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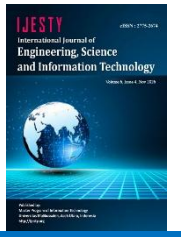

Integrated Queueing Analysis of Ship and Freight-Forwarding Truck Services at Nabire Port

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Abstract

Nabire Port is the main logistics node of Central Papua Province, yet its service performance has rarely been examined from a queueing perspective using operational data recorded at the level of individual arrivals. This study analyses ship services and freight-forwarding truck services at Nabire Port as two separately observed subsystems and combines their subsystem-level results into a constructed logistics-time indicator, not a verified tandem queue. The novelty of the study lies in its empirical comparison of classical queueing benchmarks with observed timestamps in a multi-cargo regional port, together with an explicit assessment of when those benchmarks are and are not applicable. Primary data comprising 60 ship arrivals (July-September 2026) and 60 forwarding-truck arrivals (July 2026) were analysed using M/M/1 and M/M/c models. Distributional assumptions were tested using the Kolmogorov-Smirnov test, and theoretical results were compared with observed waiting times and, for the single-server case, the Kingman approximation. The ship system was stable, with a utilisation of 0.391, a theoretical waiting time of 9.15 hours, and a time in system of 23.40 hours, whereas the observed mean waiting time was 1.33 hours. The single-server truck model gave a utilisation of 0.907 and a theoretical waiting time of 26.34 hours, far above the observed mean of 0.49 hours, because up to three trucks were served simultaneously. In the M/M/c scenario with two service channels, the theoretical truck waiting time fell to 0.70 hours and the combined ship-truck indicator to 26.81 hours, compared with 52.45 hours with one channel. The Kolmogorov-Smirnov tests rejected the exponential assumptions for all inter-arrival and service times; therefore, the M/M results are interpreted as theoretical baselines and model-based scenario indications, not as validated predictions or as an economically optimal capacity, since no cost data were analysed.

Keywords: *Queueing Theory, Port Logistics, Freight Forwarding, M/M/c Queue, Logistics Efficiency.*

1. Introduction

Central Papua has geographical conditions that make the flow of goods and passengers highly dependent on sea and air transportation. In terms of sea transportation, Statistics Indonesia (BPS) reports that sea freight activity in Central Papua Province is served by three main ports, namely Pomako and Amamapare Ports in Mimika Regency and Nabire Port in Nabire Regency. In February 2025, the number of passengers departing by domestic sea transport was 8,160, down 40.30% from 13,668 in January 2025, while arriving passengers totaled 7,214, down 52.57%. For goods, the loaded volume reached 66,854 tons, an increase of 144.26%, while the unloaded volume reached 183,121 tons, an increase of 27.53% compared with the previous month [1]. These conditions show that sea transport activity in Central Papua is quite dynamic, particularly in the flow of goods, which is an important part of interregional distribution.

Nabire Port occupies an important position in this sea transport activity. During January-February 2025, Nabire Port served 15,902 departing passengers and 15,770 arriving passengers, accounting for about 72.9% and 70.3% of the total sea transport of Central Papua Province, respectively. In the same period, the volume of goods loaded reached 58,367 tons, or about 61.9% of the province's total cargo loaded, while the volume of goods unloaded reached 123,285 tons [1]. Table 1 further illustrates substantial monthly fluctuations in port activity. The volume of goods loaded at Nabire Port increased by 478.29%, from 8,605 tons in January to 49,762 tons in February 2025. Conversely, the numbers of departing and arriving passengers decreased by 39.50% and 46.67%, respectively. These variations suggest that port operations must accommodate changing service demands, particularly in cargo handling and subsequent distribution.

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Table 1. Domestic Sea Transport Indicators at Nabire Port, January-February 2025

Indicator	January 2025	February 2025	Change (%)	January-February 2024	January-February 2025	Change (%)
Passengers departing (persons)	9.908	5.994	-39,50	15.422	15.902	3,11
Passengers arriving (persons)	10.285	5.485	-46,67	14.932	15.770	5,61
Goods loaded (tons)	8.605	49.762	478,29	13.037	58.367	347,70
Goods unloaded (tons)	45.342	77.943	71,90	92.118	123.285	33,83

Source: [1]

The distribution of goods at a port does not end when a vessel arrives or cargo handling is completed. Unloaded goods must subsequently be transferred to land transport for delivery to their next destinations. Freight-forwarding services therefore play an important role in connecting maritime cargo flows with inland distribution activities. Their operational efficiency depends not only on the time required for ships to receive services and complete cargo handling but also on the ability of land-side facilities to accommodate forwarding trucks. Delays at either stage may extend the time required for cargo handling and onward distribution. Accordingly, evaluating freight-forwarding logistics requires attention to both maritime and land-side service performance.

From an operational perspective, queues can arise when the demand for service exceeds the available capacity or when arrival and service patterns create temporary congestion. On the sea side, vessel waiting may be influenced by berth availability, service capacity, and cargo-handling duration. On the land side, forwarding trucks may experience delays when vehicle arrivals are not adequately matched with the capacity of the available service facilities. These queues can affect facility utilization, waiting time, and the time objects spend in the service system. Understanding such operational characteristics is therefore necessary to identify potential capacity constraints and evaluate feasible improvements in port logistics.

However, official statistical publications on Nabire Port generally report monthly aggregates, such as passenger numbers and cargo volumes [1]. Although these indicators describe the scale of port activity, they do not provide sufficient detail to characterize operational performance at the level of individual arrivals and services. Information such as inter-arrival times, service durations, the number of parallel service facilities, and observed waiting times is needed to estimate queueing performance and assess the adequacy of existing service capacity. An analytical approach based on arrival and service characteristics is consequently required to complement aggregate port statistics.

Queueing theory provides a framework for analyzing the relationship between arrival processes, service rates, and system performance. Its principal measures include the arrival rate (λ), service rate (μ), utilization (ρ), the average number of objects in the queue (L_q), the average waiting time in the queue (W_q), the average number of objects in the system (L_s), and the average time in the system (W_s) [2]. The M/M/1 model represents a queueing system with a single server, whereas the M/M/c model represents a system with multiple parallel servers [3]. These models can be used to estimate baseline performance and examine how changes in service capacity may influence waiting times. Nevertheless, the reliability of their estimates depends on whether the observed arrival and service processes adequately satisfy the assumptions underlying each model.

Recent international research has examined port operational efficiency through several complementary approaches. In the area of vessel operations, Li et al., reviewed berth allocation and scheduling research, highlighting the range of operational constraints and methodological approaches used to coordinate vessel services [4]. On the land side, Carboni et al., developed a simulation-based approach to assess vehicle traffic and operational performance in container terminals [5]. Their analysis considered interactions between external trucks and internal terminal vehicles and evaluated alternative operating configurations. Baldouski et al., formulated an optimization approach for truck arrival scheduling and routing, addressing congestion both outside port gates and along internal terminal routes [6]. Furthermore, Gracia et al., reviewed truck appointment scheduling models and algorithms, including deterministic, stochastic, and hybrid approaches for coordinating truck arrivals and terminal capacity [7]. Sun et al., examined data-driven and intelligent decision-making methods for improving truck appointment systems, particularly in relation to appointment quotas and the management of trucks arriving outside their scheduled times [8].

These studies demonstrate that port congestion and service efficiency can be investigated through vessel scheduling, vehicle traffic simulation, truck routing, and appointment optimization. However, the reviewed studies primarily emphasize container-terminal operations, resource coordination, or the optimization of vehicle arrivals. Their analytical objectives differ from the present study, which focuses on estimating queueing performance from observed ship and freight-forwarding truck arrivals, evaluating the fit of classical queueing assumptions, and comparing theoretical waiting-time estimates with operational observations. In addition, the operational setting of Nabire Port requires attention to freight-forwarding activities in a multi-cargo environment rather than assuming that all port operations follow the configuration of a large container terminal. The distinction is relevant because service arrangements, cargo-handling processes, and vehicle movements may differ across port types.

A further methodological issue concerns the suitability of classical queueing models for actual port operations. The M/M/1 and M/M/c models assume Poisson arrivals and exponentially distributed service times. If the observed data depart from these assumptions, model-based performance estimates may not adequately represent actual operating conditions. This study therefore examines the distributional characteristics of arrival and service data and compares theoretical waiting-time estimates with observed waiting times. The Kingman approximation is also considered as a benchmark for assessing waiting-time behavior under more general arrival and service-time variability. Because the Kingman approximation is formulated for a single-server G/G/1 system, its use in comparisons involving a multi-server system must be justified by the corresponding analytical formulation and assumptions. This validation-oriented approach is intended to clarify both the operational insights provided by the queueing models and the limitations of their application to observed port data.

The contribution of this study lies in an empirical assessment of queueing performance and model applicability across two operational subsystems relevant to freight-forwarding logistics at Nabire Port: ship services on the sea side and forwarding-truck services on the land side. Rather than proposing a new general queueing methodology, the study combines the estimation of subsystem performance measures, the examination of distributional assumptions, the comparison of theoretical and observed waiting times, and the evaluation of alternative truck-service capacity configurations. This approach provides a context-specific basis for identifying potential service-capacity constraints and assessing operational improvement scenarios. The integration of the two subsystems is analytical: because the ship and truck arrival

data are collected separately, the combined logistics-time indicator is interpreted as a measure derived from the two subsystem analyses rather than as a directly observed end-to-end cargo transit time, unless a traceable operational relationship between ship cargo availability and truck arrivals can be established.

Against this background, this study examines ship and freight-forwarding truck queues as two related but separately analyzed service subsystems to assess their respective waiting-time performance and explore the implications of alternative truck-service capacities for logistics efficiency at Nabire Port. By combining field observations with queueing-theory benchmarks, the study evaluates the applicability of conventional queueing models to the observed operating conditions and compares theoretical truck-service capacity scenarios. The analysis is intended to provide an empirical description of the two service subsystems and a preliminary assessment of alternative service capacities, rather than to establish a fully integrated tandem queueing model.

Based on the above, this study aims to: (1) estimate queueing performance measures, including λ, μ, ρ, Lq, Wq, Ls, and Ws, for the ship and freight-forwarding truck subsystems at Nabire Port; (2) examine the suitability of Poisson arrival and exponential service-time assumptions and compare theoretical waiting-time estimates with observed waiting times, using the Kingman approximation for the single-server analysis; (3) evaluate alternative numbers of truck-service channels in terms of their implications for theoretical queueing performance; and (4) assess the implications of the separate ship and truck subsystem analyses for freight-forwarding logistics efficiency at Nabire Port, while acknowledging the limitations of the available data for establishing an integrated tandem queueing system.

2. Literature Review

2.1. Queueing Theory

Queueing theory is the discipline that studies the behavior of queues or waiting lines [9]. Queueing theory is a branch of operations research that studies systems in which entities (such as customers, jobs, or data packets) wait to be served. A queueing system consists of an input source, a queue, a service facility, and an output. Queueing analysis helps in designing and optimizing service systems to minimize waiting time, queue length, and operational costs [10]. A queue is a waiting line of a number of customers who require service from one or more service facilities. The queueing process is one that involves the arrival of customers at a service facility, waiting in the queue if they cannot yet be served, being served, and finally leaving the facility after being served [11].

Queueing theory is a branch of operations research that analyzes service systems in order to determine system performance measures. In general, a queueing system consists of three main components. First, the arrival process, which describes how customers arrive at the system and is usually modeled with a Poisson distribution. Second, the service process, which shows the time required to serve customers and generally follows an exponential distribution. Third, the queue discipline, i.e., the rule that determines the order of service [12]. Queueing theory is the systematic study of the process of waiting in queues. Queueing situations occur when demand for a service exceeds the service capacity available at a given time, or when service units are busy when new entities arrive. Queueing theory provides an analytical framework for understanding and predicting the behavior of queueing systems, including the average queue length, the average waiting time, and server utilization [13].

2.2. Transportation and Logistics Theory

Transportation is the activity of moving people and goods from one location to another and is essentially a derived demand; the need for transportation arises from the economic need to obtain, produce, and consume goods in different places. In the distribution chain, the port functions as a node where sea and land modes meet. Therefore, distribution performance is determined not only by the speed of the carrying modes but also by time lost at the node, namely waiting time for berthing, cargo handling, document inspection, and transfer to the next mode [14].

Logistics constitutes an integrated operational system responsible for planning, implementing, and controlling the flow of materials, products, services, and information throughout the supply chain to achieve cost efficiency and customer service objectives simultaneously [15]. In this context, distribution efficiency can be assessed through several indicators, including travel time and waiting time (lead time), schedule reliability, facility utilization, and cost per unit of goods [16]. These indicators are particularly relevant to freight-forwarding services, which act as intermediaries in consolidating, transporting, and delivering goods from ports to final recipients. The performance of freight-forwarding operations is closely linked to the efficiency of port and land-side facilities, as delays at the quay or during land-side services can increase overall lead time and disrupt subsequent distribution activities [17].

In a multimodal transportation system, the movement of goods involves more than one mode connected in a distribution chain [18]. The port becomes a transfer point linking sea transportation with land transportation. Therefore, system efficiency is determined not only by the performance of each mode individually but also by the smoothness of goods transfers between modes. The time spent waiting for service or moving from one facility to another is part of the logistics time that must be accounted for when assessing overall system performance [18].

2.3. System Integration and Scheduling

System integration means viewing interdependent subsystems as a single whole whose performance is measured comprehensively. At a port, the output of the quay subsystem (goods that have finished unloading) becomes the input of the next subsystem (truck service), so that the two form a network of queues in series (tandem queues). For a series network with Poisson arrivals and exponential service, Burke's theorem states that the departure process of a stable M/M/c queue is also a Poisson process [19]. Thus each stage can be analyzed separately, and the total time in the system is obtained by summing the time at each stage [20]. The relationship between the number of units and waiting time is described by Little's law, $L = \lambda W$, which holds for stable systems without requiring a particular distribution [21].

On the scheduling side, the container terminal literature integrates berth allocation, quay crane assignment and scheduling, and internal transport [22], [23], [24]. The joint scheduling of quay cranes and trucks is modeled as a single decision problem [25], [26]. When the Poisson-exponential assumptions are not met, queueing performance measures can be approximated using Kingsman formula for G/G/1 systems, which incorporates the coefficients of variation of arrivals and service [27].

2.4. Sourcing and Performance

Logistics management is the process of planning, implementing, and controlling the flow of goods, services, and information from the point of origin to the point of consumption in order to meet customer needs effectively and efficiently [28]. Logistics activities cover a

range of processes, from procurement, storage, and transportation to material handling and distribution [29]. Logistics effectiveness relates to the system's ability to meet customer needs appropriately, whereas efficiency relates to the optimal use of resources in carrying out those processes. Logistics management is oriented not only toward the smooth movement of goods but also toward achieving balanced operational performance between service quality and resource use [30].

A supply chain encompasses all parties involved, directly or indirectly, in fulfilling customer demand, including suppliers, manufacturers, logistics service providers, distributors, retailers, and end customers. Each party in the supply chain is interdependent through flows of material, information, and resources. The performance of one part of the supply chain can affect the performance of the others, so coordination and integration among parties is an important aspect of achieving overall supply chain performance. Disruptions or delays at one stage can cause knock-on effects on subsequent processes, especially when service capacity is not balanced with the level of demand [31].

Supply chain performance essentially reflects the system's ability to achieve the expected level of service with efficient use of resources. One important aspect of performance assessment is the balance between responsiveness and cost efficiency [32], [33]. Responsiveness relates to the supply chain's ability to respond quickly to demand and changing needs, whereas efficiency emphasizes optimal use of resources and costs. This balance can be seen through various measures, such as waiting time, cycle time, service punctuality, facility utilization, service capacity, and operational costs. Queueing theory provides a quantitative approach to understanding the relationship between service capacity and waiting time. As facility utilization approaches maximum capacity, waiting time tends to increase nonlinearly. Conversely, excessive capacity can reduce waiting time but may cause resources to be underutilized [34].

Sourcing is a strategic activity in supply chain management concerned with obtaining goods or services from external parties able to meet an organization's needs. Sourcing decisions consider not only price or rates but also various aspects of provider performance, such as quality, reliability, capacity, timeliness, flexibility, and the ability to meet requirements consistently. Therefore, operational performance measures such as waiting time and service reliability can be considered in evaluating service providers in addition to cost. Selecting providers by considering multiple performance dimensions enables an organization to obtain a balance among cost, service quality, and responsiveness in the supply chain.

3. Methods

3.1. Research Design and Study Setting

This study employed a quantitative descriptive-analytical design to examine the performance of ship and freight-forwarding truck queues at Nabire Port, Central Papua, Indonesia. Queueing theory was used to characterize the two service subsystems, evaluate waiting-time performance, and compare alternative service-capacity scenarios. The ship and truck queues were analyzed separately because the available observations did not establish a direct shipment-level link between the completion of ship services and the arrival of the corresponding forwarding trucks.

The ship subsystem was modeled using an M/M/1 queue as a theoretical benchmark because no more than one ship was observed receiving service at a time during the observation period. For the truck subsystem, an M/M/1 model was used as a single-server reference scenario, while M/M/c models were used to examine the implications of alternative numbers of parallel service channels. Truck service facilities were shared across truck types, and service times for different truck types were pooled to estimate a common service rate for the aggregate truck subsystem. The observed possibility of serving multiple trucks simultaneously was considered when interpreting the capacity scenarios.

Because the observed inter-arrival and service-time distributions did not satisfy the exponential assumptions required by conventional M/M/1 and M/M/c models, the resulting theoretical estimates were treated as analytical benchmarks rather than validated predictions of actual port performance. The Kingman approximation was applied only to the single-server analysis, for which its assumptions and interpretation are more appropriate.

3.2. Data Collecting and Sampling

The study used primary observational data collected at Nabire Port. The ship dataset comprised 60 ship arrivals recorded from 3 July to 30 September 2026, including 21 cargo ships, 14 container ships, 11 fuel tankers, 9 pioneer ships, and 5 passenger ships. The truck dataset comprised 60 forwarding-truck arrivals recorded from 1 to 8 July 2026, including 16 Wingbox trucks, 19 CDD Box trucks, 10 Fuso trucks, 8 Tronton trucks, and 7 Engkel trucks.

Sampling followed a census of all eligible observations recorded within each respective observation period. Thus, all eligible ship and truck records available during the defined periods were included rather than selecting a subset from those records. This approach describes the observed operational activity within the specified windows; it does not imply that every ship or truck operating at Nabire Port throughout the year was observed.

Three timestamps were recorded for each observation: arrival time, service-start time, and service-completion time. These timestamps were used to derive inter-arrival time, service time, and actual waiting time. Inter-arrival time was calculated as the elapsed time between consecutive arrivals within the same subsystem. Service time was calculated as the interval between the start and completion of service, while actual waiting time was calculated as the interval between arrival and service start.

The ship and truck datasets covered different observation periods. Consequently, their estimates describe different temporal windows and should not be interpreted as directly synchronized measurements of a single logistics process. The analysis used the official port statistics from Statistics Indonesia for contextual information, while the queueing calculations were based on the primary observational records.

3.3. Queueing Model Formulation

The principal queueing parameters were the arrival rate (λ), the service rate per server (μ), the number of parallel servers (c), and server utilization (ρ). The arrival rate was estimated as the number of observed arrivals divided by the corresponding observation duration. The service rate was estimated as the reciprocal of the mean service time. Time units were kept consistent within each subsystem

The M/M/1 and M/M/c models were used as theoretical benchmarks for evaluating queueing performance under specified assumptions. These models assume Poisson arrivals, exponentially distributed service times, a first-come, first-served (FCFS) discipline, and an unlimited calling population and queue capacity. The M/M/1 model represents a single-server system, whereas the M/M/c model represents (c) identical servers operating in parallel.

For the ship subsystem, the M/M/1 model was used as a benchmark. Its utilization was calculated as:

$$\rho = \frac{\lambda}{\mu} \quad (1)$$

For the truck subsystem, the M/M/c model was used to evaluate alternative parallel-server capacities. Utilization was calculated as:

$$\rho = \frac{\lambda}{(c\mu)} \quad (2)$$

For a stable M/M/c system, the probability that no customer is in the system (P_0) was calculated as:

$$P_0 = [\sum_{n=0}^{c-1} \frac{(\frac{\lambda}{\mu})^n}{n!} + \frac{(\frac{\lambda}{\mu})^c}{c!}(\frac{1}{1-\rho})]^{-1} \quad (3)$$

The expected queue length (L_q) was calculated as:

$$L_q = \frac{P_0(\frac{\lambda}{\mu})^c \rho}{c!(1-\rho)^2} \quad (4)$$

The theoretical mean waiting time in the queue (W_q) and the theoretical mean time in the system (W_s) were calculated as:

$$W_q = \frac{L_q}{\lambda} \quad (5)$$

$$W_s = W_q + \frac{1}{\mu} \quad (6)$$

The expected number of customers in the system (L_s) was calculated using Little's law:

$$L_s = \lambda W_s \quad (7)$$

Here, (W_q) refers to waiting time before service begins, whereas (W_s) includes both waiting and service time. The terms theoretical and model-based are used to distinguish these estimates from the waiting and service times calculated directly from the observed timestamps.

For the truck subsystem, service times across Wingbox, CDD Box, Fuso, Tronton, and Engkel trucks were pooled to estimate an aggregate service rate. This pooling reflected the shared-service arrangement and allowed the overall truck queue to be analyzed as one aggregate subsystem. However, it assumes that a common service rate is an adequate approximation despite potential differences in service requirements among truck types. Therefore, the resulting estimates represent average aggregate performance and may not capture truck-type-specific service patterns.

3.4. Distributional Testing and Model Assessment

The inter-arrival-time and service-time observations for the ship and truck subsystems were examined using the Kolmogorov–Smirnov (K–S) goodness-of-fit test to assess consistency with an exponential distribution. The significance level was set at (α=0.05). The tests indicated statistically significant departures from the exponential distribution for the examined datasets ($p < 0.001$). Therefore, the exponential-distribution assumptions underlying the M/M/1 and M/M/c models were not supported by the observed data.

Accordingly, the M/M/1 and M/M/c results were interpreted as theoretical benchmarks for comparing queue structures and service-capacity scenarios, rather than as empirically validated estimates of actual waiting times. Since distribution parameters were estimated from the observations, the interpretation of K–S significance levels also depends on the goodness-of-fit procedure used; conventional K–S critical values do not directly account for parameters fitted from the same sample. Where applicable, a parameter-adjusted procedure, such as the Lilliefors correction or a parametric bootstrap, should be used to obtain appropriate significance levels.

The theoretical estimates were compared with the observed waiting times to identify differences between model-based and recorded performance. Such differences were interpreted in light of the rejected distributional assumptions and the observed operating conditions, including parallel truck service. They were not interpreted as evidence that the queueing calculations precisely reproduced actual port operations.

The Kingman approximation was applied only to the single-server analysis as an additional approximation that accounts for variability in arrivals and service times. The mean waiting time in the queue was estimated as:

$$W_q = \frac{c_a^2 + c_s^2}{2}(\frac{\rho}{1-\rho})\frac{1}{\mu} \quad (8)$$

where (c_α) and (c_s) denote the coefficients of variation of inter-arrival times and service times, respectively, and ($\rho=\lambda/\mu$) for a single-server system. This approximation was used to assess how observed variability could affect waiting-time estimates beyond the exponential assumptions of the M/M/1 model. It was not applied directly to the multi-server truck scenarios, because the standard Kingman expression above is a single-server approximation.

3.5. Truck Service-Capacity Scenarios and Analytical Integration

The truck subsystem was evaluated under alternative parallel-server scenarios using M/M/c models. The number of servers was varied to examine how theoretical queue performance changes as service capacity increases, with the single-server case serving as a reference and additional cases representing greater parallel capacity. These scenarios were used for comparative capacity analysis rather than as definitive operational forecasts, given the rejection of the exponential-distribution assumptions.

The shared truck-service arrangement was considered when interpreting these scenarios. The number of servers in a scenario represents the assumed number of simultaneously available service channels, not necessarily a verified count of permanent, independent facilities. The observation that multiple trucks could receive service concurrently supports examining parallel capacity, but a capacity recommendation should also account for the actual operating configuration and the variability of service times.

To summarize the two subsystems in a common analytical indicator, the mean time in the ship system and the mean time in the truck system may be added as follows:

$$W_{combined} = W_{s,ship} + W_{s,truck} \quad (9)$$

This quantity is defined as a constructed analytical indicator representing the sum of two subsystem-level mean times. It is not an observed end-to-end logistics duration because the ship and truck observations were collected over different periods and were not linked at the shipment or cargo level. The indicator therefore cannot establish the actual time elapsed from a particular ship's arrival or service

completion to the completion of the corresponding truck service. It is used only for cautious subsystem-level comparison, not as a direct measurement of integrated cargo flow.

3.6. Methodological Scope and Limitations

The analysis was subject to three principal limitations. First, the ship and truck datasets covered different observation periods, limiting direct temporal comparability. Second, the rejection of exponential-distribution assumptions means that conventional M/M/1 and M/M/c estimates cannot be treated as validated representations of actual operations. Third, pooling truck service times simplifies the analysis but may obscure differences between truck types.

The findings are therefore intended to describe observed queue conditions, assess the implications of alternative theoretical service capacities, and identify areas for further operational evaluation. More precise prediction of port performance would require longer, synchronized observations, assessment of service-time heterogeneity, and, where appropriate, a general-service queueing model or discrete-event simulation calibrated against observed operations.

4. Result and Discussion

4.1. Data Characteristics

Ships had a mean inter-arrival time of 36.40 hours, equivalent to an arrival rate of about 0.66 ships per day, with intervals lying entirely within the range of 24.25-48.50 hours. The mean service time was 14.24 hours. By type, passenger ships were served fastest (mean 3.70 hours), followed by pioneer ships (6.94 hours), whereas container ships, cargo ships, and tankers required 16.11-17.55 hours. Trucks arrived on average every 2.99 hours (about 8.0 trucks per day) and were served in 2.71 hours on average. Wingbox trucks took the longest (4.51 hours), while Engkel trucks were the fastest (1.21 hours). The summary statistics are presented in Table 2.

Table 2. Descriptive Statistics of Ship and Forwarding Truck Data

Parameter	Ship	Truck
Number of units (n)/number of inter-arrival times	60/59	60/59
Arrival period	3 July-30 September 2026	1-8 July 2026
Mean inter-arrival time (hours)	36.40	2.99
Standard deviation of inter-arrival time (hours)	7.90	0.99
Minimum-maximum inter-arrival time (hours)	24.25-48.50	1.12-4.50
Mean service time (hours)	14.24	2.71
Standard deviation of service time (hours)	6.27	1.34
Minimum-maximum service time (hours)	2.50-24.50	1.02-5.32
Coefficient of variation of inter-arrival time (c_a)	0.22	0.33
Coefficient of variation of service time (c_s)	0.44	0.49

4.2. Performance of the Ship and Truck Queueing Systems

Table 3 presents the M/M/1 model results calculated from the observed arrival and service rates. The ship subsystem is stable with a utilization of $\rho = 0.3913$: the quay is empty 60.9% of the time, the average number of ships in the queue is 0.2515, the theoretical waiting time is 9.154 hours (549.2 minutes), and the time in the system is 23.396 hours. Based on the theoretical M/M/1 model, the truck subsystem with one service facility has a utilization of $\rho = 0.9066$, only 9.3% below the stability limit. At such a high utilization, the system is empty only 9.3% of the time, an average of 8.80 trucks are queueing, and the theoretical waiting time reaches 26.34 hours (≈ 1,580 minutes), so the time in the system is 29.05 hours. Theoretically, the truck subsystem is much more vulnerable to capacity disruptions than the ship subsystem. These results are theoretical estimates based on the M/M/1 assumptions and must next be validated against the distributional characteristics of the data and the actual waiting times.

Table 3. /M/1 Queueing Model Results for the Ship and Truck Subsystems

Performance Measure	Ship	Truck
Arrival rate λ (units/hour)	0.02747	0.33409
Service rate μ (units/hour)	0.07022	0.36851
Number of facilities (c)	1	1
Utilization ρ	0.3913	0.9066
P_0 (empty system)	0.6087	0.0934
L_q (units in queue)	0.2515	8.7984
W_q (hours)	9.154	26.336
W_q (minutes)	549.2	1,580.1
L_s (units in system)	0.6428	9.7050
W_s (hours)	23.396	29.049
W_s (minutes)	1,403.7	1,743.0

4.3. Distribution Assumption Tests and Model Validation

The Kolmogorov-Smirnov (K-S) test shows that the inter-arrival time and service time data differ significantly from the exponential distribution ($p < 0.001$). Thus, the assumption of exponentially distributed inter-arrival and service times in the M/M/1 model is not met. Figure 2 shows why: ship inter-arrival intervals all lie between 24.25 and 48.50 hours, without the proportion of short intervals generally expected under an exponential distribution. This pattern indicates arrivals that follow a sailing schedule rather than random arrivals. The coefficients of variation of ship (0.22) and truck (0.33) intervals are far below 1, the value for an exponential distribution.

Table 4. Kolmogorov-Smirnov Test Results against the Exponential Distribution

Variable	n	D	p-value	Decision (α = 0.05)
Ship: inter-arrival time	59	0.486	2.2×10^{-13}	Reject H0
Ship: service time	60	0.272	2.1×10^{-4}	Reject H0
Truck: inter-arrival time	59	0.339	1.5×10^{-6}	Reject H0
Truck: service time	60	0.312	1.1×10^{-5}	Reject H0

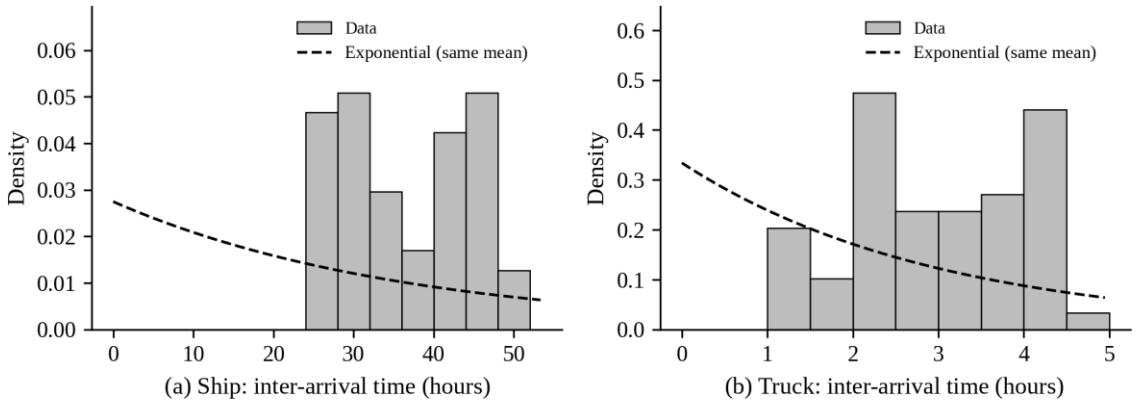

Fig 1. Histogram of inter-arrival times of (a) ships and (b) trucks compared with an exponential distribution having the same mean

Table 5 compares the theoretical waiting time with actual data. For ships, M/M/1 gives Wq = 9.15 hours, whereas the actual average waiting time is only 1.33 hours (maximum 2.75 hours), and 7 of the 60 ships were served immediately. The Kingman approximation, which accounts for arrival and service variation smaller than exponential, gives 1.10 hours, much closer to the actual value. The Kingman approximation is used as a G/G/1 approximation because it allows inter-arrival and service times that need not be exponential. Thus, M/M/1 overestimates ship waiting time by about 6.9 times. The actual time ships spend in the system (15.57 hours) is also largely (91%) the cargo handling process itself, not waiting.

For trucks, the mismatch is more fundamental. M/M/1 predicts Wq = 26.34 hours, yet no truck waited more than 0.80 hours (mean 0.49 hours). Sweeping across service times shows that up to 3 trucks were served simultaneously, so truck service actually takes place on several parallel lanes, not one. The actual value lies between the predictions of M/M/2 (0.70 hours) and M/M/3 (0.09 hours). The Kingman approximation with c = 1 still yields 4.66 hours, which confirms that reduced variability alone does not explain the gap; the cause is the number of service lanes.

Table 5. Validation of Waiting Time in the Queue (W_q) against Actual Data

Subsystem	Model/Measure	W_q (hours)	Remarks
Ship	M/M/1 (Excel)	9.15	Overestimates the actual value
Ship	G/G/1 (Kingman)	1.10	$c_a = 0.22$; $c_s = 0.44$
Ship	Actual (mean)	1.33	Maximum 2.75 hours; max. 1 ship simultaneously
Truck	M/M/1 (c = 1)	26.34	Does not match the data
Truck	G/G/1 (Kingman, c = 1)	4.66	Still too high
Truck	M/M/2	0.70	Close to the actual value
Truck	M/M/3	0.09	Below the actual value
Truck	Actual (mean)	0.49	Maximum 0.80 hours; max. 3 trucks simultaneously

4.4. Service Facility Scenarios and Integrated Indicator

Table 6 and Figure 3 show the theoretical effect of the number of truck service channels. Two different quantities must be distinguished. Utilisation per channel (ρ) falls from 0.907 with one channel to 0.453 with two channels, whereas the probability that an arriving truck must wait (the Erlang-C probability) falls from 90.7% to 28.3%. For c = 1 the two values coincide numerically (0.907 and 90.7%) because in an M/M/1 queue the probability of waiting equals the utilisation; for $c \geq 2$ they diverge. The theoretical truck time in the system falls from 29.05 hours to 3.42 hours (down 88.2%). Adding a third channel reduces the theoretical Wq from 42.1 minutes to 5.5 minutes, but utilisation per channel falls to 0.302, so most of the service capacity would be idle. Adding a fourth channel reduces $W_{combined}$ by only 0.08 hours, or about 4.8 minutes.

Table 6. Truck Service Facility Number Scenarios and Integrated Logistics Time Indicator (Ship M/M/1)

c	ρ	Probability of Waiting	L_q	W_q (minutes)	$W_{s,t}$ (hours)	W_{total} (hours)
1	0.907	90.7%	8.798	1,580.1	29.05	52.45
2	0.453	28.3%	0.234	42.1	3.42	26.81
3	0.302	7.1%	0.031	5.5	2.81	26.20
4	0.227	1.5%	0.004	0.8	2.73	26.12

Notes:

$W_{combined} = W_{s,ship} + W_{s,truck}$ with $W_{s,ship} = 23.40$ hours (ship M/M/1). The theoretical value of $W_{s,ship}$ overestimates the actual ship time (15.57 hours), so $W_{combined}$ is conservative as a theoretical benchmark

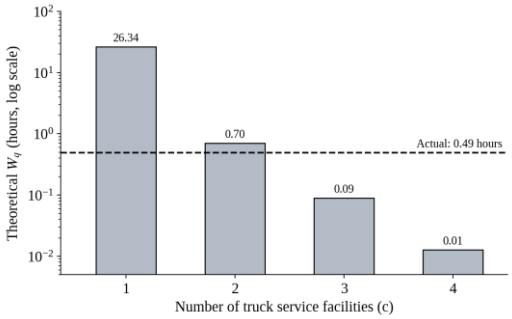

Fig 2. Theoretical truck waiting time W_q by number of service facilities (M/M/c) compared with the mean actual waiting time

In the combined indicator, $W_{combined}$ falls from 52.45 hours with one truck channel to 26.81 hours with two channels, and only to 26.20 hours with three. Once trucks have at least two channels, the largest component of $W_{combined}$ is the ship time in the system (23.40 hours). Because the ship and truck data were collected in different periods and are not linked at the cargo level, $W_{combined}$ is a sum of two subsystem means, not an observed end-to-end time. Burke's theorem, which would justify analysing the stages of a tandem M/M network separately and adding their times, cannot be invoked here, because the K–S tests reject the Poisson-exponential assumptions on which it depends. The indicator is therefore used only to compare the relative size of the ship and truck components; the term "combined" reflects this limited purpose and does not imply a validated tandem-queue model.

For ships, the M/M/2 model reduces the theoretical Wq from 9.15 to 0.57 hours. However, because the M/M/1 model does not fit the empirical distribution pattern and the observed waiting time is only 1.33 hours, this result does not indicate a need for additional berths.

Accordingly, the finding that two truck service channels markedly reduce the modelled waiting time should be presented as a model-based scenario indication under the adopted queueing assumptions, not as an empirically validated optimum. The support for it is indirect: the observed waiting time (0.49 hours) and the observed concurrency (up to three trucks) are consistent with a system that already operates with more than one effective channel, so $c = 2$ or $c = 3$ is a more realistic description of current operations than $c = 1$. Because no investment or operating costs were analysed, the results say nothing about whether a given number of lanes is economically optimal.

4.5. Comparison with Previois Studies

The findings can be set against the international studies discussed in the Introduction. Work on truck appointment systems [7] and on truck-arrival scheduling and routing [6] treats truck arrivals as something that can be shaped by scheduling, and simulation of terminal vehicle traffic [5] shows that the operating configuration of vehicles and handling resources affects terminal performance. The low coefficient of variation of truck arrivals at Nabire Port ($c_a = 0.33$) is consistent with arrivals that are already partly regulated, which supports the view that coordination mechanisms, and not only added capacity, influence congestion. Reviews of berth allocation and scheduling [4] likewise highlight the range of operational constraints that affect vessel service; this agrees with the present finding that ship time at Nabire Port is dominated by cargo handling (about 91% of the observed time in the system) rather than by waiting. These studies, however, concern container terminals, whereas Nabire Port handles multi-cargo flows with simple service arrangements, so the comparison is one of mechanisms rather than of magnitudes. Finally, the large divergence between the M/M estimates and the observed times shows that applying classical M/M models without testing their assumptions can lead to misleading operational conclusions, which is why the distributional tests and the Kingman benchmark were included in this study.

4.6. Implications and Limitations

The implications for port managers and forwarding companies are presented as cautious, model-based indications. First, the scenario analysis suggests that organising truck service with at least two parallel channels would keep theoretical utilisation per channel at about 0.45 instead of 0.91, which lowers the modelled risk of long queues; this is consistent with the parallel service of up to three trucks that was observed. Second, because truck arrivals are relatively regular ($c_a = 0.33$), an appointment mechanism and completion of documents before arrival could be considered to reduce processing time, especially for Wingbox trucks, which have the longest mean service time; the effect of such measures should be tested before they are adopted. Third, because ship time is dominated by cargo-handling activities, dock performance indicators should not focus only on waiting time but should also include the rate and duration of cargo handling.

These results have several limitations, among them: (1) The amount of data is relatively limited, namely 60 units in each subsystem, with different observation periods: three months for ships, whereas trucks cover only eight days; (2) The exponential distribution assumption of the M/M models was rejected based on the K-S test, so the M/M/1 and M/M/c results cannot be regarded as a direct representation of operational conditions; G/G/c models or discrete-event simulation can be used in further research; (3) The truck cargo data in the sample cover only capacity labels of 4-25 tons per truck and do not yet cover the entire flow of goods at the port, so the representativeness of the sample for the port's overall logistics activity remains limited; (4) The actual truck waiting time, which was never less than 0.15 hours, probably does not entirely represent queueing caused by limited service capacity but may include administrative processes, document checks, or other operational procedures; (5) Data on investment and operating costs of the facilities are not yet available, so this study cannot yet determine the optimal number of lanes on the basis of economic considerations.

5. Conclusion

Empirical findings. This study analysed ship and freight-forwarding truck services at Nabire Port as two separately observed queueing subsystems. Ships arrived at fairly regular intervals (mean 36.40 hours, $c_a = 0.22$) and were served in 14.24 hours on average; their observed mean waiting time was 1.33 hours, and about 91% of their observed time in the system was cargo handling. Trucks arrived on average every 2.99 hours ($c_a = 0.33$), were served in 2.71 hours on average, and waited 0.49 hours on average, with up to three trucks served simultaneously. The Kolmogorov-Smirnov tests rejected the exponential distribution for all four inter-arrival and service-time variables ($p < 0.001$), so the M/M assumptions are not satisfied by the observed data.

Theoretical queueing scenarios. Under the M/M/1 benchmark, the ship subsystem has a utilisation of 0.391 and a theoretical waiting time of 9.15 hours, about 6.9 times the observed value, whereas the Kingman approximation (1.10 hours) was much closer to the observation. For trucks, the single-server benchmark gives a utilisation of 0.907 and a theoretical waiting time of 26.34 hours, which does not correspond to observed operations. The M/M/c scenarios show that two truck service channels reduce the theoretical waiting time to 0.70 hours and the combined indicator from 52.45 to 26.81 hours, with progressively smaller gains beyond two channels. These figures are theoretical baselines. The combined indicator is a sum of two subsystem means from different observation periods; it is neither an observed end-to-end time nor a validated tandem queue.

Managerial implications and limitations. Two truck service channels appear to be a promising capacity scenario under the adopted queueing assumptions, not an empirically proven optimum. Measures such as truck appointments, advance document completion, and cargo-handling performance indicators for ships merit evaluation before adoption. The study does not determine the economically optimal number of service lanes, because no investment or operating costs were analysed. Future research should use longer and synchronised observation periods, link ship and truck records at the cargo level, apply G/G/c models or discrete-event simulation, and include cost data.

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