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Using discrete-event simulation to compare congestion management initiatives at a port terminal

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ABSTRACT

This research compares the impact of infrastructure congestion management initiatives at a bulk cargo marine terminal on truck queuing and emissions. Researchers have studied the impact of individual congestion management initiatives in marine terminals extensively. However, limited research has been conducted to comparatively evaluate the impact of several initiatives. Furthermore, researchers have mainly focused on container terminals to the detriment of bulk cargo terminals even though bulk cargo marine terminals can face significant congestion challenges.

A discrete-event simulation model of a bulk cargo marine terminal is developed in this research using empirical data collected from weighbridges and truck geo-positioning systems. The model is used to conduct a scenario analysis of several congestion management initiatives and assess their sensitivity to increasing terminal throughput. The performance indicators used are truck turnaround times, waiting times, turnaround time reliability, and engine idling emissions. The modelling results indicate that terminal appointment systems are one of the most effective congestion mitigation initiatives, reducing truck turnaround times by up to 65% and engine idling emissions by up to 80% compared to no intervention. The benefits accrued from terminal infrastructure expansions rival those of appointment systems only in high terminal throughput scenarios.

This research contributes to the body of knowledge by presenting an approach that improves understanding of the differential impacts of congestion management initiatives on truck and environmental performance in bulk cargo marine terminals. For practitioners, this research presents congestion management considerations that balance the competitive operational, cost, and efficiency interests of individual port users with tactical and strategic concerns regarding environmental impacts.

1. Introduction

The reduction of environmental footprint in port and logistics operations has increasingly gained attention from port operators worldwide. Air pollutants are major contributors to ports environmental footprint [20]. Truck transport causes most air pollution at

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ports [26,43]. Terminals can reduce emissions arising from truck transportation by addressing congestion.

Truck congestion is an issue that affects terminals and transporters alike but also has consequences on the broader supply chain. One of the most visible effects of congestion is the increase in truck turnaround or service times [15]. Other consequences include increased fuel consumption, time losses [32], reductions in transport operators' earnings [24], and increased greenhouse gasses emissions. For the supply chain, congestion is a disruption that contributes to increased inventory, warehousing, and transportation costs and environmental impact [28].

Truck congestion is primarily managed by marine terminals using a range of technology and infrastructure initiatives [30] or by governments using regulatory instruments [18]. These initiatives include extended gate working hours [33], terminal appointment systems [24], or either incentive [2] or disincentive schemes [18,22] for influencing truck arrival frequency, particularly during peak utilisation.

This research is motivated by several gaps in the research literature. First, few comparative studies have investigated whether congestion management initiatives impact truck and environmental performance differently with increased throughput. Second, the research literature is unclear on why some congestion management initiatives are chosen over others. In most situations, the environmental footprint of operations is, if any, a secondary concern. Third, congestion mitigation has received significant attention in container terminals, whereas truck congestion in the context of bulk cargo terminals has received relatively limited attention. However, truck congestion in bulk cargo terminals is a critical issue due to the high-volume, low-value nature of the commodities handled. Discrete-event simulation is highly suitable for addressing these gaps because it lends itself easily to scenario and sensitivity analysis without superimposing an optimisation objective as an outcome of the analysis process.

Therefore, this research aims to compare the impact of congestion management initiatives at a bulk cargo marine terminal in terms of truck queuing and emissions using a discrete-event simulation model. The model is used to conduct a scenario analysis of several congestion management initiatives and assess their sensitivity to increasing terminal throughput. The performance of congestion management initiatives is compared using truck turnaround times, service time reliability, truck waiting times, and engine idling emissions.

The paper is organised as follows: the next section presents a literature study, including congestion management in marine terminals and discrete-event simulation uses in modelling port and terminal operations. Next, the simulated case is described, followed by the methodology adopted for this research. The results of the simulation are then presented, followed by the implications for research and practitioners. Finally, the conclusions, limitations and future research direction are discussed.

2. Related work

The vast majority of the research literature on landside congestion management is concerned with the impact on truck turnaround and waiting times of a more even distribution of truck arrivals at marine terminals [16,19,23,33]. Analytical approaches include queuing models [8,19,48], simulation [24,25,28,39], and linear programming [1,10,41,47]. Chen, Zhou, and List [11] reported a theoretical truck turnaround time reduction from 100 to 40 min through queuing theory to optimise truck arrivals. Chen, Govindan, and Yang [9] reported a hypothetical decrease in truck waiting times from 103 to 13 min on average through an optimisation model. Furthermore, the impact of optimal arrival patterns on turnaround times varies depending on the terminal's utilisation rate [11]. A more evenly spread distribution of truck arrivals is clearly beneficial to improving turnaround times and may positively impact the terminal's utilisation. However, the research literature is less clear on whether and how congestion management initiatives vary in effectiveness under various terminal utilisation levels.

The use of technology to manage congestion has also been considered by several researchers. Technology can be used to automate procedures at an operational and tactical level and increase document processing speeds [21] or manage truck arrivals [24]. Furthermore, terminal working hours can be extended to increase the terminal's potential capacity [18]. At a strategic level, terminals can invest in additional equipment and infrastructure to increase the handling capacity.

Operational port and terminal performance indicators primarily relate to berth and vessel performance and include vessel turnaround and wait time, on-time reliability, berth occupancy and others [3,12,42]. On the land-side, few performance indicators are considered by ports and terminals. The most common land-side performance indicator is the average truck turnaround time [38,41,46]. Interestingly, Brooks & Schellinck [3,4] highlight that port and terminal users – both on the marine and land-side - are often more interested in port services' reliability rather than their speed. On-time reliability measures are common in sea-side terminal operations concerning vessel service times. Currently, there are no examples of reliability measures on the land-side pertaining to truck turnaround times. In this work, maritime indicators on reliability will be adapted for the land-side.

It remains unclear how some congestion management initiatives are chosen over others, and few comparative studies between various initiatives have been undertaken. Terminals often benefit financially from terminal appointment systems (TAS) implementations as the fees charged can become a source of revenue for terminal operators [14], which may partly explain their choice of congestion management initative. The authors have previously argued that terminals may not have an incentive to address congestion because congestion can be perceived as a way to maintain high utilisation levels of equipment and infrastructure [34]. In most situations, the environmental footprint of operations is of secondary concern. Congestion mitigation has also received significant attention in the context of container terminals. However, researchers have paid relatively limited attention to truck congestion in the context of bulk cargo terminals.

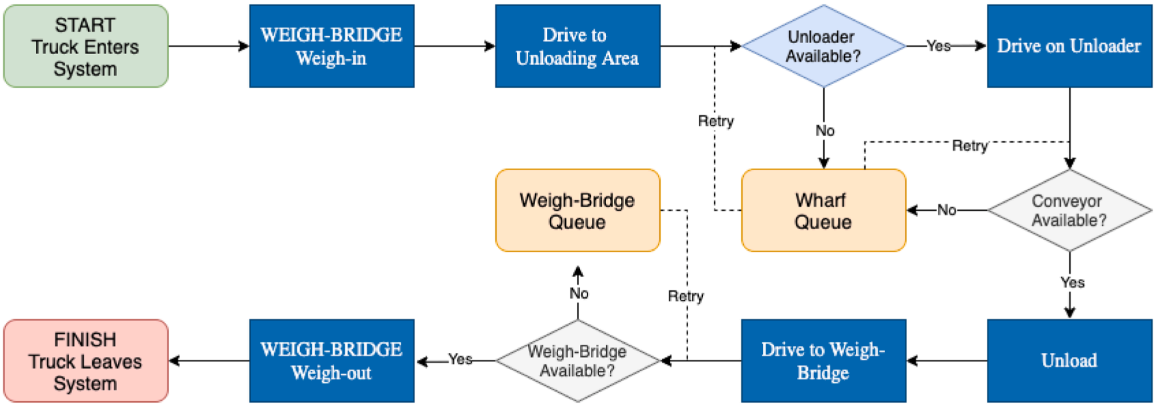


Fig. 1. Terminal unloading process.

2.1. *Discrete-Event simulation modelling of port terminals operations*

Discrete event simulation is widely accepted in the literature as a suitable approach to explore and compare a set of scenarios in many different domains. Simulation is frequently used for transportation systems modelling [17] and supply chain modelling [13,31,37]. Simulation modelling has been used both to explore sea-side and land-side operations at marine terminals. For sea-side operations, simulation modelling is typically employed to evaluate the impact of equipment and infrastructure changes on berth productivity [6,12,44]. On the land-side, congestion management at container terminals is modelled using simulation, often in combination with queuing and optimisation models [23,29,49].

Simulation modelling has increased in popularity since the turn of the century due to the technique's ability to represent the complex interactions taking place at a terminal [23] and the inherent uncertainty of terminal operations [27]. Simulation is beneficial in industry settings due to its ability to create a digital twin of physical infrastructure [27]. Under controlled conditions, simulation can help better understand the system's behaviour [7] and explore the effect of a limited number of variables [31]. *What-if* scenarios can be developed and analysed [13] while circumventing the additional costs and potential service disruption that a physical experiment or intervention would require. Finally, simulation modelling is conducive to support the development of tangible solutions [17]. Other approaches, such as linear programming and queuing theory, allow for optimising specific parameters for a desirable, unidimensional outcome, as is generally the case in queuing theory and analytical applications. In this study, simulation modelling was chosen to allow comparing the impact of various congestion management initiatives.

3. Bulk cargo marine terminal

The bulk cargo marine terminal handles wood chips and is located in Australia. Wood chips are a processed wood product used as biofuel or as raw material in the production of paper. The terminal operates 24-hours per day for land deliveries and vessel loading. On the land-side, the terminal receives more than 52,000 truck deliveries per year. On the sea-side, approximately 40 vessels are loaded each year. Each vessel requires the equivalent of 1500 to 2000 truckloads to be fully loaded.

The terminal receives truck deliveries from two customers, both procuring wood chips in each their manufacturing plant located within approx. 50 km of the terminal. Each customer operates two types of trucks with a maximum payload of 30 and 43 tonnes. Formal coordination between customers is minimal.

The truck's unloading process at the terminal is illustrated in Fig. 1. The process starts at a weigh-bridge that records the trucks' gross weight and arrival time. Next, trucks drive onto the wharf, where they can unload using two hydraulic platforms. The hydraulic platforms lift the truck at an angle forcing the product to slide into a common container located at the bottom of the platforms. A conveyor belt system empties the common container to the appropriate customer stockpile. Because the conveyor belt system is shared between the hydraulic platforms, concurrent unloading of trucks belonging to two different customers cannot occur. Once trucks are emptied and back on the ground, they return to the weigh-bridge for an empty weight reading and a departure timestamp. The difference between the arrival and departure times determines the truck turnaround time. The terminal throughput and the average truck turnaround times are the terminal's and customers' two main performance indicators.

During the last five years, the number of truck arrivals at the terminal increased by close to 500%. Following the increase in terminal throughput, congestion ensued impacting the service time and truck utilisation. A truck can be processed at the terminal without interruptions in 10 to 12 min. Average turnaround times have increased steadily as volumes have increased and are currently approx. 22–24 min. More than 60% of turnaround times are below 25 min, and approximately 95% of trucks are unloaded within an hour of arrival. The remaining trucks have turnaround times larger than 60 min and can reach 120–150 min.

Considering the round-trip driving time between the production facilities and the terminal and the drivers' 12-hour working window, an increase in terminal turnaround time over 25 min impacts the completed number of daily deliveries. Specifically, trucks running on a 40-minute loop between the terminal and the manufacturing plant can only complete 10 instead of 11 daily deliveries,

Table 1
Distribution Fitting Results.

Inputs	Offset	Distribution	SSE [e]
Inter Arrival Time	−0.5	G [c] ($k = 1.49$, θ=6.97)	0.002
Unloading Type II Truck	5.5	LOGN [a] ($\mu = 5.16$, $\sigma = 3.97$)	0.002
Weigh-Out	0	N [b] ($\mu = 3.46$, $\sigma = 1.68$)	0.016
Truck Type I	19	B [d] (α=9.77, β=6.55)	0.007
Truck Type II	0	N [b] ($\mu = 38.7$, $\sigma = 1.18$)	0.004

[a] Lognormal distribution;.
[b] Normal distribution;.
[c] Gamma distribution,.
[d] Beta distribution,.
[e] Sum of Square Errors.

while trucks running on a 90-minute loop can only complete 5 instead of 6 daily deliveries. Consequently, the 25-minute mark was considered as the threshold for truck turnaround time reliability in the performance measurement.

Given the economic impact of congestion, both the terminal operator and its users are interested in understanding the potential options to manage congestion as well as their impact over a range of scenarios.

4. Discrete-Event model formulation

The discrete-event simulation is implemented in a process-orientated view and is written in the Python programming language. The model primarily uses the pseudo-random number generator of the *random* python module. The model's algorithm follows the unloading process observed at the terminal, illustrated in Fig. 1.

4.1. Input data

The model's quantitative input data were collected from two sources – the terminal weigh-bridge database and truck telemetry data supplied by one of the transport operators. The weigh-bridge database consisted of 15,622 weigh-bridge observations covering nine months of truck arrivals. The database included information on truck arrival and departure times, truck types, gross and net weights. Weigh-bridge and unloading ramps operational times were recorded using truck telemetry data. Each site was geo-fenced and recorded truck information, entry and exit times from the area. The geo-fence data covered three months of operations and consisted of 6709 geo-fence entries.

The data collected were fitted to probability distributions using Arena Input analyzer. The resulting fitted distributions are summarised in Table 1. It was chosen to fit distributions rather than randomly sample from the empirical dataset to allow sampling of low probability events such as many trucks arriving at the same time. Such events may not have been recorded in the empirical data sample but would significantly impact the performance of congestion management initiatives.

4.2. Model specifications and assumptions

The model's specifications and assumptions were developed following discussions with terminal staff and site visits and are as follows:

(1) The terminal operates 24 h per day, 365 days per year; operations are not interrupted due to maintenance, breakdowns or weather events;
(2) The terminal has infinite product storage capacity and accepts truck deliveries at any time; vessel arrivals at the terminal do not affect the truck unloading operations;
(3) Trucks incur no waiting before entering the system;
(4) Truck arrivals are independent of one another;
(5) Trucks are served in the order in which they arrive – first-come, first-served;
(6) Both unloading ramps have the same capacity and similar operational speeds following the distribution described in Table 1.
(7) The type I truck's unloading time is 2 min faster than that of a type II truck; this is due to the differences in payload between the two trucks: type I trucks can carry up to 30 tons while type II trucks can carry up to 43 tonnes.
(8) If one unloading ramp has completed more than 60% of its unloading cycle, the other ramp can begin unloading if the trucks on the two ramps carry the same type of product(s). Otherwise, unloading (m) can take place if one ramp has completed 80% or more of its unloading cycle;
(9) The driving time between the weigh-bridge and the unloading ramps is held constant at 1 min on arrival (τ_1) and 2 min on departure (τ_2);
(10) The weighing-in time (σ) was estimated at 1.5 min per truck following on-site observation and telemetric data analysis as the weigh-bridge software does not capture the weighing-in time.

Table 2
Scenario parameters.

Description	Param.
Trucks	$t = 1, \ldots$
Unloaders	$x = 1, \ldots$
Conveyors	$y = 1, \ldots$
Weighbridges	$z = 1, \ldots$
Same Product Unloading Overlap	n
Conveyor Availability Coefficient	m
Truck Type	k
Engine CO_2 Emissions while idling**	δ

* indicates random generation through Monte Carlo technique. Input distributions for randomly generated values are presented in Table 1.
** emission factors obtained from [40].

Table 3
Truck variables.

Truck variables	Var.
Inter-arrival time (IAT)*	μ
Truck payload*	p
Unloading time (unloader x, truck t, type k*)	θ_{xtk}
Weighing-out time (weigh-bridge z, truck t*)	ρ_{zt}
Weighing-in time (constant)	σ
Drive from weighbridge time (constant)	τ_1
Drive to weighbridge time (constant)	τ_2

Table 4
Event times for truck t.

Event times for truck t	Var.
Arrival at terminal	a_t
Unloading start	b_t
Unloading finish	c_t
Weighing start	d_t
Weighing finish	e_t
Truck t Performance Measures	
Waiting time prior to unloading	υ_t
Waiting time prior to weighing	ω_i
Turnaround Time	ϕ_i

Table 5
Terminal equipment variables.

Terminal equipment variables	Var.
Unloader x available at time instant	U_x
Conveyor y available at time instant	C_y
Weighbridge z available at time instant	W_z

4.3. Model formulation and execution algorithm

The model's parameters are presented in Table 2. Truck related variables are illustrated in Table 3, while truck event times are illustrated in Table 4. Terminal equipment variables are depicted in Table 5. Algorithm 1 presents the simulation pseudocode. Finally, the performance indicators are discussed.

The terminal performance indicators used are:

(1) The *average truck turnaround time* (TTT) representing the average turnaround (ϕ_t) across all truck (t);
(2) The *average truck waiting time* (Wait) sums the waiting time prior to unloading (υ_t) and the waiting time prior to weighing (ω_t) across all trucks (t);
(3) The *turnaround time reliability* (Rel.25) is the proportion of trucks that are turned around (ϕ_t) in 25 min or less;
(4) The *truck engine idling* CO_2 *emissions* are calculated by multiplying the waiting time prior to unloading (υ_t) and the waiting time prior to weighing (ω_t) with the CO_2 emissions factor (δ).

Algorithm 1
Terminal simulation model pseudocode.

ScenarioWrapper(*endtime, Iterations*, $x = 1, \ldots, y = 1, \ldots, z = 1, \ldots$):

for s in *Scenarios*:
for i in *Iterations*
InitiateTerminalObjects (U_x, C_y, W_z)
while $a_i \leq s.endtime$:
GenerateTrucks(a_t, k)
Sort(Trucks, a_t)
for t in $t = 1, \ldots$:
ProcessTruck(t)
UpdateTruckPerformance(t)
UpdateEquipmentAvailability()
UpdateTerminalPerformance()
DataAnalysis()
Visualization()
ProcessTruck(t):
$b_t = a_t + \max((\sigma + \tau_1), \min(U_x), \min(C_y))$
$c_t = b_t + \theta_{xtk}$
$d_t = \max((c_t + \tau_2), \min(W_z))$
$e_t = d_t + \rho_{zt}$
UpdateEquipmentAvailability()
UpdateEquipmentAvailability(x,t):
$U_x = b_t + n * \theta_{xtk}$
$C_y = b_t + m * \theta_{xtk}$
$W_z = e_t$
UpdateTruckPerformance(t):
$\upsilon_t = b_t - (a_t + \sigma + \tau_1)$
$\omega_t = d_t - (c_t + \tau_2)$
$\phi_t = \sigma + \tau_1 + \upsilon_t + \theta_{xt} + \tau_2 + \omega_t + \rho_{zt}$

4.4. Model verification

The model's input distribution parameters and output were verified against the empirical data. Fig. 2 illustrates the fitted and the empirical distributions for truck inter-arrival times, weighing and unloading times.

Due to their importance in the accuracy of the simulation model's representation, it was critical that the fitted and empirical distributions would not be significantly different. Hence, the presence of statistically significant differences was tested using a Chi-Square test. The Chi-Squared test results are summarised in Table 6. The results indicate no statistically significant differences between the fitted and empirical distributions of the three components – truck inter-arrival, unloading and weighing times. In other words, the fitted distributions are representative of the observed data.

The model was also empirically verified through several site visits at the terminal and discussions with terminal staff on the model's specification and the preliminary outputs.

5. Experimental scenarios specification and sensitivity

The simulation model is used for scenario and sensitivity analysis. The goal is to illustrate the potential impact of various initiatives and potentially direct stakeholders' attention to the most effective methods given the terminal's growth and development outlook. The scenarios represent various congestion management initiatives and were developed in collaboration with the terminal and customers' staff, inspired by literature on container terminal congestion management:

- *Scenario 1:* The introduction of a **terminal appointment system (TAS)** is modelled by introducing arrival slots for each truck. The length of one slot is equal to the average inter-arrival times (IAT) of trucks in that throughput scenario (e.g. a slot is 10-minute-long in the base scenario, equal to the IAT average). A stochastic arrival component is added to the arrival time through a normal distribution with mean=0 and st.dev.=2.5 to simulate potential minor deviations from the slot start time. All trucks modelled in the scenario use the appointment system, and no missed appointments or walk-ins are considered (i.e. trucks arriving without appointments).
- *Scenario 2:* The introduction of an **integrated weigh-bridge database (IWB)** that would store trucks' empty weights is modelled by removing the weighting out of trucks. Under this system, trucks weigh upon arrival at the terminal. Their net payload is directly calculated using stored truck details. Once trucks are emptied, operators drive out directly without the requirement to weigh again. This scenario is inspired from automation technology solutions observed in the container terminal literature.

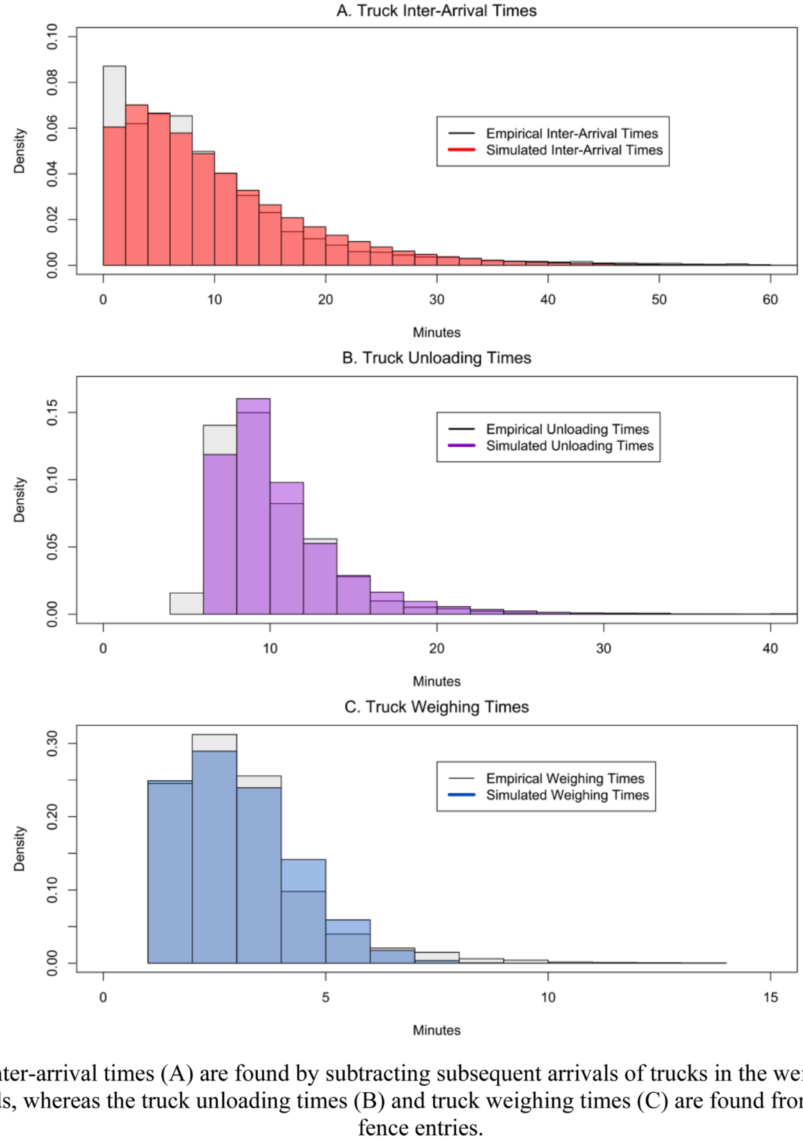


Fig. 2. Fitted and Empirical Distributions Histograms.
The inter-arrival times (A) are found by subtracting subsequent arrivals of trucks in the weigh-bridge records, whereas the truck unloading times (B) and truck weighing times (C) are found from the geo-fence entries.

Table 6
Fitted and Empirical Distribution Chi-Square Test Results.

Input	Chi-Square Test p-value
Inter-Arrival Times (IAT)	0.287
Unloading Times	0.106
Weighing Times	0.385

- *Scenario 3A:* The **extension of the conveyor (CON)** system is modelled by adding another hydraulic ramp connected to the existing conveyor system. Another identical ramp with the two already present on-site allows concurrent unloading of three trucks, subject to the limitations of the conveyor belt system.
- *Scenario 3B:* The **ramp expansion (RAM)** is modelled by connecting the 3rd ramp to a separate conveyor system that can operate independently of the existing conveyors. Each conveyor belt system would be dedicated to one customer, therefore separating truck flows between the two companies.

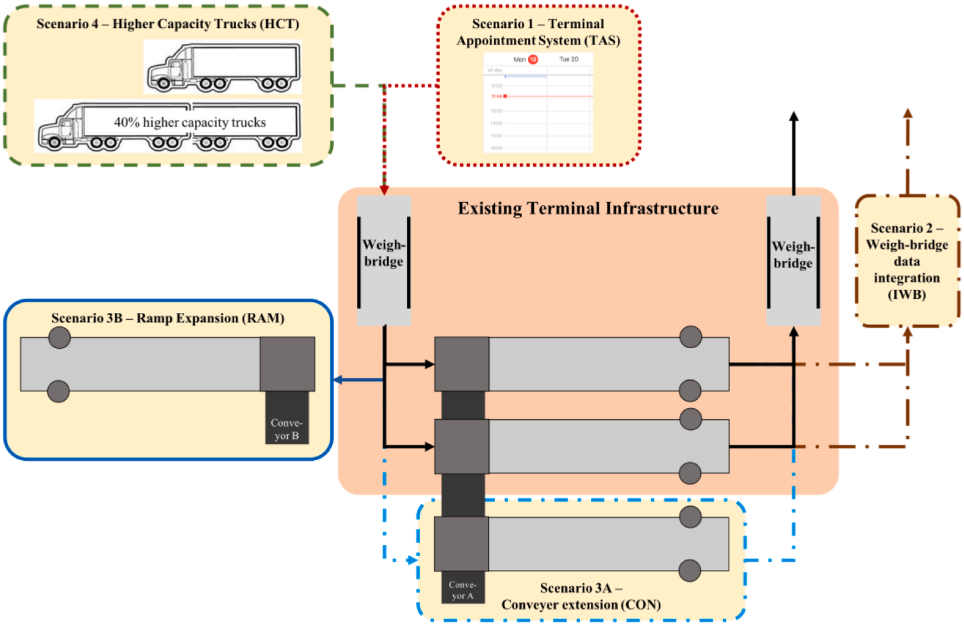


Fig. 3. Congestion management scenarios following the description above.

- *Scenario 4:* The use of **higher capacity trucks (HCT)** is modelled by forcing all trucks to a 43-ton payload. In this case, the lower capacity, 30-ton trucks, are replaced with higher capacity trucks. A wide variety of truck configurations can access the Australian public road network [36]. Introducing higher capacity trucks can be a congestion management method if processing larger trucks are less time-consuming than the equivalent standard capacity vehicles. The trucks' arrival frequency is adjusted to ensure that the terminal's throughput is comparable with previous scenarios.

The baseline for all comparisons is the scenario where no congestion management intervention (NOINT) is undertaken. The existing terminal layout and the modelled scenarios are visualised in Fig. 3.

The sensitivity of each congestion management initiative to throughput increase is modelled by increasing the truck arrival frequency. A scaling coefficient is used to reduce the average IAT from 10 min in the base case to respectively 9, 8, 7.75, 7.5, 7.25 and 7 min while maintaining the same distribution shape. The throughput scenarios are identified based on the mean IAT. In total, 42 combinations were considered in the simulation scenario analysis. For each combination, the simulation was run for 50 iterations, each iteration representing one year of terminal operations. Each congestion management initiative is measured against four key performance indicators (described in further detail in Section 4.3):

(1) Average truck turnaround times across the year (TTT);
(2) Average truck waiting times across the year (Wait);
(3) Truck turnaround time reliability (Rel.25);
(4) Emission of greenhouse gasses from idling truck engines during waiting (CO_2).

Truck turnaround time reliability is measured as the percentage of trucks with a turnaround time under 25 min from the total number of trucks. Greenhouse gasses emissions of idling truck engines during waiting are measured by multiplying the truck CO_2 emission factors [40] with the total number of minutes of waiting time in a given scenario.

The statistical significance of the differences between scenarios under each truck arrival frequency indicator is compared with ANOVA, and pair-wise differences were subsequently tested with the Tukey test using a significance threshold of 0.05 (see Appendix for further details).

6. Experiment results and analyses

The simulation model results reveal that congestion levels and truck turnaround times are highly sensitive to the terminal's throughput increase. If the terminal throughput increases by 25% from 1.6 to 2 million tonnes, truck turnaround times increase by 43%. However, each subsequent throughput increase has a progressively larger impact on turnaround times. A throughput change of approx. 3% (IAT 8 to IAT 7.75) generates an increase in the turnaround times by15%. Similarly, a throughput change of approx. 3,5% (IAT 7.25 to IAT 7.0) generates an increase in the turnaround times by 57%.

For a further increase in throughput of 40% (from 1.6 to 2.3 million tonnes), the turnaround times increase is close to 280% in the

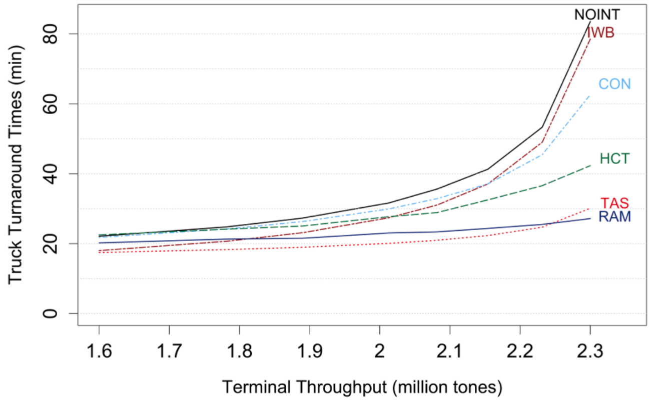


Fig. 4. Scenario analysis of truck turnaround times. NOINT = no intervention; IWB = weigh-bridge integration; CON = conveyor extension; TAS = appointment system; RAM = ramp expansion; HCT = high capacity trucks;.

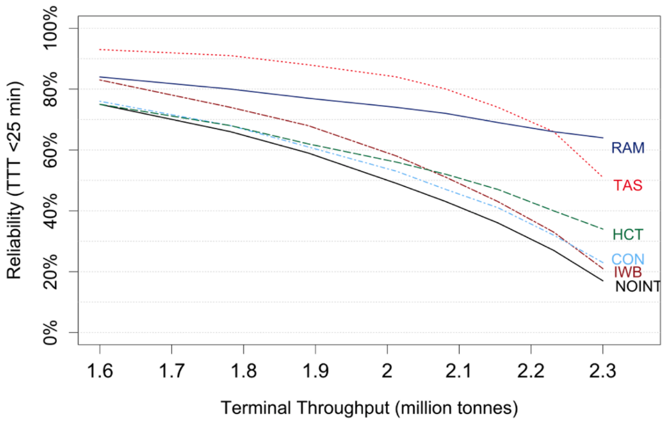


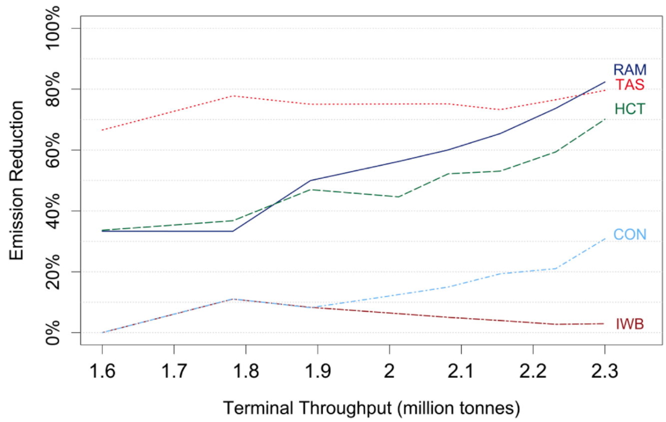
Fig. 5. Scenario analysis comparison of turnaround time reliability. NOINT = no intervention; IWB = weigh-bridge integration; CON = conveyor extension; TAS = appointment system; RAM = ramp expansion; HCT = high capacity trucks;.

NOINT scenario. The most significant increase in turnaround time can be attributed to the last 150,000 tonnes of throughput. Truck-related CO_2 emissions also increase 16-fold between the IAT 10 and IAT 7. Therefore, when terminal capacity is available to absorb operational variability in a dynamic system, congestion has a limited impact on turnaround times. However, when the system approaches its capacity limit, the consequences of congestion are more severe and, in extreme cases, bring operations to a halt. The turnaround time sensitivity to increasing throughput is depicted in Fig. 4.

It is essential to recognise that given the nature of the congestion management initiatives modelled, the terminal capacity utilisation is not an adequate performance metric. The terminal's capacity is affected by the capacity of physical infrastructure and the trucks ' capacity. An extension (CON) or an expansion (RAM) of the terminal's infrastructure is expected to influence the capacity of the terminal. Similarly, higher capacity trucks (HCT) reduce the number of truck arrivals while delivering similar volumes at the terminal.

The two technology options, namely weigh-bridge data integration (IWB) and the terminal appointment system (TAS) achieve the highest reduction in turnaround times (approximately 20%) in the baseline throughput scenario compared to the existing situation (NOINT). Both initiatives successfully improve the unloading reliability (Rel.25) by 8 and respectively 18 percentage points. Interestingly, the reduction in CO_2 emissions of the TAS is significantly larger than the IWB, although the turnaround time reduction is similar. The IWB leads to a less than 5% reduction in emission, while the TAS leads to more than 80% reduction in emissions. A closer look at the data reveals that, while the IWB reduces processing times, it does not affect the structure of the truck turnaround and waiting times. The sensitivity of the reliability indicator to increasing throughput is visualised in Fig. 5.

Across most throughput growth scenarios, the TAS is the technology initiative that produces the most positive impacts on turnaround, waiting times, and emissions. In the IAT 7.25 scenario, the appointment system (TAS) yields a comparable performance with the ramp expansion (RAM) in terms of turnaround times and emissions. Both the conveyor extension (CON) and ramp expansion



NOINT = no intervention; IWB = weigh-bridge integration; CON = conveyor extension;
TAS = appointment system; RAM = ramp expansion; HCT = high capacity trucks;

Fig. 6. Scenario analysis of emission compared to no intervention. NOINT = no intervention; IWB = weigh-bridge integration; CON = conveyor extension; TAS = appointment system; RAM = ramp expansion; HCT = high capacity trucks;.

Table 7
Scenario and Sensitivity Analysis Results.

IAT[A]	Scenario	Trucks	Throughput ('000 tonnes)	TTT (min)[B]	TTT SD[C]	Wait (min)[D]	Rel. 25[E]	CO_2 (t/yr) [F]
10	**NOINT**	52,384	1598	23	10	6	75%	23
	IWB	52,454	1601	20	9	6	83%	22
	TAS	52,559	1604	19	5	1	93%	5
	HCT	42,719	1620	24	9	5	75%	15
	CON	52,389	1599	23	9	6	76%	22
	RAM	52,385	1599	21	7	4	84%	15
8	**NOINT**	65,964	2013	33	19	15	49%	76
	IWB	65,957	2013	30	19	15	58%	74
	TAS	65,698	2006	21	7	4	84%	19
	HCT	53,736	2038	30	15	11	56%	43
	CON	65,972	2013	31	17	14	53%	67
	RAM	66,069	2016	24	10	6	74%	31
7.5	**NOINT**	70,479	2151	36	28	25	36%	130
	IWB	70,605	2155	33	29	26	43%	134
	TAS	70,077	2140	22	9	6	74%	32
	HCT	57,466	2180	31	19	15	47%	65
	CON	70,491	2151	34	24	21	41%	109
	RAM	70,477	2151	24	11	8	69%	40
7	**NOINT**	75,782	2313	83	67	66	17%	369
	IWB	75,732	2311	82	76	68	21%	381
	TAS	75,082	2291	31	16	14	51%	77
	HCT	61,662	2339	44	28	25	34%	115
	CON	75,693	2309	63	49	46	23%	258
	RAM	75,765	2312	27	12	9	64%	52

NOINT = no intervention; IWB = weigh-bridge integration; CON = conveyor extension;.
TAS = appointment system; RAM = ramp expansion; HCT = high capacity trucks;.
[A] Inter-Arrival Time;.
[B] Average Truck Turnaround Times;.
[C] Standard deviation of Truck Turnaround Times;.
[D] Average Waiting Times;.
[E] Truck Turnaround Time Reliability -% of trucks unloaded in 25 min or less;.
[F] Truck Engine Idling CO_2 Emissions (tonnes/year) –emission factors [40];.

(RAM) initially had a lower-than-expected impact on turnaround times. This is unexpected, particularly in the case of the ramp expansion, which essentially separates the two companies' flows and introduces substantial additional capacity at the terminal. The average turnaround time and reliability (Rel.25) of CON in the IAT 10 scenario are approximately 10% less than RAM. The truck CO_2 emissions are, however, close to 25% less in CON than RAM as seen in Fig. 6.

As the terminal throughput increases, the performance of the CON is significantly better than the RAM. CON is consistently the second-best alternative from the five tested in the IAT 9 to 7.25 scenarios in terms of turnaround time, reliability and emissions. As the terminal throughput increases to 2.3 million tonnes (IAT 7), CON yields the lowest turnaround and waiting times, emissions and the highest turnaround time reliability.

Although not traditionally considered a congestion mitigation initiative, higher capacity trucks (HCT) yield improvements in turnaround time and emissions. Most benefits stem from reducing the number of truck arrivals, which entail fewer opportunities for truck arrivals to overlap and fewer operating trucks generating emissions. Selected model results in terms of the four performance indicators are summarised in Table 7.

The TAS can consistently yield emission improvements by 70–80% compared to NOINT, while the IWB generally provides a significantly smaller improvement between 5 and 15%. Interestingly, the emission impact of RAM and HCT in comparison to NOINT significantly increases as the terminal throughput grows.

7. Discussion and contributions

This research has explored the impact of technology and infrastructure initiatives on congestion management. The terminal appointment system (TAS) and the integrated weighbridge (IWB) have helped reduce average truck turnaround times in lower utilisation scenarios. Infrastructure extensions (CON) and (RAM) helped reduce truck turnaround times in the higher throughput scenarios. The TAS was one of the most effective congestion mitigation initiatives across most throughput scenarios, both in waiting times, reliability, and environmental perspectives. These results are now discussed in the context of the existing literature.

Researchers have consistently hailed TAS as one of the most effective ways to mitigating congestion [10,24,46]. The results of this research are consistent with the literature. Further, terminals use TAS implementations as the lower cost alternative to comply with congestion management regulation [18] or to generate a complementary revenue stream [14]. In such conditions, TAS implementations seem unlikely to achieve the modelled benefits as the incentives for terminals are not necessarily to mitigate congestion.

The simulation model developed in this research makes assumptions regarding the usability, adoption and practical use of appointment systems. The effectiveness of the TAS is contingent on the alignment between the technology's features and its users' requirements. Transport operators represent one important group of users. Therefore, to achieve the system‘s potential gains in operational efficiency, reliability and environmental footprint, the users‘ trust and willingness to participate in the development and implementation process are vital [35].

The research literature highlights the potential operational benefits of automation and novel technologies such as radio-frequency identification and optical character recognition [21]. The results of this research support the thesis of operational efficiency gains from automation. IWB led to operational benefits, which also show less variability than the TAS. However, we draw attention to the fact that operational efficiency improvements do not necessarily entail a reduction in the levels of congestion. Thus, the IWB had a relatively limited impact on turnaround time reliability and environmental emissions than other congestion management initiatives.

In this research, the infrastructure initiatives to congestion management have shown greater effectiveness in higher throughput scenarios than in the lower ones when compared to the other initiatives. Infrastructure initiatives are traditionally considered for congestion management [30]. However, in this research, infrastructure initiatives are preferred only in certain cases. After close inspection of the scenario results and discussions with the terminal operator, the researchers uncovered that the terminal extension, while increasing the unloading ramp capacity, is constrained by the conveyor system's capacity. Therefore, the unloading ramp capacity improvements are only partially realised.

This research contributes to the extant body of knowledge in several ways: first, this research contributes to an underdeveloped body of knowledge on congestion management in bulk cargo marine terminals. The simulation approach presented in this research can be adopted in other types of bulk cargo terminals. Furthermore, truck congestion management has received significant attention from researchers in the context of container terminals [24,28,38]. Importantly, this research highlights that the congestion management techniques, many of them discussed in the context of container terminals, can be adapted to bulk cargo terminals. The IWB scenario is an instantiation of automation technology that reduces or eliminates stages in the unloading process with an effect similar to optical character recognition gates in container terminals. The infrastructure expansions (RAM) and extensions (CON) are adapted but common initiatives to addressing congestion, particularly in bulk cargo terminals [5].

Second, this research presents a method for integrating truck geo-positioning data with terminal data to enhance terminal simulation models' accuracy, leading to higher quality insights. Research on congestion management typically relies on truck arrival measurements collected through observation (e.g. [19]) or by measurement devices at terminals [38]. Manual observation is expensive, time-consuming and typically generates few data points. This research uses a three month extensive dataset with more than 15,000 weigh-bridge data points and approximately 6700 geo-fence entry records.

Third, this research highlights and discusses potential factors influencing the choice of congestion mitigation mechanisms. These factors include the terminal's strategic development in terms of growth, the stakeholders involved and affected in the congestion management initiatives, and the performance indicators relevant for stakeholders. The scenario analysis highlighted that the congestion mitigation initiatives have a different impact depending on the terminal throughput. Thus, if the throughput is expected to grow, it is more likely that infrastructure initiatives may be favoured as physical capacity is reached. If, however, the throughput is expected to remain constant or potentially decrease, technology initiatives are more likely to yield more tangible benefits.

Finally, the relevant performance criteria for the stakeholders should be considered. Average truck turnaround times are the most frequently used measures of congestion in marine terminals [15,24]. However, as the results of this research have shown, reductions in truck turnaround times do not necessarily have an equivalent effect on truck waiting times or other performance indicators. For example, turnaround times reductions realised with automation technology have a relatively limited impact on truck waiting times.

The concept of turnaround time reliability has not been used for measuring land-side congestion. Several research studies have found that turnaround reliability in shipping was one of the most critical factors for maritime port users for maintaining their schedule integrity [3,4]. While it is likely that land transport scheduling constraints are less rigid as for scheduled shipping services, this study documents that reliability plays an equally important role for land transport as shipping services.

Emission reductions considerations can also play a role in congestion management decisions. As concerns regarding environmental emissions and climate change increase, so too do pressures on logistics chains' elements to reduce their footprint [45]. Ports and terminals are uniquely positioned as intersection points of supply chains and can influence their users' logistics operations. This research has highlighted that congestion management can reduce environmental emissions emerging from truck engine idling.

8. Conclusions, limitations and future research

This research explored the impact of technology and infrastructure initiatives on congestion management at a bulk cargo terminal relating to truck queuing, waiting, and emissions. A discrete-event simulation model of a bulk cargo marine terminal in Australia was developed to investigate the impact of technology and infrastructure congestion mitigation initiatives.

The limitations of this research relate primarily to the available data and the assumptions embedded in the simulation model. At the truck operator level, behaviours that could be quantified and geo-tracked are included in the simulation model. Therefore, differences between drivers‘ skills or in performance incentives cannot be accounted for. The simulation model focuses primarily on the land-side operations and specifically on the interactions with the trucks. The authors acknowledge that the truck unloading system interacts with other systems such as production, maritime transport, terminal yard management and vessel loading systems which may influence the land-side terminal operations. While these influences are acknowledged, inaccurate and insufficient data prevent including these systems in the simulation modelling. Future research aims to account for the influence of these systems, both from a qualitative perspective and, where possible, using quantitative modelling.

The statistical generalizability of the simulation findings is also a limitation of this research. It is unlikely that the results of this research can be directly applied in other settings. Nonetheless, the congestion management considerations emerging from this research can be useful for sensitising both researchers and practitioners towards the different facets of congestion and its management.

This research is an ongoing collaboration between the research team and the terminal operator and its users. The outcomes of the research associated with this project have helped shape the decisions of the terminal operator in the case study in regard to the implementation of congestion mitigation methods. The research project ultimately aims to follow the implementation and evaluate the effectiveness of congestion management initiatives in an empirical setting.

Credit author statement

Mihai Neagoe: Writing - Original Draft, Conceptualization, Methodology, Formal Analysis **Hans-Henrik Hvolby:** Conceptualization, Writing - Review & Editing **Mohammad Sadegh Taskhiri:** Writing - Review & Editing **Paul Turner:** Conceptualization, Writing - Review & Editing, Supervision

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Appendix

Tables 8 and 9

Table 8
Simulation Scenarios ANOVA Test Results.

ANOVA Results	Df	Sum Squares	Mean Squares	F-value	P-Val
IAT 7	5	4.62×10^9	9.24×10^8	389,296	<0.001
Residuals	8794,322	2.09×10^{10}	2373		
IAT 7.25	5	1.14×10^9	2.27×10^8	269,743	<0.001
Residuals	8484,533	7.15×10^9	843		
IAT 7.5	5	4.36×10^8	8.71×10^7	188,481	<0.001
Residuals	8191,905	3.79×10^9	462		
IAT 7.75	5	2.20×10^8	4.40×10^7	146,096	<0.001
Residuals	7921,854	2.39×10^9	301		
IAT 8	5	1.33×10^8	2.66×10^7	118,440	<0.001
Residuals	7667,915	1.72×10^9	224		
IAT 8.5	5	6.17×10^7	1.23×10^7	86,102	<0.001
Residuals	7206,467	1.03×10^9	143		
IAT 9	5	3.64×10^7	7.29×10^6	69,134	<0.001
Residuals	6794,902	7.16×10^8	105		
IAT 10	5	1.98×10^7	3.97×10^6	56,869	<0.001
Residuals	6097,783	4.25×10^8	70		

Table 9
Simulation Scenarios Tukey Test Results.

Scenario	IAT 7	IAT 7.25	IAT 7.5	IAT 7.75	IAT 8	IAT 8.5	IAT 9	IAT 10
HCT-NOINT	−39.25	−16.77	−8.18	−5.15	−3.30	−1.36	−0.46	0.25
IWB-NOINT	−0.957	−3.672	−2.20	−3.08	−3.34	−3.34	−3.21	−3.29
TAS-NOINT	−51.83	−28.74	−18.50	−14.20	−11.65	−8.35	−6.50	−4.59
CON-NOINT	−19.69	−7.984	−3.90	−2.69	−1.90	−1.07	−0.64	−0.35
RAM-NOINT	−56.27	−28.74	−17.10	−12.10	−9.10	−5.60	−3.76	−2.08
IWB-HCT	38.29	13.09	5.97	2.06	−0.04	−1.97	−2.75	−3.55
TAS-HCT	−12.58	−11.97	−10.4	−9.13	−8.35	−6.99	−6.03	−4.85
CON-HCT	19.55	8.78	4.27	2.45	1.39	0.29	−0.18	−0.61
RAM-HCT	−17.01	−11.97	−8.96	−6.95	−5.80	−4.24	−3.29	−2.34
TAS-IWB	−50.87	−25.07	−16.38	−11.2	−8.31	−5.01	−3.28	−1.30
CON-IWB	−18.73	−4.312	−1.70	0.39	1.44	2.27	2.57	2.93
RAM-IWB	−55.31	−25.07	−14.93	−9.02	−5.76	−2.26	−0.54	1.20
CON-TAS	32.13	20.76	14.68	11.59	9.75	7.28	5.85	4.24
RAM-TAS	−4.43	0.01	1.45	2.18	2.54	2.74	2.73	2.51
RAM-CON	−36.57	−20.75	−13.23	−9.41	−7.20	−4.53	−3.11	−1.72

*All differences significant at $p<0.001$ except RAM-TAS under IAT 7.25 and IWB-HCT under IAT 8.

References

[1] D. Ambrosino, C. Caballini, Congestion and truck service time minimization in a container terminal, in: Maritime-Port Technology and Development - Proceedings of the International Conference on Maritime and Port Technology and Development, MTEC, 2015, pp. 1–10, 2014.

[2] D.J. Bentolila, R.K. Ziedenveber, Y. Hayuth, T. Notteboom, Off-peak truck deliveries at container terminals: the "Good Night" program in Israel, Maritime Bus. Rev. 1 (1) (2016) 2–20, https://doi.org/10.1108/MABR-03-2016-0005.

[3] M.R. Brooks, T. Schellinck, Measuring port effectiveness in user service delivery: what really determines users' evaluations of port service delivery? Res. Transport. Bus. Manage. 8 (2013) 87–96, https://doi.org/10.1016/j.rtbm.2013.04.001.

[4] M.R. Brooks, T. Schellinck, Measuring Port Effectiveness. Transportation Research Record, J. Transport. Res. Board 2479 (2479) (2015) 42–48, https://doi.org/10.3141/2479-06.

[5] U. Bugaric, D. Petrovic, Increasing the capacity of terminal for bulk cargo unloading, Simul. Modell. Pract. Theory 15 (10) (2007) 1366–1381, https://doi.org/10.1016/j.simpat.2007.09.006.

[6] U.S. Bugaric, D.B. Petrovic, Z.V. Jeli, D.V. Petrovic, Optimal utilization of the terminal for bulk cargo unloading, Simulation 88 (12) (2012) 1508–1521, https://doi.org/10.1177/0037549712459773.

[7] Y. Chang, H. Makatsoris, Supply chain modeling using simulation, Int. J. Simulation 20 (1) (2001) 24–30.

[8] G. Chen, K. Govindan, M.M. Golias, Reducing truck emissions at container terminals in a low carbon economy: proposal of a queueing-based bi-objective model for optimizing truck arrival pattern, Transport. Res. Part E: Logistics and Transport. Rev. 55 (X) (2013) 3–22, https://doi.org/10.1016/j.tre.2013.03.008.

[9] G. Chen, K. Govindan, Z. Yang, Managing truck arrivals with time windows to alleviate gate congestion at container terminals, Int. J. Prod. Econ. 141 (1) (2013) 179–188, https://doi.org/10.1016/j.ijpe.2012.03.033.

[10] G. Chen, L. Jiang, Managing customer arrivals with time windows: a case of truck arrivals at a congested container terminal, Ann. Oper. Res. 244 (2) (2016) 349–365, https://doi.org/10.1007/s10479-016-2150-3.

[11] X. Chen, X. Zhou, G.F. List, Using time-varying tolls to optimize truck arrivals at ports, Transport. Res. Part E: Logistics and Transport. Rev. 47 (6) (2011) 965–982, https://doi.org/10.1016/j.tre.2011.04.001.

[12] R. Cimpeanu, M.T. Devine, C O'Brien, A simulation model for the management and expansion of extended port terminal operations, Transport. Res. Part E: Logistics and Transport. Rev. 98 (2017) 105–131, https://doi.org/10.1016/j.tre.2016.12.005.

[13] T.G. Crainic, G. Perboli, M. Rosano, Simulation of intermodal freight transportation systems: a taxonomy, Eur. J. Oper. Res. 270 (2) (2018) 401–418, https://doi.org/10.1016/j.ejor.2017.11.061.

[14] P. Davies, Container terminal reservation systems design and performance, in: METRANS International Urban Freight Conference Long Beach CA, 2013, pp. 1–24.

[15] P. Davies, M.E. Kieran, Port Congestion and Drayage Efficiency, in: METRANS International Urban Freight Conference, 2015, pp. 1–20.

[16] N.A.D. Do, I.E. Nielsen, G. Chen, P Nielsen, A simulation-based genetic algorithm approach for reducing emissions from import container pick-up operation at container terminal, Ann. Oper. Res. 242 (2) (2016) 285–301, https://doi.org/10.1007/s10479-014-1636-0.

[17] B. Dragović, E. Tzannatos, N.K. Park, Simulation modelling in ports and container terminals: literature overview and analysis by research field, application area and tool, Flexible Services and Manufact. J. 29 (1) (2017) 4–34, https://doi.org/10.1007/s10696-016-9239-5.

[18] G. Giuliano, T O'Brien, Reducing port-related truck emissions: the terminal gate appointment system at the Ports of Los Angeles and Long Beach, Transport. Res. Part D: Transport and Environ. 12 (7) (2007) 460–473, https://doi.org/10.1016/j.trd.2007.06.004.

[19] C. Guan, R. Liu, Container terminal gate appointment system optimization, Maritime Econ. Logistics 11 (4) (2009) 378–398, https://doi.org/10.1057/mel.2009.13.

[20] L. Heilig, E. Lalla-Ruiz, S. Voß, Multi-objective inter-terminal truck routing, Transport. Res. Part E: Logistics and Transport. Rev. 106 (2017) 178–202, https://doi.org/10.1016/j.tre.2017.07.008.

[21] L. Heilig, S. Voß, Information systems in seaports: a categorization and overview, Info. Technol. Manage. 18 (3) (2017) 179–201, https://doi.org/10.1007/s10799-016-0269-1.

[22] J. Holguín-Veras, K. Ozbay, A. Kornhauser, M. Brom, S. Iyer, W. Yushimito, S. Ukkusuri, B. Allen, M. Silas, Overall Impacts of Off-Hour Delivery Programs in New York City Metropolitan Area, Transport. Res. Record: J. Transport. Res. Board 2238 (2011) 68–76, https://doi.org/10.3141/2238-09.

[23] N. Huynh, Reducing Truck Turn Times at Marine Terminals with Appointment Scheduling, Transport. Res. Record: J. Transport. Res. Board 2100 (2009) 47–57, https://doi.org/10.3141/2100-06.

[24] N. Huynh, D. Smith, F. Harder, Truck Appointment Systems, Transport. Res. Record: J.Transport. Res. Board 2548 (2016) 1–9, https://doi.org/10.3141/2548-01.

[25] N. Huynh, C.M. Walton, J. Davis, Finding the Number of Yard Cranes Needed to Achieve Desired Truck Turn Time at Marine Container Terminals, Transport. Res. Record: J. Transport. Res. Board 1873 (1873) (2004) 99–108.

[26] J.S.L. Lam, E Van de Voorde, Green port strategy for sustainable growth and development, in: Proceedings of the International Forum on Shipping,Ports and Airports (IFSPA), 2012, pp. 27–30.

[27] H. Li, L.H. Lee, E. Peng Chew, A. Stephen, C. Zhou, W. Liu, Challenges and Opportunities in Integration of Simulation and Optimization in Maritime Logistics, in: Winter Simulation Conference (WSC) 2018, 2019, pp. 2897–2908, https://doi.org/10.1109/wsc.2018.8632202.

[28] N. Li, G. Chen, K. Govindan, Z. Jin, Disruption management for truck appointment system at a container terminal: a green initiative, Transport. Res. Part D: Transport. Environ. 61 (2018) 261–273, https://doi.org/10.1016/j.trd.2015.12.014.
[29] N. Ma, C. Zhou, A. Stephen, Simulation Modelling Practice and Theory Simulation model and performance evaluation of battery-powered AGV systems in automated container terminals, Simul. Modell. Pract. Theory 106 (July 2020) (2021), 102146, https://doi.org/10.1016/j.simpat.2020.102146.
[30] A Maguire, S. Ivey, M.M. Golias, M.E Lipinski, Relieving Congestion at Intermodal Marine Container Terminals: review of Tactical/Operational Strategies, Proceedings of the 51st Annual Transport. Res. Forum 1 (2010) 631–645.
[31] I. Manuj, J.T. Mentzer, M.R. Bowers, Improving the rigor of discrete-event simulation in logistics and supply chain research, In Int. J. Phys. Distribution & Logistics Manage. 39 (Issue 3) (2009) 172–201, https://doi.org/10.1108/09600030910951692.
[32] H. Meersman, E.Van de Voorde, T Vanelslander, Port Congestion and Implications to Maritime Logistics, in: D. Song, P. Panayides (Eds.), Maritime Logistics, Emerald Group Publishing Limited, 2012, pp. 49–68, https://doi.org/10.1108/MRR-09-2015-0216.
[33] P. Morais, E. Lord, Terminal Appointment System Study, Transport. Res. Board 1 (March) (2006) 123.
[34] M. Neagoe, M.S. Taskhiri, H.-.O. Nguyen, H.-.H. Hvolby, P. Turner, Exploring congestion impact beyond the bulk cargo terminal gate, Logistics 4.0 and Sustainable Supply Chain Manage., Proceedings of HICL 2018 (2018) 63–82.
[35] M. Neagoe, M.S. Taskhiri, H.-.O. Nguyen, P. Turner, Exploring the Role of Information Systems in Mitigating Gate Congestion Using Simulation: theory and Practice at a Bulk Export Terminal Gate, in: IFIP International Conference on Advances in Production Management Systems, 2018, pp. 367–374, https://doi.org/10.1007/978-3-319-99704-9.
[36] NHVR. (2018). Common Heavy Freight Vehicle Configurations. https://www.nhvr.gov.au/road-access/mass-dimension-and-loading/general-mass-and-dimension-limits.
[37] L. Opacic, T. Sowlati, Applications of discrete-event simulation in the forest products sector: a review, Forest Products J. 67 (3–4) (2017) 219–229, https://doi.org/10.13073/fpj-16-00015.
[38] A. Ramírez-Nafarrate, R.G. González-Ramírez, N.R. Smith, R. Guerra-Olivares, S. Voß, Impact on yard efficiency of a truck appointment system for a port terminal, Ann. Oper. Res. 258 (2) (2017) 195–216, https://doi.org/10.1007/s10479-016-2384-0.
[39] O. Sharif, N. Huynh, J.M. Vidal, Application of El Farol model for managing marine terminal gate congestion, Res. Transport. Econ. 32 (1) (2011) 81–89, https://doi.org/10.1016/j.retrec.2011.06.004.
[40] Starcrest Consulting Group. (2018). Inventory of Air Emissions for Calendar Year 2018.
[41] M. Torkjazi, N. Huynh, S. Shiri, Truck appointment systems considering impact to drayage truck tours, Transport. Res. Part E: Logistics and Transport. Rev. 116 (September 2017) (2018) 208–228, https://doi.org/10.1016/j.tre.2018.06.003.
[42] D. Tsamboulas, P. Moraiti, A. Lekka, Performance Evaluation for Implementation of Port Community System, Transport. Res. Record: J. Transport. Res. Board 2273 (2012) 29–37, https://doi.org/10.3141/2273-04.
[43] Y.C. Tsao, V.T. Linh, Seaport- dry port network design considering multimodal transport and carbon emissions, J. Clean Prod. 199 (2018) 481–492, https://doi.org/10.1016/j.jclepro.2018.07.137.
[44] T. Van Vianen, J. Ottjes, G. Lodewijks, Simulation-based determination of the required stockyard size for dry bulk terminals, Simul. Modell. Pract. Theory 42 (2014) 119–128, https://doi.org/10.1016/j.simpat.2013.12.010.
[45] X. Xu, Q. Zhang, W. Wang, Y. Peng, X. Song, Y. Jiang, Modelling port competition for intermodal network design with environmental concerns, J. Clean Prod. 202 (2018) 720–735, https://doi.org/10.1016/j.jclepro.2018.08.018.
[46] S. Yi, B. Scholz-Reiter, T. Kim, K.H. Kim, Scheduling appointments for container truck arrivals considering their effects on congestion. Flexible Services and Manufacturing Journal, Springer US, 2019, https://doi.org/10.1007/s10696-019-09333-y.
[47] E. Zehendner, D. Feillet, Benefits of a truck appointment system on the service quality of inland transport modes at a multimodal container terminal, Eur. J. Oper. Res. 235 (2) (2014) 461–469, https://doi.org/10.1016/j.ejor.2013.07.005.
[48] X. Zhang, Q. Zeng, Z. Yang, Optimization of truck appointments in container terminals, Maritime Econ. Logistics (2018) 1–21, https://doi.org/10.1057/s41278-018-0105-0.
[49] W. Zhao, A.V. Goodchild, Using the truck appointment system to improve yard efficiency in container terminals, Maritime Econ. and Logistics 15 (1) (2013) 101–119, https://doi.org/10.1057/mel.2012.23.