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# Times of ships in container ports: automatic identification system data for analyzing traffic conditions at a maritime terminal

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Maritime shipping is the primary means connecting countries and global economies, with ports serving as critical logistics hubs in the supply chain. In recent decades, international conflicts and economic disruptions have increasingly stressed maritime transport, highlighting the need to focus more on terminal performance. This paper presents a methodology to evaluate port traffic conditions using data from open Automatic Identification System (AIS) repositories. A rule-based approach is applied to segment the vessel trajectories into underway, anchoring, and berth operations, allowing the assessment of all stages that characterize a port call and the calculation of the vessel turnaround time. The methodology is demonstrated in the Port of Los Angeles, the busiest container hub on the United States West Coast. Historical AIS data are analyzed to obtain traffic conditions, and a set of key performance indicators is computed to quantify terminal operations and docks utilization during the observation period. The proposed framework provides a scalable tool for maritime traffic monitoring and decision support in port management.

## KEYWORDS

**AIS data, container shipping, maritime transport, port congestion measures, port efficiency, rule-based approach, spatial-temporal analysis, vessel turnaround time**

## 1 Introduction

Maritime transport is crucial in global trade, and the number of vessels at sea is growing. The United Nations Conference on Trade and Development (UNCTAD) reports that more than 80% of global trade is provided by maritime shipping (United Nations Conference on Trade and Development, 2024). Therefore, ports represent critical nodes in the supply chain. Container shipping activities are sensitive to external stress, and in recent years there have been many unexpected disruptions, such as the COVID-19 and war frictions that affected global trade. Given its crucial role, the maritime transport network is required to improve reliability, thus increasing the efficiency of the supply chain. In the context of the container shipping network, as evidenced by Yue and Mangan (2023), at least three cornerstones such as infrastructure, network configuration, and connectivity may be taken into account when developing a more resilient and reliable container shipping network. In this field, new generation ICT and five generation ports play a decisive role in increasing terminal performance (Russo and Musolino, 2021; Russo and Musolino, 2022). As stated by Kishore et al. (2024) the most recent developments demonstrate a growing interest in AIS application, with the topic shifting from a niche theme to one of relevance. The use of AIS data plays a central role in analyzing port performance, thus representing a valuable instrument to compare results achieved at port level (Musolino et al., 2026a).

Specifically, the possibility to directly extract maritime routes from AIS increases the knowledge of the shipping network and changes related to emerging crisis or new trends (Notteboom et al., 2024; Rindone, 2024). To this end, in a global market where liberalization and technologies are driving factors for economic development, undertaking a digitalization process with align to the 4.0 industry is becoming a driving strategy (Belmoukari et al., 2023). Several port authorities are investing in renewing their infrastructures under the paradigm of the communication technology (Heilig and Voß, 2017), in the view of a “smart port” (Molavi et al., 2020; Rajabi et al., 2018; Shuo et al., 2016), whose targets may consist of sustainability, stakeholders collaboration, effective management and operation efficiency (Odeck and Schøyen, 2020; Song et al., 2024).

The process towards digitalization also requires the ability to monitor and assess terminal conditions to achieve sustainable goals when managing the infrastructure (Peng et al., 2018). By this way, vessel route information represents a valuable source when performing analyses. Shipping traceability and reconstruction of vessel operations represent a challenging task. Since 2005, the International Maritime Organization (IMO) has been established to introduce devices on board for all passengers and cargo vessels as prescribed within the Safety of Life at Sea (SOLAS) agreement. AIS data include both static information on vessels (MMSI, Vessel Name, Ship type, cargo, length, width, GT, DWT), and kinematic information (latitude, longitude, SOG, COG, heading) and come from the family of spatial-temporal information set. AIS have become a well-recognized instruments when conducting analyses that range from safety and security, to environmental issues as well as on port operation and terminals development (Russo et al., 2024). For such a reason, AIS data processing became a valuable source in enhancing provisional models and management operations at the maritime terminal (Chen et al., 2023; Ziran, 2024). However, extracting information from AIS signals require handling a large amount of noisy data, whose quality may be affected by human errors and lack of coverage (Eljabu and Etemad, 2023; Ribeiro et al., 2023). In fact, raw data usually needs to be preprocessed and cleaned before undertaking traffic analysis and several authors approached the problem of developing an affordable structure to manage AIS (Spadon et al., 2024). For such reasons, this paper focused i) on proposing a generalized operation tool capable of extracting events from raw AIS database, and ii) on the possibility of using open data for analyzing the phases that characterize a port call, also pointing out the contribution of each operation within the vessel turnaround time. The output consists of the identification of traffic conditions for both docks and anchorage areas, outlining the most critical phases of a generic port call (anchorage and mooring). A set of key

statistical performance indicators is derived as a discriminator against terminal performance.

Thus, the paper addresses the valuable opportunities offered by the widespread presence of AIS data that can assist both analysts and planners in.

- Proposing a generalized procedure to extract vessel operations (Section 3.2);
- Introducing a set of indicators to represent the berth occupation and assessing dwell time operations directly from open data (Section 3.3);
- Quantifying annual traffic and port calls distributions utilizing AIS data (Sections 4.3 and 4.4);
- Exploring the potential connected with AIS data in analyzing terminal activities (Section 4.5 and 4.6);
- Describing the main stages that characterize a generic port call, thus achieving an evaluation of the vessel turnaround time (Section 4.6).

The structure of the paper resumed as follows. After the introduction (Section 1), Section two focuses on the emerging evidence from literature and the role of AIS data. Section three reports on the methodology as a basis of the proposed analysis tool. Section four resumes the output, and the key performance indicators developed. Following (Section five) discussion on results, and conclusion characterize the closing paragraphs.

## 2 Literature review

Data from AIS are used to identify and analyze various elements related to maritime transport, from risk analysis and emission assessment to route estimation and port performance (just to cite a few). Several authors approached the use of AIS by merging the signals from onboard devices with another source to test the devices' accuracy. As stated by Wolsing et al. (2022), who reviewed the most relevant approaches, the anomaly detection was among the first task underpinned mainly focusing on tracking deviation and missing data anomalies. As an example, Nguyen et al. (2015) and Jankowski et al. (2021) compared the accuracy of AIS signals with radar tracks from ground instruments to assess data quality and evaluate how to fix the information. In contrast, Jones et al. (2023) proposed a data mining process to merge information from AIS data and satellite imagery (synthetic aperture radar, SAR) to detect vessel behavior and navigation stages.

Over the years, as data became more widely available, several scholars have focused on route extraction as the primary approach to investigating maritime traffic. Trajectory-based methods consist of extracting information over travel and let the opportunity to observe vessel routes as spatial-temporal curves whose sub-trajectories qualify specific ship behaviors (Gao et al., 2021; Yan et al., 2020). Trajectory segmentation, in general, represents a valuable technique when dealing with AIS data, and feature extraction may assist analysts in detecting meaningful indicators of port congestion and performance (Huang et al., 2024; Wijaya and Nakamura, 2024). Data management and analysis of AIS signals require a great effort (Zhang et al., 2018) for this reason, several approaches have been developed to focus on specific problems that

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**Abbreviations:** AIS, Automatic Identification System;  $B_{ur}$ , Blocked Utilization Ratio;  $B_{use,l}$ , Berth Utilization (length);  $B_{use,t}$ , Berth Utilization (time); CCI, Cumulative Congestion Index; CI, Congestion Index; COG, Course Over Ground; DWT, Dead Weight Tonnage;  $F_{ur}$ , Full Utilization Ratio; GT, Gross Tonnage; IMO, International Maritime Organization; MMSI, Maritime Mobile Service Identity;  $R_{ur}$ , Residual Utilization Ratio; SOG, Speed Over Ground; SOLAS, International Convention for the Safety of Life at Sea;  $T_b$ , Blocked time;  $T_{ber}$ , Time to access berth;  $T_{eb}$ , Total Empty Time;  $T_{fu}$ , Full Utilization Time;  $T_l$ , Time to leave port;  $T_{op}$ , Dwell Time;  $T_{ot}$ , Operational Time;  $T_{un}$ , Time to leave berth;  $T_{us}$ , Docks Underused Time;  $T_v$ , Vessel Turnaround Time;  $T_w$ , Anchorage time;  $V_r$ , Vacancy Ratio; Zol, Zone of Interest.

range from safety and security in navigation to traffic evolution in an area. For example, Zhang et al. (2019) employed AIS data to analyze ship traffic demand and utilized an analytical approach to analyze spatial temporal dynamics at the Singapore port. Vessel traffic analyzes are conducted starting from origin-destination trajectories. Port management strategies, centered on traffic safety, are evaluated by linking traffic conditions with a historical dataset of collisions. On the contrary, Yan et al. (2022) analyzed historical AIS data extracted from several vessels along the South Sea Silk Road to identify their destination. The paper proposes a random forest approach to classify the vessel stops, to identify the trajectories and to analyze spatial-temporal distribution of AIS signals. Similarly, Lee et al. (2022) analyzed the most crowded channels and main routes for different classes of vessels and mapped the trajectory through a statistical analysis. It proposed a workflow that relies on data cleaning and clustering, then trajectories are processed, and waypoints are aggregated through a density-based clustering approach. Finally, the shipping network is completed by connecting the waypoints.

AIS data also emerged as a valuable source when interpreting phenomena that occurred in the terminal area: Feng et al. (2020) employed AIS signals in analyzing the vessel turnaround time for different classes of vessels and informing over the navigation status. AbuAlhaol et al. (2018) used AIS data to predict congestion indexes in both anchorage and berth areas. Kim et al. (2023) analyzed traffic conditions in coastal waters of Korea to verify vessel navigation security. Therefore, traffic conditions and seasonality for different Korean sea areas were analyzed to assess a vessel traffic index (VTI) as a descriptive measure. Kweon et al. (2022) analyzed operations in the Port of Ulsan between 2016 and 2019 by collecting data on vessel traffic, berth allocation and weather conditions, focusing on the development of strategies for managing demurrage rate and on the definition of policies aimed at reducing terminal congestion. Port performance analysis represents a prolific field of study, and several scholars addressed the research using information from AIS (Meng et al., 2023). Several procedures formulated in the literature can be framed within the perspective of transportation system models, often simulating terminal status through an equilibrium approach (Russo and Musolino, 2024). As stated by Sahoo and Song (2022), big data in the maritime field could be integrated into policy making, thus uncovering the most appropriate strategies for port operators. Conversely, Xu et al. (2024) starting from AIS data route analysis, tackled the problem from the perspective of shipping companies, highlighting the contribution of each actor to the global container shipping network. Similarly, in Di Gangi et al. (2026) the shipping network was explored by identifying how operational time may affect container routes. The focus is on the trip of a container moved from the origin to the destination, and the performance is simulated to measure and compare the magnitude of travel time, transshipment operations, and handling. Ship arrivals, loading and unloading operations, and port transitions are elements considered relevant in the simulation. Ducruet and Itoh (2022) utilized historical AIS to investigate route delays and the evolution of vessel turnaround time through the years, by linking it to external factors such as the financial crisis of 2007 and digitalization. The outputs were then analyzed at national and regional level. AIS data were used by Kruse et al. (2018) to evaluate a freight fluidity index and to assess port congestion conditions, thus estimating the vessel

turnaround time. The total port system time and the port cycle time, as well as the channel navigation time (travel time inbound, were used as discriminants for the operation within the port area. As stated by Chu et al. (2024), uncertainty over vessel turnaround time and delays on arrival time can affect handling operation and berths efficiency. This recalls a great emphasis on dwell times, and the analyses of AIS data over berth calls may improve the management experience (Smith, 2021). Several maritime infrastructures were observed by evaluating performance in terms of handled TEUs, and the analyses demonstrated that vessel scheduling may represent a determinant over dwell time and berth efficiency.

Kolley et al. (2022) used different machine learning methods to predict vessel arrival time. The accuracy of the forecasts is then analyzed to improve the robustness of the berth scheduling. Peng et al. (2023) used AIS data to identify anchorage areas through the clustering technique and convex hull method to define the involved operations areas, thus forecasting the traffic congestion using a neural network model. Finally, Xin et al. (2024) developed a model to reconstruct common vessels patterns using machine learning techniques, to assess navigation status (underway, anchorage, and berth). The messages delivered by onboard devices were at the basis of their work, and both SOG (speed over ground) and COG (course over ground) were used as critical features to interpret the status of the vessel.

The review analysis highlighted the wide variety of approaches used in the interpretation of AIS signals. Clustering approaches, spatio-temporal analysis, and trajectory features extraction are among the most used methods in analyzing AIS data. Similarly, port performance and competition among actors, analyzed using data and route information from AIS, represent a novel field of application, remarking the growing interest in the use of information technologies within the transportation field.

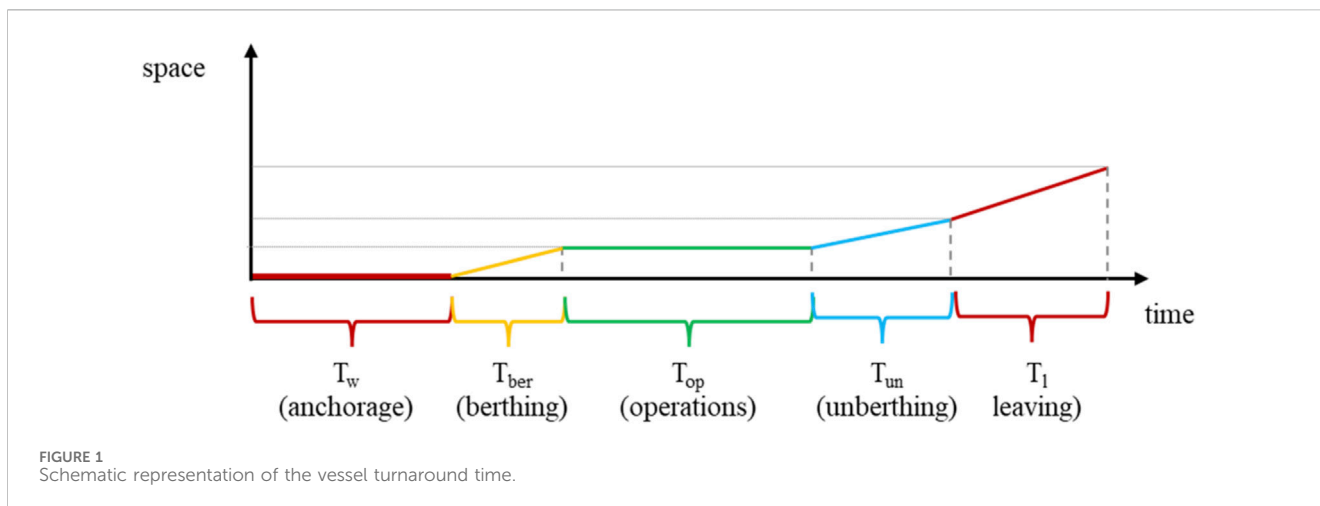
In the following, the paper will focus on maritime terminal berth utilization and vessel turnaround time dimension analyses. Two specific aspects will be highlighted: the feature extractions from AIS signals, and the interpretation of the events detected to assess terminal operations. In this way, the proposed approach addresses some critical issues related to data utilization by defining a generalized methodology able of identifying terminal traffic conditions, leveraging AIS data and publicly available resources.

This study aims to answer the following research questions.

- To what extent can the extraction of features from AIS signals facilitate the identification of events characterizing a port call?
- How can these events be interpreted to assess terminal operations and traffic phenomena within the port area?
- To what degree does AIS-based feature extraction allow for reliable estimation of vessel turnaround times and the identification of critical phases of a port call?

### 3 Materials and methods

This section outlines the workflow and its main components. The outline of the methodological framework is discussed. The theoretical model that guides the analysis is then introduced, followed by a detailed overview of the analysis tool to provide



context for the forthcoming results. The section concludes with the presentation of performance indicators used to describe the activities of the vessel during a port call.

### 3.1 Vessel turnaround time

The time spent in port for each vessel,  $T_v$ , can be considered as a function of multiple operational factors and can be summarized as follows:

$$T_v = f(T_w; T_{ber}; T_{op}; T_{un}; T_l) \quad (1)$$

In the previous equation, the vessel turnaround time  $T_v$  is a function of several components.

- $T_w$  is the time spent by a vessel within the anchorage area;
- $T_{ber}$  and  $T_{un}$  represent the operative time needed to access the berth ( $T_{ber}$ ) and the time spent by the vessel to leave the area ( $T_{un}$ );
- $T_{op}$  is the dwell time, it includes loading/unloading operations;
- $T_l$  is the time to leave the port.

Figure 1 reports a qualitative diagram of the components of the turnaround time. During the anchorage, the vessel remains within a fixed area around the anchor point. Berthing implies the travel of the vessel from the anchorage area to the berth, and both the variables time and space change in value. During operations, the vessel is at the berth (changes in time, but not in space). Finally, unberthing and port departure imply a variation in both space and time.

Figure 1 reports the phases that may characterize a port call, whose events are detected by analyzing AIS signals. The key features of the procedure, introduced in the following paragraphs, are further detailed in Belcore and Polimeni (2025) where the workflow for the detection and classification of the main stages of a port call was tested. Considering the seaside, the vessel arrives and, in general, waits at anchor ( $T_w$ ) before entering the port ( $T_{ber}$ ). When a berth is available, the loading/unloading operations start ( $T_{op}$ ), then the vessel leaves the berth ( $T_{un}$ ) and the port ( $T_l$ ). Note that there may be situations where the vessel stops at anchor again. Thus,

addressing the above-mentioned stages, allows the analyst to evaluate performance indexes and congestion measures for the maritime terminal. In the following sections, the generalized procedure used for processing information related to vessel navigation phases (specifically, for container vessels) within port areas and its boundaries are presented. Unlike the approach adopted in Belcore et al. (2025a), which analyzed terminal traffic by considering spatial density and average service time at the berth, this approach advances further by providing a detailed quantification of the phases that characterize the port call. Moreover, the analysis of the identified phenomena enables reconstruction of berth utilization and the quantification of anchoring and maneuvering operations within a port call, providing a set of statistical indicators based on the detected events.

### 3.2 AIS toolkit

A flexible and modular framework is designed to process and analyze AIS data for the detection and classification of the main stages of a port call. The architecture is organized into interconnected components that span from raw data acquisition and cleaning, through navigation status segmentation and event classification, to final visualization and reporting over traffic conditions at the terminal area.

#### 3.2.1 Overview

Figure 2 resumes the architecture of the proposed tool, it comprises five modules.

1. A *data layer* capable of managing data from different repositories;
2. A *model system* whose pipelines operate on raw data to segment trajectories by differentiating sub-events for a generic vessel route;
3. A user *interface* helps the analyst in analyzing the process through maps and data sheets;
4. An *events dataframe* stores the data on the extracted events that are ready to be analyzed;

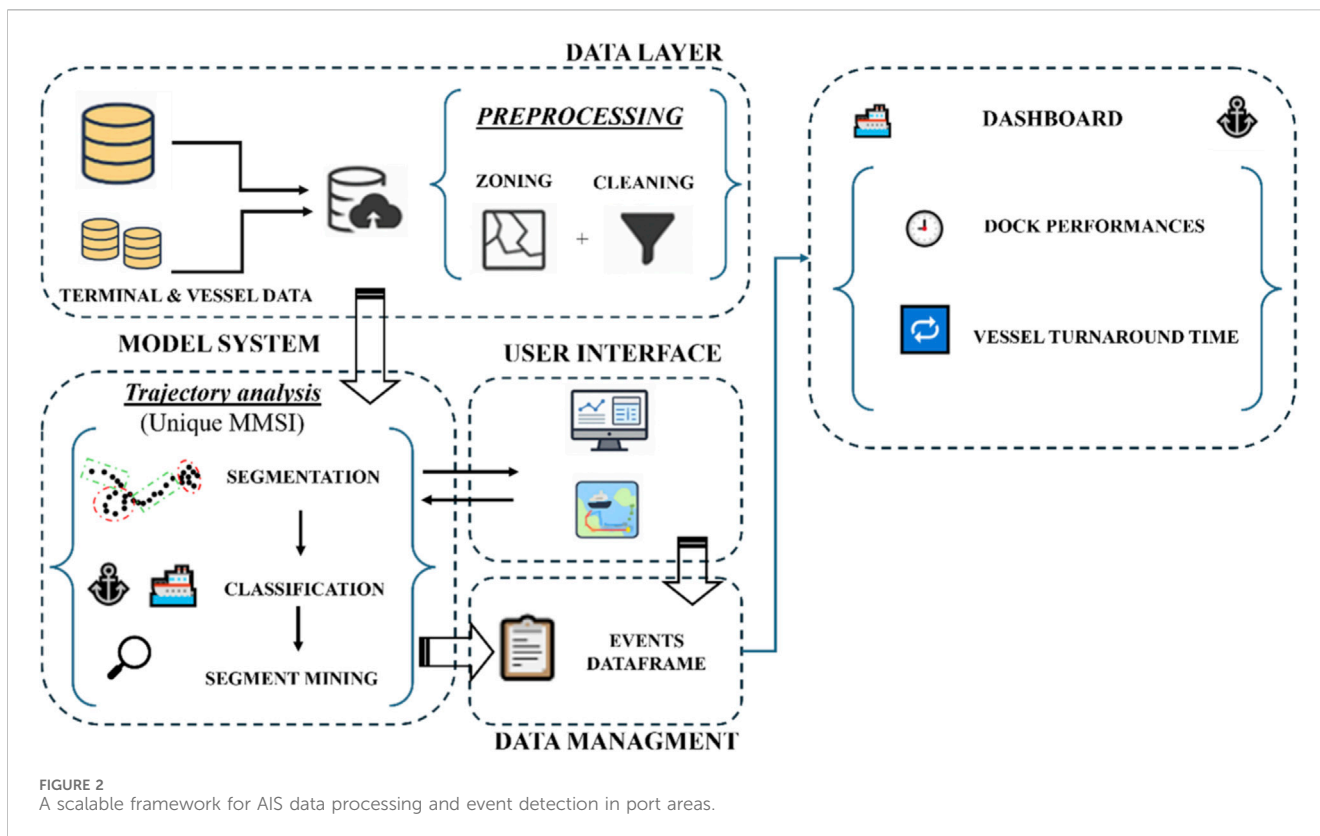


FIGURE 2 A scalable framework for AIS data processing and event detection in port areas.

5. A *dashboard* summarizes aggregated results, enabling flexible data export and comparative analyses across docks, time frames, or vessel classes.

### 3.2.2 Functional modules

Open AIS data are characterized by a high sampling frequency and may contain anomalies or missing signals. Therefore, preprocessing is crucial to ensure consistency and reliability of the dataset.

#### 3.2.2.1 Data layer (Terminal and vessel data and preprocessing)

This stage includes spatial and temporal filtering, data cleaning, and trajectory validation, providing a robust basis for subsequent analysis. The tool extracts historical AIS records from authoritative online sources; it applies spatial and temporal filters based on a predefined Zone of Interest (ZoI) and cleans the resulting dataset. The filters allow us to optimize data input, speed up computation, and restrict analyses to those signals that fall within the ZoI and the temporal scope. Subsequently, the filtering stage ensures that only significant vessel routes and reliable trajectories are stored, while incomplete or fragmented data are discarded to reduce noise and bias. Pre-processing includes a down-sampling procedure used to purge inconsistent values, thus were confirmed as valid those records where (1) the MMSI string consists of nine characters; (2) headings values ranged between [0–360] degrees; (3) 1-min interval sampling was applied to reduce redundancy and mitigate the impact of duplicate or noisy signals. Finally, distance checks are applied between consecutive points, and unrealistic speeds are

flagged as noise. This cleaned dataset serves as the foundation for subsequent analyses, including vessel status extraction, operational state classification, and visual reporting.

#### 3.2.2.2 Model system (segmentation)

Rule-based methods detect shifts along vessel tracks, distinguishing underway, maneuvering, and stationary phases. Therefore, the kinematic attributes SOG (speed over ground), COG (course over ground) and heading are analyzed to detect changes along the trajectories and perform the classification. The underway phases are typically characterized by higher and stable speeds with limited heading variation, whereas stationary phases present low speeds and irregular heading changes. Therefore, the rule-based segmentation algorithm captures these transitions without requiring supervised learning or clustering, isolating operational blocks within vessel tracks and facilitating downstream classification. As also stated by [Wijaya and Nakamura \(2024\)](#) and [Eljabu and Etemad \(2023\)](#), the rule-based approach represents a robust alternative to the most advanced data-driven methods. This technique ensures rapid convergence and generalizability across different vessel types, although parameter tuning, especially speed thresholds, may impact accuracy ([AbuAlhaol et al., 2018](#); [Yan et al., 2020](#)).

#### 3.2.2.3 Model system (Classification and segment mining)

Each identified event is analyzed to determine its spatial extent and duration. The system aggregates signals over time and matches geospatial information achieved from event segmentation to reveal anchorage stages and mooring operations, enabling both point-in-time analysis and trend tracking over longer periods. Some synthetic

geometrical features are used to distinguish anchoring from berthing. Key features include.

1. *Convex hull area*, as the area occupied by the signals falling within the same event;
2. *Mean event radius*, as the ideal radius marked by the signals that fall within the same event;
3. *Geohash coverage*, as the number of occupied cells of the geohash grid during an event;
4. *Point density per square meter*, that refers to how signals are distributed during an event.

To further improve accuracy, the framework integrates external geospatial sources: (i) reverse geocoding of event centroids (it lets verify the position of a vessel within an area, and it highlights unexpected behaviors by crossing navigation status with the geographic area); (ii) the overlap with official berth and anchorage boundaries. These enrichments improve classification reliability.

### 3.2.2.4 User interface and data management

Classified events can be visualized *via* interactive maps and exported. The tool enables individual vessel analysis as well as system-level summaries over docks, vessel classes, and time frames, thus allowing the possibility of inspecting both routes and events. The information achieved from the set of port calls highlights activities and trends over different time frames.

## 3.3 Port statistics indicators

The output of the events classification is used to obtain aggregate port statistics, and some key performance indicators are evaluated to assess terminal performance over the observation window.

By default, an overview of berth activity at dock level, is achieved through assessing the total number of vessel calls. Thus, berthing operations may be resumed through a synthetic estimator as the dwell time, evaluating the *total dwell time* ( $T_{dt}$ ), that represents the cumulative time all the vessels occupy the berth during the observation period, and the *average dwell time* that captures the average time spent by a vessel at the dock. Even if aggregate measures offer a valuable portrait on the berth use (Section 4.4), these statistics may be lacking in describing the effective use of the infrastructures and as far as performance may be defined from different perspectives, a further set of performance indicators will be introduced involving both spatial and temporal dimensions.

### 3.3.1 Congestion indicators

Congestion in a maritime terminal occurs when the capacity of the berth cannot meet demand, either due to a lack of available berths or insufficient length to accommodate incoming vessels. Under such conditions, vessel turnaround time is expected to increase with a significant amount of time spent at the anchorage. A simplified way to evaluate the berth occupation status is through the congestion index  $CI$ , defined as the ratio between the number of occupied berths at interval  $t$  ( $N_{ob}(t)$ ) and the number of available berths ( $N_{bert}$ ):

$$CI(t) = \frac{N_{ob}(t)}{N_{bert}} \quad (2)$$

The index  $CI$  ranges from 0 to 1 and represents a measure of berth occupation rate but, although it can be calculated at different instants of the day, it does not consider ships waiting at anchor. For such reasons another measure is introduced to capture port performance analyzing the balance between vessels waiting at the anchorage and those engaged in berth activities. Its purpose is to assess whether the port system is accumulating vessels at the anchorage or efficiently serving the incoming traffic. The basic assumption cores on the variation of vessel counts in discrete time steps, based on net inflows and outflows as:

$$N_w(t) = N_{w\_in}(t) - N_{w\_out}(t) \quad (3)$$

$$N_{ob}(t) = N_{ob}(t-1) + (N_{ob\_in}(t) - N_{ob\_out}(t)) \quad (4)$$

where.

- $N_w(t)$  is the number of vessels at anchor interval  $t$ ;
- $N_{w\_in}(t) - N_{w\_out}(t)$  is the variation between the entries and the exits of vessels from the anchorage area;
- $N_{ob\_in}(t) - N_{ob\_out}(t)$  is the variation between the entries and the exits of vessels at docks.

Thus, considering the variation for these two sets of vessels that occupy the berth, and the anchorage area let the analysis visualize if the number of waiting vessels increases or not. Therefore, the so-called Cumulative Congestion Index  $CCI$  highlights whether queues at anchorage are accumulating or being reduced, offering a system-level view of port balance, and can be expressed as in Equation 5.

$$CCI(t) = CCI(t-1) + \frac{N_{w\_in}(t) - N_{w\_out}(t)}{\max\{1, N_{ob}(t)\}} \quad (5)$$

Equation 5 represents a proxy of the balanced demand/supply, where the structure of the denominator ensures avoiding singularity. Interpreting the equation, an increase in  $CCI$  implies an accumulation process in the anchorage area, a constant value over the time reports about a balanced system.

Since vessels cannot always be accommodated at the first available berth (due to draft, length, or terminal assignment constraints), it should be of interest to analyze terminal conditions at the dock level, and for this reason, additional indicators will be introduced in the following.

### 3.3.2 Berths performance indicators

In the following, the use of the berth will be analyzed by highlighting both the rate of berth length and the current usage time. The proposed variables highlight berth vacancy, full operational capacity, partial operations, or temporary overcapacity that may restrict access to a vessel waiting at anchor. From this perspective, dock activity may be analyzed using a set of indicators that address the spatial and temporal dimensions. A first indicator, the yearly total empty time  $T_{eb}$ , considers the amount of time, in a year, when the infrastructure is empty. Conversely, when a set of vessels at the dock occupies all the available berths, no further operations can be hosted, the full

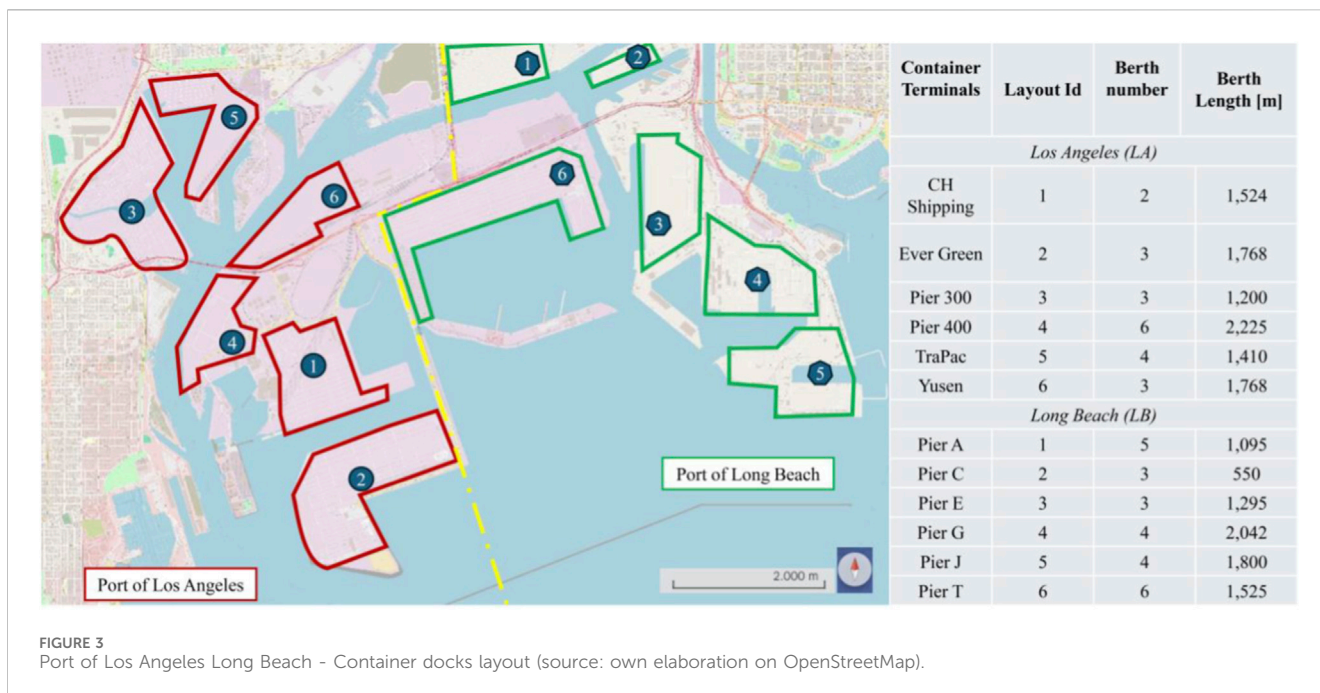


FIGURE 3 Port of Los Angeles Long Beach - Container docks layout (source: own elaboration on OpenStreetMap).

capacity time indicator  $T_{fu}$  can be considered (it defines, for a year, the amount of time the port is working at full capacity).

In the case when the available berth length is sufficient to operate on the incoming vessel, but there are no other vessels at the dock, it is possible to quantify the elapsed time  $T_{us}$  when the docks is underused; in contrast when the incoming vessel length is over the available space resources, the incoming berth call is rejected, the elapsing time under this scenario is  $T_b$ .

Therefore, it is possible to define.

- The *operational time* ( $T_{ot}$ ) is evaluated as the time intercurrent between the first and the last served vessel;
- The *vacancy ratio* ( $V_r = T_{eb}/T_{ot}$ ) accounts for the share of hours when no vessel activity occurred.
- The *berth utilization* ( $B_{use,t} = T_{dt}/T_{ot}$ ) measures the proportion of time when a berth is occupied; such an indicator can also be measured considering the space dimension ( $B_{use,l} = O_{length}/B_{length}$ ) as the ratio between the portion of the berth occupied vessels and the maximum available length;
- The *full utilization ratio* ( $F_{ur} = T_{fu}/T_{ot}$ ) identifies the share of time when all berths are occupied, the dock is working at its maximum capacity;
- The *residual utilization ratio* ( $R_{ur} = T_{us}/T_{ot}$ ) identify the time when at the dock a residual length is available, and the incoming vessel may be moored;
- The *blocked utilization ratio* ( $B_{ur} = T_b/T_{ot}$ ) resumes all those events where the available berth length is not enough to host the incoming vessel.

## 4 Results

This section summarizes the output obtained. It is structured in multiple subparagraphs that highlight tool outputs, berths operation

and traffic conditions at the dock, finally the vessel turnaround time is resumed to highlight the capability enabled using AIS data when analyzing a generic port call. First an overview of the annual traffic and its distribution is offered. Then it focuses on two main aspects: berths activities though the evaluation of two crucial synthetic statistics at berth level, the average and the total dwell time, then it focuses on docks operations thus resuming their degree of utilization and occupancy. Finally, it reports an overview about traffic conditions at the maritime terminal by focusing on the main stages that characterize a generic port call. To ensure the capability of the tool, a previous study was conducted on a small case test (Belcore et al., 2025b). In it the trajectory analysis was applied to test the effectiveness of clustering methods in distinguishing between anchorage and berthing. The dwelling time was compared with official statics delivered by the Bureau of Transportation Statistics (2025). In addition, segmentation and classification results were also compared with other case study (Liang et al., 2021; Yan et al., 2022) whose finding was in accordance with the output of the developed procedure.

### 4.1 Study area

The study area is the ports of Los Angeles-Long Beach (LALB), California (CA), United States of America, a maritime infrastructure that represents a critical container hub that links the USA and Asia, as well as a critical node for the marine traffic along the West Coast. Figure 3 shows the container dock layout of LALB port, resuming some synthetic characteristics of the docks represented in the layout. The port throughput, in the last 15 years, ranged between eight and ten million TEUs (Port of Los Angeles, 2025).

The infrastructure has several docks, and among them, ten are directly connected to both road and rail services. Official statistics also report on the availability of approximately ninety super post

panamax cranes (able to operate on more than 20 parallel rows of containers). Yearly, container docks host approximately one thousand and five hundred port calls (Bureau of Transportation Statistics, 2025).

## 4.2 Dataset

AIS data used in the experiment were sourced from an online repository provided by the National Oceanic and Atmospheric Administration (NOAA) and the U.S. Coast Guard Navigation Centre (NOAA, 2025). The open service delivers vessel traffic signals organized by day, and up now the agencies provide AIS data collected continuously since the beginning of 2009 covering the coastal areas of the United States.

The dataset relies on historical data spanning from January to December 2023 related to the area of the container ports of Los Angeles-Long Beach (LALB). Table 1 reports on the structures of data; each record includes both kinematic and static data. Specifically, the archive stores timestamp such as *BaseDateTime*, longitude (*LON*), latitude (*LAT*), speed (speed over ground, *SOG*), course (course over ground, *COG*), heading, and ship information (*MMSI*, *name*, *type*, *length*, *width*, *draft*).

The *Vessel Type* attribute, as previously stated by Huang et al. (2023) and Kraus et al. (2018), does not define specific types of vessel, but only their category, for such a reason a more comprehensive view on vessel distribution required to match the information contained in the open data with external repositories using the *MMSI* as pivotal variable. So far, a further set of additional static information upon vessels was achieved; thus adding (i) the capacity (TEU) of a vessel, (ii) the gross tonnage (GT) as a volume measure of the vessel, (iii) the dead weight tonnage (DWT) as maximum mass in metric tons that a vessel can carry in safe conditions.

The original data set contained more than seven million records. Therefore, a down-sampling strategy was applied as a preprocessing step, complemented by a control to verify the distances between consecutive positions and to exclude speeds beyond acceptable limits.

After removing incomplete or inconsistent entries, more than five million valid records fall within the ZoI, and through segmentation and classification analyses, a valid number of 5,127 events were classified, including stopping, underway, and piloting operations. So, the refined dataset is ready for visualization and to support statistical analyses on port operations. Since the quality of observations directly affects the reliability of the results, by following the evidence emerging from the literature (Chen et al., 2016; Zhang et al., 2019), and focus only on statistically significant operations, just those events whose berths operation lasts a minimum of 5 hours were included in the analyzes.

Finally, detailed information on port configuration (docks, berths, terminal operators) was integrated into the database to support the case study.

## 4.3 Annual traffic

The port call distribution offers a solid overview of the activities that take place at the terminals. Therefore, considering just container vessels, Figure 4 reports the week-based trend of arrivals.

TABLE 1 Feature class of information delivered from AIS devices.

Information	Variables
Static	MMSI, IMO, call sign vessel name, vessel type, length, width, draft, cargo
Kinematic	BaseDateTime, LON, LAT, speed over ground (SOG) course over ground (COG) heading
Route related	Navigation status

Approximately 30–40 operations are recorded per week. Even if the official statistics reports that exchanged volumes were in line with the year 2022, the first quarter suffered a reduction with a critical point falling between February and March, where a sensible port calls reduction was detected. In line with this evidence, online reports (Port of Los Angeles, 2023) in February states a reduction of 43.13% of total TEUs values with respect to the previous year and approximately a 33% reduction with respect to the previous month. Similarly, the daily distribution of arrivals (Figure 5) shows no clear trend; and, differentiating between the two maritime infrastructures, it emerges that in Los Angeles, berth operations are more concentrated at the beginning of the week, whereas in Long Beach no significant variation is observed across weekdays. Figure 5 reports the hour-based arrivals/departures trend over the year. It emerges how arrivals at the dock usually are concentrated between 11 a.m. and 2 p.m., with a further peak in the last couple of hours of the day from 9 p.m. to 11 p.m. Departures are concentrated mainly within two-time windows: the first one centered between 10 a.m. and 13 p.m., the second one between midnight and 3 a.m.

## 4.4 Berth calls activities

A total amount of 1,591 valid berth calls were extracted from the database, whose share is 52% in LA and 48% in LB. Table 2 offers an overview of the distribution of dwell time frequencies. It emerged that the dwell time ( $T_{op}$ ) can largely vary, encompassing different classes of time windows, so a frequency analysis on dwelling time was executed to identify time intervals distribution. The analysis was carried out by evaluating different options, including fixed hour time windows, quantile distributions, and automated data-driven solutions. Considering the need to reduce the number of bins, and to minimize the variance among the data, the Scott formula (Cunningham, 2021) was chosen as the most effective to reproduce class time windows for berthing operations. Most of the operations are completed in less than a week, one out two vessels spend approximately 3 days at the dock, and approximately 90% of operations are completed in less than 5 days.

Observing the dwelling time for the port calls over the year does not emerge significant variations, however, the elapsed time varies among different docks. The Figures 6, 7 report information above the average dwell time by differentiating between Los Angeles and Long Beach docks. Similarly, Figures 8, 9 informs over total berth use for month. It is possible to differentiate between two classes of docks, those where the average dwell time usually lasts a maximum of 2 days, and the others where operation usually takes at least three to 5 days to complete their activities.

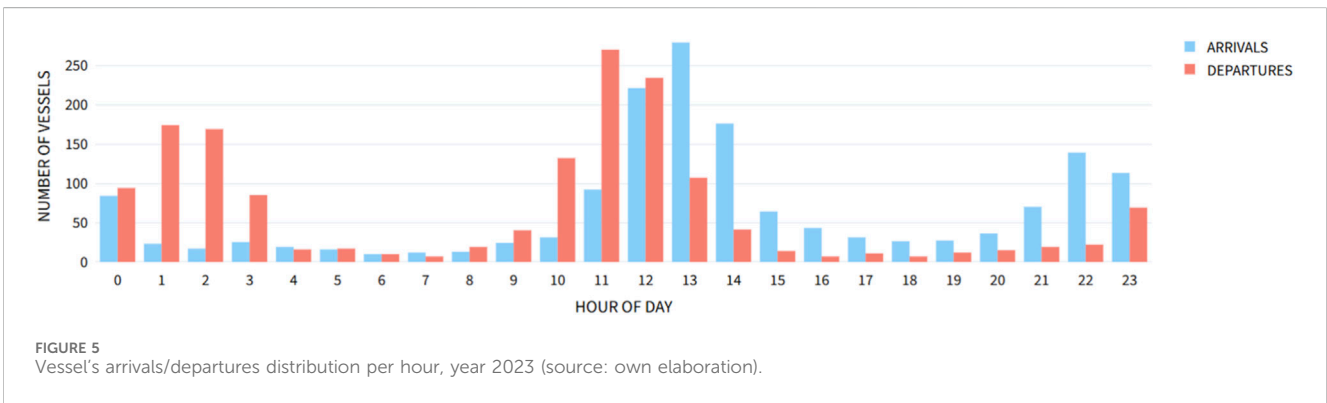
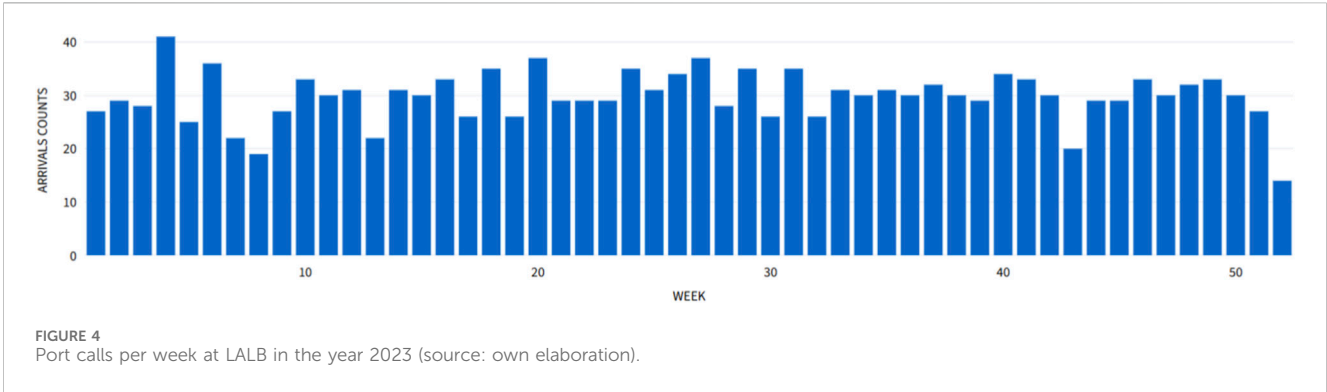


TABLE 2 Berthing events and frequency distribution at LALB year 2023.

Time windows [h]	Vessels count [units]	Frequency [%]	Cumulated frequency [%]
7–21	99	6.22	6.22
21–35	219	13.76	19.99
35–49	245	15.40	35.39
49–63	145	9.11	44.50
63–77	126	7.92	52.42
77–91	126	7.92	60.34
91–105	133	8.36	68.70
105–119	164	10.31	79.01
119–133	94	5.91	84.92
133–147	87	5.47	90.38
147–161	59	3.71	94.09
161–175	32	2.01	96.10
175–189	21	1.32	97.42
189–203	20	1.26	98.68
203 +	21	1.32	100.00

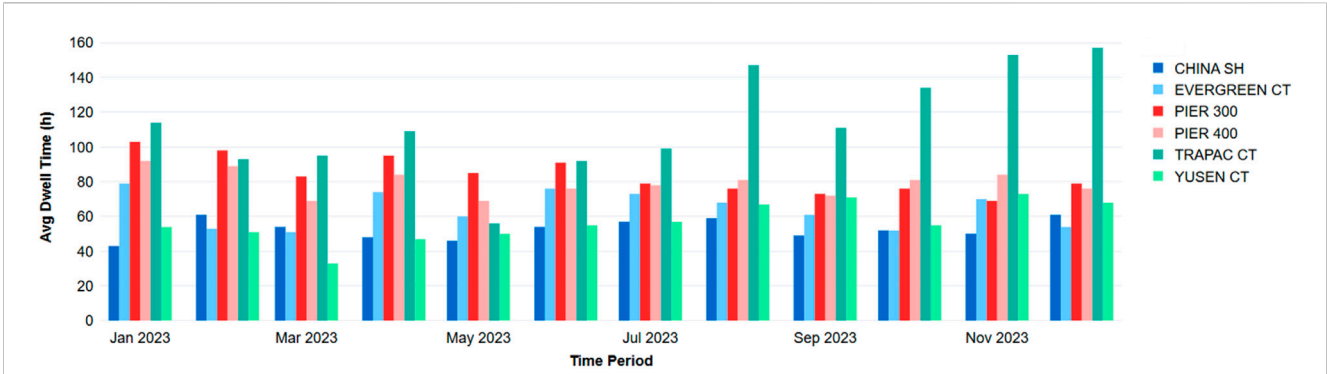


FIGURE 6 Average dwell time in Los Angeles docks, year 2023.

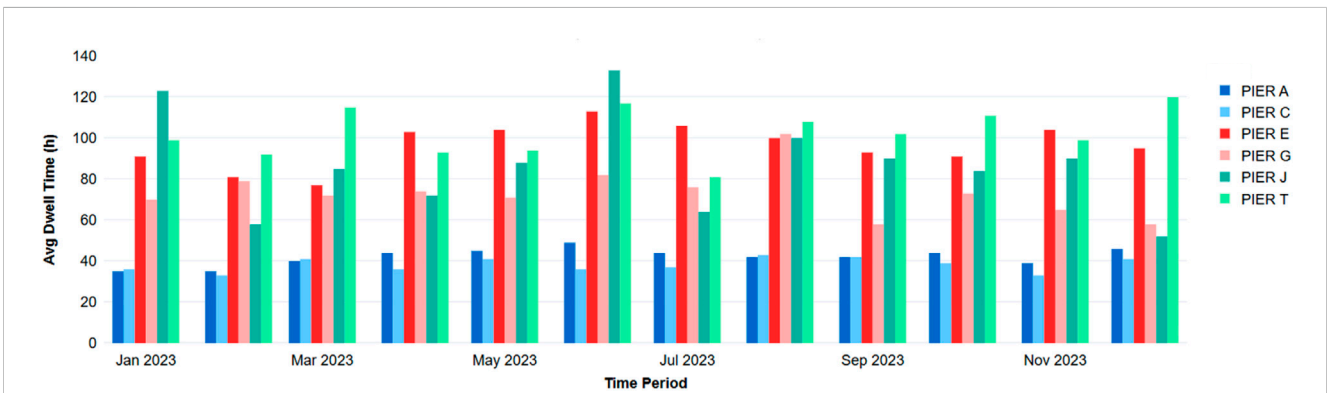


FIGURE 7 Average dwell time in Long Beach docks, year 2023.

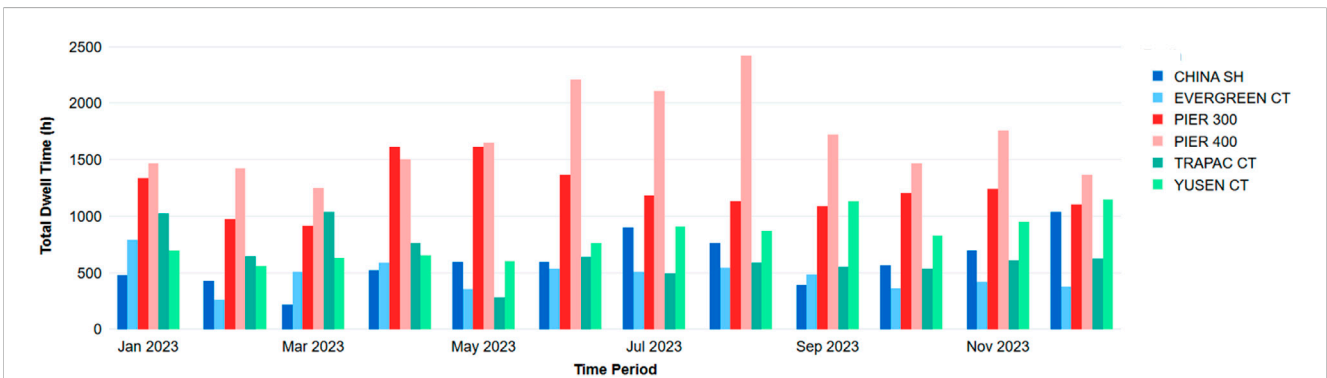


FIGURE 8 Total dwell time in Los Angeles docks, year 2023.

From Figures 6, 7, the average dwell time of Pier A and Pier C in Long Beach has a range of approximately 35–50 h (two working days), with a slight inter-period variation, thus suggesting a good degree of performance in terms of efficiency. Those performances are not affected by the increasing total amount for served vessels during the summer period. It also emerged that increasing the number of visits also decreases the time necessary to complete operations, so a good margin of resources and workload is available at the dock.

Between June and August, the total dwell time (Figures 8, 9) sensibly increases, and considering that the average time for this period is quite stable with the trend performance, this confirms how this quarter represents the most active. It emerged that the average dwell time is higher for Pier 300 and 400 for Los Angeles and Pier G for Long Beach; this evidence may be motivated by the presence of vessels of different shipping lines. Moreover, it opens the way for further detailed analyses that will focus on

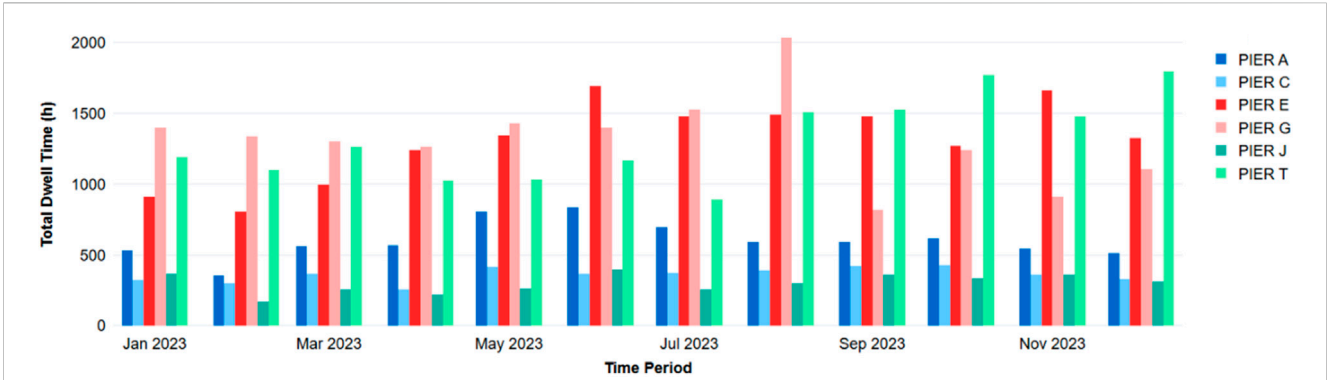


FIGURE 9 Total dwell time in Long Beach docks, year 2023.

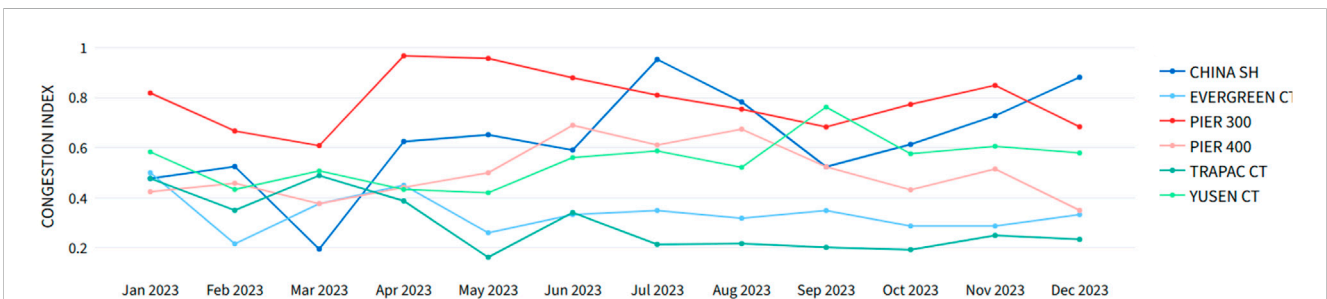


FIGURE 10 Congestion Index (average value) per dock in Los Angeles (LA), year 2023.

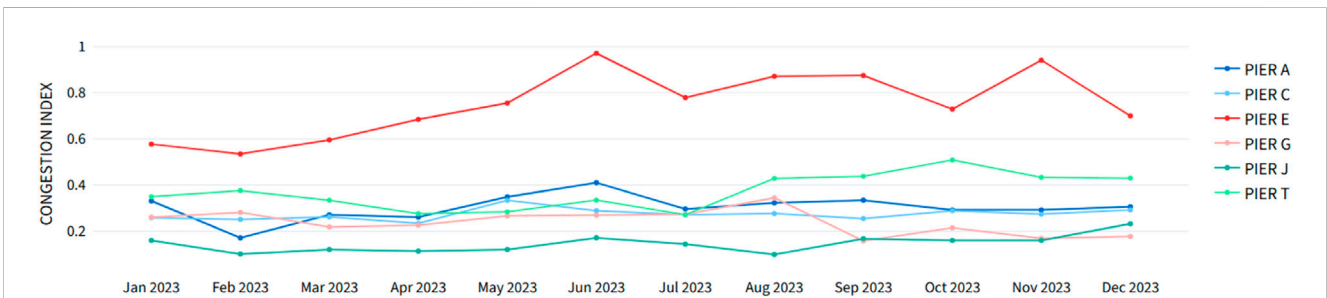


FIGURE 11 Congestion Index (average value) per dock in Long Beach (LB) year 2023.

dock equipment and workloads that are out of the scope of the paper.

### 4.5 Congestion and performance measures analysis

The analysis on annual vessel traffic opened the way to a further degree of analysis to find some statistical measures to quantify the effective berth utilization rate using key performance indicators and enhanced measures. At first, the indicator that is considered in relation to the average berth utilization, is the Congestion Index. It is

a congestion measure that lets the analyst observe, over different time frames, the average availability of a free berth for each dock. Figures 10, 11 report the monthly average occupation index. The monthly analyses states how the occupation index ranges between 30% and 60%, thus implying the possibility of having an available berth for an incoming vessel. The availability of a free berth sensibly varies depending on the dock. In Los Angeles average occupation values are higher for those docks whose total exchange values have a higher market share. For example, Pier 400 and Pier 300 account for more than the 50% port calls handled. A similar trend is observed in Long Beach, where the average degree of occupation is higher at Pier E that yearly handles most of the container traffic.

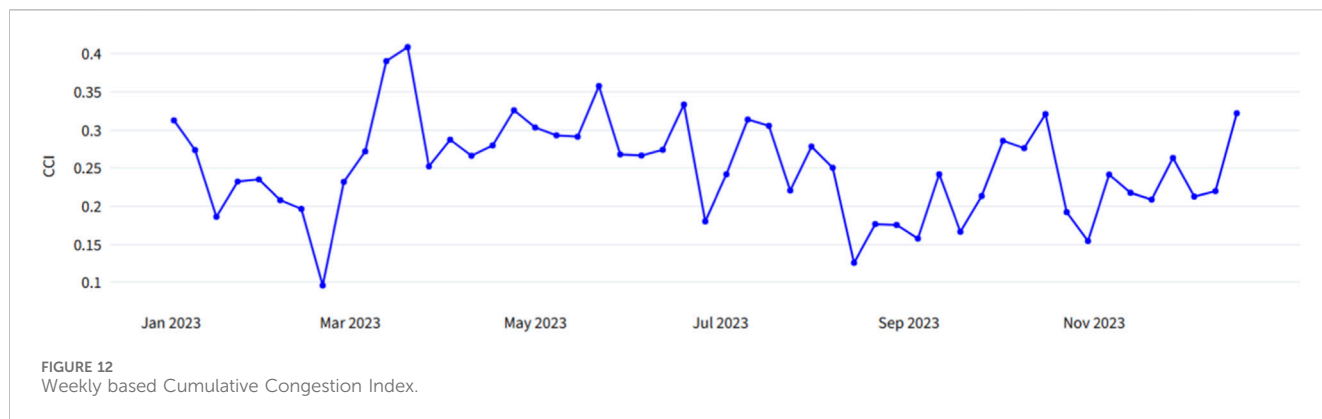


TABLE 3 Docks activities measures.

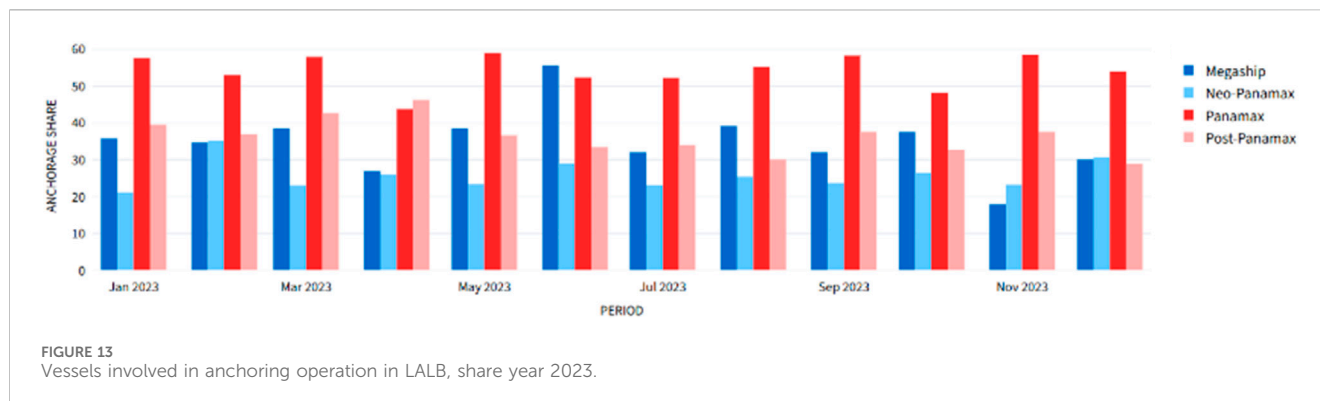
Dock	$B_{use,l}$ [%]	$B_{use,t}$ [%]	$V_r$ [%]	$F_{ur}$ [%]	$R_{ur}$ [%]	$B_{ur}$ [%]
Los Angeles (LA)						
CH shipping	88.50	63.60	0.36	0.20	0.43	---
EverGreen	35.00	57.80	0.42	0.05	0.53	---
Pier 300	83.20	93.20	0.07	0.25	0.68	---
Pier 400	53.00	96.70	0.04	0.03	0.94	---
TraPac	38.30	75.40	0.25	0.05	0.70	---
Yusen	46.90	79.90	0.20	0.07	0.72	---
Long Beach (LB)						
Pier A	63.20	62.70	0.37	0.07	0.53	0.02
Pier C	48.00	50.40	0.49	---	0.48	0.03
Pier E	81.70	94.20	0.06	0.32	0.62	---
Pier G	56.40	90.20	0.10	0.05	0.79	0.05
Pier J	26.40	39.10	0.60	---	0.39	---
Pier T	70.80	88.40	0.11	0.05	0.78	0.06

It is noticeable that, in general, Long Beach docks have a lower rate than those in Los Angeles, suggesting that the infrastructure is underutilized. Over the year, activities are more intense in Los Angeles where docks work with a higher degree of occupation; from April to November, LA has numerous vessels, and occupancy ranges from 0.60 to 0.90. It emerges that some docks do not operate at their maximum capacity and over the year dwell time may largely vary. In fact, it was decided to focus both on the evaluation of the CCI and on the use of berth to derive some performance indicators by analyzing berth activities.

CCI (Figure 12) assesses the balance between the presence of vessels in the anchorage area and the active operation at the dock. Over the year the CCI ranges between [0.10–0.40]; the relatively low ratio of the value assesses the possibility of the vessel to be served at the first available berth. Peaks are rare so those vessels that occupy the anchorage area represent a limited share, and the majority directly access the dock.

Finally, as previously highlighted in Figure 5, the mooring arrival/departure at the berths may represent a critical issue due to the overlapping presence of multiple vessels. Therefore, a more in-depth study was conducted to effectively characterize the docks' residual capacity in both space and time dimension and quantify dock efficiency and occupancy ratio. Table 3 resumes the outputs, the analyses are conducted always at dock scale, offering an overview of expected performance under different traffic conditions.

Table 3 shows berth activities are for all docks; however at least one berth is always occupied; the average berth use ( $B_{use,l}$ ) assesses how vessels may occupy different degrees of space. For example, activities at the Evergreen docks only require an average occupation ratio of 35% with respect to available length, this implies a valuable resource of space for incoming vessels, the same circumstance is also evidenced by the higher degree of vacancy ratio on time. On the other hand, activities at Pier 300 are more intense, both spatial and temporal indexes on berth use assess how at the terminal good efficiency is reached. Similar performances were highlighted by Pier



E at Long Beach, in both the residual capacity ratio indicates the possibility to host also bigger classes of vessels. The analysis also states how vacancy time ratio ( $V_v$ ) has higher degree in those docks where the full capacity ratio is rarely reached (e.g., Evergreen and Pier A). This suggests for the year 2023 that port calls were not intense, and a further reserve of capacity is available to deal with not expected events, in general this safety margin can be considered crucial in preventing extreme events of congestion. In general, it emerged that, considering the current level of traffic, the available infrastructures guarantee a satisfying performance. Also, the value of the blocked utilization ratio ( $B_{ur}$ ) is not significant for most docks. The output implies the capability of the system to deal with the incoming vessels and possibly recovering to unexpected delays on navigation. Moreover, for those docks operated by different shipping companies, the expected waiting to recover from failures should be reduced.

## 4.6 Vessel turnaround time

Finally, port call analysis is performed ordering events at the dock level. Differentiating vessel sizes through cross-section, as defined in the official reports (Bureau of Transportation Statistics, 2025), vessels were grouped into four different classes. Figure 13 reports the monthly share of the anchoring operation, thus valuing the percentage of each vessel class that occupies the anchorage area. Figure 13 provides a valuable insight into the relationship between vessel size and anchorage operations. The analyses underline that a higher percentage of vessels involved in anchoring operation usually have a capacity is below 5,000 TEUs. However, no direct evidence emerges on how vessel size can affect the total time spent at the anchor area; the data indicate that neo-Panamax and above are generally assigned to the first available berth. From the berth side, although a preliminary analysis was carried out, the results were not fully significant. This result is consistent with the findings provided by Smith (2021), who tried to develop a model to improve the relationship between vessel size and dwelling time at the berth. Moreover, as suggested by Musolino et al. (2026b), the relationship between the dwelling time and vessel capacity should be fully addressed considering ICT technology in the port. For such a reason, this analysis was postponed, to try to overcome this limitation by analyzing further data repositories.

Table 4 assesses the sequence of operations, underlying how much each phase influences the total time spent by a vessel at the terminal. Data reported refers to an ideal port call, at dock level, for those ships who followed each subphase up to leaving the terminal area. As previously stated by AbuAlhaol et al. (2018) and Chen et al. (2016) it emerged that  $T_{ber}$  and  $T_{un}$  operations have only a limited impact on  $T_v$ .

At the Los Angeles container terminals, dwell time usually dominates vessel turnaround time, ranging from 50% to 89%, as seen at the Evergreen terminal. Anchoring time showed a wide variation, where some docks usually operate with lower anchoring stages compared to others, as is the case of Ch Shipping. For those vessels involved in anchoring operations, the occupation of the anchorage area may cover more than 40% of  $T_v$ . This output result is consistent as far as the dock mentioned above works with a degree of full capacity close to 20%. It also emerged that vessels visit the anchorage area once berth operations are concluded. Maneuvering results are usually below 3%.

Conversely, Long Beach gives back a more heterogeneous scheme; even in general dwell time strongly prevails on anchoring. Finally, Piers A and G occupy an intermediate position, with anchoring shares of 35%–47% and berth around 50%–60%. Piloting times at LB terminals are more variable than in LA, occasionally reaching values above 4%–6% (Pier A, Pier C), but still marginal compared to the total cycle.

Resuming the berthing operations still represent the main component, but anchoring operations strongly emerge as an influencing factor for that sequence of operations that may be divergent from the expected schedule. Due to the configuration of the maritime, maneuvering within the terminal is structurally negligible for both ports, the wide range in anchoring shares points to uneven capacity distribution across docks and highlights the strategic importance of berth allocation and call management.

## 5 Conclusion

Given the wider availability of AIS data, this paper has explored the potential of such data as a source for analyzing port operations, with particular emphasis on vessel activities within container terminals. The development of a modular procedure has demonstrated how raw AIS data can be transformed into structured information, allowing performance analysis and

TABLE 4 Vessel Turnaround Time composition at dock level.

Dock	Anchoring ( $T_w$ )		Maneuvering ( $T_{ber}$ )		Dwell time ( $T_{op}$ )		Maneuvering ( $T_{un}$ )	
	[h:mm]	[%]	[h:mm]	[%]	[h:mm]	[%]	[h:mm]	[%]
Los Angeles (LA)								
CH shipping	41:25'	45.0	2:15'	2.3	46:20'	50.4	2:15'	2.3
EverGreen	08:00'	9.2	1:40'	1.9	76:00	87.4	1:30'	1.6
Pier 300	24:00'	27.2	2:15'	2.5	61:50'	68.7	1:30'	1.6
Pier 400	24:50'	37.8	2:50'	2.9	38:30'	56.6	1:45'	2.7
TraPac	17:50'	20.1	3:00'	3.4	66:00'	74.3	1:50'	2.1
Yusen	40:00'	44.2	2:15'	2.5	46:25'	51.1	2:10'	2.3
Long Beach (LB)								
Pier A	14:30'	34.1	4:40'	4.6	24:15'	57.3	4:00'	4.0
Pier C	20:15'	20.2	5:45'	5.8	48:45'	68.8	5:15'	5.2
Pier E	15:15'	11.1	2:45'	2.0	117:00'	85.1	1:30'	1.7
Pier G	77:00'	47.1	1:15'	0.7	81:00'	50.7	1:15'	0.7
Pier J	38:00'	34.0	1:00'	0.9	72:00'	64.4	0:45'	0.7
Pier T	14:00'	13.5	2:00'	1.8	86:00'	83.1	1:45'	1.6

assessment of port operations. To achieve this, the proposed framework integrates several stages, including data cleaning, trajectory segmentation, and event classification. By processing data sources, this study confirmed the feasibility of integrating AIS information into maritime operational analysis. In fact, the tool allows the assessment of port operations by linking navigation phases with anchorage and berth phases, as well as maneuvering. The tool itself has been structured as a flexible modular framework designed to support automatic detection and classification of key stages in a vessel's port call. Its architecture comprises interconnected modules, starting with a data layer that manages and preprocesses raw AIS signals, through trajectory segmentation and event classification components, to advanced visualization and reporting functionalities. The framework incorporates spatial and temporal filtering, rule-based algorithms for determining vessel status, and geospatial enrichment to distinguish each step that characterizes a port call. The final dashboard provides both vessel- and system-level overviews, enabling analysts to investigate operations across different docks, vessel classes, and time frames. This modular structure not only ensures scalability and adaptability to various port environments but also provides a robust foundation for ongoing monitoring and data-driven decision-making. The ability to distinguish these phases enables calculation of berth use and area occupation, thereby allowing comparison across different time windows. This procedure also provides the analyst with the opportunity to assess the utilization of the berth and analyze in detail the cases in which the docks are fully operational and those in which incoming vessels have to wait before accessing the channel to reach the berth. Finally, the procedure provides a set of statistical indicators that represent berth utilization and resumption of ship behavior at the terminal. The tool proved to be effective in identifying and quantifying operational

patterns, measuring dwell time without relying on direct surveys or port authority records.

The case study of the Los Angeles-Long Beach port system provided empirical evidence of the framework's applicability. The results indicated that, during the period examined, the terminals retain a valuable capacity reserve to accommodate incoming vessels, ensuring that berths are generally available even during heavy traffic. Although saturation phenomena frequently appear in Los Angeles, congestion in Long Beach rarely exceeds 0.6. Furthermore, the analysis revealed that higher vessel call frequencies are associated with shorter operating times, suggesting efficient allocation of resources and robust capacity to manage variable workloads on the dock. During the vessel turnaround cycle, it was important to highlight that most docks are capable of accommodating incoming vessels. Several performance indicators were introduced to exploit information from AIS data and provide deeper detail on berth operations. These descriptors are intended to reinforce the knowledge of a port call analysis. In particular, the average and total dwell time highlight operational trends, while incorporating the length of the vessel provides a clearer understanding of how much of the berth is occupied. Furthermore, the ability to identify when a berth is fully or partially vacant, or when an incoming vessel must wait due to insufficient available length, provides information on the berth use ratio.

In general, the proposed procedure provides stakeholders with a versatile tool for visualizing and summarizing port conditions across various traffic scenarios. Extending the observations over a yearly horizon further allowed for the identification of long-term trends and potential impacts of future events. These results underscore the strategic value of AIS in understanding terminal performance and in supporting both operational decisions and infrastructure planning. This approach also enabled the detection of cyclic behaviors,

recovery times after disruptions, and the role of traffic heterogeneity across different docks.

At the current stage of development, the tool emphasized the capability enabled by AIS information extraction, however further step forward should be represented by the possibility to use historical data to foresee future port conditions and enable what-if analyses. Although the AIS database has been enriched with reference to TEU, GT, DWT, and channel depth has been verified for each berth, future work should focus on a more in-depth analysis of traffic heterogeneity. An additional research direction could involve the investigation of correlations between the volumes handled at each berth and the dwelling times and/or vessel tonnage, which would require the development of an appropriate model to reproduce handling operations.

## Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <https://hub.marinecadastre.gov/>.

## Author contributions

OB: Methodology, Investigation, Software, Data curation, Conceptualization, Writing – original draft, Formal Analysis, Writing – review and editing, Visualization. AP: Visualization, Conceptualization, Validation, Project administration, Funding acquisition, Methodology, Supervision, Writing – review and editing.

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