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Assessing Performance of Container Slot Allocation Heuristics

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Purpose: *In the last decades, the transport capacities of container vessels have tremendously increased. This leads to longer berth times and greater peak loads at container terminals, especially when schedules are perturbed. Thus, existing container handling processes need to be re-evaluated regarding their adequacy.*

Methodology: *In the first step, the current literature is reviewed: which methods have been used for container slot allocation? In the second step, a simulation study is set up to compare two rule-based heuristics of Güven and Türsel Eliiyi (2014; 2019) with Levelling Stacking and Random Stacking.*

Findings: *It is shown that the two rule-based heuristics of Güven and Türsel Eliiyi lead to shorter berth times than Levelling Stacking or Random Stacking. At the same time, the last two approaches show a clear superiority in workload balancing. The joint storage of container groups at Güven and Türsel Eliiyi leads to congestion at the stacking cranes in both cases for peak loads.*

Originality: *This study is the first to compare these four stacking policies. For generating realistic container flows, data from an existing container terminal have been used. Previously unreported performance indicators are used for comparison. Thus, this study provides new insights for improved rule-based heuristics in future.*

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1 Introduction

The increasing size of container vessels over the last years has affected container terminal operation: instead of a steady flow of containers delivered by smaller vessels, nowadays shipping companies employ larger vessels that approach ports in a lower frequency while the overall amount of traded goods is still increasing (UNCTAD, 2019). This leads to longer vessel calls and larger peak volumes that need to be handled at container terminals (UNCTAD, 2019). In 2020 and the beginning of 2021, the Corona pandemic has put additional stress on the international supply chains: reduced work force capacities in ports lead to longer port calls and such delays are propagated both within the port, terminal, and container services (UNCTAD, 2020). In addition, the reduced trade volumes in 2020 led to the cancellation of several container services. These restructured supply chains seem to be the reason for long queues in front of some ports (Bloomberg, 2020). In this situation, terminal operators need to manage their container terminals efficiently in terms of cost (e.g., low energy consumption of terminal equipment) and time (e.g., serving vessels quickly) while the arrival and departure of containers are subject to great uncertainty due to delay and cancellation.

In academia, the operation of container terminals is subject of active research (e.g., Covic, 2018; Gharehgozli, Zaerpour and Koster, 2020; Wang, 2020; Kizilay and Türsel Eliiyi, 2021). The operation is frequently described as three-dimensional chess, as each container can be positioned at many different places within the yard. Furthermore, the operators determine the sequence the vessels, barges, trucks, and trains are unloaded and loaded. This goes hand in hand with assigning handling jobs: which equipment in the yard (both horizontal transport equipment and stacking equipment) handles which container in which order? If a container terminal turns into a bottleneck in the maritime supply chain, it might be possible to allocate the bottleneck within one of the subsystems of the container terminal. While Lee, et al. (2009) allocate the bottleneck of container terminals at the ship-to-shore gantry cranes, Tan and He (2016) claim that the stacking area throttles the productivity of the average container terminal. Kizilay and Türsel Eliiyi (2021) present the literature related with the integration of quay crane scheduling and yard operations. They classify the existing literature according to the solution methodology into exact methods (e.g., mixed integer programming or constraint programming), evolutionary heuristics (e.g., genetic algorithms or particle swarm optimization), other heuristics (e.g., greedy algorithms or rule-based heuristics), simulation-optimization-based approaches, and others. Voß, et al. (2016) argue that mathematical modelling is often difficult to implement in practice because of the lack of planning information. Information regarding arrivals and departures might be not available, incomplete, or of questionable quality. This improves as the actual container delivery comes closer. This favors online heuristics which choose the container slot just-in-time when the container needs to be stored.

Rule-based heuristics are often not well-defined in scientific literature regarding container terminal operations. Terms such as online optimization (Voß, et al., 2016; Güven and Türsel Eliiyi, 2019), policies (Güven and Türsel Eliiyi, 2014; Gerrits, Mes and Schuur, 2019), and strategies (Yu, et al., 2018; Ambrosino and Xie, 2020) can be understood as synonyms for rule-based heuristics. To create a common understanding, properties rule-based heuristics commonly share are presented:

- Paradigm of solution construction: A rule-based heuristic follows an imperative approach, i.e. the formulation contains a clear control flow. Therefore, the rule-based heuristics can be represented as an algorithm (e.g., written in pseudocode) or a flowchart. This sets it apart from mathematical optimization that follow a declarative approach, i.e. a system of equations is formulated usually without explicit instructions about how to solve it. Instead, (often proprietary) solvers are used to obtain a solution.
- Central coordination: All equipment is coordinated by transport jobs issued by a central control unit. This sets it apart from agent-based modelling that follow a distributed approach. The rule-based heuristic must be formulated in a way that at no point of time an operational constraint is harmed. Likewise, as container handling processes are executed concurrently at the terminal, issues typical for distributed systems must be considered, e.g. deadlock situations must be avoided.
- Greediness: Once a container is assigned to a container slot, this decision is considered fixed, i.e. slot reservations are not swapped or changed later for further improvement. Furthermore, only a single solution is constructed and alternative solutions are not compared. This sets the rule-based heuristic apart from tree-based approaches such as branch & bound since these explore several alternative solutions. The greediness property removes the necessity

of using rolling planning horizons if (a) container slots are allocated in the sequence of the arrival time of a container and (b) the available information regarding later container arrivals is not used. This improves the computational complexity of a heuristic at the expense of suboptimal operations at the container terminal.

- Metric expressing preference: If within the control flow of the heuristic more than one option exists, a decision must be made (e.g. choosing a container slot from a set of free slots for a given container or choosing a vehicle from a set of available vehicles for a given transportation job). This can either be a random decision or an informed decision. For the latter case, some kind of scalar metric is assigned to each option to express the degree of preference. The metric term might contain a notion of time (e.g., urgency), space (e.g., equipment travel distances), or other relevant property. However, there is no guarantee that using a certain metric results in the desired behavior of the system (here: container terminal) over a longer period of observation. This must be shown with simulation studies or numerical experiments.
- Solution quality: The rules that allocate the slot for the container are based on the practitioners' experience. This makes it difficult to justify a heuristic based on its formulation on an academic level. However, the solution quality of the rule-based heuristic can be evaluated with simulation studies or numerical experiments. The proposed rule-based heuristic can be compared with a baseline (e.g., random assignment) or other established rule-based heuristics. Likewise, a comparison with solutions generated with other approaches, especially with exact methods, can be insightful.

These properties highlight some of the benefits and shortcomings of rule-based heuristics. On the one hand, typically their computational complexity is low, the formulation is either simplistic (e.g., first come first serve or nearest job first) or driven by business insights. Common events (e.g., delays or lack of information) are usually considered. On the other hand, the generated solution might be far from optimal. Here, different optima might be strived for, such as (1) a minimal travel distance of the horizontal transport equipment, (2) reducing yard crane movements to a minimum, (3) as little congestion in the yard as possible, and (4) a minimum amount of relocations (Kim and Lee, 2015). Kim and Lee (2015) also state that in practice terminal operating systems do not create a schedule but instead use real-time control (i.e., rule-based heuristics) for container handling assignments and container slot allocation due to the uncertainties of container handling times. Another argument for rule-based heuristics stems from Voß, et al. (2016). They hypothesize that “The human decision makers […] might be more interested in the staff and equipment to employ in future shifts and less in actual slots where containers are stored.” Or in more general terms, a simulation model that covers the handling processes in the container yard in detail must also cover the container slot allocation – independent from the actual research question. Here, a computationally efficient rule-based heuristic frees computational capacities for the actual research topic. Hence, the current state of the art regarding rule-based heuristics is worthwhile being examined further.

2 Literature Review

It is quite difficult to compare different approaches of yard management at container terminals in a fair manner. In academic publications, often only a subset of the container handling processes at a container terminal is inspected, e.g. only import containers, export containers, or transshipment containers (Jiang and Jin, 2017; Jacomino, et al., 2019; Ambrosino and Xie, 2020, respectively). Likewise, sometimes the containers are stored in a yard block without modelling the container slots allocation procedure in detail (Liu, Kang and Zhou, 2010; Kastner, et al., 2021). In other words, publications model different aspects of the yard management at different levels of granularity which makes it infeasible to quantitatively compare the approaches for given problem instances. Yet, this is urgently necessary because rule-based heuristics are often only compared to simplistic alternatives which they outperform with little effort (as the reported literature will show shortly). Thus, in this section publications are gathered that are similar enough for a direct comparison in the next sections.

For the literature search, the two bibliographic sources Scopus and Web of Science have been used. Elsevier (2021) claims that their product Scopus contains most high-quality content compared to their competitors for each world region with more than 82 million items in total. Web of Science is used in addition because the Web of Science Group (2020) claims to be independent from any publisher and covers more than 74 million items. Each bibliographic source contains publications unique to them and both of them are among the most used sources to explore relevant research activities (Huang, et al., 2020).

First, synonyms for “container slot allocation” are looked up. This accounts for the rich language in logistics. This leads to the following query string:

> "container terminal" and (import or inbound) and (export or outbound) and ("storage strategy" or "storage space allocation" or "location assignment" or "stacking strategy" or "yard management" or "slot allocation" or "stacking policy")

The query string is applied on the broadest option available at the respective database, i.e. TITLE-ABS-KEY for Scopus and ALL FIELDS for Web of Science. Only articles published in 2019 and before are considered. The search with that query string resulted in 14 hits on Scopus and 10 hits at Web of Science, of which 4 were duplicates. In the next step, those rule-based heuristics that could be compared in a fair manner are extracted from those 20 publications. Here, the following selection criteria have been applied:

- The chosen method must be a rule-based heuristic based on the list of properties presented in this publication.
- For a fair comparison, the rule-based heuristic must follow the free stacking approach - in distinction to remarshalling stacking, reservation stacking or scattered stacking (Kemme, 2013).
- Only container terminals at sea ports are included.
- The rule-based heuristic must cover import containers, export containers, and transshipment containers (no distinction is made for domestic transportation). They are alternatively referred to as inbound for import containers and outbound for export and transshipment containers.
- The rule-based heuristic allocates a suitable slot for a given container.

This sieving process leaves 3 publications for further examination, i.e. (Güven and Türsel Eliiyi, 2014), (Güven and Türsel Eliiyi, 2019), and (Voß, et al., 2016). At the time of writing this conference article, the two rule-based heuristics by Güven and Türsel Eliiyi are implemented and they are examined in the following sections. The six strategies of Voß, et al. are not yet implemented but the work is ongoing.

Güven and Türsel Eliiyi (2014) implement what Kemme (2013) coined as the two complementary stacking approaches of retrieval-time stacking and category stacking. Retrieval-time stacking means that the containers are stacked according to the expected pick-up time whereas category stacking refers to grouping containers according to the corresponding vessel or berth. They report the results of a simulation study that only covers the import process. Among others, the number of reshuffles and the number of used ground slots are reported. The lead times of external trucks, the travelled distances of the yard cranes or a metric to capture the work balancing between the blocks is not reported.

Güven and Türsel Eliiyi (2019) pick up their prior work from 2014 and extend it by adding a mathematical program and a more sophisticated simulation study for new insights. They alter the formulation of the rule-based heuristic by separating yard blocks for import and export containers. The authors further claim that with sufficient free yard capacity, their approach reaches the optimum number of reshuffles, i.e. none. This, however, neglects the delays and schedule perturbations which are often part of daily operations. For the simulation study, among others the number of reshuffles and the travelled distances of the yard cranes is reported. The lead times of external trucks or a metric to capture the work balancing between the blocks is not reported.

The four common goals of container stacking according to Kim and Lee (2015) are to minimize horizontal transport equipment travel distances, yard crane movements, congestion in the road network, and reshuffles. In the following simulation study, the latter three aspects are inspected and lead times are added to the consideration.

3 Methods

By definition, rule-based heuristics provide no guarantee that using them leads to optimal operational behavior – unlike exact methods. This situation is further complicated since there are different conceptions of what is optimal. In technical terms, container slot allocation is a multi-objective optimization problem for which the terminal operator must weigh up competing optimization goals. In this publication, we focus on the core activity performance indicators lead time and productivity (see Ha, Yang and Lam, 2019). While lead time, i.e. vessel turn time and truck turn time, is a rather simple concept to measure and interpret (the shorter the better), the concept of productivity is more difficult to assess. In this study, we decided to focus on potential inefficiencies in the container yard. For each yard crane, the travel distance and the number of reshuffles over time is assessed. Both processes consume time and resources (both in an economic and ecological sense) and the objective to minimize either of them might come at the cost of the other. We avoided the common metric of utilization (see Kizilay and Türsel Eliiyi, 2021) as it is more difficult to interpret: a high utilization of a yard crane might be caused by long travel distances, many reshuffles, poor work balancing, or just a major peak in operations.

Last, the number of waiting trucks (both internal yard trucks and external trucks) at a yard block is recorded. This indirectly reflects the utilization of the yard crane(s) operating in each yard block and as such it comes with all the shortcomings mentioned above. However, this metric provides the additional information of how many trucks are affected by congestions in the system. If a rule-based heuristic leads to shorter queues than others, this is seen as an indicator of better work balancing. In summary, the lead time and a selection of efficiency measures are assessed which represent the time pressure and cost pressure terminal operators are exposed to in daily operations.

As previously pointed out, rule-based heuristics can hardly be examined from an algorithmic point of view when it comes to predicting terminal performance indicators. At the same time, trying out new approaches in the field could potentially result in high lead times which in turn would inevitably strain customer relationships. A simulation study allows to estimate the operational performance metrics without any implications for the daily business. Moreover, simulation has been successfully employed in the past (Dragović, Tzannatos and Park, 2017). Thus, this method is chosen for this study.

3.1 Simulation Model

The simulation model is implemented in Tecnomatix Plant Simulation version 14. The system boundaries of the simulation model as well as its subsystems are depicted in Figure 1. Both the quay side and the truck gates are system interfaces. Here, containers (either 20-foot or 40-foot standard containers) are either delivered or picked up. At the time a container enters the system, all relevant information (i.e., empty or laden, weight, destination, estimated pick up time) is available for container slot allocation. The two approaches of estimating the truck pickup times are further explained in Section 3.3. At the quay side, vessels arrive with containers to discharge. Vessels queue up to berth in a first come first serve fashion. The time for berthing and preparing container handling is

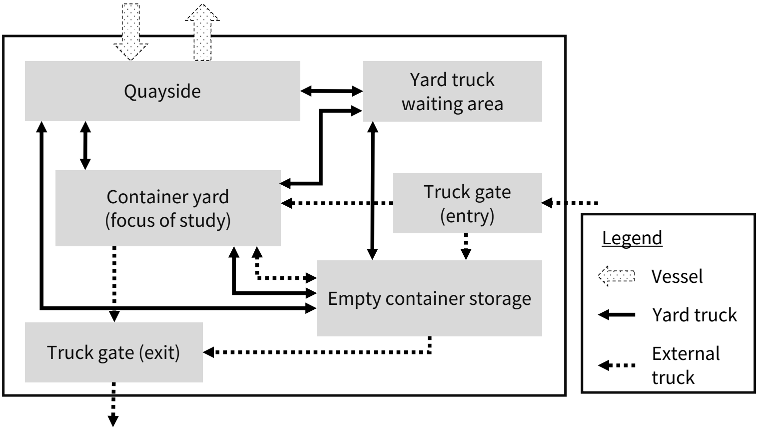

Figure 1: The considered subsystems of the container terminal

set to 106 min (Yu, et al., 2018). Then, ship-to-shore gantry cranes start to operate by loading the first container on a yard truck. If it is an empty container, the yard truck delivers the container to the empty container storage. This storage is coarsely modelled without specific container slots. If the container is laden, the container slot is allocated in the yard and the vehicle moves it there. This part is modelled in detail, i.e. with a road network and a yard block arrangement inspired by the MSC Terminal Valencia. Once 25% of the containers are discharged, the loading process is initiated so that both processes are executed in parallel. After the last handled container, the unberthing process is set to take 81 min (Yu, et al., 2018).

External trucks enter the model from the hinterland through the truck gate. This is coarsely modelled by 5 parallel optical character recognition (OCR) gates the trucks need to pass. Prior administrative processes (such as visiting an interchange) are out of scope of this study and therefore neglected. After passing the OCR gates, the external truck directly heads to the container yard or the empty container storage to either pick up or deliver a container. In case of a delivery, some of the external trucks also pick up a container afterwards, either from the container yard or the empty container storage. Then, the external truck leaves the container terminal through the truck gate without any administrative process. The road network is shared between external trucks and yard trucks.

A gang of 7 yard trucks is assigned to each of the 8 ship-to-shore gantry cranes. Transportation jobs are executed first come first serve. If a yard truck runs out of transportation jobs, it moves to the yard truck waiting area which is coarsely modelled. As soon as a new transportation job is available, it moves out of the waiting area and moves to its new destination. A yard crane always serves the nearest truck first.

In Figure 2, the storage yard layout including the road network and the yard block orientation is displayed. Each arrow indicates the allowed direction of travel. Inside the storage yard, each arrow represents a road with two lanes. The roads that connect the storage yard with related subsystems are only coarsely modelled.

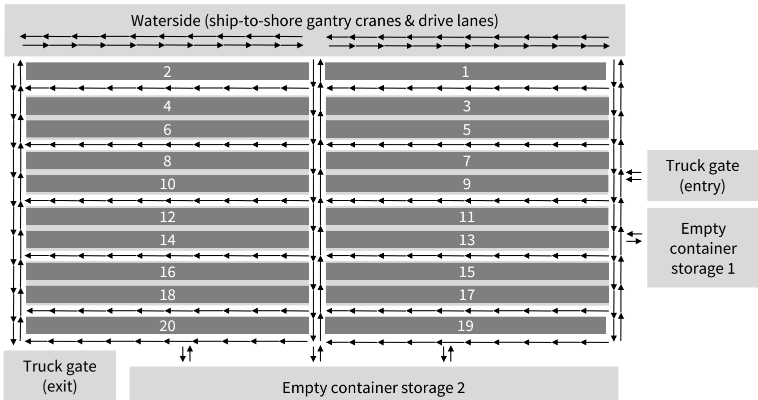

Figure 2: Storage yard layout inspired by the MSC Terminal Valencia

3.2 Generated Data

For this simulation study, special emphasis has been put in the data generation process. All rule-based heuristics are designed to cover import containers, export containers, and transshipment containers. Therefore, all three categories should be part of the generated container streams. The vessel arrival and departure times are inspired by the publicly available data of MSC Valencia between February and July 2020, i.e. 6 months. For each vessel, its service is looked up. If the service does not usually visit the terminal, it is dropped. If sufficient information regarding a container service is available, it is entered into the schedule. The number of containers that a vessel transports are estimated based on the approach of Park and Suh (2019). If no public information is available on a service, it is dropped. As a compensation, those services that reportedly only called the container terminal sporadically have been added to the schedule as frequent visitors. As a final step, the vessel capacities are scaled up to match the reported terminal capacities.

The modal split is generalized from the statistical report of the local port authority (valenciaport, 2019). Thus, it is assumed that the total terminal capacity of 1.6 million twenty-foot equivalent units (TEU) p.a. consists of 54% transshipment and 56% gateway traffic (equal shares of import and export, including domestic ingoing and outgoing trade). In the next step, container flows are generated based on the approach of Hartmann (2004). This approach is further extended to also incorporate the previously prepared vessel schedules including the average number of inbound TEU and the number of ports of destination related to a container service. The number of inbound TEU is varied by plus/minus 10% following a uniform distribution to approximate variations during daily operations. Furthermore, if possible, a truck that delivers an export container is also used to pick up an import container.

Three different workload scenarios are prepared. In the first workload scenario, any kind of peak is avoided and the container arrival and departure streams are quite homogenous. In the second workload scenario, some of the deep-sea vessels are delayed so that the container terminal must handle a few peak loads and additional reshuffles might be necessary. In the third workload scenario, the schedule is designed so that several port calls overlap so that many vessels need to queue up before berthing. This leads to many schedule perturbations and therefore more reshuffles.

3.3 Rule-based Heuristics

Containers enter the terminal either by being dropped on a yard truck on the quay side or they are loaded on an external truck that passes through the truck gate. Only at these two moments, containers are allocated a container slot. The requirements for the slot differ depending on whether it is (a) an import or (b) a transshipment container on the yard truck or (c) an export container on an external truck. For the slot allocation, some operational constraints must be adhered to by all rule-based heuristics:

- The yard crane model determines the maximum stacking height. For our implementation, it is set to 5 containers.
- For each bay, the maximum number of stored containers is limited to allow reshuffling inside a bay any time. Thus, for our stacking height of 5 containers the number of required empty slots for each bay is set to 4 containers.
- Bays are either designed for 20-foot or 40-foot containers. Containers of different lengths are never mixed inside a bay.
- Any container stack can be subject to a reservation. This means that a container slot on top of the stack has already been assigned but the container has not yet been stacked at that position.
- In the two heuristics of Güven and Türsel Eliiyi, the weights of the lightest and heaviest container in each stack are not allowed to differ more than 3 tons. For comparability, the same constraint is applied on the other two heuristics, too.

These constraints are not repeated in the following short formulation of the four rule-based heuristics. For the exact algorithmic definition of each of the heuristics, please refer to the mentioned publications.

Güven and Türsel Eliiyi (2014) present a rule-based heuristic which they call “Strategy 2”. It is hereafter called GTE14 based on the authors’ names and the publication year. For this rule-based heuristic, each bay is used for one container type (i.e., export and transshipment or import). If the container fulfills the requirements of being placed in the bay, each stack is checked regarding the destination and departure time. Export and transshipment containers can be stacked for the same destination and import containers can be stacked if the departure time of the new container is earlier than the top container in the respective stack. In our implementation, each yard block consists of some bays for 20-foot and some for 40-foot containers. Similarly, some bays are reserved for import and some for export and transshipment containers. The ratio is constant for all yard blocks.

Güven and Türsel Eliiyi (2019) extend the work of GTE14 by reworking their rule-based policy which they call "Policy 2: attribute-based stacking". It is hereafter called GTE19 based on the same naming convention as GTE14. In this publication, the authors state that each yard block is either used for import containers or for export and transshipment containers. This sets it apart from the bay-wise approach in 2014. Furthermore, in 2014 they sketched out the idea that the container slot should be chosen in order to minimize the future travel distance, i.e. import containers should be stored close to the truck gate and export and transshipment containers should be stored close to the sea side. In our implementation, the import yard blocks are placed as far away from the seaside as possible, close to the exit for external trucks.

The Levelling Strategy is borrowed from Kemme (2013). Following the author's suggestion, it is abbreviated as LeS. First, the yard block is chosen randomly. Inside the yard block, all permissible bays for the given container are selected. For each bay, all permissible stacks are gathered and sorted by stack height. A random stack is selected from the stacks of the lowest height.

Similarly, the Random Strategy is borrowed from Kemme (2013) and is abbreviated as RaS for the same reason. Here, both the yard block and the bay are selected randomly from the subset of permissible bays inside the container yard.

3.4 Experiment Plan

For the simulation study, a full-factor design has been chosen, i.e. each combination of input parameters is combined. This is depicted in Table 1. The focus lies on the four rule-based heuristics GTE14, GTE19, LeS, and RaS. Each of them is examined in all three workload scenarios. For GTE14 and GTE19, two variations are considered. In the first variation, the time an external truck picks up the import container is already known when the container is discharged from the vessel. This follows the assumption that prior to vessel arrival, the freight forwarders announce (and later successfully realize) the time their trucks arrive at the truck gate, usually through a truck appointment system (TAS) (cf. Zeng, Feng and Yang, 2019). In the second variation, the freight forwarder books a time slot after the container slot is allocated (Karsten, 2020; DAKOSY Datenkommunikationssystem AG, 2021). Thus, this information cannot be used for the slot allocation. In this second variation, at the time of slot allocation the average dwell time of the containers is assumed. In the following, the suffix “no truck slot” is appended when discussing the second variation. The two variations are skipped for RaS and LeS as their formulation does not make use of the estimated departure time of containers.

Table 1: Experiment plan

Number of experiment	Rule-based heuristic	Truck slot booked before allocating container slot	Workload scenario
1	GTE14	yes	1
2	GTE19	yes	1
3	GTE14	no	1
4	GTE19	no	1
5	RaS	-	1
6	LeS	-	1
7	GTE14	yes	2
8	GTE19	yes	2
9	GTE14	no	2

Number of experiment	Rule-based heuristic	Truck slot booked before allocating container slot	Workload scenario
10	GTE19	no	2
11	RaS	-	2
12	LeS	-	2
13	GTE14	yes	3
14	GTE19	yes	3
15	GTE14	no	3
16	GTE19	no	3
17	RaS	-	3
18	LeS	-	3

For each input parameter configuration, 50 replications are executed. For each replication, the numbers of import containers, export containers, and transshipment containers are randomly varied. For each container, its attributes (i.e., mode and time of arrival, mode and time of departure, weight, full or laden, etc.) are randomly generated. The truck arrivals are generated according to the vessel schedules. First, the yard is filled over a transient phase of 23 days. Then, for 45 days the operation is monitored. This longer period is necessary because many services call the terminal every 7 or every 10 days, leading to peak loads in longer time intervals.

4 Intermediate Results and Discussion

At the time of reporting, the implementation and evaluation of GTE14 and GTE19 including the two different assumptions of the TAS as well as the implementation of LeS and RaS are finalized. The work regarding the heuristics presented by Voß, et al. (2016) is still ongoing. In the following, the intermediate results are presented and discussed grouped by lead time and efficiency indicators. The error bars indicate one standard deviation.

4.1 Lead Time

In the maritime supply chain, container terminal operators are positioned between the shipping companies on the sea side and the freight forwarders in the hinterland. The container terminal operators need to serve both interfaces quickly and reliably to satisfy external stakeholders. Thus, lead times are important performance indicators for third parties when assessing the service level of a container terminal. As previously discussed in Section 3.1, the processes of arrival and departure of a vessel or a truck are only coarsely modelled. Hence, the reported lead times might differ from values achieved in practice. As this affects all heuristics likewise, this has no implications for the comparison.

The average vessel turn times are depicted in Figure 3. This is the timespan between the initiation of the berthing process and the end of the unberthing process. The shortest turn times are achieved by GTE14 for both TAS variations. For GTE19, the average value and the standard deviation are larger than for GTE14 and both TAS variations are very close to each other. The two baseline implementations LeS and RaS perform substantially worse. For the workload scenario 1, the average vessel turn time is approx. 18 h when using GTE14 but approx. 29 h when using RaS, an increase of roughly 67%. The shortest average vessel turn time is approx. 18 h, the longest approx. 40 h. These figures are within the range of publicly accessible data (Comtois and Slack, 2019; Statista, 2021).

The average truck turn times are depicted in Figure 4. Here, clear differences between GTE14 and GTE19 can be identified. Furthermore, the missing container pickup information at the time of slot allocation shows a severe effect on truck turn times when employing GTE19, leading to longer lead times than LeS and RaS. In terms of average truck turn time, these lead times are comparable to GTE19 even with the truck pickup times being previously announced. All reported truck turn times are rather long compared to publicly accessible data (cf. Department of Infrastructure, Regional Development and Cities, 2018). While worst-case values of approx. 45 min seem common, spending more than an hour on a container terminal is not. This can be explained by the rather large amount of trucks in our generated scenarios that both deliver an export container and pick up an import container. Thus, their turn time account for two containers.

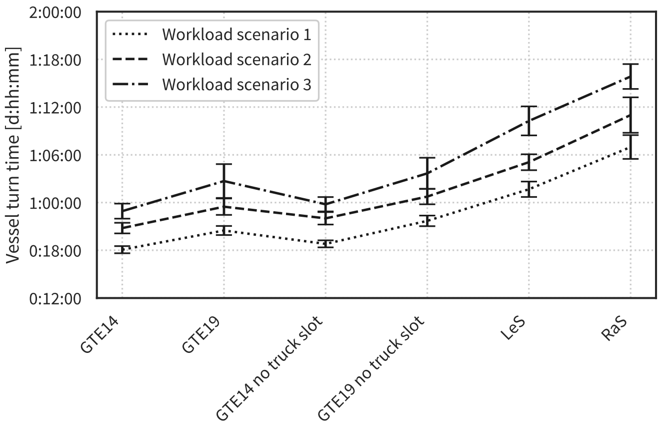

Figure 3: Vessel turn time

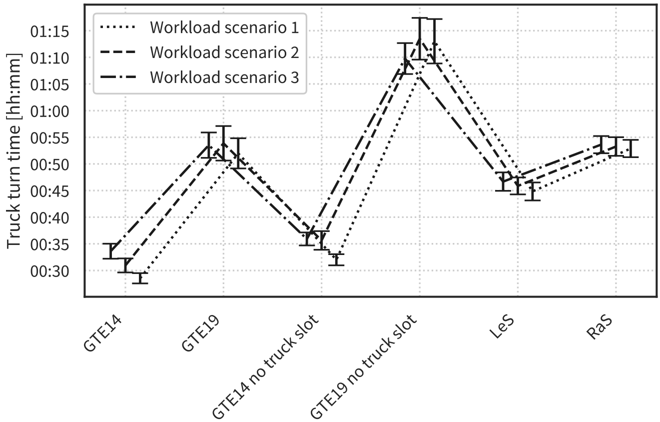

Figure 4: Truck turn time

4.2 Efficient Operations

Within the maritime supply chain, competitors do not only differ in terms of lead times. Similarly important, they need to offer their services at affordable prices. One of the important factors is to move the terminal equipment as little as possible and still obtain acceptable lead times. The more the terminal equipment needs to move, the more energy it consumes which must be purchased in form of petrol, electricity, or similar. In this section, the number of reshuffles and the travel distance of the yard cranes is reported. If a heuristic minimizes these, it reduces the operational costs.

The number of reshuffles for each of the heuristics is depicted in Figure 5. The chart indicates that if the truck slot is booked before the container slot is allocated, this leads to less reshuffles. The difference between GTE14 and GTE19 seems marginal for both TAS variations. LeS and RaS perform significantly worse, RaS causing more than three times the number of reshuffles. Here, often outbound (i.e., export and transshipment) containers need to be taken from the middle of the container stack. For inbound containers, once no slot is booked before slot allocation, the number of reshuffles between GTE14, GTE19, LeS, and RaS diminishes.

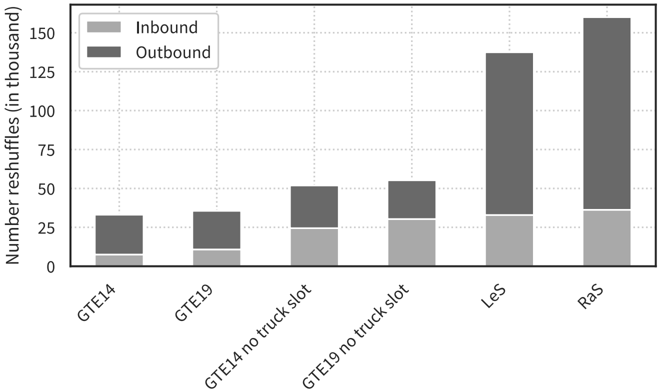

Figure 5: Number of reshuffles over the simulation period

In Figure 6, the average distance a yard crane travels is depicted. It can be seen that GTE19 in both TAS variations leads to exceptionally low travel distances. GTE14 shows slightly higher travel distances. For this performance indicator, RaS outperforms LeS. This can be explained by the levelling approach that prefers the yard crane to travel longer distances to reach a lower stack. RaS, on the contrary, creates relatively higher stacks which in turn increases the probability of reshuffles. For the absolute value range of 6 km to 7 km, the following should be considered: one yard block has a length of approx. 330 m in our terminal layout. Therefore, a yard crane travels approx. 20 times the length of its yard block that consists of approx. 35 bays (some of them 20-foot and some 40-foot container bays). Hence, each yard crane travels approx. 700 bays a day while each yard block has an average throughput of $\frac{1{,}200{,}000\,TEU}{365\,d \cdot 20\,blocks} \approx 165\frac{TEU}{d \cdot block}$ ignoring holidays and excluding empty containers. Hence, each yard crane moves a bit more than $\frac{700}{165} \approx 4$ bays for each TEU that is moved through the terminal. Güven and Türsel Eliiyi (2019) report that to move $2 \cdot 13{,}308 = 26{,}616$ containers, their yard cranes move 4,438 bays (excluding empty containers). Hence, each yard crane moves approx. 1.7 bays for each moved container which is exceptionally well in comparison. This might be related to a lower yard utilization - they report that 13,308 containers leave the terminal each month whereas this this terminal moves 100,000 TEU a month.

Last, the maximum number of waiting trucks (both internal trucks and yard trucks) over all the yard blocks and over the whole simulation time is presented in Figure 7. This metric serves as a proxy to indicate how well the work is balanced between the yard blocks. Here, LeS and RaS clearly lead the comparison with on average maximum 40 trucks waiting. When we recall the difference in the number of reshuffles, this comes as a surprise: while using LeS and RaS, the yard cranes reshuffle more for each workload scenario. Thus, each yard crane is busy for a longer timespan when handling the same capacities. On the other hand, LeS and RaS have a large random component in their formulation so that all the work is shared equally between all yard blocks (not always but with a high probability). These long queues are very unlikely to happen in production as someone of the terminal operation team would intervene, e.g. by manually reallocating the container slots or closing the truck gate until the congestion in the yard is dissolved. Thus, this performance indicator should not be taken at face value. Instead, it highlights potential issues of problematic workload balancing in a comprehensible way.

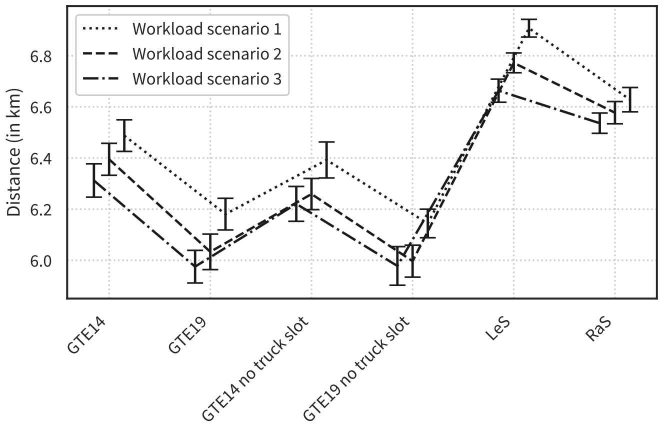

Figure 6: Daily average travelled distance of a yard crane

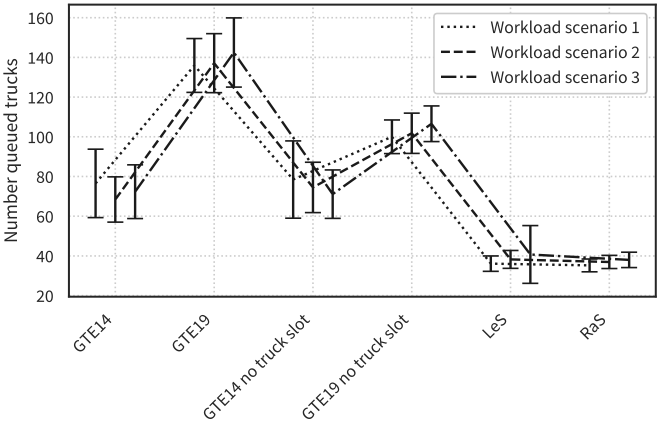

Figure 7: Maximum number of trucks waiting at a yard block

4.3 Discussion

The intermediate results in the two previous sections have provided some insights into the four rule-based heuristics GTE14, GTE19, LeS, and RaS for a given terminal layout inspired by the MSC Terminal Valencia and three given workload scenarios. In terms of lead time, GTE14 has shown superiority while GTE19 apparently struggled to handle the hinterland interface. For reshuffles and vessel turn time, the available TAS information during container slot allocation led to better results. At other times, the lack of the TAS information even showed benefits (e.g., Figure 7). This can be explained by the desire to reduce reshuffles by a consignment strategy-inspired approach and thereby concentrating a lot of work in a single yard block. When inspecting the container yard layout of Izmir as it is used in Güven and Türsel Eliiyi (2019), it can be seen that the container yard is surrounded by ship-to-shore gantry cranes in the West, North, and East. Hence, for each ship-to-shore gantry crane different yard blocks are identified as the closest and therefore the preferred location of stacking containers that will leave the terminal by vessel (Güven and Türsel Eliiyi, 2014). This is not directly transferrable to the layout used in this simulation study. At the MSC Terminal Valencia, all ship-to-shore cranes are lined up and thus the distances between the yard blocks and the ship-to-shore gantry cranes are much more similar. Therefore, the yard blocks close to the sea side are used more frequently. In such a situation, the heuristics might require an extension to ensure better work balance over the yard at the cost of longer yard truck travel distances. It is reasonable to have an operating ratio of yard cranes to ship-to-shore gantry cranes ranging from 2.6 to 2.8 (Sha, et al., 2021) which is currently not ensured by any of the heuristics – as for their assumed layout there might not have been such need.

5 Conclusions and Outlook

In this publication, first relevant rule-based heuristics were searched for in literature databases. In the subsequent simulation study, the performance of four of these retrieved heuristics were examined. For the two heuristics GTE14 and GTE19 which use information regarding the truck pickup time of the container, two variations are considered. In the first variation, the pickup time is assumed to be known before allocating the slot and in the second variation this information is (not yet) available. The heuristics are compared over four performance indicators that represent the time pressure and cost pressure terminal operators face and one to indicate the workload balance. The performance indicators highlight the strengths and potentials for improvement of the examined rule-based heuristics. Based on the observations, GTE14 shows the fastest lead times while GTE19 leads to the lowest travel distances of the yard cranes which in turn indicates a lower energy consumption. Depending on the operator's requirements, however, the container slot allocation heuristic might need to trade some of the proximity of container slots to the later destination (ship-to-shore cranes for export/transshipment or to the truck gate for import) for a better workload balancing between the yard blocks. These insights, however, are only valid for the examined parameters of this simulation study, i.e. for this specific container terminal layout and the three specific generated workload scenarios.

At the time of writing, the rule-based heuristics of Voß, et al. (2016) are still missing. Furthermore, some publications focus only on the import process (e.g., Rekik, Elkosantini and Chabchoub, 2018; Jacomino, et al., 2019) or only the export process (e.g., Ambrosino and Xie, 2020). These might be also included in the comparison as soon as an appropriate replacement for each of the missing container handling processes is determined, so that the study can cover import, export, and transshipment processes likewise. Further baseline algorithms have been designed by van Asperen, Borgman and Dekker (2013) that might shed some new light on the results. Moreover, a larger amount of representative container terminal layouts (see e.g. Taner, Kulak and Koyuncuoğlu, 2014) might help to further examine the trade-off between minimizing yard truck travel distances and balancing the workload better between the yard blocks.

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