Optimization Models for Coordinating Landside and Yard Operations in Maritime Container Terminals

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Optimization Models for Coordinating Landside and Yard Operations in Maritime Container Terminals

by

Ahmed Azab

Abstract

Container terminals are maritime transportation hubs where containers are transferred between different modes; container ships from the seaside and rail transport and road trucks from the landside. Therefore, managing container handling operations efficiently inside the terminal is always a target for the terminal operators. In container terminals, the yard is the central inventory area where containers from both the landside and seaside are stored temporarily before import containers are delivered to customers or export containers are shipped to another terminal.

Since container handling operations at the yard are highly interrelated with the seaside and landside operations, efficient coordination between those operations is essential. In this thesis, we design new models for coordinating the road (external) truck arrivals at the terminal landside with import container handling operations at the yard. To achieve this coordination, two optimization problems are jointly studied in this thesis: the truck appointment scheduling problem and the container relocation problem. The main objective of the appointment scheduling is to manage truck arrivals at the terminal landside, considering the terminal's capacity. At the yard, the relocation problem aims to optimize container handling operations to reduce the unproductive container moves (relocations).

We divide our research into two main phases. In the first phase, we propose a new optimization problem for the container (sometimes called "block") relocation problem, which considers shifting the container pickup times within a specific allowance to minimize the total number of container relocations. For this problem, we introduce two mathematical formulations: one with the goal of obtaining detailed information about the container handling plan, while the other one is a reduced model in size to get better computational performance.

Furthermore, we extend the developed models in this phase to design a solution for a container handling plan which considers a flexible container pickup service such that trucks arriving within the same time will be served based on their arrival order at the yard. In this research phase, we show how truck appointments can be deployed to improve container handling operations at the yard. We conduct extensive computational experiments using different instances from the literature.

In the second phase of the research, we consider the practical aspects of truck appointment schedules to achieve higher coordination levels with yard operations. These aspects are related to trucking companies' container pickup and delivery schedules. Also, we consider new elements at the yard related to the blockage levels that result from the partial appointments. To combine those aspects in one optimization system, we proposed a proactive decision support system that works as a coordination platform for the truck appointment schedules and container handling operations.

In this phase, new multi-objective optimization models are proposed to consider the aspects mentioned above. The model objectives consider trucking companies' satisfaction and container handling operational performance at the yard. The proposed models are solved using a set of instances generated based on a real case study. We further provide a comparative study between our proposed approach and some existing container handling practices in some container terminals.

Acknowledgment

Firstly, I would like to express my sincere gratitude to my advisor **Prof. Hiroshi Morita** for the continuous support of my Ph.D. study and related research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. Despite the stressful research moments, I felt very relaxed with his wise attitude and guidance. I could not have imagined having a better advisor and mentor for my Ph.D. study.

My thanks are also extended to the Japanese Government (Monbukagakusho: MEXT) Scholarship to fund my research and support my stay in Japan during my Ph.D. study.

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Chapter 1

Introduction

The continuous growth in the global supply chain motivates the development of seaborne container transportation, as it is the most cost-efficient transportation means so far. It has been reported that the about 80% of the global cargo is transported by sea (UNCTAD, 2020). Mega vessels that carry massive loads and a large number of containers are being built every year. In 2021, Ever Ace's container ship (see Figure 1.1), operated by Evergreen Marine Corp's, is the largest container ship globally with a capacity of 24,000 TEU (one unit of TEU is defined as a container with a 20-foot equivalent length). The Ever Ace boxship measures 400 meters in length and 61.5 meters in width. It weighs about 235,000 tons and can transport 23,992 containers. Vessels' capacity growth ignited the competition among the leading container ship operators to transport more containers. Figure 1.2 illustrates the shipped cargo in TEUs as of September 1, 2021, for the major shipping operators in the world.

In recent decades, the evolution of the container shipping industry has encouraged the flourishing of container supply-demand flow across the global supply chain. Figure 1.3 shows the increasing trend of the global containerized trade from 1996 to 2020. It can be noted that the 2009 world financial crisis and the 2020 COVID-19 pandemic affected this rising trend. However, containerized trade is expected to surpass the value of 12 billion U.S. dollars in 2027 compared to 8.7 billion U.S. dollars reported in 2019 (source: Statista 2021).

Figure 1.1: The largest container ship in the world EVER ACE crosses the Suez Canal on August 28, 2021 (source: marineinsight.com).

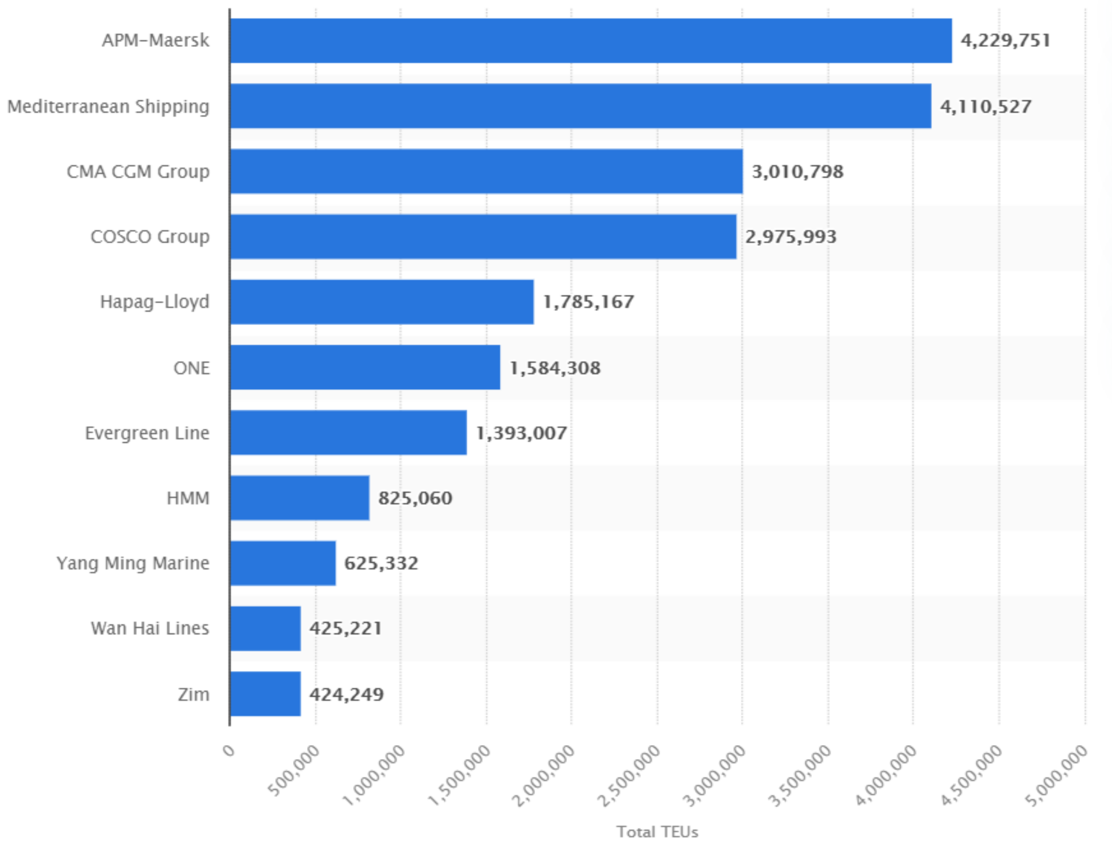


Figure 1.2: The world's leading container ship operators as of September 1, 2021, based on TEU capacity) (source: Statista 2021).

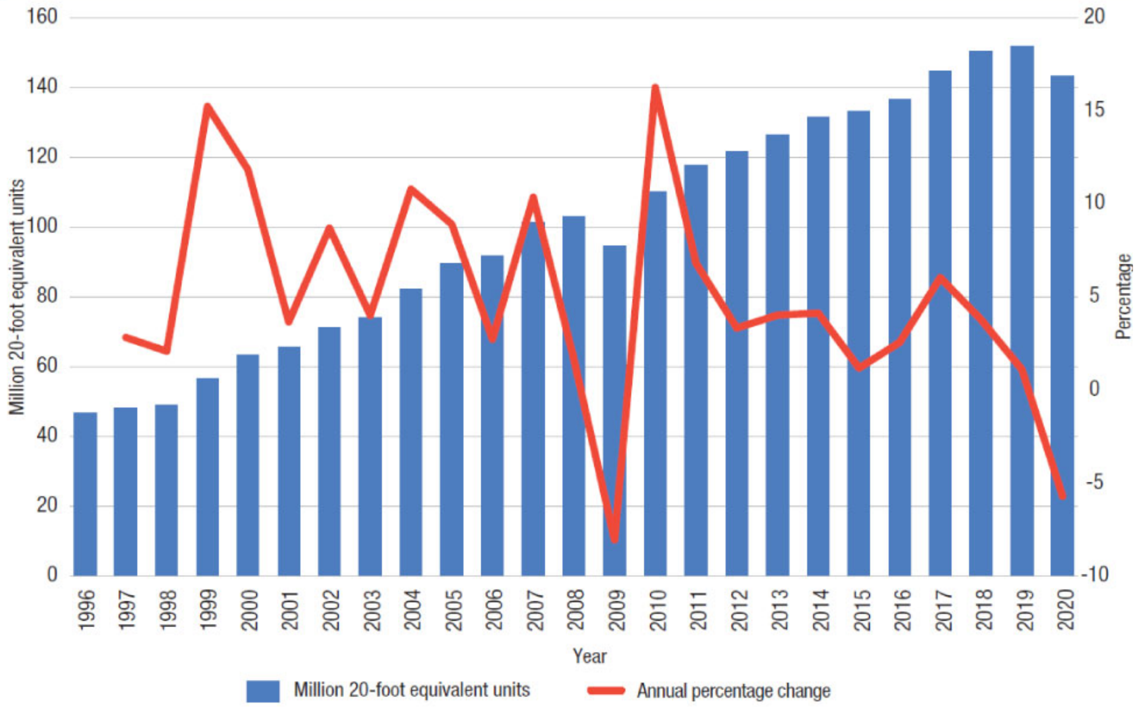


Figure 1.3: Global containerized trade, 1996–2020 (Million 20-foot equivalent units and annual percentage change) (source:UNCTAD, 2020).

The continuous growth in container shipping led to revolutionary developments in container ports as well. Ports adapt themselves to handling this massive increase in container ship capacities and supply-demand volumes. Therefore, container ports always strive to increase their throughput by investing the infrastructure and designing more efficient operations. Figure 1.4 shows the growth in container terminals throughput as a response of the container shipping increases.

1.1 Container Terminals

Container Terminals (CTs) (a container port may contain more than one terminal) act as transshipment points in the global supply chain, where containerized cargo is buffered temporarily at the terminal yards before being transported to other nodes in the container supply chain. Managing container handling operations at these terminals is of considerable importance as it impacts not only terminal performance but also other supply chain nodes. Continuous improvement in container terminal operations is no longer a choice but a necessity, especially for terminals looking for a competitive advantage.

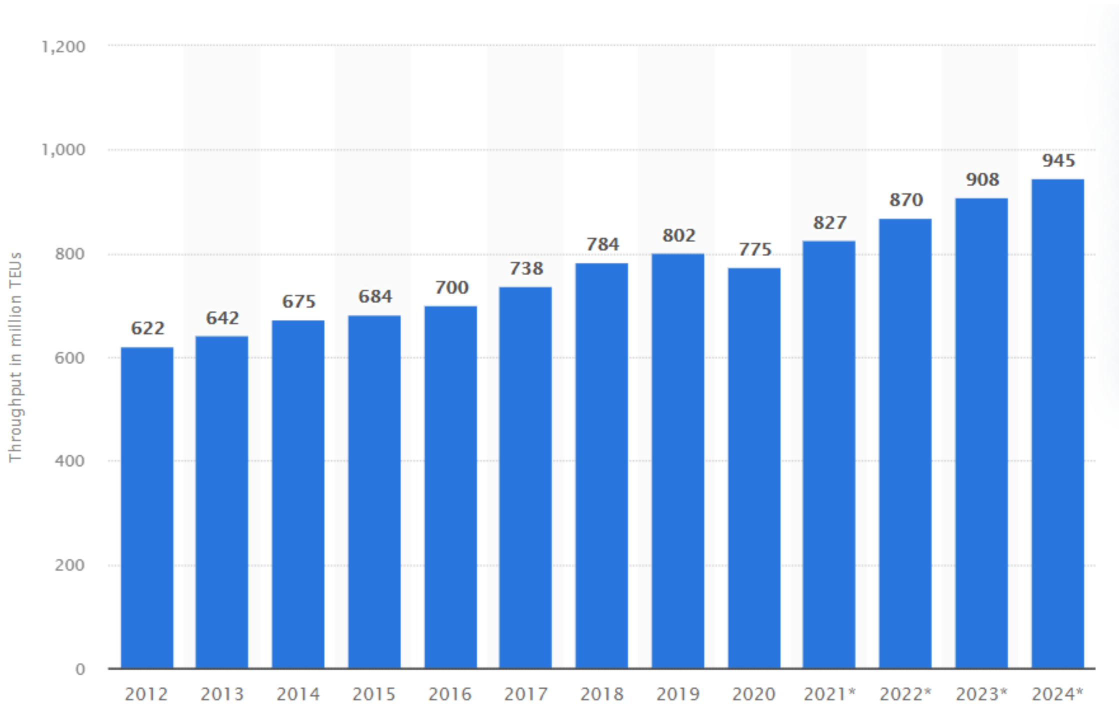


Figure 1.4: Container throughput at ports worldwide from 2012 to 2020 with a forecast for 2021 until 2024 (source: Statista 2021).

1.1.1 Container Terminals Layout and Equipment

A typical CT can be divided into sea-side, yard area, and landside, as shown in Figure 1.5. A container can belong to one of three types: export containers, import containers, and transshipment containers. External trucks typically bring export containers from the hinterland (through the terminal's gates at the landside). They remain in the yard for a time before being loaded onto their assigned vessels. At the same time, import containers are discharged from arriving vessels, then stored in the yard until external trucks pick them up for delivery to waiting customers. In many CTs, import container yard blocks are separated from export container yard blocks to smooth container handling. Therefore, the trucks arriving at the yard to pick up import containers are served separately from the trucks delivering containers for export. Finally, transshipment containers can arrive and leave on the sea-side.

Within a typical CT, terminal operators must deal with intra-terminal operations related to container storage and handling, which directly connect the container pickup and delivery operations of shipping company vessels on the sea-side and trucking company trucks on the landside. There is standard handling equip-

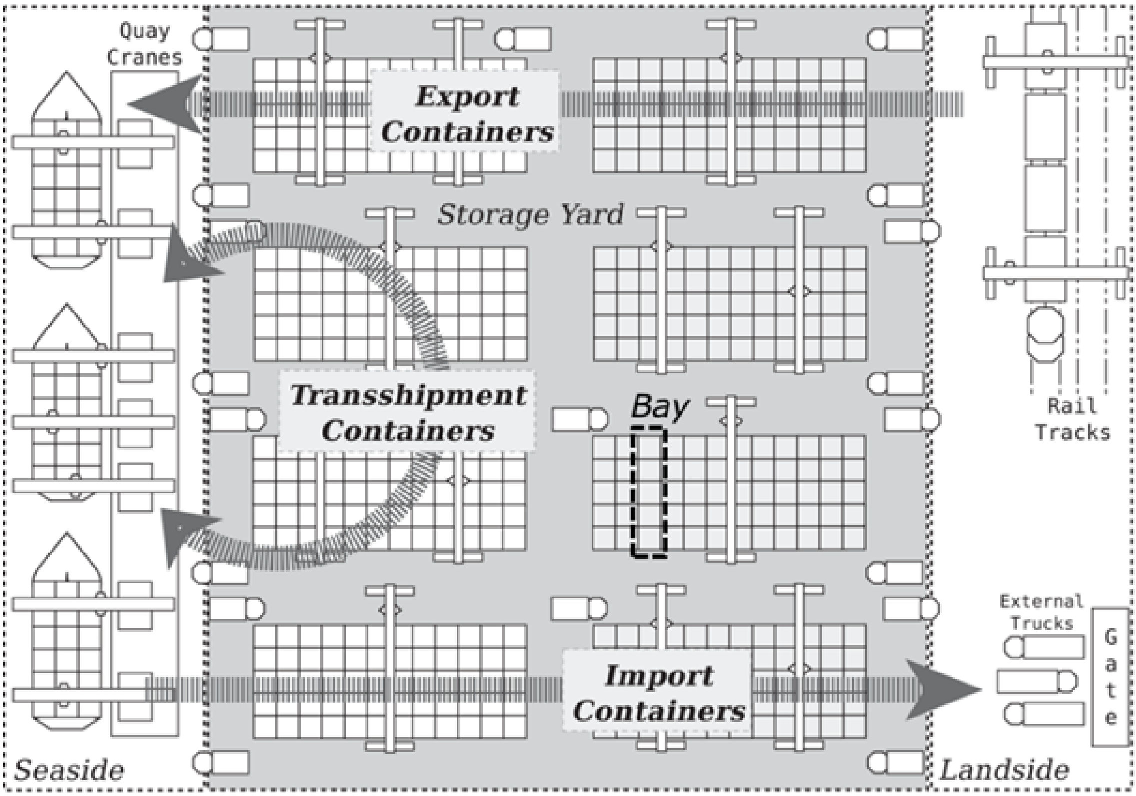


Figure 1.5: Container terminal organization and container flow directions (adapted from da Silva, Erdoğan, et al., 2018).

ment at each terminal area to achieve the container handling process at the port, as illustrated in Figure 1.6. *Quay Cranes* (QC) are used to discharge/load containers from/to the vessel at the sea-side. Those containers are transported from the sea-side to the yard area, and vice versa using internal transport means such as *Yard Trucks*, *Automated Guided Vehicles* (AGVs), or *Straddle Carrier* (SC). At the yard, *Yard Crane* (YC) is typically used to stack containers in the yard area. From the yard, external trucks and trains pickup containers to deliver to remote customers at the hinterland.

1.1.2 Operational Optimization Problems in CT

Decision problems in container terminals can be either strategic, tactical, or operational problems. The strategic decisions are related to the infrastructure of the terminal areas. They include long-term decisions such as the terminal location, capacity of all facilities, and type of equipment to be used (Taner et al., 2014). The tactical problems are concerned with medium-term decisions such as deciding the

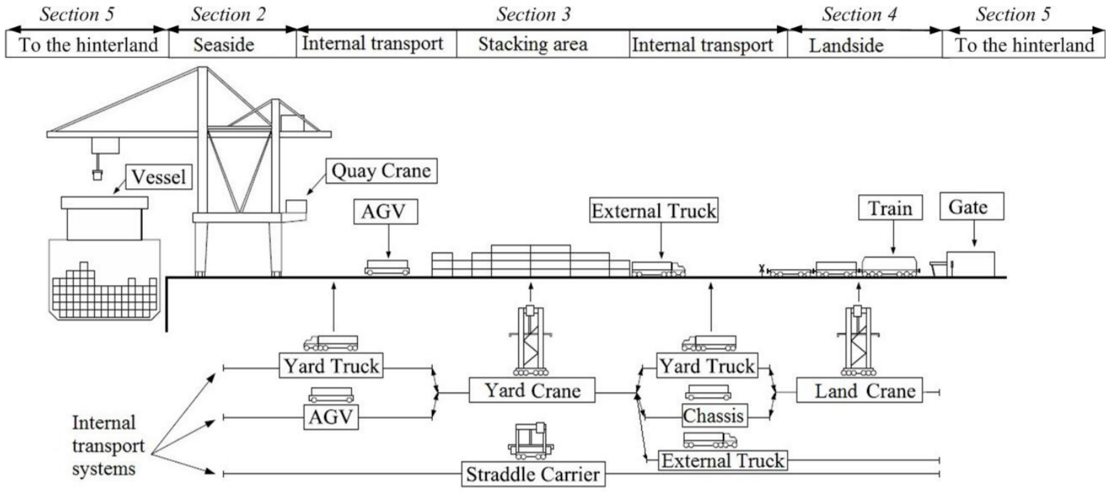


Figure 1.6: Detailed processes of loading and unloading containers at a typical container terminal (adapted from Gharehgozli et al., 2016).

number of laborers and equipment needed at each operational area, selecting the collection methods and designing the work routines (Monaco et al., 2009). On the other hand, the operational level of planning supports short-term decision-making for daily and real-time operations, such as scheduling resources and optimizing handling operations. This section focuses on the operational optimization problems and classifies them based on the terminal operational area.

Landside Optimization Problems.

It is related to managing container pickup and delivery operations at the landside, and it consists of the following:

Gate Planning includes managing the arrival process of external transport means such as external trucks and trains. One of the most common ways for truck arrival management is the *Truck Appointment Scheduling/Systems* (*TAS*) which is discussed in more detail in Chapter 2.

Internal Transportation Problems are related to the routing, dispatching, and assignment of the internal transportation equipment used to move the container between the yard and the gate side. In many terminals, external trucks can access the terminal's yard and pick up or drop off the containers. However, in the rail transportation case, a train waits at the rail area, and internal trucks or other internal container handling equipment such as straddle carriers deliver the containers between the rail area and the yard area, as shown in Figure 1.6.

Yard Area Optimization Problems.

The yard is considered the central area of the container terminal where the flow of containers from both sea-side and landside are handled. Most of the optimization problems in this area are related to the storage operations of the containers.

Yard Crane Scheduling Problems(*YCSP*) decide the sequence which a yard crane follows when loading/unloading containers at the yard area. The main objectives of the *YSCP* are to minimize the make-span of the crane, truck waiting time, truck delays, or maximize the crane utilization.

The *Container Relocation Problem* (*CRP*) is unlike the *YSCP* since the latter problem does not consider container relocation within the yard. The relocation means that a container will be moved to a different slot in the yard if it is blocking the target container. This problem will have the main focus in the thesis, and a comprehensive literature review will be given in Chapter 2.

The *Pre-marshaling Problem* (*PMP*) is usually solved to avoid future relocations such that the yard crane operators rearrange the containers based on the departure time information for each container.

The *Stacking Problem* (*SP*) is concerned with stacking the containers coming from the seaside (when they first arrive at the yard) in a sequence that avoids future relocations or pre-marshaling actions.

Sea-side Optimization Problems.

At this side of the terminal, the operational problems are more related to container ship servicing. The following are the typical optimization problems at the sea-side:

The *Container Stowage Problems* (*CSP*) is solved to decide the locations (slots) of where the containers shall be stacked on the ship to minimize the ship stay time at the port while maintaining ship stability and considering the weight distribution.

The *Berth Allocation Problem* (*BAP*) is a resources allocation problem that decides the berthing location and time for each container ship so that the overall stay time of the ships is minimized. The problem considers the berth spacial constraints (length of the terminal berth and number of berths) and service time constraints.

The *Quay Crane Assignment Problem* (*QCAP*) minimizes the number of quay cranes used to serve a certain number of container ships. Objectives such as increasing the quay crane productivity or reducing the crane travel time might also be considered.

The *Quay Crane Scheduling Problem* (*QCSP*) determines the sequence of quay crane activities when discharging import containers from the vessels and loading export containers to it.

1.1.3 Combined/Integrated Optimization Problems

Container terminal operations are very dynamic, interrelated, and interdependent. For instance, at the sea-side, the quay crane assignment plan, which defines the number of quay cranes deployed within a particular planning horizon, directly impacts quay cranes schedules and berth allocation plans. At the yard area, the yard cranes schedules are affected by the number of the assigned cranes at a specific yard block. On the land side, the routing of internal transport equipment can impact rail operations regarding service time and container handling throughput.

Coordinating the operations planning of such interrelated processes, despite their complexity, is critical to achieving a high level of operational performance. Therefore, integration efforts for the different optimization problems have been found in the literature. Examples in the sea-side include integrating three optimization problems: *BAP*, *QCAS*, and *QCSP* (Abou Kasm et al., 2020). Examples from the yard area are the integrating of *YCSP* with *CRP* in order to minimize *YC* travel times and container relocations. (Galle, Barnhart, et al., 2018b). Trials to integrate operational problems from a certain area with internal transport operations have gained recently more interest. An example of this is to jointly optimize quay crane operations with internal yard truck operations (Hop et al., 2021; Skaf et al., 2021). For a comprehensive survey about integrated optimization problems in yard-area and seaside, interested readers may refer to Kizilay and Eliiyi, 2021.

Main Research Gaps that motivate the research work in this thesis:

1. In the literature, most of the existing studies focus on integrating optimization problems by combining two or more problems that belong to the same operational area (e.g., *QCAS* and *QCSP* at the sea-side or *YCSP* with *CRP* in the yard area). However, there is a natural interrelation among the three main functional areas at container terminals. For instance, the quay crane schedules at the sea-side will impact the yard crane operations since the containers flow between both regions.

2. While most of the recent efforts are paying attention toward integrating the problems at the sea-side and yard area, there are fewer research studies that cover the integrated optimization problems between landside and yard area. This is despite the fact that the landside faces severe challenging problems due to the lack of operational optimization integrity.

Motivated by these research gaps, this thesis introduces a new study for integrated optimization problems in landside and yard areas. We focused on the *Truck Appointment Scheduling Problem* on the land side and *Container Relocation Problem* in the yard area. More explanation about the reason for choosing those problems, including practical and research motivations, is explained in Chapter 2. In the next section, we introduce the main contribution of the thesis and a brief overview of each chapter.

1.2 Thesis Overview and Contribution

Chapter 2 : Literature Review.

In this chapter, we present an extensive literature review for the *Truck Appointment Scheduling* (*TAS*) problem and *Container Relocation Problem* (*CRP*). Each problem clarification, operational research models, solution approaches, and practical aspects are explained. The most recent and related research papers are cited in this chapter. At the end of the chapter, we introduce the research motivations based on the literature.

Chapter 3: The Block Relocation Problem with Appointment Scheduling.

This chapter is based on our published paper: *"The Block Relocation Problem With Appointment Scheduling"* (A. Azab and Morita, 2021). In this chapter, we introduce the case of solving the container relocation problem considering truck appointment scheduling with a limited allowance for shifting the truck appointments. This means that the *CRP* is partially integrated with the truck appointment scheduling problem. However, in the next chapter, we propose a full integration between the truck appointment system and yard crane operations via a decision support system.

In Section 3.1, we highlight the main contributions of the chapter. Section 3.2 explains the motivation behind the studied problem in the chapter. In Section 3.3, the problem description is given, and we refer to the new optimization problem as Block Relocation Problem with Appointment Scheduling (BRPAS). In Section 3.4, two *Integer Programming* (*IP*) models are formulated. The formulations considered the mathematical programming aspects related to the problem size regarding the number of variables and constraints. In addition, a detailed numerical example is illustrated. In Section 3.5, we consider the operational aspects of the new optimization problem and introduce a unique formulation which is defined as the "flexible *BRPAS*" or *BRPAS*(*flex*). The solution of the *BRPAS*(*flex*) problems gives more scheduling flexibility for truck appointments. A post-processing algorithm for the *BRPAS*(*flex*) output is developed to describe the container handling order under the flexible schedule. A detailed numerical example is provided to show the difference between the basic *BRPAS* and the *BRPAS*(*flex*). Finally, to test the performance of all developed models, different instances from the literature are solved, and the results are explained in Section 3.6. In this section, extensive computational experiments are conducted, where the proposed mathematical models are compared against each other.

Chapter 4: A Proactive Decision Support System for Truck Appointments and Container Relocations.

This chapter is based on our submitted paper "*Coordinating Truck Appointments with Container Relocations and Retrievals in Container Terminals Under*

Partial Appointments Information." In this chapter, we build on the proposed *BR-PAS*(*flex*) model in Chapter 3. Here, we introduce a higher level of coordination between the trucking operations of import containers and the container handling operation at the yard. To achieve this, we propose a Decision Support System (DSS) that works as a decision-making platform for scheduling truck appointments and planning container relocations.

In Section 4.1, the chapter's contributions are given. In Section 4.2, we explain the main motivation of extending the *BRPAS* to consider more aspects that focuses more on the implementation side. The framework of the proposed DSS is explained in Section 4.3. In this section, the problem is described, and the modeling assumption is introduced for the mathematical formulation of the integrated problem in Section 4.4. In Section 4.4, the problem notations, variables, objectives and constraints are given. A detailed numerical example is explained. Finally, in Section 4.5, we introduce a case study of a Japanese container terminal. The terminal under the study motivates the generation of the instances we used to test our approach efficiency. Moreover, the proposed optimization approach is evaluated against the existing approximation (*heuristic*) approaches applied in many real cases.

Chapter 5 : Concluding Remarks.

In this chapter, we summarize the thesis's key objectives and findings. In addition, We introduce our vision for future work in the area that is related to coordinating optimization practices in container terminals. In this theme, we think that real-time disruption management techniques are necessary for achieving higher operational performance, especially for terminals that transform from traditional operating systems to digitalized operations.

Chapter 2

Literature Review

This chapter introduces a background for the truck appointment scheduling problem and container relocation problem and explains the related operational aspects. For each problem, an extensive literature review for the most recent research papers is explained. At the end of the chapter, we explain in detail the research question and the motivation of this thesis.

2.1 Truck Appointment Scheduling Problem

2.1.1 Background on the *TAS*

Container pickup and delivery is a typical operation managed by terminal operators, with the aim of reducing terminal congestion and increasing productivity. In this thesis, we focus more on the import containers pick-up operational optimization. In most terminals, external trucks remain one of the primary container transport means due to their operational flexibility. As shown in Figure 2.1, the pickup process begins when a truck is dispatched to the terminal during terminal working hours. For container terminals that use a Truck Appointment System (*TAS*), the trucks are scheduled to arrive at the terminal in a predetermined appointment time window (Torkjazi et al., 2018).

Terminals operating without a TAS often serve the arriving trucks on a *First-Come-First-Served* (*FCFS*) basis, where the arrivals are essentially random and out of the terminal operator's control. For both the appointment-based and random arrival conditions, trucking company dispatchers will assign, in advance, the container to be picked up by each of the trucks (e.g., in Figure 2.1, truck #1 will pick up container #1 and truck #6 will pick up container #6) and the customer to whom the container will be delivered, following a prepared delivery schedule.

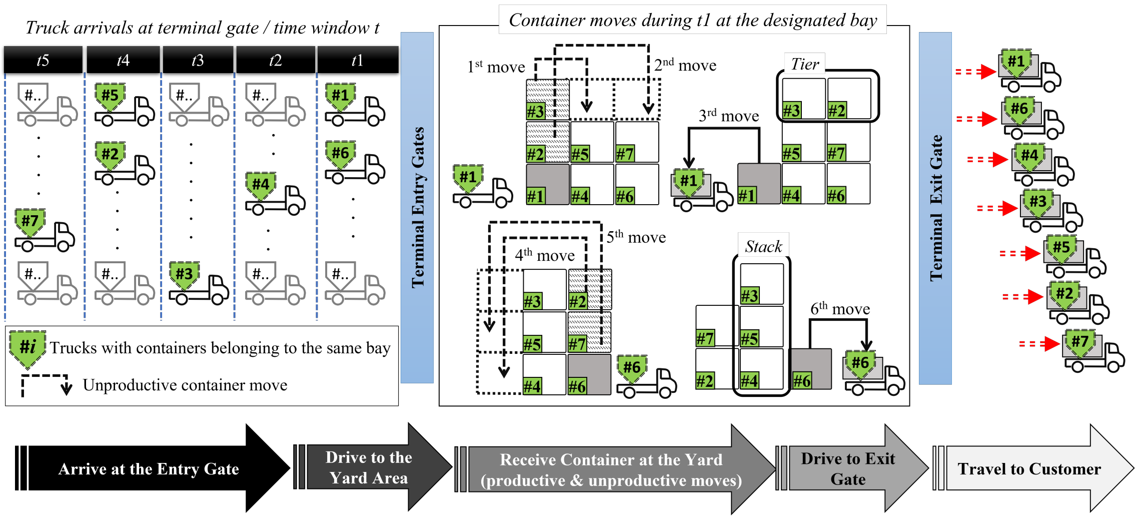


Figure 2.1: Typical import container handling operations for random/scheduled arrivals in the container terminal.

2.1.2 Selected Literature on the *TAS*

Truck arrivals can be controlled using various means to limit the number of trucks served at a yard, taking into account the terminal capacity, by capping the truck quota across the terminal gates during each time window (Huynh & Walton, 2008). However, as a result, some trucks may not have the opportunity to pick up their container before the terminal's closing time. In such a case, extending gate working hours (Morais & Lord, 2006) would allow more trucks to be served but would also increase the burden on terminal resources and add extra operating costs for both the terminal and the trucking companies. To avoid this scenario, adopting an appointment system is one of the most efficient arrival control tools that a terminal operator can use to manage external truck arrivals during the gate working hours (Huynh et al., 2016).

Typically, a truck appointment system uses information about the arrival times preferred by the various trucks and the number of containers to be picked up. The preferred times can then be rescheduled based on the terminal capacity to decide the best truck appointment times that meet terminal objectives (i.e., minimizing truck delays). Most existing appointment systems provide an online platform or cloud-based system (Heilig & Voß, 2017) that allows individual truckers or trucking company dispatchers to book and confirm their appointments. Appointment systems have been widely adopted at CTs around the world, including the TAS of Port Metro Vancouver in Canada, Navis Webaccess for the Deltaport and Vanterm terminals, the eModal appointment system, which is deployed in more than 54 U.S. terminals, the Vehicle Booking System (VBS) of Port Botany Sydney, Australia, and the VBS of the Port of Southampton United Kingdom (Huynh et al., 2016). From both practical and research perspectives, the study of truck appointment scheduling systems has received increasing attention due to the sensitivity of terminal performance to truck arrival patterns.

Some studies have focused on truck appointment scheduling using optimization models that determine either the appointment quota (Chen, Govindan, Yang, et al., 2013), the optimal appointment time for each truck (Do et al., 2016), or the optimal appointment time for a group of trucks (Phan & Kim, 2016). Such appointment systems usually seek to reduce truck turnaround time (A. Azab et al., 2020), minimize overall truck delays (X. Zhang et al., 2019), or reduce terminal congestion (Ma et al., 2019). Minimizing trucking company inconvenience by assigning trucks to appointment times close to their preferred arrival times has also been a focus of study (Phan & Kim, 2015). Several studies have targeted more than one objective and provided new methods such as data mining to process the scheduling inputs, as in Caballini et al., 2020. In this study, both the truck turnaround times and the difference between the preferred time slots of the trucks and their assigned slots are optimized.

Coordinating truck appointments with inter-terminal operations has received less attention in the literature than has the performance of a particular TAS. One exception is the study conducted by Chen, Govindan, and Yang, 2013, which proposed an approach to coordinate trucks delivering export containers with vessel operations using "Vessel Dependent Time Windows (VDTWs)" to manage truck arrivals. In a VDTW system, truck arrival patterns are estimated for each vessel time window in order to minimize the total system cost for the truck and terminal sides. Ma et al., 2019 adopted the VDTW approach and integrated it with TAS to provide more control over truck arrivals at the yard area by considering the yard's storage capacity. The proposed VDTW-based arrival management approach can be efficient for export operations in large terminals with relatively high handling rates, where export containers can be delivered a few hours before the vessel's arrival time. However, in the case of import containers, containers awaiting pickup may remain for some time—often between 1 and 10 days—in the terminal yard after being discharged from the vessel (Kim & Park, 2003) before being picked up by the external trucks. In this case, it is more practical for truck appointments to be coordinated with container handling operations at the yard, which is the focus of our thesis.

Truck arrival patterns have been shown to have a significant impact on truck service times and container handling operations inside a yard (A. E. Azab & Eltawil, 2016). Some studies have analyzed the effect of truck arrival information (arrival patterns and arrival information availability) on yard efficiency and productivity, with a greater focus on container reshuffles or relocations. Zhao and Goodchild, 2010 developed a simulation model to study the effect of various arrival information levels on container relocations during the import container retrieval process. Two different heuristic approaches are deployed. One assumes complete arrival information obtained in advance, while the other uses partial arrival information and matches the container pickup sequence with the container stacking sequence only for the first arriving truck group. Their results indicated that arrival information could affect the number of container relocations under different levels of information availability.

In another simulation study, Ramírez-Nafarrate et al., 2017 investigated the impact of using various truck appointment policies on yard efficiency. It was concluded that to reduce the number of non-value-added container moves (relocations), the TAS needs to be designed to align truck appointments with the container loading sequence at the yard. A. Azab et al., 2018 illustrated that scheduling truck arrivals could effectively smooth yard congestion regarding the number of trucks received per time window and reduce truck waiting time at the yard.

2.2 Container Relocation Problem

2.2.1 Background on the *CRP*

The *Container Relocation Problem* (CRP) or the so-called *Block Relocation Problem* (BRP) is a typical optimization problem that arises when one needs to retrieve a number of *blocks* (steel billets, containers, boxes, etc.) with the minimum number of moves. Through the thesis, we use both abbreviations (BRP and CRP) interchangeably to express this optimization problem. The problem arises in steel factory yards, container terminal yards, retailer depots, etc. In container terminals, due to the spatial constraints on container storage, containers are stacked in bays in the terminal yard (Caserta, Schwarze, et al., 2011). To conceptualize the situation, we can think of a bay representing a two-coordinate stacking configuration, where a set of vertical stacks and horizontal tiers of containers are constructed, as shown in Figure 2.2. In the terminal yard, several consecutive bays form a 3D layout known as the yard block (left side of Figure 2.2). The intersection of a stack and a tier in the bay represents a "slot" where a container can be stacked (Caserta et al., 2012). To stack/unstack a container to/from a bay, a yard crane is used, with accessibility to the container stacks only from the top.

In many CTs, import container yard blocks are separated from export container yard blocks to smooth container handling. Therefore, the trucks arriving at the yard to pick up import containers are served separately from the trucks delivering containers for export. This research focuses specifically on import container pickup operations, treating trucking operations, and container handling at the yard. The efficiency of container handling is one of the essential Key Performance Indicators (KPIs) for terminal productivity. This drives terminal operators to strive to reduce the container handling time in order to reduce power consumption, emissions, and operational costs, and therefore maximize productivity. However, unproductive container moves at the yard are unavoidable, especially when there is a need to pick up containers that do not occupy the topmost slots of a bay (Ku & Arthanari, 2016a). In such a case, the yard crane must remove the upper containers blocking the target container, relocate them to empty slots, then retrieve the target container (Figure 2.2). For a practical reason, containers are relocated only within the bay they oc-

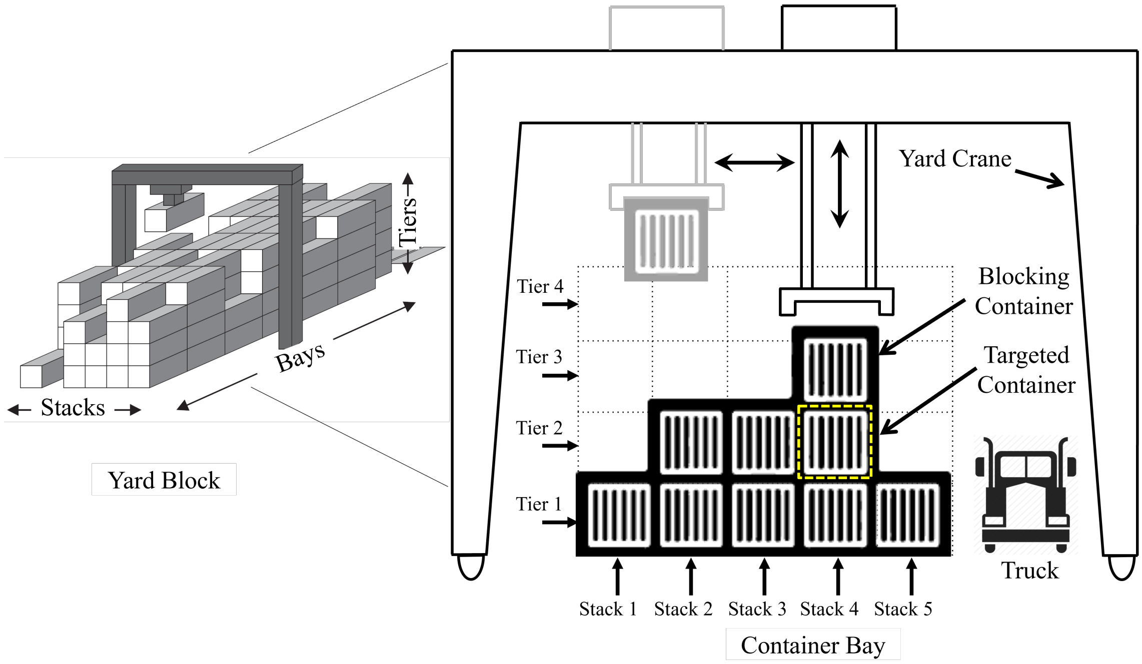
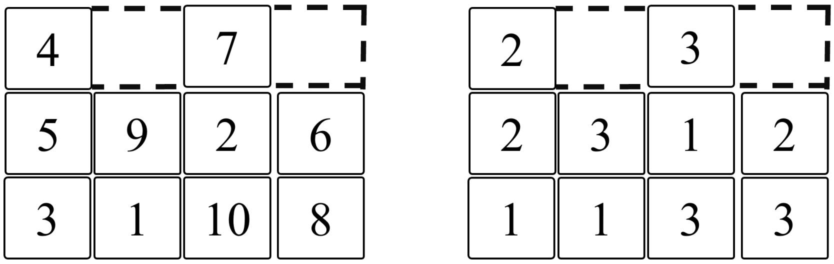


Figure 2.2: Bay layout in a container terminal yard and the container relocation operation.

cupy. This means that the yard crane does not relocate a container from one bay to another since it is a time-consuming process. Container-handling delays negatively impact the departure time of both vessels and external trucks. Thus, minimizing the unproductive moves is vital for improving the terminal throughput.

Minimizing container relocations as an optimization problem has been extensively studied under different names, including the Container Relocation Problem (CRP), the Block Relocation Problem (BRP), or the Block Retrieval Problem (BRTP) (da Silva, Erdoğan, et al., 2018). Generally, the CRP is a combinatorial optimization problem in which the aim is to determine the best slots in the bay where blocking containers can be relocated during the retrieval process for a set target container (Caserta et al., 2012), typically with the objective of minimizing the total number of relocations. CRP versions can be classified based on the following metrics: retrieval priority, relocation rule, handling dynamism, and container retrieval information certainty.

Single vs. Duplicate Container Retrieval Priority in *CRP*: For a set of containers stacked in a certain bay, when each container has a unique retrieval priority, the BRP is known as distinct BRP or CPR. The case in which more than one container shares the same retrieval priority is referred to as duplicate (group) BRP (Figure 2.3).



(a) Distinct pickup priority (b) Group pickup priority

Figure 2.3: The CRP under container pickup priority

Restricted vs. Unrestricted *CRP*: Regarding container relocation rules, restricted CRP assumes that only the containers above the target container can be relocated, whereas, in the unrestricted version, containers can be relocated from any slot regardless of the slot of the target container.

Static vs. Dynamic *CRP*: In the static version of the CRP, the bay will not receive any container while retrieving the set of the targeted containers. However, in the dynamic version, new arriving containers are stacked to the bay while existing containers in the bay are being retrieved.

Deterministic vs. Stochastic *CRP*: In the deterministic CRP, container pickup order or time is assumed to be known in advance while in the stochastic CRP (*SCRP*), containers pickup times are unknown and can be defined by a certain probability distribution in some cases.

2.2.2 Selected Literature on *CRP*

Under the classifications mentioned above, various mathematical formulations have been proposed (Caserta et al., 2012; Eskandari & Azari, 2015; Expósito-Izquierdo et al., 2014; Galle, Barnhart, et al., 2018a) with a greater focus on computational performance in solving this NP-hard problem. The BRP is solved using both exact approaches (Bacci et al., 2020; da Silva, Toulouse, et al., 2018; Expósito-Izquierdo et al., 2015; Ku & Arthanari, 2016b; Lu et al., 2020; Tanaka & Mizuno, 2018; Tanaka & Takii, 2016; Tanaka & Voß, 2022) and heuristic approaches (Bacci et al., 2019; Caserta et al., 2009; Caserta, Voß, et al., 2011; Expósito-Izquierdo et al., 2014; Feillet et al., 2019; Forster & Bortfeldt, 2012; Ji et al., 2015; Jovanovic, Tanaka, et al., 2019; Jovanovic et al., 2017; Jovanovic & Voß, 2014; Petering & Hussein, 2013; Ting & Wu, 2017; Tricoire et al., 2018; C. Zhang et al., 2020). However, most of the existing work has studied the BRP with distinct priority. This version of the BRP is best suited to the export container handling process, where the retrieval priority is mostly matched with the stacking sequence of containers on the vessel obtained in advance from the stowage plan.

Receiving far less attention has been the BRP with duplicate container retrieval priority, which fits the case in which multiple trucks arrive at the terminal within the same time window to pick up import containers (Kim & Hong, 2006; Ku & Arthanari, 2016a; Tanaka & Takii, 2016). In this case, the target containers are given the same retrieval priority, corresponding to the arrival time window of the corresponding trucks. Recently, the BRP with container group retrieval priority has been studied under the assumption of a stochastic pickup time window for containers, such as in Galle, Manshadi, et al., 2018, or a deterministic pickup time, such as in the work of Zeng et al., 2019. The majority of studies solve the problem under the restricted relocation assumption in order to reduce the search space for obtaining the optimal solution(da Silva, Toulouse, et al., 2018) whereas the unrestricted version yields more optimization opportunities (Tricoire et al., 2018).

Considering more realistic aspects in solving the BRP is rarely addressed in the literature. Due to the complexity of the problem, only a small minority of existing papers explicitly consider the terminal's interrelated operations that directly impact the relocation plan obtained from the BRP. This would include operational planning such as yard crane scheduling, ship stowage planning, and external truck appointment scheduling, all of which are apt to have important implications for the BRP solution. Among the limited studies seeking to address such elements, Ji et al., 2015, Jovanovic, Tuba, et al., 2019, and Tanaka and Voß, 2019 examined the BRP considering the stowage plan for export containers for ships and yards. The idea is to coordinate the loading of export containers onto the vessel with container retrieval operations in the yard in order to minimize the number of container relocations, vessel time, or crane time.

From another perspective, Galle, Barnhart, et al., 2018b combined the BRP, or the so-called CRP, with yard crane scheduling and introduced a novel optimization problem that considers scheduling yard crane operations along with relocations and retrievals using the distinct priority and restricted CRP. Determining the container pickup sequence that reduces container relocations is addressed in the literature as well. Borjian et al., 2015; Zeng et al., 2019, and, more recently, Feng et al., 2020 showed that adopting a flexible policy to reorder the container retrieval sequence for a group of trucks after their arrival at the terminal can reduce the number of relocations, with implications for truck delays. Table 2.1 summarizes some of the BRP literature. The bottom row of the table shows the nature of our work.

Table 2.1: Summary of the recent BRP literature under different considerations

Author/s (year)	Retrieval priority		Relocation rule		Coordination aspects			
	Dist.	*Dup.*	*Rest.*	*Unrest.*	*SP*	*YCS*	*CPS*	*AS*
Kim and Hong (2006)	✓	✓	✓					
Wan et al. (2009)	✓		✓	✓				
Zhu et al. (2012)	✓		✓					
Caserta et al. (2012)	✓		✓	✓				
Expósito-Izquierdo et al. (2014)	✓		✓	✓				
Ji et al. (2015)	✓		✓		✓	✓		
Expósito-Izquierdo et al. (2015)	✓		✓					
Zehendner et al. (2015)	✓		✓					
Ku and Arthanari (2016a)		✓	✓					
Tanaka and Takii (2016)	✓	✓	✓					
Tanaka and Mizuno (2018)	✓		✓	✓				
Tricoire et al. (2018)	✓			✓				
Galle et al. (2018a)	✓		✓					
Galle et al. (2018b)	✓		✓			✓		
Jovanovic et al. (2019)	✓		✓		✓			
Tanaka and Voß (2019)	✓		✓	✓	✓			
Borjian et al. (2015)		✓	✓	✓			✓	
Zeng, Feng, & Yang, (2019)		✓	✓				✓	
Feng et al. (2020)		✓	✓				✓	
This work	✓	✓		✓			✓	✓

Note: *Dist.*: Distinct, *Dup.*: Duplicate, *Rest.*: Restricted, *Unrest.*: Unrestricted, *SP*: Stowage Plan, *YCS*: Yard Crane Scheduling, *CPS*: Container Pickup Sequence, *AS*: Appointment Scheduling

2.3 Research Motivation

Most of the existing studies, including recent ones, propose solutions to the container relocation problem based on complete/partial information regarding truck arrival times that can only be applied after the trucks arrive at the terminal. Importantly, these approaches fail to consider container handling operations at the yard when determining truck appointments. Furthermore, solving either the stochastic or deterministic relocation problem in real-time makes it challenging to obtain an exact solution when large numbers of trucks and containers are involved. Consequently, in many cases, practitioners have no choice but to develop simple heuristic approaches to solve the problem in a shorter time, even when this means accepting more relocations.

Two main conclusions related to truck appointments and their interrelation with container handling in the terminal yard can be drawn from the existing literature. First, both truck appointment time windows and arrival order within each time window have a significant effect on the number of unproductive container relocations in the yard. Second, most truck appointment systems proposed in the literature predetermine the best truck appointment schedule to improve yard operations by smoothing the arrival peaks and keeping the arrivals under the terminal capacity. Notwithstanding the previously cited works, coordinating the truck appointment scheduling with the container relocation problem is still under-covered in the literature.

In this thesis, we take one step back in our consideration of managing truck appointments and container handling operations in the yard. Rather than passively accepting the information output by an appointment system or assuming real-time random arrivals in solving the container relocation problem, we propose several mathematical models that simultaneously align, in advance, truck appointment times and truck service order with container handling operations at the yard to avoid unproductive container relocations while optimizing the truck appointment times.

Note that even the few existing studies that address the coordination of the BRP with other terminal operations tend to focus only on inter-yard operations and the ship stowage operation at the terminal seaside using distinct priority and the restricted version of the BRP. In contrast, we address the coordination between appointment scheduling for import container pickup and container handling operations using the unrestricted BRP with duplicate container retrieval priority, which better suits appointment scheduling purposes for import containers. The proposed approaches can fit the unrestricted BRP with distinct container retrieval priority as explained in Chapter 3.

Chapter 3

The Block Relocation Problem with Appointment Scheduling

3.1 Chapter Contributions

The contributions of this chapter are:

1. The Block Relocation Problem with Appointment Scheduling (*BRPAS*) is introduced as a new optimization problem in container terminal operational management. The proposed problem considers solving the block/container relocation problem under a limited allowance for shifting trucks appointments.

2. Two new IP formulations are proposed for the new problem considering the modeling aspects such as the model size and complexity.

3. A third mathematical formulation is introduced to consider the flexibility of container pickup based on the First-Come-First-Served (*FCFS*) policy.

4. The proposed models considered the main scheduling aspects related to container terminal spatial capacity and yard crane handling capacity.

5. The developed models are solved using subsets of CRP instances from the literature. New parameters are added to used instances to consider the new aspects that are considered in the BRPAS. In addition, the modified instances are published to enable future benchmark studies for the BRPAS.

3.2 Motivation

In many container terminals that adopt truck appointment systems, individual drivers and trucking companies are encouraged to submit their preferred arrival times in advance via a web-based information system (Phan & Kim, 2016; X. Zhang et al., 2019). The preferred times are considered along with terminal capacity and the expected terminal workload per each time window (e.g., 30 minutes) to decide whether the terminal can accommodate the truck during the indicated time. In order to avoid congestion, service rates in the yard area and yard crane capacity are considered. Typically, the queue lengths at the gates and in the terminal yard are the main factors in the appointment scheduling process (Chen, Govindan, & Yang, 2013). After deciding the appointment schedules, the terminal operators notify the trucking companies/truckers of the final appointment window. In turn, the companies/truckers are expected to be punctual, despite the fact that not all containers will be picked up according to the originally submitted preferred times but rather according to the appointment windows determined by the terminal operators.

At the terminal, the yard operators use the final appointments schedule produced by TAS to define a time-window-based pickup priority for each container stacked in a certain bay (Ku & Arthanari, 2016a). When a truck arrives at the designated bay, there is a considerable likelihood that the target container is not in the top slot of a stack. The yard crane is then used to relocate the blocking containers with minimum relocations by solving the *BRP* (Figure 3.1). It is common that several trucks are waiting at the same bay during a particular time window while some of the target containers are buried under one or more blocking containers. Thus, a truck may experience more delays resulting from relocations performed to access its container or from the relocations associated with other target containers with earlier pickup times. The lack of coordination between the pickup appointment times and the container handling operation at the bay can lead to unproductive container moves and, consequently, more truck delays.

The motivation for this study is to introduce a new optimization problem aimed at coordinating the appointment scheduling, under limited appointment shift, for import container pickup with the container relocation process. The proposed *BR-*

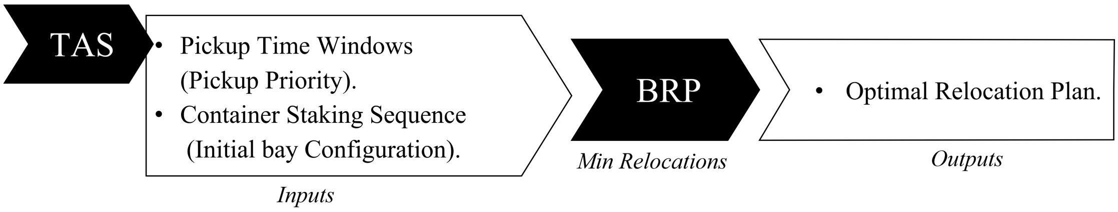


Figure 3.1: Classical BRP under the TAS

PAS determines the container pickup times from the expected relocations that will be performed if trucks arrive within certain time windows. Two binary IP mathematical models are proposed with the objective of minimizing the overall number of container relocations. The adopted version of the BRP is unrestricted with duplicate container pickup priority (see Chapter 2, Section 2.2), which is rarely featured in the existing literature but best fits the case of import container pickup scheduling.

3.3 Problem Description

3.3.1 The Modeling Framework of the *BRPAS*

Unlike the classical BRP, which assumes that the actual container pickup time/priority is already decided in advance, the *BRPAS* (Figure 3.2) assumes that the trucking companies will submit appointment requests to pick up their containers at least one day before heading to the terminal. An appointment request gives information about the preferred pickup time window for each container and the container/truck ID. Following this submission, the *BRPAS* determines the optimal pickup time window and pickup order within the time window for each container. The main goal of the *BRPAS* is to provide a relocation-based appointment schedule that achieves the minimum number of relocations where both the relocation plan and appointment schedule are to be determined simultaneously. The container retrieval times determine the appointment schedules to be shared with the trucking companies; the expected relocation plan is given to the yard crane operators. It is worth mentioning that both plans are decided in advance, before the arrival of the first truck at the terminal.

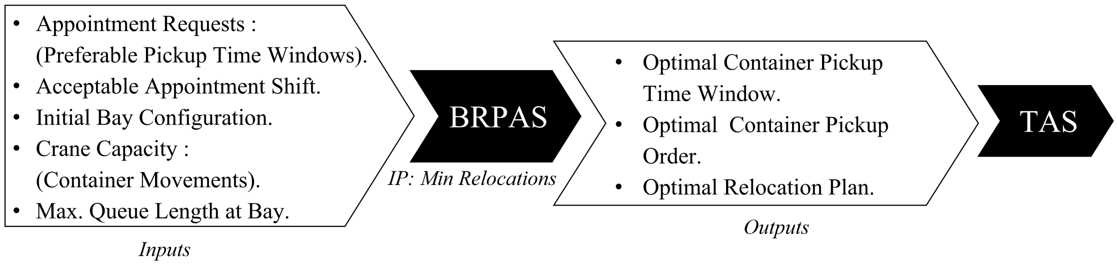


Figure 3.2: The proposed block relocation problem with appointment scheduling

Note that the terminal operator uses the *BRPAS* to reschedule the container pickup times submitted in the appointment requests and determines the final appointments that achieve the problem objective. However, to keep the gap between the preferred pickup times (i.e., the preferred times submitted to the online appointment system) and the final appointment times within reason, it is assumed that an acceptable appointment shift has been agreed to by the company side and the terminal side. Therefore, the proposed *BRPAS* assumes that the trucking companies will accept the appointment plan and follow the pickup order, considering their arrival preferences. This shift allowance is to be applied equally for all containers in the bay to guarantee fairness in the appointment scheduling process. The proposed *BRPAS* (Figure 3.2) recognizes, as well, scheduling factors related to yard crane capacity, defined here by the number of container moves that a crane can perform during a given time window at the designated bay. In addition, the maximum queue length at the bay, which is the maximum number of trucks that can wait at the designated bay to receive their containers, is specified.

3.4 *BRPAS* Mathematical Formulations

To formulate the *BRPAS*, the following assumptions are made: (1) the initial bay configuration is known in advance; (2) all containers in the bay will be picked up within the planning horizon, and no containers are received during the retrieval process; (3) each container has a predefined preferable pickup time window which may be changed due to scheduling; (4) the *BRPAS* mainly adopts the unrestricted version of BRP, where containers can be relocated from any slot in the bay; (5) and containers can be relocated only within the same bay they are occupying.

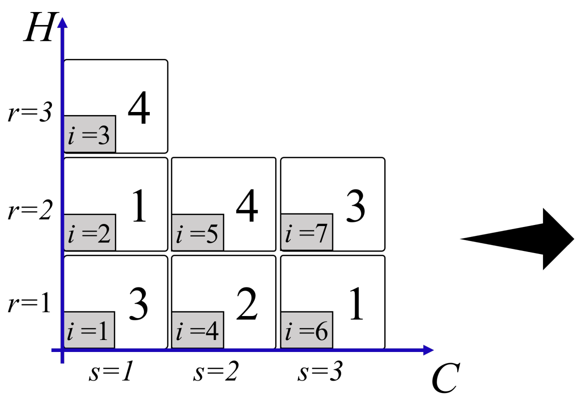
3.4.1 Binary IP Model for *BRPAS*: Model 1

The basic binary IP mathematical model of the *BRPAS* is inspired by the mathematical formulation proposed by Caserta et al., 2012 for the BRP with distinct priority, which defines the decision variables as the binary status of containers in certain bay slots at a certain time. In our *BRPAS*, two mathematical formulations are proposed. The indices and parameters for both models are defined in (Table 3.1). Each container is given a unique index $i \in \{1, \ldots, N\}$ which is used primarily for tracking the container status, since the actual container pickup time, pickup order, and stacking sequence change dynamically during the solution process. In the *BRPAS*, the preferred pickup time window p_i and the initial position I_{isr} for each container in the bay are assumed to be known in advance. The planning horizon T is divided into smaller time windows $t \in \{1, \ldots, T\}$, where T is the latest time a container can be picked up from the bay. The time window length is not specified in this work and is expressed as a time unit for generalization. In a bay of C stacks (columns) and H tiers (max height), container i can occupy slot (s, r), where stack $s \in \{1, \ldots, C\}$ is indexed from left to right and tier $r \in \{1, \ldots, H\}$ is indexed from bottom to top (Figure 3.3a). To identify the initial bay layout, the input parameter I_{isr} is a binary encoding of the initial stacking for N containers in different bay slots (Figure 3.3b). Both the p_i and I_{isr} parameters are used to describe the initial bay configuration and layout as shown in (Figure 3.3). In this chapter, the bay layout refers to the stacking sequence of containers in the bay slots, while the bay configuration refers to the layout where each container has a pickup time attached to it.

In the *BRPAS*, assuming that only trucks with the same arrival time window at the designated bay will be kept waiting at that bay during the retrieval process, the maximum queue length at that bay is defined in terms of the maximum number of retrievals per time window using the parameter L. The crane capacity, i.e., the maximum number of container moves that a crane can perform per time window, is considered by defining parameter G where $G \geq L$. Note that the bay configuration changes with each container move (either relocation or retrieval); to update the configuration, each container move is referred to as a stage, with $k \in \{1, \ldots, G\}$ indicating the stage number.

Table 3.1: IP model parameters and indices for the *BRPAS* problem

N	Number of containers in the bay initial configuration.
i	Index for container, $i \in \{1, \ldots, N\}$.
C	Number of stacks
s	Index for stack, $s \in \{1, \ldots, C\}$.
H	Maximum Height of bay
r	Index for tier, $r \in \{1, \ldots, H\}$.
T	Number of time windows
t	Index for time window, $t \in \{1, \ldots, T\}$.
L	Maximum Queue length at bay (appointments per time window).
G	Maximum number of containers moves (*retrievals and relocations*) per time window.
k	Index of the stage, $k \in \{1, \ldots, G\}$, where each stage k represents one container move.
I_{isr}	Whether container i occupies slot (s, r) in the initial bay layout, $I_{isr} \in \{0, 1\}$.
p_i	Preferable pickup time for each container, $i \in \{1, \ldots, N\}$.
δ	Acceptable shift of container pickup appointment time window.



(a) Initial bay configuration

(s,r) \ i	1	2	3	4	5	6	7
(1,1)	1	0	0	0	0	0	0
(1,2)	0	1	0	0	0	0	0
(1,3)	0	0	1	0	0	0	0
(2,1)	0	0	0	1	0	0	0
(2,2)	0	0	0	0	1	0	0
(2,3)	0	0	0	0	0	0	0
(3,1)	0	0	0	0	0	1	0
(3,2)	0	0	0	0	0	0	1
(3,3)	0	0	0	0	0	0	0

(b) binary encoding for initial bay layout (I_{isr})

Figure 3.3: Container bay configuration for *BRPAS*

Defining the stages based on each move makes it easier to formulate the problem and update the configuration dynamically. Consequently, we have the following characterization for container status in the bay: First, container i is in its slot (s, r); second, container i is relocated from the slot (s,r); third, container i is relocated to slot $(s^{'}, r^{'}) : s^{'} \in \{1, \ldots, C\} | s^{'} \neq s, r^{'} \in \{1, \ldots, H\}$; fourth, container i is picked up (by the waiting truck) and removed permanently from the slot (s, r). In the first mathematical formulation of the $BRPAS(1)$, the four container statuses are expressed as the binary decision variables of the model, as shown in Table 3.2.

Table 3.2: Decision variables of the $BRPAS(1)$

$$u^t_{isrk} = \begin{cases} 1 & \text{if container } i \text{ occupies the slot } (s, r) \text{ at stage } k \text{ of time window } t \\ 0 & \text{otherwise} \end{cases}$$

$$x^t_{isrk} = \begin{cases} 1 & \text{if container } i \text{ relocated from slot } (s, r) \text{ at stage } k \text{ of time window } t \\ 0 & \text{otherwise} \end{cases}$$

$$y^t_{isrk} = \begin{cases} 1 & \text{if container } i \text{ relocated to slot } (s, r) \text{ at stage } k \text{ of time window } t \\ 0 & \text{otherwise} \end{cases}$$

$$v^t_{isrk} = \begin{cases} 1 & \text{if container } i \text{ picked up from slot } (s, r) \text{ at stage } k \text{ of time window } t \\ 0 & \text{otherwise} \end{cases}$$

The first of the two binary IP mathematical formulations of the $BRPAS$ under the conditions noted above is described below.

***BRPAS(1) Model*:**

Objective:

$$Min \sum_{i=1}^{N} \sum_{s=1}^{C} \sum_{r=1}^{H} \sum_{k=1}^{G} \sum_{t=1}^{T} y^t_{isrk} \tag{3.1}$$

Subjected to:

$$\left| p_i - \sum_{s=1}^{C} \sum_{r=1}^{H} \sum_{k=1}^{G} \sum_{t=1}^{T} t v^t_{isrk} \right| \leq \delta, \qquad \forall i \in \{1, \ldots, N\} \tag{3.2}$$

$$\sum_{i=1}^{N} \sum_{s=1}^{C} \sum_{r=1}^{H} \sum_{k=1}^{G} v^t_{isrk} \leq L, \qquad \forall t \in \{1, \ldots, T\} \tag{3.3}$$

$$\sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H} v_{isrk}^{t} + \sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H} x_{isrk}^{t} \leq 1, \qquad \forall k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\} \tag{3.4}$$

$$\begin{gathered}\sum_{i=1}^{N} x_{isrk}^{t} \leq \sum_{i=1}^{N} (u_{isrk}^{t} - u_{is(r+1)k}^{t}), \\ \forall s \in \{1,\ldots,C\}, r \in \{1,\ldots,H-1\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.5}$$

$$\begin{gathered}\sum_{s'=1, s'\neq s}^{N} \sum_{r=1}^{H} y_{is'rk}^{t} \geq \sum_{r=1}^{H} x_{isrk}^{t}, \\ \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.6}$$

$$\begin{gathered}\sum_{i=1}^{N} v_{isrk}^{t} + \sum_{i=1}^{N} y_{isrk}^{t} + \sum_{i=1}^{N} x_{isrk}^{t} \leq 1, \\ \forall s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.7}$$

$$u_{isr1}^{1} = I_{isr}, \qquad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\} \tag{3.8}$$

$$\begin{gathered}u_{isrk+1}^{t} = u_{isrk}^{t} + y_{isrk}^{t} - x_{isrk}^{t} - v_{isrk}^{t}, \\ \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, \\ k \in \{1,\ldots,G-1\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.9}$$

$$\begin{gathered}u_{isr1}^{t} = u_{isrG}^{t-1} + y_{isrG}^{t-1} - x_{isrG}^{t-1} - v_{isrG}^{t-1}, \\ \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, t \in \{2,\ldots,T\}\end{gathered} \tag{3.10}$$

$$\begin{gathered}\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=k+1}^{G} u_{isrk'}^{t} + \sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=1}^{G}\sum_{t'=t+1}^{T} u_{isrk'}^{t'} \leq GT\left(1 - \sum_{s=1}^{C}\sum_{r=1}^{H} v_{isrk}^{t}\right), \\ \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.11}$$

$$\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k=1}^{G}\sum_{t=1}^{T} v_{isrk}^{t} = 1, \quad \forall i \in \{1,\ldots,N\} \tag{3.12}$$

$$\begin{gathered}\sum_{i=1}^{N} u_{isrk}^{t} \leq 1, \\ \forall s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.13}$$

$$\sum_{s=1}^{C}\sum_{r=1}^{H} u_{isrk}^{t} \leq 1, \qquad \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\} \tag{3.14}$$

$$\begin{gathered}u_{isrk}^{t}, x_{isrk}^{t}, y_{isrk}^{t}, \text{and } v_{isrk}^{t} \in \{0,1\}, \\ \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, \\ k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\}\end{gathered} \tag{3.15}$$

The objective function (3.1) here is to minimize the total number of relocations needed for all of the containers in the bay to be picked up. Constraint (3.2) is used to restrict the shifting of the container pickup appointment time from the preferred pickup time submitted by the trucking company. To control this shift, parameter δ limits the pickup time shift to $\pm\delta$ time windows from the original preferred time for each container. In constraint (3.3), the queue length at the bay is limited to L trucks/container retrievals, assuming that a truck can pick up only one container. Constraint (3.4) controls crane capacity by limiting the number of container moves per time window to the value of the parameter G. This constraint is also used to define the stage k at which each container move can take place. Constraints (3.5), (3.6), and (3.7) describe the relocation process. Under constraint (3.5), when relocating containers, the topmost blocking container must be relocated first, before the containers below it, following the *Last-In-First-Out* (*LIFO*) rule. Constraint (3.6) requires that the relocated container must go to a different stack. In constraint (3.7), when a container is moved from or to a slot, it is either relocated or retrieved. This constraint prevents transitive and cyclic container moves within the bay.

Constraints (3.8), (3.9), and (3.10) are used to update the bay layout when containers are moved: Constraint (3.8) initiates the bay layout before the first container move, constraint (3.9) updates the bay layout from one stage to the next within a time window, and constraint (3.10) updates the layout transition from the last stage of time window $t-1$ to the first stage in the next time window t. Constraints (3.11) through (3.14) are logical constraints. Constraint (3.11) establishes that if a container is retrieved, it can no longer occupy any slot in the configuration. Constraint (3.12) guarantees that each container must be retrieved. Constraint (3.13) states that each slot must be occupied by at most one container; similarly, constraint (3.14) specifies that a container must not belong to more than one slot. Finally, the constraints in (3.15) define the binary domain of the decision variables.

3.4.2 Numerical Example

Figure 3.4 shows a numerical example for a set of $N = 7$ containers stacked in a bay of dimensions $C \times H = 3 \times 3$, with a planning horizon of $T = 4$ time windows. The preferred container pickup times π can be advanced or delayed by a $\delta = 1$ time window; maximum bay queue length is set as $L = 2$, with crane capacity $G = 3$ container moves per time window. The preferred pickup time windows for containers are intentionally shown in faded font to indicate that these times are not necessarily the final appointment times. Once the model determines the target containers that minimize container relocations, the final pickup appointment times are uncovered, and the related retrieval and relocation operations are performed.

As shown in Figure 3.4, at time window $t1$, container $i2$ is the target container. Since the pickup time of container $i3$ cannot be advanced to $t1$ due to the strict appointment shifting allowance of ($\delta = 1$), container $i3$ needs to be relocated. This differs from the case of containers $i6$ and $i7$ at time window $t2$, where the pickup time can be shifted by one time window, allowing both containers to be picked up without a relocation. However, at time window $t3$, container $i4$ cannot remain in the bay, constrained by the $\delta = 1$ limit in constraint (3.2). Thus, $i4$ is a target container at $t3$. The reason that containers $i3$, $i5$, and $i4$ cannot be retrieved together at t3 despite satisfying the allowable appointment shift is that the number of containers to be retrieved is limited by the bay queue length constraint (3.3), with $L = 2$. In this case, only $i3$ and $i4$ can be picked up, while $i5$ must be relocated and then retrieved with $i1$ at $t4$. Note that the model can give multi-optimal solutions for the same instance. This is because the BRP is a combinatorial optimization problem, motivating the *BRPAS* proposed in this chapter. For example, at $t1$ in Figure 3.4, we started with container $i2$ as a target container. However, in an alternative optimal solution, we could pick up container $i6$ first as a target container at $t1$ and then delay container $i2$ one time window, to be picked up later at $t2$.

In a general sense, shifting the container appointment pickup times from the preferred times may result from one or more of the following scenarios: (1) when a container is blocking the target container and changing the pickup time by $\pm\delta$ will prevent relocation; (2) when a container is blocked by other containers and changing the pickup appointment time will prevent the relocation of containers above it; (3) when the number of containers that can be retrieved exceeds the corresponding queue length at the bay (In this situation, the model tends to shift the pickup times of some containers to avoid the excessive queue length); (4) when the number of container moves exceeds the limit and the model changes the pickup times to keep

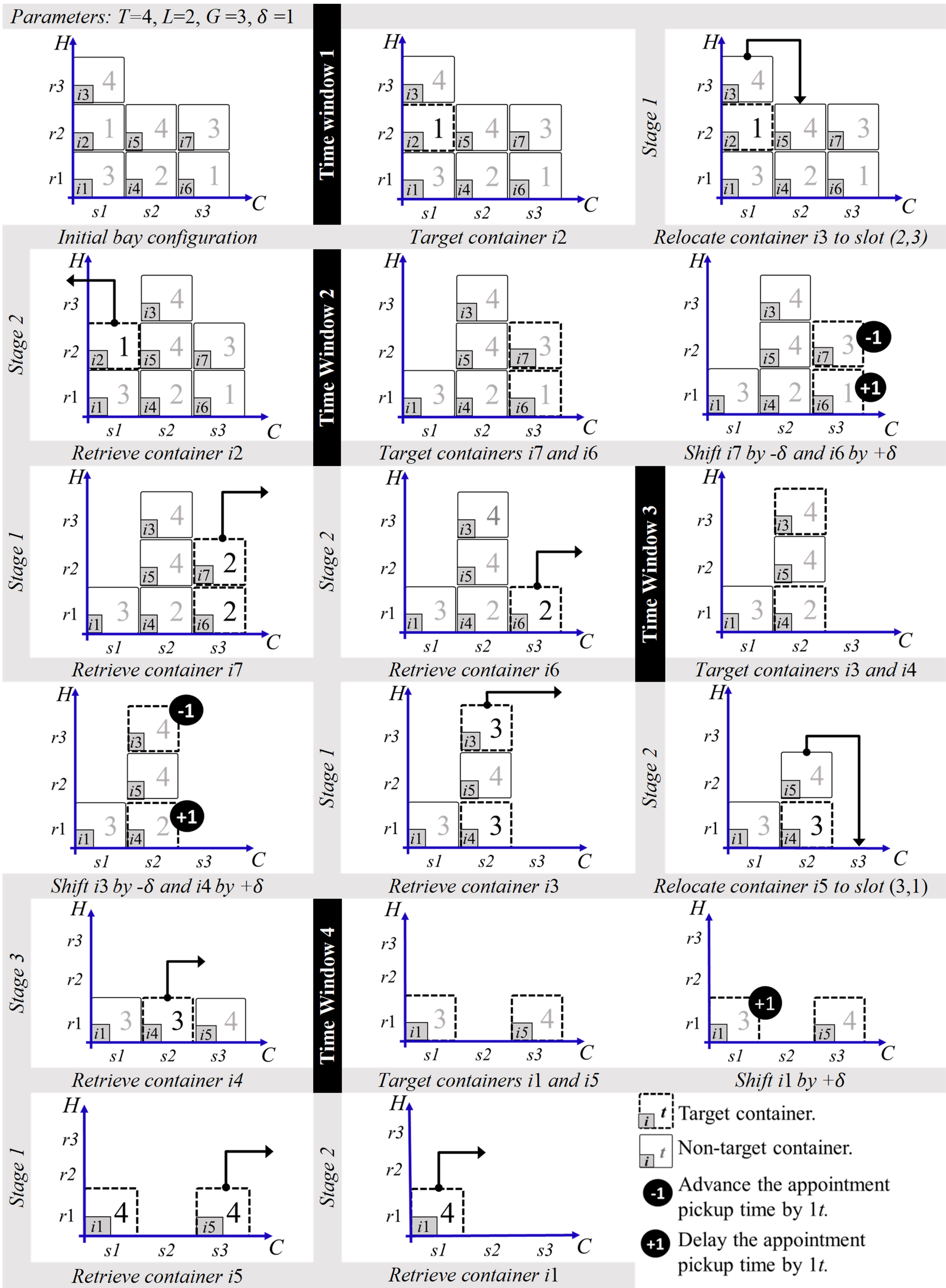


Figure 3.4: A numerical example for *BRPAS*

the crane capacity under control. Note that coordinating truck appointments with container relocations can significantly reduce the number of relocations compared to having trucks arriving at the terminal at their original preferred times. For instance, in the numerical example in Figure 3.4, the initial bay configuration shows that containers $i3$, $i5$, and $i7$ are blocking containers $i2$, $i4$, and $i6$, respectively. This will lead to "four relocations" to retrieve all containers based on the preferred pickup times (i.e.,$\delta = 0$).

3.4.3 *BRPAS*: Model 2

Although the first formulation (shown above) is informative and provides important details regarding both the relocation and appointment plan in an organized manner, the model is quite large. To deal with this issue, we introduce a second formulation, $BRPAS(2)$, in which the number of variables and constraints is reduced by replacing the retrieval variable v^t_{isrk} with binary variables z^t_{ik} to indicate whether container i is retrieved at stage k of time window t. In the new formulation, the variable x^t_{isrk} does not distinguish between a container retrieval and a container relocation; rather, it defines whether the container is moved from its slot at a certain stage and a certain time window.

***BRPAS(2) Model*:** The $BRPAS(2)$ model uses the same objective function (3.1) and constraints (3.5), (3.8), (3.13), and (3.14) from the $BRPAS(1)$ model. For the remainder of the $BRPAS(2)$ model, constraints (3.16)-(3.26) are formulated using the new decision variables z^t_{ik} and the new definition of x^t_{isrk}, as shown below:

$$|p_i - \sum_{k=1}^{G}\sum_{t=1}^{T} z^t_{ik}| \leq \delta, \qquad \forall i \in \{1,\ldots,N\} \tag{3.16}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{G} z^t_{ik} \leq L, \qquad \forall t \in \{1,\ldots,T\} \tag{3.17}$$

$$\sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H} x^t_{isrk} \leq 1, \qquad \forall k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\} \tag{3.18}$$

$$\sum_{r=1}^{H} y^t_{isrk} + \sum_{r=1}^{H} x^t_{isrk} \leq 1, \quad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, k \in \{1,\ldots,G\}, t \in \{1,\ldots,T\} \tag{3.19}$$

$$\sum_{s=1}^{C}\sum_{r=1}^{H} y_{isrk}^{t} + z_{ik}^{t} = \sum_{s=1}^{C}\sum_{r=1}^{H} x_{isrk}^{t}, \qquad \forall i \in \{1,\dots,N\}, k \in \{1,\dots,G\}, t \in \{1,\dots,T\} \tag{3.20}$$

$$u_{isrk+1}^{t} = u_{isrk}^{t} + y_{isrk}^{t} - x_{isrk}^{t}, \qquad \forall i \in \{1,\dots,N\}, s \in \{1,\dots,C\}, r \in \{1,\dots,H\}, k \in \{1,\dots,G-1\}, t \in \{1,\dots,T\} \tag{3.21}$$

$$u_{isr1}^{t} = u_{isrG}^{t-1} + y_{isrG}^{t-1} - x_{isrG}^{t-1}, \qquad \forall i \in \{1,\dots,N\}, s \in \{1,\dots,C\}, r \in \{1,\dots,H\}, t \in \{2,\dots,T\} \tag{3.22}$$

$$\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=k+1}^{G} u_{isrk'}^{t} + \sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=1}^{G}\sum_{t'=t+1}^{T} u_{isrk'}^{t'} \le GT(1 - z_{ik}^{t}), \qquad \forall i \in \{1,\dots,N\}, k \in \{1,\dots,G\}, t \in \{1,\dots,T\} \tag{3.23}$$

$$\sum_{k=1}^{G}\sum_{t=1}^{T} z_{ik}^{t} = 1, \qquad \forall i \in \{1,\dots,N\} \tag{3.24}$$

$$u_{isrk}^{t}, x_{isrk}^{t}, \text{ and } y_{isrk}^{t} \in \{0,1\}, \qquad \forall i \in \{1,\dots,N\}, s \in \{1,\dots,C\}, r \in \{1,\dots,H\}, k \in \{1,\dots,G\}, t \in \{1,\dots,T\} \tag{3.25}$$

$$z_{ik}^{t} \in \{0,1\}, \quad \forall i \in \{1,\dots,N\}, k \in \{1,\dots,G\}, t \in \{1,\dots,T\} \tag{3.26}$$

In the $BRPAS(2)$ model, constraints (3.16), (13.17), and (3.18) correspond to constraints (3.2), (3.3), and (3.4) in the $BRPAS(1)$ model, respectively. Note that constraint (3.18) defines the stage using only the variable x_{isrk}^{t}. Constraints (3.19) and (3.20) are equivalent to constraints (3.6) and (3.7), respectively. In constraint (3.19), the container cannot occupy the same stack s when moved from that stack. Constraint (3.20) defines the variable x_{isrk}^{t} using variables y_{isrk}^{t} and z_{ik}^{t} while implying the same condition as constraints (3.7) of the $BRPAS(1)$ model. Constraints (3.21), (3.22), (3.23), and (3.24) correspond to constraints (3.9), (3.10), (3.11), and (3.12) of the $BRPAS(1)$ model, respectively. Finally, constraints (3.25) and (3.26) are equivalent to constraint (15) in the $BRPAS(1)$ model; constraint (3.26) defines the binary domain of the decision variable z_{ik}^{t}.

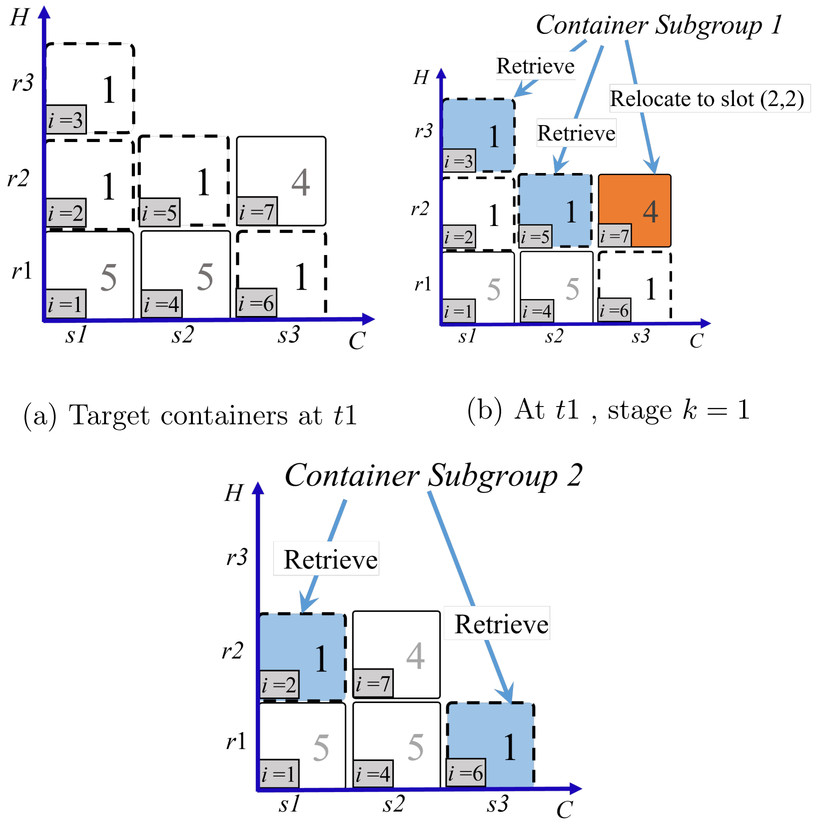
3.5 The Flexible *BRPAS*

In the *BRPAS* formulations, the adopted modeling approach tracks container status after each move and updates the bay layout. In this sense, the approach forces specific container relocation and retrieval orders based on the minimization of the total number of relocations. This provides a substantial amount of information about the solution behavior of the model through the obtained optimal solution and makes it simpler for the terminal operator to adopt the solution. However, flexibility in retrieving containers might be required in order to load containers onto the waiting trucks based on a (*FCFS*) basis rather than being forced to retrieve containers in the order prescribed by the basic mathematical models (*BRPAS*(1) and *BRPAS*(2)).

This flexibility can be relatively achieved for the *BRPAS* if the bay configuration is updated based on container relocation rather than on every container move (both relocation and retrieval). The idea is to give the target containers occupying the topmost slots in the bay an equal retrieval priority (to be retrieved at the same stage without assigning a unique pickup order/stage for each). Updating the bay layout based on container relocations helps achieve retrieval flexibility while leaving the optimal solution of the *BRPAS* unchanged.

For such retrieval flexibility under the *BRPAS*, the stage definition no longer defines a container move, but rather it defines a container relocation; more than one container can be moved in one stage. As a result, a container subgroup schedule is obtained, unlike the individual container schedule per each stage in the original *BRPAS*. For example, in Figure 3.5a, suppose containers $i2$, $i3$, $i5$, and $i6$ are the target containers at time window 1, and we have two stages (maximum number of relocations) to flexibly retrieve the four containers. Containers $i3$, $i5$, and $i7$ could form the first container subgroup to be moved at time window $t = 1$ at stage $k = 1$ (Figure 3.5b), while containers $i2$ and $i6$ would comprise the second container subgroup (Figure 3.5c). The flexibility in this example means that the crane operator could retrieve $i3$ or $i5$ at the first stage of time window $t1$ when either of the corresponding trucks arrives first at the bay. Similarly, at the second stage, after the relocation of $i7$ at the first stage, if the truck picking up container

$i6$ arrives first, it will pick up its container and leave the terminal without the need to wait for the truck picking up container $i2$ to be served first.



(a) Target containers at $t1$

(b) At $t1$, stage $k = 1$

(c) At $t1$,stage $k + 1 = 2$

Figure 3.5: Updating bay layout based on relocations in the flexible $BRPAS$

3.5.1 The Flexible $BRPAS$ formulation

To formulate the flexible $BRPAS$, we introduce a new parameter μ that defines the stage based on the maximum number of container relocations. We use μ in the second $BRPAS$ formulation (the $BRPAS(2)$ model) to introduce the $BRPAS(flex)$ model.

The $BRPAS(flex)$ Model:

Objective:

$$Min \quad \sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k=1}^{\mu}\sum_{t=1}^{T} y_{isrk}^{t} \tag{3.27}$$

Subjected to:

$$\sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H} y_{isrk}^{t} \leq 1 \qquad \forall k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\} \tag{3.28}$$

$$\sum_{i=1}^{N}\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k=1}^{\mu} x_{isrk}^{t} \leq G \qquad \forall t \in \{1,\ldots,T\} \tag{3.29}$$

$$\begin{aligned}&\sum_{i=1}^{N} x_{isrk}^{t} \leq \sum_{i=1}^{N}(u_{isrk}^{t} - u_{is(r+1)k}^{t}),\\ &\qquad \forall s \in \{1,\ldots,C\}, r \in \{1,\ldots,H-1\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.30}$$

$$u_{isr1}^{1} = I_{isr}, \qquad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\} \tag{3.31}$$

$$\begin{aligned}&\sum_{i=1}^{N} u_{isrk}^{t} \leq 1,\\ &\qquad \forall s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.32}$$

$$\sum_{s=1}^{C}\sum_{r=1}^{H} u_{isrk}^{t} \leq 1, \qquad \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\} \tag{3.33}$$

$$|p_i - \sum_{k=1}^{\mu}\sum_{t=1}^{T} z_{ik}^{t}| \leq \delta, \qquad \forall i \in \{1,\ldots,N\} \tag{3.34}$$

$$\sum_{i=1}^{N}\sum_{k=1}^{\mu} z_{ik}^{t} \leq L, \qquad \forall t \in \{1,\ldots,T\} \tag{3.35}$$

$$\begin{aligned}&\sum_{r=1}^{H} y_{isrk}^{t} + \sum_{r=1}^{H} x_{isrk}^{t} \leq 1,\\ &\qquad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.36}$$

$$\begin{aligned}&\sum_{s=1}^{C}\sum_{r=1}^{H} y_{isrk}^{t} + z_{ik}^{t} = \sum_{s=1}^{C}\sum_{r=1}^{H} x_{isrk}^{t},\\ &\qquad \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.37}$$

$$\begin{aligned}&u_{isrk+1}^{t} = u_{isrk}^{t} + y_{isrk}^{t} - x_{isrk}^{t},\\ &\quad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\},\\ &\qquad\qquad k \in \{1,\ldots,\mu-1\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.38}$$

$$\begin{aligned}&u_{isr1}^{t} = u_{isr\mu}^{t-1} + y_{isr\mu}^{t-1} - x_{isr\mu}^{t-1},\\ &\qquad \forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, t \in \{2,\ldots,T\}\end{aligned} \tag{3.39}$$

$$\begin{aligned}&\sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=k+1}^{\mu} u_{isrk'}^{t} + \sum_{s=1}^{C}\sum_{r=1}^{H}\sum_{k'=1}^{\mu}\sum_{t'=t+1}^{T} u_{isrk'}^{t'} \leq \mu T(1 - z_{ik}^{t}),\\ &\qquad\qquad \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}\end{aligned} \tag{3.40}$$

$$\sum_{k=1}^{\mu}\sum_{t=1}^{T} z_{ik}^{t} = 1, \qquad \forall i \in \{1,\ldots,N\} \tag{3.41}$$

$$u_{isrk}^{t}, x_{isrk}^{t}, \text{and } y_{isrk}^{t} \in \{0,1\},$$
$$\forall i \in \{1,\ldots,N\}, s \in \{1,\ldots,C\}, r \in \{1,\ldots,H\}, \tag{3.42}$$
$$k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\}$$

$$z_{ik}^{t} \in \{0,1\}, \qquad \forall i \in \{1,\ldots,N\}, k \in \{1,\ldots,\mu\}, t \in \{1,\ldots,T\} \tag{3.43}$$

To produce the *BRPAS*(*flex*) model, three main modifications are made to the *BRPAS*(2) formulation. First, parameter μ is defined and used instead of parameter G (number of container moves per time window) to define the stage in the *BRPAS*(*flex*) model so that the stage index $k \in \{1,\ldots,\mu\}$. This appears clearly in the objective function (3.27), subject to constraints (3.28)-(3.43). Second, to define the stage based on the relocation decision variable y_{isrk}^{t}, constraint (3.18) in the *BRPAS*(2) model is replaced by constraint (3.28) in the *BRPAS*(*flex*) model. Third, in the *BRPAS*(2) model, crane capacity (which is a key characteristic of the proposed *BRPAS*) is tacitly considered in constraint (3.18). To ensure that the total number of container moves remains within the crane capacity in the *BRPAS*(*flex*) model, constraint (3.29) is introduced. In the remainder of the *BRPAS*(*flex*) model formulation, constraints (3.30), (3.31), (3.32), and (3.33) correspond to constraints (3.5), (3.8), (3.13), and (3.14), respectively. Constraints (3.34) and (3.35) correspond to constraints (3.16) and (3.17), respectively. Finally, constraints (3.36)-(3.43) correspond to constraints (3.19)-(3.26) in sequence.

3.5.2 A Post-processing Algorithm

As can be noted from Figure 3.5b, containers $i3$ and $i5$ can be retrieved in any order, but container $i7$ cannot be relocated to slot $(2,2)$ until the retrieval of container $i5$. In the flexible *BRPAS*, the relocation order is not distinguished from the retrieval order when the blocking container is in the same subgroup (stage) with the target container(s). Therefore, we propose an online post-processing algorithm that can be implemented to guide the crane operator to the optimal sequence of moves using the actual arrival information of trucks. In the proposed **Algorithm 1**, we refer to the container and the truck by the same index i, where the containers subgroup is

Algorithm 1: Online post-processing for the *Flexible BRPAS* solution

Input: *BRPAS*(*flex*) optimal solution

```
for time window t ∈ {1..T} do
    for container subgroup at the stage k ∈ {1..μ} do
        for container i belongs to subgroup k do
            if container i is a target container and truck i arrived at the bay do
                Retrieve container i to truck i according to FCFS
            end if
            if container i is a blocking container do
                Check if the decided relocation slot is occupied by another container j
                that belongs to the same subgroup k
                if the relocation slot is occupied by the container j do
                    Do not relocate container i until the retrieval of container j
                else
                    Relocate container i to the relocation slot
                end if
            end if
        end for
    end for
end for
```

Output: Retrieval and relocation order for all containers in the bay

defined with its stage k. Note that the $BRPAS(\mathit{flex})$ model, with its post-processing algorithm, applies the FCFS policy only for containers in the same subgroup; however, containers within the same time window may not be served following the FCFS if this will increase the pre-determined optimal relocations. This can be seen clearly in Figure 3.5, where containers $i2$ and $i6$ are not picked up before containers $i3$ and $i5$ even if their trucks arrive earlier than the trucks for $i3$ and $i5$.

3.5.3 A numerical example of $BRPAS(\mathit{flex})$

A detailed example of the flexible *BRPAS* is shown in Figure 3.6. Sixteen containers are planned to be picked up within 5 time windows from a 4×5 bay. The following parameters are assumed for the solved example: $L = 4$, $\mu = 3$, $G = 7$, and $\delta = 1$. The initial bay configuration in Figure 3.6. shows that several containers will be blocked if they are to be picked up according to their preferred times. Moreover, the number of containers with preferred pickup times of $t1$ and $t2$ exceeds the maximum queue length of 4 container retrievals per time window.

Figure 3.6: A numerical example of the flexible *BRPAS*

The *BRPAS*(*flex*) model tends to shift the pickup times for some containers and form a container subgroup schedule per stage. For instance, at $t1$, containers $i4$, $i8$, $i12$ and $i16$ are targeted for retrieval; however, i4 is blocked by i5. Consequently, at stage $k = 1$ of t1, containers $i8$, $i12$ and $i16$ will be picked up and container $i4$ will be relocated to the slot that container $i5$ is occupying (slot $(2, 3)$). In this situation, the online post-processing algorithm helps the crane operator retrieve the three target containers based on the arrival of their trucks but not relocate $i5$ until the retrieval of $i8$. After relocating $i5$, container $i4$ will be retrieved at the second stage. At $t2$, all remaining containers from time window $t1$ must be picked up in order to satisfy the $\delta = 1$ limit. Thus, container $i1$, $i2$, $i3$ and $i11$ will be retrieved in three stages, given that the flexible *BRPAS* approach can group only the topmost containers at once. Similarly, the remaining containers ($i9$ and $i13$) from $t2$ will be shifted to $t3$, while $i15$ is shifted to $t3$ from $t4$ to avoid relocating it when $i3$ is being picked up. At $t3$, we relocate containers $i10$ and $i14$ to enable picking up $i9$ and $i13$. For $t4$ and $t5$, the remaining containers will be retrieved, one container per stage, without a relocation.

3.6 Computational Experiments

To evaluate the proposed models, different subsets of instances from Tanaka and Takii, 2016 and da Silva, Erdoğan, et al., 2018 are solved as container group priority cases, and a subset of instances from Caserta et al., 2012 is solved as a distinct container priority case. The container retrieval group/distinct priority in the selected instances is assumed to be the preferred pickup time window for the containers and not the final pickup priority. All selected subsets of instances, which are modified to fit the *BRPAS* approach, can be found in the dataset repository of A. Azab, 2021. In this data-set, for all instances, the modeling parameters are defined so as to provide an opportunity for future benchmark studies.

To solve the proposed models, we used the IBM ILOG CPLEX Optimization Studio 12.9. on a PC with Intel Core™ i7-8700 CPU 3.20 GHz and 32.0 GB of RAM running under OS 64-bit Windows 10. Comparisons of the formulations considering the various modeling aspects proposed in Sections 3.3 and 3.4 are presented below, along with some analytical insights. The abbreviations used here are as follows: ***Inst.***, the instance number; ***Obj.***, the objective function value for the solved instances;***Opt.***, the optimal value of the objective function for instances that solved to optimality within the time limit; ***Sec.***, the solution time in seconds;***#Feas.***, the number of instances that had a feasible solution within the time limit; and ***#Opt.***, the number of instances that solved to optimality within the time limit. ***#LB.*** is the number of instances that had a lower bound for the LP relaxation of IP models within the time limit, and ***lb.*** is the lower bound obtained within the time limit for the LP relaxation of the IP models.

The $BRPAS(1)$ and $BRPAS(2)$ formulations were solved using a subset of instances from Tanaka and Takii, 2016 without any time limitation (Table 3.3) and a subset of instances from da Silva, Erdoğan, et al., 2018 for which a time limit of 3600 seconds was set (Table 3.4). From Tanaka and Takii, 2016, we selected four bay sizes to be solved, with ten instances for each, as shown in Table 3.3. From da Silva, Erdoğan, et al., 2018, 360 instances were selected, with 12 different bay sizes and 30 instances for each bay size, as illustrated in Table 3.4. This subset of instates was also used to solve the $BRPAS(flex)$ model, as shown in Table 3.5. Note that da Silva, Erdoğan, et al., 2018 developed their instances in order to study the Block Retrieval Problem where each container subgroup in the bay is given a retrieval priority, and only the target subgroup (e.g., the subgroup with a priority of 1) is picked up, while the other container subgroups remain in the bay. We used their instances, assuming that all container subgroups will be picked up. It is worth mentioning that we selected the most difficult subset of instances from de Melo da Silva et al. (2018)—instances where the bay is 80% occupied (that is, the number of empty slots is 20% of the total number of slots), with a planning horizon of $T = 5$ (the number of container groups)—rather than the easier instances, where the occupation rates are 70% and 75% and $T = 3$ and 4, which can be solved in a relatively short time.

Typically, examples of the duplicate BRP in the literature give only the bay configuration; accordingly, the remainder of our model parameters are assumed as follows: To allow a balanced retrieval workload at the bay over time windows, and because all containers are assumed to be retrieved within the planning horizon of T time windows, the maximum queue length L is derived from $L = \left\lceil \frac{N}{T} \right\rceil$. For queue length L (container retrievals), crane capacity (G) is assumed to equal $L + 2$ container moves. The acceptable shift of a container pickup time (δ) is set to 1 (i.e., one time window) for all the solved instances. (Later in this section, we investigate the impact of changing this parameter on the total number of relocations.)

The results in Table 3.3 and Table 3.4 show that both the $BRPAS(1)$ and $BRPAS(2)$ models were able to produce the same optimal solutions for the solved

Table 3.3: Solving $BRPAS(1)$ and $BRPAS(2)$ models using a subset of instances from *Tanaka and Takii, 2016*.

Inst.	***BRPAS*(1)**								***BRPAS*(2)**							
	6×3 (a)		7×3 (b)		8×3 (c)		6×4 (d)		6×3 (a)		7×3 (b)		8×3 (c)		6×4 (d)	
	Opt.	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*	*Opt.*	*Sec.*
1	3	9.37	1	4.39	7	526.25	3	449.64	3	2.10	1	1.77	7	110.10	3	20.40
2	3	7.04	2	3.22	2	25.70	4	574.49	3	1.46	2	1.68	2	3.16	4	4.27
3	0	0.71	5	64.52	6	666.06	7	8603.64	0	0.55	5	9.98	6	400.71	7	854.61
4	3	6.69	5	76.54	2	164.79	6	1079.37	3	1.24	5	15.13	2	4.44	6	159.96
5	1	3.05	3	45.85	3	374.40	6	251.62	1	1.08	3	11.59	3	29.76	6	73.92
6	2	3.11	2	2.48	4	287.44	3	400.48	2	4.15	2	1.50	4	31.81	3	13.73
7	0	0.99	5	262.15	4	383.19	9	2516.17	0	0.67	5	36.52	4	26.41	9	2133.36
8	4	18.56	3	198.45	4	816.41	3	79.07	4	2.79	3	3.72	4	14.94	3	14.46
9	1	2.63	3	11.32	4	311.51	6	1915.72	1	1.26	3	4.03	4	33.84	6	652.92
10	1	3.59	3	26.78	5	798.82	3	243.64	1	0.98	3	8.10	5	134.60	3	5.49
Avg.	1.8	5.57	3.2	69.57	4.1	435.46	5	1611.38	1.8	1.63	3.2	9.40	4.1	78.98	5	393.31

Note: $\delta = 1$,[*(a)* $T = 6, N = 15$, *(b)* $T = 7, N = 18$, *(c)* $T = 8, N = 21$, *(d)* $T = 8, N = 20$]

instances. It is noteworthy that the $BRPAS(2)$ model, having fewer decision variables, computationally outperformed the $BRPAS(1)$ model for most instances. For the da Silva, Erdoğan, et al., 2018 instances, more instances were solved to optimality with $BRPAS(2)$, and more have feasible solutions with $BRPAS(2)$, especially for the larger-size instances. For the smaller-size instances, the two models were both able to produce the optimal solution within the time limit for most instances; however, for only a few instances was the $BRPAS(1)$ model able to produce the optimal solution in less time than $BRPAS(2)$. For the LP relaxation of the IP models, the $BRPAS(1)$ and $BRPAS(2)$ models both exhibited a relatively low level of performance for obtaining a good lower bound (compared to the optimal solution), although the $BRPAS(1)$ formulation produced relatively better lower bound values compared to the $BRPAS(2)$ formulation, as shown in Table 3.4. Despite this shortcoming, almost all instances were solved easily under LP relaxation within the time limit.

Table 3.4: Solving $BRPAS(1)$ and $BRPAS(2)$ using a subset of instances from *da Silva, Erdoğan, et al., 2018*.

		BRPAS$_{(1)}$							***BRPAS$_{(2)}$***						
		IP Model				*LP relaxation*			*IP Model*				*LP relaxation*		
$C \times H$	*N*	*#Feas.*	*#Opt.*	*Avg. Opt.*	*Avg. Sec.*	*#LB*	*Avg. lb.*	*Avg. Sec.*	*#Feas.*	*#Opt.*	*Avg. Opt.*	*Avg. Sec.*	*#LB*	*Avg. lb.*	*Avg. Sec.*
4×4	12	30	30	0.83	3.09	30	0.19	1.00	30	30	0.83	1.20	30	0.12	0.96
4×5	16	30	30	1.13	165.43	30	0.17	3.50	30	30	1.13	20.42	30	0.10	3.09
4×6	19	28	28	2.25	447.92	30	0.30	8.53	29	28	2.25	84.81	30	0.25	5.85
6×4	19	30	29	1.86	221.50	30	0.27	10.19	30	30	2.00	71.66	30	0.21	5.54
6×5	24	28	26	1.58	297.33	30	0.33	34.50	28	28	1.79	159.39	30	0.23	17.43
6×6	28	25	20	1.40	706.58	30	0.32	73.66	27	25	1.68	754.64	30	0.25	45.67
8×4	25	29	27	0.93	168.00	30	0.24	38.98	30	28	1.04	70.26	30	0.17	20.17
8×5	32	20	16	1.06	593.24	30	0.33	146.16	25	21	1.29	396.31	30	0.24	100.06
8×6	38	14	12	0.67	896.18	30	0.33	337.74	17	15	0.80	452.94	30	0.29	231.22
10×4	32	22	14	1.14	596.73	30	0.35	134.32	29	23	1.83	783.77	30	0.28	82.98
10×5	40	12	9	0.56	1446.60	30	0.39	451.34	17	13	1.08	916.04	30	0.35	916.04
10×6	48	7	5	0.00	1772.74	29	0.51	1191.16	8	6	0.17	615.32	30	0.48	760.61
Total		275	246			359			300	277			360		

Note: $\delta = 1, T = 5$, *bay occupation rate is 80%*

Table 3.5 shows results for the $BRPAS(flex)$ model. For this experiment, to ensure the model's input equivalence to the inputs of $BRPAS$ models, we assumed that parameter $\mu = G = L+2$. As can be seen here, the flexible $BRPAS$ formulation produced the exact same optimal solutions as the original $BRPAS$ formulations and had similar lower bounds to those of the linearly relaxed $BRPAS(2)$ model. Note that the $BRPAS(flex)$ model showed better computational performance and solved more instances to optimality within the time limit.

As mentioned in chapter 1, there are two versions of the classical BRP under the retrieval priority: BRP with distinct priority and BRP with group priority. This chapter mainly adopts the duplicate container retrieval priority since it is more compatible with time-window-based appointment scheduling. However, the models can also handle the distinct retrieval priority. In the distinct priority case, the number of containers to be picked up per time window is reduced to one container. This would be applicable when the terminal operator needs to precisely control container pickup with shorter time intervals instead of a time-window-based retrieval

Table 3.5: Flexible *BRPAS* solutions for the instances from *da Silva, Erdoğan, et al., 2018.*

				BRPAS(flex) model		**LP relaxation of BRPAS(flex) model**		
$C \times H$	*N*	*#Feas.*	*#Opt.*	*Avg. Opt.*	*Avg. Sec.*	*#LB*	*Avg. lb.*	*Avg. Sec.*
4 × 4	12	30	30	0.83	1.17	30	0.12	0.84
4 × 5	16	30	30	1.13	16.88	30	0.10	2.89
4 × 6	19	29	28	2.25	88.76	30	0.25	6.53
6 × 4	19	30	30	2.00	83.24	30	0.21	5.96
6 × 5	24	28	28	1.79	151.52	30	0.23	18.49
6 × 6	28	28	27	1.81	480.65	30	0.25	45.05
8 × 4	25	30	29	1.17	36.26	30	0.17	21.87
8 × 5	32	26	22	1.32	201.22	30	0.24	98.50
8 × 6	38	20	18	1.22	703.23	30	0.27	238.21
10 × 4	32	27	26	2.04	490.60	30	0.28	85.03
10 × 5	40	21	18	1.39	448.80	30	0.34	284.73
10 × 6	48	9	7	0.29	832.75	30	0.48	796.32
Total		308	293			360		

Note: *$\delta = 1$, $T = 5$, bay occupation rate is 80%,* $\mu = G = L + 2$

process. Here, the parameter L in the mathematical formulations is set to 1 in constraints (3.3) and (3.17) in the $BRPAS(1)$ and $BRPAS(2)$ models, respectively. Since the container pickup priority is not duplicated in the distinct BRP, parameter T can be set equal to N, the total number of containers.

Table 3.6 gives the results when the distinct retrieval priority is used in solving the subset of instances from Caserta et al., 2012, with different bay sizes and with $\delta = \{0, 1, 2\}$. In the Caserta et al., 2012 instances, the two highest tiers are left empty to allow container relocations, and all stacks are filled with a similar number of containers, equal to $H - 2$. Therefore, in the initial bay configuration, assuming that the lowest container in a particular stack is blocked, the number of stages (parameter G) required for relocation and retrieval is set equal to $H - 2$ when using the $BRPAS$ models. Table 3.6 gives the results under each δ value in the following form: "Objective function value(Solution time in seconds)." As is evident here, the δ value can, quite reasonably, impact the number of relocations. Thus, the acceptable appointment shift δ is an essential parameter in the $BRPAS$. Note that when $\delta = 0$, this is equivalent to the unrestricted BRP with a distinct retrieval priority for containers.

Table 3.6: Solutions using the $BRPAS(2)$ model and distinct priority for instances from *Caserta et al., 2012.*

Inst.	$(C \times H) = (3 \times 5)$, $N = 9$			$(C \times H) = (4 \times 5)$, $N = 12$			$(C \times H) = (5 \times 5)$, $N = 15$		
	$\delta = 0$	$\delta = 1$	$\delta = 2$	$\delta = 0$	$\delta = 1$	$\delta = 2$	$\delta = 0$	$\delta = 1$	$\delta = 2$
1	6 (1.66)	4 (3.22)	2 (1.28)	5 (11.77)	4 (57.14)	2 (10.95)	6 (255.31)	5 (295.52)	4 (157.14)
2	5 (0.55)	3 (1.19)	2 (1.33)	3 (1.20)	2 (1.75)	0 (1.844)	7 (25.88)	7 (1963.45)	6 (3181.42)
3	2 (0.52)	1 (0.66)	0 (0.86)	7 (7.63)	5 (26.28)	4 (73.92)	8 (64.74)	4 (16.30)	4 (73.39)
4	4 (0.75)	3 (1.02)	1 (1.00)	5 (1.74)	4 (4.91)	2 (5)	6 (22.84)	5 (417.70)	4 (772.34)
5	1 (0.52)	0 (0.59)	0 (0.91)	6 (4.16)	4 (5.44)	3 (24.97)	9 (23.88)	9* (*TL*)	6 (1329.03)
6	6 (0.28)	5 (1.56)	3 (1.59)	7 (3.27)	6 (90.06)	4 (47.84)	7 (11.53)	7 (2828.86)	5 (2644.03)
7	6 (0.55)	3 (1.06)	3 (1.99)	10 (5.33)	7 (127.47)	4 (42.42)	7 (25.56)	5 (149.11)	5 (2969.14)
8	2 (0.56)	1 (0.69)	0 (0.84)	5 (19.92)	4 (12.39)	2 (11.86)	10 (10.98)	8 (41.05)	7 (2269.91)
9	8 (0.33)	5 (2.78)	4 (3.95)	4 (1.25)	4 (3.58)	3 (3.70)	8 (201.17)	7 (1734.56)	7* (*TL*)
10	5 (0.61)	2 (0.89)	1 (1.02)	10 (1.95)	10 (360.2)	7 (795.13)	4 (4.64)	2 (7.11)	2 (7.50)
11	3 (0.56)	2 (1.14)	1 (0.89)	7 (4.52)	5 (23.63)	4 (33.58)	11 (7.84)	11* (*TL*)	8 (3284.39)
12	5 (0.52)	3 (0.95)	1 (0.94)	7 (14.49)	6 (177.88)	5 (174.08)	6 (3.36)	4 (5.91)	3 (17.53)
13	8(0.45)	5 (2.92)	3 (5.48)	3 (1.52)	2 (2.30)	1 (3.02)	11 (322.86)	9 (3319.55)	7* (*TL*)
14	7 (0.33)	4 (1.31)	3 (3.42)	7 (1.69)	5 (13.77)	5 (172.3)	4 (4.06)	4 (10.77)	4 (50.39)
15	6 (0.45)	5 (6.84)	3 (4.33)	5 (1.66)	3 (2.95)	2 (6.05)	7 (13.75)	5 (170.36)	4 (38.34)
Avg.	4.93 (0.57)	3.1 (1.79)	1.8 (1.99)	6.07 (5.47)	4.7 (60.65)	3.2 (93.78)	7.4 (66.56)	5.54 (843.1)	4.77 (1291.9)

***Note*:** Time Limit (*TL*) = 3600 sec., * Not optimal, $T = N$, $L = 1$, $G = H - 2$

To investigate the impact of the acceptable appointment shifts on the objective function value in the case of container group pickup, we solved 180 instances with different bay configurations from Tanaka , Takii (2016). Specifically, a (7×3) bay layout with $(N, T) = (18, 10)$, $(19, 11)$ and $(20, 12)$, and a (6×3) bay layout with $(N, T) = (15, 9)$,$(16, 9)$ and $(17, 10)$ were solved. Under each combination of bay layout and (N, T), 30 instances were solved using allowable appointment shift values of $\delta = \{0, .., 5\}$. The solved subset of instances is also included in the dataset repository mentioned above. It should be noted that the average number of relocations can be reduced by accepting more appointment shifts. For example, Table 3.7 shows that accepting an appointment shift of one time window (i.e., changing from $\delta = 0$ to $\delta = 1$) can reduce container relocations by an average of 42% for (6×3) bays and 36.5% for (7×3) bays. In addition, zero relocations can be obtained for most instances when $\delta = 5$. However, the appointment shift value should be acceptable to the other stakeholders, including the individual truckers and trucking companies.

Table 3.7: Impact of acceptable appointment shifts on the number of relocations *Tanaka and Takii, 2016.*

Bay conf.	$(C \times H) = (7 \times 3)$						$(C \times H) = (6 \times 3)$					
	(N=18, T=10)		(N=19, T=11)		(N=20, T=12)		(N=15, T=9)		(N=16, T=9)		(N=17, T=10)	
δ	*Avg. Opt.*	*Avg. Sec.*	*Avg. Opt.*	*Avg. Sec.*	*Avg. Opt.*	*Avg. Sec.*	*Avg. Opt.*	*Avg. Sec.*	*Avg. Opt.*	*Avg. Sec.*	*Avg. Opt.*	*Avg. Sec.*
0	6.17	42.28	6.07	42.35	7.10	80.99	4.50	3.2	5.67	21.35	5.43	9.19
1	3.77	114.13	3.70	362.81	4.47	464.67	2.9	12.4	2.97	12	3.17	52.91
2	2.43	51.24	2.13	125.96	2.87	342.50	1.4	6.1	1.5	3.6	1.4	32.87
3	0.93	10.07	1.17	24.29	1.53	275.72	0.4	2.8	0.4	2.9	0.6	26.94
4	0.03	4.65	0.20	6.57	0.57	13.65	0.0	2.4	0.0	2.8	0.1	3.74
5	0.0	5.91	0.0	6.63	0.13	8.67	0.0	2.7	0.0	3.2	0.0	4.22

Chapter 4

A Proactive Decision Support System for Truck Appointments and Container Relocations

4.1 Chapter Contributions

The contributions of this chapter are:

1. A proactive decision-making approach is proposed as a DSS to consider more practical elements that help coordinate landside and yard area operations.
2. The *BRPAS*(*flex*) is extended to consider essential features in appointment scheduling and more realistic aspects of container handling operations. A new bi-objective IP model is proposed.
3. A new data set for the integrated problem is fabricated based on practical aspects in a real case study.
4. The case study involves an active Japanese container terminal provides a foundation for the experimental study of our work and is used to evaluate the performance of the proposed DSS and compare it to the performance of existing practices.
5. The proposed multi-objective model is extended to consider minimization of

the yard crane time.

4.2 Motivation

In Chapter 3, we introduced the *BRPAS*, which coordinates container relocations with truck appointment scheduling given a limited appointment shift allowance. The *BRPAS* is considered a partial integration for the two optimization problems: the block/container relocation problem and the truck appointment scheduling problem. In *BRPAS*, the level of information (represented by the scheduling parameters) sharing between the terminal and trucking companies is limited. Therefore, the *BRPAS* provides a lower level of decision-making cooperation which is appropriate for CTs with concerns regarding the full integration between the terminal appointment system and yard operating system. These concerns could represent the technical challenges in systems integration or operational difficulties in decision-making integration and collaboration.

However, for terminals that can build a collaborative platform that achieves a higher integration between the truck appointment systems with the yard operating system, we propose a new "proactive coordination approach" that simultaneously aligns, in advance, truck appointment times and truck service order with container handling operations at the yard so as to avoid unproductive container relocations that result from random or uncoordinated truck arrivals. Motivated by the *BRPAS(flex)* model presented in Chapter 3, we introduce a coordinating Decision Support System (DSS) for achieving the coordination. The proposed approach captures the more operational elements that terminal operators consider when planning container handling operations and the scheduling challenges that trucking company dispatchers encounter when scheduling container pickups from the terminal.

The proposed DSS has several distinctive features:

First, it optimizes the Truck Appointment Scheduling problem together with the Container Relocation Problem (TAS-CRP). The DSS is based on a bi-objective optimization approach that focuses more on the practical aspects of truck appointment scheduling and container-handling yard operations. Unlike most existing studies that introduce real-time reordering techniques for container retrievals, the proposed method provides a new way to schedule truck appointment times in advance by considering both the container pickup and delivery schedules of the trucking companies and the yard capacity (both spatial and resource capacity).

Second, the approach considers realistic aspects of the problem that are frequently ignored and treats container relocations under various partial appointment conditions and the possibility that not all containers will be picked up within the planning horizon. This differs from prior studies that assume the bay will be empty by the end of the day or within the planning horizon, and adds a new version of CRP—CRP with partial container pickup.

Third, our DSS removes some of the stress facing practitioners to determine the exact solution to the combinatorial relocation problem and to quickly respond to real-time arrivals or, alternatively, forcing them to apply a rule-based heuristic whose optimality is not guaranteed. The proposed approach provides a longer decision-making time frame for solving the integrated TAS-CRP problem since truck appointments are usually scheduled at least one day before the trucks arrive at the terminal.

4.3 The Proposed DSS Framework

Figure 4.1 illustrates the framework for the proposed DSS. In this framework, the trucking companies act as the initiators of the procedure when they submit their appointment requests through the appointment system (i.e., an online appointment platform). Each appointment request includes a container identification number, information related to the preferred pickup time window, and the container delivery (to the final destination or customer) time limits for the import container. Since the terminal side is dominant in most container terminal TASs, incorporating the desired container-to-customer delivery schedule serves to balance the dominance of the terminal with the satisfaction of the trucking companies. It is vital that a trucking company's delivery schedule not be seriously disrupted by the terminal's final appointment schedule. Sharing the container delivery schedule also adds a collaborative decision-making aspect to the proposed approach.

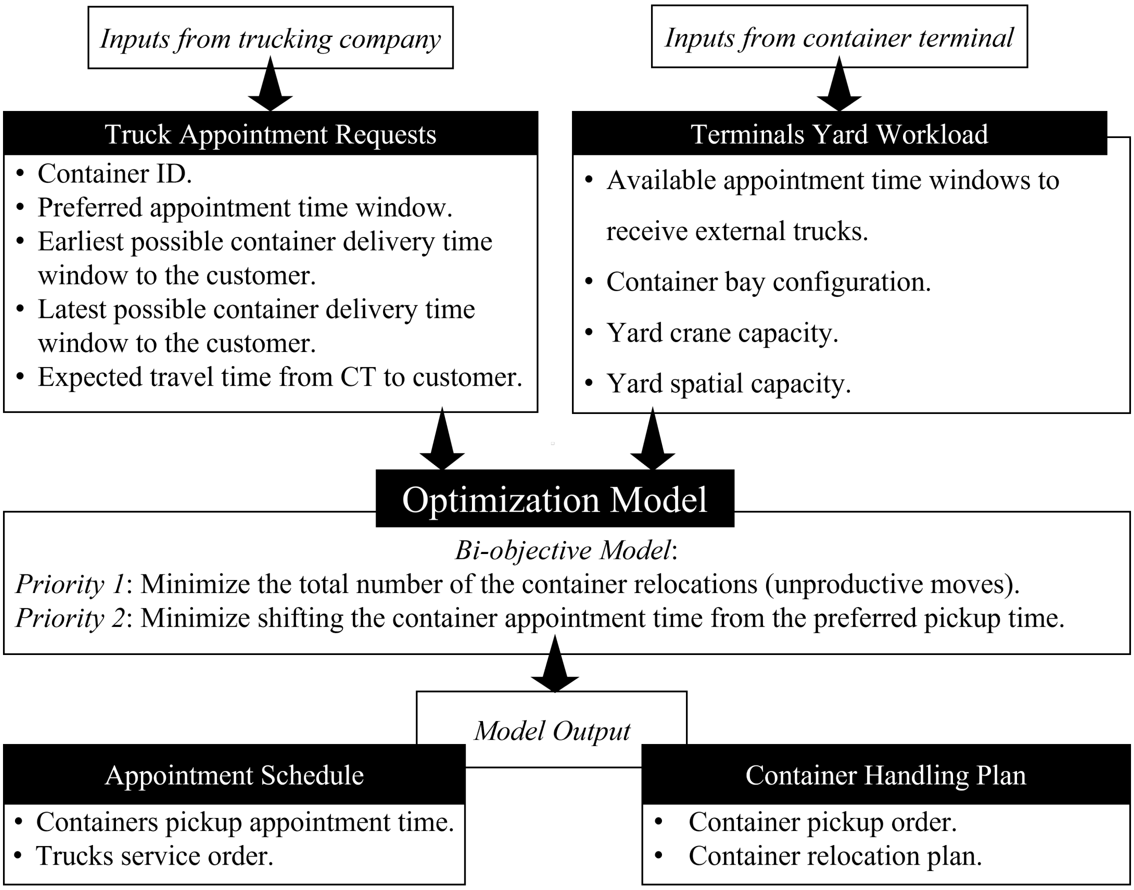
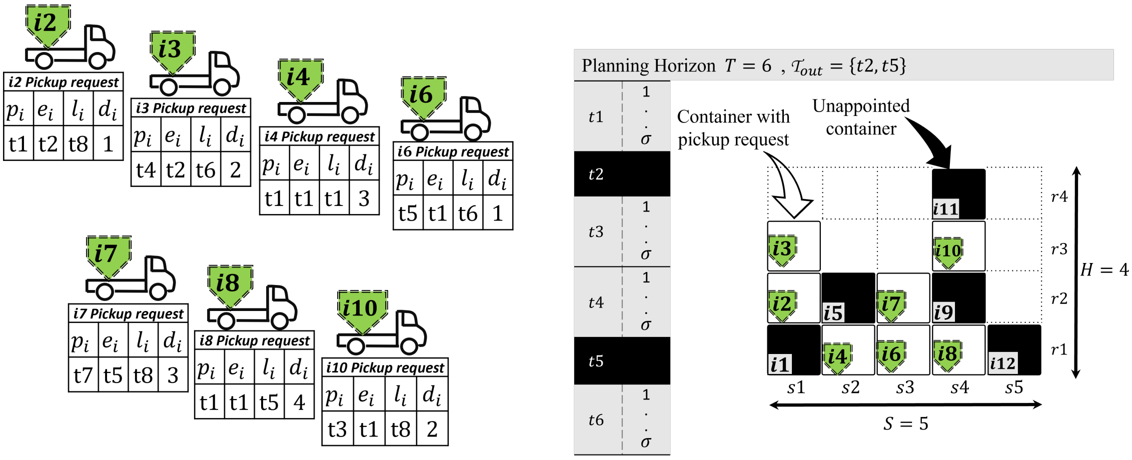


Figure 4.1: Modeling framework of the proposed Decision Support System

After receiving the appointment requests, the terminal operators use the information, along with the terminal workload, to set the appointment schedule. For operational and practical purposes, the container appointment requests are sorted based on the bay in which the required containers are located; the set of containers located in the same bay forms a standalone scheduling problem (see Assumption 2 below). Note that the terminal side constantly faces constraints that limit its ability to schedule appointments that perfectly match the companies' desired schedule. These constraints include the available time windows for serving the arriving trucks at the yard, the maximum truck queue length at the bay, and the container handling capacity of the yard crane (YC). After considering the inputs from all the stakeholders (i.e., the trucking companies and the container terminal), the optimization model solves both the scheduling problem and the relocation problem in one model.

From the terminal's perspective, the priority is to reduce the number of unproductive container moves (relocations) that may result from the derived appointments schedule. This will allow the servicing of more trucks with less waiting time and improve YC productivity. From the trucking companies' perspective, the primary goal is to maintain the companies' container delivery schedules with only minor disturbances by allowing them to pick up their containers at a time near to their preferred appointment time. Accordingly, our approach uses a *bi-objective* IP model that integrates the truck appointment scheduling problem with the container relocations problem. The primary objective is to determine which group of containers should be picked up in a specific time window in order to minimize the total number of container relocations. The secondary objective is to make minimum changes to the truckers' delivery schedules. With the proposed DSS, terminal operators are able to set both the container pickup appointment schedule and the corresponding container handling plan. (The term "*container handling*" is used here to refer to the process of container relocation and retrieval in a bay.)

As in the BRPAS problem in Chapter 3, the planning horizon (i.e., terminal working shift or day) is divided into several appointment time windows with a time unit of $t \in \{1, .., T\}$, where T is the last time window in which a container can be picked up from the terminal. However in this chapter we replace the definition of the "*stage*" (which mainly defines the container moves in BRPAS in Chapter 3) to *time interval.* Each time window is divided into shorter time intervals σ, as shown in Figure 4.2a. This further division of the time windows into several shorter intervals enables more control over the arriving trucks and provides container handling flexibly for trucks scheduled for the same interval. Based on the terminal's workload, there will be certain time windows within the planning horizon during which the terminal is unable to receive external trucks. This is a typical scenario wherein the terminal shuts down its service of external trucks while receiving at a particular yard block or bay import containers from a seaside vessel. Break time windows between working shifts, planned maintenance time windows, etc., are also considered inoperative times and thus unavailable for servicing external trucks. The set of such inoperative or out-of-service time windows is considered in our model as T_{out} (Figure 4.2b).



(a) Containers appointment requests (b) Planning parameters and bay layout)

Figure 4.2: Main parameters in the proposed DSS

It is assumed that the bay is filled with N containers. Because it is possible that the terminal may not receive appointment requests for all of the stacked containers in a particular bay, we define the subset of appointed containers ($\mathcal{N}_a$) and the subset of the unappointed containers ($\mathcal{N}_u$). The unappointed containers cannot leave the bay during the planning horizon. Each container in a bay has a unique identification number or index (i), which is used by the trucking companies when they make their requests and specify their preferred container pickup time (p_i), the earliest possible time window for container delivery to the customer (e_i), the latest possible time window for container delivery to the customer (l_i) and the expected time (in time windows) for the truck to deliver the container from the terminal to the customer (d_i) (as shown above in 4.2a).

The following assumptions describe the remaining problem settings:

Assumption A1: Trucking companies submit their appointment requests one day before heading to the terminal. The terminal operators develop the final appointment schedules and share them with the trucking companies before the trucks leave for the terminal. The container relocation plan is provided to the YC operators before the start of their work shift or planning horizon.

Assumption A2: From a practical perspective, containers are relocated only within the bay they occupy. This is a typical assumption for the *CRP* in most studies reported in the literature. Relocating containers between bays is a time-consuming process for the yard crane, with many safety concerns. Therefore, each bay represents a standalone optimization problem. This means that for a set of target containers belonging to a particular bay, corresponding appointments are scheduled and simultaneously aligned with a relocation plan that has them picked up from that bay.

Assumption A3: The bay will not receive any containers (e.g., from the ship side) from the start of the scheduling process to the time the last appointed container is picked up. This condition is equivalent to the static *CRP*, where no new containers are stacked in the bay until all target containers have been picked up (Caserta et al., 2012). The Dynamic *CRP*, in contrast, allows stacking the containers in the bay during the container retrievals (Borjian et al., 2013).

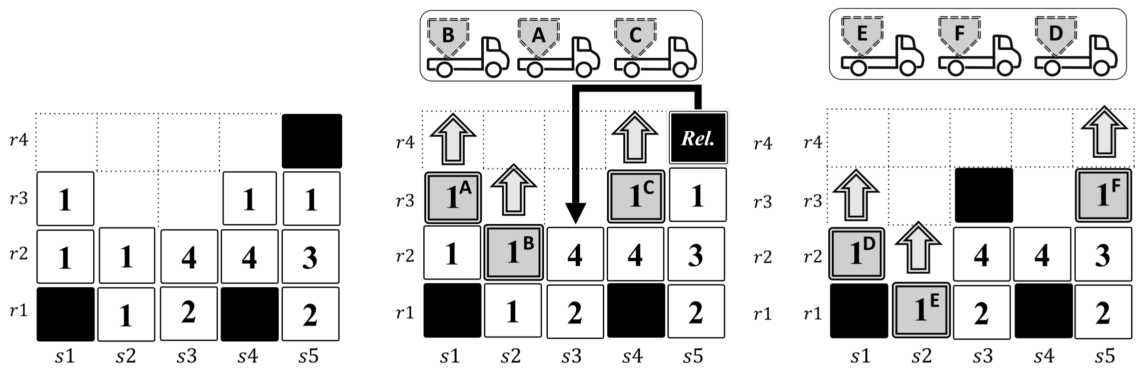
Assumption A4: Trucking companies will accept the appointment schedule and dispatch their trucks to the terminal according to the terminal's developed schedule. However, to ensure that arrival punctuality can be achieved in reality, the proposed approach considers the company's desired container delivery schedule in its appointment scheduling, as mentioned earlier (see Figure 4.2).

Assumption A5: The approach does not consider the gate queuing system, but only the yard's container retrieval and relocation operations. Therefore, the appointment time window decided by solving the proposed model represents the time window for container pickup from the yard.

4.4 Problem Formulation

To formulate the problem, we extended the *BRPAS*(*flex*) model in Chapter 3 and introduced a bi-objective integer programming model with a *bi-level lexicographical* objective function. Note that the proposed mathematical model simulates container handling operations that are driven by future truck arrivals, which are generated by the final appointment schedule. Thus, there are two types of decision variables: appointment scheduling variables and container handling variables. The container handling variables track container locations in the bay and optimize the expected relocations, while the appointment scheduling variables are used to optimize the final appointment times. The appointment sets the time window and the time interval for picking up the container; for all the trucks arriving during a specific time window, the service order is applied via the decided time interval. Note that more than one truck can be scheduled for a particular time interval and that we do not assume a specific service order for those trucks.

The container handling operation in each time interval is designed in a way that allows serving the trucks appointed to the same interval based on the FCFS policy. This is achieved by taking advantage of the fact that the topmost containers in the bay can be picked up in any order without increasing container relocations, as Figure 4.3 illustrates. The arrival order of the trucks (A, B, C) during interval-1 of Time Window 1 (TW1) (Figure 4.3b) and of the trucks (D, E, F) during interval-2 of the same time window 1 does not impact the number of relocations. However, each truck dispatch must commit to its time interval to ensure this condition. The container handling task within a time interval can be a container retrieval to satisfy a final appointment or a container relocation that facilitates future retrievals. This can be seen in Fig 4.3b and 4.3c, when the unappointed container in slot $(5, 4)$ is relocated to slot $(3, 3)$ at time interval-1 to allow access to the container in slot $(5, 3)$ that is scheduled for pickup at time interval-2. In our approach, retrievals are always prioritized over relocations when they are planned for the same time interval.



(a) Before TW1 starts (b) Interval-1 of TW1 (c) Interval-2 of TW1

Figure 4.3: The flexible scheduling of truck arrival during the time window

In the following, the model sets, indices, and parameters are defined. To make it clear for the reader, we repeated the definition of some parameters from Chapter 3 and introduce the new parameters. Moreover, to keep the consistency of chapter presentation, we rewrote some the constraints that already defined in Chapter 3 even if it used in this chapter without any modifications. Note that, some notations in this chapter are *changed* from the notation given for the same indices or parameters in Chapter 3.

***Sets, indices, and parameters*:**

$\mathscr{N}$ Set of all containers stacked in the bay $\mathscr{N} = \{1, \ldots, N\}$. ,$N$ is the total number of containers in the designated bay.

$\mathscr{N}_a$ Set of containers with appointment requests, $\mathscr{N}_a \subseteq \mathscr{N}$.

$\mathscr{N}_u$ Set of unappointed containers $\mathscr{N}_u = \mathscr{N} \setminus \mathscr{N}_a$.

$\mathscr{S}$ Set of stacks in the bay, $\mathscr{S} = \{1, \ldots, S\}, S$ is the total number of stacks in the bay.

$\mathscr{R}$ Set of the bay tiers, $\mathscr{R} = \{1, \ldots, H\}, H$ is the maximum height of the bay.

$\mathscr{T}$ Set of time windows, $\mathscr{T} = \{1, \ldots, T\}, T$ is the last time window for a truck to access the terminal.

$\mathscr{T}_{out}$ Set of *out-of-service* time windows where the yard crane cannot serve at the bay.

$\mathscr{V}$ Set of time intervals, $\mathscr{V} = \{1, \ldots, \sigma\}$, σ is the number of time interval per time window.

L The maximum trucks queue length at the designated bay in a time interval.

C The capacity of the yard crane in terms of the maximum number of container moves the crane can perform per time window.

i Index of the container, $i \in \mathscr{N}$.

s Index of stack, $s \in \mathscr{S}$.

r Index of tier, $r \in \mathscr{R}$.

t Index of time window, $t \in \mathscr{T}$.

τ Index of time interval, $\tau \in \mathscr{V}$.

I_{isr} Whether container $i \in \mathscr{N}$ occupies slot (s, r) in the initial bay layout, $I_{isr} \in \{0, 1\}$.

p_i Preferred appointment time window for each container $i \in \mathscr{N}_a$, $p_i \in \{1, \ldots, T\}$.

e_i Earliest possible container delivery time to customer/destination.

l_i Latest possible container delivery time to customer/destination.

l_i Expected time (in terms of time windows) to deliver the container from terminal to customer/destination.

***Binary Decision Variables*:**

$z^t_{i\tau}$ Whether to pick up container $i \in \mathscr{N}_a$ at interval τ of the time window t.

$u^t_{isr\tau}$ Whether container $i \in \mathscr{N}$ will occupy the slot (s, r) at interval τ of the time window t.

$x^t_{isr\tau}$ Whether container $i \in \mathscr{N}$ will be moved from the slot (s, r) at interval τ of the time window t.

$y^t_{isr\tau}$ Whether container $i \in \mathscr{N}$ will be moved to the slot (s, r) at interval τ of the time window t.

***Integer Derived Variables*:**

The following appointment variables λ_i and δ_i are derived from the above binary variables to determine the appointment time window and appointment shift for each requested container. These variables are also formulated to improve the model's readability.

λ_i The final appointment time for a truck to pick up the container $i \in \mathscr{N}_a$.

δ_i The difference between the final appointment time window and preferred time window to pick up the container $i \in \mathscr{N}_a$.

4.4.1 IP Model

Objective Function:

$$f_1 = \sum_{i \in \mathscr{N}} \sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} \sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} y^t_{isr\tau}$$

$$f_2 = \frac{\sum_{i \in \mathscr{N}} \delta_i}{N_a}$$

$$\boldsymbol{LexMin}(f_1, f_2)$$

The first function f_1 minimizes the total number of relocations required to pick up all the appointed containers. The second objective function f_2 minimizes the average appointment shift, i.e., the average difference between the final pickup appointment and the trucking company's preferred appointment. The bi-objective model optimizes functions f_1 and f_2 in a using lexicographical objective function $\boldsymbol{LexMin}(f_1, f_2)$, where the first priority is to reduce the number of container relocations in f_1 over minimizing the average appointment shift in f_2. The main reason for applying the lexicographical method is that the terminal operator is the typical decision-maker for appointment scheduling and relocation planning. Therefore, since container relocations directly impact terminal operations, priority is given to reducing the number of relocations (f_1). Reasonably, minimizing the relocations can reduce truck delays at the yard and increase the productivity of the trucking companies. Note that the model can shift the appointment times (f_2) for some trucks within the container delivery schedule prepared by the trucking companies.

Objective function $\boldsymbol{LexMin}(f_1, f_2)$ is subjected to:

(a) Appointment scheduling constraints(4.1)-(4.8):

$$\lambda_i = \sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} t z_{i\tau}^t, \qquad \forall i \in \mathscr{N}_a \tag{4.1}$$

$$\delta_i = |\lambda_i - p_i|, \qquad \forall i \in \mathscr{N}_a \tag{4.2}$$

$$\lambda_i + d_i \leq l_i, \qquad \forall i \in \mathscr{N}_a \tag{4.3}$$

$$\lambda_i + d_i \geq e_i, \qquad \forall i \in \mathscr{N}_a \tag{4.4}$$

$$\sum_{i \in \mathscr{N}_a} z_{i\tau}^t \leq L, \qquad \forall \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.5}$$

$$\sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} z_{i\tau}^t = 1, \qquad \forall i \in \mathscr{N}_a \tag{4.6}$$

$$\sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} z_{i\tau}^t \leq 0, \qquad \forall i \in \mathscr{N}_u \tag{4.7}$$

$$\sum_{i \in \mathscr{N}} \sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} \sum_{\tau \in \mathscr{V}} x_{isr\tau}^t \leq 0, \qquad \forall t \in \mathscr{T}_{out} \tag{4.8}$$

The first group of constraints (4.1)-(4.8) describes the appointment scheduling for a set of trucks to pick up a set of containers $\mathscr{N}_a$ within the operative time windows $\{\mathscr{T} - \mathscr{T}_{out}\}$. Constraint (4.1) determines the appointment time (λ_i) for a truck to pick up container i for which there is an appointment request. The decision variable (λ_i) is derived from the binary variable $z_{i\tau}^t$ indicating which appointment time will be the pickup time window for the container under assumption A5. Note that the decision variable $z^t_{i\tau}$ also describes in which time interval τ container i will be picked up, while (λ_i) defines only the time window. Such detailed information about the container pickup interval can be shared with the trucking companies to help their drivers arrive punctually during the appointment time window. However, the time interval decides the priority of serving the subgroup of trucks arriving in the same time window. A truck with an appointment window of t and container pickup time interval $\tau + 1$ cannot pick up its container in an earlier interval.

In constraint (4.2), the derived variable δ_i defines the appointment shift of container i from its preferred pickup time p_i, so that, in the second objective f_2, the average appointment shift is minimized for the containers with appointment requests. Constraints (4.3) and (4.4) ensure that the container can be delivered to the customer under the final appointment. The model forces a container delivery time window $\lambda_i + d_i$ to have a value within the desired acceptable delivery period $[e_i, l_i]$. Constraint (4.5) limits the maximum number of trucks served (container retrievals) during the designated time interval to keep the queue length at the bay controllable. Constraint (4.6) guarantees fulfillment of the appointment requests, while constraint (4.7) ensures that unappointed containers cannot be picked up from the bay without an appointment request. Constraint (4.8) provides that no trucks will be allowed be pick up containers from the bay during the *out-of-service* time windows ($\mathscr{T}_{out}$); correspondingly, relocations required for any retrievals will not be performed during these times under the assumption that the yard crane is unavailable to work on the bay during $\mathscr{T}_{out}$.

(b) Bay configuration constraints (4.9)-(4.14) :

$$u^1_{isr1} = I_{isr}, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R} \tag{4.9}$$

$$\begin{aligned} u^t_{isr\tau+1} &= u^t_{isr\tau} + y^t_{isr\tau} - x^t_{isr\tau}, \\ &\quad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V} \setminus \sigma, t \in \mathscr{T} \end{aligned} \tag{4.10}$$

$$\begin{aligned} u^{t+1}_{isr\tau} &= u^t_{isr\sigma} + y^t_{isr\sigma} - x^t_{isr\sigma}, \\ &\quad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, t \in t \in \mathscr{T} \setminus T \end{aligned} \tag{4.11}$$

$$\sum_{i \in \mathscr{N}} u^t_{isr\tau} \leq 1, \qquad \forall s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.12}$$

$$\sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} u^t_{isr\tau} \leq 1, \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.13}$$

$$\sum_{s\in\mathscr{S}}\sum_{r\in\mathscr{R}}\sum_{\tau'\in\mathscr{V}\setminus 1} u^{t}_{isr\tau'} + \sum_{s\in\mathscr{S}}\sum_{r\in\mathscr{R}}\sum_{\tau'\in\mathscr{V}}\sum_{t'\in\mathscr{T}\setminus 1} u^{t'}_{isr\tau'} \leq \sigma T(1 - z^{t}_{i\tau}), \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.14}$$

The proposed approach determines truck appointments that contribute to deciding expected container relocations and retrievals. Since the relocation and retrieval processes change the bay configuration, constraints (4.9)-(4.14) are used to track this change for the expected container handling process. Constraint (4.9) initiates the bay configuration using parameter I_{isr}. The decision variable u^{1}_{isr1} describes the stacking sequence of each container i in the bay slots just before handling the first container at $(t, \tau) = (1, 1)$. During container handling operations, there are three possibilities for the status of each slot (s, r) in the bay; the slot remains in its previous status ($u^{t}_{isr\tau} = 1$), a container is removed from the slot ($x^{t}_{isr\tau} = 1$), or a container is moved to the slot ($y^{t}_{isr\tau} = 1$). Constraint (4.10) updates the bay configuration over time intervals within the same time window, while constraint (4.11) updates the bay configuration status transition from time window t to the next time window $(t+1)$. Constraints (4.12) and (4.13) are formulated to define the bay configuration's static features. In constraint (4.12), each slot (s, r) cannot hold more than one container. Constraint (4.13) establishes that a container i can only occupy one slot. Constraint (4.14) eliminates a container from the bay configuration once it is picked up (i.e., $z^{t}_{i\tau} = 1$); hence, the container cannot appear again in the bay.

(c) Container handling constraints (4.15)-(4.19) :

$$\sum_{r\in\mathscr{R}} x^{t}_{isr\tau} + \sum_{r\in\mathscr{R}} y^{t}_{isr\tau} \leq 1, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.15}$$

$$\sum_{s\in\mathscr{S}}\sum_{r\in\mathscr{R}} x^{t}_{isr\tau} = \sum_{s\in\mathscr{S}}\sum_{r\in\mathscr{R}} y^{t}_{isr\tau} + z^{t}_{i\tau}, \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.16}$$

$$\sum_{i\in\mathscr{N}} x^{t}_{isr\tau} \leq \sum_{i\in\mathscr{N}} (u^{t}_{isr\tau} - u^{t}_{is,r+1,\tau}), \qquad \forall s \in \mathscr{S}, r \in \mathscr{R} \setminus H, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.17}$$

$$x^{t}_{isr\tau} - u^{t}_{isr\tau} \leq 0, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.18}$$

$$\sum_{i\in\mathscr{N}}\sum_{s\in\mathscr{S}}\sum_{r\in\mathscr{R}}\sum_{\tau\in\mathscr{V}} x^{t}_{isr\tau} \leq C, \qquad \forall t \in \mathscr{T} \tag{4.19}$$

Constraints (4.15)-(4.19) model the dynamicity of the retrieval and relocation process. Under constraint (4.15), a container cannot occupy the same stack s if it is relocated from it. This constraint also defines the relocation variable $y^t_{isr\tau}$ through the variable $x^t_{isr\tau}$. Constraint (4.16) links the decision variables $x^t_{isr\tau}$, $y^t_{isr\tau}$ and $z^t_{i\tau}$ so that if a container is moved, it is either relocated within the bay or picked up by the appointed truck. Constraints (4.17) and (4.18) enforce the Last-In-First-Out (*LIFO*) policy so that a container cannot be moved from its slot unless the above slot is empty. The last-in container indicates that the last container stacked in the bay (originally based on when the bay received the import container from the vessel) is the first-out container to be moved (when the crane operator needs to retrieve or relocate it). In constraint (4.17), the topmost container in a particular stack must be moved first. Constraint (4.18) ensures the LIFO rule by preventing each individual container from floating in the bay but is only transferred from its current slot. Constraint (4.19) is the yard crane capacity constraint that restricts the overall number of container moves (relocations + pickups) per time window at the designated bay.

(d) Decision variables domain ((20) - (25)):

Finally, the decision variable domains are defined in following constraints.

$$u_{isr\tau} \in \{0,1\}, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.20}$$

$$x_{isr\tau} \in \{0,1\}, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.21}$$

$$y_{isr\tau} \in \{0,1\}, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.22}$$

$$z_{i\tau} \in \{0,1\}, \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.23}$$

$$\lambda_i \in \mathbb{Z}^{+}, \qquad \forall i \in \mathscr{N}_a \tag{4.24}$$

$$\delta_i \in \mathbb{Z}^{0+}, \qquad \forall i \in \mathscr{N}_a \tag{4.25}$$

4.4.2 Numerical Example

A simple example can be used to illustrate the procedure. Assume we have a bay that is six stacks wide and four tiers high, and that the bay contains 18 containers, as shown in Figure 4.4. The small box in the lower left corner of each container defines the container index i. Let the unappointed containers (shown as black boxes) be containers $i2$, $i5$, and $i17$, while the remaining containers have appointment requests. The upper rows of Table 4.1 show the detailed pickup appointment requests for the various containers. (The bottom two rows in the table show the final appointment

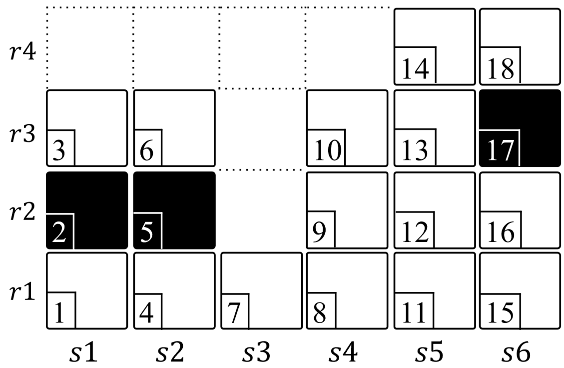


Figure 4.4: Container stacking order and the bay layout for the numerical example

schedule obtained by solving the proposed model.) The remainder of the scheduling parameters are set as follows: the terminal working hours (T) = 6 time windows (e.g., 9:00 am to 3:00 pm), the *out-of-service* time window $T_{out} = \{t4\}$, each time window is divided into two time intervals ($\sigma = 2$), the maximum queue length at the bay in each interval is $L = 2$ trucks (container retrievals), and, for this bay, the crane capacity (C) = 6 container moves/time window. The solution to this numerical example is shown in detail in Figure 4.5.

Table 4.1: Appointment requests and decided appointment schedule for the numerical example.

	Container index (i)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Container Appointment Request	Preferred pickup time (p_i)	5	-	3	4	-	6	1	2	2	2	6	2	4	6	3	6	-	5
	Earliest container delivery time (e_i)	3	-	1	2	-	4	2	2	2	1	3	2	2	5	2	3	-	3
	Estimated travel time (d_i)	3	-	1	1	-	2	3	3	4	2	2	1	2	1	2	4	-	4
	Latest container delivery time (l_i)	8	-	8	8	-	11	8	9	9	11	8	11	6	10	12	10	-	9
Final Schedule	*Final appointment* (λ_i)	5	-	3	5	-	3	1	2	2	1	6	2	2	6	6	6	-	5
	Appointment shift (δ_i)	0	-	0	1	-	3	0	0	0	1	0	0	2	0	3	0	-	0

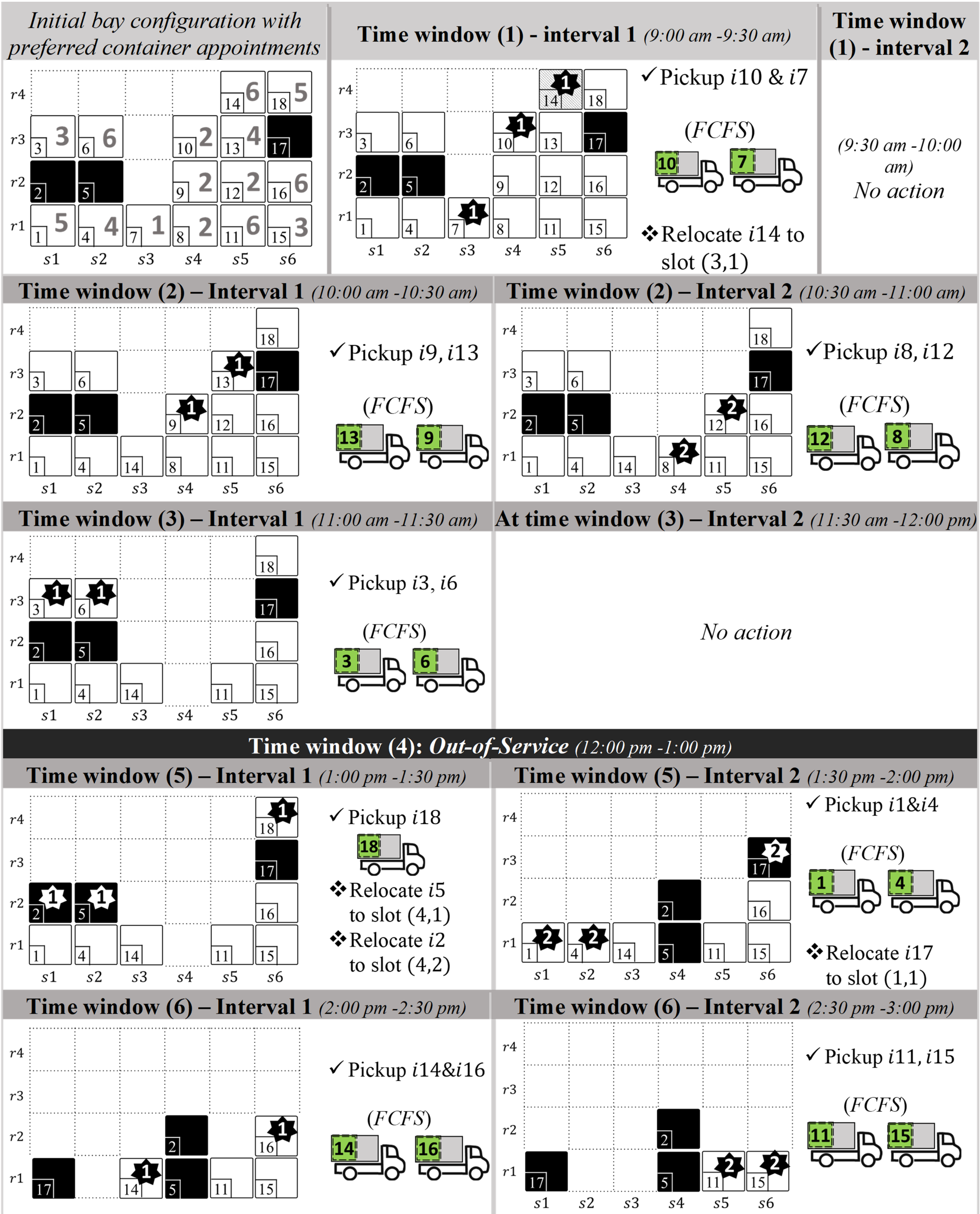


Figure 4.5: Solution to the numerical example

To understand how the proposed approach works, the initial bay layout is given at the upper left of Figure 4.5, where the preferred appointment time of each container is attached. According to the appointment requests, container $i7$ has a preferred pickup time in the first-time window ($t1$). Note that there are no containers above $i7$; thus, its preferred appointment time can be approved as the final appointment. Container $i10$'s preferred pickup time is shifted from $t2$ to $t1$. In this case, containers $i7$ and $i10$ can be picked up in any order (FCFS). The reason for shifting $i10$'s pickup time is explained below. As noted, we can still schedule relocations to facilitate future pickups in the coming time windows. This is the case for container $i14$. It can be seen from the initial bay configuration that the preferred pickup time for container $i12$ is time window $t2$. However, containers $i13$ and $i14$, with their later preferred appointment times ($t4$ and $t6$, respectively), are stacked above and thus block container $i12$. In this case, the model's first priority is to minimize the number of relocations needed to retrieve container $i12$.

Typically, our approach avoids relocations by assigning earlier appointment times to the topmost containers and later appointment times to the bottom-most containers, as long as the container delivery schedules submitted by the companies are not violated. For the blocking container $i14$, the earliest pickup time ($\lambda_{14} = e_{14} - d_{14} = 4$) is time window $t4$ (note, however, that $t4$ is an *out-of-service* time window). Then, container $i14$ cannot have an appointment time before time window 5. Consequently, it will be relocated to the empty slot $(3, 1)$ after container $i7$ is picked up. We still have container $i13$ located above container $i12$, but its delivery schedule is more flexible than container $i14$. We could schedule $i13$ for pickup in $t2$ (i.e., shift its pickup time from $t4$ to $t2$), then avoid relocating it given that its original preferred time at $t4$ is an *out-of-service* time. However, doing so would mean we would have four containers to be picked up in $t2$—$i8$, $i9$, $i12$ and $i13$. It is for this reason that the appointed time for i10 is moved from $t2$ to $t1$; without such a shift, the number of containers to be picked up in $t2$ would exceed the queue length limit of four trucks (two in each time interval). Thus, in the first time interval of $t2$, $i9$ and $i13$ will be retrieved following the FCFS policy; similarly, containers $i8$ and $i12$ will be picked up in the second interval of window $t2$.

As shown in Table 4.1, containers $i3$ and $i15$ have preferred pickup times in window $t3$. In the bay configuration, container $i3$ will be at the top of the bay in $t3$; however, $i15$ will be buried under three containers. Thus, our approach approves $t3$ as the appointment time window for $i3$, but shifts $i15$ to a later appointment time to avoid three relocations ($i16$, $i17$ and $i18$) while creating no disruption to its delivery schedule. To avoid more relocations for future arrivals after t4, container $i6$ will be appointed to $t3$, along with $i3$. Consequently, the FCFS policy will be applied to the trucks picking up $i6$ and $i3$ in the first interval of $t3$. Containers $i1$,$i4$ and $i18$ will have pickup appointments in time window $t5$, meaning that $i18$ and i1 will not need to be shifted from their preferred times, while $i4$ will be shifted from $t4$ (the out-of-service time window). At the beginning of window $t5$, container $i18$ will be in the topmost slot of stack $s6$; its truck will pick it up during $t5$'s first time interval. However, $i1$ and $i4$ are not at the top of their stacks, $s1$ and $s2$, as unappointed containers $i2$ and $i5$ occupy the upper tier. Thus, the crane will relocate the two blocking containers during the first interval so that $i1$ and $i4$ can be picked up during the second time interval of window $t5$.

Up to this point, we have scheduled five container moves for time window $t5$ (relocating $i2$ and $i5$ and retrieving $i1$,$i4$ and $i18$), which is still under the maximum crane capacity of six container moves per time window. The proposed approach always prepares for future retrievals whenever there is an opportunity to do so. Here, the crane will relocate container $i17$ to slot $(1, 1)$ at the end of the second time interval in $t5$. Now, $t6$ will be ready for the trucks picking up the remaining containers, $i11$, $i14$, $i15$ and $i16$. Since we have only a maximum of two trucks per time interval, and considering that $i16$ is above $i15$; $i14$ and $i16$ will be appointed to the first time interval, and $i11$ and $i15$ will be scheduled for the second.

At the end of the planning horizon, we will have had a total number of four container relocations ($f_1 = 4$) and an average appointment shift of $f_2 = \frac{10}{15} = 0.67$ time windows per appointment container. Note that serving the trucks at their original preferred times would create many more relocations, impacting the overall performance of the process. To demonstrate, consider each blocking container in the initial bay configuration (See Figure 4.5) as an unavoidable relocation. For instance, in stack $s6$, to pick up container 15 at its preferred time window ($t2$), we must relocate containers 16, 17, and 18. Similarly, for the remaining stacks, if we treat the preferred times as the actual pickup times, we would have eight blocking containers, leading to at least eight relocations.

4.4.3 Yard Crane Time Optimization

One of the main objectives that draw the attention of terminals operators is to minimize the YC working time. The crane relocates the blocking containers to empty candidate slots at each bay to load the target containers to the waiting trucks. Minimizing the number of container relocations leads, by default, to reduce the crane working time. However, it is expected that the crane operator might have more than one candidate slot to relocate the container to it. In this case, the travel distance from the current slot of the blocking container to the destination slot contributes to the crane working time. Note that the blocking container can be an "appointed" container (e.g. container $i14$ in Figure 4.5). This means that the relocation action for this container at a particular moment might impact future YC retrieval time depending on the height of the destination slot after relocation. Therefore, we consider the overall crane time for both relocation and retrieval actions.

Figure 4.6 shows the crane moves required to load a container to a waiting truck. We can distinguish the crane move as a horizontal move and vertical move Moving a container requires the crane trolley to travel horizontally until reaching the target stacks. We assume that a fixed time (t_s) is consumed by the crane's trolley to cross one stack. The spreader travels up and down to perform the vertical moves. For the vertical move, the crane speed differs when it travels empty or travels loaded with the container. Therefore, we define the parameter (t_{r0}) as the time consumed by the crane's spreader to travel empty in the vertical direction. On the other hand, (t_{r1}) is the time consumed by the crane to travel vertically while being loaded with the container. The total time to cross one trier vertically with and without the container is $t_r = t_{r0} + t_{r1}$

To define YC time decision variables, for modeling simplicity, we define an extra stack q ($q = S + 1 : \mathscr{S}' = \mathscr{S} \cup \{q\}$) outside the bay to represent the location where the waiting trucks are queuing (see Figure 4.6). This stack is used to determine the distance traveled horizontally by the crane during container retrieval. As a result, there is no need anymore to use the variable $z^t_{i\tau}$ in the formulation. Instead, the variable $y^t_{i(q,1)\tau}$ defines the state of container i if it is moved to the the slot $(q, 1)$; loaded to the designated truck waiting at time interval τ of time window t. Note that the height of the extra stack is always 1.

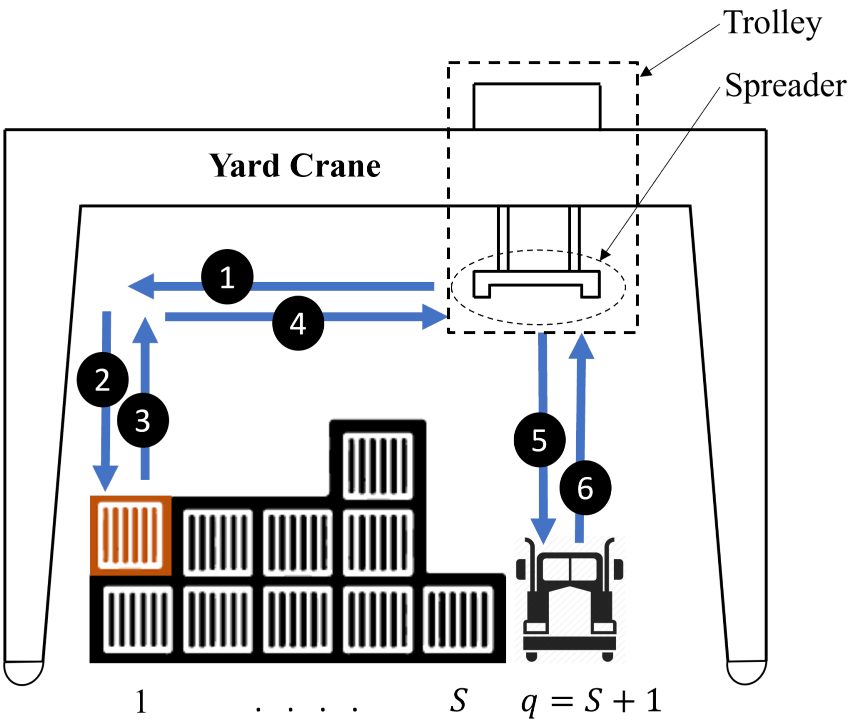


Figure 4.6: Yard crane moves while handling containers at the bay

Now, We define the following decision variables for the crane moves:

h_i : The time required by the crane to move the container i horizontally; either for relocation or retrieval (time for steps 1 and 4 in Figure 4.6).

$$h_i = 2t_s \left| \sum_{r\in\mathscr{R}} \sum_{\tau\in\mathscr{V}} \sum_{t\in\mathscr{T}} \left(\sum_{s\in\mathscr{S}} s x_{isr\tau} - \sum_{s\in\mathscr{S}'} s y_{isr\tau} \right) \right|, \qquad \forall i \in \mathscr{N} \tag{4.26}$$

v_i : The time required by the crane to move the container i vertically; either for relocation or retrieval (time for steps 2, 3, 5 and 6 in Figure 4.6). We assume that the crane travels horizontally at a level above the maximum bay height $(H+1)$ even if the bay does not have any fully occupied stacks.

$$v_i = t_r \sum_{\tau\in\mathscr{V}} \sum_{t\in\mathscr{T}} \left(\sum_{s\in\mathscr{S}} \sum_{r\in\mathscr{R}} (H+1-r) x_{isr\tau} + \sum_{s\in\mathscr{S}'} \sum_{r\in\mathscr{R}} (H+1-r) y_{isr\tau} \right), \qquad \forall i \in \mathscr{N} \tag{4.27}$$

The objective function that optimizes the crane working time can be defined as follows:

$$\hat{f}_1 = \sum_{i\in\mathscr{N}} (h_i + v_i)$$

The mathematical formulation is modified to consider the replacement of variable $z_{i\tau}^t$ with the variable $y_{i(q,1)\tau}^t$ and the definition of the extra stack q. The new YC time model consists of most of constraints from the previous formulation (*subsection 4.4.1*), but some constraints are reformulated as follows:

$$\lambda_i = \sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} t y_{i(q,1)\tau}^t, \qquad \forall i \in \mathscr{N}_a \tag{4.28}$$

$$\sum_{i \in \mathscr{N}_a} y_{i(q,1)\tau}^t \leq L, \qquad \forall \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.29}$$

$$\sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} y_{i(q,1)\tau}^t = 1, \qquad \forall i \in \mathscr{N}_a \tag{4.30}$$

$$\sum_{\tau \in \mathscr{V}} \sum_{t \in \mathscr{T}} y_{i(q,1)\tau}^t \leq 0, \qquad \forall i \in \mathscr{N}_u \tag{4.31}$$

$$\sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} \sum_{\tau' \in \mathscr{V} \setminus 1} u_{isr\tau'}^t + \sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} \sum_{\tau' \in \mathscr{V}} \sum_{t' \in \mathscr{T} \setminus 1} u_{isr\tau'}^{t'} \leq \sigma T (1 - y_{i(q,1)\tau}^t), \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.32}$$

$$\sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} x_{isr\tau}^t = \sum_{s \in \mathscr{S}} \sum_{r \in \mathscr{R}} y_{isr\tau}^t + y_{i(q,1)\tau}^t, \qquad \forall i \in \mathscr{N}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.33}$$

$$y_{isr\tau} \in \{0,1\}, \qquad \forall i \in \mathscr{N}, s \in \mathscr{S}' : \mathscr{S}' = \mathscr{S} \cup \{q\}, r \in \mathscr{R}, \tau \in \mathscr{V}, t \in \mathscr{T} \tag{4.34}$$

Constraints (4.28) to (4.34) correspond to constraints (4.1), (4.5), (4.6), (4.7), (4.14), (4.16), and (4.22) , in sequence. In the next section, we first focus on studying the original model introduced in *subsection 4.4.1.* After that, we test the model as the yard crane time ($\hat{f}_1$) is considered the primary objective in the lexicographical function. Finally, we introduce an analytical experiment to compare the lexicographical approach with the weighted objective function model.

4.5 Experimental Work

We tested the performance of our model by applying it to a case study involving an operational Japanese container terminal. The case study not only allows us to realistically examine the applicability of our approach to an existing container terminal, but also motivates a comparison study to show the benefits of the proposed approach over existing practices in other similar terminals where appointment scheduling is not considered part of the truck arrival management system, and container handling operations are not synchronized with truck arrivals.

4.5.1 The Case of a Japanese Container Terminal

At the terminal in our study, trucks arrive randomly at their preferred times and join the gate queues. As in most terminals, the policy is to serve the arriving trucks following the FCFS rule. As a result, drivers strive to reach the terminal at their earliest possible time to get favorable places in the long queue, hoping to meet their schedule of container delivery to their customers. Gate operators allow the queued trucks to proceed to their designated bay once the yard crane is available. The terminal works approximately 8 hours per day for container delivery and pickup operations, with a one-hour break (from 12:00 pm to 1:00 pm). During this break time, trucks cannot access the terminal, while other vessel operations continue. In the bays, import and export containers are held separately in order to facilitate handling operations. The crane operator serves the arriving trucks at the bay based on the FCFS rule.

At the bay, when a truck arrives to pick up its import container, the container is immediately loaded onto the truck if the container is not positioned under other containers. Otherwise, any blocking containers will need to be relocated. The relocation process follows a simple rule-based heuristic: the crane operator looks for the lowest stack in the bay to which it can relocate the blocking container. If there is more than one stack with the same lowest height, the nearest stack to the target container stack will receive the blocking container. However, if there is more than one stack with the same lowest height and these stacks are at the same distance from the target container, the terminal operator can choose either/any of the stacks. The relocation process continues until the target container is reached, then loaded onto the truck. The next waiting truck is served in the same manner. It should be noted that the crane operator chooses the Lowest and Nearest Stack to the target container when relocating a blocking container, hence we call this the ***LNS Algorithm***.

We simulate this online container handling process as a greedy heuristic algorithm, labeling it Algorithm 1 (see below). Here, we assume that the containers that will be picked up (i.e., the trucks that arrive at the terminal) correspond to the containers that have appointments ($\mathscr{N}_a$) as described in our approach, and that the random arrival times of the trucks correspond to the preferred appointment times

(p_i). Later in this section, we compare our proposed approach to the LNS algorithm.

Algorithm 1: LNS greedy heuristic for online container relocation

This greedy algorithm decides on the relocation actions based on the arrival time and order of trucks at a specific bay

Input: bay layout (I_{isr}) and set of targeted containers $\mathcal{N}_a$

while $\mathcal{N}_a \neq \emptyset$ ***do***
  for $t = \{1, .. T\}$ ***do***
    if $t \in \mathcal{T}_{out}$ ***then***
      Trucks wait outside the yard until $t = t + 1$
    else
      Initialize random truck arrivals at $p_i = t$ (container $i \equiv$ truck i)
      Truck $i \in \mathcal{N}_a$ arrives at the bay to pick up container i from slot (s, r)
      if the slot $(s, r^{'})$, $\forall$ $r^{'} = \{r + 1 \ldots H\}$ above container i is empty ***then***
        Load the container i to the truck i
        Update the bay layout
      else (container i is blocked) ***do***
        while container i in the slot (s, r) is blocked ***do***
          Find the set of lowest stacks $\mathcal{S}_{low}$ in the bay $| \mathcal{S}_{low} \subseteq \mathcal{S}, s \notin \mathcal{S}_{low}$
          if $|\mathcal{S}_{low}| = 1$ ***then***
            Relocate the topmost blocking container to stack $\hat{s}$=$\mathcal{S}_{low}$
            Update the bay layout
          else
            Find nearest stack to the stack s: $\mathcal{S}_{Near} \subseteq \mathcal{S}_{low} \leftarrow s^{'} \in \mathcal{S}_{Near}$ if $|s^{'} - s| = min\ distance, \forall s^{'} \in \mathcal{S}_{low}$ ($|\mathcal{S}_{near}| = 1$ or 2)
            if $|\mathcal{S}_{near}| = 1$ **then**
              Relocate the topmost blocking container in the stack s to stack $s^{'}$=$\mathcal{S}_{near}$
              Update the bay layout
            else
              Select random stack $s^{'} \in \mathcal{S}_{near}$ (either the left or the right stack to the target stack s)
              Relocate the topmost blocking container to stack $s^{'}$
              Update the bay layout
            end if
          end if
        end while
      end if
    end if
  end for
end while

Output: container relocations sequence

4.5.2 Instances generation

Our proposed approach is generalized for the bi-objective (lexicographical) optimization of container relocations and pickup appointment scheduling. We used the case study to set the input parameters for the DSS and produce random instances to evaluate the proposed model. Accordingly, the planning horizon T in the terminal is defined in terms of eight working hours or time windows (time window $=$ 60 min) from 9:00 am – 5:00 pm. Time window $t4$ is a fixed out-of-service (break) time window; trucks can access the terminal during any other time window. We assume that each time window is further divided into two time intervals ($\sigma = 2$) such that the time interval length is 30 minutes.

At the terminal yard, a bay is designed to accommodate a maximum of six containers horizontally and four containers vertically, so that in our instances, we define $S \times H = 6 \times 4$. Consequently, 24 slots are formed. We introduce three different occupancy levels for the 6×4 bay configuration: high occupancy, with $(H-1)$ empty slots; medium occupancy, with $2(H-1)$ empty slots; and low occupancy, with $3(H-1)$ empty slots. The empty slots are intentionally created to enable relocations since there is no available space outside the bay. For each instance, the bay is assumed to have random stack heights of zero (empty stack) to four containers (full stack) to accommodate the total number of containers N.

In the illustrative instances, we assumed a wide range of appointment ratios for each occupancy level, starting from only 10% of the containers that are requested for pickup, up to 100% of the containers requested for pickup. The number of appointed containers N_a is derived as $N_a = \lceil \text{appointment ratio} \times N \rceil$; the remainder will be the unappointed containers. Containers in the set of unappointed containers N_u are randomly withdrawn from the set of all containers $N = \{1, \ldots, N\}$ so that $\mathscr{N}_u = \mathscr{N} \setminus \mathscr{N}_a$. The maximum number of trucks that can wait at a particular bay is defined as two trucks ($L = 2$) in each time interval, leading to a maximum of four container pickups per time window at that bay. Moreover, the total number of crane container moves, including both relocations and retrievals, is set at six moves per time window at any bay ($C = 6$).

We assumed that trucking companies develop a same-day container delivery schedule to generate the appointment requests for the appointed containers. In most Japanese terminals, containers are typically shipped to the terminal nearest to the customers' destinations, as most of the coastal cities have container terminals. This means that a container will be picked up from the terminal between time window $t1$

and $t8$ (preferred container pickup period), and that the container will be delivered to the customer between time window $t2$ (earliest) and $t12$ (latest). To consider the randomness in the appointment requests when generating the instances, we set the discrete ranges in which the various parameters will take on a random value as follows: between $t2$ and $t4$ for the earliest container pickup time (e_i); between $t1$ and $t8$ (terminal working hours) for the preferred appointment time (p_i); from one hour (one time window) to four hours for the container delivery time from the terminal to the customer (d_i); and, finally, between $t8$ and $t12$ for the latest container delivery time (l_i). We randomly generated 1500 instances: 500 for each occupancy level (High, Medium, and Low) with ten appointment ratios (from 10%to100%), each having 50 instances. For simplicity, the uniform distribution was used to generate the parameter values for each of the instances according to the above-described settings.

4.5.3 Numerical Experiments and Discussion

We used the CPLEX solver to solve the generated instances on a PC with Intel Core™ i7-8700 CPU 3.20 GHz and 32.0 GB of RAM running under OS 64-bit Windows 10. The LNS greedy algorithm was coded in the Python programming language. Table 4.2 to Table 4.4 show the results of the solved instances. In each table, columns (1)-(3) show the results of the optimization model, and columns (4)-(6) show the results of the *LNS heuristic*. The averages (determined for the 50 instances for each appointment ratio) for objective function f_1 (container relocations) and objective function f_2 (average appointment shift) are given in columns (1) and (2), respectively. Column (3) shows the computational time for the optimization model. For the bi-objective optimization model, the results indicate that all instances could be solved within a reasonable time, keeping in mind that the computational process could be performed only after all appointment requests are received (one day prior).

We used the *LNS heuristic* algorithm to solve the same instances that were solved with the optimization model. In this greedy heuristic algorithm, containers will be picked up according to their preferred appointment times (p_i) and the crane operator follows the steps mentioned above in Algorithm 1. The container retrieval process is performed based on FCFS for trucks arriving at the same time window, where the truck arrival process is assumed to be random (step 6 in Algorithm 1). When searching for empty slots for relocating blocking containers in the bay, it may be the case that the crane operator will choose a random stack, as shown in step 23 in Algorithm 1. To consider this randomness, for each instance, we ran the LNS Algorithm 100 times (100 iterations), and the minimum, maximum and average number of relocations were determined. In Table 4.2 - Table 4.4, columns (4), (5), and (6) show, respectively, the average values of the minimum, maximum and average number of container relocations for every 50 instances (each with 100 iterations) corresponding to the appointment ratio. The computational time was less than 1 second for each instance in the simulation experiment.

Table 4.2: Results for the bay with high occupancy.

App.	***Proposed Bi-Objective Optimization model***			***LNS Greedy Heuristic***		
Ratio	*f1 Avg.* (1)	*f2 Avg.* (2)	*Time* (*s*) (3)	*Min Rel.* (4)	*Max Rel.* (5)	*Avg. Rel.* (6)
10%	3.42	0.87	36.44	3.8	3.9	3.86
20%	4.70	0.91	165.21	6.22	6.88	6.55
30%	5.30	1.08	502.20	7.96	9.52	8.69
40%	5.14	1.08	459.10	8.76	11.44	9.99
50%	5.26	1.04	548.63	10.58	14.3	12.21
60%	5.04	1.15	712.44	11.22	16.54	13.64
70%	3.76	1.22	217.05	11.46	17.98	14.45
80%	2.60	1.19	38.45	11.42	18.86	14.88
90%	1.64	1.23	8.05	11.56	18.78	15.11
100%	0.06	1.40	0.25	11.16	19.27	14.85

Figure 4.7 shows the number of container relocations obtained from the bi-objective IP model and the *LNS heuristic* for each of the three occupancy rates. As can be seen in the figure, the minimum number of container relocations determined by the *LNS heuristic* is consistently larger than the number of relocations decided by the proposed approach. The only exception is in those few instances in which the appointment ratio is very low (10% or 20%). For such low appointment ratios, this seems quite reasonable given that the container blocking mainly results from the unappointed containers. Even the proposed optimization model cannot avoid relocating the unappointed containers if those containers are located above the appointed ones. However, interestingly, as the number of appointed containers

increases, the number of required relocations generally decreases with the proposed optimization approach, especially for appointment ratios from 60% to 100%. On the other hand, with the *LNS heuristic*, the minimum number of relocations always increases when more containers are demanded.

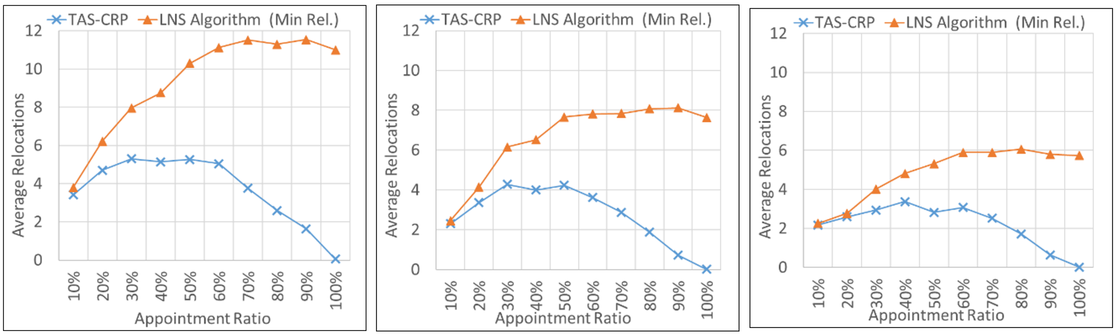
Table 4.3: Results for the bay with medium occupancy.

App. Ratio	***Proposed Bi-Objective Optimization Model*** *f1 Avg.* (1)	*f2 Avg.* (2)	*Time* (*s*) (3)	***LNS Greedy Algorithm*** *Min Rel.* (4)	*Max Rel.* (5)	*Avg. Rel.* (6)
10%	2.3	0.33	2.01	2.5	2.6	2.54
20%	3.36	0.67	7.09	4.14	4.46	4.29
30%	4.28	0.81	112.19	6.16	7.34	6.71
40%	4	0.81	45.01	6.52	8.52	7.47
50%	4.24	0.90	108.93	7.64	10.32	8.87
60%	3.62	0.94	72.99	7.82	11.04	9.30
70%	2.88	1.02	118.69	7.86	12.26	9.80
80%	1.88	1.02	8.06	8.12	13.08	10.36
90%	0.72	1.11	1.98	8.16	13.36	10.49
100%	0.02	1.08	0.14	7.62	13.04	10.08

Table 4.4: Results for the bay with low occupancy.

App. Ratio	***Proposed Bi-Objective Optimization Model*** *f1 Avg.* (1)	*f2 Avg.* (2)	*Time* (*s*) (3)	***LNS Greedy Algorithm*** *Min Rel.* (4)	*Max Rel.* (5)	*Avg. Rel.* (6)
10%	2.18	0.41	1.34	2.3	2.3	2.27
20%	2.6	0.36	1.63	2.78	2.9	2.84
30%	2.94	0.73	7.14	4.02	4.38	4.19
40%	3.38	0.81	16.03	4.82	5.76	5.26
50%	2.82	0.80	18.33	5.32	6.74	5.96
60%	3.08	0.89	26.49	5.92	7.68	6.69
70%	2.52	0.84	17.49	5.9	8.66	7.17
80%	1.72	1.02	5.25	6.02	8.92	7.30
90%	0.64	0.99	1.46	5.78	9.36	7.38
100%	0.02	1.06	0.13	5.78	9.56	7.51

Considering panels (a), (b), and (c) in Figure 4.7 together, the results of the optimization approach reveal the following: The number of relocations increases with appointment ratios from 10% to 30%, then is relatively stable for ratios from 40% to 60%, and decreases sharply from 70% to 100%. This is unlike the results of the *LNS* *heuristic*, which show a gradual increase in relocations for appointment ratios from 10% to 50% then relative stability for ratios from 60% to 100%. Under the proposed optimization approach, the reason for the declining number of relocations when the appointment ratios are high (70% to 100%) is that when there are more containers to be picked up, container relocations can be avoided by scheduling containers in the lower bay tiers to be picked up in later time windows and time intervals than containers in the higher tiers.

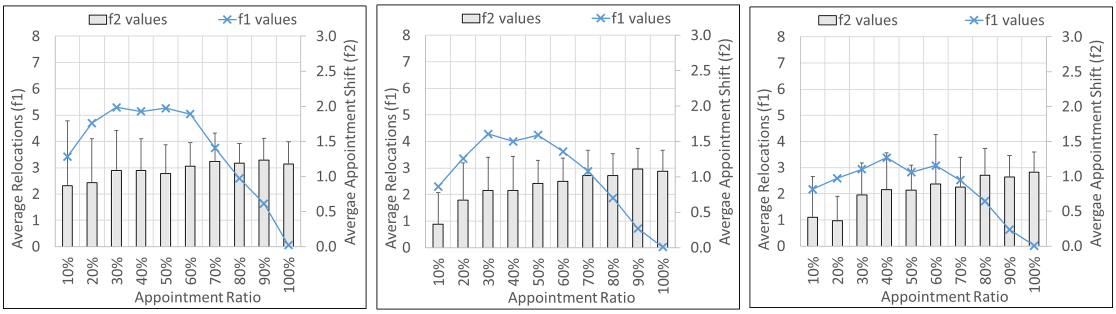


(a) High bay occupancy (b) Medium bay occupancy (c) Low bay occupancy

Figure 4.7: The average number of relocations obtained from the bi-objective optimization model and the *LNS Greedy algorithm*.

Note that changing the pickup time windows from their preferred appointment times is done while satisfying the container delivery schedule of the trucking company. Our results also show that the bay occupancy level has a noticeable impact on the number of relocations. For both the proposed optimization approach and the heuristic approach, higher bay occupancies lead to more relocations because containers are more likely to block one another when larger numbers are stacked within the limited stacking area of the bay. Finally, for the 100% appointment ratio, container relocations were completely eliminated using the optimization approach in most of the instances.

Figure 4.8 provides the basis for our investigation of how container relocations (f_1) and the average appointment shifts for the appointment containers (f_2) might be related and affected by the container appointment ratio and the bay occupancy level. Results did not indicate a unique relationship between container relocations and the average appointment shift obtained by solving the bi-objective IP model. On the other hand, the average appointment shifts show a slight increase with higher container appointment ratios. This could be explained (as mentioned above) by the fact that the more appointed containers there are, the more flexibility there will be for changing the pickup times of containers to reduce the relocations.



(a) High bay occupancy (b) Medium bay occupancy (c) Low bay occupancy

Figure 4.8: The number of relocations and appointment shifts using the optimization approach.

Generally, the appointment shift (f_2) results show that a truck could be shifted from its preferred arrival time (container pickup time) by a maximum of approximately 1.4 hours (in a bay with 100% appointments and high occupancy) and a minimum of 30 minutes (in a bay with 10% appointments and medium occupancy). While shifting the preferred pickup time specified in their appointment requests by more than one hour might seem an unpleasant scenario for the trucking companies, there are compensatory advantages. Consider the case in Figure 4.7a, where we have a 50% appointment ratio with high bay occupancy. In this case, the proposed approach avoids an average of approximately five relocations at each bay, with an average appointment shift of approximately 1 hour. When we have a yard block with 30 or 40 bays, a reduction of five relocations, on average, at each bay can save considerable time and reduce overall truck delays at the terminal.

Further study of the influence of objective function f_1 on objective function f_2 produced several interesting results. From an operational perspective, terminal operators might be curious to know the impact of performing more relocations in order to reduce the appointment shifts, and thus potentially increasing the trucking companies' satisfaction. To address this question, we changed our bi-objective model to a single objective model that minimizes appointment shifts, with the objective function f_1 inserted into the model as an inequality constraint. The left-hand side of the constraint was changed from 0 to 15, and the model determined the minimum appointment shifts for each value. The experiment was conducted for the high bay occupancy level with a 100% and 50% appointment ratio. The results displayed in Figure 4.9 show that accepting more relocations can, to some extent, reduce the appointment shift value. However, after a certain value, more relocations do not improve the situation. The main reason for this is that an appointment shift is sometimes unavoidable, as when a truck's preferred appointment is in an out-of-service time window.

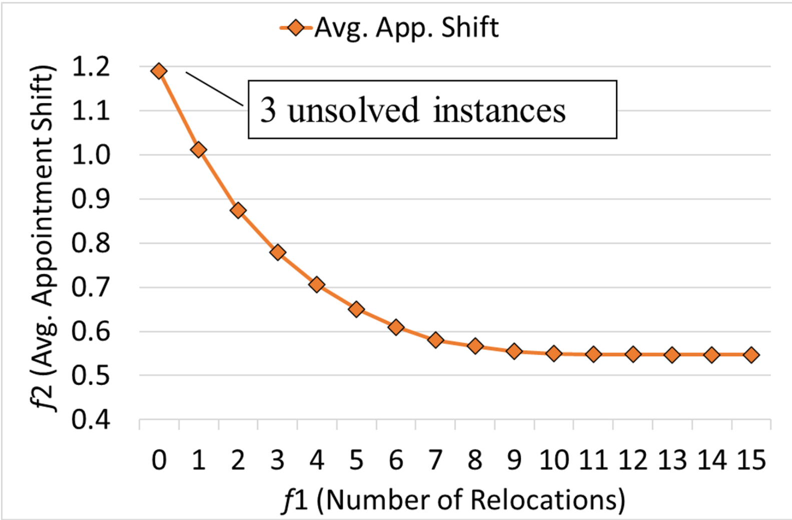
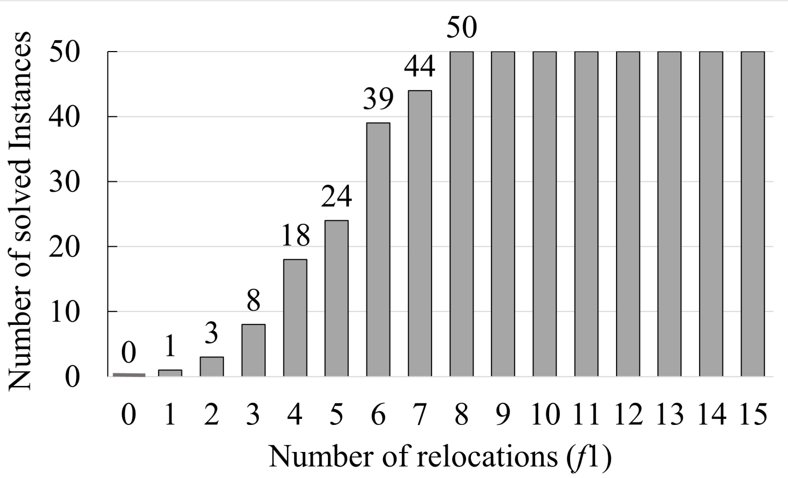


Figure 4.9: The single objective (f_2) optimization model results for a 100% appointment ratio with high bay occupancy

The results in Figure 4.9 also illustrate that not all cases reach zero relocations (there are three infeasible instances when $f_1 \leq 0$). The reason for this is that the appointment schedule for some trucks does not give sufficient flexibility to shift the appointment times in a way that prevents all relocations (see the numerical example in section 3.3). In Figure 4.10, the 50% appointment ratio results show a smaller number of instances that could be solved when the number of relocations goes below a certain level. This is understandable since unappointed containers are the primary source of unavoidable relocations. Thus, some instances are infeasible when the allowed number of relocations is limited. Based on the complete set of solved instances (i.e., 50 in all), Figure 4.10 indicates that by accepting more relocations, the model will produce fewer appointment shifts, as shown in the table below the bar chart. To sum up, this experiment gives both sides insight into the cost and benefit tradeoffs that may be available when implementing the proposed DSS. For instance, in the case of 100% appointed containers, a solution that involves four or five relocations, with an average appointment shift of 40 minutes, might be satisfactory to both the terminal and the truckers.



Number of relocations	8	9	10	11	12	13	14	15
Average Appointment shift	0.56	0.45	0.37	0.34	0.32	0.31	0.30	0.30

Figure 4.10: The single objective ($f2$) optimization model results in a 50% appointment ratio with high bay occupancy.

In our approach, we assume that trucks will follow the scheduled appointment time widows. In response to the punctual arrival times, the terminal operator will relocate containers according to the pre-determined container handling plan. However, traffic uncertainly outside the terminal may cause some trucks to not arrive within their scheduled time windows. Here, we investigate the impact of trucks' arrival unpunctuality on yard operations. In this experiment, 50 instances with a 100% appointment ratio and medium bay occupancy rate are tested under different truck arrival unpunctuality scenarios. Each scenario defines the number/percentage of deviated trucks and the time deviation. We assume five percentages of deviation: from 20% to 100%. For example, an instance with 20% deviated trucks means that 20% will not arrive at the terminal at the optimal scheduled time window, while the remaining 80% of trucks will be punctual. The arrival time deviation from the optimal appointment time window has four levels; from the light deviation (1 tw; 1 time window (tw) equals one hour) to the severe deviation (4 tw). In total, 20 scenarios are to be investigated. As mentioned previously, each truck corresponds to one container in the bay. In this experiment, using the container i index, based on the deviation percentage, the deviated trucks are randomly drawn from the set of all trucks. In addition, the “deviation time” is randomly added or subtracted (e.g., $+1tw$ or $-1tw$) from the optimal appointment time. This means that deviated trucks might arrive earlier or later than their scheduled appointed time.

The proposed bi-objective IP model is slightly modified to determine the minimum container relocations under different deviation scenarios.The decision variable (λ_i) in the model is transformed to an input parameter to define the actual container pickup time from the bay. This pickup time might be the optimal scheduled time or the deviated arrival time. We make the model a single objective IP model ($Min \sum_{i\in\mathscr{N}} \sum_{s\in\mathscr{S}} \sum_{r\in\mathscr{R}} \sum_{\tau\in\mathscr{V}} \sum_{t\in\mathscr{T}} y^t_{isr\tau}$). Some appointment scheduling constraints are omitted from the model. Those constraints are 4.2, 4.3, 4.4, 4.5, 4.24, and 4.25. Constraint 4.2 is redefined to force the retrieval time window for each container to follow the actual arrival time window (λ_i) at the bay.

The experiment results is shown in Figure 4.11. Each bar in the figure shows the average number of relocations for the 50 instances under the corresponding scenario. It can be noted that the deviated arrivals from the optimally coordinated appointment negatively impact the optimal container relocation plan. This experiment provides an insight for the terminal operator about the arrival deviation. To resolve this, the terminal operator can define the maximum deviation level that the terminal can accept before being harmed. Above that level, a penalty cost on the deviated trucks can be applied. Remember that the proposed approach already considered the trucking company preferences and container delivery schedule. Therefore, the penalty for unpunctuality is more reasonable.

We extend the experimental work to investigate the yard crane time optimization that is introduced in the *subsection 4.4.3*. The yard crane time parameters setting are taken from Lin et al., 2015, where $t_s = 1.2$ s, $t_{r0} = 2.59$ s, and $t_{r1} = 5.18$ s. A number of 20 instances (50% appointment ration in a highly occupied bay) are solved under three different objective function configurations as shown in Table 4.5. The first configuration gives the results of the original lexicographical function $LexMin(f_1, f_2)$. In this experiment, the optimal values of the container relocations

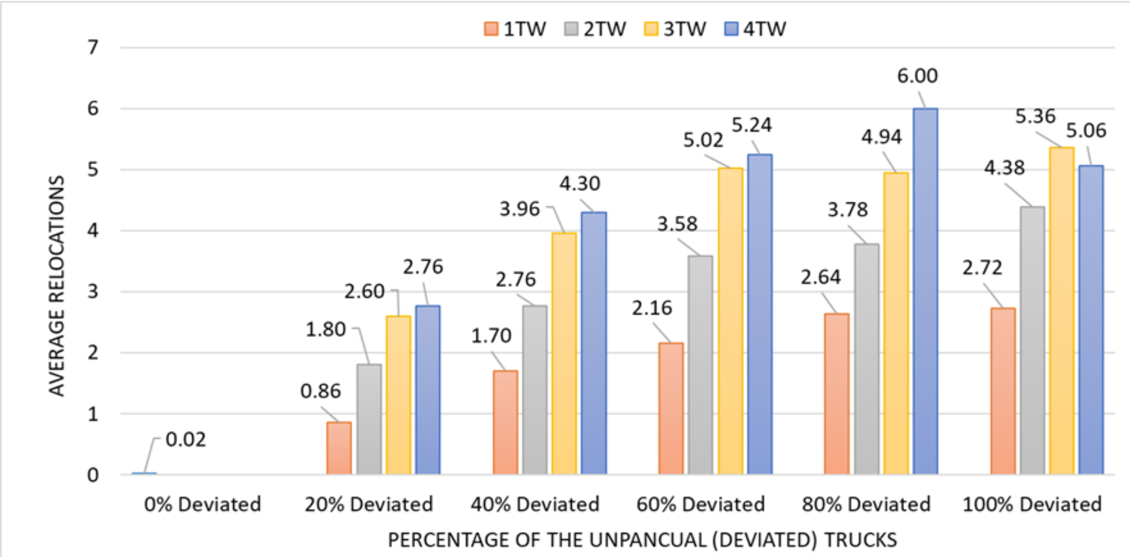


Figure 4.11: : Impact of arrival truck unpunctually on container relocations

and appointment shift (illustrated as $Opt.f_1$ and $Opt.f_2$ in columns (2) and (3) in Table 4.5, respectively) are obtained while the value of yard crane time value ($\hat{f}_1$ in column (4)) is calculated (not optimized). In the second configuration, we replace the relocation function f_1 by the yard crane time function $\hat{f}_1$ and obtain the optimal values of $\hat{f}_1$ and f_2 (columns (5) and (6) in Table 4.5) by solving the model with the objective function $LexMin(\hat{f}_1, f_2)$. The resultant values for container relocations when optimizing the yard crane time in the objective $LexMin(\hat{f}_1, f_2)$ are given in column (7) of Table 4.5.

Up to this point, the results in Table 4.5 illustrate that optimizing the yard crane time leads to the optimal value for the number of container relocations for most of the instances (compare column (2) and (7) in Table 4.5). However, the opposite is not guaranteed. This can be noted when comparing the yard crane time values ($\hat{f}_1$) in column (4) with the corresponding optimal crane time values in column (5). For the optimal value of the average appointment shift, the objective function $LexMin(f_1, f_2)$ gives better results than $LexMin(\hat{f}_1, f_2)$. This can be noted from the results shown in columns (3) and (4) in Table 4.5. Out of the 20 solved instances, 13 depicted higher average appointment shift under the $LexMin(\hat{f}_1, f_2)$ objective function.

This results inspired us to introduce the *weighted* objective function: $w_1 f_1 + \hat{w}_1 \hat{f}_1 + w_2 f_2$. The main reason that we involved both f_1 and $\hat{f}_1$ in the weighted function is that some instances may not achieve an optimal number of relocations when optimizing the yard crane time. This can be seen in instances 13 and 18 in Table 4.5. In this experiment, the model is solved with a single weighted objective function where the weights are set to be $w_1 = 0.5$, $\hat{w}_1 = 0.01$, and $w_2 = 2$. The chosen weight values are based on a trial and error approach till reaching a satisfactory result that the terminal operators and the trucking companies might accept. The results of the solved instances show that the average appointment shift can be reduced while both the number of relocations and crane time are slightly increased. In other words, terminal operators can accept that the yard crane performs one or two more relocations (or take a few more seconds during container handling), but in return, reducing the truck appointment shift that achieves more satisfaction for trucking companies. It is worth mentioning that trucking companies' satisfaction is an important performance indicator that terminal operators pay attention to achieving.

Table 4.5: Comparison between different objective functions configuration.

	Lex. Min (f_1, f_2)			***Lex. Min*** $(\widehat{f_1}, f_2)$			$(w_1 f_1 + \widehat{w}_1 \widehat{f_1} + w_2 f_2)$		
(1) Inst.	(2) *Opt.* f_1 *(Rel.)*	(3) *Opt.* f_2 *(TW)*	(4) $\widehat{f_1}$ (Sec.)	(5) *Opt.* $\widehat{f_1}$ *(Sec.)*	(6) *Opt.* f_2 *(TW)*	(7) f_1 (Rel.)	(8) *Opt.* f_1 *(Rel.)*	(9) *Opt.* $\widehat{f_1}$ *(Sec.)*	(10) *Opt.* f_2 *(TW)*
1	5	1.11	788.22	760.68	1.44	5	5	767.88	1.11
2	2	1.00	587.22	566.88	1.00	2	3	582.42	0.56
3	5	1.44	760.68	751.08	1.44	5	6	786.96	1.00
4	6	1.00	807.3	761.82	2.11	6	6	792.33	1.00
5	3	0.89	632.7	624.93	0.89	3	4	640.47	0.57
6	3	1.44	706.89	673.38	1.77	3	5	748.11	0.56
7	1	0.67	592.02	571.11	0.67	1	1	571.11	0.67
8	3	1.22	739.2	708.69	1.56	3	3	711.09	1.22
9	6	0.44	812.67	754.62	0.78	6	6	771.42	0.44
10	4	0.76	777.48	755.88	1.56	4	4	777.48	0.67
11	5	0.67	781.02	749.37	0.67	5	5	749.37	0.67
12	5	0.44	732.57	691.89	0.67	5	5	696.69	0.56
13	6	1.22	837.81	802.5	1.56	7	8	827.64	0.56
14	3	0.67	674.52	669.72	1.11	3	3	674.52	0.67
15	5	1.56	755.65	745.14	1.56	5	5	745.14	1.56
16	4	0.56	761.91	729.6	1.33	4	5	749.94	0.11
17	4	1.00	689.49	669.15	1.11	4	4	671.55	1.00
18	5	0.78	755.65	722.4	0.78	6	5	730.17	0.78
19	3	0.89	745.14	706.86	1.33	3	3	709.26	0.89
20	4	1.00	693.03	661.38	1.22	4	5	697.83	0.44
Avg.	4.10	0.94	731.56	703.85	1.23	4.20	4.55	720.07	0.75
St. Dev.	1.37	0.33	69.49	63.46	0.41	1.51	1.50	67.24	0.33

Chapter 5

Concluding Remarks

In this chapter, we conclude this thesis with insights from the proposed integrated optimization approach. We summarize the thesis contributions, emphasize our technical contributions, and discuss the future research directions.

5.1 Insights from Integrating TAS and CRP

To the best of our knowledge, the research introduced in this thesis is the first work that integrates the Container Relocation Problem (CRP) with the Truck Appointment Scheduling (TAS) problem in container terminals. Each problem belongs to a different operational area in CT. The integration is motivated by both research and practical reasons. From the research perspective, integrating optimization problems is a growing research topic in container terminals. However, most of the research efforts related to operations research models are directed to integrating the optimization problems in the seaside and yard areas with less attention to the land side. Therefore, this thesis considered new untouched areas where landside and yard area operations can be integrated.

From a practical point of view, the operational problems in container terminals are highly interdependent; the need for coordination approaches that consider the practical and realistic aspects is a fundamental necessity for practitioners. Therefore, integrating the TAS and CRP has a practical necessity since the external trucks' arrival process at the terminal landside is highly interrelated with container handling operations inside the yard. We focused in our thesis on this practical side and introduced various insights for implementation.

Generally, one of the main challenges that face integrating the optimization problems is the *problem scale* that leads to higher complexity in many cases. Therefore, the efforts in this area are very careful, especially when dealing with some hard problems like the CRP. In addition, choosing which optimization problems to integrate sometimes is unclear for practitioners. For instance, the arrival schedule of external trucks at the yard is also interrelated with the yard crane schedule that deals with the whole yard block with hundreds of containers. In our research, we developed the coordination approach, which considers both problems' complexity and reflects the implementation possibility of the integration.

In this sense, we intentionally selected the CRP to integrate with the TAS since the CRP is typically solved on the bay scale. This makes the integration more efficient than the TAS with a larger scale problem in the yard, such as a yard crane scheduling problem (YCSP). In addition, the container relocations are considered a root cause of the truck delays and crane time wast at the yard. We believe that such TAS-CRP integration will improve the performance of the yard crane since more yard crane time can be saved when more non-value added container relocations are avoided.

From the perspective of integration performance vs. separability, we also showed how the integration could achieve better performance than the existing separated practices. However, this requires a certain level of implementation applicability; integrating the TAS with CRP might be difficult in some cases. An example of this is when the landside management authority is different from the yard management authority. Such a situation applies to some terminals. In addition to the possible dominance conflicts in managing the integrated system, many questions might be raised regarding the systems development and application cost. In such cases, it could smother to solve both problems hierarchically; the TAS problem first and then used its input to solve the CRP. However, this does not guarantee superior operational performance over the integrated approach.

5.2 Thesis Summary

Chapter 1 discussed the growing importance of container terminals and their role in the global supply chain. We provided background information about the container terminal layout, operational areas, container handling equipment, and operational problems. We highlighted the main operational optimization problems in container terminals and examples for the integrated optimization problems. At the end of the chapter, we introduce an overview of the thesis.

In Chapter 2, we described the two optimization problems: the truck appointment scheduling problem and the container relocation problem. For each problem, we highlighted the related research work in the literature and discussed some research gaps. Finally, we explain in more detail the motivation behind our research.

In Chapter 3, we have proposed a new optimization problem: the *BRPAS*. *BRPAS* adds several new aspects to the classical BRP, with consideration given to the preferred appointment time window for each container pickup, acceptable appointment shift, yard crane capacity, and maximum queue length at the yard bay. The problem is considered a partial integration of relocation problem with appointment scheduling problems by considering the possibility of shifting the appointments within acceptable limits. To formulate the problem, two binary integer programming models, $BRPAS(1)$ and $BRPAS(2)$ were proposed. The proposed models are extended to give more flexibility to yard operators servicing arriving trucks within the same appointment time window using the FCFS strategy under relocation minimization.

To demonstrate the method, several instances involving different bay sizes and configurations were solved. It was found that $BRPAS(2)$ formulation outperformed $BRPAS(1)$ formulations in terms of computational time. The flexible *BRPAS* achieved container retrieval flexibility with high computational performance. Results also showed that coordinating appointments with container handling operations at the bay can reduce the number of relocations, which, in turn, impacts truck delays.

Chapter 4 introduced a new DSS that is quite different from the current appointment systems. The proposed DSS addresses one of the root causes of truck delays in import container pickup and delivery by coordinating truck arrival times and service orders with container handling operations at the yard. The idea is to schedule container appointments and pickup orders in a way that has the upper containers in a particular bay being picked up before the lower containers in that same bay. To this end, we developed a bi-objective optimization model that considers some of the more realistic aspects of the appointment scheduling problem and the container relocation problem. These aspects include the trucking companies' preferred appointment times and container delivery schedules, the capacity of the yard crane and bay area, and the possibility of partial appointment levels for containers in the same bay. We further considered the yard crane time optimization and extended the proposed bi-objective model to consider one more objective function.

A case study was used to generate the input instances used to illustrate and analyze the proposed model. Model results were compared to existing practices in terminals operating without such a coordinated appointment scheduling and container handling system. The results show that container relocations could be substantially reduced, with an average shift in preferred appointment times of less than two time windows. It was also found that, under different appointment ratios, having more containers requested for pickup does not increase relocations but, on the contrary, leads to fewer relocations without affecting the average appointment shift. It was shown that yard operators could not completely avoid container relocations, especially when unappointed containers were in the bay. Finally, we solved the proposed models in this thesis under different objective function configurations. Results illustrated that to reduce the truck appointment shift; the terminal operators will accept more relocations and crane time (slight increase in most cases) to achieve this goal.

5.3 Future Research Directions

5.3.1 Future Extensions From the Thesis

In the BRPAS(1) and BRPAS(2) proposed in Section 3.4, the number of container moves (stages) required to relocate and retrieve all containers in the bay provides an upper bounds for the problem. It will be interesting to study better upper and lower bound for these formulations. This will help applying other exact approaches such as branch-and-bound or branch-and-cut to solve the BRPAS. More generally, more efficient methods will be interesting to develop to solve large-size instances. In addition, developing a distributive management system for the deviation from the scheduled appointment can also be helpful to overcome trucks arrival uncertainty. This might be considered in two ways. First, to apply a penalty cost for deviated arrivals and include this penalty in the mathematical model. Second, to consider the probabilistic arrival process and solve the problem under uncertainty. However, the latter increases the problem complexity.

In the fully integrated problem formulation introduced in Section 4.4, considering other objectives such as truck waiting time or truck delays will be interesting from the practical perspective. However, one should keep in mind that formulating the waiting time based on queuing theory might increase the problem complexity and impact the linearity of the mathematical formulation. Finally, the *LNS algorithm* introduced in Section 4.5 determines only the number of relocations under the random arrivals and compares it with the proposed optimization approach. However, it will be interesting to extend the *LNS heuristic* to consider the appointment scheduling so that the comparison opens more insights for the deployment of a heuristic approach vs. the optimization approach.

5.3.2 Future Insights for Container Terminal Related Research

Since the COVID-19 pandemic hit the world, the global supply chain has been struggling, and container terminal operations have been severely affected by supply and demand uncertainty. Therefore, it is necessary to develop a robust approach to dealing with such harsh supply chain fluctuations. From an Operational Research point of view, it will be beneficial for container terminal operators to implement predictive models to evaluate the delays, expected congestion, etc. It will also be interesting to study how such predictive models can be implemented along with optimization approaches. The predictive approaches may also require process a lot of data to make good predictions. As a result, research related to using the massive amount of data recorded daily for port operations will be exciting when related to the existing practical aspects. Approaches from the AI field could be adopted and developed to achieve more intelligence in optimizing terminal operations.

Bibliography

Abou Kasm, O., Diabat, A., & Cheng, T. (2020). The integrated berth allocation, quay crane assignment and scheduling problem: Mathematical formulations and a case study. *Annals of Operations Research*, *291*(1), 435–461.

Azab, A. (2021). Data set : The block relocation problem with appointment scheduling (brpas) [Mendeley Data, V1]. https://doi.org/10.17632/wctcbp5z4h.1

Azab, A., Karam, A., & Eltawil, A. (2018). Impact of collaborative external truck scheduling on yard efficiency in container terminals. *International Conference on Operations Research and Enterprise Systems*, 105–128.

Azab, A., Karam, A., & Eltawil, A. (2020). A simulation-based optimization approach for external trucks appointment scheduling in container terminals. *International Journal of Modelling and Simulation*, *40*(5), 321–338.

Azab, A., & Morita, H. (2021). The block relocation problem with appointment scheduling. *European Journal of Operational Research*. https://doi.org/10.1016/j.ejor.2021.06.007

Azab, A. E., & Eltawil, A. B. (2016). A simulation based study of the effect of truck arrival patterns on truck turn time in container terminals. *ECMS*, 80–86.

Bacci, T., Mattia, S., & Ventura, P. (2019). The bounded beam search algorithm for the block relocation problem. *Computers & Operations Research*, *103*, 252–264.

Bacci, T., Mattia, S., & Ventura, P. (2020). A branch-and-cut algorithm for the restricted block relocation problem. *European Journal of Operational Research*, *287*(2), 452–459.

Borjian, S., Manshadi, V., Barnhart, C., & Jaillet, P. (2013). Dynamic stochastic optimization of reshuffles in container terminals. *Manufacturing and Service Operations Management (MSOM) conference.*

Borjian, S., Galle, V., Manshadi, V. H., Barnhart, C., & Jaillet, P. (2015). Container relocation problem: Approximation, asymptotic, and incomplete information. *arXiv preprint arXiv:1505.04229*.

Caballini, C., Gracia, M. D., Mar-Ortiz, J., & Sacone, S. (2020). A combined data mining–optimization approach to manage trucks operations in container terminals with the use of a tas: Application to an italian and a mexican port. *Transportation Research Part E: Logistics and Transportation Review*, *142*, 102054.

Caserta, M., Schwarze, S., & Voß, S. (2009). A new binary description of the blocks relocation problem and benefits in a look ahead heuristic. *European Conference on Evolutionary Computation in Combinatorial Optimization*, 37–48.

Caserta, M., Schwarze, S., & Voß, S. (2011). Container rehandling at maritime container terminals. *Handbook of terminal planning* (pp. 247–269). Springer.

Caserta, M., Schwarze, S., & Voß, S. (2012). A mathematical formulation and complexity considerations for the blocks relocation problem. *European Journal of Operational Research*, *219*(1), 96–104.

Caserta, M., Voß, S., & Sniedovich, M. (2011). Applying the corridor method to a blocks relocation problem. *OR spectrum*, *33*(4), 915–929.

Chen, G., Govindan, K., & Yang, Z. (2013). Managing truck arrivals with time windows to alleviate gate congestion at container terminals. *International Journal of Production Economics*, *141*(1), 179–188.

Chen, G., Govindan, K., Yang, Z.-Z., Choi, T.-M., & Jiang, L. (2013). Terminal appointment system design by non-stationary m (t)/ek/c (t) queueing model and genetic algorithm. *International Journal of Production Economics*, *146*(2), 694–703.

da Silva, M. d. M., Erdoğan, G., Battarra, M., & Strusevich, V. (2018). The block retrieval problem. *European Journal of Operational Research*, *265*(3), 931–950.

da Silva, M. d. M., Toulouse, S., & Calvo, R. W. (2018). A new effective unified model for solving the pre-marshalling and block relocation problems. *European Journal of Operational Research*, *271*(1), 40–56.

Do, N. A. D., Nielsen, I. E., Chen, G., & Nielsen, P. (2016). A simulation-based genetic algorithm approach for reducing emissions from import container pick-up operation at container terminal. *Annals of Operations Research*, *242*(2), 285–301.

Eskandari, H., & Azari, E. (2015). Notes on mathematical formulation and complexity considerations for blocks relocation problem.

Expósito-Izquierdo, C., Melián-Batista, B., & Moreno-Vega, J. M. (2014). A domain-specific knowledge-based heuristic for the blocks relocation problem. *Advanced Engineering Informatics*, *28*(4), 327–343.

Expósito-Izquierdo, C., Melián-Batista, B., & Moreno-Vega, J. M. (2015). An exact approach for the blocks relocation problem. *Expert Systems with Applications*, *42*(17-18), 6408–6422.

Feillet, D., Parragh, S. N., & Tricoire, F. (2019). A local-search based heuristic for the unrestricted block relocation problem. *Computers & Operations Research*, *108*, 44–56.

Feng, Y., Song, D.-P., Li, D., & Zeng, Q. (2020). The stochastic container relocation problem with flexible service policies. *Transportation Research Part B: Methodological*, *141*, 116–163.

Forster, F., & Bortfeldt, A. (2012). A tree search procedure for the container relocation problem. *Computers & Operations Research*, *39*(2), 299–309.

Galle, V., Barnhart, C., & Jaillet, P. (2018a). A new binary formulation of the restricted container relocation problem based on a binary encoding of configurations. *European Journal of Operational Research*, *267*(2), 467–477.

Galle, V., Barnhart, C., & Jaillet, P. (2018b). Yard crane scheduling for container storage, retrieval, and relocation. *European Journal of Operational Research*, *271*(1), 288–316.

Galle, V., Manshadi, V. H., Boroujeni, S. B., Barnhart, C., & Jaillet, P. (2018). The stochastic container relocation problem. *Transportation Science*, *52*(5), 1035–1058.

Gharehgozli, A. H., Roy, D., & De Koster, R. (2016). Sea container terminals: New technologies and or models. *Maritime Economics & Logistics*, *18*(2), 103–140.

Heilig, L., & Voß, S. (2017). Information systems in seaports: A categorization and overview. *Information Technology and Management*, *18*(3), 179–201.

Hop, D. C., Van Hop, N., & Anh, T. T. M. (2021). Adaptive particle swarm optimization for integrated quay crane and yard truck scheduling problem. *Computers & Industrial Engineering*, *153*, 107075.

Huynh, N., Smith, D., & Harder, F. (2016). Truck appointment systems: Where we are and where to go from here. *Transportation Research Record*, *2548*(1), 1–9.

Huynh, N., & Walton, C. M. (2008). Robust scheduling of truck arrivals at marine container terminals. *Journal of transportation engineering*, *134*(8), 347–353.

Ji, M., Guo, W., Zhu, H., & Yang, Y. (2015). Optimization of loading sequence and rehandling strategy for multi-quay crane operations in container terminals. *Transportation Research Part E: Logistics and Transportation Review*, *80*, 1–19.

Jovanovic, R., Tanaka, S., Nishi, T., & Voß, S. (2019). A grasp approach for solving the blocks relocation problem with stowage plan. *Flexible Services and Manufacturing Journal*, *31*(3), 702–729.

Jovanovic, R., Tuba, M., & Voß, S. (2017). A multi-heuristic approach for solving the pre-marshalling problem. *Central European Journal of Operations Research*, *25*(1), 1–28.

Jovanovic, R., Tuba, M., & Voß, S. (2019). An efficient ant colony optimization algorithm for the blocks relocation problem. *European Journal of Operational Research*, *274*(1), 78–90.

Jovanovic, R., & Voß, S. (2014). A chain heuristic for the blocks relocation problem. *Computers & Industrial Engineering*, *75*, 79–86.

Kim, K. H., & Hong, G.-P. (2006). A heuristic rule for relocating blocks. *Computers & Operations Research*, *33*(4), 940–954.

Kim, K. H., & Park, K. T. (2003). A note on a dynamic space-allocation method for outbound containers. *European Journal of Operational Research*, *148*(1), 92–101.

Kizilay, D., & Eliiyi, D. T. (2021). A comprehensive review of quay crane scheduling, yard operations and integrations thereof in container terminals. *Flexible Services & Manufacturing Journal*, *33*(1).

Ku, D., & Arthanari, T. S. (2016a). Container relocation problem with time windows for container departure. *European Journal of Operational Research*, *252*(3), 1031–1039.

Ku, D., & Arthanari, T. S. (2016b). On the abstraction method for the container relocation problem. *Computers & Operations Research*, *68*, 110–122.

Lin, D.-Y., Lee, Y.-J., & Lee, Y. (2015). The container retrieval problem with respect to relocation. *Transportation Research Part C: Emerging Technologies*, *52*, 132–143.

Lu, C., Zeng, B., & Liu, S. (2020). A study on the block relocation problem: Lower bound derivations and strong formulations. *IEEE Transactions on Automation Science and Engineering*, *17*(4), 1829–1853.

Ma, M., Fan, H., Jiang, X., & Guo, Z. (2019). Truck arrivals scheduling with vessel dependent time windows to reduce carbon emissions. *Sustainability*, *11*(22), 6410.

Monaco, M. F., Moccia, L., & Sammarra, M. (2009). Operations research for the management of a transhipment container terminal: The gioia tauro case. *Maritime Economics & Logistics*, *11*(1), 7–35.

Morais, P., & Lord, E. (2006). Terminal appointment system study. transport canada publication tp 14570e. *Transportation Development Centre of Transport Canada*.

Petering, M. E., & Hussein, M. I. (2013). A new mixed integer program and extended look-ahead heuristic algorithm for the block relocation problem. *European Journal of Operational Research*, *231*(1), 120–130.

Phan, M.-H., & Kim, K. H. (2015). Negotiating truck arrival times among trucking companies and a container terminal. *Transportation Research Part E: Logistics and Transportation Review*, *75*, 132–144.

Phan, M.-H., & Kim, K. H. (2016). Collaborative truck scheduling and appointments for trucking companies and container terminals. *Transportation Research Part B: Methodological*, *86*, 37–50.

Ramírez-Nafarrate, A., González-Ramírez, R. G., Smith, N. R., Guerra-Olivares, R., & Voß, S. (2017). Impact on yard efficiency of a truck appointment system for a port terminal. *Annals of Operations Research*, *258*(2), 195–216.

Skaf, A., Lamrous, S., Hammoudan, Z., & Manier, M.-A. (2021). Integrated quay crane and yard truck scheduling problem at port of tripoli-lebanon. *Computers & Industrial Engineering*, *159*, 107448.

Tanaka, S., & Mizuno, F. (2018). An exact algorithm for the unrestricted block relocation problem. *Computers & Operations Research*, *95*, 12–31.

Tanaka, S., & Takii, K. (2016). A faster branch-and-bound algorithm for the block relocation problem. *IEEE Transactions on Automation Science and Engineering*, *13*(1), 181–190.

Tanaka, S., & Voß, S. (2019). An exact algorithm for the block relocation problem with a stowage plan. *European Journal of Operational Research*, *279*(3), 767–781.

Tanaka, S., & Voß, S. (2022). An exact approach to the restricted block relocation problem based on a new integer programming formulation. *European Journal of Operational Research*, *296*(2), 485–503.

Taner, M. E., Kulak, O., & Koyuncuoğlu, M. U. (2014). Layout analysis affecting strategic decisions in artificial container terminals. *Computers & Industrial Engineering*, *75*, 1–12.

Ting, C.-J., & Wu, K.-C. (2017). Optimizing container relocation operations at container yards with beam search. *Transportation Research Part E: Logistics and Transportation Review*, *103*, 17–31.

Torkjazi, M., Huynh, N., & Shiri, S. (2018). Truck appointment systems considering impact to drayage truck tours. *Transportation Research Part E: Logistics and Transportation Review*, *116*, 208–228.

Tricoire, F., Scagnetti, J., & Beham, A. (2018). New insights on the block relocation problem. *Computers & Operations Research*, *89*, 127–139.

UNCTAD. (2020). *Shipping in times of the covid-19 pandemic*. The United Nations Conference on Trade and Development. https://unctad.org/webflyer/review-maritime-transport-2020

Zeng, Q., Feng, Y., & Yang, Z. (2019). Integrated optimization of pickup sequence and container rehandling based on partial truck arrival information. *Computers & Industrial Engineering*, *127*, 366–382.

Zhang, C., Guan, H., Yuan, Y., Chen, W., & Wu, T. (2020). Machine learning-driven algorithms for the container relocation problem. *Transportation Research Part B: Methodological*, *139*, 102–131.

Zhang, X., Zeng, Q., & Yang, Z. (2019). Optimization of truck appointments in container terminals. *Maritime Economics & Logistics*, *21*(1), 125–145.

Zhao, W., & Goodchild, A. V. (2010). The impact of truck arrival information on container terminal rehandling. *Transportation Research Part E: Logistics and Transportation Review*, *46*(3), 327–343.