A queuing theory-based operating capacity model for multi-modal port operations

Debojjal Bagchi[a,*], Kyle Bathgate[a], Stephen D. Boyles[a], Kenneth N. Mitchell[b], Magdalena I. Asborno[b], Marin M. Kress[b]

[a] *Fariborz Maseeh Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin, 301 E. Dean Keeton St, Austin, 78712, TX, USA*

[b] *Coastal Hydraulics Laboratory, US Army Corps of Engineers Research and Development Center, 3909 Halls Ferry Rd, Vicksburg, 39180, MS, USA*

arXiv:submit/6832693 [stat.ME] 26 Sep 2025

Abstract

This paper investigates how "operating capacity" can be meaningfully defined in multi-modal maritime freight systems with limited data. Shipping channels and ports are complex systems that interact deeply, and the capacities of individual components may differ from the overall capacity of these systems. Traditional methods for port capacity assessment often rely on data-driven simulations, which can be difficult to calibrate due to complex interactions among port systems and the large volume of data required.

We present a data-efficient alternative for estimating port capacities by developing a novel queuing theory-based formulation. We define the operating capacity of a port system as the maximum vessel arrival rate that can be sustained over an extended period of stable operations. Furthermore, we define terminal-level operating capacities for import and export processes in terms of the maximum achievable throughput for each process per unit time. Our approach requires only minimal data, which can be readily obtained from archival Automatic Identification System (AIS) vessel trajectories and historical port terminal logs, thereby making implementation both robust and efficient.

We demonstrate the utility of the proposed method using data from the Port of Houston. The results suggest that the model is a viable approach for estimating port operating capacity. Specifically, the inbound operating capacity of the Port of Houston was estimated to be approximately 0.8 vessels per hour. At the Barbour's Cut Container Terminal, the operating capacities were found to be 57.8 containers per hour for import processes and 74.6 containers per hour for export processes.

Keywords: Port capacity, queuing theory, multi-modal freight, maritime logistics

1. Introduction

Over 80% of global trade by volume is transported by sea and handled through ports [1]. Given this critical role, the ability to evaluate the current and future operating capacity of port systems is needed to inform large-scale investment decisions and long-term infrastructure expansion plans [2]. Unlike roadways, no equivalent version of the Highway Capacity Manual exists to provide a standard definition of "capacity" for maritime systems. Past studies have attempted to define the capacity of a port based on individual components [2] or using a simulation [3]. However, both of these methods have limitations. Bellsolà Olba et al. [3] emphasized that network capacity should not be measured by defining capacities for individual components and identifying the most limited capacity, as there might be interdependencies between subsystems. On the

*Corresponding author (Email: debojjalb@utexas.edu)

other hand, using simulation to estimate capacity requires highly accurate representations of port functions, which can be time-consuming to model, and the input data can often be inaccessible.

In these simulation and interaction model studies, maritime system capacity is typically defined as the maximum cargo or vessel throughput over a finite time period. Yet, this definition does not capture the idea of a long term, sustainable maximum throughput. In practice, ports may temporarily handle much higher vessel volumes per unit of time, but such conditions are unstable and cannot be sustained in the long run. This creates a need for a metric that defines the long-term operating capacity of multi-modal maritime transportation systems. Such a metric should account for the interactions between both waterside and landside systems and reflect the long-term freight-moving ability of the integrated port system. This metric would have value for stakeholders interested in understanding how infrastructural investments, such as channel expansion or terminal construction projects, may influence the overall capacity of an integrated port system. A metric capable of predicting the long-term outcomes of these initiatives and drawing comparisons between different project alternatives over an extended period would provide value to port planners and stakeholders.

Another limitation of current multi-modal port capacity measurement approaches is that they require a large amount of data, which is often difficult to acquire due to complexity or unavailability. Furthermore, available data may lack the required level of granularity and fidelity to accurately build simulation or interaction models. There remains a practical research gap for developing a model that can accurately predict the operating capacity of a port without relying on extensive data collection and processing efforts. This would aid in fast and data-efficient computation of capacity without the need for a heavyweight simulation framework.

This paper proposes a queuing theory-based capacity model for multi-modal port freight systems. Queuing theory-based models to estimate system capacity have been successfully applied in other domains, such as healthcare [4, 5] and logistics [6]. These studies estimate system capacity by analyzing arrival rates and mean queue times or lengths using simulations or empirical data [7]. However, these queuing models do not directly apply to port operations. We develop queuing models to suit port operations and compute the operating capacity of the port. Our proposed model incorporates long-term behavior while accounting for level-of-service parameters, such as vessel dwell times, truck turn times, and yard utilization.

Contributions. The key contributions of this paper are as follows. We develop a queuing theory–based model for analyzing long-term port operations, which can be calibrated using real-world data. The model predicts operating capacity at both the port and terminal levels. It is broadly applicable to any port that handles one or more cargo types and has an anchorage area, followed by a channel leading to multiple terminals. Unlike many existing capacity models in the literature, our approach requires only data that can be readily obtained from archival Automatic Identification System (AIS) vessel trajectories and historical terminal logs, avoiding the need for extensive simulation or highly detailed datasets. The resulting capacity predictions can support stakeholders in disruption planning and in identifying the need for capacity expansion projects under future demand scenarios. To demonstrate the effectiveness and extensibility of the model, we present a detailed case study at the Port of Houston. In summary, our work makes three distinct contributions to the literature:

a) It presents a method for estimating long-term sustainable port operating capacity rather than maximum throughput, which is often unsustainable for multimodal ports over extended periods.
b) The proposed model can be calibrated using readily available archival AIS data and historical port data without requiring extensive data collection or simulation, and
c) The proposed model is validated using a real-world data from Port of Houston, enhancing confidence in the model's practical applicability.

The remainder of the paper is structured as follows: Section 2 provides a brief review of relevant literature. Next, Section 3 presents the queuing models for each subsystem and introduces the framework for computing operating capacity. Section 4 compares the proposed techniques' performance on empirical data for the Port of Houston. Finally, Section 5 summarizes our findings and suggests potential extensions to the research.

2. Literature review

Defining capacity in a multi-modal port system is challenging due to the complex interactions among multiple resources and parameters [8]. Consequently, there is no universally accepted definition of long-term port operating capacity [3]. Several studies have proposed capacity definitions for specific port components. Liu and Li [9] used arrangement theory to calculate the carrying capacity of navigable waterways by determining the number of ships that can be safely accommodated on the water. Fan and Cao [10] defined anchorage capacity as “the maximum number of vessels that can be accommodated by the anchorage over a period of time.” Using automatic identification system (AIS) vessel tracking data, Liu et al. [11] defined waterway capacity as “the ratio of the spatiotemporal resources of the port waterway to the spatiotemporal resources occupied by a single ship generally sailing in and out of the port waterway.” However, in real-world operations, vessels are rarely packed tightly, and waterway capacity is often constrained by factors beyond channel dimensions such as pilot and tug availability, downstream terminal resources, and navigation restrictions.

Static and dynamic capacity concepts have also been used to model capacities of individual port components [12]. Static capacity is based on channel dimensions or resource availability, while dynamic capacity is based on the volume a component can handle over time. Interaction functions have been used to mathematically model the interactions between components [13]. However, calculating network capacities based on the capacities of individual components may not sufficiently capture the interdependent effects present among system components [3]. Aggregate port performance metrics, such as congestion level [14] and turnaround time [15], are often used to account for these interdependencies. However, these performance measures do not directly correlate with port capacity as it is commonly defined in transportation networks.

The Bureau of Transportation Statistics [16] defines port capacity as a “measure of the maximum throughput in tons, twenty-foot equivalent unit (TEU), or other units that a port and its terminals can handle over a given period." Calculating an exact capacity for the entire port system is challenging because of the extensive interactions between systems such as channels, pilotage, terminal operations, and the different cargo modes. Therefore, most capacity models focus on simulating numerous scenarios to derive insights on capacity and identify potential bottlenecks [17]. For instance, Huang et al. [18] evaluated anchorage capacity by simulating a realistic mix of vessels and analyzing anchorage utilization. They defined anchorage capacity as “the mean utilized area when a new vessel cannot be accommodated, weighted by the time period from the rejection of the vessel to the acceptance of the next vessel.” O’Halloran et al. [19] used query-and-simulate loops to determine waterway capacity by establishing the minimum channel dimensions required for safe sailing. Recently, researchers have developed the concept of port network traffic capacity (PNTC), which incorporates the interdependencies among port subsystems [3]. Bellsolà Olba et al. [3] defined PNTC as “the maximum average vessel flow that can be handled by a port, with its specific infrastructure layout, vessel fleet, traffic composition, and demand, satisfying the required safety and service level.” The authors ran multiple simulations with varying demands to identify stable and unstable conditions and determine PNTC. However, these models strongly depend on the underlying simulation model and how “stable conditions” are defined.

Apart from determining capacity, understanding the operation of ports has been of significant research interest. Several studies [20, 21, 22, 23] used queuing theory to model port operations. Zrnić et al. [24] used an anchorage-ship-berth link as a multiple server queuing system. Mrnjavac and Zenzerovic [25] described how a container terminal could be simulated using known arrival and service rates. They also analyzed the effect of increasing the arrival rate with a fixed number of berths on port operations. Queuing theory and simulations have also been used to determine the optimal number of berths in a seaport [26] and the impact of disruptions [27]. Souf-Aljen et al. [28] used a simulation model and AIS data for a container terminal to estimate port throughput. Bugaric and Petrovic [29] analyzed how to increase terminal capacity without making large investments. Furthermore, landside infrastructure and port-hinterland connections are often modeled using queuing theory. For instance, Chen et al. [30] estimated truck waiting and emissions at port container terminals using queuing models at truck gate and terminal yard. Networks of ports have also been analyzed using closed Jackson network queuing models [31].

Queuing models have been employed in a wide variety of domains to determine system capacities, including production [32], healthcare [33, 4], rail [34], and aerial vehicles [35]. As observed by Lantz and Rosén [7], capacity definitions typically stem from two types of approaches: engineering-based or time-based, both of which have inherent limitations. Engineering-based capacity measurements, such as estimating annual berth throughput from crane numbers, crane design rates, and assumed operating hours, are highly sensitive to input variables. Time-based studies in ports, on the other hand, may rely on measuring operational durations such as pilot boarding and vessel service times can introduce behavioral biases such as the Hawthorne effect [36]. These limitations are magnified when capacity is computed component-wise for an interdependent system. Queuing theory-based capacity computations [7] help mitigate these challenges while still considering all interdependencies. Zenzerović and Vilke [37] provided evidence that queuing models can be used to optimize capacities in container terminals, while Lee et al. [38] proposed a queuing model explicitly designed for the unique characteristics of container terminals to estimate capacity. However, a research gap exists in determining the long-term operating capacity of a multi-modal port system using queuing models and assessing the viability of such models in predicting the operating capacity of real-world systems. This research aims to fill this gap by proposing an operating capacity formulation by applying queuing models to the entire port system.

3. Port queuing model

Queuing models rely on a well-defined abstraction of the processes and services observed in real-world port operations. In particular, they require knowledge of arrival processes and queuing disciplines. Prior studies have shown that vessel arrival rates at anchorages and terminals often follow a Poisson process [39, 40]. Wang et al. [41] investigated various arrival rules for queuing models, noting that the first-come-first-serve (FCFS) rule is the most common and fundamental for ships entering and leaving ports, although alternative rules, such as prioritizing large-tonnage ships (large-ton-ship first service or LSFS), are also utilized.

On the landside, Poisson processes are also widely used to represent truck arrivals at container terminal gates. For instance, Chen and Yang [42] and Liu et al. [43] modeled truck arrivals as Poisson processes, while Zhang et al. [44] applied an $M/M/1$ queuing model using exponentially distributed truck inter-arrivals and exponentially distributed service times in the storage yard subsystem. Similarly, several studies have assumed exponentially distributed service times in port subsystems. For example, Jones and Blunden [45] used exponential service times to study ship turnaround at the Port of Bangkok, Schonfeld and Frank [46] applied exponential service time assumptions to optimize container ship berth utilization, and simulation-based studies by Demirci [47] incorporated exponential inter-arrival and service distributions to analyze terminal operations.

To outline our multi-modal port queuing model, we first explain the life cycle of a vessel in a port and introduce the notations used in our model. We then propose queuing models that represent the waterway, terminal import, and terminal export processes. A vessel's port life cycle begins with it entering the anchorage area and queuing until it can proceed to its destination terminal. In narrow waterways, a set of restrictions may govern navigation, such as combined beam, combined draft, and/or daylight. Once a berth is available and channel restrictions are met, the vessel requests resources (pilots and tugboats) to navigate to its terminal berth. Let L_a^i denote the average number of ships waiting in the anchorage for vessel type i, where i can be either container, break bulk, or liquid bulk vessels, and W_a represent the average time vessels of all types spend waiting in the anchorage queue.

We employ a multiclass $M/M/1$ queuing model with equal priorities for the ship channel operation. Each class represents a cargo type, and since all vessels pass through the same channel, they are serviced at the same rate. However, each class of cargo arrives at a different arrival rate λ_a^i, following a Poisson process. We further assume that service times to enter the channel follow an exponential distribution with a mean service rate μ_a, and departing vessels are prioritized over arriving vessels in the waterway channel. Consequently, we assume queues only form at the anchorage.

Once a vessel arrives at its terminal berth, cargo is unloaded and transferred to the terminal yard for storage. The cargo is then queued in the yard and awaits transfer to landside transport modes such as trucks or trains.

Let L_c^I represent the average amount of cargo in the yard due to imports and W_c^I represent the mean cargo waiting time in the yard for the entire import process. We assume that vessels arrive at the terminal using a Poisson process with a mean inter-arrival rate λ^I. Each arrival consists of a batch of cargo, where the amount of cargo in each batch is a random variable X with first and second moments $E[X]$ and $E[X^2]$, respectively. The entire import process is assumed to have exponentially distributed service times with a mean service rate μ_c^I. We use an $M^{[X]}/M/1$ queuing model to represent the import process.

Concurrently with imports, the export process occurs. For exports, a truck arrives at the terminal's gate and queues until it can be serviced by the gate. We assume cargo from trucks arrive following a Poisson process with a mean inter-arrival rate λ_c^G. Once a truck enters the gate, it waits in the holding area until its cargo can be offloaded and stored in the terminal yard. Finally, we assume cargo from the yard is loaded onto the ship in a process independent of the cargo offloading. For the export process, queues form at three locations: the truck gate, the holding area, and the terminal yard. We model this using a tandem queue of three processes. We assume cargo arrivals from trucks at the terminal gate follow a Poisson process with an inter-arrival rate λ_c^G, and each gate has exponentially distributed service times. Suppose there are S_c gates. We employ an $M/M/S_c$ queue to model gate behavior. Since the gates follow an $M/M/S_c$ model, the arrival rate of cargo in the holding area is the same as that of the arrival rate at the gate. The holding area is modeled as an $M/M/1$ queue with exponentially distributed service times. Then, the arrival rate of cargo at the yard (λ_c^E) is also the same as the arrival rate at the gate. Finally, we assume exponentially distributed service times with a mean μ_c^E for processing cargo in the yard. We model the export yard processes using an $M/M/1$ queuing model. Let W_c^E denote the time cargo spends in the yard before being loaded onto the ship, and L_c^E the average amount of cargo in the yard due to exports.

Each queue follows FCFS behavior throughout the system, and service rates are assumed to be independent of arrival rates. Additionally, all other assumptions for the respective queuing models apply. The length of the cargo queue due to import and export combined is denoted by L_c. Further details on each of the queuing models are described next. The notations used in this study are summarized in Table 1, and Figure 1 illustrates the queuing network.

Symbol	**Meaning**	**Units**
λ_a^i	Vessel arrival rate to the system (at anchorage) for type i	vessels / hour
L_a^i	Mean length of queue of vessels of type i at the anchorage	vessels
μ_a	Service rate of the waterway	vessels / hour
W_a	Mean waiting time at anchorage for all vessel types	hour
ρ_a	Traffic intensity of vessels at anchorage	–
λ^I	Import vessel arrival rate	vessels / hour
L_c^I	Mean queue of import cargo in the terminal yard berth	cargo
μ_c^I	Rate of processing import cargo	cargo / hour
W_c^I	Mean import waiting time of cargo at the yard	hour
X	Random variable indicating cargo batch size per vessel	cargo
$E[X]$	First moment of X	cargo
$E[X^2]$	Second moment of X	cargo^2
ρ_c^I	Traffic intensity of import cargo at the yard process	–
λ_c^G	Cargo arrival rate via truck	cargo / hour
L_c^E	Mean queue of export cargo in the terminal yard	cargo
W_c^E	Mean export waiting time of cargo at the yard	hour
S_c	Total number of truck gates	–
λ_c^E	Export cargo arrival rate at the yard	cargo / hour
ρ_c^E	Traffic intensity of export cargo at the yard process	–
L_c	Mean total amount of cargo in the terminal yard	cargo

Table 1: Notations, their meanings, and units (cargo units are measured as number of containers for container terminals, tons for break bulk terminals, and cubic meters for tanker terminals).

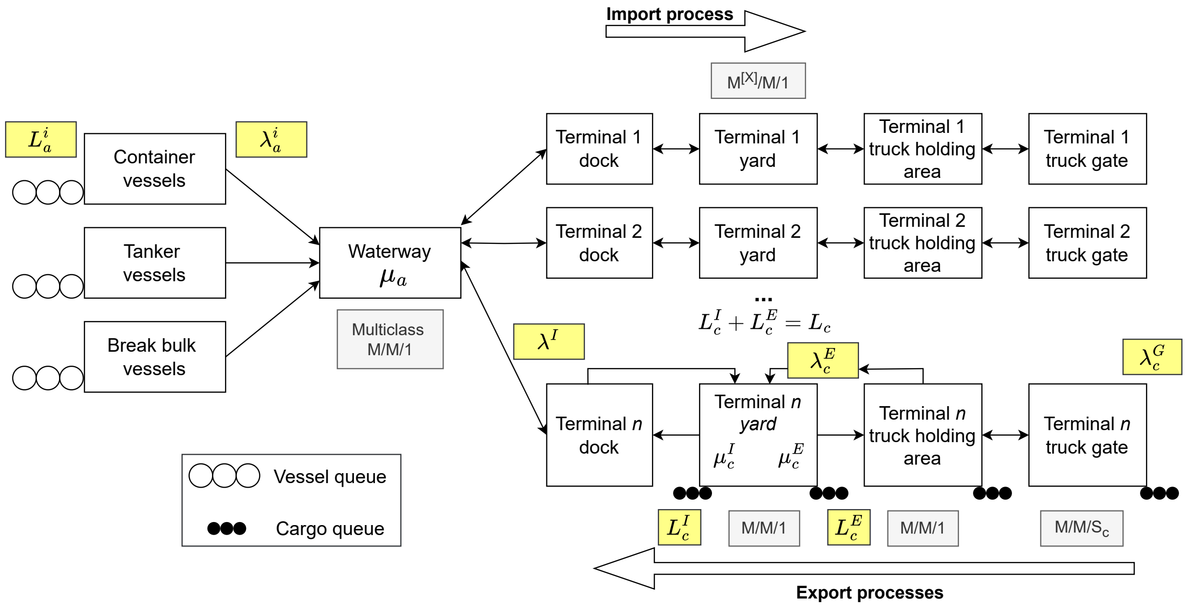


Figure 1: Structure of port queuing model.

3.1. The anchorage queuing model

We model the anchorage area using a multiclass $M/M/1$ queuing model, where the "server" represents an imaginary gate to the waterway channel. Each vessel requests service for channel entry, which is granted once all requirements, such as pilot and tug availability, navigation restrictions, and downstream terminal resources are satisfied. In this way, the service time distribution captures all channel restrictions and resource availability constraints that the vessels experience throughout the analysis period. The server is assumed to treat all vessels identically, with the same restrictions applying to every cargo class. This assumption allows us to compute a single effective service rate for the entire port, which we interpret as the port's operating capacity. However, under this assumption, channel entry is indifferent to vessel class, so all vessel types experience the same average waiting time. Differences in expected queue lengths across classes arise solely from differences in their respective arrival rates. This is acceptable for our purpose, since we can estimate capacity based on queue lengths, and validation can still be performed using the mean waiting time across classes.

The mean waiting time for a multiclass $M/M/1$ queue with equal priorities [48, 49] can be computed using Equation (1). The mean queue length for each class can be determined by applying Little's law [50], as shown in Equation (2). Empirical data can provide the waiting times and queue lengths for each ship class at the anchorage, which can then be used to compute μ_a.

$$W_a = \frac{\sum_i \frac{\lambda_i}{\mu_a^2}}{1 - \sum \frac{\lambda_i}{\mu_a}} \tag{1}$$

$$L_a^i = \frac{\lambda_a^i \left(\sum_j \frac{\lambda_a^j}{\mu_a^2}\right)}{1 - \sum_j \frac{\lambda_a^j}{\mu_a}} \tag{2}$$

The equations (1) and (2) only apply under stable queue formation, or when the traffic intensity $\rho_a = \sum_i \lambda_a^i/\mu_a < 1$. Using the observed queue lengths of each class, $\hat{L}_a^i$, we apply a least square minimization model (3) to compute the service rate, μ_a. The model minimizes the least squared errors between predicted and actual queue length at anchorage. We compare the observed waiting times with those calculated using

Equation (1) to validate the computed service rate. The *port operating capacity* is defined as *the service rate that maintains the desired anchorage queue length over an extended period of stable queue formation.* In this context, the estimated μ_a values should be interpreted as the rate at which inbound vessels can be processed by the port over a long, stable period of operations. Furthermore, the operating capacity reflects all port-level constraints, including pilotage requirements, channel restrictions, and terminal-level resource limitations, since channel entry ultimately depends on all of these factors.

$$\min_{\mu} \sum_i \left(\frac{\lambda_a^i \left(\sum_j \frac{\lambda_a^j}{\mu^2} \right)}{1 - \sum_j \frac{\lambda_a^j}{\mu}} - \hat{L}_a^i \right)^2 \text{ subject to } \quad \sum_i \frac{\lambda_a^i}{\mu} < 1. \tag{3}$$

3.2. The terminal queuing model

We model terminal imports using a batch Markov arrival process [51], specifically $M^{[X]}/M/1$. We assume cargo arrives in batches, where the inter-arrival times between different batches follow an exponential distribution with mean λ^I. The amount of cargo arriving is considered a batch at each arrival instance, with the batch size represented by the random variable X with first and second moments $E[X]$ and $E[X^2]$, respectively.

The condition for the formed queue to be stable is given by Equation (4). The arrival rate λ^I can be observed empirically from archival AIS data for a terminal. The import dwell time (W_c^I) and the moments of the batch size can be derived from historical port data. Equation (5) is then solved numerically to compute the cargo processing rate for imports subject to the stability constraint that $\rho_c^I < 1$. The *import process operating capacity* is defined as *the service rate of processing cargo that maintains the desired import cargo dwell over an extended period of stable queue formation.*

$$\rho_c^I = \frac{\lambda^I E[X]}{\mu_c^I} < 1 \tag{4}$$

$$W_c^I = \frac{\frac{\rho_c^I}{1-\rho_c^I} \left[\frac{E(X)+E(X^2)}{2E(X)} \right]}{\lambda^I E[X]} - \frac{1}{\mu_c^I} \tag{5}$$

$$L_c^I = \frac{\rho_c^I}{1-\rho_c^I} \left[\frac{E(X)+E(X^2)}{2E(X)} \right] - \rho_c^I \tag{6}$$

We employ a tri-tandem $M/M/S_c - M/M/1 - M/M/1$ queuing model for export processes. Specifically, the gate processes are modeled as an $M/M/S_c$ system, while the holding area and yard processes are each modeled as an $M/M/1$ system. By applying Burke's theorem [52], we assume cargo arrives at the terminal for export following a Poisson process. Empirical observations can provide the waiting times in the yard queue (W_c^E) and the cargo arrival rate at the gate λ_c^G. The service rate for exports can then be estimated using Equation (7) as derived by [7]. The *export process operating capacity* is defined as *the service rate of processing cargo that maintains the desired export dwell time over an extended period of stable queue formation.*

$$\mu_c^E = \frac{\lambda_C^E}{2} + \sqrt{\left(\frac{\lambda_c^E}{2}\right)^2 + \frac{\lambda_c^E}{W_c^E}} \tag{7}$$

$$L_c^E = \frac{(\lambda_c^E)^2}{\mu_c^E(\mu_c^E - \lambda_C^E)} \tag{8}$$

To validate the model, we compare the total average cargo stored in the terminal, considering both import and export processes ($L_c = L_c^E + L_c^I$), with the observed yard utilization. Although service rates at the gate and holding area for trucks can be determined using gate wait times and truck turn times, these rates are not computed in this study due to the lack of data needed to validate the model. Nonetheless, the model can be validated if the gate and holding area queue lengths are known. Table 2 summarizes the various queuing models described in this section.

Model	**Model 1 (Anchorage)**	**Model 2 (Import)**	**Model 3 (Export)**		
Queuing model	Multiclass $M/M/1$	$M^{[X]}/M/1$	Tandem $M/M/S_c - M/M/1 - M/M/1$		
Location	Anchorage	Yard	Truck gate	Holding area	Yard
Model input − 1 (Q.O.S)	Queue length at anchorage (L_a^i)	Import dwell time in yard (W_c^I)	Wait time in gate queue	Truck turn time	Export dwell time in yard (W_c^E)
Model input − 2 (Arrival)	Arrival rate of classes (λ_a^i)	Arrival rate and batch dist. (λ^I, X)	Arrival rate cargo from trucks (λ_c^G)	Arrival rate of cargo at holding	Arrival rate of cargo (λ_c^E)
Model output	Rate of service (μ_a)	Rate of service for import (μ_c^I)	Rate of service at gate	Rate of service at holding	Rate of service for export (μ_c^E)
Validation	Wait time in anchorage (W_a)	Yard Utilization (L_c)	Queue length at gate*	Queue length at holding*	Yard utilization (L_c)

Table 2: Summary of queuing models used in this study. The table presents the specific queuing models, their application locations within the port, and the key inputs and outputs. The model inputs are categorized by quality of service (Q.O.S.) and arrival rates, and the model outputs are also shown. Validations marked with an asterisk (*) are not performed in this study due to a lack of available data.

4. Results and discussions

We tested our models using data from the Port of Houston, which includes the Houston Ship Channel and over 200 terminals handling container, liquid, break bulk, and general cargo. The Port of Houston is one of the largest in the US, ranking first in foreign waterborne tonnage and fifth in total TEUs among US container ports [53]. The high complexities and interdependencies make the Port of Houston an ideal candidate for validating the models proposed in this study. We obtained various input parameters for our model from archival AIS data, reports from the Port of Houston, and relevant literature. To demonstrate the application of the models, we analyzed the Houston anchorage area and the Barbours Cut Container Terminal (BCT) on a quarterly basis from the last quarter of 2021 through the last quarter of 2023 to ensure stable queue formations. For a queue to be stable, the mean and variance of the performance indicators (queue length and waiting time) should not change significantly over time. Consequently, a very short timescale (on the order of days) would be insufficient to ensure stable queues, as the mean values of these performance indicators fluctuate daily. On the other hand, very long stable periods are rare in port operations due to disruptions, seasonal demand fluctuations, operational adjustments, and more. A three-month period strikes a balance between the two time-scales.

To evaluate our proposed model for the port, we analyzed archival AIS data to determine input values for different cargo classes at the anchorage. The AIS-derived values for vessel arrival rates, mean anchorage wait times and anchorage queue lengths are shown in Table 3. The computed mean service rate was approximately 0.8 vessels processed by the ship channel per hour. It is important to note that the mean service rate does not reflect the maximum number of vessels that the channel can accommodate at any given time. Instead, it indicates the mean inbound number of vessels that the port can handle over an extended period. For example, the computed μ_a values in Table 3 represent the average hourly processing rate of inbound vessels over each three-month period. The operating capacity value account for all operating conditions—including nights, weekends, holidays, channel restrictions, and terminal-level resource constraints. Thus, capacity values derived from this queuing model should only be compared against capacity values from the same queuing model for the same location under different conditions to assess various capacity scenarios.

Year	Quarter	Cargo type	λ_a^i	L_a^i	μ_a	W_a (calculated)	W_a (actual)	ρ_a	Relative error (%)
2021	Q4	Container Break bulk Liquid	0.09 0.17 0.52	3.77 4.87 21.87	0.8	41	39.67	0.975	3.35
2022	Q1	Container Break bulk Liquid	0.09 0.17 0.49	6.03 6.89 20.24	0.77	41.89	44.3	0.974	-5.44
	Q2	Container Break bulk Liquid	0.09 0.17 0.53	7.11 4.27 23.74	0.81	43.47	44.38	0.975	-2.04
	Q3	Container Break bulk Liquid	0.1 0.16 0.52	9.41 5.34 22.68	0.79	44.59	48.55	0.987	-8.16
	Q4	Container Break bulk Liquid	0.1 0.17 0.52	5.79 5.71 23.93	0.81	45.2	45.04	0.975	0.35
2023	Q1	Container Break bulk Liquid	0.09 0.15 0.54	2.97 4.13 28.05	0.8	49.68	44.97	0.975	10.47
	Q2	Container Break bulk Liquid	0.1 0.15 0.52	1.1 3.84 20.41	0.8	37.15	32.97	0.962	12.68
	Q3	Container Break bulk Liquid	0.1 0.14 0.55	2.1 3.82 26.18	0.81	45.54	40.82	0.975	11.56
	Q4	Container Break bulk Liquid	0.09 0.13 0.57	1.25 2.35 26.96	0.81	45.19	38.70	0.975	16.78

Table 3: Anchorage results (λ_a^i: *arrival rate per hour;* L_a^i: *queue length;* μ_a: *operating capacity of the port;* W_a *(calculated): calculated mean wait time in hours;* W_a *(actual): observed mean wait time in hours from AIS;* ρ_a: *traffic intensity.)*

We observed that the port's operating capacity remained relatively stable over the analysis period, although the mean anchorage waiting time varied from 32.97 hours to 48.55 hours, a variation of about 47%. Our model predicted the waiting time within close margins to the observed waiting times from archival AIS data, with relative errors ranging from 0.35% in the fourth quarter of 2022 to 16.78% in the fourth quarter of 2023. Table 3 summarizes the calculated service rate, traffic intensity, and anchorage queue length for the port. It is important to note that the traffic intensity during each analysis period was extremely high (close to 1), indicating that the entire port system was operating very near its capacity with minimal slack available. This, in turn, implies that even slight surges in arrivals could lead to disproportionately large increases in queue lengths.

To demonstrate the applicability of the terminal import and export models, we examined the Barbours Cut Container Terminal at the Port of Houston from the fourth quarter of 2021 to the fourth quarter of 2023. Arrival rates were computed from archival AIS data [54], while the import and export container dwell times were obtained from Port of Houston terminal reports [55]. The first and second moments of batch size were predicted from the mean and variance of import container distribution using data from BCT terminal reports [56]. Table 4 summarizes the calculated service rate and yard queue length for the import processes. The export model was analyzed during the same period. The truck arrival rates were estimated from the Port of Houston Lynx portal [57], which has a database of all gate transactions for imports and exports at BCT. The container arrival rates were assumed to be the same as truck arrival rates, assuming each truck carries one container. Table 5 summarizes the export processes' calculated service rate and yard queue length. The operating capacity for import and export processes was found to be about 53.77 and 72.43 containers per hour. As in the case of the waterway, the values should be interpreted as the long-term operating capacity for import and export processes and not the maximum rate at which imports and exports could happen in one instant.

To validate our proposed import and export models, we estimated the yard capacity using BCT yard inventory data from the Lynx database [57] and yard utilization information [55] as of July 2024. The estimated capacity was found to be 25,208 containers. Our estimate aligns closely with the latest value in the literature by Huynh and Hutson [58], where the yard capacity was estimated to be about 23,000 containers. To validate our terminal model, we calculated the total queue length for imports and exports and compared it with yard utilization data obtained from the BCT terminal reports [55], averaged over each three-month period. The validation results are summarized in Table 6. The predicted and actual utilization of the yard space were close, with an error margin of 0.86% to 17.79%, except for the first four quarters, indicating the validity of our models.

Year	**Quarter**	λ^I	$E[X]$	$E[X^2]$	W_c^I	μ_c^I	L_c^I	ρ_c^I
2021*	Q4	0.045			7.90	41.61	7262	0.92
2022*	Q1	0.054			6.83	49.79	7534	0.92
2022*	Q2	0.055			6.13	51.08	6887	0.92
2022*	Q3	0.057			6.30	52.67	7335	0.92
2022	Q4	0.056	851.2	10.66×10^5	5.11	52.78	5845	0.90
2023	Q1	0.057			4.46	54.38	5193	0.89
2023	Q2	0.063			3.41	61.29	4388	0.87
2023	Q3	0.065			3.32	63.2	4408	0.88
2023	Q4	0.058			3.37	57.12	3993	0.86

Table 4: Terminal imports model results (*λ^I: vessel arrival rate per hour; $E[X]$: first moment of batch size; $E[X^2]$: second moment of batch size; W_c^I: import dwell time in yard in days; μ_c^I: calculated import operating capacity of containers per hour; L_c^I: calculated yard queue length due to import; ρ_c^I: traffic intensity; *: unstable queues in container terminal during COVID-19 period where model predictions are not applicable*).

Year	**Quarter**	λ_c^E	W_c^E	μ_c^E	L_c^E	ρ_c^E
2021*	Q4	60.47	10.40	$\approx$60.48	15093	≈ 1
2022*	Q1	68.66	10.13	$\approx$68.67	16698	≈ 1
2022*	Q2	73.75	10.87	$\approx$73.75	19233	≈ 1
2022*	Q3	76.15	10.55	$\approx$76.15	19281	≈ 1
2022	Q4	70.65	9.73	$\approx$70.65	16498	≈ 1
2023	Q1	75.70	9.05	$\approx$75.70	16442	≈ 1
2023	Q2	72.35	8.08	$\approx$72.35	14029	≈ 1
2023	Q3	80.43	8.11	$\approx$80.43	15647	≈ 1
2023	Q4	73.65	8.56	$\approx$73.66	15130	≈ 1

Table 5: Terminal export model results (λ_c^E: container arrival rate per hour; W_c^E: export dwell time in yard in days; μ_c^E: calculated export operating capacity of containers per hour; L_c^E: calculated yard queue length due to export; ρ_c^E: traffic intensity; *: unstable queues in container terminal during COVID-19 period where model predictions are not applicable).

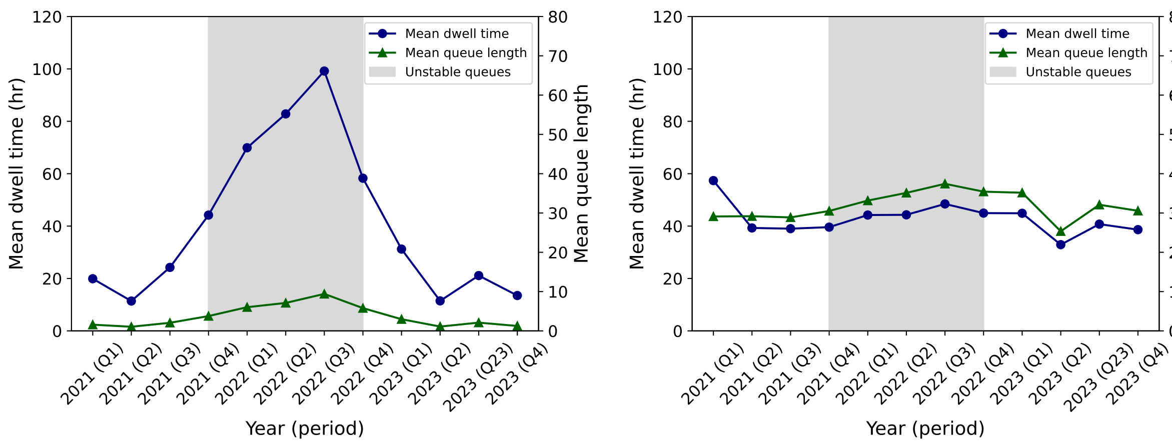
Year	Quarter	Calculated				Observed	Relative error (%)
		L_c^I	L_c^E	L_c	Y_c (%)	Y_c (%)	
2021*	Q4	7262	15093	22356	88.69	53.03	67.23
2022*	Q1	7534	16698	24233	96.13	57.53	67.09
2022*	Q2	6887	19233	26121	103.6	54.83	88.98
2022*	Q3	7335	19281	26617	105.5	87.97	20.03
2022	Q4	5845	16498	22344	88.64	81.80	8.36
2023	Q1	5193	16442	21635	85.83	72.87	17.79
2023	Q2	4388	14029	18418	73.07	73.70	-0.86
2023	Q3	4408	15647	20056	79.56	82.33	-3.37
2023	Q4	3993	15130	19123	75.86	77.57	-2.20

Table 6: Terminal model validation (L_c^I: calculated yard queue length due to import, L_c^E: calculated yard queue length due to export, L_c: calculated total yard queue length; Y_c: yard utilization; *: Unstable queues in container terminal during COVID-19 period where model predictions not applicable).

The terminal model predictions show high errors during the first four quarters of the analysis period, from 2021 Q4 to 2022 Q3. We attribute this error to unstable queues and high container dwell times at the Barbour's Cut container terminal during this period due to the outbreak of COVID-19 pandemic [59, 60]. This period coincides with a peak in container dwell times at the anchorage, as observed in Figure 2(a). As discussed in Section 3, our capacity prediction models are only applicable for long-term periods of stable queue formation. Hence, the results from these periods are likely not valid. The anchorage model, however, made accurate predictions for all the time periods, including that of COVID-19. This could be attributed to the fact that, despite the relatively high dwell times and queue lengths for container vessels, the overall dwell times and queue lengths remained stable, as observed in Figure 2(b). The overall vessel mix of the Houston ship channel comprises about 70% tankers, which did not experience similar congestion levels as a significant cause of congestion in container dwell times was related to truck and chassis availability, issues that did not impact tankers.

Excluding the analysis period from 2021 Q4 to 2022 Q3, the mean (standard deviation) operating capacity for the import process at BCT was 57.8 (4.4) containers per hour, while that for the export process was 74.6 (3.8) containers per hour. The results indicate that the export process had a 29% higher operating capacity than the import processes. It should be noted that the traffic intensity for the import process was approximately 0.88, whereas for the export process it approached 1. This indicates that the export operations are functioning very close to their effective capacity, while the import operations at BCT still retain considerable slack. Consequently, even slight surges in truck arrivals carrying export cargo could lead to significantly increased delays at the BCT terminal. These results are consistent with the observed higher dwell times at BCT, with the export process averaging about nine days compared to about four days for the import process [55].

Similar to the port-level operating capacity, these values represent long-term averages during stable queue formations, accounting for variations due to weekend operations, night hours, and seasonal fluctuations. The maximum capacity that can be sustained over shorter periods can be considerably higher than the operating capacity; however, it is unlikely that such high-capacity conditions can be maintained without causing significant delays.



(a) Container vessels at anchorage

(b) All vessels at anchorage

Figure 2: Mean dwell times and mean queue length at anchorage for Port of Houston as obtained from archival AIS data. The shaded region shows the period where our container terminal model predictions had high relative errors.

5. Conclusion

We propose a queuing theory–based model to estimate operating capacities for multi-modal port processes without relying on data-intensive simulations. An advantage of queuing models is that they allow for modeling the entire port system rather than individual components. Furthermore, they provide a framework to incorporate port performance measures as quality-of-service variables in the capacity model. Unlike existing studies on port capacity, our model emphasizes long-term stable capacity—the throughput that can be sustained over an extended period of stable queue conditions—rather than the absolute maximum throughput a port can achieve under unstable conditions.

The approach requires only information on vessel arrival rates and queuing dynamics under operating conditions, which can be readily obtained from AIS data. Because the model relies on minimal and easily obtainable data, it is extendable to any port that has a structure similar to Figure 1 without the need to develop a detailed simulation. However, the model can predict capacities only under current resource availability, since it relies on real-world quality-of-service measures such as queue lengths and wait times. If a simulation is developed, these quality-of-service parameters could instead be derived from the simulation, allowing the model to predict operating capacity under different alternative scenarios.

The models were tested using archival AIS and port data from the Port of Houston. The results demonstrate that queuing models are effective for estimating the operating capacity of ports under stable conditions. At the port level, the operating capacity of Port of Houston was approximately 0.8 vessels per hour. At the BCT terminal, the operating capacity was found to be 57.8 containers per hour for import processes and 74.6 containers per hour for export processes. Further, the export processes were found to function much closer to capacity than import processes.

Nevertheless, our model has several limitations. First, several assumptions were made regarding the arrival process, service time distributions, and queuing disciplines. Although Poisson arrivals and exponentially distributed service times are common assumptions in queuing theory, several studies indicate that seaports may behave differently in practice. For instance, Legato and Mazza [61] noted that while Poisson processes and exponential service times are widely adopted, they may not accurately capture real-world port operations. Similarly, Demirci [47] observed that Erlang-distributed service times better reflect seaport behavior. In addition, our anchorage model assumes that all vessel classes are treated with equal priority and thus experience the same mean waiting time. This is an assumption that, while simplifying the analysis, may not hold in practice. Extending the capacity estimation techniques presented here to accommodate more general assumptions on arrivals, service distributions, and priority rules remains a promising direction for future research. Further, due to a lack of available data, we could not validate our models in greater detail on the terminal side. These models should be further tested with real data or a simulation to ensure their validity and extensibility. It should be emphasized that the goal of our work is not to propose the most realistic queuing model of port operations, but to demonstrate that queuing theory-based model provide a data-efficient framework for estimating port operating capacity.

Second, queuing theory–based models omit several lower-level details, and much information is inevitably lost through aggregation. Although the presented models can predict port and terminal-level capacities, they do not account for important operational details such as inter-terminal vessel movements or the capacities of individual components. The model is instead based solely on aggregate quality-of-service parameters (such as dwell times and mean queue lengths). While such models have the advantage of requiring less data, this benefit can backfire if the underlying data are erroneous. This issue becomes particularly critical when terminals operate very close to, or effectively at, capacity. Under such conditions, queuing models, like the ones used in this study, become extremely sensitive to input data and small errors may translate into disproportionately large deviations in predicted performance. A promising direction for future work is to examine how uncertainty in input parameters affects capacity estimation, as vessel data are often subject to significant variability and measurement errors.

Acknowledgements

This work was partially funded through U.S. Army Engineer Research and Development Center (ERDC) contract #W912HZ23C0052, "Data-Driven, Multimodal Freight Modeling for Waterways and Ports." The findings of this study reflect the authors' work and are not official policies or standards of the U.S. Army Corps of Engineers. This work was also partially supported by the University Transportation Center (UTC) National Center for Understanding Future Travel Behavior and Demand (TBD).

The authors also thank Mr. Mark A. Cowan of ERDC for his valuable feedback throughout this work.

Author Contributions

The authors confirm their contribution to the paper as follows:
Conceptualization: D.B., K.B., S.B., K.M., M.A., M.K.
Methodology: D.B., K.B.
Data curation: D.B., K.B., M.K.
Formal analysis: D.B., K.B., S.B.
Writing—original draft: D.B., K.B.
Writing—review and editing: D.B., K.B., S.B., K.M., M.A., M.K.
All authors reviewed and approved the final version of the manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used GPT-5 in order to improve writing in select parts of the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

References

[1] UNCTAD, Review of Maritime Transport 2023: Towards a Green and Just Transition, United Nations, Geneva, 2023. URL: https://unctad.org/webflyer/review-maritime-transport-2023.

[2] J. B. Salminen, Measuring the capacity of a port system: a case study on a Southeast Asian Port, Ph.D. thesis, Massachusetts Institute of Technology, 2013.

[3] X. Bellsolà Olba, W. Daamen, T. Vellinga, S. P. Hoogendoorn, Network capacity estimation of vessel traffic: An approach for port planning, Journal of Waterway, Port, Coastal, and Ocean Engineering 143 (2017) 04017019.

[4] B. Lantz, P. Rosén, Measuring effective capacity in an emergency department, Journal of Health Organization and anagement 30 (2016) 73–84.

[5] O. Bittencourt, V. Verter, M. Yalovsky, Hospital capacity management based on the queueing theory, International Journal of Productivity and Performance Management 67 (2018) 224–238.

[6] M. Annas, Humairoh, Developing a sustainable and effective capacity major logistic hubs in indonesia, Asian Journal of Management, Entrepreneurship and Social Science 2 (2022) 245–260.

[7] B. Lantz, P. Rosén, Using queueing models to estimate system capacity, Production Planning & Control 28 (2017) 1037–1046.

[8] M. Vasheghani, M. Abtahi, Strategic planning for multimodal transportation in ports, Maritime Policy & Management 50 (2023) 957–979.

[9] C. Liu, X. Li, Research on carrying capacity of navigable waters based on ship dense arrangement theory, in: Seventh International Conference on Electromechanical Control Technology and Transportation (ICECTT 2022), volume 12302, SPIE, 2022, pp. 1375–1383.

[10] H. S. Fan, J.-M. Cao, Sea space capacity and operation strategy analysis system, Transportation Planning and Technology 24 (2000) 49–63.

[11] C. Liu, J. Liu, X. Zhou, Z. Zhao, C. Wan, Z. Liu, AIS data-driven approach to estimate navigable capacity of busy waterways focusing on ships entering and leaving port, Ocean Engineering 218 (2020) 108215.

[12] I. N. Lagoudis, J. Rice Jr, Revisiting port capacity: A practical method for investment and policy decisions, Proceedings, ECONSHIP, Chios, Greece (2011) 1–13.

[13] A. Tafur, J. E. Padgett, A flow-based commodity-independent port capacity model for resilience assessment of intermodal freight networks subjected to coastal hazards, Reliability Engineering & System Safety (2024) 110280.

[14] S. N. Nicolaou, Berth planning by evaluation of congestion and cost, Journal of the Waterways and Harbors Division 93 (1967) 107–132.

[15] C. Ducruet, H. Itoh, O. Merk, Time Efficiency at World Container Ports, Technical Report 2014-08, OECD, 2014. doi:10.1787/5jrw2z46t56l-en.

[16] U.S. Department of Transportation, 2024 Port Performance Freight Statistics Program: Annual Report to Congress, Technical Report, Bureau of Transportation Statistics, Washington, DC, 2024. https://doi.org/10.21949/1529945, Accessed: 2025-08-28.

[17] L. Chen, J. Mou, H. Ligteringen, Simulation of traffic capacity of inland waterway network, in: IWNTM13: International Workshop on Nautical Traffic Models 2013, Delft University of Technology, Delft, The Netherlands, 2013.

[18] S. Y. Huang, W. J. Hsu, Y. He, Assessing capacity and improving utilization of anchorages, Transportation Research Part E: Logistics and Transportation Review 47 (2011) 216–227.

[19] M. R. O'Halloran, K. Wahren, T. Heise, A dynamic approach to determining waterway capacity, in: Coasts and Ports 2005: Coastal Living-Living Coast; Australasian Conference; Proceedings, Institution of Engineers, Australia Barton, ACT, 2005, pp. 161–166.

[20] P. Canonaco, P. Legato, R. M. Mazza, R. Musmanno, A queuing network model for the management of berth crane operations, Computers & Operations Research 35 (2008) 2432–2446.

[21] B. Dragović, N.-K. Park, N. Đ. Zrnić, R. Meštrović, Mathematical models of multiserver queuing system for dynamic performance evaluation in port, Mathematical Problems in Engineering 2012 (2012) 710834.

[22] P. Legato, R. M. Mazza, et al., Queuing network models in port logistics, in: The 2014 International Conference on Logistics and Maritime Systems, 2014.

[23] S. M. Easa, Approximate queueing models for analyzing harbor terminal operations, Transportation Research Part B: Methodological 21 (1987) 269–286.

[24] D. N. Zrnić, B. M. Dragović, Z. R. Radmilović, Anchorage-ship-berth link as multiple server queuing system, Journal of waterway, port, coastal, and ocean engineering 125 (1999) 232–240.

[25] E. Mrnjavac, Z. Zenzerovic, Modelling of port container terminal using the queuing theory, Trasporti Europei (2000).

[26] M. El-Naggar, Application of queuing theory to the container terminal at alexandria seaport, Journal of Soil Science and Environmental Management 1 (2010) 77–85.

[27] S. Guo, H. Wang, S. Wang, Network disruptions and ripple effects: Queueing model, simulation, and data analysis of port congestion, Journal of Marine Science and Engineering 11 (2023) 1745.

[28] A. S. Souf-Aljen, A. Maimun, R. Rahimuddin, N. Zairie, Port capacity forecasting and the impact of the dredging works on port sea operations using discrete event simulation, Jurnal Teknologi 78 (2016).

[29] U. Bugaric, D. Petrovic, Increasing the capacity of terminal for bulk cargo unloading, Simulation Modelling Practice and Theory 15 (2007) 1366–1381.

[30] G. Chen, K. Govindan, M. M. Golias, Reducing truck emissions at container terminals in a low carbon economy: Proposal of a queueing-based bi-objective model for optimizing truck arrival pattern, Transportation Research Part E: Logistics and Transportation Review 55 (2013) 3–22.

[31] D. Roy, R. de Koster, Stochastic modeling of unloading and loading operations at a container terminal using automated lifting vehicles, European Journal of Operational Research 266 (2018) 895–910.

[32] M. Marsudi, Application of queuing theory in analyzing the use of production capacity, International Journal of Integrated Engineering 2 (2010).

[33] J. Boulton, N. Akhtar, A. Shuaib, P. Bourke, Waiting for a stroke bed: Planning stroke unit capacity using queuing theory, International Journal of Healthcare Management 9 (2016) 4–10.

[34] X.-y. Xu, J. Liu, H.-y. Li, J.-Q. Hu, Analysis of subway station capacity with the use of queueing theory, Transportation research part C: emerging technologies 38 (2014) 28–43.

[35] H. Zhang, Y. Fei, J. Li, B. Li, H. Liu, Method of vertiport capacity assessment based on queuing theory of unmanned aerial vehicles, Sustainability 15 (2022) 709.

[36] E. A. Gale, The hawthorne studies—a fable for our times?, QJM: An International Journal of Medicine 97 (2004) 439–449.

[37] Z. Zenzerović, S. Vilke, Queuing theory in function of planning the capacity of the container terminal in port of rijeka, Pomorstvo 25 (2011) 45–69.

[38] B. K. Lee, L. H. Lee, E. P. Chew, Analysis on container port capacity: A markovian modeling approach, OR spectrum 36 (2014) 425–454.

[39] I. de la Peña-Zarzuelo, M. J. Freire-Seoane, B. López-Bermúdez, New queuing theory applied to port terminals and proposal for practical application in container and bulk terminals, Journal of Waterway, Port, Coastal, and Ocean Engineering 146 (2020) 04019031.

[40] A. Shabayek, W. Yeung, A simulation model for the kwai chung container terminals in hong kong, European Journal of Operational Research 140 (2002) 1–11.

[41] W. Wang, Y. Peng, Q. Tian, X. Song, Key influencing factors on improving the waterway through capacity of coastal ports, Ocean Engineering 137 (2017) 382–393.

[42] G. Chen, Z.-Z. Yang, Methods for estimating vehicle queues at a marine terminal: A computational comparison, International Journal of Applied Mathematics and Computer Science 24 (2014) 611–619.

[43] C.-I. Liu, H. Jula, P. A. Ioannou, Design, simulation, and evaluation of automated container terminals, IEEE Transactions on intelligent transportation systems 3 (2002) 12–26.

[44] X. Zhang, Q. Zeng, Z. Yang, Modeling the mixed storage strategy for quay crane double cycling in container terminals, Transportation Research Part E: Logistics and Transportation Review 94 (2016) 171–187.

[45] J. H. Jones, W. Blunden, Ship turn-around time at the port of bangkok, Journal of the Waterways and Harbors Division 94 (1968) 135–148.

[46] P. Schonfeld, S. Frank, Optimizing the use of a containership berth, Transportation Research Record 984 (1984) 56–62.

[47] E. Demirci, Simulation modelling and analysis of a port investment, Simulation 79 (2003) 94–105.

[48] C. Ancker Jr, A. Gafarian, Queuing with multiple poisson inputs and exponential service times, Operations Research 9 (1961) 321–327.

[49] T. E. Moore, Queuing of multiple Poisson inputs to a single channel with Erlang service, Master's thesis, Oklahoma State University, 1963.

[50] J. D. Little, S. C. Graves, Little's law, in: Building intuition: insights from basic operations management models and principles, Springer, 2008, pp. 81–100.

[51] N. Gautam, Analysis of queues, CRC Press, LLC, Boca Raton, Florida, United States 10 (2012) 2222496.

[52] P. J. Burke, The output process of a stationary m/m/s queueing system, The Annals of Mathematical Statistics 39 (1968) 1144–1152.

[53] Martin Associates, 2022 economic impact of houston ship channel activity, 2023. `https://porthouston.com/wp-content/uploads/2023/05/2022-Economic-Impact-Report_Final.pdf`, Accessed: 2025-08-28.

[54] BOEM, NOAA, and USCG, AccessAIS, n.d. `https://marinecadastre.gov/accessais/`, Accessed: 2024-07-21.

[55] Port Houston, Container terminals status updates, 2024. `https://porthouston.com/toolbox/container-terminals/schedules-arrivals/status-updates/`, Accessed: 2025-08-28.

[56] Port Houston, BCT vessel services description, 2024. `https://porthouston.com/wp-content/uploads/2024/06/BCT-Vessel-Services-Description.pdf`, Accessed: 2025-08-28.

[57] Port Houston, Lynx portal, n.d. `https://csp.porthouston.com/lynx/`, Accessed: 2025-08-28.

[58] N. Huynh, N. Hutson, Mining the sources of delay for dray trucks at container terminals, Transportation Research Record 2066 (2008) 41–49.

[59] P. Tirschwell, Container shipping supply chains will remain disrupted well into 2022, S&P Global (2022). https://www.spglobal.com/marketintelligence/en/news-insights/research/container-shipping-supply-chains-will-remain-disrupted-well-into-2022, Accessed: 2025-08-28.

[60] G. Miller, New year brings new all-time high for shipping's epic traffic jam, Freightwaves (2022). https://www.freightwaves.com/news/new-year-brings-new-all-time-high-for-shippings-epic-traffic-jam, Accessed: 2025-08-28.

[61] P. Legato, R. M. Mazza, Queueing analysis for operations modeling in port logistics, Maritime Business Review 5 (2020) 67–83.