Vol. 34, No. 1 (2024) | DOI: 10.37190/ord240102

OPEN ACCESS

Operations Research and Decisions

www.ord.pwr.edu.pl

OPERATIONS RESEARCH AND DECISIONS QUARTERLY

The reloading of a ship in a maritime container terminal as a queuing problem of interacting processes

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Abstract

In this work, we propose a multi-server queuing system for modeling the processes that occur in a maritime container terminal. In our study, the main operations that take place at the quay and in the yard are first disaggregated into several elementary activities. Then we propose the step-by-step calculation of the times of each operation that influences both the unloading and the loading of a container. Next, we analyze the vessel cycle time while separately investigating the STS (ship to shore) crane cycle time, the RTG (rubber tyred gantry) cycle time, as well as the IMV (internal movement vehicle) transfer time. Finally, we apply two process-driven simulation experiments to the system analysis. The paper demonstrates the proposed model's effectiveness with data from the BCT Gdynia container terminal. We show that, among others, even with properly planned work of STS cranes and RTGs, there is still a high probability that the quay will become a bottleneck of the described processes.

Keywords: *maritime container terminal, queuing theory, optimization, simulation*

1. Introduction

A container terminal is a complex logistic system where the flow of cargo is carried out in reloading zones and in a buffer zone, which plays the role of a warehouse. Maritime container terminals are, therefore, an example of the optimization problem for a complex transshipment process. There are several logistics areas of key importance for the operation of maritime container terminals. The most important is the allocation of ships to berths, and of STS cranes (ship to shore cranes), RTGs (rubber tyred gantry cranes), and terminal vehicles (IMVs -– internal movement vehicles, or TTs — terminal tractors) to the container handling. When vessels arrive at the terminal, containers must be loaded and unloaded as quickly as possible. From each ship that comes to the port for service, the terminal earns money. One of the most important performance measures is the turnaround time of ships in the port, and it is necessary to keep this time to a minimum [31]. The terminal operator needs to properly assign berths to the ships, while the

Received 4 January 2023, accepted 15 November 2023, published online 28 March 2024
ISSN 2391-6060 (Online)/

The costs of publishing this issue have been co-financed by the program *Development of Academic Journals* of the Polish Ministry of Education and Science under agreement RCN/SP/0241/2021/1

performance of quay cranes is key to the operational efficiency of the entire berth system [18]. Yet, such assignment involves high uncertainty (demand, container availability) and dynamism (arrival of orders throughout time), which has a crucial impact on how decision-making is done [14].

Transshipment operations must be carried out quickly due to the necessity to shorten the ship's mooring time in the port, as well as to minimize transport and handling costs. Thus, each maritime container terminal strives to manage an undisturbed flow of cargo while ensuring the movement of containers to appropriate blocks on the yard and optimizing the use of available means of transport. Loading and unloading processes can be described using queuing models. There are jobs (containers) that appear at random intervals and go to the handling system (e.g., STS cranes) which performs repetitive activities. It is a queuing system of processes that occur in a maritime terminal and simulation is one of the methods of estimating the parameters of these processes. We present a system with STS cranes that put containers on IMVs. Terminal vehicles transport cargo further to the storage yard where RTGs assemble it in appropriate storage blocks.

The article aims to present container loading and unloading as a sum of single processes and to examine how long individual stages of container reloading last. In our analysis, we study individual activities performed by port devices which are subject to random factors. To estimate numerical characteristics that enable the identification of bottlenecks in the entire process we use the simulation tool. Thus, the paper presents a methodology that can be used as a decision-making support tool for the management and planning of port operations. The model we propose in this study can provide useful insight when the terminal manager wants to evaluate, under stationary conditions and relaxation of some realistic features, the system. In other words, the decision-maker can execute a fast 'what-if' analysis to explore the benefits or the drawbacks in the longrun of adopting some basic organizational choices concerning the number of cranes along the quay or on the yard, as well as the number of vehicles for internal transfer of containers [21].

In our study, we assume that a terminal's performance is judged on the overall performance of its individual components and disaggregate main operations that take place at the quay and in the yard into several elementary activities. We studied the time it took to complete each of them. Some activities are performed automatically and always take the same amount of time. The duration of the remaining steps can be represented as random variables with specific distributions. Then we analyze the vessel cycle time while separately investigating the STS crane cycle time, the RTG cycle time, as well as the IMV transfer time. At the same time, we assume that elements of network analysis can be used to determine the optimal time for all reloading activities. Therefore, we propose a triangular distribution function for STS and RTG operation times, as well as for IMVs' arrival times. We chose the triangular distribution because it suited the assumptions of our study. Finally, we use the PERT (program evaluation and review technique) method to estimate the times of individual reloading operations for one container. Container handling becomes a job in a series of queuing systems that differ in the type of queue discipline.

After the first modeling step, further steps should drive the operation manager to provide confidence intervals upon the expected values of the performance metrics of interest using discrete-event simulation. Thus, following the preliminary assumptions, we apply a process-driven discrete event simulation approach to system analysis. We obtain a relevant quantitative evaluation of the model's basic characteristics. In addition, we consider two alternative scenarios. Finally, we use data from BCT (Baltic Container

Terminal) Gdynia to compare the results of the proposed model application. The block diagram in Figure 1 summarizes the main steps of the presented methodology.

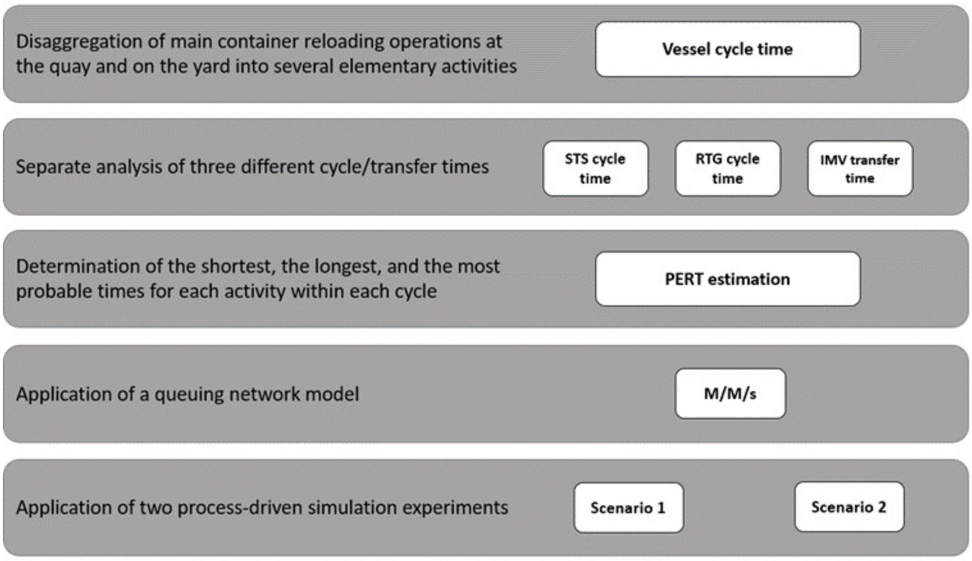

Figure 1. Block diagram of research methodology.

2. Literature review

Various queueing models have been proposed for different types of port operations, like optimum number and berth capacity, optimal berth and crane combination, ship turnaround time at the port, optimum port capacity related to congestion and berth occupancy, or handling equipment assignment and deployment. Recently, Meštrović et al. [25] used queueing theory to consider batch arrivals of containers at a storage yard which is a multi-channel system with c-yard cranes, and to calculate the total cost of the port system. Park et al. [27], on the other hand, quantitatively analyzed vessel traffic service communications in ports and suggested improvements to more efficiently control the service that follows the queue of M/G/1.

In recent years, simulation tools have also evolved extensively. As simulation is one of the techniques for solving mathematical models with random variables, numerous mathematical models on which experiments are carried out are built to test container terminal performance. The existing literature reports approaches to either managing a container terminal as a system and trying to simulate all its elements or managing a subset of activities. For example, Beskovnik and Twrdy [5] proposed a productivity simulation model to monitor the competitiveness of a certain maritime terminal with terminals from the same group. He and Hu [15] investigated the operating sequence of different hatches in a bay using a synchronized loading and unloading method. To this end, they put forward simultaneous hatch operations to improve the efficiency of quay cranes and vehicles. Elentably [12] focused on the effects that different hypotheses on handling equipment calibration may have on the discrete event simulation of container terminal operations, thus pointing out the strengths or weaknesses of different approaches. Deja et al. [9], in turn, applied a discrete-event simulation to a system analysis of quayside transport and storage yard operations.

Finally, there is a group of authors who combine queuing models with a simulation approach. The main contributions in this research area seek to maximize overall terminal efficiency or the efficiency of a specific activity inside the terminal. Thus, container terminal activities are usually schematized through single queue models or a network of queues. Legato and Mazza [21] [20] adopted a process view approach to the simulation of logistics activities related to a vessel's arrival and departure. Their steady-state simulation results illustrate the use of the queuing network model for a 'what if' optimization approach to the berth planning problem. Canonaco et al. [6], in turn, developed a complex queuing network model that is solved by an event graph-based discrete-event simulation and is validated against real data.

On the other hand, Gui and Yang [13] suggested a new queuing model that considers liner transport and is solved through a simulation. To describe the arrival time of ships, they introduce the relative arrival time of ships instead of the interval arrival time used in traditional queuing models. Then they designed three sub-systems to simulate the internal and external conditions in operating container terminals. More recently, Mishra et al. [26] proposed a novel semi-open queuing network (SOQN) model for the inter-terminal transportation problem where multiple container terminals use a common fleet of vehicles to transport containers between terminals. To solve the overall queuing network, they decomposed the original SOQN to a closed and an open queuing network with bulk-service capacity, while they used simulated data to numerically validate the model.

Meanwhile, Meng et al. [24] evaluated the impacts of mega vessels on a maritime container terminal, using both a queuing network model and a simulation model. Their findings indicated that building a longer continuous berth would help the terminal meet the container handling demand in the future. Ruscă et al. [29] first modeled a maritime container terminal as a queuing system and then showed how to develop a discrete simulation model in ARENA software. Dirman et al. [10] tried to determine the performance of a container loading and unloading service using container cranes at the Makassar Container Terminal. Based on the projection results, they performed calculations using both analytical and queuing simulation methods.

Network decomposition into a set of queueing sub-networks for effective support of strategic decisions in maritime logistics deserves greater attention. Some authors have used network planning to investigate particular aspects of everyday port operations [8, 23], but there seem to be no papers that use a similar approach to the one proposed in this study as regards container reloading at the quay and in the storage yard. Sgouridis and Angelides [30] and Meng et al. [24] are most related to this paper. The first study describes the building and use of a discrete event simulation model of real-life processes concerning inbound container handling in a maritime container terminal. It also investigates issues regarding optimized equipment use for improving service levels. The second work develops a queuing network model to capture all key operational processes in a container terminal and proposes a simulation tool to implement the model. However, there are significant contextual and methodological differences. First, our study considers all small activities that comprise container reloading. We determine times for individual container reloading operations using a triangular distribution and PERT method treating these operations as elements of a multi-level system. After several visits to BCT Gdynia and DCT Gdańsk, we know that terminal operators are interested in managing the duration of simple activities at such a low process level. Second, in a queueing network model, we assume that the arrival and service processes follow a Poisson (exponential) distribution. Third, the proposed approach uses a process-driven method to model discrete events of the analyzed model. Thus, our article fills the existing research gap as it enables an in-depth analysis of all system elements to which special attention should be paid when optimizing port operations. At the same time, this paper is the first study to disaggregate reloading container operations and combine the PERT method, queueing theory, and Monte Carlo simulation in the context of reloading a ship in a maritime container terminal.

3. Problem formulation

In this section, we provide details of the problem we address, discuss the methodology behind our research, and state our assumptions. The problem we describe is inspired by the operations of maritime container terminals in Poland. Yet, it could be easily associated with other container terminals of similar size. In the container terminal operating system, the gantry crane seems to be a major bottleneck that restricts the working efficiency of the entire port system [32]. Thus, port managers and terminal operators pay more and more attention to a proper arrangement of port operations where quay cranes can handle containers at their best efficiency. However, decision-makers usually cannot improve the operational efficiency of gantry cranes, as they lack sufficient information on the system's performance which should be perceived from a broader perspective.

For a better understanding of the container reloading processes at the maritime container terminal, we decided to first disaggregate the operations that take place at the quay and on the yard into several elementary activities, and then separately analyze in detail the STS crane cycle time, the RTG cycle time, and the IMV transfer time. At this stage, we used formulas for the step-by-step calculation of times of each operation that influences both the unloading and the loading of a container [3, 4]. Considering the specificity of the work of the STS and the RTG winch trolleys, we assumed that the unloading and loading times of containers at the quay and on the yard can be calculated as the sum of the following times needed:

- unhook the load,
- lift the load,
- drive the winch trolley and lower the load,
- unhook the load,
- lift the spreader and drive the winch trolley,
- lower the spreader.

The driving time of the IMV, in turn, was calculated by multiplying the distance traveled by the IMV and its known speed. The distance traveled by the terminal vehicle considered components such as [2]:

- the number of yard sectors passed along the quay,
- the adopted length of the yard sector,
- the adopted straight-line distance from the quay to the storage yard,
- the number of rows passed in the storage yard,
- the adopted width of the yard row,
- the number of sectors passed in the storage yard.

We found that elements of PERT analysis can be used to estimate the overall optimal time for the loading/unloading of a container. We proposed a triangular distribution function for the operation times of STS [20, 29] and RTGs [19], as well as for IMVs' arrival times [30]. Thus, we determined three times for each reloading operation: the shortest, the most likely, and the longest.

We also believe that a network of several interconnected queues is an ideal tool to capture the nature of unloading and loading processes in a container terminal. The work uses a multi-server queueing network model where the arrival time and the service time follow the Poisson and exponential distribution (M/M/s). At this point, we should notice that assumptions on the distribution of random variables are one of the biggest limitations of all queuing models. The same applies to the size of the population or the length of the queue. In the described model, the population of jobs and the queue length are infinite while the jobs do not leave the system. It stems from the fact that we assume that if a job (container or IMV) arrives and finds a long queue, it joins the waiting jobs and does not leave the terminal [7, 11]. Depending on the process step (sub-network), the number of servers, distribution parameters, as well as queue discipline vary. After the ship is moored at the quay, STS cranes start the unloading with LIFO queuing discipline (stage I). At this stage, the unloaded containers are treated as jobs coming to the system supported by s servers (STS cranes). In this network, many-to-one server-to-job assignment for the container reloading is very difficult to cope with. Thus, we must relax this assumption and assume independent parallel cranes, each acting on its section of the vessel. STS cranes load containers taken from the ship onto IMVs, which transport them to the yard. At the yard (stage II), IMVs are jobs handled by RTGs (servers). In this case, vehicles with containers go to the yard following the FIFO queueing discipline, while the expected arrival rate depends on the expected arrival rate of the previous stage. In the next stage (stage III), IMVs take the containers from the yard and transport them to the quay. Containers are jobs that are served by RTGs (servers). RTGs pick up the containers from the yard following LIFO queueing discipline. In the last stage (stage IV), IMVs (jobs) transport containers to the quay, where they are handled by s servers (STS cranes). In this case, FIFO queuing discipline applies, and the expected arrival rate depends on the capacity of stage III. After reloading is completed, the ship leaves the port. The queueing network model for the STS and the RTG cycles, as well as the vehicle round trip process, is a closed one. This means, among others, that the fleet of circulating IMVs corresponds to the jobs' population in stages II, III, and IV.

Finally, to test the efficiency of the analyzed queuing system, we applied a process-driven discrete event simulation, which, apart from the event-driven and activity-driven method, is one of the techniques for modeling discrete events. The flexibility of the simulation results from the adoption of a small number of assumptions, especially when some assumptions of traditional models are violated in the queuing system and there are no known formulas for calculating numerical characteristics. The chosen method involves grouping activities into processes performed on single dynamic objects (jobs) and registering their status from the moment they appear in the system until their disappearance. Such a model distinguishes as many processes as there are jobs. We were interested in numerical characteristics, such as the average queue length, the average waiting time, and the system capacity.

We considered two alternative scenarios. In Scenario 1, we determined basic numerical characteristics without interfering with the allocation of a container to a crane. In Scenario 2, we determined the impact of allocating a container to the most available crane. Both simulations are discussed in more detail in Chapter 5. They used parameters from the empirical distribution based on the observed times of individual activities. We performed all calculations in the MS Excel spreadsheet. The MS Excel spreadsheet is the most widely available and best-known analytical tool. The complexity of the container handling is within the capabilities of such a program. A manager familiar with MS Excel can simulate the queuing process and reuse a previously prepared file template, updating only the most important parameters.

Due to the complexity of the formulas, we used the above-described process-driven interaction method. First, it corresponded best to the research problem in question. Second, the process-driven method allowed us to place a sequence of events related to one job in one line of the spreadsheet, making it easier to track. In our article, we do not deal with the numerical or IT aspects of using MS Excel as a simulation tool. Our solution used proposals of Hora [16] and Ingolfsson and Grossman [17], with modifications by Leong [22]. Although in the literature the process-driven method is most often recommended for use during classes, we decided to use it in practice. Thus, there was no need to use VBA macros, and calculations were based on worksheet formulas with a moderate degree of complexity. Finally, the simulation based on the empirical distribution allowed us to verify and confirm the correctness of the theoretical assumptions of the queueing model.

4. Computational experiment and results

4.1. Case study. BCT Gdynia

The presented case study of BCT Gdynia maritime terminal considers a system that involves STS cranes operating at the quay and IMVs that transport containers to a yard consisting of 32 sectors. RTGs assemble the 20-ft containers in storage blocks up to 7 m wide, 22 m long, and 1–5 tiers high. We assume that IMVs always stop on the left side of a given storage bay, and the imported and exported containers are stocked in a column arrangement. Unloaded containers can only be placed in a free place at the yard while IMV trucks move along designated routes between the quay crane and the yard crane. Most often, they do it at a speed of up to ca. 30 km/h; however, according to the technical documentation, half of the maximum speed should not be exceeded when making turns. The places where IMV drivers stop under STS cranes are predetermined by the terminal operating system (TOS) [1].

We further describe the problem of reloading containers from MSC Antonia, moored to the quay with the port side. From the visiting studies at BCT Gdynia, we know that 2,402 containers with a total capacity of 3,736 TEU were reloaded there. The containers were arranged on the ship as follows: 24 containers along, 17 containers across, and up to 6 containers high (40 ft). Four gangs were assigned for reloading, each consisting of one STS crane, three RTGs, five IMVs, and the employees necessary to carry out operations at the quay and in the yard. Unloading was executed first, followed by loading. Moreover, we assume that all containers were placed on the deck of the ship (none of the containers were in the cargo hatch). Furthermore, the unloading of containers starts from the land side (the port side of the ship) and ends on the seaside. The loading process takes place in the reverse order. Import, transit, and empty containers are unloaded by STS cranes and then transported by IMVs to the selected sectors of the yard. During unloading, all containers are treated similarly, regardless of their weight or content, and they can be stacked in the yard according to the basic safety rules only. Finally, the model also assumes that STS cranes work simultaneously with similar performance, 20-ft containers are transported by STS cranes and RTGs individually while STS cranes and RTGs do not make ineffective movements (rehandles).

As mentioned before, in our study, we disaggregate operations taking place at the quay and in the yard into several elementary activities and then perform a step-by-step calculation of the duration of each operation that influences both the unloading and the loading of a container at BCT Gdynia. To this end, we use basic technical data for the equipment that operates at the terminal and thus determine three times (the shortest, the most probable, and the longest) for each reloading operation, individually for the STS crane cycle, the RTG cycle, and the IMV transfer (Table 1).

Table 1. The shortest (t_o), most probable (t_d), and longest (t_p) times for each operation that comprises the unloading and loading of one container at the terminal [s]

Equipment	Operation	Unloading			Loading		
		t_o	t_d	t_p	t_o	t_d	t_p
STS	hooking the load	3	3	3	3	3	3
	lifting the load[1]	4	4	4	17	25	32
	driving the trolley and lowering the load	34	48	60	15	20	25
	unhooking the load	10	10	10	5	5	5
	lifting the spreader and driving the trolley	16	25	33	12	18	23
	lowering the spreader[1]	12	12	12	12	15	18
IMV	transfer to the storage yard	37	74	131	37	74	131
RTG	hooking the load	3	3	3	3	3	3
	lifting the load[2]	26	26	26	8	19	29
	driving the gantry	0	36	66	0	36	66
	driving the winch trolley	5	14	20	5	14	20
	lowering and unhooking the load	28	38	49	46	46	46
	lifting the spreader	7	12	17	15	15	15
	driving the gantry and the winch trolley	5	36	66	5	36	66
	lowering the spreader[2]	20	20	20	12	17	22

[1] All containers are unloaded from the ship's deck, so the container is always lifted, and the empty spreader is always lowered at 3 m.

[2] The RTG lifts each container at 15 m; the empty spreader is lowered from this height.

Finally, considering the above-mentioned information, we use the PERT method to estimate the duration of each reloading activity at BCT Gdynia. In each case, both for the unloading and the loading, we assume that all activities listed in Table 1 follow one another. Table 2 presents the estimates of the expected value and the standard deviation for reloading operations given for three-terminal sub-areas (STS, IMV, RTG).

Table 2. Time of individual unloading and loading operations for one container handled at the terminal [s]

Equipment	Operation	Unloading	Loading
STS	Reloading a container from the ship to the IMV	101.5 ± 5.18	85.67 ± 3.66
IMV	Transfer to the storage yard	77.33 ± 12.6	77.33 ± 12.6
RTG	Reloading a container from the IMV to the storage yard	183.5 ± 15.67	184.2 ± 15.67

The results show that the average working time of the STS unloading (loading) a container from a ship is ca. 102 s (ca. 86 s). The IMV transport of a container through the terminal, to or from the yard, takes less than 78 s, while the RTG container transport in the yard takes an average of 184 s.

4.2. Queuing network model

Considering the results obtained in earlier stages of the study (subsection 4.1), the expected service time for one container by the STS crane is 1.7 min. Therefore, we can assume that the expected arrival rate of jobs coming to the system per min (with parallel operation of all four STS cranes) equals two containers. In such a case, the time interval between subsequent jobs is 30 s; while STS cranes are used at 85% capacity, the expected number of containers in the system is eight, with four containers in the queue. The expected time of unloading the container is less than four min, with ca. two min waiting time for the container handling (Table 3, stage I).

When STS cranes are unloading the ship, IMVs transport containers to the yard. If we know from the previous stage (stage I) that every minute two containers are waiting for the IMV at the quay, and the transport of a container by a terminal vehicle to the yard takes less than 75 s, the model characteristics are as given in Table 3 (stage I′). IMVs are used at only 12.5% capacity, the expected number of containers to be transported to the yard is two, and there is no queue of containers waiting for service. At this point, the container is expected to stay in the system for 75 s.

While STS cranes are reloading containers from the ship on IMVs, the containers previously delivered to the yard are transported by RTGs. Based on the previous results, we can assume that two new containers are delivered to the yard every minute. As the transfer of a container from the IMV to the yard takes an average of 183.5 s, it should be assumed that the expected service rate is 3.06 min. Thus, RTGs in stage II are used at ca. 52% capacity. The probability of a container waiting for handling is only 0.03, with an expected time in the queue of 1.2 s. This means that a container transported to the yard is in the system for ca. 187 s (Table 3, stage II).

Table 3. Basic characteristics of a queuing model for ship unloading

Characteristic	Result Stage I STS	 Stage I′ IMV	 Stage II RTG
Expected arrival rate (λ), 1/min	2.00	2.00	2.00
Intensity of arrivals ($1/\lambda$), min	0.50	0.50	0.50
Expected service rate (μ), 1/min	0.59	0.80	0.33
Intensity of service ($1/\mu$), min	1.70	1.25	3.06
Utilization of the server (Erlang) (ρ), %	85.00	12.50	51.67
Expected number of jobs in a system (N)	7.31	2.50	6.23
Expected number of jobs in a queue (Q)	3.91	0.00	0.03
Expected waiting time in a system (R), min	3.65	1.25	3.12
Expected waiting time in a queue (W), min	1.95	0.00	0.02
The probability that there are N jobs in a system (P)	0.69	0.00	0.03

In stage III, the container is loaded on the IMV waiting at the yard. The expected service time, in this case, is 3.07 min. Therefore, the expected arrival rate of jobs coming to the system per minute (assuming parallel operation of all RTGs) is three containers. Compared to stage II, the use of RTGs (77.5%) and the probability of waiting in the queue (0.31) increases. The expected number of containers in the yard is 11, and the expected time in the queue is less than 22 s. For the containers loaded on IMVs waiting at the yard, the expected arrival rate is three as it depends on the capacity of stage III. Compared to the stage I′, however, it will not significantly change the results of basic characteristics of the system. Finally, the expected arrival rate for containers loaded on a ship may not exceed two containers, as the expected service time for one container is 1.43 min. STS cranes are used at 71.5% capacity, the expected number of jobs in the system is four containers, and the expected length of the queue is two containers. The probability of waiting in the queue is relatively low (0.45), as the expected time in the queue is less than a minute (Table 4).

Table 4. Basic characteristics of a queuing model for ship loading

Stage III	Characteristic	Result		
		Stage III′	Stage IV	
		STS	IMV	RTG
Expected arrival rate (λ), 1/min		3.00	3.00	2.00
Intensity of arrivals ($1/\lambda$), min		0.33	0.33	0.50
Expected service rate (μ) 1/min		0.33	0.80	0.69
Intensity of service ($1/\mu$), min		3.07	1.25	1.43
Utilization of the server (Erlang) (ρ, %		77.50	18.75	71.50
Expected number of jobs in a system (N)		10.38	3.75	3.99
Expected number of jobs in a queue (Q)		1.08	0.00	1.13
Expected waiting time in a system (R), min		3.46	1.25	1.99
Expected waiting time in a queue (W), min		0.36	0.00	0.57
The probability that there are N jobs in a system (P)		0.31	0.00	0.45

4.3. Total time to reload the containers

In the last stage (stage IV), the system can handle two containers per minute, while in the preceding stage (stage III′), three containers can leave the yard within 1 min. Thus, there is a high probability that the quay will become a bottleneck of the described process. For this purpose, we introduce an additional assumption that IMVs can stop at the quay on one of four different tracks located under STS cranes.

In practice, this means that the total time to drive the winch trolley and lower the load will differ for each STS crane. The travel time of the winch trolley will change since it depends on the assumed distance to the first container in the row (L). In the original variant, we assume that the IMV stops at the quay on the track located as close to the ship's side as possible (L = 15 m). In subsequent variants, we assume that this distance will increase to 18, 21, and 24 m, respectively. Table 5 shows how it affects the times of each operation and the estimated time of unloading and then loading one container by each STS crane.

Table 5. The shortest (t_o), most probable (t_d), and longest (t_p) times for each variant that comprises driving the trolley, lowering the load, lifting the spreader and driving the trolley for one container unloaded and loaded at the terminal [s]

L	Operation	Unloading			Loading		
		t_o	t_d	t_p	t_o	t_d	t_p
18	Driving the trolley and lowering the load	35	49	61	16	21	26
21		36	49	62	16	22	27
24		37	50	63	17	23	28
18	Lifting the spreader and driving the trolley	17	26	34	13	18	24
21		18	27	35	14	19	25
24		19	28	36	15	20	26

Changing the position of the IMV at the quay will slightly affect the times of driving the winch trolley and lowering the load, as well as lifting the spreader and driving the trolley. For this reason, the estimated operating time of STS cranes will slightly differ in each of the discussed variants (Table 6).

Table 6. Times of reloading a container from the ship to the IMV and vice versa for each variant that comprises driving the trolley and lowering the load, as well as lifting the spreader and driving the trolley [s]

L	Operation	Time
18		103.5 ± 5.18
21	Reloading of a container from the ship to the IMV	104.8 ± 5.18
24		106.8 ± 5.18
18		87.00 ± 3.66
21	Reloading of a container from the IMV to the ship	88.83 ± 3.74
24		90.83 ± 3.74

The estimates presented in Table 6 show that, depending on the position of the IMV, within one hour, STS cranes can unload 35, 34, 34, and 33 containers (± 1 container), respectively. On the other hand, they can load 42, 41, 40, and 39 containers (± 1 container) within an hour. This means that, for example, the first STS crane would unload a row of 102 containers (17 containers across, and 6 containers high) in 2 h and 55 min, the remaining two STS cranes – in 3 h, and the fourth crane in 3 h and 6 min. Similarly, the loading of 85 containers by each of the STS cranes would take: 2 h 1 min, 2 h 4 min, 2 h 8 min, and 2 h 11 min, respectively (Table 6). After this period, all STS cranes will automatically move 3 m to the side to unload/load the next row of containers (3 min).

The model also assumes that the containers unloaded from MSC Antonia are in bays 3–22, which means that during the unloading, STS cranes change their position at the quay five times. Due to the smaller number of loaded containers (1001), it was assumed that before loading operations began, STS cranes would move two rows to the side and start loading containers into bays 5-20. This means that they change their position four times.

Since STS cranes operate in parallel, but each reloads one container at different times, in practice, in the presented four-server model, the total ship reloading time equals the longest service time by one of four STS cranes assigned to the task:

$$T_s = \max\left(\sum_{i=1}^{4} T_s^1, \sum_{i=1}^{4} T_s^2, \sum_{i=1}^{4} T_s^3, \sum_{i=1}^{4} T_s^4\right)$$

where T_s^i is the total working time of the STS crane i, $i = 1, 2, 3, 4$.

Table 7 presents the times of the container reloading from MSC Antonia (assuming that the maximum number of rows is 17 and the maximum number of layers is 6). Considering that all cranes work in parallel, Table 7 shows only the times for the longest-operating cranes. The times in brackets do not affect the total time needed to reload the ship. The values are only given to show which cranes were involved in handling the last containers on board the ship.

The total unloading of MSC Antonia takes 11 h and 7 min (± 2 hours), while the total loading of 1001 containers takes 6 h and 46 min (± 1 hour). It means that with the adopted work organization, favorable weather conditions, and no unforeseen technical failures, the ship is reloaded in a total time of 17 h 53 min (± 3 h), with each STS crane making 38 movements per hour (± 1 movement) on average. To the total reloading time, we should add the total time of breaks, which are needed for the shift of employees assigned to each gang. Such breaks are usually necessary after ca. eight hours of working time. It was assumed that the total time of these breaks was about an hour. Then, the sum of the working time of all STS cranes, counted from the first to the last movement of the spreader, is 66 h 29 min. BCT Gdynia achieves ca. 38 lifts/hour. This result sounds reasonable, especially if we take into account that most terminals only achieve 25 lifts/hour on average [24]. According to Petering and Murty [28], a quay crane's peak service rate could be 40 lifts/hour.

Table 7. Times of unloading and loading containers (MSC Antonia) [h]

SMS	Unloading (1401 containers, 11.11 h)												
	102	MCB	85	MCB	68	MCB	51	MCB	34	MCB	17	4	3
4 ($L = 24$)	3.09		2.58		2.06		1.55		1.03				(0.09)
1–4		0.06		0.06		0.06		0.06		0.06			
3 ($L = 21$)											0.5		
1 ($L = 15$)												(0,11)	
SMS	Loading (1001 containers, 6.77 h)												
	85	MCB	68	MCB	51	MCB	34	MCB	17	8	7		
4 ($L = 24$)	2.18		1.74		1.31		0.87				(0.18)		
1–4		0.06		0.06		0.06		0.06					
3 ($L = 21$)									0.43				
1 ($L = 15$)										(0.19)			

MCB – movement of the crane bridge.

After several study visits to Gdynia, we know that the reloading of 2,402 containers from MSC Antonia at BCT Gdynia took 75 h 48 min, which is ca. 9 hours longer than in the model described in this article. First, STS cranes in Gdynia did not work in parallel. For example, during the first 7 hours, only two STS cranes were used in Gdynia for the reloading of containers, while the fourth one was involved in the reloading only for 1 hour and 45 min. Moreover, some of the containers were located below the ship's deck, which extended the reloading time. Finally, the actual time of a ship service at the quay is usually longer due to the necessity to perform ineffective movements (rehandles), which are not considered in the described model.

5. Simulation

5.1. Assumptions and formulas

In the last part of the research, we check the queuing model's behavior under the influence of random changes in the controlling parameters. For this article, six separate simulations were made for the previously described stages I, I′, II, III, III′, and IV.

First, we assumed that STS cranes form a closed four-server system in which jobs are assigned randomly to individual cranes (Scenario 1). In Scenario 2, we decided which crane would handle a given container during the simulation. Both scenarios assume that the queue is infinite, and no job leaves the system. In simulated queuing systems, there are two random variables: one expressing the time interval between jobs and the other representing the expected service time of a job. In this research, we assumed that both variables are uniformly distributed. Table 8 shows time intervals between jobs and for service duration. These intervals are determined based on the previously collected information on the duration of the activities that constitute the individual stages of the described processes.

Table 8. Time intervals between jobs and for service duration [s]

Stage	Time interval between jobs	Time interval for service duration
I	$[24, 35]$	$[79, 122]$
I′	$[24, 35]$	$[37, 131]$
II	$[24, 35]$	$[94, 267]$
III	$[8, 23]$	$[94, 267]$
III′	$[8, 23]$	$[37, 131]$
IV	$[16, 27]$	$[64, 106]$

As noted earlier, the simulation is performed using the process-driven method. A single iteration corresponds to one job that is handled at a given stage. A single iteration of the simulation includes all operations that the container was subjected to at a given stage. One complete simulation consists of 1001 or 1401 iterations depending on whether the stage involves loading or unloading a ship. The article presents the results for 100 repetitions of such a set of calculations, which gives 100.1 or 140.1 thousand operations. During the study, we also checked other variants of the number of replications — up to 1000, which would correspond to a thousand ships. The results were very stable, while 100 repetitions required much less time for calculations. In Scenario 1, the following characteristics of the process are determined: the moment of the job's arrival, the beginning and the end of the job's service, the mean waiting time in the queue, the average time spent in the system, and the mean number of jobs in the system, which is the number of jobs in the queue plus the jobs currently handled by the system before the arrival of a given job. In Scenario 2, the appropriate formulas allocate the container to the fastest available STS crane (stages I and IV). Thus, the rest of the numerical characteristics remain unchanged. Elements such as breakfast breaks or the time needed to replace employees who have finished their shifts have been omitted.

5.2. Scenario 1

In stage I, jobs (containers) appear in the system every half a minute, and their service takes an average of 1 min and 40 s. The containers usually do not have to wait in the queue, and if it happens, the waiting lasts a maximum of 1 second throughout the simulation. After 100 repetitions, the average time spent in the system equals 1 min and 41 s (for 95% of cases, this time ranges from 1:40 to 1:42 min). The mean number of jobs in the system is ca. 2.91 with a 95% confidence interval ranging from 2.88 to 2.94. Three jobs are the dominant number in the system (ca. 70% of all cases). If STS cranes work continuously, it will take 11 and a half hour to unload the entire ship.

The containers taken from the ship are put on IMVs, which deliver them to the yard (stage I′). The intervals between jobs coincide with those from stage I, while the mean service time is 1 min and 24 s. Due to the large number of IMVs available exceeding the number of containers appearing in the system, no job must wait in the queue. The average time spent in the system is the same as the mean service time. With 95% probability, it will be within the range from 1:22 to 1:25 min. The average number of jobs in the system is ca. 2.35 (with the confidence interval for the expected value from 2.31 to 2.39), while two jobs are the most common (47%). It would take 11 and a half hour to transport all containers at this stage.

During stage II, IMVs are unloaded by RTGs. The results of the simulations repeated 100 times show that with jobs coming every 29 s, on average, the mean service time is 2 min 59 s. The handling system is so efficient that IMVs do not wait in the queue. Their stay in the system depends only on the time the container is placed in the right place in the yard. With a 95% probability, the average time spent in the system is between 2 min 58 s and 3min 3 s. There is an average of 5.61 jobs in the system, with a 95% probability of this parameter ranging from 5.56 to 5.66. In stage II, the distribution of the number of jobs is bimodal, with dominating values of 5 and 6 IMVs, respectively. On average, all unloading operations should be completed in 11 h and 30 min.

In stage III, RTGs should load 1001 containers on IMVs. The adopted interval between jobs gives an average of 15 s. The mean service time is 3;01 min. The high frequency of new jobs means that at least some of them spend some time in the queue. On average, it takes 30 s. Still, it is possible that jobs must wait for service for up to 2;30 min. The 95% confidence interval of the mean waiting time is within 28–30 s. For this reason, the time spent in the system is extended, and the average value is 3:31 min. For 95% of cases, this time varies between 3:27 and 3:34 min. The disproportion between the appearance of jobs and their service time means that the mean number of jobs in the system is 13.01. Yet, the distribution of this variable is trimodal, with values of 11, 12, and 13 jobs. In total, the operations performed at this stage take an average of 4 h and 24 min.

Then, IMVs deliver the containers to the quay (stage III′). Like in stage III, the adopted interval between jobs gives an average of 15 s. The mean service time is 1:23 min. At this stage, there are no queues of containers, so the time spent in the system is equal to the service time. The 95% confidence interval of this time ranges between 1:22 min and 1:26 min. Considering 100 repetitions of the simulation, the average number of jobs is 4.94, with a dominance of 5 containers (33% of cases). Stage III′ lasts, on average, 4 h and 20 min.

In the fourth and final stage, containers are loaded onto the ship. The average time between jobs is 21 s, and the mean service time is 1:24 min. Most containers are queued (ca. 60%). The average waiting time for service is 35 s but in individual cases, it reaches even 2 min. The average time spent in the system is 2 min and, at the 95% confidence level, it ranges from 1:58 to 2:02 min. In the system, there are, on average, 5.08 jobs (queued and being handled) with a dominance of four containers. Stage IV takes an average of 6 h. All the results described above are summarized in the Table 9.

Table 9. Time intervals between jobs and for service duration in the system [min:s]

Specification	Stage I	Stage I′	Stage II	Stage III	Stage III′	Stage IV
Average time	1:41	1:24	2:59	3:31	1:23	2:00
95% confidence interval	[1:40, 1:42]	[1:22, 1:25]	[2:58, 3:03]	[3:27, 3:34]	[1:22, 1:26]	[1:58, 2:02]
Average number of jobs	2.91	2.35	5.61	13.01	4.94	5.08
95% confidence interval	[2.88, 2.94]	[2.31, 2.39]	[5.56, 5.66]	[12.85, 13.17]	[4.87, 5.01]	[4.99, 5.17]
Dominant number of jobs	3	2	5/6	11/12/13	5	4

5.3. Scenario 2

In the second scenario, the allocation of STS cranes at stages I and IV is different than in the first scenario. The container goes to the first available STS crane that has just served the previous job. Therefore, there is no situation where a container is allocated to a device that is currently busy, as can happen if we allocate it randomly. It means that additional numerical operations must be performed, such as selecting the STS crane for a job that has just appeared in the system or determining the start and end times of container handling by each of the STS cranes.

Jobs in stage I of Scenario 2 appear at the same intervals as those in Scenario 1. The service time is randomized based on the same schedule, and it averages 1:41 min. In such a situation, 12% of containers must wait in a queue, and the maximum waiting time for service is 20 s. The average time spent in the system is 1:41 min, with the 95% confidence interval ranging from 1:40 to 1:42 min (like Scenario 1). The mean number of jobs in the system oscillates around 2.92, with the dominance of three jobs (ca. 70% of cases). According to the simulation, the unloading of the ship should take about 11 and a half hours.

In Scenario 2, stage IV, the intervals between jobs and the service time are similar to those in Scenario 1. On average, ca. 60% of containers are waiting in the queue. In this case, the average time spent in the queue is 32 s, with the longest waiting time for service being 1:54 min. With a probability of 95%, the mean waiting time for service ranges between 31 and 34 s. The average time spent in the system is 1:57 min, and for 95% of cases, it ranges from 1:55 to 1:59 min. In total, there is an average of 4.94 jobs in the queue and the system, with the dominance of four containers. In this variant, loading all 1001 containers takes ca. 6 hours, on average (Table 10).

Table 10. Basic results of the simulation experiment for stages I and IV (Scenario 2) in the system

Specification	Stage I	Stage IV
Average time	1:41	1:57
95% confidence interval	[1:40, 1:42]	[1:55, 1:59]
Average number of jobs	2.92	4.94
95% confidence interval	[2.89, 2,95]	[4:86, 5:02]
Dominant number of jobs	3	4

Comparing both scenarios shows that the most important numerical characteristics for stages I and IV assume similar or even identical values. In this situation, it seems reasonable to use Scenario 2, which provides greater control over the ship reloading at the maritime container terminal thanks to the assignment of containers to the chosen STS cranes. At the same time, the high standard deviation for some measures, e.g., waiting time for service, does not result from too few iterations or replications but is the effect of the number of incoming jobs, the time needed to handle them, etc. In other words, it is a property of a given process, independent of the simulation parameters.

6. Conclusions

Logistic processes in maritime container terminals are defined around complex operations requiring careful decisions on effective cost-performance policies. At the same time, queueing networks are perfectly suited to bottleneck detection and quantitative evaluation of both system and user performance metrics under congestion [21]. In our study, we used a simulation tool to estimate numerical characteristics that enable the identification of bottlenecks of the container reloading treated as a sum of single processes. Thus, we examined how long individual stages of the container loading and unloading last. The results show that the proposed model is well-adjusted and is useful for decision-makers and terminal operators who are interested in optimizing the processes that take place at seaports. The PERT method enables to indicate, among others, time intervals of activities in all stages of the described processes, improving the efficiency of the container reloading operations at the maritime container terminal. Time savings lead to lower costs and the use of the project management network enables tracking which stage of the container reloading consumes the most time and generates the biggest costs. Our results show, for example, that the most time-consuming activities during the unloading include transfer to and from the storage yard (IMV transfer time), driving the trolley and lowering the load (STS cycle), or driving the gantry and the winch trolley (RTG cycle). It also appears that during the loading of one container at the terminal, terminal managers should pay special attention to such aspects as the IMV transfer time, or the time needed by the STS and the RTG to lift, lower, and unhook the load.

Furthermore, although the problem is very complex and requires constant timing of all steps, the decision-makers who decide to use the multiserver queuing network model proposed by us can easily identify bottlenecks that may arise during the reloading of the ship. In our case study, it turned out that even with properly planned work of STS cranes and RTGs, there is a high probability that the quay will become a bottleneck of the described processes. Thus, we proposed an additional assumption. IMVs can stop at the quay on one of four different tracks located under STS cranes. Such a variant at least partially limits the queues of IMVs waiting at the quay for service by one of four STS cranes.

Importantly, the model is quite resistant to random disturbances introduced into it. This is confirmed by the conducted simulation experiments, especially as the results were very stable for even 1000 replications. In both scenarios presented in the paper, disturbances only slightly changed the basic characteristics of the analyzed process. Numerical characteristics were determined individually for each of them, and the average values after multiple repetitions turned out to be close to the expected values. Moreover, during the simulation, we determined confidence intervals for the duration of individual stages. Low spreads of these intervals proved accurate estimates. Due to the analysis of each job, it was also possible to distinguish specific situations in the service process. It turns out that at some stages, the dominant number of jobs has a multimodal distribution. Considering the high standard deviation that appeared for some measures, this indicates the instability of processes at the stages that the supervisor should take a closer look at.

Maritime container terminals differ in size and access to infrastructure offered. BCT Gdynia is one of the biggest terminals in the Baltic Sea Region. The conclusions presented in this article can be a starting point for analyses of terminals of similar size, equipped with a similar number of STS and other port devices. The proposed model, due to the possibility of changing some of its assumptions, can be further developed and easily adapted to various systems. On the other hand, the adopted assumptions constitute the model's limitations. Monte Carlo simulation has drawbacks, too. A separate experiment must be prepared for each problem. The simulation gives an approximate solution and obtaining a near-accurate estimate of a single statistic requires multiple repetitions of calculations. Finally, the usage of the tool, for example, the programming language, may be another limitation for some practitioners. However, we overcame this problem as we resigned from macro commands in the spreadsheet.

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