

Article

Estimating Truck Gate Demand Under Data Scarcity: A Provenance Audit and Profile-Based Disaggregation Framework for Shuwaikh Port, Kuwait

Sharaf Alkheder ^{1,*} and Abdulaziz Aldawish ^{1,2,*} ¹ College of Engineering and Energy, Abdullah Al Salem University, Khaldiya 72303, Kuwait² School of Engineering, Cardiff University, Queen's Buildings, The Parade, Cardiff CF24 3AA, UK

* Correspondence: sharaf.alkheder@asuu.edu.kw (S.A.); aldawisha@cardiff.ac.uk (A.A.)

Abstract

Background: Authority-supplied daily port figures may be allocations of coarser records rather than measurements. Treating them as observed gate counts can produce spurious model accuracy. **Methods:** Using 365 daily container-discharge records for 2019 from the Kuwait Ports Authority (KPA), we apply four provenance diagnostics and a stochastic-count benchmark, formalize the allocation chain, distinguish discharge from pickup through a release-lag kernel, and explore assumed uncertainties by Monte Carlo simulation. **Results:** The daily series has a strong allocation signature (median within-month ratio coefficient of variation 2.1%; 141 of 308 operating days share repeated pairs). Under an assumed uniform pairing share, mean-preserving day-level noise, same-day pickup, and allocation of all modeled visits to six hourly slots from 11:00 to 17:00, peak-hour truck-visit medians are about 143, 185, and 259 for the three design levels. The maximum-day central 90% simulation interval reaches about 354 visits. **Conclusions:** The contribution is a provenance audit and conditional scenario framework for the import-discharge component. The intervals depend on uncalibrated assumptions and have no demonstrated coverage of observed gate traffic. Classified gate counts, container-to-truck linkage, and broader expert elicitation are required before operational use.

Keywords: port drayage; gate demand; data scarcity; temporal disaggregation; uncertainty analysis; Kuwait

1. Introduction

Seaport gates are where maritime and road freight systems meet, and the hourly pattern of truck arrivals determines queue lengths inside the port, congestion on the surrounding urban network, and the workload of customs inspection. Planning decisions about gate lanes, appointment systems, inspection staffing, and truck routing therefore depend on estimates of gate truck demand at daily and hourly resolution. In ports equipped with automated gates, loop detectors, or number-plate recognition, such estimates come directly from measurement, and a mature literature uses these measurements to develop short-term forecasting models. In many ports of the developing world and the Gulf region, however, no such infrastructure exists. When truck counts are unavailable, port authorities may instead supply aggregate throughput records, sometimes distributed to finer time scales by internal rules of thumb, together with the professional judgment of operations staff.



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This situation creates a methodological trap that is rarely acknowledged in the applied literature. Data supplied by an authority at daily or hourly resolution look like observations, and it is natural to feed them into regression or machine learning models and report the resulting accuracy statistics. If the fine-resolution series was in fact allocated from coarser totals, such accuracy is an artifact of the allocation arithmetic rather than evidence about the port, and models built on it can mislead subsequent planning. These data may still contain useful aggregate information and expert knowledge about temporal patterns. Their provenance and disaggregation process must be established, and the resulting uncertainty carried through to the planning estimates.

Shuwaikh Port is an important interface between maritime freight and Kuwait's urban road network. Its mixed-cargo operations make classified truck-visit data necessary for landside planning. The available 2019 records describe container discharge, while the 2024 KPA statistics describe a later and broader operating context [1]. The present study therefore treats the historical container records as the subject of a provenance audit and does not infer current total gate demand from them.

This paper applies this approach to Shuwaikh Port, the principal commercial port of Kuwait, which sits inside a dense urban area whose road network is sensitive to heavy-vehicle congestion. Working from 365 daily container-discharge records for 2019 supplied by the Kuwait Ports Authority (KPA), together with a single-expert hourly profile documented in the 2021 capstone project records, the paper makes four contributions. First, it specifies a provenance audit based on mix-ratio constancy, repeated value pairs, scalar multiples, and additivity, and benchmarks the first three diagnostics against a stochastic-count null model. Second, it formalizes the monthly-to-daily allocation chain while making explicit that the recovered weekday structure is the authority's allocation rule rather than an observed demand distribution. Third, it converts discharged containers to discharge-associated truck visits through a chassis-pairing parameter and introduces a general release-lag kernel to distinguish vessel discharge from later terminal pickup. Fourth, it explores assumed planning uncertainties by Monte Carlo simulation. Because neither the release-lag distribution nor gate counts are observed, the resulting envelopes are conditional planning scenarios for the discharge-associated component of traffic, not validated estimates of realized gate demand.

The paper does not fit a forecasting model. The audit results show that the daily series is an allocation of monthly totals, so a model predicting one column from another would largely reproduce allocation arithmetic. The analysis is therefore limited to provenance diagnostics and conditional discharge-associated planning envelopes under transparent assumptions. Realized calendar-day gate demand can differ because discharged containers may remain in the terminal for customs clearance, storage, and transport organization before pickup, and because exports, empty returns, and non-containerized traffic are outside the source data.

2. Literature Review and Research Gap

2.1. Short-Term Truck and Traffic Prediction

Short-term traffic prediction is a mature field whose methods range from parametric time-series models to neural networks, and whose reviews emphasize that data availability, rather than algorithm choice, is usually the binding constraint [2]. Applications to freight corridors follow the same pattern. Moniruzzaman et al. [3] modeled short-term truck volumes and crossing times at the Ambassador Bridge, the busiest land crossing between the United States and Canada, using two independent data sources: a year-long GPS truck trace database and a month of volume counts from remote traffic microwave sensors. The

common feature of these studies is measured high-frequency data; none of them addresses what an analyst should do when the fine-resolution series itself is of uncertain provenance.

Methodologically, the short-term prediction literature is conventionally organized into naive, parametric, and non-parametric families [2]. Naive methods carry the last observation or a historical average forward and serve mainly as benchmarks. Parametric methods, including traffic simulation models, ARIMA-class time-series models, and Kalman filtering, prespecify a functional form and estimate its parameters, and are comparatively economical in data. Non-parametric methods, including k-nearest neighbours, fuzzy logic systems, and neural networks, let the data determine model structure and generally require substantially larger samples. These methods share a requirement for a measured target series. Because this requirement is not met here, the paper focuses on establishing provenance and propagating uncertainty.

2.2. Freight Demand Estimation from Secondary Data

A complementary literature estimates freight demand from secondary and aggregate sources when direct observation is unavailable. Gonzalez-Calderon and Holguín-Veras [4] synthesized freight tour patterns from traffic counts and zonal trip generation estimates through an entropy maximization formulation, explicitly treating the limited secondary data as constraints rather than observations. At the measured end of the spectrum, recent work at the port of Rotterdam predicted next-hour outbound truck volumes from operational messages exchanged between terminal operators, carriers, and shippers through the local Port Community System [5], an alternative to gate detectors that requires a mature digital logistics system. This literature supports inference from aggregates but generally assumes that the analyst knows which values are measured. The present paper first examines the provenance of the supplied values to determine how they can be used. The container-dwell-time literature also establishes that vessel discharge and truck gate-out are distinct events. Kourounioti et al. [6] analysed 13,733 import containers from a Middle Eastern terminal and showed that pickup occurs after a variable yard dwell period, with customs inspection adding further delay in the reported case. Lee et al. [7], using event data for approximately 160,000 containers at Busan, explicitly represent the import workflow as discharge, yard storage, and subsequent gate-out and show that dwell time is affected by operational and cargo factors. Recent real-time evidence from Mombasa likewise shows strong temporal and modal variation in container dwell time [8]. These studies rule out treating vessel discharge as an observed same-day truck-arrival process and motivate the release-lag formulation introduced in Section 4.

The problem of distributing an aggregate total across finer time periods also has a long formal tradition in econometrics. Chow and Lin [9] derived best linear unbiased procedures for interpolating and distributing low-frequency series using related high-frequency indicator series; the approach has been extended to dynamic settings [10], and statistical offices use it to construct quarterly accounts from annual totals. The allocation framework in Section 4 follows this tradition but uses expert-elicited calendar weights because no observed indicator series is available. The uncertainty introduced by this substitution is represented explicitly.

2.3. Gate Congestion Management and Truck Appointment Systems

Because gate queues are among the most visible costs of unmanaged truck arrivals, a substantial literature addresses the landside gate directly. Guan and Liu [11] modeled marine container terminal gate congestion with a multi-server queuing formulation, while appointment-system studies subsequently optimized time windows, collaboration, and yard coordination [12–15]. Recent work has moved further toward stochastic and robust

formulations: Bett et al. [16] used simulation-based optimization for dual truck transactions under stochastic gate and yard conditions, and Li et al. [17] developed a two-stage robust gate-appointment design that explicitly treats uncertain yard service capacity. Xu et al. [18] modeled dynamic appointment rescheduling when actual truck arrival times deviate from appointments, while Ma et al. [19] predicted actual truck arrivals using measured terminal-operating-system gate-in records together with appointments, no-shows, weather, and traffic. A 2025 review by Gracia et al. [20], covering 65 appointment-scheduling studies published through 2024, likewise identifies uncertainty, dynamic adaptation, and real-time data integration as central current directions. These developments reinforce the need for empirically defensible arrival-demand inputs and uncertainty estimates when setting appointment quotas.

Two features of this literature matter here. First, appointment models use truck-arrival information as an exogenous input, including measured arrival rates, assumed distributions, or historical demand by time slot. Second, recent stochastic and robust formulations explicitly recognize that service and arrival uncertainty must be carried into slot-capacity decisions [16,17,20]. A port without measured arrival data therefore cannot infer an empirically validated quota from throughput allocations alone. The scenarios developed below are best understood as pre-measurement planning inputs that show the scale of discharge-associated demand and the value of obtaining actual gate observations. Evaluation of appointment-system outcomes must also distinguish modeled improvements from demonstrated operational effects [21].

2.4. Shuwaikh Port Studies

Previous Shuwaikh studies provide the local operating context. AlRukaibi et al. [22] documented road congestion, empty-container return delays, storage shortages, and changes in vessel calls. AlKheder et al. [23] evaluated an automated port configuration using VISSIM, with assumptions about truck volumes and inspection times. These two case-specific studies are retained because they describe the same port and supply the operational context used in Section 5.5. Their assumed demand inputs do not independently validate the discharge-associated scenarios developed here.

2.5. The Gap

Forecasting requires measured fine-resolution targets that are unavailable in the supplied Shuwaikh dataset; formal disaggregation generally assumes known provenance or observed indicator series; and contemporary appointment-system research increasingly models uncertainty but still presumes an arrival-demand input [16,17,20]. The specific gap addressed here is therefore provenance-first analysis under severe data scarcity. The paper supplies an auditable protocol for detecting administratively disaggregated series and demonstrates how to convert the information that remains into explicitly conditional planning scenarios. It does not claim to reconstruct the unobserved realized gate-demand process.

3. Study Area and Data

3.1. Shuwaikh Port and Its Road Environment

Shuwaikh Port, operating since 1960, is Kuwait's main commercial port. The historical study description used for the 2019 analysis reports 21 berths, about 4055 m of quay, and substantial closed and open storage areas [22]. Container operations concentrate at berths 10, 12, and 13, and container trucks reach the yards through northern gates. The internal access road and the surrounding Al-Ghazali and Jamal Abdul Nasser corridors make landside congestion operationally important. For 2024, the KPA website reports 613,093 TEU, 3.23 million tonnes of general cargo and 1419 vessel calls at Shuwaikh [1].

Those contemporary statistics are not directly comparable with the 2019 discharge-only tables used here, but they demonstrate why the present analysis should not be interpreted as a forecast of current traffic levels.

Berth allocation reflects the port's mixed cargo base. Of the 21 berths, fourteen (1 to 14) have a depth of 10 m, four (18 to 21) of 8.5 m, and three (15 to 17) of 6.7 m. Grain is handled at berth 1 and bulk cement at berth 8; general cargo occupies most of berths 2 to 7, 11 and 14 to 17; roll-on roll-off vessels use berths 5 and 18; berth 16 serves passengers; berths 19 and 20 handle reefer and general cargo and berth 21 livestock; container operations with two quay cranes concentrate at berths 10, 12, and 13 (Table 1). Because containers, reefer cargo, and roll-on roll-off vehicles all leave the port by road, the container-based truck estimates developed below represent only the import-discharge-associated component. The supplied records do not establish its share of total gate visits; the conditional hourly scenarios are not a verified lower bound on realized total hourly traffic.

Table 1. Usage of the 21 berths at Shuwaikh Port (source: KPA, as compiled in the underlying capstone study).

Berth	Commodity Use	Berth	Commodity Use
B1	Grain	B11, B14	General cargo/self-geared vessels
B2–B4, B6, B7	General cargo	B15, B17	General cargo, draft restricted
B5	Ro/Ro or general cargo	B16	Passenger
B8	Cement in bulk	B18	Ro/Ro vessels
B9	Lay-by (2019)	B19, B20	Reefers/general cargo
B10, B12, B13	Containers, 2 quay cranes	B21	Livestock/general cargo

Four structural problems frame the port's landside operations [22]. The first concerns road conditions and congestion. Truck restrictions cause heavy vehicles to wait on the internal road, while congestion on Al-Ghazali and Jamal Abdul Nasser Roads increases travel and stopping times and accelerates pavement deterioration. The second is the return cycle of empty containers, delayed by the congestion itself. The third concerns storage. Warehouses are aging and open yard space is insufficient; supplier warehouses run at capacity, shipping lines levy detention fines, and empty-container collection is delayed. The fourth is the vessel-call trajectory, which declined steadily before recovering for geopolitical reasons after 2018. These problems both affect and are affected by unmanaged truck arrivals, making demand estimation relevant to landside planning.

3.2. Data Obtained from the Kuwait Ports Authority

This study reanalyses the existing capstone report and associated KPA records. The report documents three meetings with KPA operations staff on 15 November 2021, 28 November 2021, and 16 December 2021, the last including a site tour. No new meetings, surveys, or interviews were conducted for the present manuscript. The first author supervised the original capstone project. The supplied material comprised the following: (i) twelve tables listing 20 ft and 40 ft containers discharged from vessels for every calendar day of 2019, with printed monthly totals and daily averages; (ii) the KPA planning assumption that discharged containers can be mapped to truck activity; and (iii) a six-hour percentage profile of 25, 22, 12, 10, 17, and 14% for the hours beginning 11:00 through 16:00. The source documentation identifies one KPA expert as the provider of the operational information; the profile is therefore treated as a single-expert elicitation rather than a multi-expert consensus. It was elicited in 2021 and applied retrospectively to 2019, so temporal stability of the within-day pattern is an assumption. The six labels denote one-

hour slots beginning at 11:00, 12:00, 13:00, 14:00, 15:00, and 16:00, covering 11:00–17:00. The percentages sum to 100%; consequently, the numerical scenarios assume that all modeled discharge-associated visits occur within this window. They do not establish that actual gate traffic is zero outside it. The twelve tables were transcribed to 365 calendar-day records; the entries for 28 June are blank and are retained as missing, and zero/closure days are retained separately rather than treated as measured zero gate demand.

The underlying capstone report documents the monthly-to-daily allocation and container-to-truck assumption in its Data Collection and Tools and Methods sections (PDF pp. 27–30); its Future Work section (p. 51) proposes installing detectors and extending coverage to other truck classes. These records establish the documented origin of the assumptions, but do not provide an independent gate-count dataset. Three meetings with one identified expert do not constitute three independent expert assessments or a Delphi exercise. No additional expert panel or field-validation campaign was conducted for the present analysis.

4. Methods

4.1. Provenance Audit

The audit asks whether the supplied daily two-column series behaves more like stochastic daily counting or administrative allocation. Four diagnostics are used. Diagnostic A measures the within-month coefficient of variation (CV) of the 40-ft/20-ft ratio; a proportional allocation preserves the monthly mix and therefore produces unusually low within-month variation. Diagnostic B counts operating days that share an exact (20-ft, 40-ft) pair within the same month. Diagnostic C counts exact collinear/scalar-multiple pairs across both columns. Diagnostic D checks small additivity gaps between printed monthly totals and the sum of rounded daily entries. Because low counts, closures, and reduced-activity days can themselves increase repetition, A–C are benchmarked by simulation rather than interpreted visually. For each month, a conservative stochastic-count null preserves the observed operating-day intensity weights and the sums of the transcribed operating-day 20-ft and 40-ft counts within each month, but allocates the two box types independently by multinomial sampling. Five thousand replicates provide empirical one-sided probabilities for a ratio CV at least as small as observed and for repeated/scalar-pair counts at least as large as observed. The diagnostics are therefore evidence about provenance, not formal proof that every individual daily entry was generated by one deterministic rule.

4.2. Disaggregation Model

Let M_m denote the monthly discharge aggregate and $w(d)$ the KPA calendar-allocation weight for day d , so $C_d = M_m w(d)$. Because $w(d)$ is recovered from a series shown by the audit to be allocated, it is interpreted only as the authority's nominal operating-day rule, not as an empirical weekday demand distribution. Discharged boxes are mapped to discharge-associated truck visits, not to gate crossings. Let $N_{20,d}$ and $N_{40,d}$ denote the day's discharged 20 ft and 40 ft box counts, and s the share of 20 ft boxes paired on one chassis. Then $V_d = N_{40,d} + N_{20,d}(1 - s/2)$. One truck visit denotes one terminal pickup visit associated with transporting discharged containers; it may create separate entry and exit gate transactions and is therefore not synonymous with a single gate crossing. Discharge and pickup need not occur on the same day. Published dwell-time studies explicitly separate discharge, yard storage, and gate-out and report substantial variability before pickup [6,7]. Let q_l be the probability that a discharge-associated visit occurs l days after vessel discharge, with $q_l \geq 0$ and $\sum_l q_l = 1$. The calendar-day discharge-associated visit process is then a convolution $A_t = \sum_l q_l V_{t-l}$. The q_l distribution is not observed in the available data; customs clearance, release, storage, and transport organization can all create

delay. Consequently, the numerical results below set $q_0 = 1$ only as a transparent same-day association scenario and are not interpreted as realized daily gate counts.

Formally, with M_m the monthly container total, the allocation chain and truck mapping are as follows:

$$C_d = M_m \cdot w(d), \sum_{d \in m} w(d) = 1 \quad (1)$$

$$V_d = N_{40,d} + N_{20,d}(1 - s/2) \quad (2)$$

$$A_t = \sum_l q_l V_{t-l}, \sum_l q_l = 1 \quad (3)$$

where $w(d)$ encodes the KPA calendar allocation, $s \in [0, 1]$ is the unknown share of 20 ft boxes travelling paired on one chassis, q_l is the unobserved release-lag kernel, and p is the single-expert six-hour profile. The bounding cases of Equation (2) are $V = N_{20} + N_{40}$ at $s = 0$ and $V = N_{40} + N_{20}/2$ at $s = 1$. The hourly scenario is $H_{t,h} = A_t p_h$ with $\sum_h p_h = 1$ (4). Equation (1) is analogous to a temporal-distribution problem [9], but no observed high-frequency indicator series is available. Because q_l is unidentified, only conditional scenarios can be calculated from the present records. All hourly values therefore condition jointly on same-day pickup and full allocation to the six-hour window. If a proportion of these visits occurs outside the window, the within-window total would need to be reduced before applying its normalized profile; neither that proportion nor the out-of-window timing can be estimated from the supplied records.

4.3. Uncertainty Propagation

The scenarios use three nominal design-day discharge levels: the median operating day (630 boxes), the 85th percentile (816), and the maximum recorded discharge day (1141). For each, 20,000 Monte Carlo draws explore explicitly assumed distributions; their parameters are not estimated from gate observations. First, because no chassis or gate-transaction sample supports a narrower range, the base case uses $s \sim U(0, 1)$ over the full feasible interval of the simplified mapping. Uniform probability within that interval is an assumption, not an empirically established pairing distribution; narrower ranges are sensitivity cases only. Second, residual day-level multiplicative uncertainty is represented by $\varepsilon \sim \text{Lognormal}(-\sigma^2/2, \sigma^2)$, $\sigma = 0.15$, so that $E[\varepsilon] = 1$ exactly; this corrects the upward mean shift produced by $\text{Lognormal}(0, \sigma^2)$. Third, profile uncertainty is represented by $p \sim \text{Dirichlet}(\kappa p_0)$, $\kappa = 200$, centred on the single-expert KPA six-hour profile. The 5th, 50th, and 95th percentiles are reported. Because no dwell-time observations are available, no distribution is assigned to release-lag uncertainty q_l . The numerical scenarios condition on $q_0 = 1$, and this assumption limits their interpretation. Sensitivity is reported for κ , s , and σ . The dispersion $\sigma = 0.15$ and concentration $\kappa = 200$ are illustrative settings, not calibrated estimates of daily variability or expert reliability. The Dirichlet distribution varies shares around one supplied profile and cannot represent agreement among experts or detect systematic bias in that profile. The reported central 90% intervals contain 90% of simulated outcomes under the specified assumptions; they are not empirically calibrated prediction intervals. Expert-elicitation and transport-uncertainty literature motivates transparent reporting of assumptions [24,25], but does not validate these parameter values for Shuwaikh. The nominal design levels are split into 20 ft and 40 ft boxes using the aggregate 20 ft share in the transcribed operating records. The analysis uses random seed 20260915, restarts that seed for each scenario, and reports unrounded outputs; displayed counts are rounded to the nearest visit. The analysis was run with Python 3.12.14, NumPy 2.3.5, pandas 2.2.3 and Matplotlib 3.10.8.

5. Results

5.1. The Daily Series Is an Allocation

All four diagnostics show an allocation signature, and the simulation benchmark indicates that the repeated-pair and scalar-multiple patterns are not explained by low counts or reduced-activity days alone. The median within-month CV of the 40-ft/20-ft ratio is 2.1%, with July at 0.25%; December is the clear exception at 21.5%. Sixty distinct value pairs recur within their month, covering 141 of 308 operating days. Exact scalar proportionality is also frequent. Under the conservative stochastic-count benchmark, the empirical probability of obtaining at least the observed number of repeated-pair days is <0.001 in every month, and the probability of at least the observed number of scalar pairs is <0.001 in every month. For the ratio-CV diagnostic, $p < 0.001$ in nine months, $p = 0.005$ in March and $p = 0.018$ in November; December is not unusual under the stochastic benchmark ($p = 0.999$), consistent with its visibly irregular entries. Small one-to-three-box additivity gaps remain consistent with rounded allocation. Figures 1 and 2 show the daily series and the month-specific mix structure.

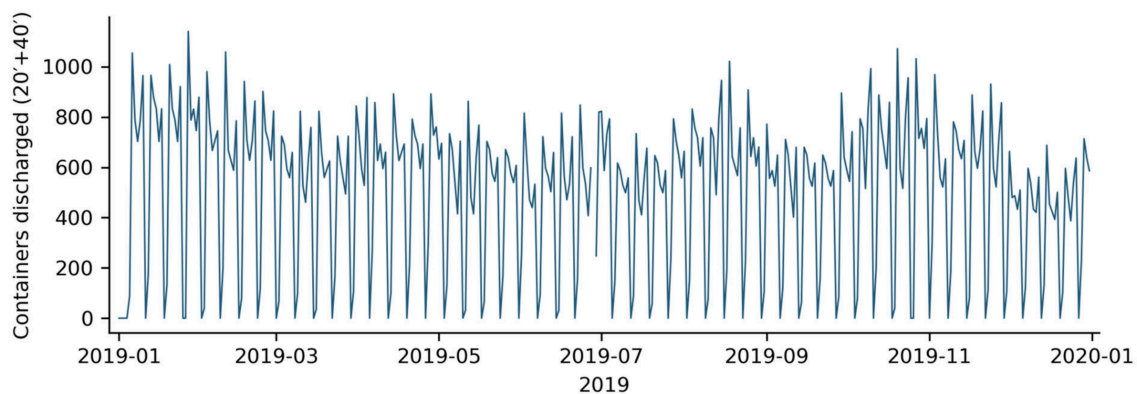


Figure 1. Daily container discharge at Shuwaikh Port, 2019, as supplied by KPA. Regular Friday closures and reduced Saturdays are visible; the series is shown here as the object of the provenance audit, not as measured gate data.

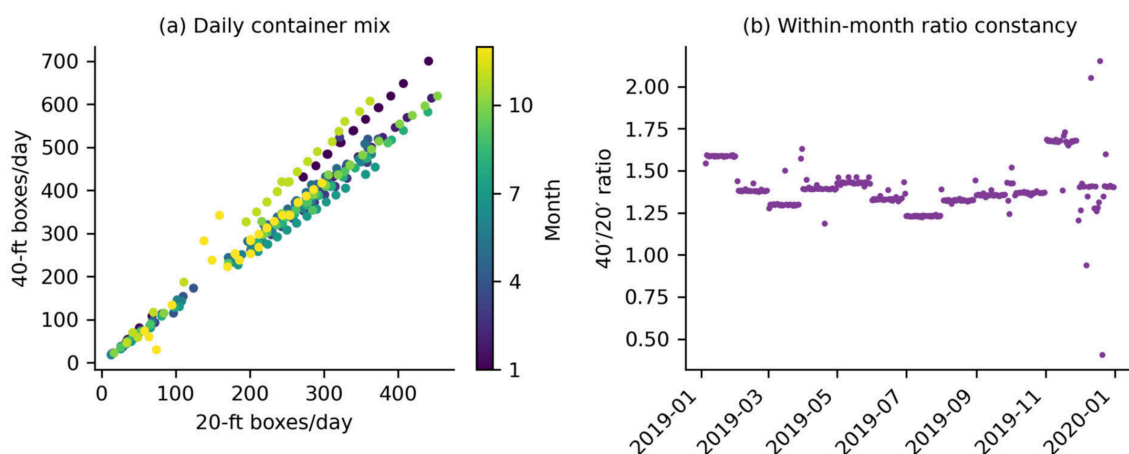


Figure 2. Provenance audit. (a) Daily 40 ft versus 20 ft box counts, coloured by month: operating days lie on tight month-specific rays through the origin. (b) The daily 40 ft to 20 ft ratio forms flat within-month bands (median within-month CV 2.1 percent); December shows the widest scatter. The colour scale in (a) identifies the month (1 = January; 12 = December) and applies only to (a); all operating-day ratios in (b) are shown in purple.

Table 2 gives the descriptive audit by month. The simulation benchmark is intentionally conservative because it preserves each month's observed relative day-intensity

pattern while independently sampling the two container-size totals. Thus, Friday closures and low-activity days are already reflected in the null comparison. The repeated-pair and scalar-multiple results remain extreme under that benchmark, strengthening the allocation interpretation. December is treated separately because its ratio scatter is compatible with stochastic variation and may reflect manual corrections or a different allocation practice.

Table 2. Provenance audit by month, 2019. CV: within-month coefficient of variation of the 40' / 20' ratio. Repeated-pair days: operating days sharing an exactly repeated (20', 40') value pair within the month. Additivity gap: transcribed daily sum minus printed monthly total.

Month	Ratio Mean	Ratio CV (%)	Operating Days	Repeated-Pair Days	Gap 20'	Gap 40'
January	1.58	0.6	23	8	−3	−1
February	1.38	1.1	24	13	−2	+1
March	1.33	6.8	26	13	0	+1
April	1.39	3.1	26	15	−1	+1
May	1.43	1.0	26	12	−1	+1
June	1.34	1.8	26	10	−2	0
July	1.23	0.2	27	16	0	0
August	1.33	2.0	26	11	0	+1
September	1.35	2.1	26	16	+1	0
October	1.38	2.4	26	9	0	+1
November	1.65	6.7	25	10	+1	+3
December	1.38	21.5	27	8	−1	−2

A practical consequence is that any regression of one column of this dataset on the others, including a regression of assumed truck counts on box counts, recovers the allocation arithmetic and will report near-perfect fit statistics that carry no information about gate operations. An earlier student analysis of these tables conducted under the first author's supervision obtained a coefficient of determination of 0.997 in exactly this way, and that experience motivated the audit protocol formalized here. The framework therefore uses the twelve monthly totals, the closure calendar, the authority's allocation weights, and the expert hourly profile.

5.2. Contextual Comparison of the Monthly Aggregates

If the daily series is allocated, the 12 printed monthly totals become the highest-resolution source quantities. Their accuracy cannot be independently validated from the available material. The Central Statistical Bureau's monthly count of all commercial vessel arrivals [26] is therefore used only as a contextual comparison, not as validation. Figure 3 presents the monthly comparison. Across the 12 months of 2019, the Pearson correlation between container discharge totals and all commercial vessel calls is $r = 0.32$. With only $n = 12$ observations and a vessel series that includes non-container ships, this association has limited inferential power. A container-vessel-call series, terminal operating records, customs releases, or monthly TEU records of matching scope would be preferable, but none was available for this study. The KPA monthly totals are therefore retained as an explicitly unverified input.

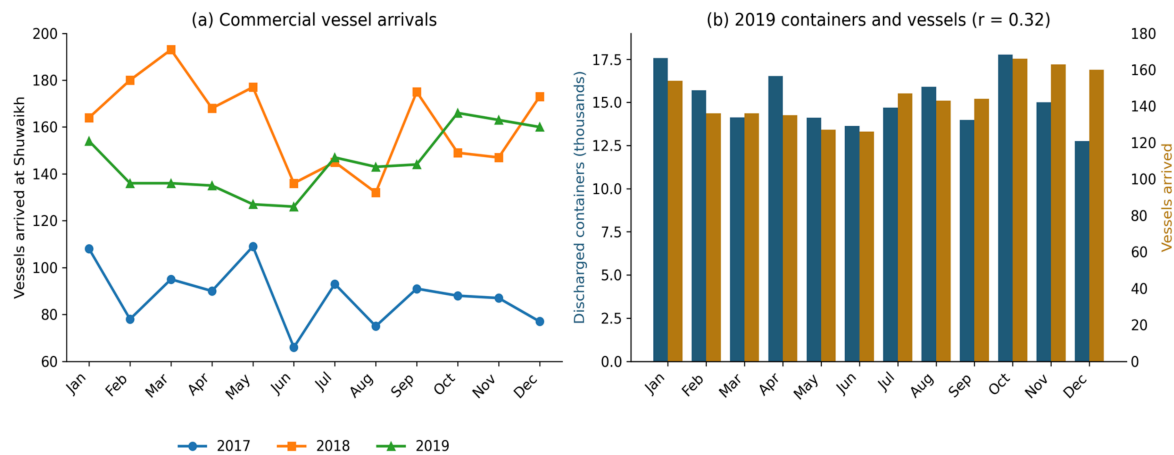


Figure 3. Contextual monthly comparison. (a) Commercial vessel arrivals at Shuwaikh, 2017–2019 (Central Statistical Bureau). (b) 2019 container-discharge totals (blue bars, left axis, thousands of containers) and all commercial vessel arrivals (orange bars, right axis, vessel counts); $r = 0.32$. The comparison is contextual and does not validate the KPA monthly container totals.

5.3. KPA Allocation-Rule Temporal Structure

The weekday pattern recovered from the supplied daily tables is an allocation-rule structure, not an observed gate-demand pattern. Fridays are predominantly assigned zero and Saturdays are assigned substantially lower values; Sundays and Thursdays receive larger nominal weights than Tuesdays and Wednesdays. These features may have been designed to reflect operational knowledge, but the present dataset cannot establish that realized truck demand followed the same weekday distribution. Accordingly, no empirical claim is made about Sunday backlog clearance or true weekday differences. Figure 4a therefore labels the bars as the KPA allocation-rule profile. Figure 4b shows the separate single-expert six-hour profile; 47% of the elicited daily profile lies in the 11:00–13:00 window. That concentration is an expert planning assumption, not an observed hourly count.

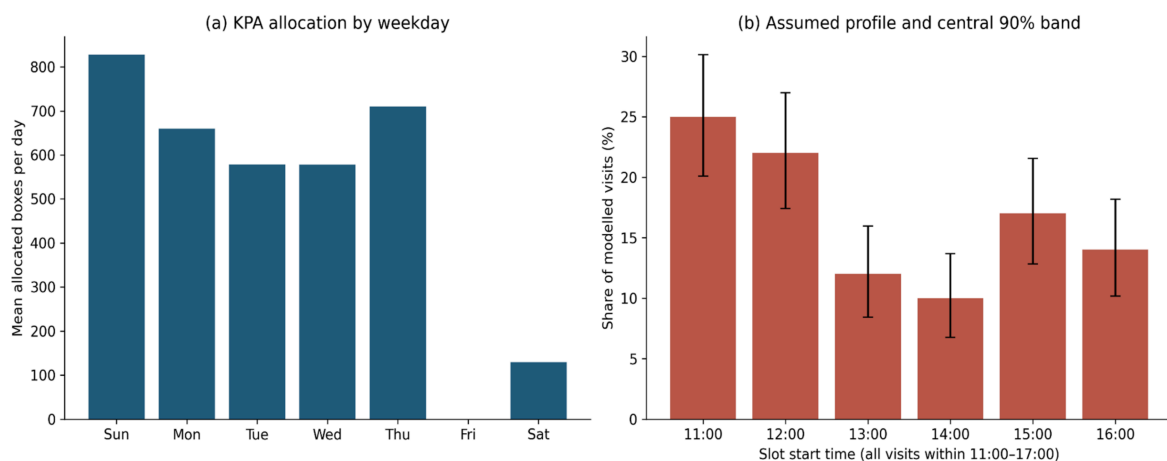


Figure 4. (a) Mean KPA allocated container discharge by weekday, shown as an allocation-rule profile rather than observed demand. (b) Single-expert KPA profile with the central 90% band from the assumed Dirichlet distribution. Labels indicate slot start times; 100% of modeled visits are allocated to 11:00–17:00. The band is not an empirically calibrated measure of expert accuracy.

5.4. Discharge-Associated Planning Envelopes

Table 3 reports the Monte Carlo scenarios using $s \sim U(0, 1)$ and the mean-preserving lognormal multiplier. For the 630-box median design level, discharge-associated daily truck

visits have a median of about 557 with a 90% interval of 424–728, and the peak hourly slot within the six-hour profile has a median of about 143 visits with a 90% interval of 105–195. For the 816-box design level, the peak median is about 185 (136–253); for the 1141-box maximum discharge level it is about 259 (190–354). Figure 5 shows the corresponding hourly scenario envelopes and peak-hour distributions. These are conditional same-day discharge-associated planning quantities, not validated calendar-day gate counts. The comparison with approximately 650 trucks/day in the smart-gate simulation study [23] is retained only as an order-of-magnitude observation; the scopes differ and the figures are not direct mutual validation.

Table 3. Conditional same-day discharge-associated truck-visit scenarios (percentiles of 20,000 Monte Carlo draws). All modeled visits are allocated to the six one-hour slots from 11:00 to 17:00; intervals summarize assumed simulation distributions, not demonstrated coverage of observed traffic.

Design Day	Boxes (20' + 40')	Daily Truck Visits P50 [P5, P95]	Peak-Hour Truck Visits P50 [P5, P95]
Median operating day	630	557 [424, 728]	143 [105, 195]
85th percentile day	816	721 [550, 943]	185 [136, 253]
Maximum recorded day	1141	1008 [769, 1318]	259 [190, 354]

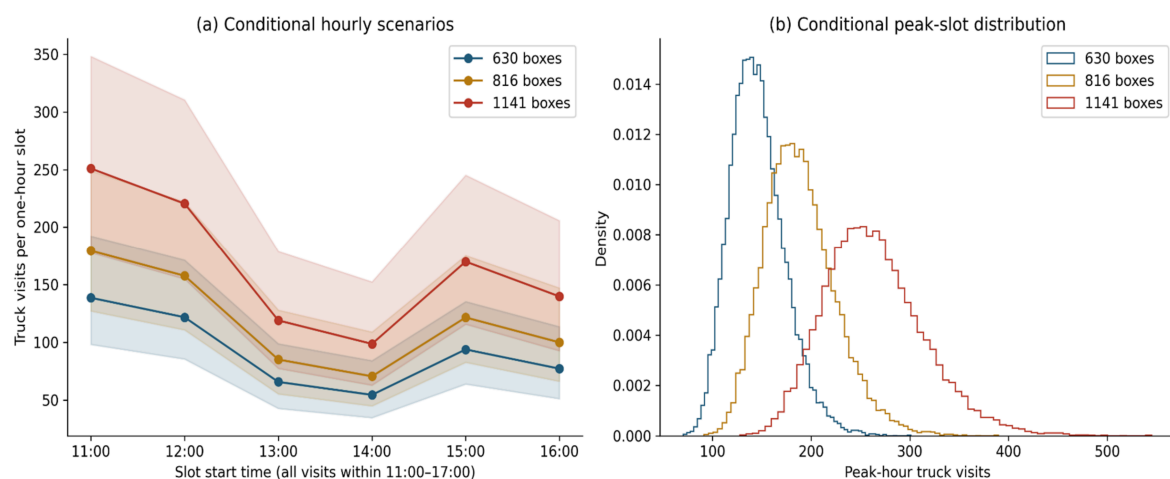


Figure 5. (a) Conditional same-day discharge-associated truck-visit envelopes for the three design levels (median lines with shaded central 90% simulation bands). Blue, orange, and red represent the 630-, 816-, and 1141-box design levels, respectively. (b) Distribution of visits in the peak hourly slot within the six-hour profile. All modeled visits are assigned to the six one-hour slots from 11:00 to 17:00. The bands are conditional simulation intervals; these scenarios are not observed gate counts.

Table 4 reports sensitivity for the maximum discharge-day scenario. The base case uses the full physically feasible pairing interval $s \sim U(0, 1)$; narrower 0.2–0.8 and 0.4–0.6 ranges are shown only as sensitivity cases. The median remains comparatively stable, whereas interval width responds most strongly to the day-level dispersion and profile concentration. This stability does not provide empirical validation. The source data cannot identify release-lag uncertainty, export and empty-container traffic, or activity outside the six-hour profile. For a distribution-free reference within the simplified pairing model, Equation (2) bounds the daily discharge-associated visits between $N_{40} + N_{20}/2$ and $N_{40} + N_{20}$ before the residual multiplier is applied. These algebraic bounds require no probability law for the pairing share, but still assume the stated container-to-visit mapping. They are not bounds on observed total gate traffic. Sensitivity of the Monte Carlo outputs to selected distributions cannot replace field calibration or establish empirical coverage.

Table 4. Sensitivity of maximum-design-day peak-hour truck visits (P50 [P5, P95]) to assumed uncertainty settings; base case in the first row. Results condition on same-day pickup and allocation of all modeled visits to 11:00–17:00.

Setting	Peak-Hour Truck Visits P50 [P5, P95]
Base ($\kappa = 200$; $s \sim U(0, 1)$; $\sigma = 0.15$)	259 [190, 354]
Profile concentration $\kappa = 100$	266 [192, 375]
Profile concentration $\kappa = 400$	255 [190, 343]
Pairing share $s \sim U(0.2, 0.8)$	259 [192, 350]
Pairing share $s \sim U(0.4, 0.6)$	260 [193, 348]
Day-level dispersion $\sigma = 0.10$	261 [203, 336]
Day-level dispersion $\sigma = 0.20$	257 [175, 376]

5.5. Illustrative Capacity Scenarios

The scenario envelopes can be translated into illustrative workload arithmetic, but not into a validated capacity design. Using the 15 min manual-inspection time and roughly 65% inspection share reported in the earlier Shuwaikh simulation study [23], the maximum-discharge scenario has a peak-slot median near 259 discharge-associated visits; applying 65% would correspond to roughly 168 inspections if the scopes and timing aligned. This calculation ignores stochastic service times, queue interactions, entry/exit coupling, lane configuration, resource sharing, no-shows, appointment compliance, and the discharge-to-pickup lag. It is therefore presented only as a scenario illustrating why queueing or discrete-event simulation is required before selecting inspection capacity or appointment quotas.

6. Discussion and Policy Implications

6.1. Using the Envelopes

For KPA and port planners, the immediate use of the analysis is diagnostic rather than prescriptive. First, it identifies which parts of the supplied dataset are aggregate records, allocation rules, and expert assumptions, preventing artificial model accuracy from being mistaken for observed performance. Second, the conditional envelopes provide order-of-magnitude inputs for testing candidate gate or appointment-system configurations in a queueing or simulation model. Third, the uncertainty assumptions and unobserved release-lag process indicate priorities for direct measurement; the analysis does not quantify the expected information gain or economic value of collecting these data. The assumed 47% concentration in the 11:00–13:00 part of the six-hour profile should be treated as a scenario to test, not as an empirically observed peak that an appointment system has already been shown to smooth.

Appointment-system design requires demand and service-capacity information jointly [16,17,20]. The present scenarios can be passed to such a model, but they do not justify a specific quota. In particular, 170 truck visits per hour is used only as a hypothetical threshold. Any operational quota should be estimated with measured gate transactions, observed service-time distributions, lane and inspection-resource configuration, container availability, appointment compliance, and a queueing or discrete-event model. Likewise, weekday-specific quotas cannot be inferred from the recovered Sunday–Thursday pattern because that pattern is embedded in the KPA allocation rule rather than observed gate counts.

The analysis remains relevant to KPA modernization because it specifies what additional data a future smart-gate or appointment platform should capture. The 2024 KPA statistics [1] show that Shuwaikh remains a large mixed-cargo operation; therefore, a total

gate-demand model must include import pickups, export deliveries, empty-container returns, and non-containerized truck classes. Incorporating those flows would not be a minor adjustment to the present discharge-only scenarios; it requires classified gate measurement or transaction data. The methodological role of the present framework is to bridge that pre-measurement period without presenting allocated source data as observations.

6.2. *The Case for Measurement*

The analysis makes the measurement priority explicit. A short campaign of classified gate counts or timestamped entry/exit transactions could directly identify truck visits, gate crossings, direction, daily and hourly variation, and the contribution of non-container traffic. Linking container discharge/release timestamps to pickup transactions would additionally identify the release-lag kernel q_l and the chassis-pairing share. Those observations would convert the current assumption-dependent scenarios into an estimable arrival process and would support short-term forecasting and queueing-model validation. Until then, the framework should be viewed as a bridge to measurement rather than a substitute for it. Validation would require an independently observed series with matching dates, gates, truck-visit definitions, and cargo scope, followed by comparison of observed visits with scenario outputs and interval coverage. Container identifiers linked to truck visits would be needed to estimate pairing, and independent expert assessments would be needed to evaluate the hourly profile. Neither annual cargo totals nor agreement with another assumption-based model provides those checks.

6.3. *Transferability*

The provenance diagnostics are transferable because they require only the supplied tables, but the empirical benchmark and decision rules should be retested when applied elsewhere. Appendix A and Supplementary Table S1 provide the transcribed daily source data. A multi-port study could estimate false-positive and false-negative rates for the diagnostics using datasets known to contain either measured gate counts or administratively allocated values. The present single-port case demonstrates the protocol but does not, by itself, establish universal diagnostic thresholds.

7. Limitations

The study has seven main limitations. First, the KPA monthly totals are treated as source aggregates but remain independently unverified; the broad all-vessel comparison in Section 5.2 is contextual only. Second, vessel discharge is not equivalent to same-day truck pickup. Customs clearance, release, storage, and transport organization create an unobserved lag q_l , a distinction supported by container-dwell-time studies that separate discharge from later gate-out [6,7]. The reported $q_0 = 1$ results are therefore conditional discharge-associated scenarios rather than realized daily gate demand. Third, the analysis covers import discharge only; export deliveries, empty returns, reefer/general cargo, Ro/Ro, bulk, livestock, and other road traffic are excluded, so the results are a partial component rather than total gate throughput. Fourth, the 20 ft pairing share, residual day-level dispersion, and profile concentration are not empirically calibrated. Using $U(0, 1)$ spans the pairing model's feasible range but still imposes a probability distribution; the resulting simulation intervals have no demonstrated coverage of observed arrivals. Fifth, the hourly pattern is a single-expert profile elicited in 2021 and applied retrospectively to 2019; no multi-expert or Delphi assessment was conducted. The numerical scenarios place all modeled visits within 11:00–17:00, an unverified temporal assumption that excludes out-of-window activity. Sixth, the weekday pattern is the KPA allocation rule and must not be interpreted as measured Sunday–Thursday behavior. Seventh, the empirical case is pre-

pandemic. Current KPA statistics confirm a materially different 2024 operating context [1], so the numerical scenarios are methodological illustrations rather than current-demand forecasts. Multi-expert elicitation, classified gate counts, release/pickup transaction linkage, and multi-port validation are the principal next steps. The shares of export deliveries, empty returns, and non-containerized traffic in total truck visits remain unknown. Tonnage, TEU, and vessel-call totals cannot determine those shares without cargo-to-truck and visit-level information; no percentage is imputed for the excluded flows.

8. Conclusions

This paper examines whether fine-resolution data supplied by port authorities are measured or administratively disaggregated. In the Shuwaikh case, descriptive diagnostics and a stochastic-count benchmark show a strong allocation signature in the 2019 daily container tables. The framework shows how monthly source aggregates and allocation rules can be audited and discharged boxes converted to truck-visit scenarios with explicit chassis uncertainty. The discharge-to-pickup lag, total mixed-cargo gate traffic, and realized hourly arrivals still require measurement. Under the conditional same-day scenario, peak-slot medians are about 143, 185, and 259 visits for the median, 85th-percentile, and maximum discharge design levels, with the maximum-day 90% interval extending to about 354. These values are planning scenarios, not forecasts or validated gate counts. The contribution is a method for checking data provenance before modeling, stating the limits of inference, and identifying the measurements needed to move from scenario analysis to operational prediction.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/logistics10100224/s1>, Table S1: transcribed daily container-discharge data for Shuwaikh Port, 2019 (CSV).

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Appendix A. Daily Container Discharge Tables Supplied by the Kuwait Ports Authority, 2019

The 12 monthly tables are reproduced as supplied (20 ft and 40 ft boxes discharged from vessels per calendar day; dash entries in the source, denoting closure days, are shown as 0; the blank entries for 28 June are shown as n/a). Totals are the printed monthly totals

from the source tables; as discussed in Section 5.1, transcribed daily values reproduce them to within one to three boxes.

Table A1. Daily discharge, January and February 2019.

Day	January 20'	January 40'	February 20'	February 40'
1	0	0	0	0
2	0	0	16	23
3	0	0	412	569
4	0	0	330	455
5	35	54	280	387
6	407	648	297	409
7	305	484	313	432
8	272	431	0	0
9	305	484	82	114
10	373	592	445	614
11	0	0	280	387
12	68	108	264	364
13	374	592	247	341
14	339	538	330	455
15	322	511	0	0
16	272	431	33	47
17	322	511	396	546
18	0	0	297	409
19	51	81	264	364
20	390	619	297	409
21	323	511	364	500
22	305	484	0	0
23	272	431	49	68
24	356	565	379	523
25	0	0	313	432
26	0	0	297	409
27	441	700	264	364
28	304	484	346	478
29	321	511		
30	289	457		
31	340	539		
Total	6789	10,767	6597	9098

Table A2. Daily discharge, March and April 2019.

Day	March 20'	March 40'	April 20'	April 40'
1	0	0	304	423
2	29	37	249	346
3	315	409	221	307
4	301	390	359	519
5	258	335	0	0
6	243	316	110	154
7	287	372	359	499
8	0	0	262	365
9	43	56	290	403
10	358	465	249	346
11	229	297	276	384
12	201	260	0	0
13	272	353	41	58
14	331	428	373	519
15	0	0	304	424
16	14	21	262	365
17	358	465	276	384
18	287	372	290	403
19	244	316	0	0
20	258	335	97	115
21	272	353	331	461
22	0	0	304	423
23	72	93	290	403
24	315	409	249	346
25	273	353	290	403
26	244	316	0	0
27	215	279	124	173
28	315	409	373	519
29	0	0	305	423
30	42	66	318	443
31	321	523		
Total	6097	8027	6907	9607

Table A3. Daily discharge, May and June 2019.

Day	May 20'	May 40'	June 20'	June 40'
1	261	372	108	143
2	283	413	350	466
3	0	0	270	358
4	53	75	202	269
5	302	432	189	251
6	276	395	229	304
7	224	320	0	0
8	171	244	40	54
9	290	414	310	412
10	0	0	256	340
11	13	19	243	322
12	355	508	216	287
13	197	282	283	376
14	171	244	0	0
15	263	376	13	18
16	317	451	350	466
17	0	0	243	322
18	26	38	202	269
19	290	413	230	304
20	276	395	310	412
21	237	338	0	0
22	224	320	67	90
23	263	376	364	484
24	0	0	258	340
25	69	97	229	304
26	276	395	175	233
27	263	376	256	342
28	237	338	n/a	n/a
29	219	320	102	146
30	251	357	347	473
31	0	0		
Total	5808	8307	5844	7785

Table A4. Daily discharge, July and August 2019.

Day	July 20'	July 40'	August 20'	August 40'
1	369	454	278	386
2	263	324	0	0
3	329	405	65	86
4	356	437	358	474
5	0	0	326	431
6	66	81	310	409
7	277	340	260	345
8	263	324	309	409
9	237	292	0	0
10	224	275	33	43
11	250	308	326	431
12	0	0	309	409
13	40	49	211	280
14	329	405	342	452
15	211	258	407	539
16	184	227	0	0
17	250	308	81	108
18	303	373	440	582
19	0	0	277	366
20	26	32	260	345
21	290	357	244	323
22	277	340	326	431
23	237	292	0	0
24	224	275	98	129
25	263	324	391	517
26	0	0	277	366
27	105	130	309	409
28	356	437	260	345
29	316	389	293	388
30	290	356	0	0
31	250	308	43	62
Total	6585	8100	6833	9064

Table A5. Daily discharge, September and October 2019.

Day	September 20'	September 40'	October 20'	October 40'
1	328	444	243	346
2	236	320	216	328
3	249	338	306	436
4	223	302	0	0
5	276	373	34	46
6	0	0	335	458
7	52	71	319	436
8	302	409	218	298
9	278	373	352	482
10	223	302	419	574
11	171	231	0	0
12	289	391	84	115
13	0	0	374	514
14	26	36	319	436
15	289	391	285	390
16	276	373	251	344
17	236	320	364	495
18	223	302	0	0
19	262	355	17	23
20	0	0	453	619
21	66	89	252	344
22	276	373	218	298
23	262	355	335	459
24	236	320	402	554
25	223	302	0	0
26	249	338	0	0
27	0	0	436	596
28	35	50	302	413
29	386	510	319	436
30	285	354	285	390
31			335	459
Total	5956	8022	7473	10,288

Table A6. Daily discharge, November and December 2019.

Day	November 20'	November 40'	December 20'	December 40'
1	0	0	276	387
2	111	187	212	268
3	362	607	201	286
4	278	467	180	253
5	209	350	212	298
6	195	327	0	0
7	237	397	64	60
8	0	0	254	342
9	70	117	223	313
10	291	490	180	253
11	278	467	138	283
12	251	419	233	328
13	237	397	0	0
14	264	443	58	74
15	0	0	286	402
16	34	47	201	253
17	328	560	186	238
18	243	420	170	223
19	223	373	159	342
20	253	420	0	0
21	311	513	74	30
22	0	0	254	342
23	42	70	201	283
24	348	583	149	238
25	223	373	223	313
26	195	327	265	372
27	264	443	0	0
28	320	537	95	134
29	0	0	297	417
30	49	59	265	372
31			244	342
Total	5615	9390	5301	7448

References

1. Kuwait Ports Authority. Shuwaikh Port: 2024 Port Statistics. Available online: <https://www.kpa.gov.kw/en/shuwaikh-port/> (accessed on 15 September 2026).
2. Vlahogianni, E.I.; Karlaftis, M.G.; Golias, J.C. Short-term traffic forecasting: Where we are and where we're going. *Transp. Res. Part C* **2014**, *43*, 3–19. [[CrossRef](#)]

3. Moniruzzaman, M.; Maoh, H.; Anderson, W. Short-term prediction of border crossing time and traffic volume for commercial trucks: A case study for the Ambassador Bridge. *Transp. Res. Part C* **2016**, *63*, 182–194. [\[CrossRef\]](#)
4. Gonzalez-Calderon, C.A.; Holguín-Veras, J. Entropy-based freight tour synthesis and the role of traffic count sampling. *Transp. Res. Part E* **2019**, *121*, 63–83. [\[CrossRef\]](#)
5. Nadi, A.; Sharma, S.; Snelder, M.; Bakri, T.; van Lint, H.; Tavasszy, L. Short-term prediction of outbound truck traffic from the exchange of information in logistics hubs: A case study for the port of Rotterdam. *Transp. Res. Part C* **2021**, *127*, 103111. [\[CrossRef\]](#)
6. Kourounioti, I.; Polydoropoulou, A.; Tsiklidis, C. Development of models predicting dwell time of import containers in port container terminals—An Artificial Neural Networks application. *Transp. Res. Procedia* **2016**, *14*, 243–252. [\[CrossRef\]](#)
7. Lee, Y.; Park, K.; Lee, H.; Son, J.; Kim, S.; Bae, H. Identifying key factors influencing import container dwell time using eXplainable Artificial Intelligence. *Marit. Transp. Res.* **2024**, *7*, 100116. [\[CrossRef\]](#)
8. Chhetri, P.; Nguyen, S.; Gekara, V.; Sharma, S. Container dwell time predictive modelling: An application of ML algorithms. *Marit. Policy Manag.* **2026**, *53*, 731–761. [\[CrossRef\]](#)
9. Chow, G.C.; Lin, A. Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *Rev. Econ. Stat.* **1971**, *53*, 372–375. [\[CrossRef\]](#)
10. Santos Silva, J.M.C.; Cardoso, F.N. The Chow-Lin method using dynamic models. *Econ. Model.* **2001**, *18*, 269–280. [\[CrossRef\]](#)
11. Guan, C.Q.; Liu, R. Modeling gate congestion of marine container terminals, truck waiting cost, and optimization. *Transp. Res. Rec.* **2009**, *2100*, 58–67. [\[CrossRef\]](#)
12. Chen, G.; Govindan, K.; Yang, Z. Managing truck arrivals with time windows to alleviate gate congestion at container terminals. *Int. J. Prod. Econ.* **2013**, *141*, 179–188. [\[CrossRef\]](#)
13. Phan, M.-H.; Kim, K.H. Collaborative truck scheduling and appointments for trucking companies and container terminals. *Transp. Res. Part B* **2016**, *86*, 37–50. [\[CrossRef\]](#)
14. Azab, A.; Morita, H. Coordinating truck appointments with container relocations and retrievals in container terminals under partial appointments information. *Transp. Res. Part E* **2022**, *160*, 102673. [\[CrossRef\]](#)
15. Abdelmagid, A.M.; Gheith, M.S.; Eltawil, A.B. A comprehensive review of the truck appointment scheduling models and directions for future research. *Transp. Rev.* **2022**, *42*, 102–126. [\[CrossRef\]](#)
16. Bett, D.K.; Ali, I.; Gheith, M.; Eltawil, A. Simulation-Based Optimization of Truck Appointment Systems in Container Terminals: A Dual Transactions Approach with Improved Congestion Factor Representation. *Logistics* **2024**, *8*, 80. [\[CrossRef\]](#)
17. Li, S.; Jia, S.; Tao, Y.; Lin, X. Gate appointment design in a container terminal: A robust optimization approach. *Transp. Res. Part E* **2024**, *184*, 103495. [\[CrossRef\]](#)
18. Xu, B.; Liu, X.; Li, J.; Yang, Y.; Wu, J.; Shen, Y.; Zhou, Y. Dynamic Appointment Rescheduling of Trucks under Uncertainty of Arrival Time. *J. Mar. Sci. Eng.* **2022**, *10*, 695. [\[CrossRef\]](#)
19. Ma, M.; Li, X.; Fan, H.; Qin, L.; Wei, L. Actual Truck Arrival Prediction at a Container Terminal with the Truck Appointment System Based on the Long Short-Term Memory and Transformer Model. *J. Mar. Sci. Eng.* **2025**, *13*, 405. [\[CrossRef\]](#)
20. Gracia, M.D.; Mar-Ortiz, J.; Vargas, M. Truck Appointment Scheduling: A Review of Models and Algorithms. *Mathematics* **2025**, *13*, 503. [\[CrossRef\]](#)
21. Giuliano, G.; O'Brien, T. Reducing port-related truck emissions: The terminal gate appointment system at the Ports of Los Angeles and Long Beach. *Transp. Res. Part D.* **2007**, *12*, 460–473. [\[CrossRef\]](#)
22. AlRukaibi, F.; AlKheder, S.; AlMashan, N. Sustainable port management in Kuwait: Shuwaikh port system. *Asian J. Shipp. Logist.* **2019**, *36*, 20–33. [\[CrossRef\]](#)
23. AlKheder, S.; Naif, D.; Musaed, D.; Al Shrekah, S.; Al Rshaid, M.; Al Anzi, N.; Baqer, I. Maritime transport management in Kuwait toward an automated port logistical city. *Clean. Logist. Supply Chain* **2022**, *3*, 100031. [\[CrossRef\]](#)
24. O'Hagan, A. Expert knowledge elicitation: Subjective but scientific. *Am. Stat.* **2019**, *73*, 69–81. [\[CrossRef\]](#)
25. de Jong, G.; Daly, A.; Pieters, M.; Miller, S.; Plasmeijer, R.; Hofman, F. Uncertainty in traffic forecasts: Literature review and new results for The Netherlands. *Transportation* **2007**, *34*, 375–395. [\[CrossRef\]](#)
26. State of Kuwait Central Statistical Bureau. *Annual Statistical Bulletin of Transport*; Central Statistical Bureau: Kuwait, State of Kuwait, 2019.

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