vessels that do not wait, the inbound transit time is measured from the moment they pass the mouth of the harbor until arrival at the terminal. For vessels that do wait, the inbound transit time begins when they depart the anchorage area. The average inbound transit time for vessels coming from anchorage is 8.20 hours, while for vessels not visiting anchorage it is 2.83 hours.

Inbound transit times are longer than outbound times, likely due to increased maneuvering and reduced vessel speed when arriving fully loaded.

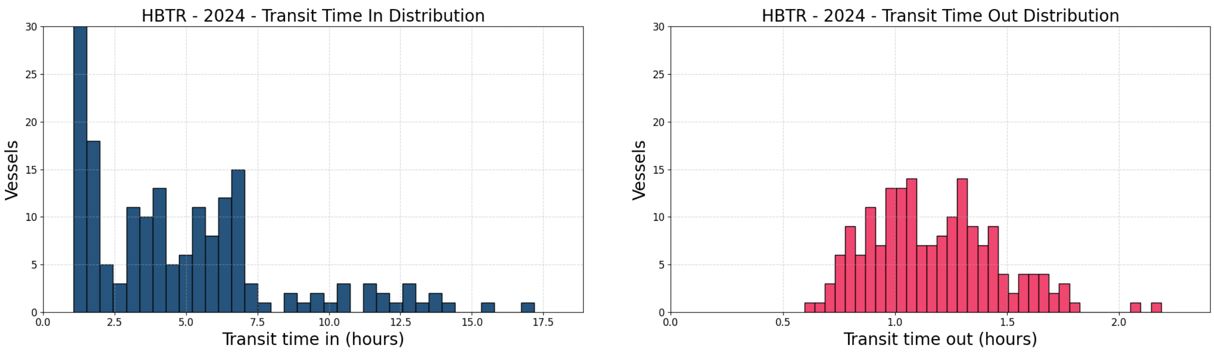


Figure 6.5: The distribution of transit times in and out of the harbor of importing vessels at HBTR during 2024

The origin and next port countries for vessels importing at HBTR are shown in Figure 6.6. Most material is imported from North and South America and Australia, which aligns with the fact that these regions are major exporters of iron ore and coal. The next port data indicates that many vessels return directly to the same continent they arrived from, although some vessels first visit another port in Europe before returning.

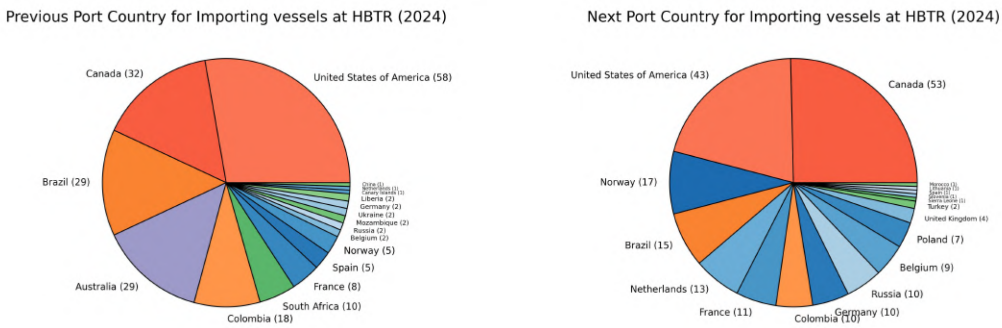


Figure 6.6: The previous and next port countries for importing vessels at HBTR in 2024

6.2.2. Terminal layout

The terminal layout is analyzed using the trained object detection model. The results can be seen in Figure 6.7 and Table 6.3.

Figure 6.7: Crane detections of aerial images of multiple years at HBTR.

Date	Cranes Detected
28-05-2013	7
27-08-2014	5
23-08-2016	5
27-09-2016	5
08-05-2018	5
27-03-2020	6
10-03-2022	4
15-04-2023	7
23-06-2024	4
01-12-2024	5
23-03-2025	4

Table 6.3: Cranes detected at HBTR from aerial images

As can be seen in Table 6.3, 5 times 5 cranes were detected, 3 times 4 cranes, 2 times 7 cranes, and 1 time 6 cranes. It can therefore be concluded that five cranes are present at the terminal. However, after consultation with the terminal operator, it became apparent that one of the cranes, as of 2025, is being decommissioned. Therefore, only four cranes are deemed operational. Lastly, no more than two cranes are seen operating on a single vessel at the same time. The maximal number of operational cranes per vessel is therefore set at two.

6.2.3. Parameters & performance indicators

Three cranes at HBTR have a safe working load of 85 tons, while one older crane has a safe working load of 50 tons. This results in an average safe working load of 76.25 tons. Using Equation 4.2 and the parameters provided in Table 4.5, the nominal ratings are calculated. The results are presented in Table 6.4. These values, along with the other operational parameters used as input for the crane utilization model, are detailed in Appendix F.

Parameter	value
Nominal rating NR	3244 tons/h
Nominal rate iron ore NR_{iron}	3244 tons/h
Nominal rate coal NR_{coal}	2745 ton/h

Table 6.4: Nominal rates for HBTR

With these input parameters and the constructed call log, the crane utilization model can be executed. The model results can be seen in Table 6.5 below. A visual representation per month can be seen in Figure 6.8. As can be seen, the terminal operates with little idle time, although July and August are less productive months. Since HBTR features a continuous quay. The parameters are defined as averages across all cranes.

Parameter	Value
TT	8784
IDL	738
IDL_{nv}	141
UNV	0
PM	0
PM_{nv}	500
WC	72
TR	149
TR_{nv}	40
PO	72
CM	503
OS	1045
BE	360
OT	5164
OT_{coal}	2672
OT_{iron}	2276
THR (kt)	23064
$\#Calls$	209
$LOAD$ (kt)	113
ER (t)	1143
NR_{coal} (t)	2745
NR_{iron} (t)	3244
NR (t)	3244

Table 6.5: Parameters for HBTR in 2024

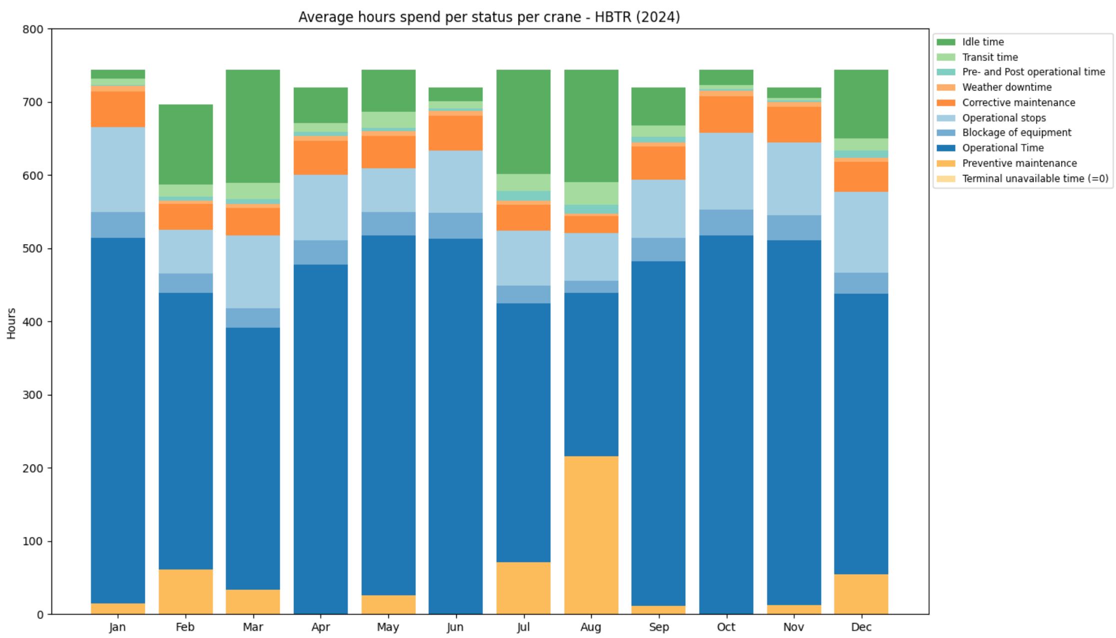


Figure 6.8: Average hours spent in different states per month.

The derived parameters yield the performance indicators presented in Table 6.6. As shown, the terminal experiences minimal losses due to transit time and pre- or post-operational activities. This efficiency is largely attributed to the terminal's configuration of four berths and four cranes, which enables seamless transitions of cranes between vessels. Vessels can often already moor at an available berth while cranes complete tasks on another, allowing immediate continuation of handling activities without significant downtime.

Description	Indicator	Value
Idleness	$ID1_v$	0.170
Idleness (no vessel)	$ID1_{nv}$	1.6%
Unavailability	$ID2$	0.0%
Preventive maintenance	$ID3_v$	0.000
Preventive maintenance (no vessel)	$ID3_{nv}$	5.7%
Weather downtime (h per vessel)	$ID4$	0.352
Transit Time (h per vessel)	$ID5_v$	0.775
Transit Time (no vessel)	$ID5_{nv}$	0.5%
Pre- and Post-operational time (h per vessel)	$ID6$	0.376
Corrective maintenance	$ID7$	0.098
Operational Stops	$ID8$	0.209
Blockage of equipment	$ID9$	0.070
Exogenous downtime	$ID10$	0.000
Variation in effective rate	$ID11$	38.2%
Cargo type nominal rate variation	$ID12$	92.3%
Quay occupancy	OCC	92.3%
Crane utilization	$UTIL$	64.9%
Crane productivity	$PROD$	35.2%
Overall Equipment Effectiveness	OEE	22.5%

Table 6.6: Performance Indicators for HBTR in 2024

An yearly overview of the OEE assessment can be seen in Figure 6.9 below.

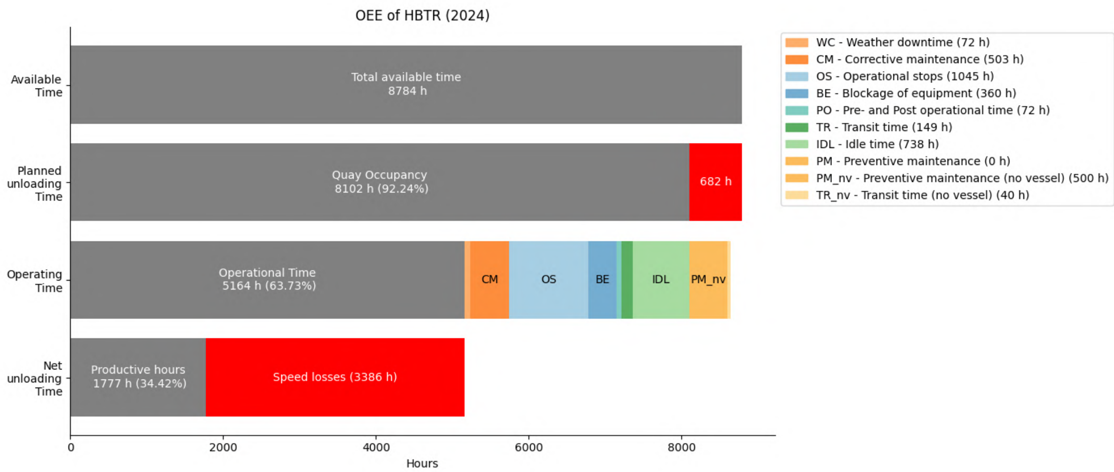


Figure 6.9: The total OEE assessment of HBTR in 2024

The OEE metrics of berth occupancy, crane utilization, and crane productivity per month can be seen in Figure 6.10.

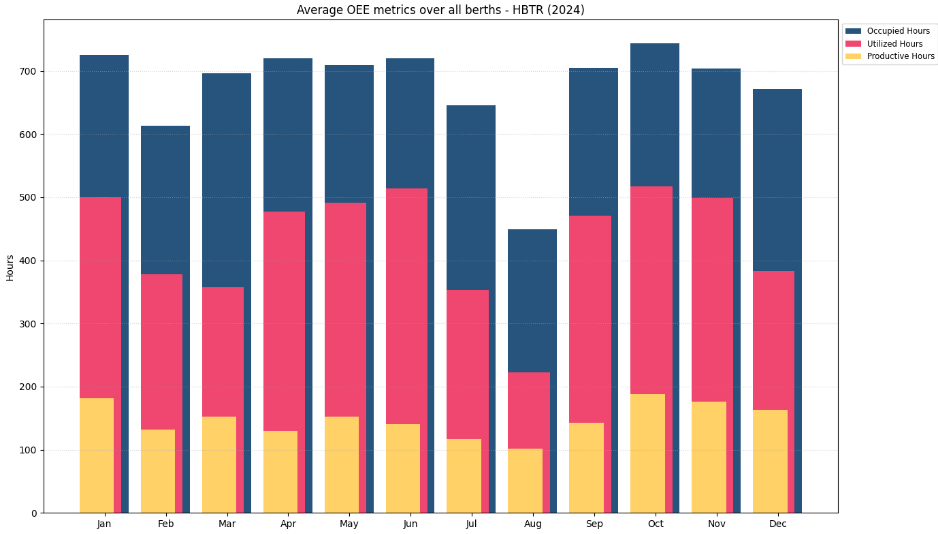


Figure 6.10: The average berth occupancy, crane utilization, and crane productive hours for HBTR in 2024.

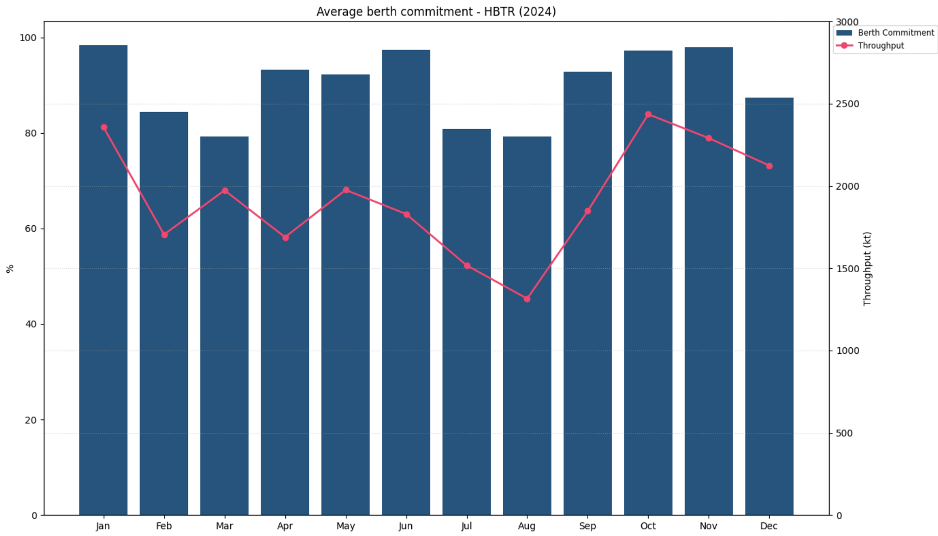


Figure 6.11: The berth commitment and throughput per month per berth for HBTR in 2024.

In Figure 6.11, the average berth commitment and throughput per month are shown. Both commitment and throughput show a noticeable dip in July and August, which may be attributed to the summer holiday period. According to R. Slikkerveer (personal communication, May 16, 2025), the terminal has been facing a shortage of workers, which could explain the reduced activity during these holiday months.

The average berth commitment across all berths and months was 92.8%, placing it at the upper limit of the range recommended by PIANC for multi-berth terminals. Although the terminal has four mooring positions for vessels, two of these are considered lay-by berths as the commitment is only calculated as the idle time of the cranes. Vessels at the other berth positions can moor, complete paperwork, and prepare for unloading while the cranes are still servicing another vessel, thus allowing the cranes to operate at a higher commitment.

This highlights the ambiguity in defining berth commitment for continuous quay terminals. In these cases, the number of cranes and their operational capacity are more relevant than the number of berths when evaluating terminal commitment. The additional berths mainly serve to increase flexibility in vessel and crane movement, rather than directly influencing the terminal's operational capacity.

HBTR is one of the largest dry bulk terminals in Europe. The estimated overall throughput is 23,1 Mt for 2024.

6.3. EECV, Tata Steel IJmuiden & Hansaport

The complete results for EECV, Tata Steel IJmuiden, and Hansaport can be found in Appendix B. An overview of the OEE analysis for all terminals is given in Table 6.7.

EECV reports a very high quay occupancy of 99.1%, which means that there is almost always at least one vessel moored at the quay. The terminal also reports the highest variation in nominal cargo type rate ($ID12$), which indicates that it mainly unloads iron ore. This is consistent with the fact that the terminal is owned by German steel manufacturers as it primarily handles iron ore and only expanded with a coal terminal after 2003 (EECV, 2025). Hansaport shows more idleness ($ID1$) and transit time ($ID5$) than the other terminals because it has a long access channel and relatively less traffic. At the same time, Hansaport reports high crane productivity at 71.4%. The Tata Steel IJmuiden terminal also services the adjacent steel manufacturing plant. Its quay occupancy is lower than that of EECV and HBTR because it experienced reduced traffic during January and February (R. Schuurmans, personal communication, August 15, 2025).

Description	**Indicator**	**EECV**	**Hansaport**	**HBTR**	**Tata Steel**
Idleness	$ID1_v$	0.036	0.554	0.170	0.204
Idleness (no vessel)	$ID1_{nv}$	0.4%	19.4%	1.6%	6.0%
Unavailability	$ID2$	0.00%	0.00%	0.00%	0.00%
Preventive maintenance	$ID3_v$	0.080	0.000	0.020	0.000
Prev. maintenance (no vessel)	$ID3_{nv}$	0.4%	5.7%	5.7%	4.39%
Weather downtime (h/vessel)	$ID4$	0.575	0.312	0.352	0.502
Transit Time (h/vessel)	$ID5_v$	0.761	1.928	0.775	1.742
Transit Time (no vessel)	$ID5_{nv}$	0.1%	5.5%	0.5%	0.4%
Pre- and Post-op. time (h/vessel)	$ID6$	0.214	1.058	0.376	0.772
Corrective maintenance	$ID7$	0.094	0.105	0.098	0.093
Operational Stops	$ID8$	0.120	0.245	0.209	0.133
Blockage of equipment	$ID9$	0.067	0.074	0.070	0.067
Exogenous downtime	$ID10$	0.000	0.000	0.000	0.000
Variation in effective rate	$ID11$	32.57%	74.79%	38.18%	34.62%
Cargo type nominal rate variation	$ID12$	96.6%	95.2%	92.3%	93.9%
Quay occupancy	OCC	99.1%	69.4%	92.3%	87.9%
Crane utilization	$UTIL$	71.5%	50.3%	64.9%	66.8%
Crane productivity	$PROD$	31.4%	71.4%	35.2%	32.5%
Overall Equipment Effectiveness	OEE	22.5%	35.5%	22.5%	21.8%

Table 6.7: Performance indicators and OEE factors across terminals in 2024

6.4. Comparison between terminals

After analyzing all terminals, a benchmark comparison was performed. The benchmarked OEE ($OEE_{benchmark}$) was calculated according to Equation 2.14. To isolate terminal-specific performance, exogenous indicators were averaged across all terminals and excluded from the comparison.

Exgeonous influences Performance indicators defined by exogenous factors are replaced with the average value across the full sample.

Endogenous influences Performance indicators defined by endogenous influences remain unchanged and therefore determine differences in $UTIL_{benchmark}$, $PROD_{benchmark}$, and $OEE_{benchmark}$.

Since crane utilization, crane productivity, and OEE can be derived from these indicators, comparative values were calculated. The results are shown in Table 6.8.

Hansaport shows a high amount of idle time while a vessel is present. This is likely due to the frequent presence of only one vessel at the terminal, which limits crane deployment. In contrast, EECV experiences minimal downtime. The terminal operates under high occupancy, with multiple vessels present simultaneously, allowing cranes to remain active.

As seen for $ID6$ terminals with more berths (HBTR and EECV) lose less time to pre- and post-operational activities. Vessels can shift between berths, and cranes can continue operations without waiting. For $ID11$, Hansaport demonstrates significantly higher crane productivity compared to the other terminals. This contributes to a higher overall equipment effectiveness. The other three terminals show similar performance levels across the benchmarked indicators.

The HBTR terminal has the highest share of coal handled among the four terminals, which is expressed in an $ID12$ value of 92.3% in Table 6.7. This represents an exogenous influence on lower crane productivity, as coal is more difficult to handle and therefore unloaded at a slower rate than iron ore. By averaging $ID12$, the relative crane productivity $PROD_{benchmark}$ for HBTR increases, while that of the other three terminals decreases. This demonstrates how the benchmarking method enables fairer comparisons between terminals.

Description	Indicator	EECV	Hansaport	HBTR	Tata Steel
Idleness	$ID1_v$	0.036	0.554	0.170	0.204
Idleness (no vessel)	$ID1_{nv-avg}$	6.81%	6.81%	6.81%	6.81%
Unavailability	$ID2_{avg}$	0.00%	0.00%	0.00%	0.00%
Preventive maintenance	$ID3_{v-avg}$	0.020	0.020	0.020	0.020
Prev. maintenance (no vessel)	$ID3_{nv-avg}$	4.39%	4.39%	4.39%	4.39%
Weather downtime (h/vessel)	$ID4_{avg}$	0.435	0.435	0.435	0.435
Transit Time (h/vessel)	$ID5_{v-avg}$	1.302	1.302	1.302	1.302
Transit Time (no vessel)	$ID5_{nv-avg}$	1.61%	1.61%	1.61%	1.61%
Pre- and Post-op. time (h/vessel)	$ID6$	0.214	1.058	0.376	0.772
Corrective maintenance	$ID7$	0.094	0.105	0.098	0.093
Operational Stops	$ID8$	0.120	0.245	0.209	0.133
Blockage of equipment	$ID9$	0.067	0.074	0.070	0.067
Exogenous downtime	$ID10$	0.000	0.000	0.000	0.000
Variation in effective rate	$ID11$	32.57%	74.79%	38.18%	34.62%
Cargo type nominal rate variation	$ID12_{avg}$	94.48%	94.48%	94.48%	94.48%
Quay occupancy	OCC_{avg}	87.19%	87.19%	87.19%	87.19%
Crane utilization	$UTIL_{benchmark}$	74.12%	50.10%	63.73%	66.18%
Crane productivity	$PROD_{benchmark}$	30.78%	70.66%	36.07%	32.70%
Overall Equipment Effectiveness	$OEE_{benchmark}$	22.77%	35.01%	22.71%	21.65%

Table 6.8: Benchmarked performance indicators across terminals in 2024

6.5. Conclusion

The performance assessment showed clear differences in operational characteristics across the analyzed terminals. Key metrics such as waiting time, transit duration, and crane productivity were benchmarked to enable comparison. Tata Steel IJmuiden and EECV showed consistently high waiting times, which may indicate limitations in berth availability or scheduling. Hansaport had long transit durations but showed high crane productivity, suggesting efficient unloading once vessels are berthed. Overall, most terminals demonstrated similar unloading performance, but under different operational conditions, such as high waiting times and high berth commitment.

The benchmarking results between terminals show that more comprehensive comparisons can be made by averaging the performance indicators defined by exogenous influences. This approach allows for fairer comparisons and a more constructive assessment of performance.

7 Discussion of results

Chapter Sub-question: 8. How do the results align with dry bulk terminal design guidelines, and what improvements to design methodologies can be derived from observed differences?

In this chapter, the results are further discussed and compared across terminals. Additionally, a comparison is made between the observed outcomes and values reported in the literature.

Literature research, as presented in chapter 2, reveals that numerous guidelines and rules of thumb exist for effective port planning. This chapter evaluates the empirical values obtained in the study against these established design principles. By comparing actual terminal performance metrics with theoretical benchmarks, the analysis aims to identify alignment, deviations, and potential areas for optimization in capacity factors and berth commitment.

7.1. Capacity factor

As shown by van Vianen et al. (2011) in Table 2.7, unloaders at an import-oriented dry bulk terminal are expected to have a capacity factor between 3 and 4.5. The found capacity factors for terminals analyzed in this research can be seen in Table 7.1. As can be seen, besides EECV, all terminals are above the suggested range from van Vianen et al. (2011). Especially, Tata Steel shows very low throughput relative to their nominal rating.

Terminal	Capacity factor	Throughput	Nominal rate	Effective rate	Cranes
HBTR	4.94	23.0 Mt	3244 ton/h	1143 ton/h	4
EECV	4.56	20.1 Mt	2606 ton/h	819 ton/h	4
Tata Steel	5.37	11.7 Mt	1968 ton/h	640 ton/h	4
Hansaport	4.28	11.6 Mt	1617 ton/h	1155 ton/h	4

Table 7.1: Capacity factors and crane performance per terminal.

Crane performance per terminal is presented in Table 7.2. This table does not reflect the benchmarked values of crane utilization, crane productivity, or OEE, which are based on averaged performance indicators.

HBTR, EECV, and Tata Steel IJmuiden show similar overall performance. However, crane utilization is lower at Tata Steel IJmuiden and Hansaport. This is mainly due to lower berth occupancy. In these terminals, there are frequent periods when only one vessel is present, limiting the number of cranes that can be used. In contrast, HBTR and EECV have longer quays that allow multiple vessels to moor simultaneously, increasing crane availability.

Hansaport shows notably high crane productivity. This may suggest that the nominal rating used in the analysis does not accurately reflect the actual unloading capacity. According to Hansaport's website, the terminal is fully automated (Hansaport, 2023). It is also possible that this operational strategy may contribute to the observed high productivity.

Terminal	Quay Occupancy	Crane Utilization	Crane Productivity	OEE
HBTR	92.2%	71.8%	35.2%	22.5%
EECV	99.1%	72.2%	30.7%	22.4%
Tata Steel	87.9%	66.8%	32.5%	21.8%
Hansaport	69.4%	50.3%	71.4%	35.4%

Table 7.2: Capacity factors and crane performance per terminal.

As shown, the capacity factors identified in this study are lower than those reported by van Vianen et al. (2011). For Hansaport, this discrepancy is primarily attributed to low quay occupancy rather than suboptimal crane performance. In contrast, Tata Steel IJmuiden exhibits genuinely low crane performance. HBTR and EECV operate near the upper bound of the observed capacity factor range. Although inaccuracies in nominal rating could influence the calculated capacity factors, and the specific nominal rating used by van Vianen et al. (2011) remains unknown, these findings may suggest that the dry bulk terminals examined in this research possess higher nominal ratings relative to their annual throughput than previously assumed.

7.2. Berth commitment

In general, PIANC recommends maintaining berth commitment levels between 85% and 90%. A lower commitment indicates that not all available capacity is being used effectively, while a higher commitment increases the risk of vessel delays and the associated demurrage costs. However, the optimal threshold depends on the operational context, as previously seen in Table 2.13.

In a multi-berth system, higher commitment levels may be acceptable because the presence of additional berths provides flexibility, helping to keep waiting times low. The economic context of the terminal also influences the optimal berth commitment. If demurrage costs remain low despite longer waiting times, a higher berth commitment might be justified to maximize throughput.

The average berth commitment over all months and berths per terminal can be seen in Table 7.3.

Terminal	Berth commitment	Quay occupancy	Service time	Waiting time	Average vessel DWT
HBTR	90.0%	92.2%	87.98 h	37.82 h	130 504 t
EECV	97.3%	99.1%	142.52 h	137.73 h	156 509 t
Tata Steel	84.3%	87.9%	96.65 h	167.82 h	111 707 t
Hansaport	63.6%	69.4%	56.23 h	35.66 h	109 103 t

Table 7.3: Yearly average values per terminal.

As shown in Table 7.3, HBTR and Tata Steel IJmuiden operate within the recommended berth commitment range. Despite this, Tata Steel exhibits high vessel waiting times. This may suggest that the terminal is operating near or above its ideal capacity. However, since Tata Steel IJmuiden supplies a steel production facility, maintaining a queue of one or two waiting vessels may be intentional to ensure continuous material flow.

In contrast, HBTR, aims to minimize waiting times to provide efficient service and attract customers. EECV operates with a very high berth commitment, which results in long average waiting and service times. This terminal is also owned by steel manufacturers, and its focus appears to be on maintaining high throughput rather than minimizing delays. As they obtain a yearly throughput close to HBTR, with less berths and lower capacity cranes as can be seen in Table 7.1.

Hansaport operates below the advised berth commitment level. As a result, it has the lowest waiting and service times among the terminals studied. However, this may indicate that the terminal is not utilizing its available assets to their full capacity.

The relationship between high berth commitment and increased waiting times, as described by PIANC (2018), is reflected in the results. Still, this relationship may be too simplified. Terminals operate under different economic conditions, and their tolerance for waiting times and demurrage costs can vary. Therefore, when designing a new terminal, the selected berth commitment should be aligned with the desired waiting time and a clear decision on whether the priority is high throughput or low vessel delay.

7.3. Conclusion

The performance results presented in this chapter show that capacity factors at the studied terminals are higher than those previously reported by van Vianen et al. (2011). This suggests that current operations may exceed traditional expectations and that design benchmarks could benefit from being updated. The measured berth commitment for terminals allings with values recommended by PIANC (2018). While high berth commitment is often associated with increased waiting times, this relationship is not straightforward. The economic role of each terminal must be considered to fully understand its performance. Terminals that serve integrated industrial complexes or operate under long-term supply contracts may accept higher waiting times as part of a broader logistical strategy. These findings indicate that design methodologies should incorporate not only technical parameters but also the economic and operational context of each terminal. This approach would lead to more realistic and adaptable design practices that better reflect the complexities of modern dry bulk logistics.

8
Conclusion

Main Research Question: How can open data be used to assess the handling performance of a dry bulk terminal?

This research set out to investigate whether the handling performance of dry bulk terminals can be assessed using open data. To answer this question, a method was developed that combines AIS vessel data, aerial imagery, and literature-based assumptions to estimate key performance indicators. These indicators were structured around the Overall Equipment Effectiveness (OEE) framework, which was adapted to the context of dry bulk unloading operations.

Port performance in this study was defined as the ability of a terminal to efficiently and reliably unload cargo from vessels. It was quantified using three main components: quay occupancy, crane utilization, and crane productivity. Together, these form the basis for calculating OEE, which serves as a benchmarkable metric for operational effectiveness.

The open data used in this method included vessel movement logs from Sea-web AIS, satellite images from Google Earth, and publicly available information on vessel specifications and cargo types. These sources allowed for the reconstruction of vessel call logs, estimation of crane availability, and modeling of unloading operations without requiring direct access to proprietary terminal data.

The accuracy of the performance assessment was evaluated through validation with two terminals: HBTR and Tata Steel IJmuiden. The model showed good alignment with reported crane hours and cargo volumes, indicating that average performance values can be reliably estimated using open data. However, certain operational details, such as crane allocation strategies and internal logistics, remain difficult to observe and introduce uncertainty into the results.

A Monte Carlo simulation showed that the confidence interval of the OEE assessment is 18.3% when considering the standard deviation of the error in the nominal rating of unloaders, the quay occupancy, and the cargo throughput. The uncertainty in the nominal rating of the equipment has the largest influence on the OEE assessment.

The analysis of four terminals revealed a range of performance outcomes. HBTR and EECV showed high berth commitment and utilization, while Hansaport demonstrated the highest crane productivity at 71.4%. Tata Steel had a commitment of 84.3% and lower productivity. One contributing factor may be operational restrictions: according to Tata Steel, only three cranes can be used simultaneously due to noise regulations. These differences reflect the unique characteristics and limitations of each terminal and highlight the importance of contextual interpretation when benchmarking results.

Uncertainties in the results stem from assumptions about crane ratings, downtime events, and equipment availability. For example, the nominal crane rating used to calculate productivity may not reflect actual maximal operational capacity, which affects the OEE percentage and complicates comparisons between terminals. Similarly, the number of cranes in use is not directly observable and varies due to factors such as personnel availability or regulatory limits. This was confirmed during discussions with terminal operators at the HBTR and Tata Steel terminals.

Despite these uncertainties, the study shows that open data can be used to assess the handling performance of dry bulk terminals in a structured and repeatable way. The method enables benchmarking across different terminals and provides insights into operational efficiency without requiring internal data access. It offers a scalable approach for performance analysis that can support design validation, strategic planning, and future research into port logistics.

9 Reflection & Recommendations

In this chapter, the research is critically reflected upon, and recommendations for future studies are proposed.

9.1. Reflection on research

Although this research is based on open data, which inherently includes uncertainties and inaccuracies, several observations can be made. Open data offers a valuable opportunity to accelerate terminal analysis and assess performance on a large scale. However, terminal operations are often more complex than what can be inferred from publicly available sources.

Aerial imagery provides a useful first impression of terminal layout and equipment availability, such as the number of cranes. Yet, it does not always reflect actual operational conditions. For example, floating cranes may not be visible in the images but could be used during operations. Consultations with port operators at Tata Steel and HBTR revealed that, although four cranes are present at each terminal, typically only three are used simultaneously. At HBTR, five cranes appear in aerial images, but one is currently being dismantled. The reduced use of cranes is largely due to a shortage of workers. Tata Steel acquired a new crane in 2019, increasing the total to four, but one of the old cranes is consistently out of service for revisions. Eventually, one crane will be removed, returning the terminal to its original configuration of three cranes. These examples show that aerial images must be interpreted with caution and supplemented with operational context. Despite assuming four operational cranes at these terminals, the model still produced reasonably accurate estimates of operational hours.

The accuracy of the object detection model can be improved. The current model has a recall of 82%, meaning approximately one in five cranes is not detected. Since most terminals have four cranes, this often results in one crane being missed. This affects the reliability of the analysis. Improving the model is possible by expanding the training dataset with more aerial images of cranes. Such images are widely available through satellite services like Google Maps. However, collecting and labeling these images requires considerable time.

The limited accuracy of crane detection also affects the analysis of the maximum number of cranes operating on a single vessel. In many cases, at least one crane is not recognized, which leads to underestimation. If future models can detect both cranes and vessels, the number of cranes operating per vessel could be determined automatically by analyzing overlapping bounding boxes.

In this study, historical aerial images were used to increase detection accuracy by providing more data. If future models improve crane recognition, fewer images may be needed. This would allow the use of only recent images, which improves consistency and reduces the influence of outdated operational layouts.

The economic context of each terminal also plays a significant role in its operations, though this is not always evident in open data. Terminals such as Tata Steel IJmuiden and EECV are directly linked to steel production, which can fluctuate independently of vessel movements. At Tata Steel, vessels were observed waiting for extended periods even when berths were available. Although the terminal operator confirmed that demurrage costs are high and influence operational decisions, these long waiting times may be explained by specific contractual arrangements between the terminal and the vessels.

Material quality was also identified as a key factor affecting operational efficiency. Both Tata Steel and HBTR reported that coal with high moisture content or the presence of ice can significantly slow down unloading. At Tata Steel, there were cases where water-filled cargo holds required material from other holds to be transferred in order to reduce moisture levels before further handling. HBTR reported instances where large chunks of ice in the coal had to be melted on the quay before unloading could continue. These edge cases are difficult to model and may not reflect the terminal's inherent handling performance. In such situations, the third term of the OEE formula, quality, could be used to account for double handling. In traditional factory settings, the quality factor represents the percentage of products that pass inspection. In this context, double handling due to material issues could be interpreted as a reduction in handling quality.

Waiting times in this research were derived from how long the vessels were within the anchorage area from AIS data. However, it is possible that vessels slow down intentionally to arrive just in time, which is also a form of waiting but more efficient and harder to detect through AIS alone.

Definitions of downtime vary across literature and between terminals. For example, blockage of equipment and corrective maintenance are interpreted differently. van Vianen et al. (2012) describes equipment blockage as transport losses, such as when a conveyor system is occupied with other operations. Pinto et al. (2017) defines it as a mismatch in nominal rates between cranes and supporting conveyor systems. At HBTR, repairs and malfunctions were reported separately, although this research categorizes both as corrective maintenance. HBTR also described cases where large objects blocked the hopper grid. While this should be considered corrective maintenance according to this research, the terminal classified it as unscheduled stoppage. These discrepancies highlight the importance of clearly defining parameters and categorizing all terminal events consistently to improve the clarity and comparability of performance assessments.

The research assumes that two cranes typically operate on one vessel and that Tata Steel and Hansaport use discrete berths where equipment does not move between berths. However, validation with the Tata Steel operator showed that three cranes are used on a single vessel. At HBTR, it was also observed that sometimes only one crane is active per vessel. Although operational hours were still estimated with reasonable accuracy, this assumption proved too simplistic. Future research on continuous quays would benefit from focusing on OEE assessment per crane rather than per theoretical berth, which would yield more accurate results. For terminals with truly discrete berths, the current method remains valid and supports the assessment of exogenous and endogenous factors, as well as berth commitment.

For continuous quay terminals, the entire terminal should be treated as a single operational system. This reflects how such terminals function in practice. The model could be improved by setting a maximum number of operational cranes per vessel size class. While two cranes may be typical, larger vessels may require more. Incorporating this adjustment could lead to more accurate estimates of operational hours and better reflect the dynamics of continuous quay operations.

Crane productivity and OEE assessments rely on the nominal unloading rate of the equipment. The actual maximum unloading speed may differ from this nominal value depending on the terminal. This variation can affect productivity calculations, as there is no universally accepted reference point for 100% performance.

For example, the Tata Steel terminal set its nominal unloading rate at 6000 tons per hour, based on three cranes each rated at 2000 tons per hour. In 2019, a fourth crane was added, with a manufacturer-stated capacity of 3000 tons per hour. However, the terminal did not update its nominal rating on their internal system. This decision was partly due to noise regulations that limit simultaneous crane operation to three units. Also, the new crane was not yet operating at full capacity due to technical issues. As a result, the nominal rate remained at 6000 tons per hour. Clearly, this affects the calculated crane productivity and OEE values.

Such differences make benchmarking between terminals difficult. In this research, all nominal ratings were calculated using the same method based on the safe working load. This approach supports a fair comparison.

There is also inconsistency in the literature regarding the definition of nominal rating. Terms such as nominal rating, free digging rate, cream digging rate, peak capacity, and design capacity are used with slightly different meanings. These differences can lead to confusion. Therefore, it is important to clearly define crane capacity when assessing crane productivity.

9.2. Recommendations for future research

Although this research focuses on dry bulk terminals, the method developed could be extended to other types of port operations, including liquid bulk and container terminals. In the case of liquid bulk, jetty layouts may simplify the definition of discrete berths, although input parameters and performance indicators would differ. Container terminals operate under different constraints, typically avoiding long waiting times due to the time-sensitive nature of cargo delivery. These terminals often have lower berth occupancy rates but require highly organized landside operations, as cargo is often destined for specific inland terminals. So, although the method is applicable for these terminals, the definition of good performance will be different.

The model could also be applied to export terminals or those handling both import and export operations. Export terminals often use continuous loaders, which may affect utilization and productivity outcomes. While the method remains applicable, the economic context of export terminals differs. These terminals may aim for maximum utilization to optimize asset performance, even if this results in long waiting times. Export terminals generally face less competition and are less affected by demurrage costs, allowing for more flexibility in scheduling. For terminals that use the same berths and equipment for both import and export, the definitions of OEE and berth commitment become more complex. Since performance characteristics differ between loading and unloading, it would be more accurate to assess these operations separately.

Terminals using geared vessels also present a different operational dynamic. Internal transport may rely on trucks rather than conveyors, introducing more variability in performance. Trucks tend to have less predictable behavior than conveyor systems, which could reduce the accuracy of assessments based on open data. Additionally, the gear configuration on vessels changes from one vessel to another, adding further uncertainty. However, if cargo load and service time can be reliably extracted from AIS data, a basic performance assessment remains feasible.

In this research, 500 hours of planned maintenance per year were assumed. Often, approximately 300 hours are attributed to a major maintenance shift. Future studies could attempt to identify this maintenance period directly from AIS data by observing significant drops in vessel activity or throughput over a defined time frame.

Expanding the object detection model used in this study could also enhance future research. If the model can identify conveyor systems, stacker reclaimers, train loaders, and other equipment, a simplified internal operational model of the terminal could be developed. Combined with standard failure rates for each piece of equipment, this would allow for a more detailed estimation of stoppage times due to equipment breakdowns or blockages. For example, if aerial imagery shows that only one conveyor connects a crane to a stacker reclaimer, it can be inferred that a failure in that conveyor would halt crane operations. In contrast, multiple conveyors would suggest greater resilience. Image analysis could also be used to identify the location and size of stockyards, silos, or sheds, providing further insight into terminal layout and operational capacity.

Weather and tidal conditions are another area where the model could be improved. Incorporating actual weather data, such as wind speeds exceeding 8 BFT, would allow for more precise attribution of delays, rather than assuming a uniform weather-related downtime across all vessels. This would be particularly useful for bulk terminals handling materials sensitive to rain or operating in regions with distinct wet seasons. Similarly, using real tidal data could improve assessments of terminal availability, especially for ports where access is restricted by water depth. For example, the operator at Tata Steel noted that the largest vessels could not be fully loaded due to draft limitations at the berth.

Vessel size class has a significant impact on unloading performance. Larger vessels often have more and bigger cargo holds, which decreases the relative time needed for trimming during the final stages of unloading. This affects the overall unloading rate and stoppage time. Since the terminal operator does not control which vessel arrives in the short term, vessel size class can be considered an external factor. To account for this, the OEE analysis could be split per vessel size class. Alternatively, an additional performance indicator can be included in the crane productivity calculation to reflect the influence of vessel size on unloading efficiency.

Large-scale OEE analysis using open data could be a valuable direction for future research. By collecting performance data across a wide range of terminals, operational contexts, and cargo types, researchers could identify patterns and establish benchmarks. This could help terminal designers and operators improve efficiency and planning. A broader dataset could also support the development of unloading speed standards based on vessel size, cargo type, and unloader configuration.

In this research, OEE was benchmarked between terminals by separating exogenous and endogenous factors. A similar approach could be applied to berth commitment. Analyzing the exogenous and endogenous components of berth commitment may provide useful insights. This could support port planning, especially for terminals affected by external conditions such as weather, long access channels, or locks in the access route.

Incorporating more detailed cargo characteristics would further enhance the accuracy of crane productivity assessments. For instance, coal from different regions of the world may vary in moisture content, affecting handling speed. Differentiating between types of bulk material, such as coking coal and iron ore pellets, would also improve the model's precision.

Finally, vessel size classes should be considered when estimating operational stops. Smaller vessels typically have fewer cargo bays, resulting in fewer crane movements and potentially shorter service times. Including vessel size in the model would allow for more accurate predictions of crane utilization and terminal performance.

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Research paper

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Benchmarking Dry Bulk Terminal Unloading Performance Using Open Data and OEE Analysis

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Abstract -- This study demonstrates that unloading performance at dry bulk terminals can be effectively assessed using open data sources such as AIS and aerial imagery. By structuring terminal operations into measurable performance indicators and applying the Overall Equipment Effectiveness (OEE) framework, we show that productivity, utilization, and occupancy can be quantified and benchmarked across terminals. The method is validated using data from two dry bulk terminals, revealing consistent patterns and highlighting operational differences. This approach enables scalable, low-cost performance analysis without requiring direct access to proprietary terminal data.

Keywords: Dry bulk terminal operations, Overall Equipment Effectiveness, Open data, Benchmarking, AIS

1. Introduction

Dry bulk terminals play a critical role in global trade, handling unpackaged commodities such as coal and iron ore. The three major dry bulk types, coal, iron ore, and grain, account for 29.2% of the global maritime trade (UNCTAD, 2020). Their performance directly influences supply chain efficiency and industrial productivity. This research focuses on unloading operations at import-oriented dry bulk terminals handling coal and iron ore.

For port designers and terminal operators, improving productivity is a key objective. It is the main driver behind port reforms (Deda Đelović, 2020). Planning decisions often involve choosing between optimizing operational efficiency and expanding infrastructure.

Despite its importance, terminal performance is difficult to evaluate. Port operators often lack insight into how their terminals compare to others. Designers face challenges validating their design strategies due to limited access to operational data. Data acquisition is often slow, and differences in reporting formats further complicate analysis. As a result, there is a need for a structured assessment method that does not rely on cooperation from terminal operators.

This study proposes a method to evaluate unloading performance using publicly available data. The approach is based on the Overall Equipment Effectiveness (OEE) framework (Nakajima, 1988), which measures equipment performance during planned operational time.

To enable comparison across terminals with different operating conditions, a benchmarking framework is applied. This framework follows a structure that differentiates between endogenous and exogenous influences in operational performance (Pinto et al., 2017).

In addition to OEE, the concept of berth commitment is included. As defined by PIANC (2018), berth commitment measures the share of total available time used for operations. This metric provides insight into asset utilization and supports decisions about future port expansion.

The combination of OEE and berth commitment provides a comprehensive view of terminal performance. OEE captures the efficiency of unloading operations during planned service time, while berth commitment reflects how much of the available berth time is actively used. Together, these metrics offer valuable insight into both operational effectiveness and capacity utilization. This approach supports port designers in evaluating infrastructure needs and helps terminal operators identify opportunities for performance improvement.

This paper presents a method intended for application across various types of dry bulk terminals. The calibration and validation of the method in this case are based on terminals that handle coal and iron ore. These terminals feature continuous quays where multiple vessels can berth at the same time. Cranes at these sites can move freely along the full length of the quay.

The structure of this paper is as follows. Section 2 reviews relevant literature on Overall Equipment Effectiveness (OEE) and berth commitment. It also introduces a framework and a set of performance indicators for assessing dry bulk terminal performance. Section 3 outlines the open data sources available for performance assessment. Section 4 describes the method used to derive performance indicators from open data and to calculate OEE. Section 5 presents a comparison between model outputs and terminal-supplied data to validate the results and assess the confidence interval and accuracy of the method. Section 6 summarizes the results obtained for several terminals. Section 7 provides the conclusion, and Section 8 offers a reflection and recommendations for future research.

2. Literature

The Overall Equipment Effectiveness (OEE) framework divides system performance into three components (Nakajima, 1988):

$$OEE = \text{Availability} \times \text{Performance} \times \text{Quality} \quad (2.1)$$

Availability refers to the proportion of planned operational time during which the system is active.

Performance measures the actual operating speed as a fraction of the system's nominal speed.

Quality represents the share of usable output at the end of the process

In dry bulk unloading, the planned operational time is defined as the period when a vessel is moored at the quay. The share of this time during which cranes are actively unloading is referred to as crane utilization, which corresponds to the availability factor. During crane operation, a certain unloading rate is achieved. This rate, known as crane productivity, represents the performance factor (van Vianen et al., 2012).

At a dry bulk terminal, material is typically fully used at the terminal, with minimal losses due to spillage or double handling. Therefore, quality losses are considered negligible, and the quality factor is assumed to be 1.

As a result, the OEE for dry bulk unloading operations can be simplified to:

$$OEE = \text{Crane Utilization} \times \text{Crane Productivity} \quad (2.2)$$

This formulation provides a practical way to assess unloading performance using measurable operational data. A visual representation is provided in Figure 2.1.

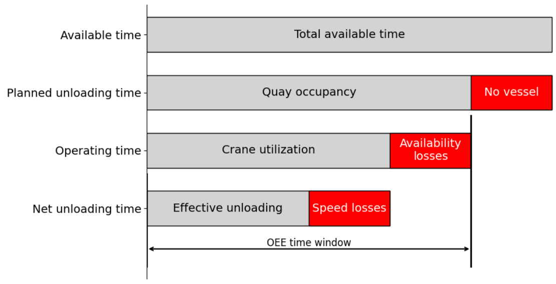

Figure 2.1 The OEE time window at a dry bulk terminal(van Vianen et al., 2012).

Crane utilization is influenced by availability losses caused by other processes and events. These include maintenance activities, weather-related interruptions, and operational stops. Such factors reduce the time cranes are actively used during the vessel's stay at the berth.

To evaluate the overall capacity usage of a dry bulk terminal, PIANC (2018) introduces the concept of berth commitment. Berth commitment represents the fraction of total berth time occupied by all terminal activities and processes, excluding idle periods. It reflects how intensively the berth is used and provides insight into the terminal's operational saturation.

A visual representation of berth commitment and the various processes and events that occur at a dry bulk terminal is shown in Figure 2.2.

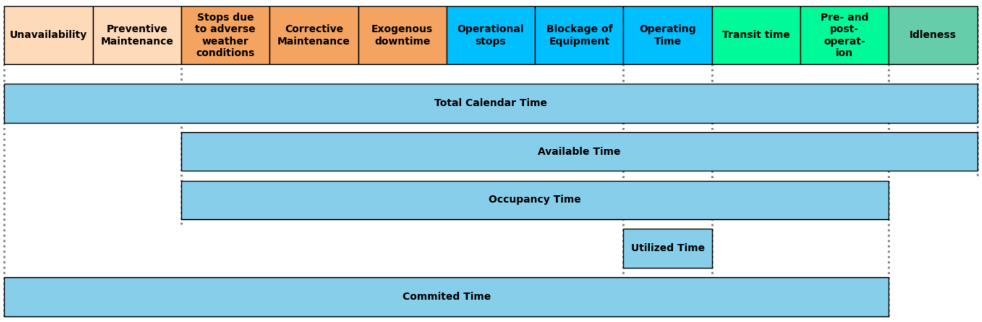

Figure 2.2 The commitment of a dry bulk terminal (PIANC, 2018).

Symbol	State	Influence
	Unscheduled downtime	
WC	Stops due to adverse weather conditions	Exogenous
CM	Corrective maintenance	Endogenous
ED	Exogenous downtime	Exogenous
	Scheduled downtime	
UNV	Unavailability	Exogenous
PM	Preventive maintenance	Exogenous
	Operational time	
OS	Operational stops	Endogenous
BE	Blockage of equipment	Endogenous
OT	Operating time	Endogenous
	Set time	
TR	Transit time	Exogenous
PO	Pre- and post-operational time	Endogenous
	Idle time	
IDL	Idle time	Exogenous

Table 2.1 Endogenous and exogenous states in a dry bulk terminal system (Pinto et al., 2017).

To support the assessment of Overall Equipment Effectiveness (OEE) and berth commitment at dry bulk terminals, a structured set of parameters is proposed, as shown in Table 2.1. These indicators are divided into two categories:

Endogenous influences Influenced by internal operational decisions and directly controlled by the terminal operator.

Exogenous influences Determined by external factors such as weather conditions, vessel arrival patterns, or regulatory constraints. These are outside the control of the terminal operator.

The sum time spent on all processes and events in Table 2.1 is equivalent to the total time TT. In a terminal system with multiple cranes, the distribution over the processes and events should be calculated as an average over all cranes. Idle time IDL, preventive maintenance PM, and waiting for transit TR can occur both with or without a vessel present along the quay.

Based on the parameters in Table 2.1, a set of performance indicators is set up in Table 2.2. $ID1$ to $ID10$ are based on the different processes and events occurring at the terminal. Indicators $ID11$ and $ID12$ together define crane productivity.

Indicator	Indicator name	Driver	Formula
$ID1_v$	Idle time (vessel)	Operational time	$\frac{IDL_v}{OT}$
$ID1_{nv}$	Idle time (no vessel)	Total time	$\frac{IDL_{nv}}{TT}$
$ID2$	Unavailability	Total time	$\frac{UNV}{TT}$
$ID3_v$	Preventive maintenance (vessel)	Operational time	$\frac{PM_v}{OT}$
$ID3_{nv}$	Preventive maintenance (no vessel)	Total time	$\frac{PM_{nv}}{TT}$
$ID4$	Weather downtime	Number of vessel calls	$\frac{WC}{\#Calls}$
$ID5_v$	Waiting for transit (vessel)	Number of vessel calls	$\frac{TR_v}{\#Calls}$
$ID5_{nv}$	Waiting for transit (no vessel)	Total time	$\frac{TR_{nv}}{TT}$
$ID6$	Pre- and post-operational time	Number of vessel calls	$\frac{PO}{\#Calls}$
$ID7$	Corrective maintenance	Operational time	$\frac{CM}{OT}$
$ID8$	Operational stops	Operational time	$\frac{OS}{OT}$
$ID9$	Blockage of equipment	Operational time	$\frac{BE}{OT}$
$ID10$	Exogenous downtime	Operational time	$\frac{ED}{OT}$
$ID11$	Variation in effective rate	Cargo type NR variation	$\frac{ER}{NR_{CT}}$
$ID12$	Variation in cargo type nominal rate	Nominal rating	$\frac{NR_{CT}}{NR}$

Table 2.2 The performance indicators defining the port performance assessment (Pinto et al., 2017).

Crane utilization can be expressed in the performance indicators as seen in Equation 2.3. Here, NR is the nominal rating of the unloaders and $LOAD$ is the average vessel load.

$$Crane\,Utilization = \frac{1}{\frac{NR}{LOAD}(ID11 \times ID12) \times (ID4 + ID5_v + ID6) + ID1_v + ID3_v + ID7 + ID8 + ID9 + ID10 + 1} \tag{2.3}$$

Crane productivity is defined as the ratio between the effective rating ER and the nominal rating NR. As seen in Equation 2.4, this can also be expressed as the product of two performance indicators: $ID11$ and $ID12$.

$$Crane\,productivity = \frac{ER}{NR} = ID11 \times ID12 \tag{2.4}$$

Different cargo types have different nominal ratings due to variations in material properties and the type of grabs used. Therefore, crane productivity is split into two components. $ID11$ represents the endogenous variation in the effective unloading rate. $ID12$ accounts for the exogenous variation in nominal rating, which depends on the specific cargo type and its physical characteristics.

As shown in Table 2.2, indicators $ID11$ and $ID12$ are determined by NR_{CT}, which represents the relative nominal rating based on the proportion of unloading time spent on coal versus iron ore. The calculation method for NR_{CT} is provided in Equation 2.5.

$$NR_{CT} = \frac{OT_{coal} \times NR_{coal} + OT_{iron\ ore} \times NR_{iron\ ore}}{OT} \tag{2.5}$$

Combining Equations 2.2, 2.3, and 2.4, OEE can be expressed in the performance indicators as follows:

$$OEE = \frac{ID11 \times ID12}{\frac{NR}{LOAD}(ID11 \times ID12) \times (ID4 + ID5_v + ID6) + ID1_v + ID3_v + ID7 + ID8 + ID9 + ID10 + 1} \tag{2.6}$$

To compare performance between terminals, known as benchmarking, only indicators influenced by endogenous processes and events should be considered. These are defined by decisions and actions under the control of the terminal operator. Including only these indicators allows for comparison of operational performance between terminals.

Idleness ($ID1$) is determined by vessel arrival patterns and cannot be directly influenced by the terminal operator in the short term. Preventive maintenance duration ($ID3$) is generally fixed and does not reflect operational performance. Weather-related downtime ($ID4$) is an exogenous factor. Transit waiting time ($ID5$) depends on the length and characteristics of the access channel, which is also exogenous. Other exogenous disruptions, such as power outages, are grouped under $ID10$. The variation in cargo-specific nominal rate ($ID12$) is influenced by the mix of cargo types handled and is not controlled by the terminal operator.

All other performance indicators are considered endogenous and should be included when comparing terminal performance. The benchmarked OEE ($OEE_{benchmark}$) of a sample is calculated by averaging the values of the indicators affected by exogenous factors across all compared terminals, as shown in Equation 2.7.

$$OEE_{benchmark} = \frac{ID11 \times ID12_{avg}}{\frac{NR}{LOAD}(ID11 \times ID12_{avg}) \times (ID4_{avg} + ID5_{v-avg} + ID6)} \times \frac{ID11 \times ID12_{avg}}{ID1_{v-avg} + ID3_{v-avg} + ID7 + ID8 + ID9 + ID10_{avg} + 1} \tag{2.7}$$

3. Open data sources

With the dry bulk terminal unloading performance framework established, the next step is to determine the input parameters from Table 2.1 as accurately as possible. In addition to these, the effective rate (ER), the average nominal rating of the unloaders

(NR), and the average vessel load ($LOAD$) must be defined. These values are required to calculate the Overall Equipment Effectiveness (OEE) according to Equation 2.5.

To enable fast and structured performance assessment without requiring direct input from terminal operators, open data sources are used. These include AIS data, aerial imagery, publicly available web sources, and standard values from literature to fill data gaps.

Vessel position data transmitted via the Automatic Identification System (AIS) is publicly accessible and provides reliable and accurate information on vessel movements near the terminal (De Boer, 2010).

Aerial images, such as those from Google Earth, help identify the terminal layout. They can be used to determine the number of unloaders and their positions.

Public web sources provide useful supplementary data. Terminals often publish the safe working load or nominal rating of their unloaders in terminal booklets or on their websites. For example, the terminal booklet of Ertsoverslagbedrijf Europoort c.v. (2024).

AIS data can be used to identify the departure port of incoming vessels. By combining this with publicly available information, such as cargo types exported from those ports, one can estimate whether a vessel is likely carrying coal or iron ore.

Some operational details are not publicly available, especially those related to internal processes. Missing values for parameters such as pre- and post-operational time (PO) and preventive maintenance (PM) can be estimated using standard values from literature.

4. Method

The method used to construct performance indicators $ID1$ to $ID12$, and to assess unloading performance at dry bulk terminals, is shown in Figure 4.1.

4.1. Constructing call log

The process begins with the construction of a vessel call log. This log is created by extracting arrival times, draught changes, and voyage histories from AIS data. A Naïve Bayes classifier is applied to estimate whether a vessel is importing or exporting, based on its origin, destination, draught change, and deadweight tonnage (DWT).

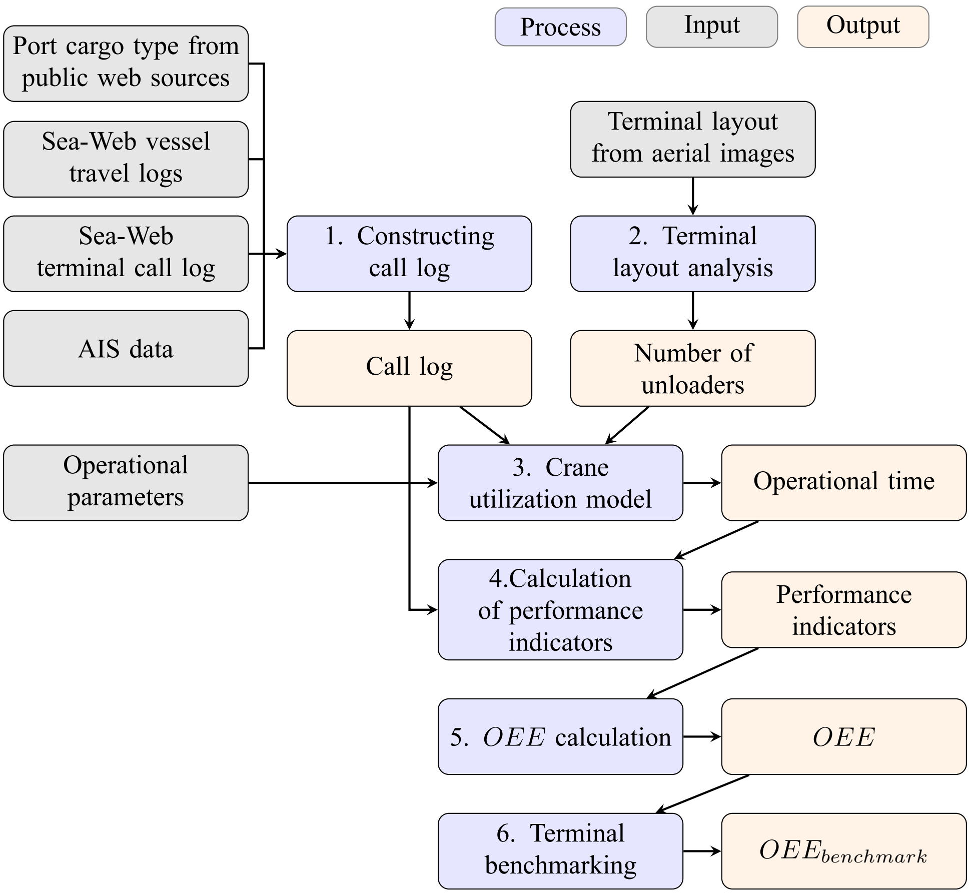

Figure 4.1 Flowchart of the method of determining OEE and $OEE_{benchmark}$

The cargo type of a vessel's parcel is inferred from the vessel's previous port, allowing a distinction between coal and iron ore. To assess the parcel size of vessels, the cargo load utilization is assumed to be 80% of DWT for coal carriers and 90% for iron ore carriers (Adland et al., 2018).

4.2. Terminal layout analysis

Second, the terminal layout is analyzed from aerial images. The number and location of equipment, such as unloaders and stackers/reclaimers, can be identified. The layout of the conveyor system and the size of the stockyard are also visible. This information can be used to build a basic simulation model to assess potential chokepoints or equipment failures in landside operations, similar to the approach described by Vianen (2015, p. 79). Results from such a simulation can be used to define blockage of equipment BE and corrective maintenance CM.

To support efficient model setup, object detection techniques can be applied to analyze terminal layouts. To demonstrate this, an object detection model was trained to identify gantry cranes in aerial images. A YOLOv8 model was used for this purpose. The output of the model is shown in Figure 3.1.

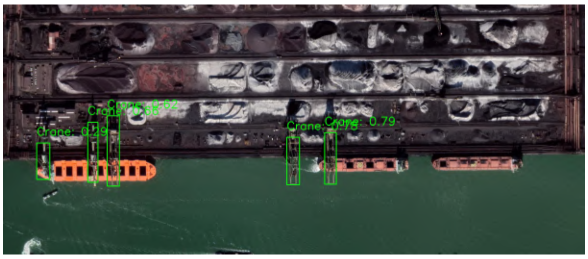

Figure 3.1 Crane detections from aerial images.

4.3. Crane Utilization Modeling

A discrete-time model is developed to estimate crane operational hours per month, serving as the foundation for calculating crane utilization and productivity. The model processes each vessel call individually, assigning time to operational states based on arrival and departure timestamps, measured transit times, and estimated cargo type. These states include transit, pre- and post-operational procedures, scheduled and unscheduled downtime, and operational time. The model does not track the operational state of each individual crane. Instead, it calculates the average number of hours spent in each state across all cranes. This approach provides a general overview of crane activity without assigning specific tasks to specific cranes.

Transit time is defined as the period during which a vessel moves through the access channel toward the berth or departs from it. This is determined using AIS data and varies depending on whether the vessel waits in the anchorage area. Pre-operational time (1 hour) includes activities such as mooring, paperwork, and equipment setup, while post-operational time (2 hours) accounts for customs clearance and departure preparation. These durations are estimated using standardized values from literature.

Downtime events are modeled using fixed percentages derived from previous studies and expert consultation. Corrective maintenance is assumed to occur randomly during operational time, with a downtime fraction of 7%, reflecting equipment failures and breakdowns. Blockage of equipment, such as unavailable stacker/reclaimers or congested conveyor systems, is modeled at 5% of operational time. Weather-related delays are set at 1%, accounting primarily for high wind conditions that prevent crane operation.

Preventive maintenance is modeled as a fixed annual downtime of 500 hours per crane, distributed across months based on idle time availability. This ensures maintenance is scheduled during periods of low activity, minimizing its impact on crane utilization. The model does not simulate individual crane behavior but provides reliable average estimates over time, suitable for benchmarking and design validation.

4.4. Performance indicators calculation

With the parameters determined, the performance indicators can be calculated according to the formulas presented in Table 2.2.

4.5. OEE Calculation

Using Equations 2.3, 2.4, and 2.6 along with the calculated performance indicators, the Overall Equipment Effectiveness (OEE) of a terminal can be determined. This calculation can be applied to monthly data or aggregated over a full year.

4.6. Terminal benchmarking

Using Equation 2.7, multiple terminals can be compared based on performance indicators that reflect qualitative aspects of port management. The value of $OEE_{benchmark}$ is not a directly measurable quantity, but it allows relative comparison. If one terminal has a higher $OEE_{benchmark}$ than another, it indicates more effective operation. By examining the individual performance indicators, the source of the difference can be identified

5. Model Accuracy Evaluation

To validate the model accuracy, data were collected from the HBTR terminal in Rotterdam and the Tata Steel terminal in IJmuiden.

Discussions with terminal operators revealed that estimating the number of cranes is more difficult than initially expected (R. Slikkerveer, personal communication, May 16, 2025). Unloaders visible in aerial images may be out of service, which complicates identification. However, for the accuracy assessment in this study, the number of cranes is assumed to be known.

The HBTR terminal in Rotterdam provided monthly throughput data for coal and iron ore. A comparison between model-estimated throughput and reported values is shown in Figure 5.1. The mean square error for monthly coal estimates was 0.13 Mt, and 0.11 Mt for iron ore. These results indicate that estimating vessel cargo type based on the previously visited port provides an accurate method for this type of terminal.

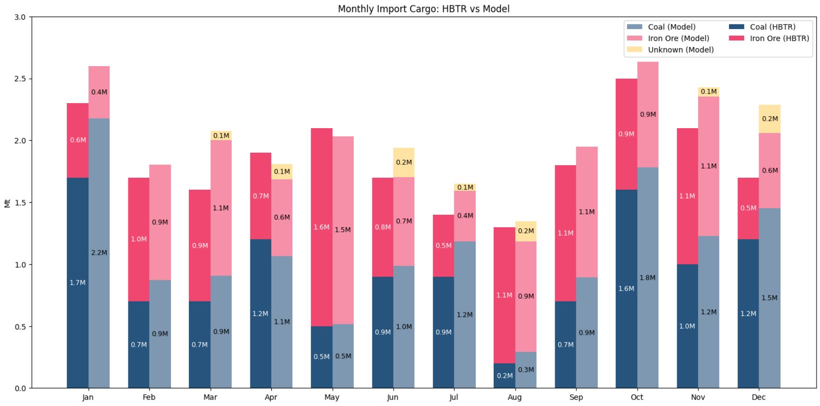

Figure 5.1 Comparison of model results and values supplied by HBTR for overall imported cargo volume per cargo type.

To further assess the accuracy of the model in calculating OEE, a Monte Carlo simulation was performed. This method uses the standard deviation of multiple input parameters to estimate a confidence interval and output distribution for the model (Harrison, 2010). For this purpose, OEE is expressed using a minimal set of input parameters, as shown in Equation 5.1. This simplification helps isolate the influence of key variables.

$$OEE = \frac{\text{Throughput}}{\text{Quay Occupancy} \times \text{Total Time} \times \text{Nominal Rating} \times \text{Number of Cranes}} \tag{5.1}$$

HBTR and Tata Steel IJmuiden supplied monthly cargo throughput data for 2024. The nominal rating error was assessed by comparing calculated ratings, based on safe working load, with reported values for cranes at Tata Steel and EECV. Tata Steel also provided quay occupancy and OEE data. The average error and standard deviation are summarized in Table 5.1.

Parameter	Mean error	Std dev.	Sample size	Sample
Throughput (Mt)	-0.1105	0.1537	24	12 months for both HBTR and Tata Steel IJmuiden
Quay occupancy (%)	-3.70%	6.31%	12	12 months at Tata Steel IJmuiden
Nominal rate (ton/h)	-25.6250	276.6214	8	4 cranes at both EECV and Tata Steel IJmuiden

Table 5.1 The mean error and standard deviation of the error found for the three parameters that define the OEE assessment.

Using the model values for Tata Steel IJmuiden and the calculated standard deviations for throughput, quay occupancy, and unloader nominal rate, a Monte Carlo simulation was performed. The model was run 10,000 times with randomly sampled input parameters based on these standard deviations and initial estimates. The resulting output distribution is shown in Figure 5.2. The 95% confidence interval is 18.3%, indicating a relatively wide range. This variation is most significantly caused by uncertainty in the nominal rate of the unloading equipment.

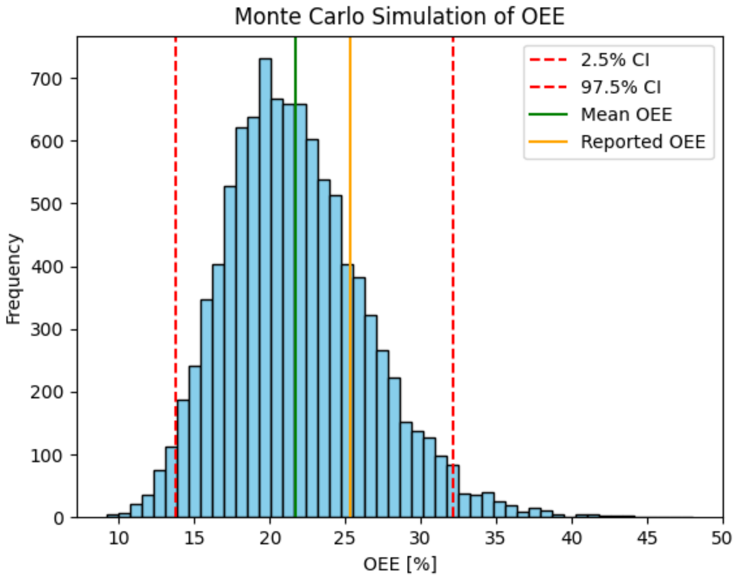

Figure 5.2 The results of the Monte Carlo simulation of the OEE assessment based on Equation 5.1, standard deviations found in Table 5.1, and initial estimates for Tata Steel IJmuiden. The yellow line represents the OEE value reported by Tata Steel in 2024.

Additionally, to calibrate the estimated crane utilization and downtime causes, a comparison was made between the model output and data provided by HBTR, as shown in Table 1. The results showed that weather downtime and corrective maintenance were initially overestimated. Based on this, the input parameters were adjusted to 1% for weather downtime and 7% for corrective maintenance.

Model state	HBTR	Model
Operational time OT	71.2%	66.3%
Weather downtime WC	0.6%	5.1%
Corrective maintenance CM	6.9%	9.0%
Operational stops OS	13.6%	14.6%
Blockage of equipment BE	3.3%	5.1%
Preventive maintenance PM	2.9%	-
Other	1.5%	-

Table 1 Comparison between berth states of HBTR and the model output.

Comparison of crane utilization using data provided by Tata Steel IJmuiden revealed that corrective maintenance and equipment blockages were underestimated for this terminal. This highlights significant variation in operational parameters across terminals. The lack of detailed insight into internal terminal operations emerges as the primary source of inaccuracy in the crane utilization model.

6. Results

The method was applied to four dry bulk terminals in Northwestern Europe: HBTR (Rotterdam), EECV (Rotterdam), Tata Steel (IJmuiden), and Hansaport (Hamburg). All terminals specialize in unloading coal and iron ore from seagoing vessels. The analysis focused on estimating crane utilization, productivity, and berth commitment using open data and the OEE framework.

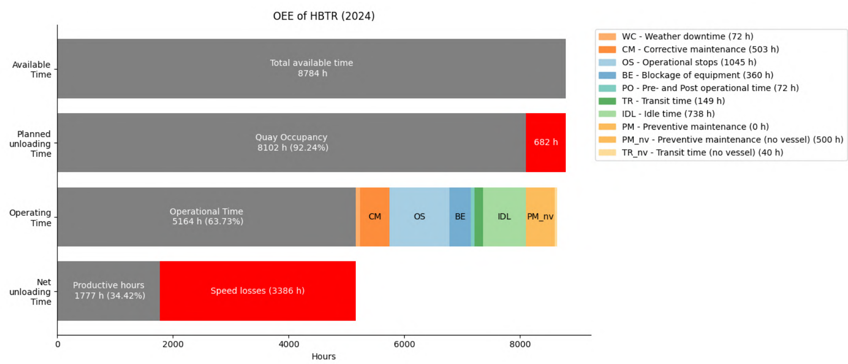

Figure 6.1 The OEE assessment of HBTR in 2024

6.1 Terminal results

The results for the HBTR terminal are shown in Figure 6.1. A vessel was present at the terminal for 92% of the time. The main causes of availability losses were operational stops, corrective maintenance, and crane idle time. Crane idle time occurs when only one vessel is present and not all cranes can be operational at the same time. During operational periods, the cranes reached an average throughput of 34% of their nominal rating.

An overview of results for all terminals can be seen in Table 6.1. The four analyzed terminals showed OEE values between 21% and 36%. HBTR and EECV achieved high crane utilization, while Hansaport demonstrated the highest crane productivity.

Crane productivity was highest at Hansaport (71.4%), despite its lower utilization. This suggests efficient unloading during active hours, possibly due to favorable cargo characteristics or optimized crane operations. HBTR and EECV showed balanced performance, with utilization around 70% and productivity between 30–35%. Tata Steel had slightly lower productivity, which may be attributed to older equipment and operational constraints.

Terminal	Quay Occupancy	Crane Utilization	Crane Productivity	OEE
HBTR	92.2%	71.8%	35.2%	22.5%
EECV	99.1%	72.2%	31.4%	22.4%
Tata Steel	87.9%	66.8%	32.5%	21.8%
Hansaport	69.4%	50.3%	71.4%	35.4%

Table 6.1 The OEE results per terminal for 2024.

Berth commitment ranged from 63% at Hansaport to 97% at EECV. The lower commitment at Hansaport is partly explained by long transit times along the 110km long Elbe River, which allows for less flexibility. EECV, owned by German steel producers, operates with high commitment, which results in long waiting times, reflecting its role in just-in-time supply for steel manufacturing.

Terminal	Berth commitment	Average waiting time	THR
HBTR	90.0%	37.82 h	23.0 Mt
EECV	97.3%	137.73 h	20.1 Mt
Tata Steel	84.3%	167.82 h	11.7 Mt
Hansaport	63.6%	35.66 h	11.6 Mt

Table 6.2 The berth commitment per terminal for 2024.

6.2 Terminal benchmarking

The four terminals were benchmarked using Equation 2.7, with results presented in Table 6.3. Quay occupancy, being only influenced by exogenous factors, was standardized by applying the average value across all terminals. EECV shows the highest relative crane utilization, primarily because the quay is frequently occupied by multiple vessels, allowing all unloaders to operate simultaneously. Hansaport demonstrates the highest relative crane productivity, which leads to the highest relative $OEE_{benchmark}$. According to Hansaport's website, the terminal operates with full automation (Hansaport, 2023). This operational approach may contribute to the observed high productivity.

Terminal	Quay Occupancy (benchmarked)	Crane Utilization (benchmarked)	Crane Productivity (benchmarked)	$OEE_{Benchmark}$
HBTR	87.2%	63.7%	36.0%	22.7%
EECV	87.2%	74.1%	30.8%	22.8%
Tata Steel	87.2%	66.2%	32.7%	21.7%
Hansaport	87.2%	50.1%	70.7%	35.0%

Table 6.3 The benchmarked OEE between four terminals for 2024.

7. Conclusion

This research shows that dry bulk terminal unloading performance can be assessed using open data and structured performance indicators. The adapted OEE framework enables structured unloading performance assessment across dry bulk terminals, even without operator cooperation. Validation showed that throughput per cargo type, quay occupancy, and crane utilization can be reasonably estimated based on AIS-measured service times and other open data sources. The method is scalable, efficient, and applicable to early-stage design validation and operational analysis.

8. Reflection

While open data provides valuable insights, limitations remain. Internal logistics, crane allocation strategies, and material quality are difficult to observe remotely. Future work could expand object detection to include conveyors and stacker/reclaimers, or integrate weather and tidal data for more precise downtime modeling. The method may also be extended to container or liquid bulk terminals with adjusted performance definitions.

Key discussion points:

- The perceived nominal rating of cranes strongly influences calculated productivity and OEE values. If this rating does not reflect actual operational capacity, benchmarking between ports becomes unreliable.
- Crane allocation strategies remain uncertain. Interviews with Tata Steel and HBTR revealed that both operators only operate a maximum of three cranes simultaneously. Tata Steel is restricted by noise regulations, while HBTR faces personnel shortages. These examples show that operational context is often not visible in open data.
- Despite these uncertainties, average productivity estimates derived from AIS and satellite data appear to be reasonably accurate, as supported by validation results. The proposed method should always be accompanied by a further investigation into the terminals operational context.

Future improvements could include expanding object detection to identify conveyors, stacker/reclaimers, and other equipment. This would allow for better modeling of internal logistics and equipment dependencies. Integrating weather and tidal data could also improve the accuracy of downtime estimation, especially for terminals affected by environmental conditions. The method may be adapted for container or liquid bulk terminals, although performance indicators would need to be redefined to match the operational characteristics of those systems.

The method developed in this study enables fast and efficient performance assessments using open data. Future research should apply this approach on a larger scale to analyze differences between terminal types, vessel size classes, unloader configurations, and material categories. A broader dataset could help refine existing design guidelines, such as the berth commitment thresholds proposed by PIANC. By comparing performance across a wide range of terminals and operational contexts, researchers may identify patterns that support more accurate planning and benchmarking in dry bulk logistics.

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B

Additional results

The results for HBTR are covered in chapter 6. The other three terminals are discussed below.

B.1. EECV, Rotterdam

Also located in Rotterdam, EECV is a transshipment terminal specializing in iron ore and coal. Unlike HBRT, EECV is owned by German steel plants, which gives it greater control over its supply chain and reduces its exposure to demurrage costs from waiting vessels. This ownership structure shapes its operational priorities. As noted in their terminal information book: *"We intend to deliver iron ore and coal just in time to our customers on a cost efficient basis"* (Ertsoverslagbedrijf Europoort c.v., 2024, p. 6). This statement underscores that the terminal's focus is on optimizing the efficiency of the steel plants it serves, rather than prioritizing turnaround times or service levels for incoming vessels.

The terminal features three berths along the Calandkanaal for seagoing vessels. Barges are loaded on the other side of the terminal in the Dintelhaven. The terminal operates 4 gantry cranes. The terminal is connected by rail. On the terrain, there are 7 stacker/reclaimers, connected by a conveyor system. Barges are loaded on the Dintelhaven with three barge loaders.

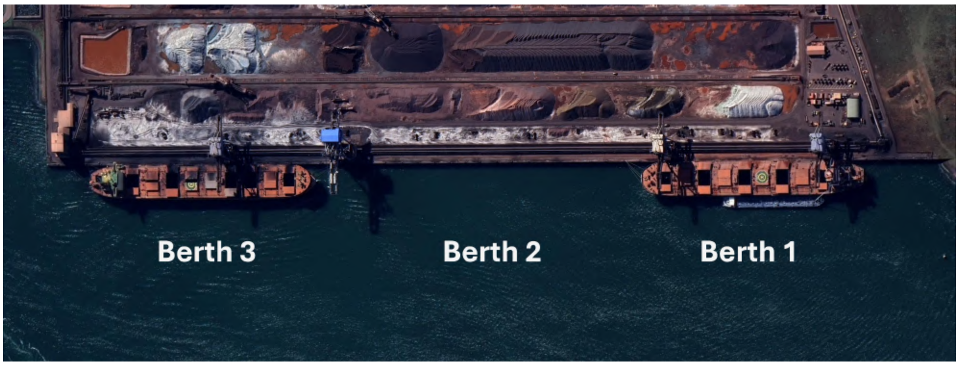


Figure B.1: Aerial image of the EECV terminal quay along the Calandkanaal with berth 1,2, and 3 (Google Earth, 2025).

B.1.1. Call log

The original Sea-Web call log consists of 723 vessels. After filtering, the following vessels per category were found:

Vessel Type	Number found
BULK CARRIER	147
ORE CARRIER	7
OPEN HATCH CARGO SHIP	4

Table B.1: Vessels found at EECV for 2024

For these 158 vessels, 3 duplicate arrivals were found, leaving 155 unique vessel arrivals.

After estimation of the cargo direction, 147 vessels were found to be importing material:

Classification	Number found	Percentage
Importing	147	94.8%
Exporting	3	1.9%
Unknown	5	3.2%

Table B.2: Number of vessels categorized as importing/exporting or unknown for EECV in 2024.

The EECV terminal comprises three berths along the Calandkanaal, all designated for unloading bulk materials. The distribution of vessel presence across these berths is illustrated in Figure B.2. Notably, a vessel is present nearly 100% of the time at berth 3. The newest and largest capacity crane, recognizable by its blue engine house, is the second crane from the left in Figure B.1 (Ertsoverslagbedrijf Europoort c.v., 2024). Berth 3 is likely occupied as often as possible to allow this crane to operate as much as possible.

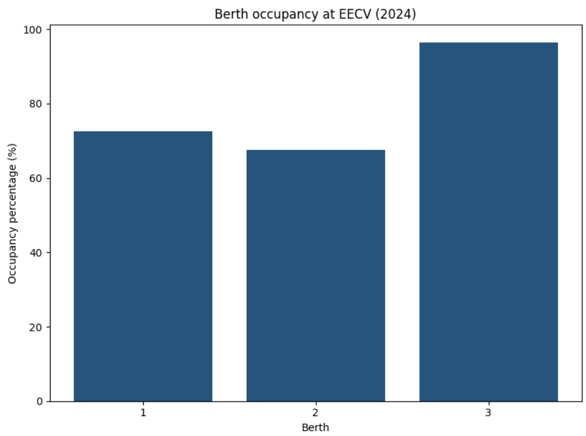


Figure B.2: The observed percentage of time a vessel was present at each berth at EECV in 2024.

In Figure B.3 the distribution of DWT and cargo type for importing vessels at EECV can be seen. EECV receives more vessels carrying iron ore than coal.

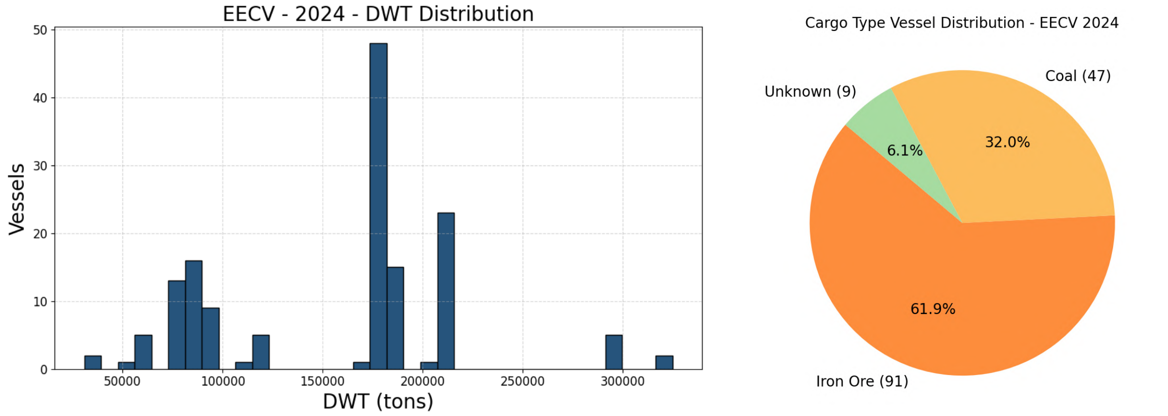


Figure B.3: The distribution of DWT and the number of vessels per cargo type of importing vessels at EECV in 2024

In Figure B.4 the transit times in and out of the terminal can be seen. Since the quay is located directly on the channel towards the sea vessel can enter and leave the port quickly.

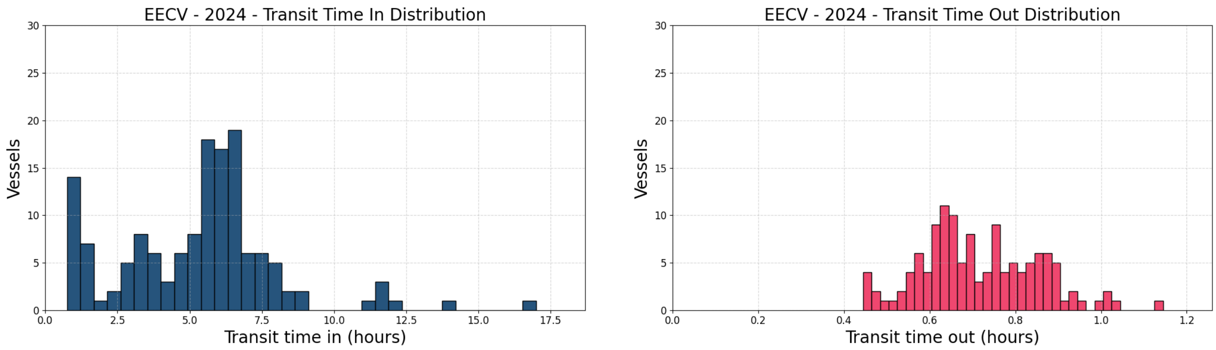


Figure B.4: The distribution of transit times in and out of the harbor of importing vessels at EECV during 2024

In Figure B.5 show the service time and waiting time distribution. While some vessels have no waiting time, the average waiting time is very high, which indicates that is likely not a top priority of the terminal. The service times are also higher than other terminals. The previous and next port country of importing vessels can be seen in Figure B.6. Many vessels import material form Canada, South Africa and Australia which are all well known exporters of coal and iron ore.

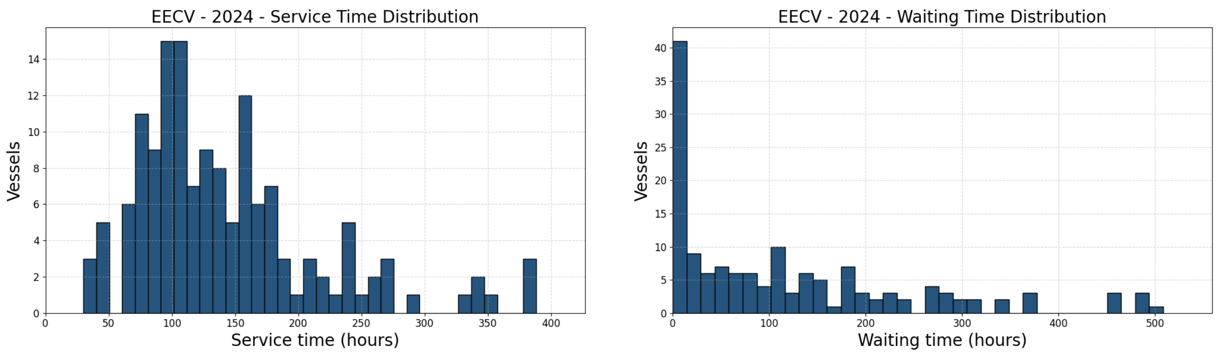


Figure B.5: The distribution of service time and waiting time of importing vessels at EECV during 2024

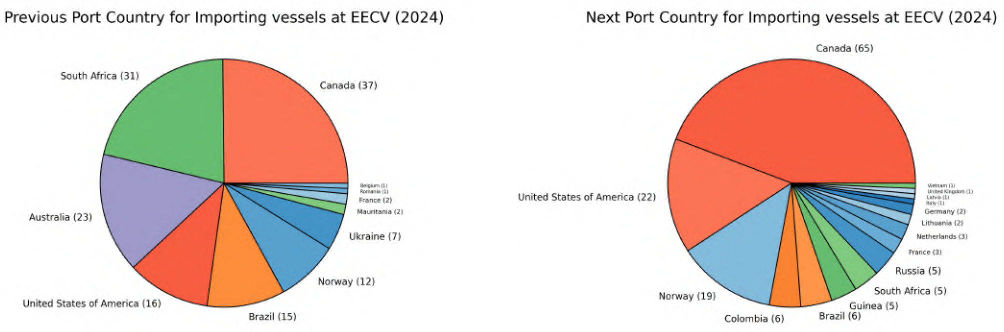


Figure B.6: The previous and next port countries for importing vessels at EECV in 2024

B.1.2. Terminal layout

The terminal layout is analyzed using the trained object detection model. The results can be seen in Figure B.7 and **??**.

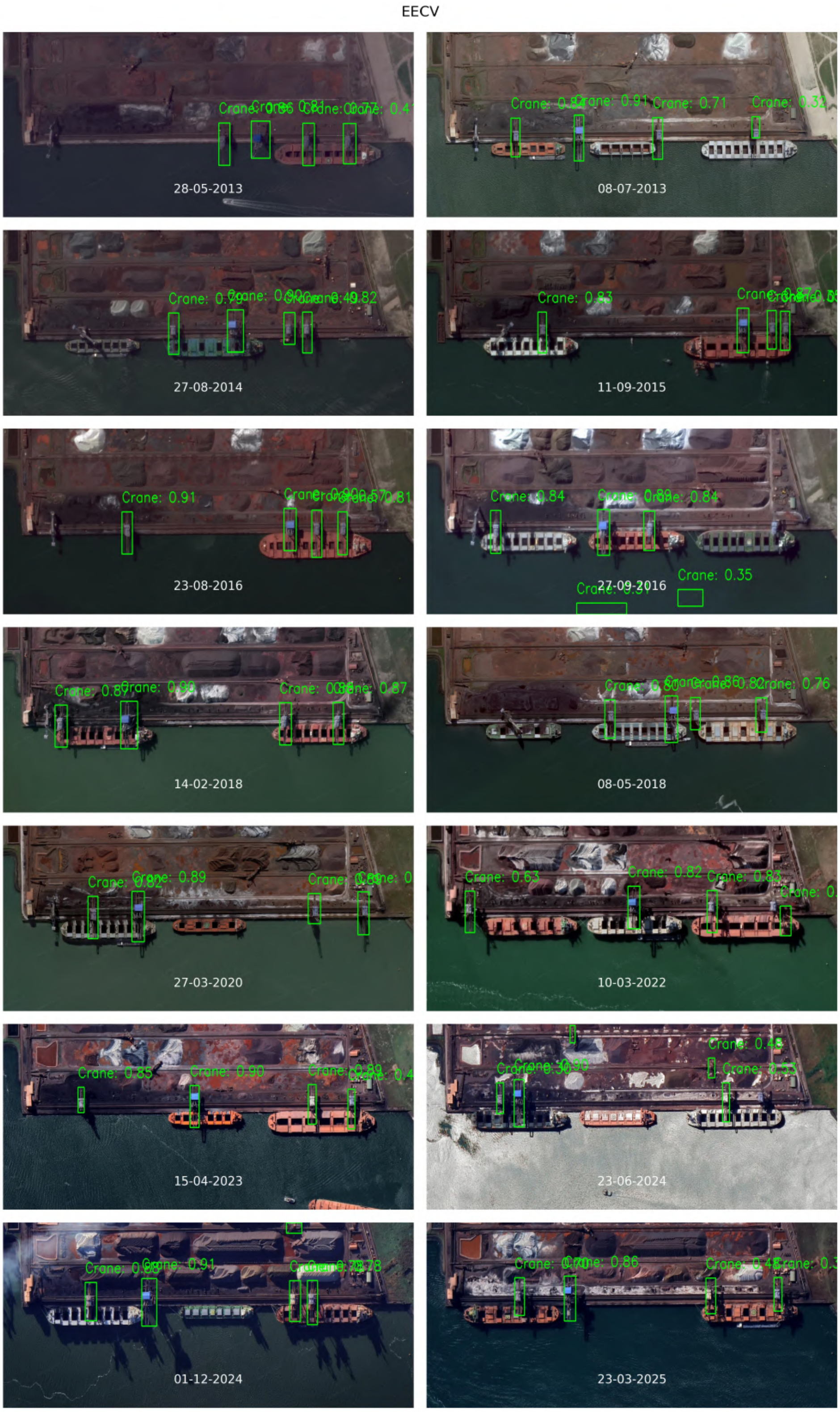


Figure B.7: Crane detections of aerial images of multiple years at EECV.

Date	Cranes Detected
2013-05-28	4
2013-07-08	4
2014-08-27	4
2015-09-11	4
2016-08-23	4
2016-09-27	5
2018-02-14	4
2018-05-08	4
2020-03-27	4
2022-03-10	4
2023-04-15	4
2024-06-23	5
2024-12-01	5
2025-03-23	4

Table B.3: Cranes detected at EECV from aerial images

As shown in Table B.3, four cranes were detected on 11 occasions, and five cranes were detected three times. Based on this, it can be concluded that four cranes are present at the terminal. Next to these cranes, a continuous unloader was located on the east side (left) of the quay until 2020. This unloader is no longer present. Lastly, no more than two cranes are seen operating on a single vessel at the same time. The maximal number of operational cranes per vessel is therefore set at two.

B.1.3. Parameters & performance indicators

EECV features three cranes with a safe working load of 60 tons and one crane with a safe working load of 65 tons. The cranes therefore have a average safe working load of 61.25. However only one of the 60 tons cranes is used for coal, together with the 65 ton crane (Ertsoverslagbedrijf Europoort c.v., 2024). Therefore the average safe working load for a crane handling coal is 62.5 tons.

Parameter	value
Nominal rating NR	2606 tons/h
Nominal rate iron ore NR_{iron}	2606 tons/h
Nominal rate coal NR_{coal}	2250 ton/h

Table B.4: Nominal rates for EECV

The parameter results for EECV can be seen in Table B.5. EECV is the only analyzed terminal that has so little idle time that preventive maintenance must partly be done during operational time.

Parameter	Value
TT	8784
IDL	200
IDL_{nv}	32
UNV	0
PM	462
PM_{nv}	38
WC	80
TR	108
TR_{nv}	7
PO	30
CM	574
OS	735
BE	409
OT	6111
OT_{coal}	1534
OT_{iron}	4397
THR (kt)	20067
$\#Calls$	147
$LOAD$ (kt)	138
ER (t)	819
NR_{coal} (t)	2250
NR_{iron} (t)	2606
NR (t)	2606

Table B.5: Parameters for EECV in 2024

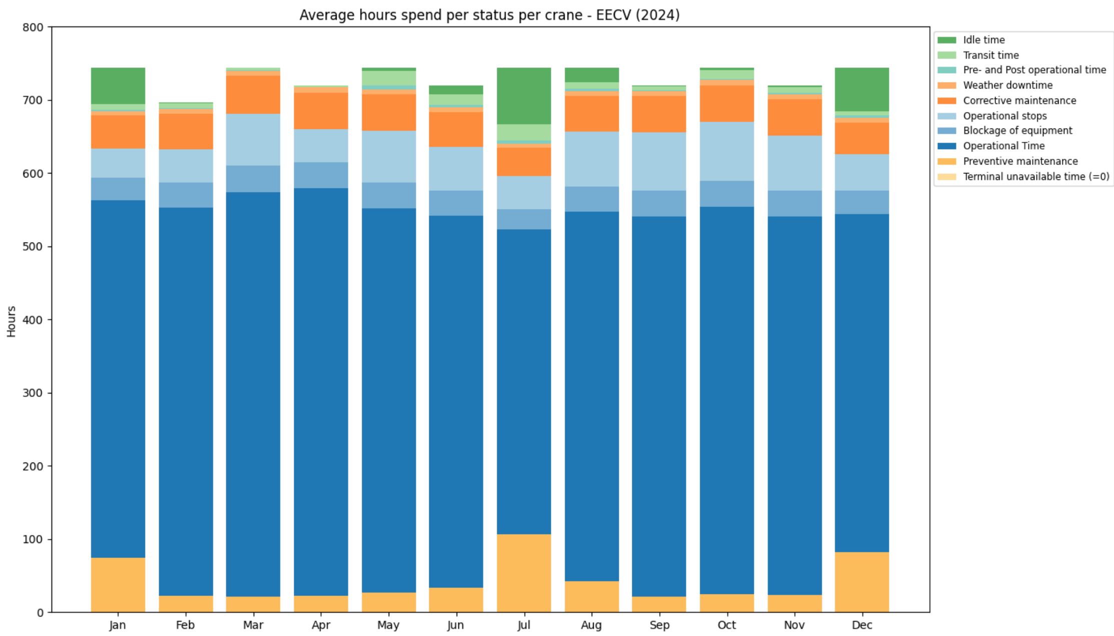


Figure B.8: Average hours spent in different states.

Description	Indicator	Value
Idleness	$ID1_v$	0.036
Idleness (no vessel)	$ID1_{nv}$	0.4%
Unavailability	$ID2$	0.0%
Preventive maintenance	$ID3_v$	0.080
Preventive maintenance (no vessel)	$ID3_{nv}$	0.4%
Weather downtime (h per vessel)	$ID4$	0.575
Transit Time (h per vessel)	$ID5_v$	0.761
Transit Time (no vessel)	$ID5_{nv}$	0.1%
Pre- and Post-operational time (h per vessel)	$ID6$	0.214
Corrective maintenance	$ID7$	0.094
Operational Stops	$ID8$	0.120
Blockage of equipment	$ID9$	0.067
Exogenous downtime	$ID10$	0.000
Variation in effective rate	$ID11$	32.6%
Cargo type nominal rate variation	$ID12$	96.6%
Quay occupancy	OCC	99.1%
Crane utilization	$UTIL$	71.5%
Crane productivity	$PROD$	31.4%
Overall Equipment Effectiveness	OEE	22.5%

Table B.6: Performance Indicators for EECV in 2024

An overview of the yearly OEE assement can be seen in Figure B.9 below.

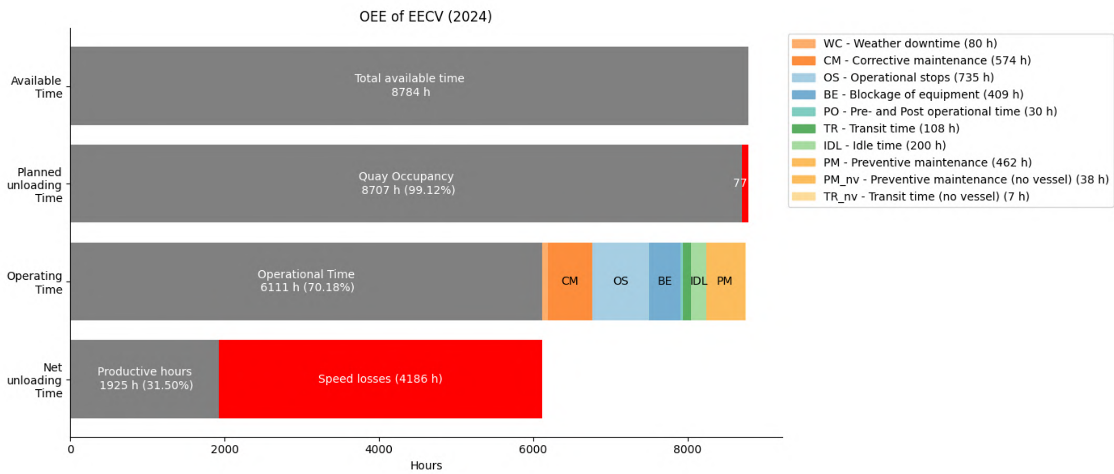


Figure B.9: The total OEE assessment of EECV in 2024

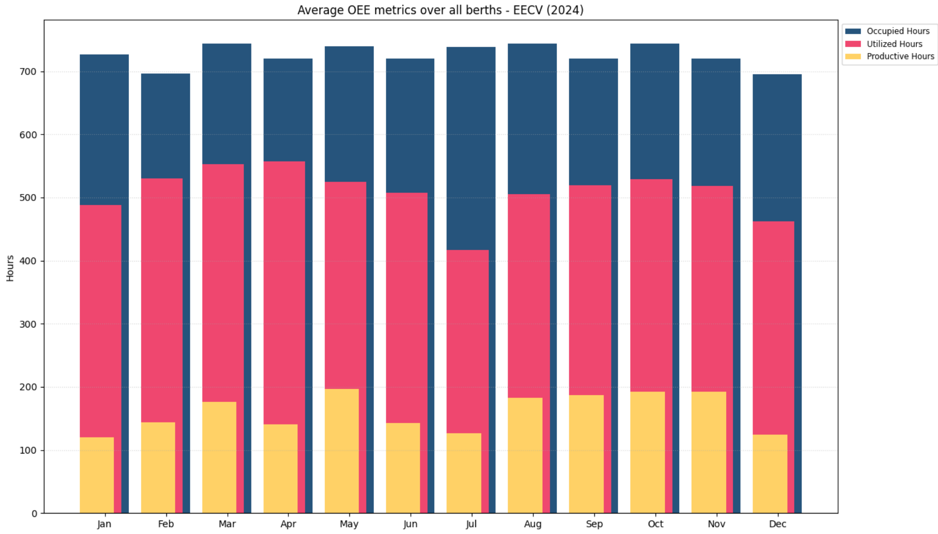


Figure B.10: The average berth occupancy, crane utilization, and crane productive hours for EECV in 2024.

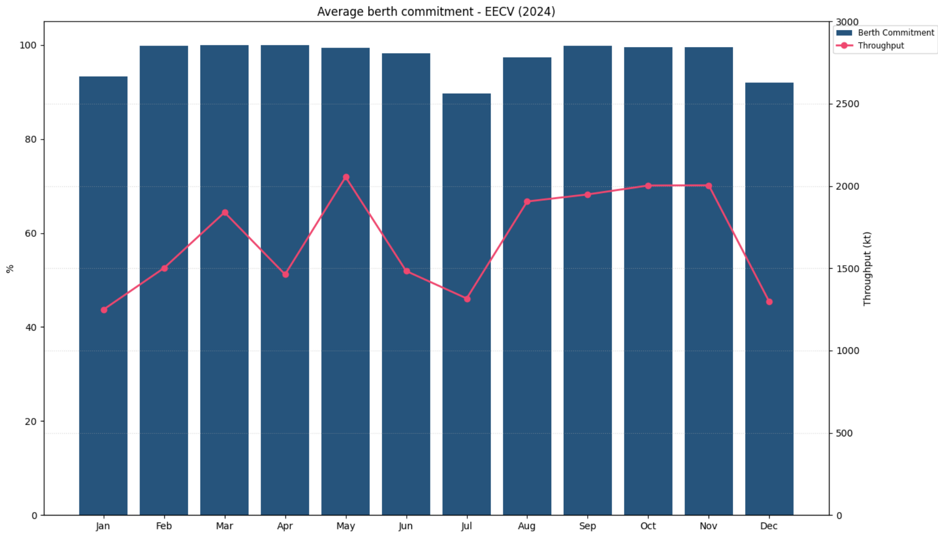


Figure B.11: The berth commitment and throughput per month per berth for EECV in 2024.

The average berth commitment and monthly throughput are presented in Figure B.11. Across all berths and months, EECV maintained an average berth commitment of 97.3%, with a total throughput of 20.1 Mt in 2024. Among the analyzed terminals, EECV exhibits the highest quay occupancy and berth commitment, suggesting a strategic emphasis on continuous operations rather than minimizing vessel waiting and service times. This operational focus is reflected in the average vessel waiting time of 138 hours, nearly four times longer than that of HBTR, which prioritizes service quality and reduced waiting times for vessels.

B.2. Tata Steel, IJmuiden

The steel mill at Tata Steel IJmuiden recieves sea-going bulk carriers at the buitenkade 2, which can be seen in Figure B.12. It features two berths and four cranes which are used to unload coal and iron ore needed for steel production. The material is unloaded onto a conveyor system which transports the material to the stockyard. Then it is transported again with the conveyor system to the blending fields where the right mix of material is blended (R. Schuurmans, personal communication, August 15, 2025).

Figure B.12: Aerial image of the Tata Steel IJmuiden buitenhaven with berth 1 and 2 (Google Earth, 2025).

B.2.1. Call log

The original Sea-Web call log has 381 vessels. After filtering, the following vessels per category were found:

Vessel Type	Number found
BULK CARRIER	151
OPEN HATCH CARGO SHIP	1

Table B.7: Vessels found at Tata Steel for 2024

For these 152 vessels, 16 duplicate arrivals were found, leaving 136 unique vessel arrivals.

After estimation of the cargo direction, 134 vessels were found to be importing material:

Classification	Number found	Percentage
Importing	134	98.5%
Exporting	0	0%
Unknown	2	1.5 %

Table B.8: Number of vessels categorized as importing/exporting or unknown for Tata Steel IJmuiden in 2024.

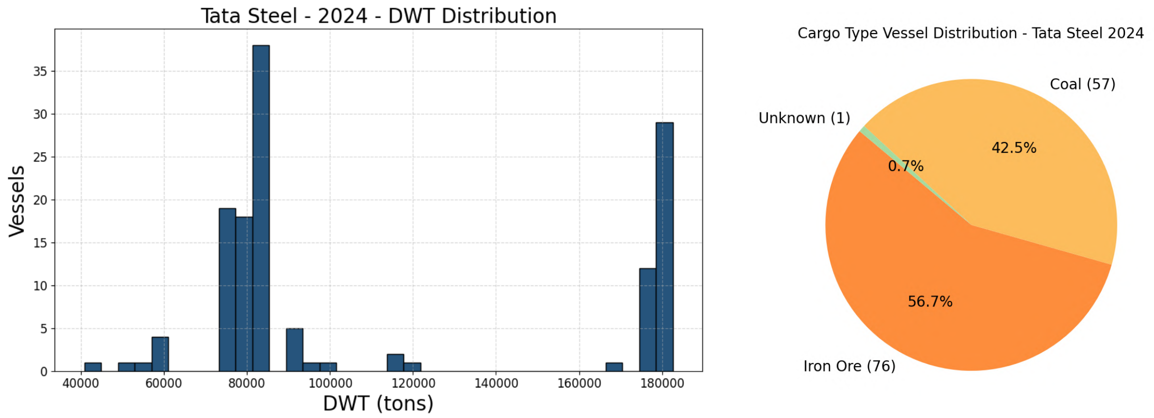


Figure B.13: The distribution of DWT and the number of vessels per cargo type of importing vessels at Tata Steel IJmuiden in 2024

The service time and waiting time distributions are shown in Figure B.14. The average service time is 96.65 hours, while the average waiting time is 167.82 hours, resulting in a waiting-to-service time ratio of 1.74. This represents the highest waiting time and ratio among all analyzed terminals.

During January and February, the terminal experienced reduced production at the steel mill due to renovation work at one of the factories, which may have contributed to some of the longer waiting times. However, extended waiting times were also observed throughout the year, including periods when the terminal was available for berthing. It is likely that production scheduling influenced when vessels were required to berth.

The distribution reveals a few high outliers in waiting time. By filtering out the top 3% of waiting times, which corresponds to any waiting time exceeding 703.93 hours, the average waiting time decreases to 142.65 hours.

Of the 134 arriving vessels, 109 were observed waiting in the anchorage area, further confirming that a significant number of vessels experienced waiting times, often for extended durations.

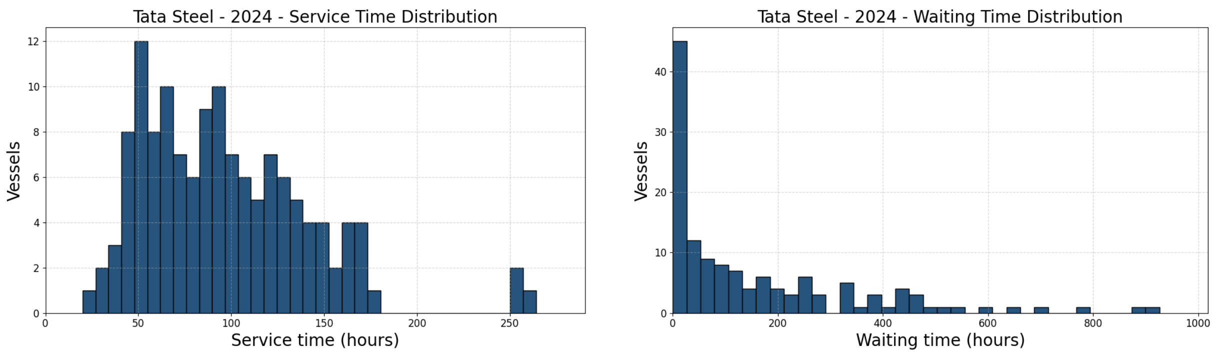


Figure B.14: The distribution of service time and waiting time of importing vessels at Tata Steel IJmuiden during 2024

The transit time into the harbor and toward the terminal, as well as the transit time when leaving the harbor, are shown in Figure B.15. The overall average inbound transit time is 5.35 hours, while the average outbound transit time is 0.59 hours.

The definition of inbound transit time differs depending on whether a vessel waits in the anchorage area. For vessels that do not wait, the inbound transit time is measured from the moment they pass the mouth of the harbor until arrival at the terminal. For vessels that do wait, the inbound transit time begins when they depart the anchorage area. The average inbound transit time for vessels coming from anchorage is 5.92 hours, while for vessels not visiting anchorage it is 1.89 hours.

Inbound transit times are longer than outbound times, likely due to increased maneuvering and reduced vessel speed when arriving fully loaded.

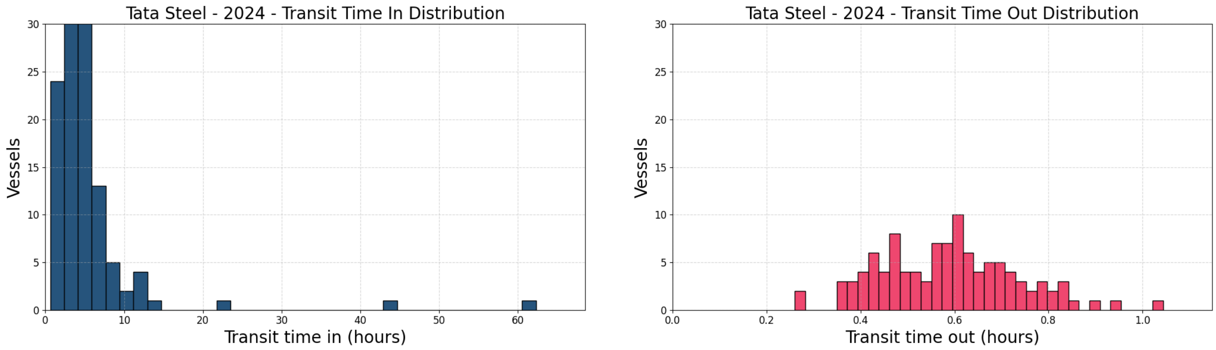


Figure B.15: The distribution of transit times in and out of the harbor of importing vessels at Tata Steel IJmuiden during 2024

The origin and next port countries for vessel importing to Tata Steel can be seen in Figure B.16. Most material is imported from

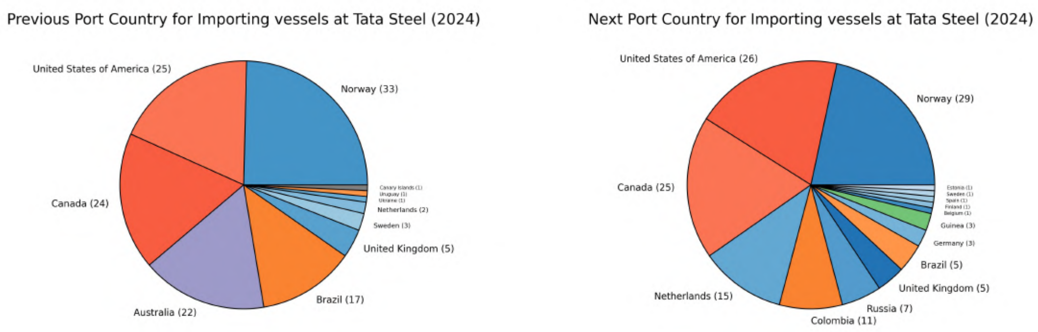


Figure B.16: The previous and next port countries for importing vessels at Tata Steel IJmuiden in 2024

B.2.2. Terminal layout

The results of the crane detection model can be seen below.

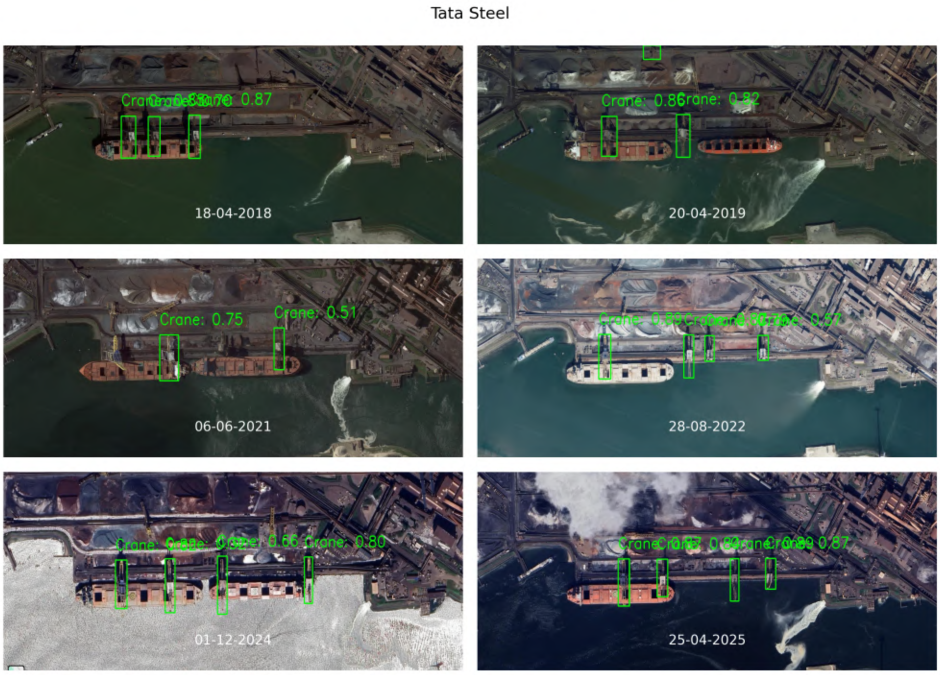


Figure B.17: Crane detections of aerial images of multiple years at Tata Steel IJmuiden.

Date	Cranes Detected
18-04-2018	3
20-04-2019	3
06-06-2021	2
28-08-2022	4
01-12-2024	4
25-04-2024	4

Table B.9: Cranes detected at Tata Steel IJmuiden

As can be seen in Table B.9, 3 times 4 cranes were detected, thus the mode of the results is four. It can therefore be concluded that four cranes are present at the terminal. Furthermore, three cranes are seen operating on a single vessel at the same time in 2018. The maximal number of operational cranes per vessel is therefore set at three. Tata Steel acquired the fourth crane in 2020, as can be seen from the images.

B.2.3. Parameters & performance indicators

Berth 1 at Tata Steel features a crane with a safe working load 65 tons and a crane with a safe working load of 40 tons. Therefore, the average safe working load of a crane at berth 1 is 52.5 tons. Berth 2 has two cranes, each with a safe working load of 40 tons.

Parameter	Berth 1 value	Berth 2 value
Nominal rating NR	2234 tons/h	1702 tons/h
Nominal rate iron ore NR_{iron}	2234 tons/h	1702 tons/h
Nominal rate coal NR_{coal}	1890 ton/h	1440 tons/h

Table B.10: Nominal rates for Tata steel IJmuiden

The found parameters can be seen in Table B.11 below.

Parameter	Value
TT	8784
IDL	843
IDL_{nv}	518
UNV	0
PM	0
PM_{nv}	500
WC	66
TR	244
TR_{nv}	30
PO	99
CM	465
OS	670
BE	333
OT	5016
OT_{coal}	1830
OT_{iron}	3161
THR (kt)	12888
$\#Calls$	134
$LOAD$ (kt)	96
ER (t)	640
NR_{coal} (t)	1665
NR_{iron} (t)	1968
NR (t)	1968

Table B.11: Parameters for Tata Steel in 2024

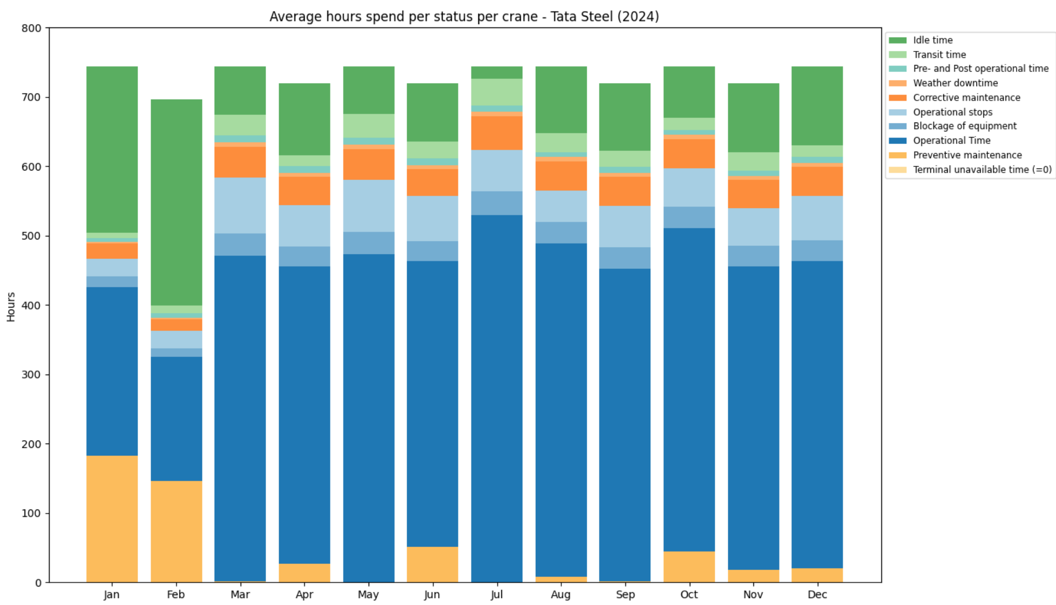


Figure B.18: Hours spent in different states per berth.

The found parameters result in the following performance indicators, which can be seen in Table B.12 below.

Description	Indicator	Value
Idleness	$ID1_v$	0.204
Idleness (no vessel)	$ID1_{nv}$	6.0%
Unavailability	$ID2$	0.0%
Preventive maintenance	$ID3_v$	0.000
Preventive maintenance (no vessel)	$ID3_{nv}$	5.7%
Weather downtime (h per vessel)	$ID4$	0.502
Transit Time (h per vessel)	$ID5_v$	1.742
Transit Time (no vessel)	$ID5_{nv}$	0.4%
Pre- and Post-operational time (h per vessel)	$ID6$	0.772
Corrective maintenance	$ID7$	0.093
Operational Stops	$ID8$	0.133
Blockage of equipment	$ID9$	0.067
Exogenous downtime	$ID10$	0.000
Variation in effective rate	$ID11$	34.6%
Cargo type nominal rate variation	$ID12$	93.9%
Quay occupancy	OCC	87.9%
Crane utilization	$UTIL$	66.8%
Crane productivity	$PROD$	32.5%
Overall Equipment Effectiveness	OEE	21.8%

Table B.12: Performance Indicators for Tata Steel in 2024

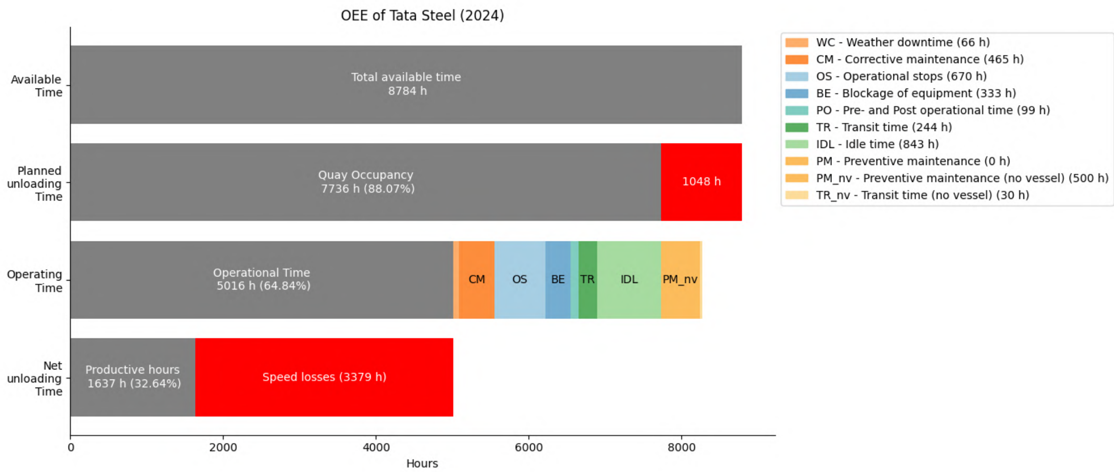


Figure B.19: The total OEE assessment of Tata Steel in 2024

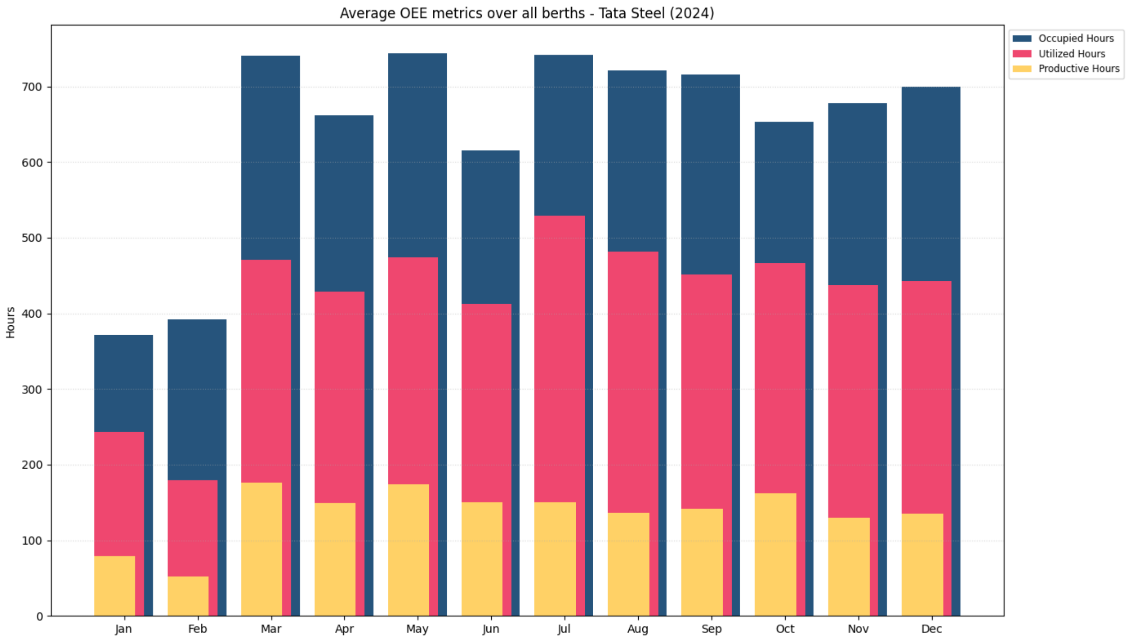


Figure B.20: The berth occupancy, crane utilization, and crane productive hours per berth for Tata Steel IJmuiden in 2024.

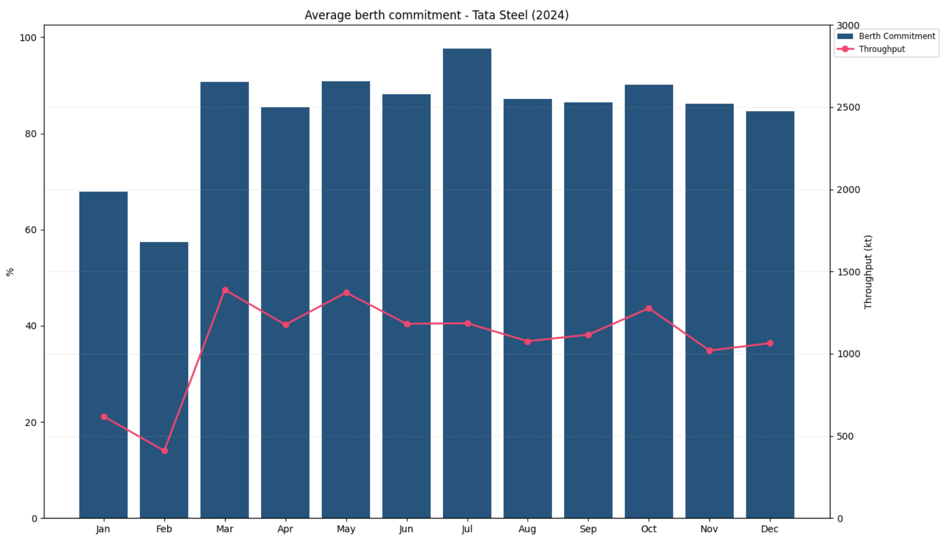


Figure B.21: The berth commitment and throughput per month per berth for Tata Steel IJmuiden in 2024.

The average commitment across all berths and all months was 84.3%. The overall throughput was 11.6 Mt in 2024.

B.3. Hansaport, Hamburg

The Hansaport bulk terminal in Hamburg functions as a transshipment hub, handling iron ore and coal. A notable distinction from the other terminals is that vessels must travel around 100 kilometers over the Elbe River before reaching the terminal. Although the river is influenced by tidal conditions, dredging operations maintain a navigable draught of 13 metres throughout, allowing most vessels to pass unhindered. Nonetheless, the largest vessels can only access or depart from the port during high tide (Hamburg Port Authority, 2021).

The terminal is equipped with four gantry cranes dedicated to unloading seagoing vessels. Additionally, a barge loader operates from a separate berth. The terminal is connected by rail. Within the stockyard, five stacker/reclaimers manage bulk material handling and storage.

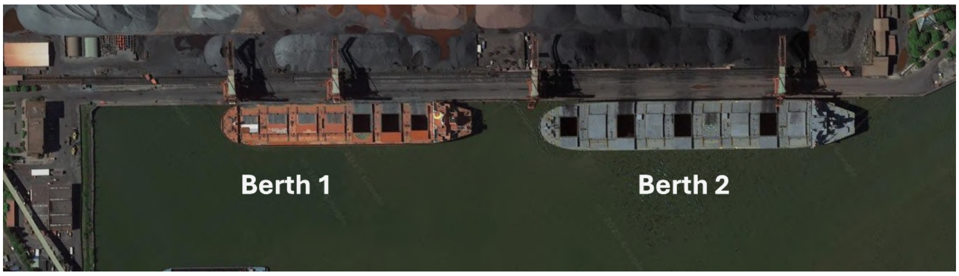


Figure B.22: Aerial image of the Hansaport terminal with berth 1 and 2 (Google Earth, 2025).

B.3.1. Call log

The original Sea-Web call log has 397 vessels. After filtering, the following vessels per category were found:

Vessel Type	Number found
BULK CARRIER	150
OPEN HATCH CARGO SHIP	2

Table B.13: Vessels found at Hansaport for 2024

For these 152 vessels, 5 duplicate arrivals were found, leaving 147 unique vessel arrivals.

After estimation of the cargo direction, 140 vessels were found to be importing material:

Classification	Number found	Percentage
Importing	140	95.2%
Exporting	4	2.7%
Unknown	3	2.0 %

Table B.14: Number of vessels categorized as importing/exporting or unknown for Hansaport in 2024.

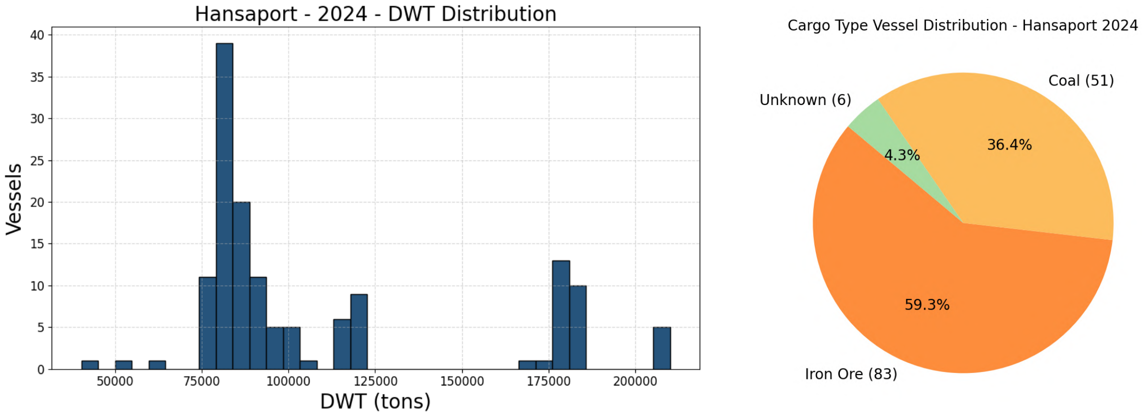


Figure B.23: The distribution of DWT and the number of vessels per cargo type of importing vessels at Hansaport in 2024

The service time and waiting time distributions are shown in Figure B.24. The average service time is 56.23 hours, while the average waiting time is 35.66 hours, resulting in a waiting-to-service time ratio of 0.63.

The distribution reveals a few high outliers in waiting time. By filtering out the top 3% of waiting times, which corresponds to any waiting time exceeding 188.22 hours, the average waiting time decreases to 29.01 hours.

Of the 147 arriving vessels, 95 were observed waiting in the anchorage area.

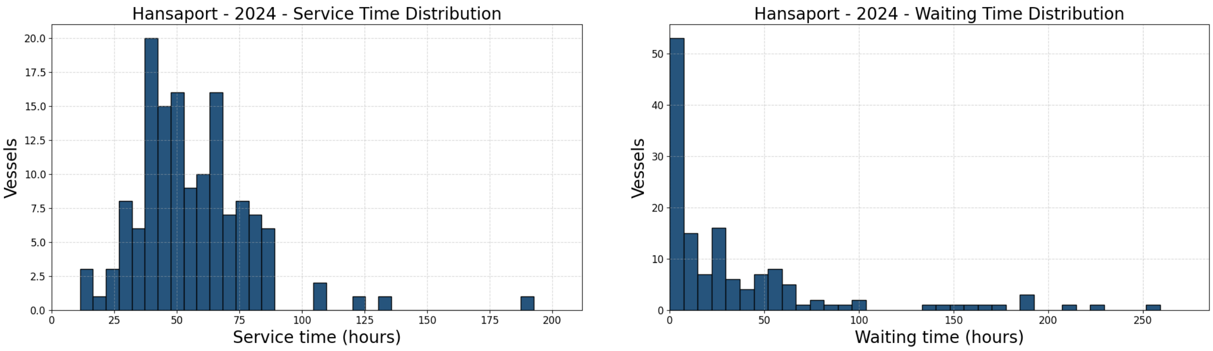


Figure B.24: The distribution of service time and waiting time of importing vessels at Hansaport during 2024

The transit time into the harbor and toward the terminal, as well as the transit time when leaving the harbor, are shown in Figure B.25. The overall average inbound transit time is 9.14 hours, while the average outbound transit time is 5.33 hours. This is high since vessels have to traverse 110km of the Elbe River to enter or leave the port.

The definition of inbound transit time differs depending on whether a vessel waits in the anchorage area. For vessels that do not wait, the inbound transit time is measured from the moment they pass the mouth of the harbor until arrival at the terminal. For vessels that do wait, the inbound transit time begins when they depart the anchorage area. The average inbound transit time for vessels coming from anchorage is 10.62 hours, while for vessels not visiting anchorage it is 5.79 hours.

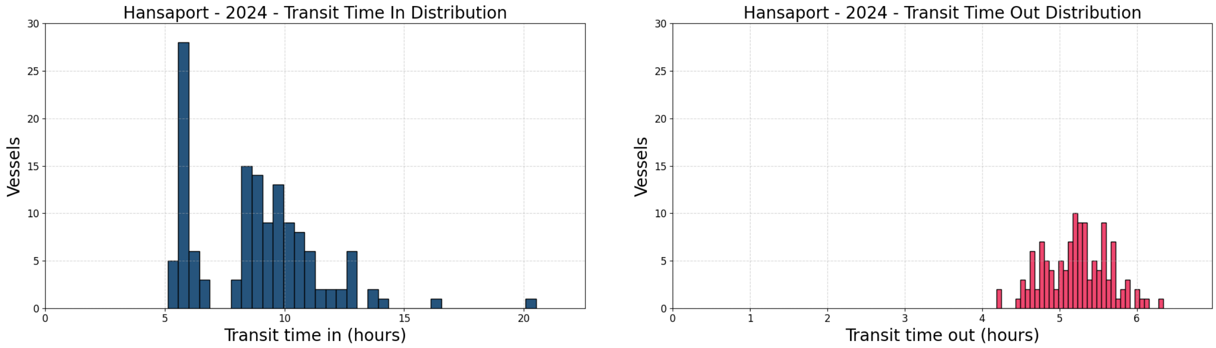


Figure B.25: The distribution of transit times in and out of the harbor of importing vessels at Hansaport during 2024

The origin and next port countries for vessel importing to Hansaport can be seen in Figure B.26. Most material is imported from

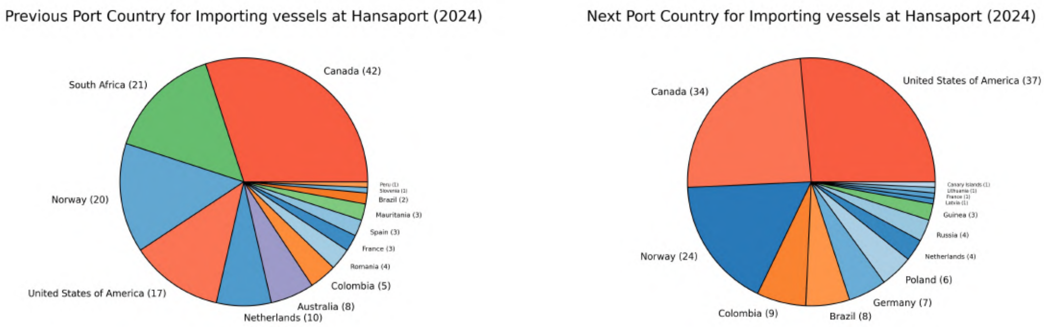


Figure B.26: The previous and next port countries for importing vessels at Hansaport in 2024

B.3.2. Terminal layout

The results of the crane detection model can be seen below.

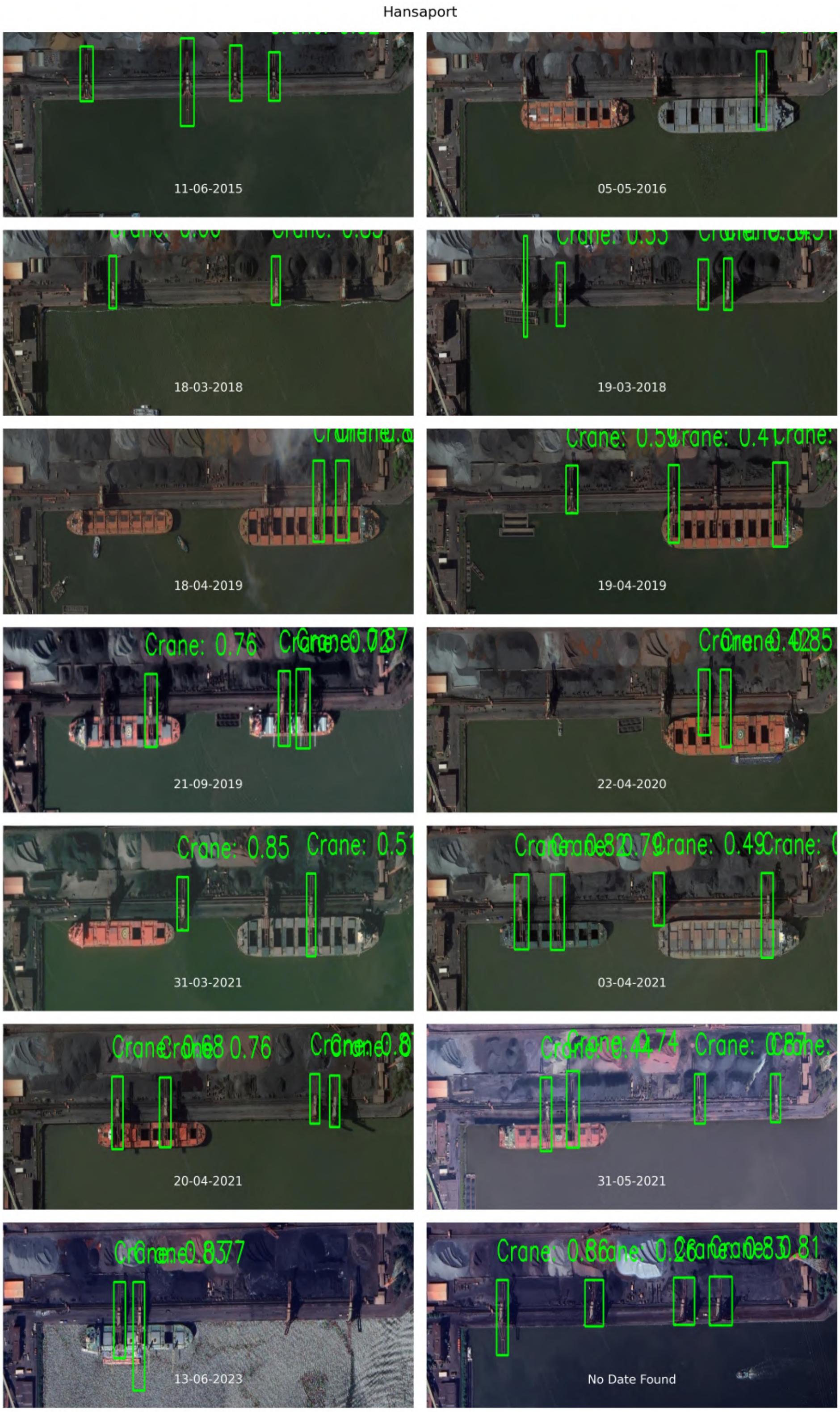


Figure B.27: Crane detections of aerial images of multiple years at Hansaport, Hamburg.

Date	Cranes Detected
2015-06-11	4
2016-05-05	1
2018-03-18	2
2018-03-19	4
2019-04-18	2
2019-04-19	3
2019-09-21	3
2020-04-22	2
2021-03-31	2
2021-04-03	4
2021-04-20	4
2021-05-31	4
2023-06-13	2
unknown date	4

Table B.15: Cranes detected at Hansaport, Hamburg

As can be seen in Table B.15, 6 times 4 cranes were detected, thus the mode of the results is four. It can therefore be concluded that four cranes are present at the terminal. Furthermore, three cranes are seen operating on a single vessel at the same time in april 2019. The maximal number of operational cranes per vessel is therefore set at three.

B.3.3. Parameters & performance indicators

The four cranes at Hansaport each have a safe working load of 38 tons.

Parameter	value
Nominal rating NR	1617 tons/h
Nominal rate iron ore NR_{iron}	1617 tons/h
Nominal rate coal NR_{coal}	1368 ton/h

Table B.16: Nominal rates for Hansaport

The found parameters can be seen in Table B.17 below.

Parameter	Value
TT	8784
IDL	1492
IDL_{nv}	1700
UNV	0
PM	0
PM_{nv}	500
WC	43
TR	285
TR_{nv}	486
PO	142
CM	303
OS	700
BE	214
OT	2918
OT_{coal}	935
OT_{iron}	1854
THR (kt)	13257
$\#Calls$	140
$LOAD$ (kt)	96
ER (t)	1155
NR_{coal} (t)	1368
NR_{iron} (t)	1617
NR (t)	1617

Table B.17: Parameters for Hansaport in 2024

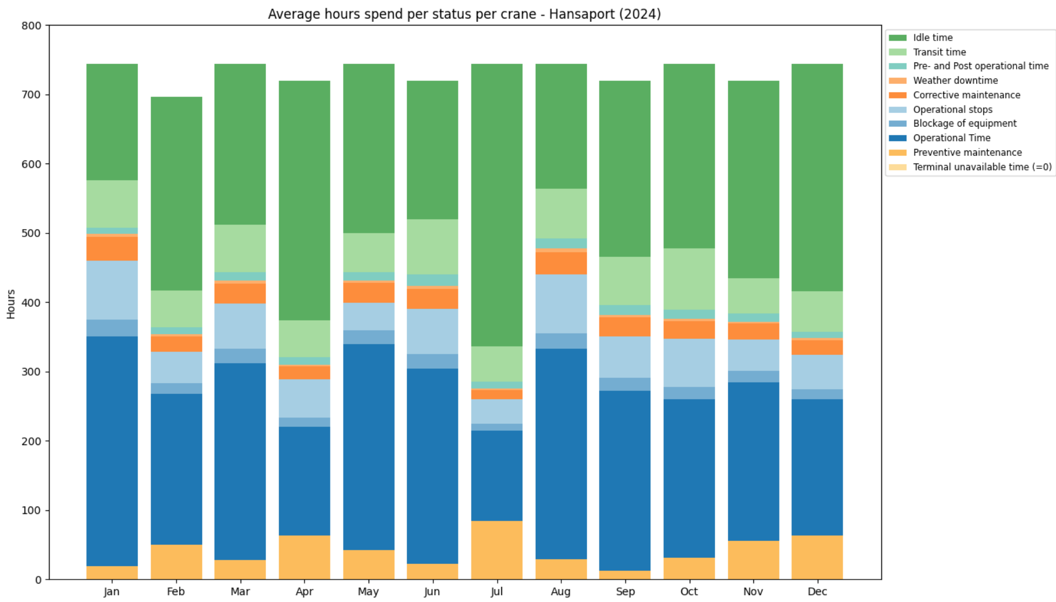


Figure B.28: Hours spent in different states per berth at Hansaport in 2024.

The found parameters result in the following performance indicators, which can be seen in Table B.18 below.

Description	Indicator	Value
Idleness	$ID1_v$	0.554
Idleness (no vessel)	$ID1_{nv}$	19.4%
Unavailability	$ID2$	0.0%
Preventive maintenance	$ID3_v$	0.000
Preventive maintenance (no vessel)	$ID3_{nv}$	5.7%
Weather downtime (h per vessel)	$ID4$	0.312
Transit Time (h per vessel)	$ID5_v$	1.928
Transit Time (no vessel)	$ID5_{nv}$	5.5%
Pre- and Post-operational time (h per vessel)	$ID6$	1.058
Corrective maintenance	$ID7$	0.105
Operational Stops	$ID8$	0.245
Blockage of equipment	$ID9$	0.074
Exogenous downtime	$ID10$	0.000
Variation in effective rate	$ID11$	74.8%
Cargo type nominal rate variation	$ID12$	95.2%
Quay occupancy	OCC	69.4%
Crane utilization	$UTIL$	50.3%
Crane productivity	$PROD$	71.4%
Overall Equipment Effectiveness	OEE	35.5%

Table B.18: Performance Indicators for Hansaport in 2024

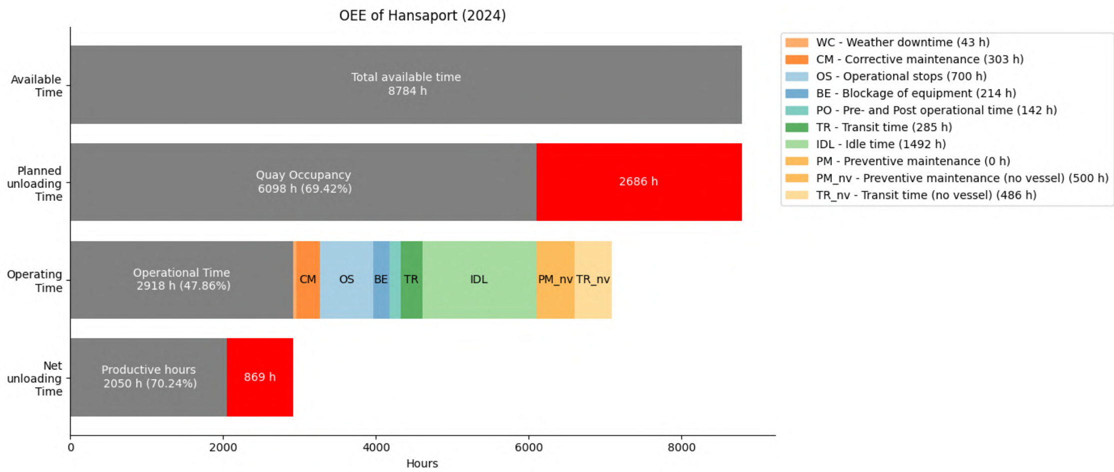


Figure B.29: The total OEE assessment of Hansaport in 2024

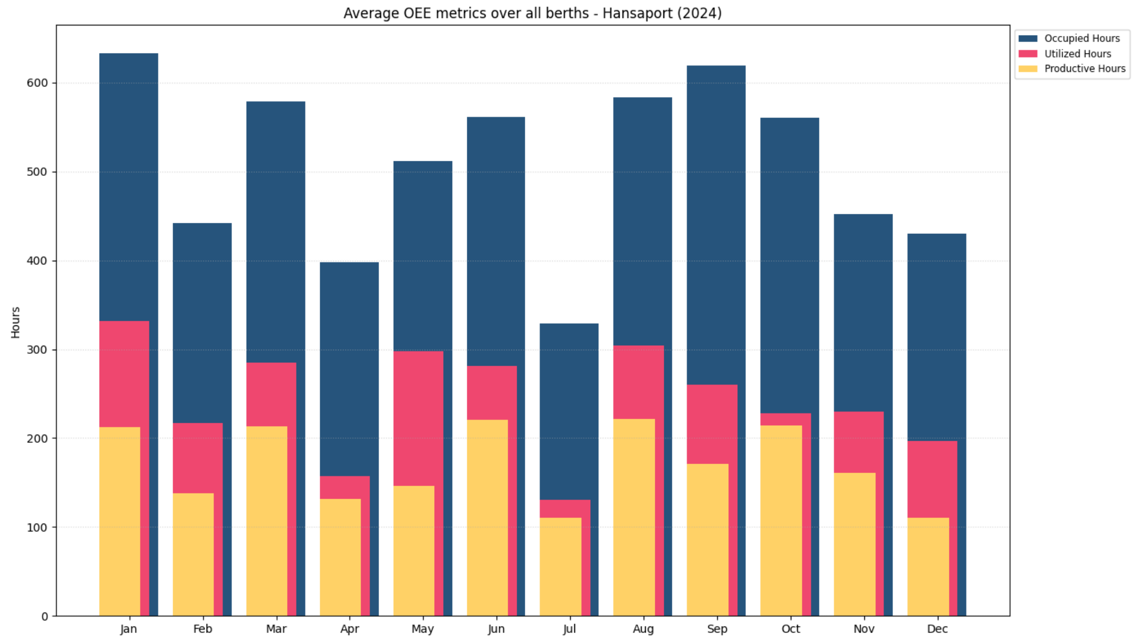


Figure B.30: The berth occupancy, crane utilization, and crane productive hours per berth for Hansaport in 2024.

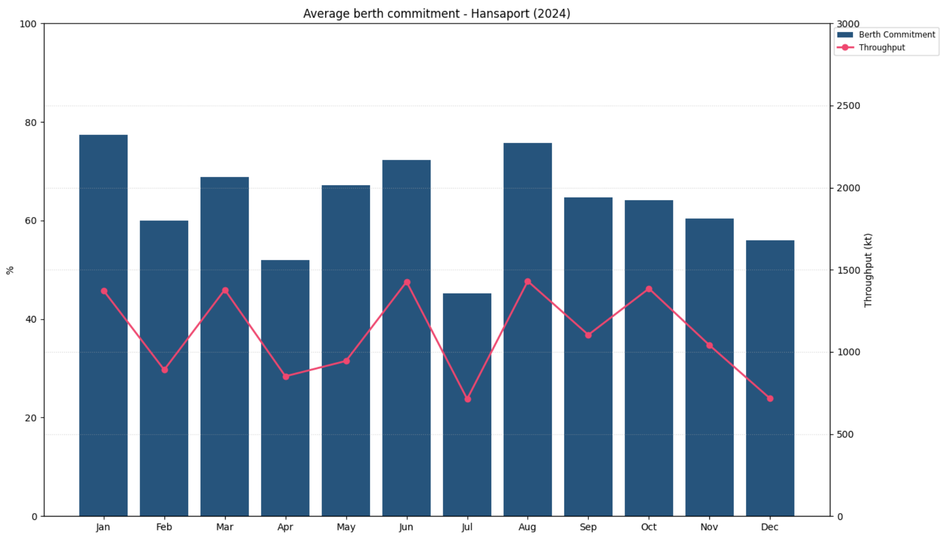


Figure B.31: The berth commitment and throughput per month per berth for Hansaport in 2024.

The average commitment across all berths and all months was 63.6%. The overall throughput was 11.6 Mt in 2024.

C
Validation of Sea-web data

Sea-web provides multiple data fields in the vessel call log, with static vessel characteristics such as MMSI and DWT considered reliable. The 'Arrival Time,' 'Sailed Time,' 'Draught Change,' and 'Berth' are validated using AIS data from the Haskoning AIS platform in this appendix. A sample of vessels arriving at the Hes Bulk Terminal Rotterdam (HBTR) in January 2025 is used for validation.

Arrival times are first examined. Sea-web determines the 'Arrival Time,' and vessel speeds derived from AIS data before and after this timestamp are plotted in Figure C.1. Most vessels are moving before arrival and show minimal speed afterward, confirming the reliability of Sea-web's reported arrival times.

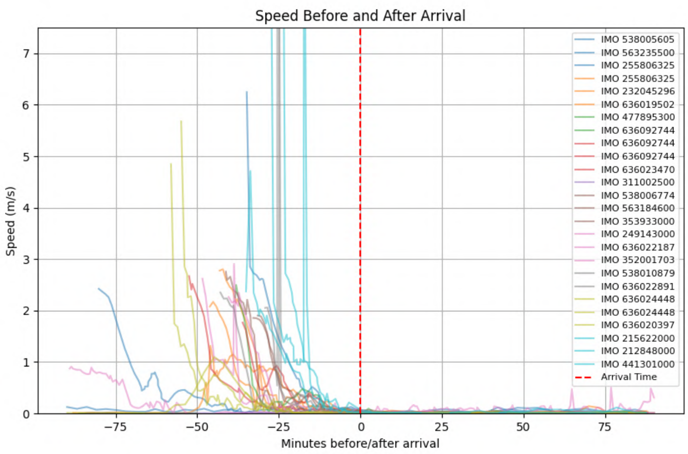


Figure C.1: Speeds of all vessels before and after arriving at HBTR according to Sea-web during January 2025

Similarly, departure times are assessed, as shown in Figure C.2. Most vessels exhibit little movement before departure and accelerate after leaving, supporting Sea-web's accuracy in recording departure times. Consequently, service times for vessels can be reliably determined using Sea-web data.

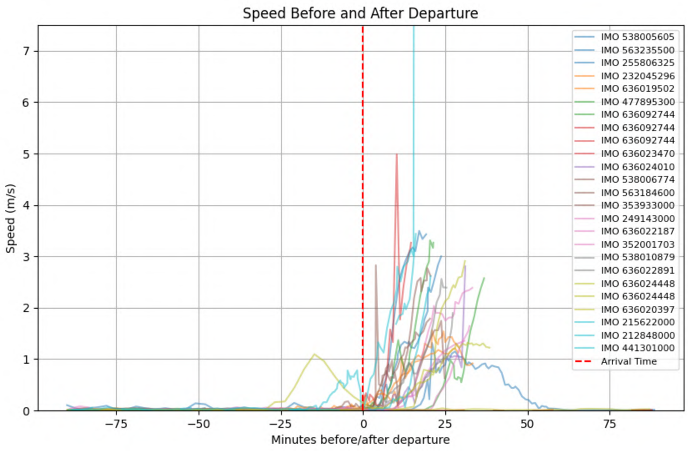


Figure C.2: Speeds of all vessels before and after departure from HBTR according to Sea-web during January 2025

However, some vessels display minimal movement post-departure. Further investigation revealed duplicate arrivals, as seen in Table C.1. This discrepancy is likely due to either a rogue AIS data point outside the terminal perimeter or an extended gap between AIS data transmissions, which Sea-web interprets as a departure. The AIS data from the same time range is shown in Figure C.3, which shows the three appearances in separate colors. To correct these duplicate arrivals, a filter is applied to the call log, merging arrivals with the same MMSI occurring within 24 hours. For the HBTR analysis in 2025, this occurred five times, with all duplicate arrivals recorded within one hour of the departure time. Figure C.4 provides an overview of these cases.

Appearance	IMO	Vessel Name	Arrival Time	Departure Time
1	9498846	CORNELIE OLDENDORFF	14/01/2025 08:30	14/01/2025 22:00
2	9498846	CORNELIE OLDENDORFF	14/01/2025 22:15	15/01/2025 03:57
3	9498846	CORNELIE OLDENDORFF	15/01/2025 04:27	17/01/2025 16:10

Table C.1: Sea-web results for CORNELIE OLDENDORFF. Which shows duplicate arrivals.

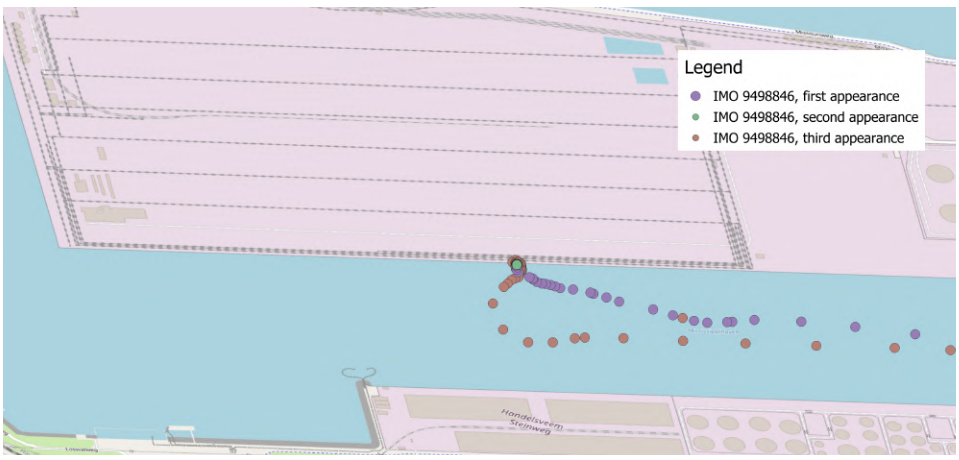


Figure C.3: AIS data of the Cornelie Oldendorff during the three instances of arrival

```
Merged two lines for IMO/LR/IHS No. 9514224: Found arrival within 0 days 00:18:00 of
    departure at 2024-04-11 06:28:00
Merged two lines for IMO/LR/IHS No. 9884978: Found arrival within 0 days 00:16:00 of
    departure at 2024-07-02 17:42:00
Merged two lines for IMO/LR/IHS No. 9952505: Found arrival within 0 days 00:12:00 of
    departure at 2024-09-23 15:57:00
Merged two lines for IMO/LR/IHS No. 9586629: Found arrival within 0 days 00:26:00 of
    departure at 2024-03-13 21:15:00
Merged two lines for IMO/LR/IHS No. 9186687: Found arrival within 0 days 00:33:00 of
    departure at 2024-03-10 07:42:00
```

Figure C.4: Code output after merging duplicate arrivals in the HBTR call log of 2025

The draught was also analyzed using AIS data and compared to the Sea-web data. As shown in Figure C.5, no vessels in the AIS data showed a draught change during their terminal visit. Since the vessel crew manually updates the draught value, this is likely done later after departure rather than during maneuvering within the port.

A comparison between AIS draught data at arrival time and the 'Arrival Draught' recorded by Sea-Web is presented in **??**. While the values are not identical, the deviations are reasonable. In most cases, the Sea-Web arrival draught is lower than the AIS-observed draught, possibly because Sea-Web records draught at a later stage or averages measurements from the initial moments in port when the vessel has already been partially unloaded. Since this research requires information on whether the draught change during a port visit is negative, zero, or positive, the accuracy of Sea-Web-based draught data is considered sufficient.

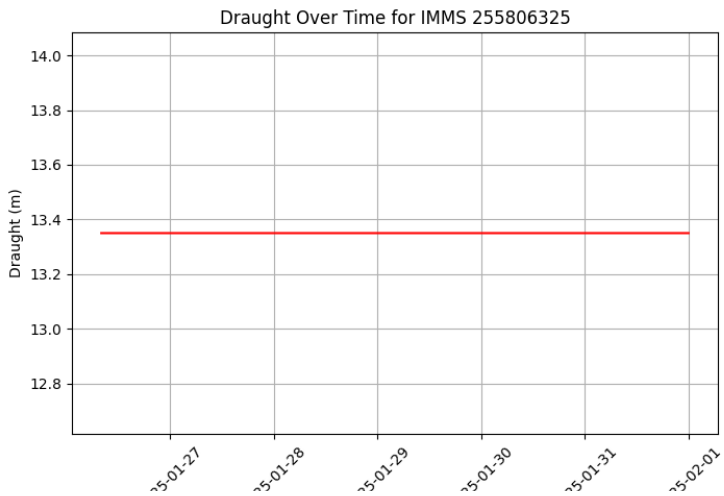


Figure C.5: No draught changes observed in AIS data within the terminal.

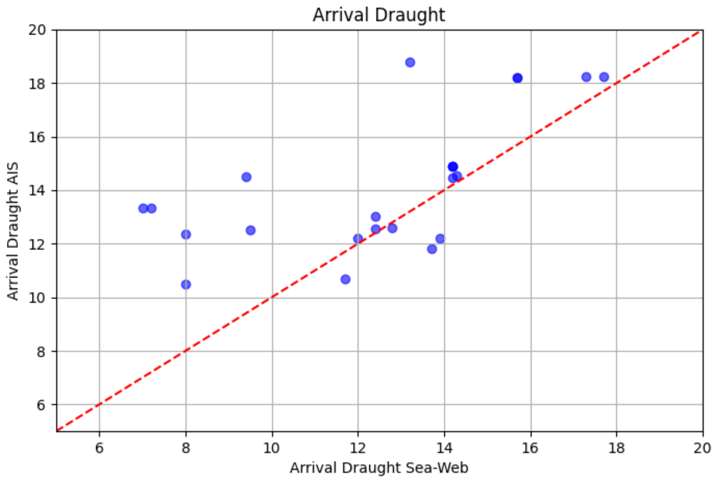


Figure C.6: The relation of AIS measured draught and Sea-Web arrival draught.

Sea-Web also provides data on berth visits at the HBTR terminal, which consists of six berths in the Mississippihaven. Berth 1 is located at the westernmost part, which is on the left of the figures. The first four berths are designated for unloading with grab cranes, while berths 5 and 6 handle loading operations for sea-going vessels. Vessel paths for those visiting berths 1, 2, 3, and 4, as defined by Sea-Web, are shown in Figure C.7, while the paths for vessels visiting berths 5 and 6 are depicted in Figure C.8.

However, Sea-Web's berth classification has proven to be inaccurate, likely due to vessels moving between multiple berths within a single visit. Since correct berth classification is crucial for determining whether a vessel is importing or exporting, the Sea-Web data is deemed unreliable for this purpose. Instead, berth classification is determined by averaging vessel position data over time using AIS data.

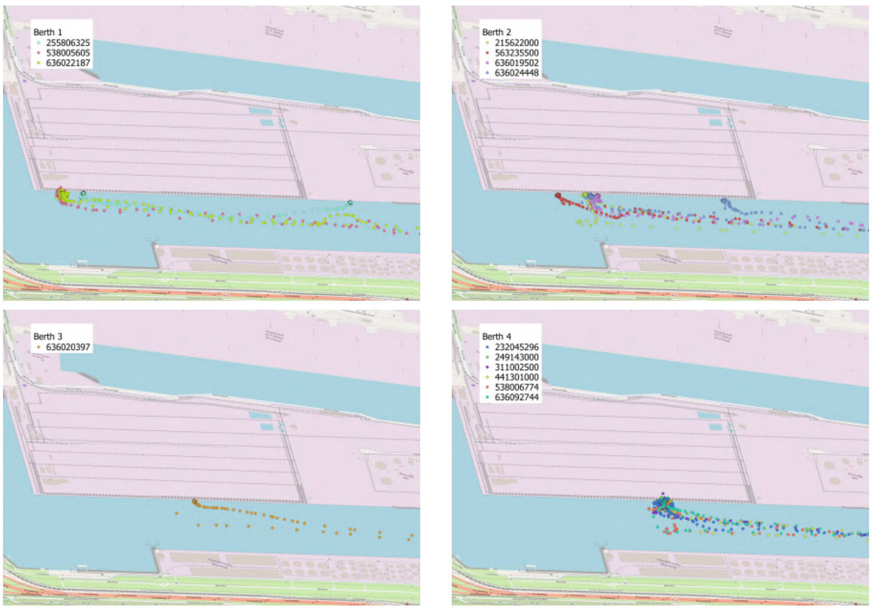


Figure C.7: Visualization of AIS vessel paths of different berth allocations from Sea-web.

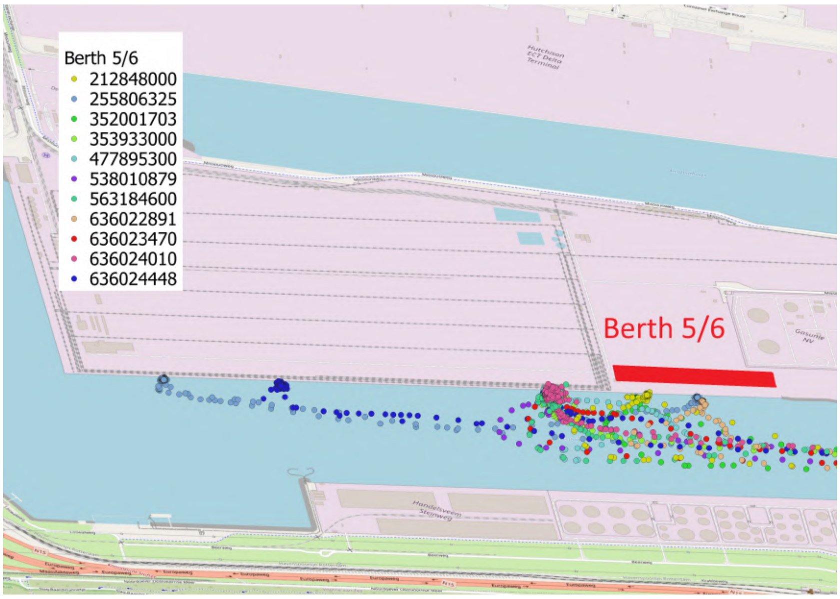


Figure C.8: Visualization of AIS vessel paths served at berth 5 and 6 according to Sea-web. The actual loading area for berths 5 and 6 is highlighted in red. The two rightmost vessels (255806325 & 636022891) are classified under berth 6.

D
Analysis of service time

This research measures service time through AIS data. Then explores its context through modeling the port operation. Therefore, the model depends on expert insights and technical knowledge, requiring a degree of intuition in its application. Consequently, several hypotheses are formulated and tested below to understand better what defines the duration of the service time.

D.1. Size

As expected, vessel size influences service time, as shown in Figure D.1. However, both low and high service times occur across all vessel size classes. The service time distribution for Handysize, Panamax, and Capesize vessels is illustrated in Figure D.2, Figure D.3, and Figure D.4, respectively.

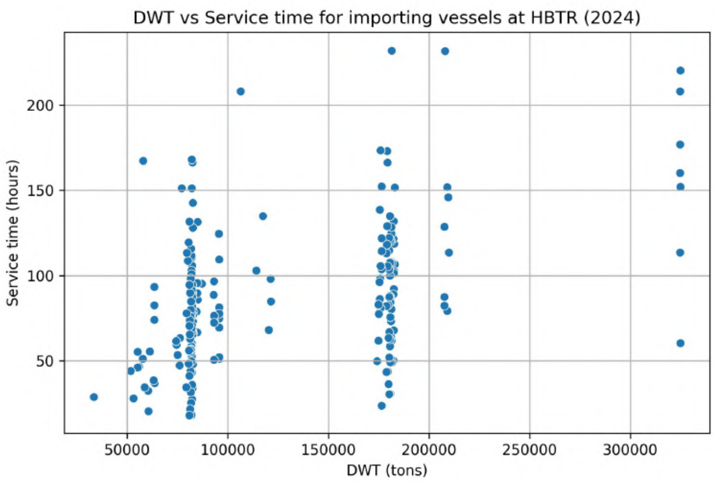


Figure D.1: The correlation of DWT and Service time.

Notably, while Handysize vessels may be involved in both import and export operations, larger vessels are exclusively used for importing bulk material. As shown in Table D.1, an importing Handysize vessel, on average, experiences a service time approximately 12 hours longer than an exporting Handysize vessel.

Size Class	Average Service Time (hours)
Capesize	104.69
Panamax	74.73
Handysize (total)	46.90
Handysize (importing)	55.12
Handysize (exporting)	43.00

Table D.1: The average service time for vessels at HBTR in 2024

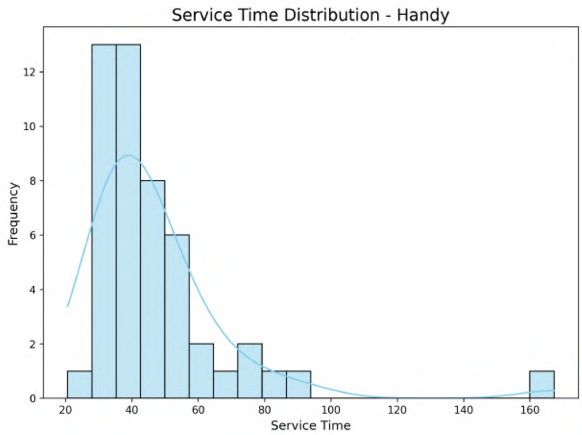


Figure D.2: Service time distribution for handy size vessels (DWT=<65000).

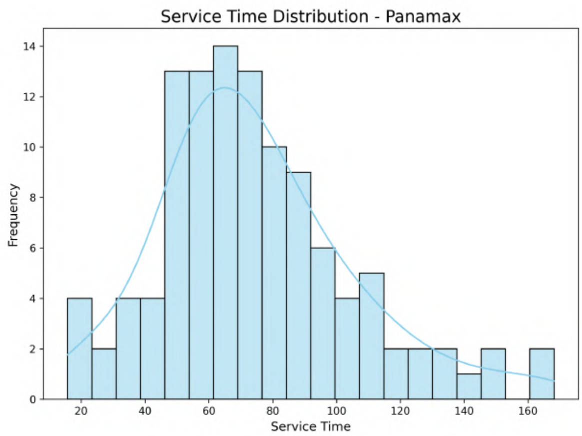


Figure D.3: Service time distribution for Panamax size vessels (65000<DWT<100000).

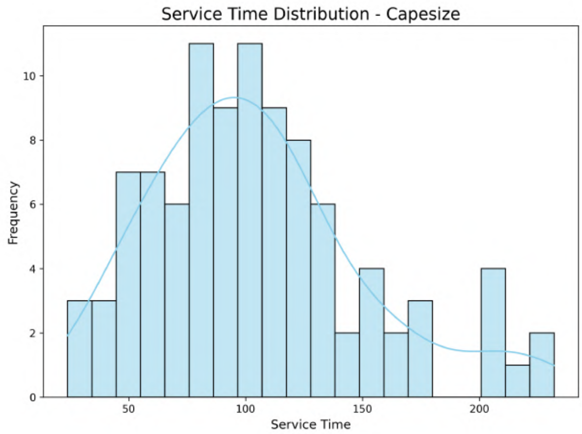


Figure D.4: Service time distribution for cape size vessels (DWT => 100000).

D.2. Other vessels along the quay

Another cause of a longer servicetime might be because of congestion at the terminal. It would be expected that if many vessels are present at the terminal at once, all service times will increase. For every port call the average other vessels present for every hour is calculated therefore. The resulting correlation between the service time and the average other vessels present can be seen in Figure D.5. Vessels that have zero other vessels present at the terminal druing their visit do experience lower service times, as can seen at the lower left of the figure. However, further there seems to be little correlation between how many other vessels are present at the terminal and the service time.

Operations at the terminal are generally limited to a maximum of two vessels at any given time (R. Slikkerveer, personal communication, May 16, 2025). As a result, when three or four vessels are present, one or two will remain inactive. Additionally, when terminal congestion is low, vessels may not be in a rush to depart, potentially extending their stay.

Furthermore, unexpected delays or technical issues affecting a vessel are independent of the number of other vessels at the terminal. Therefore, exceptionally high service times do not correlate with the presence of additional vessels. The combination of these factors likely explains the observed lack of correlation between service time and vessel presence at the terminal.

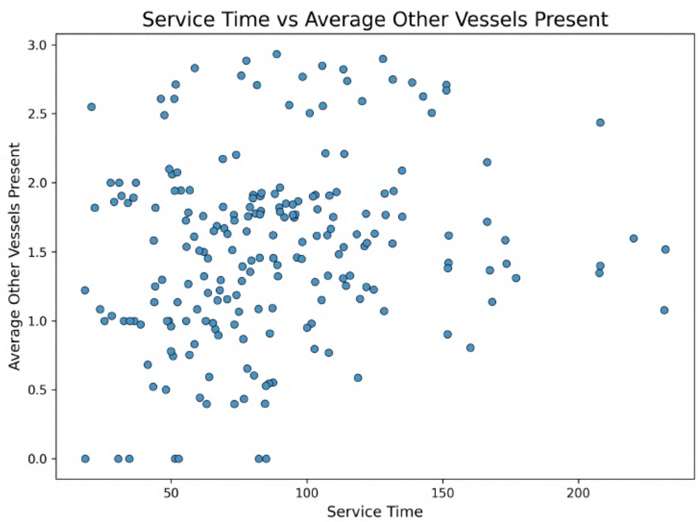


Figure D.5: The correlation of Service Time and the average number of other vessels present during terminal visit.

D.3. Draught change and origin continent

Draught change serves as a reliable indicator of whether a vessel is loading or unloading cargo. The distribution at the HBTR terminal during 2024, shown in Figure D.6, highlights that many vessels experience a reduction in draught, reflecting the terminal's import-oriented operations. A noticeable peak at zero is caused by instances where draught data was not updated by the crew, hindering material flow assessment solely on draught change for these vessels.

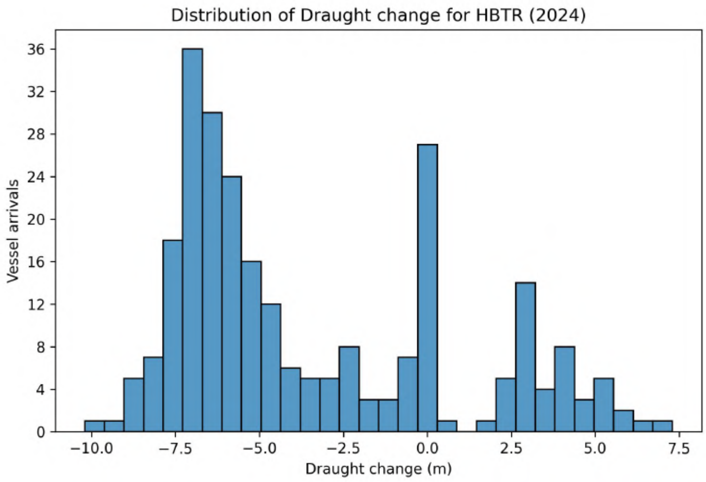


Figure D.6: The distribution of draught change during the terminal visit.

Figure D.7 presents draught changes at both the origin port and HBTR, categorized by continent. A distinct pattern emerges, where vessels arriving from outside Europe tend to gain draught before departure, then lose draught at HBTR, aligning with typical import activity. For vessels moving within Europe, the division is less pronounced, as they may be engaged in either import or export operations. Therefore, combining origin port continent data with draught changes provides a strong basis for predicting a vessel's cargo flow direction.

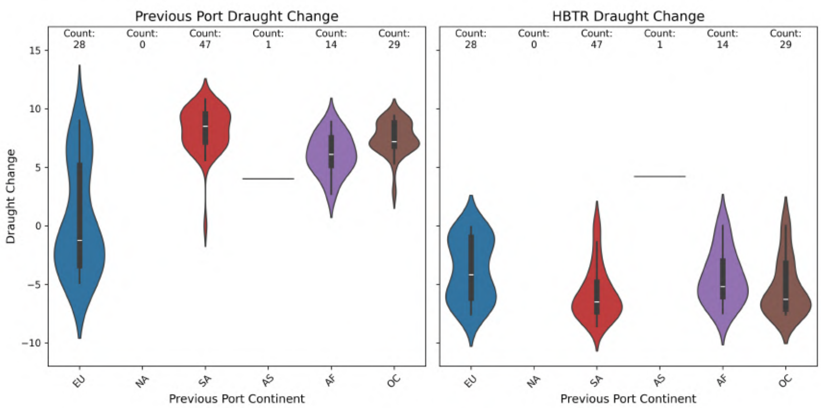


Figure D.7: The draught change at the last terminal and HBTR, categorized per origin continent.

D.4. Cargo type

Coal and iron ore differ significantly in physical properties such as density and angle of repose. These differences affect how the materials are handled during unloading. Terminals use different types of grabs depending on the cargo, which influences the unloading rate. Iron ore carriers generally have a higher deadweight tonnage (DWT), which also affects handling procedures and berth occupancy.

Due to these factors, unloading speeds and service times vary between cargo types. The average tons unloaded per hour of service time for the four analyzed terminals are shown in Table D.2.

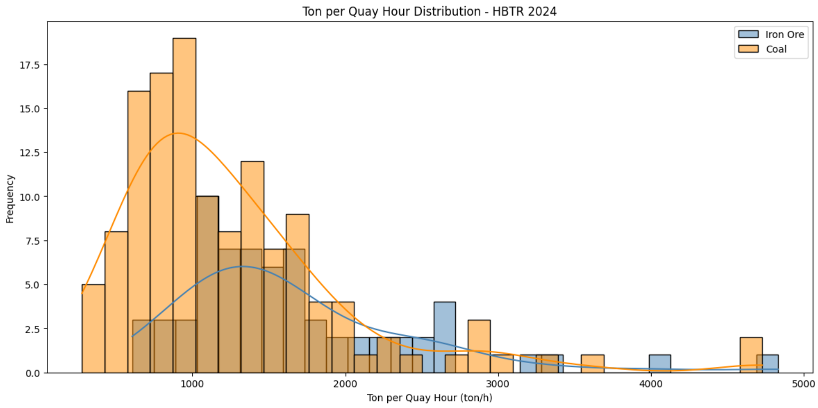


Figure D.8: The ton of unloaded cargo per service time hour for coal and iron ore at HBTR.

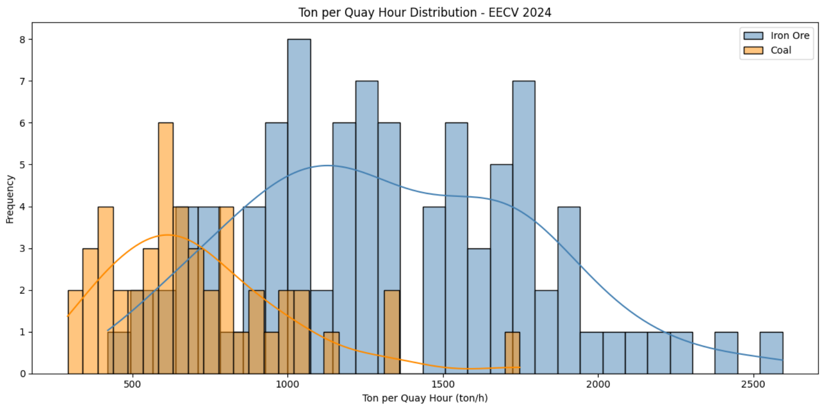


Figure D.9: The ton of unloaded cargo per service time hour for coal and iron ore at EECV.

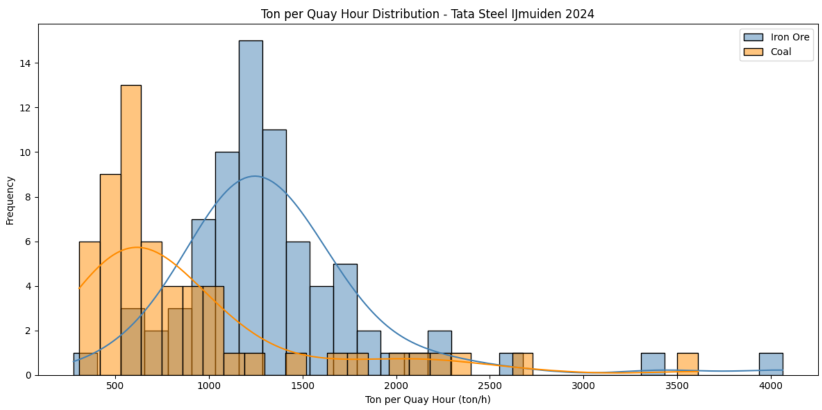


Figure D.10: The ton of unloaded cargo per service time hour for coal and iron ore at Tata Steel IJmuiden.

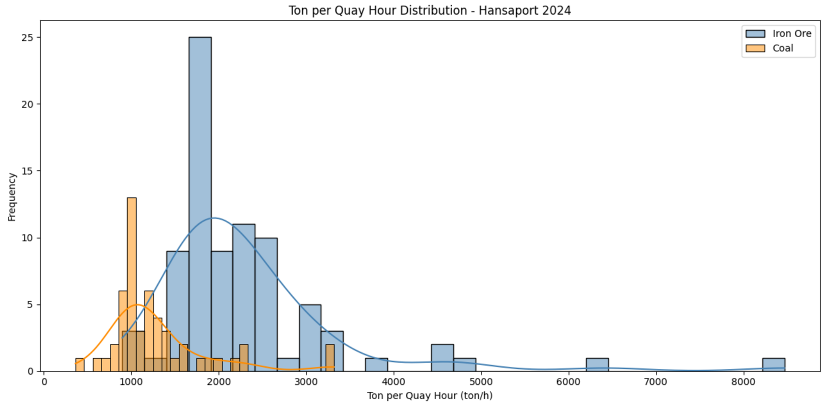


Figure D.11: The ton of unloaded cargo per service time hour for coal and iron ore at Hansaport.

As shown in Table D.2, more tons of iron ore are unloaded per service time hour than coal across all terminals. The difference ranges from 31.9% more at HBTR to 88.0% more at EECV.

Several factors contribute to this difference. Coal has a density that is approximately three times lower than iron ore. As a result, volume becomes the limiting factor in many parts of the unloading process. Conveyors may overflow, hoppers reach capacity more quickly, and grabs may not be filled to their maximum weight limit (R. Slikkerveer, personal communication, May 16, 2025).

Coal also generates more dust and behaves less predictably. Variations in moisture content can affect flow and handling. In addition to these physical properties, operational priorities may play a role. Terminals may assign more equipment and personnel to iron ore handling. For instance, the EECV terminal uses only two of its four cranes for coal, while all four are available for iron ore unloading (Ertsoverslagbedrijf Europoort c.v., 2024). This difference in resource allocation can contribute to the higher unloading rates observed for iron ore.

Terminal	Cargo type	Average unloaded ton per service time hour	Difference
HBTR	Coal	1259 ton/h	
HBTR	Iron Ore	1661 ton/h	+31.9%
EECV	Coal	704 ton/h	
EECV	Iron Ore	1326 ton/h	+88.0%
Tata Steel	Coal	906 ton/h	
Tata Steel	Iron Ore	1359 ton/h	+50.0%
Hansaport	Coal	1283 ton/h	
Hansaport	Iron Ore	2314 ton/h	+80.4%

Table D.2: The average unloaded ton per service time hour of coal and iron ore at different terminals

E

Probability of importing or exporting

After consultation with the HBTR terminal, it was confirmed that at the HBTR termianl all vessels at berth 1,2,3,4 were concerned with importing and all vessels at berth 5,6 were concerned with exporting during 2024. This has not always been the case. In previous years, exporting might also occur at berth 1 and 2, when the grab cranes were used to export choking coal. Using this knowledge, we can determine the probabilities for importing and exporting, given the other data known for the vessels.

It was observed that there are correlations in some vessel characteristics and wether the vessel was importing or exporting material. An overview of observed things(R. Slikkerveer, personal communication, May 16, 2025):

- Large vessels are exclusively used for importing material
- Vessel originating from outside of Europe are used for importing material
- Vessel leaving Europe after departure have been used for importing material

Besides this draught changes indicate the load of a vessel. It will gain draught when loaded and lose draught when unloaded. Since bulk vessels are often either completely empty or completeyl loaded, these changes in draught often indicate the import or export of material. Therefore both the draught change at the port and the draught change at the last port indicate wether the vessel is importing or exporting.

To express the correlation between these factors and the probability of importing or exporting, naive Bayes classifiers are used. The naive Bayes theorem makes use of Bayes' theorem(Leung, 2007):

$$\mathbb{P}(y|X) = \frac{\mathbb{P}(X|y) \times \mathbb{P}(y)}{\mathbb{P}(X)} \tag{E.1}$$

In this equation, y is the output of the classification and is either importing or exporting, and X is a vector containing all conditions:

$$\vec{X} = \begin{pmatrix} x1 \\ x2 \\ x3 \\ x4 \\ x5 \end{pmatrix} = \begin{pmatrix} O \\ D \\ N \\ PD \\ DWT \end{pmatrix} \tag{E.2}$$

Symbol	Condition	Possible states
O	Whether the origin port is outside of Europe	Yes or No
D	The draught change at the terminal	Negative, 0 or Positive
N	Whether the next port is outside of Europe	Yes or No
OD	The draught change at the origin port	Negative, 0 or Positive
DWT	Whether the DWT is even or smaller than 50000 tons (handymax)	Small or Large

Table E.1: Symbols in vector X

Since all events(draught change, origin outside of Europe, etc.) are assumed to be independent, the probability of x given y (either importing or exporting) can be expressed:

$$\mathbb{P}(x1,x2,x3,x4,x5|y) = \mathbb{P}(O,D,N,OD,T|y) = \mathbb{P}(O|y)\times\mathbb{P}(D|y)\times\mathbb{P}(N|y)\times\mathbb{P}(OD|y)\times\mathbb{P}(DWT|y) \tag{E.3}$$

Using Bayes Theorem this becomes:

$$\mathbb{P}(y|x1,x2,x3,x4,x5) = \frac{\mathbb{P}(y)\times\prod_i \mathbb{P}(x_i|y)}{\mathbb{P}(x1)\times\mathbb{P}(x2)\times\mathbb{P}(x3)\times\mathbb{P}(x4)\times\mathbb{P}(x5)} \tag{E.4}$$

Since the denominator is constant for any input, we get the following proportionality:

$$\mathbb{P}(y|x1,x2,x3,x4,x5) \propto \mathbb{P}(y)\times\prod_y \mathbb{P}(x_i|y) \tag{E.5}$$

Therefore, the likelihood of importing can be expressed as:

$$\hat{y} = \arg\max_y \mathbb{P}(y)\times\prod_i \mathbb{P}(x_i|y) \tag{E.6}$$

This means $\mathbb{P}(y)\times\prod_i \mathbb{P}(x_i|y)$ is calculated for both importing and exporting, and the largest probability defines whether the port call is classified as importing or exporting.

The data for 2024 is defined as either exporting or importing based on the information that berth 5,6 is only used for export, and berth 1,2,3,4 are only used for import. This gives the following distribution:

- Total call logs: 259
- Importing: 198 (76%)
- Exporting: 44 (17%)
- Unknown: 17 (7%)

Vessels with an unknown berth are classified as unknown and are removed from the sample, leaving 242 call logs. This gives the following class probabilities:

- $\mathbb{P}$(Import) = 0.818
- $\mathbb{P}$(Export) = 0.182

Based on the 2024 dataset, the conditional probabilities for every condition can be determined:

Whether the origin port is outside of Europe				
State	Import	Export	$\mathbb{P}$(Import)	$\mathbb{P}$(Export)
Outside	167	2	0.843	0.048
Inside	31	42	0.157	0.952
Total	198	44	1	1

Table E.2: Conditional probabilities for vessels with an origin outside of Europe

The draught change at the terminal				
State	Import	Export	$\mathbb{P}$(Import)	$\mathbb{P}$(Export)
Positive	1	41	0.005	0.932
0	22	2	0.111	0.045
Negative	175	1	0.884	0.023
Total	198	44	1	1

Table E.3: Conditional probabilities for vessels depending on the draught change

Whether the next port is outside of Europe				
State	Import	Export	$\mathbb{P}$(Import)	$\mathbb{P}$(Export)
Outside	122	8	0.616	0.182
Inside	76	36	0.384	0.812
Total	198	44	1	1

Table E.4: Conditional probabilities for vessels with a next port outside of Europe

The draught change at the origin port				
State	Import	Export	$\mathbb{P}$(Import)	$\mathbb{P}$(Export)
Positive	169	4	0.854	0.091
0	11	4	0.055	0.091
Negative	18	36	0.091	0.818
Total	198	44	1	1

Table E.5: Conditional probabilities for vessels depending on the draught change

Whether the DWT change is even or smaller than 50000 tons				
State	Import	Export	$\mathbb{P}$(Import)	$\mathbb{P}$(Export)
Large	197	25	0.995	0.568
Small	1	19	0.005	0.432
Total	198	44	1	1

Table E.6: Conditional probabilities for vessels depending on their DWT

With the combination of the class probabilities and conditional probabilities, an estimation can be made. An example input is given below:

$$\vec{X} = \begin{pmatrix} x1 \\ x2 \\ x3 \\ x4 \\ x5 \end{pmatrix} = \begin{pmatrix} O \\ D \\ N \\ PD \\ DWT \end{pmatrix} = \begin{pmatrix} Outside \\ 0 \\ Outside \\ Positive \\ Large \end{pmatrix}$$

This gives the following calculation:

$$
\begin{aligned}
\mathbb{P}(I|X) &\propto \mathbb{P}(I) \times \mathbb{P}(O|I) \times \mathbb{P}(D|I) \times \mathbb{P}(N|I) \times \mathbb{P}(OD|I) \times \mathbb{P}(DWT|I) \\
&= 0.818 \times 0.843 \times 0.111 \times 0.616 \times 0.854 \times 0.995 = 0.04006503 \\
\mathbb{P}(E|X) &\propto \mathbb{P}(E) \times \mathbb{P}(O|E) \times \mathbb{P}(D|E) \times \mathbb{P}(N|E) \times \mathbb{P}(OD|E) \times \mathbb{P}(DWT|E) \\
&= 0.182 \times 0.048 \times 0.045 \times 0.182 \times 0.091 \times 0.568 = 0.00000370
\end{aligned}
$$

These can be normalized to get:

$$
\begin{aligned}
\mathbb{P}(Import|X) &= \frac{0.04006503}{0.04006503 + 0.00000370} = 0.9991 = 99.91\% \\
\mathbb{P}(Export|X) &= \frac{0.00000370}{0.04006503 + 0.00000370} = 0.0009 = 0.09\%
\end{aligned}
$$

Therefore, this vessel is highly likely to be importing, as it is a large vessel coming from outside of Europe, and gained draught at the origin port. Conditions that align with an importing vessel.

The distribution of probabilities for import and export classification is shown in Figure E.1, where a clear distinction is observed in most cases. This indicates that many vessels align with expected classifications, such as a combination of a negative draught change and arriving from outside Europe. If the probabilities for import and export fall between 0.4 and 0.6, the classification is marked as unknown, which applies to three vessels in the dataset. Thereafter, call logs are classified as either importing or exporting depending on which probability is larger.

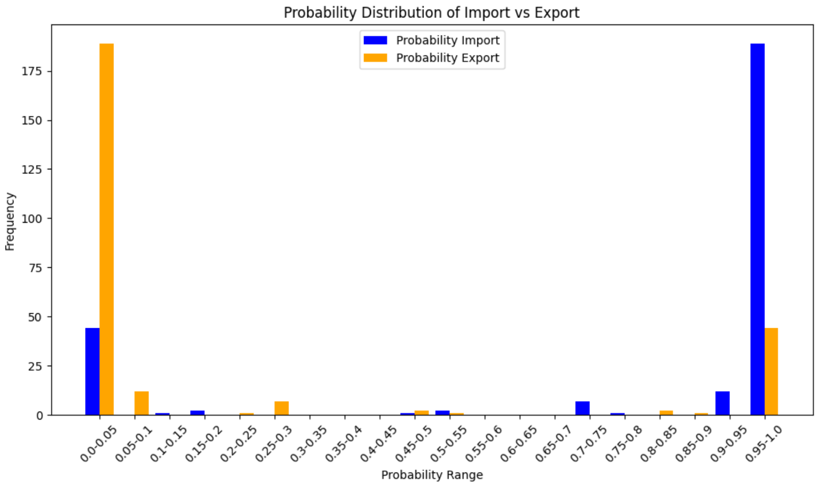
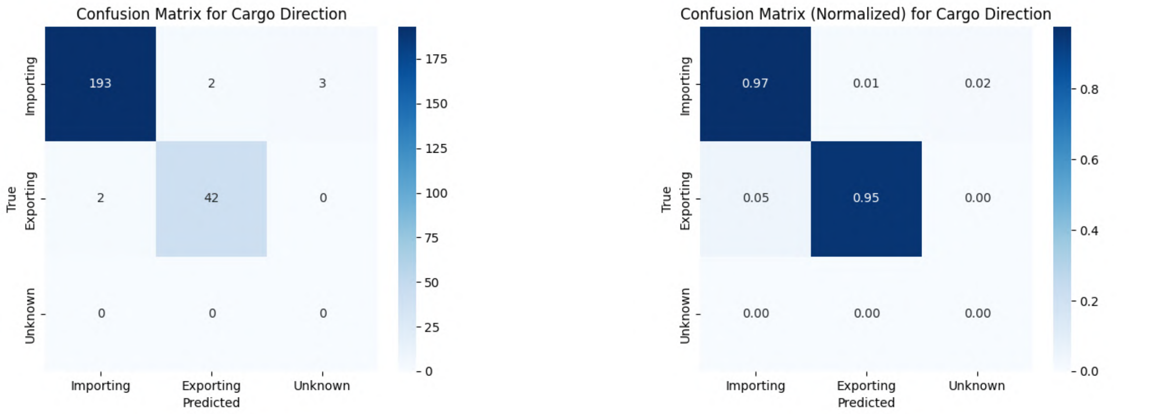


Figure E.1: The distribution of import and export probabilities for HBTR over 2025

The confusion matrices in Figure E.2 show that two vessels were incorrectly classified as importing, and 2 vessels were incorrectly classified as exporting. The model achieves an accuracy of 97% for identifying importing vessels and 95% for exporting vessels. However, these results are based on the same year the model was trained, so additional data was tested for further validation.

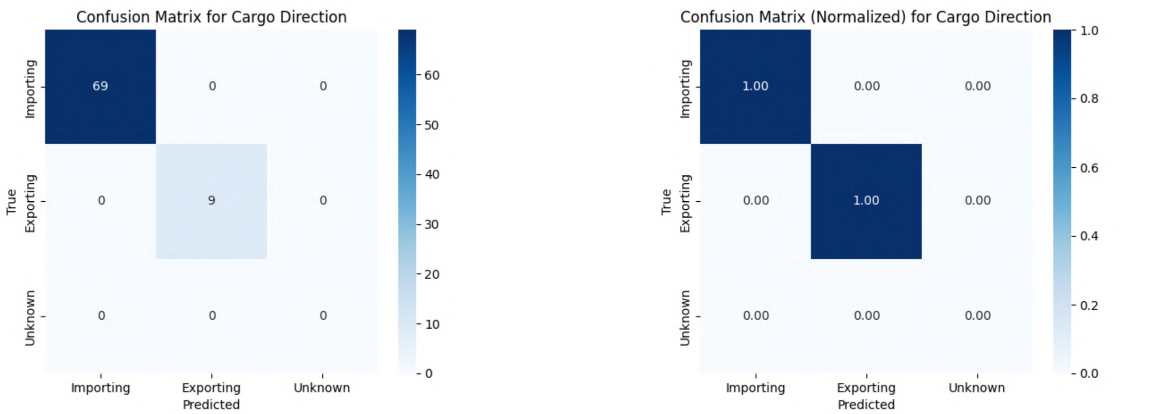


(a) The confusion matrix of cargo direction

(b) The normalized confusion matrix of cargo direction

Figure E.2: The confusion matrices of cargo direction for HBTR over 2024

To validate the calculation on unknown data, the same probabilities are applied to the first 4 months of 2025. The direction of cargo was predicted correctly 100% of the time, as can be seen in Figure E.3.



(a) The confusion matrix of cargo direction for January-April 2025

(b) The normalized confusion matrix of cargo direction for January-April 2025

Figure E.3: The confusion matrices of cargo direction for HBTR over the first 4 months of 2025

F

Operational parameters per terminal

The operational parameters that were used for each terminal as input for the model can be seen in Table 4.3 below.

Parameter	HBTR	EECV	Tata Steel	Hansaport
Number of Cranes	4	4	4	4
Maximal cranes per vessel	2	2	3	3
Nominal rating NR (ton/h)	3244	2606	1968	1617
Free Digging iron ore NR_{iron} (ton/h)	3244	2606	1968	1617
Free Digging coal NR_{coal} (ton/h)	2745	2250	1665	1368
Pre-operational time per vessel (h)	1	1	1	1
Post-operational time per vessel (h)	2	2	2	2
Operational stoppage time per vessel (h)	5	5	5	5
Weather downtime (% of service time)	1	1	1	1
Corrective maintenance (% of service time)	7	7	7	7
Blockage of equipment (% of service time)	5	5	5	5
Cargo load utilization of coal vessels (%)	80	80	80	80
Cargo load utilization of iron ore vessels (%)	90	90	90	90
Preventive maintenance hours per year (h)	500	500	500	500

Table F.1: Operational parameters for each terminal, which are used as input for the model.

The nominal ratings, and free digging rates for coal and iron ore are based on the following safe load factors:

HBTR (Hentzepeter, 2012)

- 3 cranes: 85 tons
- 1 crane: 50 tons
- Average: 76.25 tons

EECV (Ertsoverslagbedrijf Europoort c.v., 2024)

- 3 cranes: 60 tons
- 1 crane: 65 tons
- Average: 61.25 tons

Tata Steel IJmuiden (Tata Steel Nederland, 2020)

- 3 cranes: 40 tons
- 1 crane: 65 tons
- Average: 46.25 tons

Hansaport (Hafen Hamburg, 2025)

- 4 cranes: 38 tons

G

Berth polygons per terminal

The polygons used to determine which berth was visited, combined with all average vessel positions can be seen in the figures below.

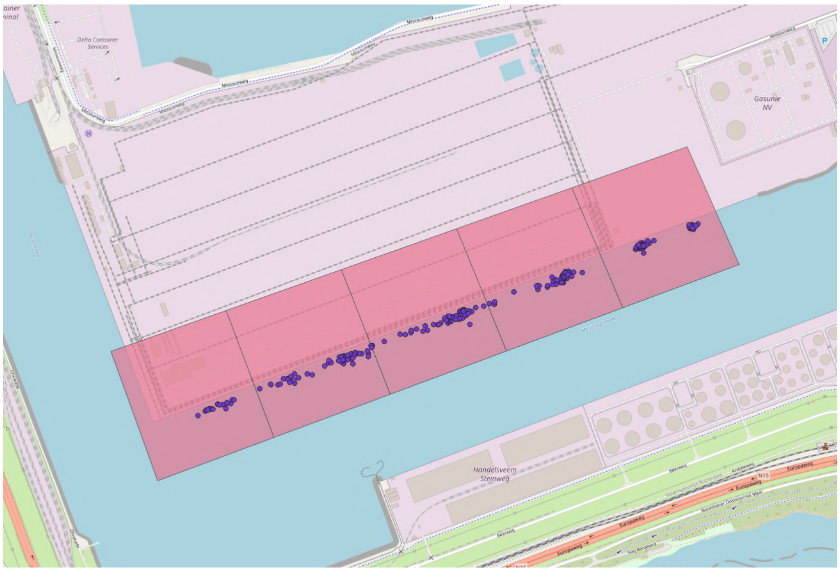


Figure G.1: The polygons used to determine berth 1(left) to berth 5(right) for HBTR, Rotterdam. With the average position of all vessels that visited the terminal in 2024. Berth 5 is exclusively used for exporting material since the vessel loader is located there.

Figure G.2: The polygons used to determine berth 1(right) to berth 3 (left) for EECV, Rotterdam. With the average position of all vessels that visited the terminal in 2024.

Figure G.3: The polygons used to determine berth 1(left) and berth 2(right) for Tata Steel IJmuiden. With the average position of all vessels that visited the terminal in 2024.

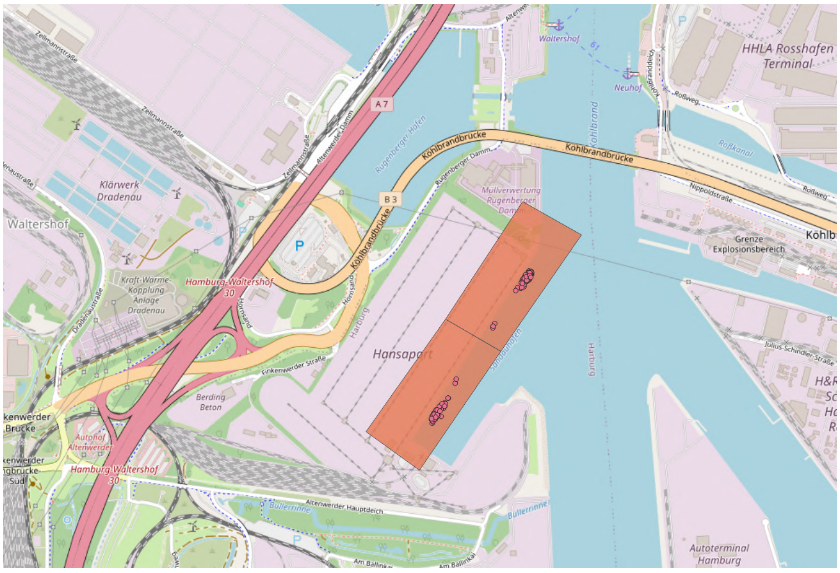


Figure G.4: The polygons used to determine berth 1(left) and berth 2(right) for Hansaport, Hamburg. With the average position of all vessels that visited the terminal in 2024.