Master Thesis
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Optimizing berth planning at container terminals utilizing shore power

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Abstract

This thesis explores the impact of shore power and berth planning on the quayside operations of container terminals, with a focus on optimizing berth planning to improve terminal performance. The primary objective is to study the extent to which an allocation algorithm can enhance berth planning for terminals utilizing shore power. Key performance indicators such as waiting time, waiting costs, and distance to berth position were used to assess the impact of shore power and planning algorithms on terminal efficiency. A simulation model, Portwise's TRAFALQUAR, was employed to evaluate various planning algorithms under realistic operational scenarios. The scenarios described typical container terminals configured with various Shore Power designs.

For this study, a simulated annealing algorithm was proposed to optimize a Greedy algorithm which uses vessel-specific waiting costs to define vessel priorities as a soft constraint. The simulated annealing algorithm is compared to TRAFALQUAR's Base berth allocation algorithm which handles vessel priorities as a hard constraint. Results indicated that the Simulated Annealing algorithm consistently provided the most robust and efficient berth schedules, outperforming the other algorithms across all evaluation metrics. Furthermore, the study revealed that shore power can significantly impact berth flexibility and deteriorate a container terminal's operations. However, advanced berth planning can mitigate the constraints set by shore power designs, and even enhance operational performance to levels comparable to terminals without shore power.

The thesis underscores the importance of integrating advanced berth planning strategies with shore power designs to optimize terminal operations and reduce the negative impact of shore power designs. Future work should focus on refining modelling assumptions to better reflect real-world conditions, exploring alternative optimization techniques, and testing a variety of shore power designs and vessel mixes to develop more generalized and effective solutions. This study provides valuable insights for terminal operators aiming to improve berth planning and implement shore power systems efficiently.

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Contents

1

Introduction

The container shipping industry is an important part of global trade and has grown exponentially over the past few decades. It is expected that the industry keeps growing in the foreseeable future as the use of containerized cargo is still gaining popularity. Container terminals are a crucial part of the container shipping supply chain, serving as hubs where goods are efficiently transferred between ships and shore. Container ships that moor at container terminals are usually propelled and powered by combustion engines and emit greenhouse gasses continuously. However, the container shipping industry is facing increasing environmental pressure and stricter regulations to reduce emissions. Shore power has been identified as an effective solution to reduce the environmental impact of ships when docked at a container terminal.

Shore power is often referred to as On-shore Power Supply (OPS). With OPS, ships are connected to the local shoreside electricity grid while docked meaning that onboard auxiliary engines can be switched off. Turning off the auxiliary engines reduces emissions, noise levels and vibrations which negatively impact the environment. When implemented, OPS would therefore be a direct measure to make ports more sustainable and future-proof.

1.1 Motivation

The Port of Rotterdam estimates that vessels at berth in Rotterdam generate approximately 600-kilo tonnes (kt) of CO_2 yearly to generate a similar amount of electricity as 250,000 to 300,000 households [1]. Stolz et al estimate that the total CO_2 emissions of all ships at berth in the EU account for approximately 5,000 kt and that the application of shoreside electricity in the EU can save up to 3,000 kt of CO_2 emissions. In the case of container vessels, Stolz et al show that the introduction of shore power could potentially reduce their total CO_2 emissions with 6.4% [2].

Consequently, OPS is part of the European Union's Fit For 55 legislation package [3] which aims to reduce greenhouse gas emissions by at least 55% in 2030. The Fit For 55 proposal states that all container vessels larger than 5,000 gross tonnes (GT) that are berthed for longer than two hours are obliged to connect to shore power from 2030 onwards unless they use an alternative zero-emission solution.[4]. With the current EU directive, all container terminals will have to comply with the OPS regulations in 2030. However, in October 2023, it was estimated that a mere 51 of the 489 ports in the EU have implemented some form of shore power [5]. Thus, many ports still need to implement OPS before 2030 to comply with EU regulations. A substantial investment is needed by the terminals to implement a shore power system. Moreover, a shore power system is not a one-size-fits-all solution. Different terminals might require different OPS designs to remain operationally efficient and maximize the sustainable advantages. Therefore, to support the investment decisions, it is valuable for a terminal operator to know what the impact of different OPS system designs can be on the terminal operations.

While the environmental benefits of shore power are well-documented, its impact on the operational efficiency of container terminals is explored to a lesser extent. Shore power mainly influences operations at the quay when vessels are docked, with quay performance strongly relying on berth planning. Berth planning determines which vessel is allowed to dock at which part of the quay. If the berth planning is done effectively it can potentially increase the number of vessels serviced by a terminal and improve the service level. Additional restrictions for berth planning apply when container ships can only dock if a shore power connection is available.

1.2 Research Objective

This thesis explores the influence of shore power and berth planning on the quayside operations of a container terminal. Ultimately, the objective is to see if an allocation algorithm can improve berth planning for a container terminal which utilizes OPS. To accomplish this, the following research question is addressed:

To what extent can berth planning be optimized to improve the performance of a container terminal with shore power?

To investigate this topic, it is important to recognize how shore power constrains berth planning and what parts of shore power infrastructure can be optimized to reduce operational constraint. Moreover, the key performance indicators of a berth schedule need to be identified to describe the effect of planning algorithms and shore power designs. A simulation model will be used to evaluate the performance of planning algorithms in detailed scenarios that mimic realistic container terminal operations.

1.3 Host organization

Portwise was founded in 1996 as part of TBA Group and became independent in 2022. Portwise is a world-leading consultancy and simulation firm for logistics in ports, terminals and warehouses. They stand for progress and impact; they work mission-driven and help transform logistics to become future and planet-proof. They use their state-of-the-art models, expertise, and skills to make a positive impact on business, people, and the planet.

This research was conducted within the simulation department of Portwise. At the simulation department, they use the self-built most accurate simulation model for container terminals in the world to investigate various design alternatives for container terminals, design optimal logistical rules and prototype new developments.

This thesis aims to contribute to Portwise's already vast inventory of knowledge of container terminals with the introduction of shore power design and berth planning optimization. A shore power module will be integrated into one of their simulation models which can potentially be used to support terminal operators in their decision-making process regarding shore power design.

1.4 Thesis structure

This report continues with Chapter 2 where context on container terminal practices is given and where a concise description is given of shore power systems and design possibilities. Chapter 3 discusses previous research on berth planning algorithms and the integration of shore power. Chapter 4 describes the methods and algorithm used to answer the research question. Chapter 5 highlights the experimental setup and model assumptions used to evaluate performance. Finally, in Chapters 6, 7 and 8 the results are presented, discussed and concluded.

2

Background

2.1 Container Terminal

A container terminal can be divided into three main sections. The gate, essentially is the entrance and exit through which containers arrive and leave via trucks. The yard is where stacks of containers are stored awaiting their next destination. Finally, the quay, where container vessels are moored and quay cranes load and unload containers from the ship. This report focuses on the operations at the quayside of a container terminal.

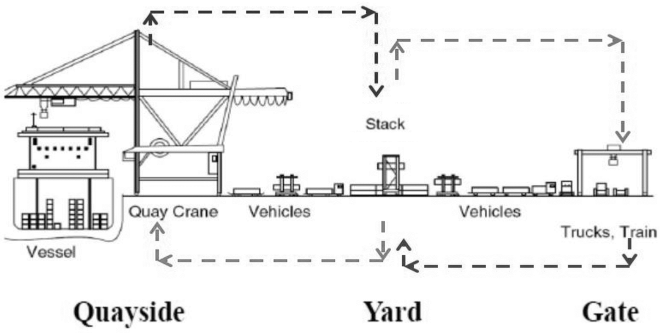

Figure 2.1: Schematic representation of a container terminal

2.1.1 Quayside operations

At the quay, vessels are docked at a berth. A quay consists of a single berth or is divided into multiple berths. Common reasons for numerous berths at a quay are different water depths, the quay having corners or berths which are reserved for specific shipping lines. A berth can be categorised as discrete or continuous. A discrete berth means that vessels can only be berthed at discrete locations. A continuous berth means that vessels can dock anywhere along the berth.

When a vessel is berthed, it is serviced by quay cranes (QC). The QC loads and unloads containers from the vessel with a certain productivity. The productivity of a QC is expressed in boxes (containers) per hour (bx/h). The height and outreach of a QC determine if the crane is suitable to serve a vessel. The productivity of a vessel is therefore determined by the number of QC that are working on the vessel and the QC productivity.

When a container vessel arrives at a port it has to wait at an anchorage point until a space to berth becomes available. Other factors can also contribute to waiting time at the anchorage point such as tides, winds or availability of tug pilots. From the anchorage point, it then makes the journey through the port to the quay, this time is referred to as the journey time. Upon arrival at the quay, the vessel starts to berth. The time it takes to berth a vessel is referred to as berthing time.

When a vessel is berthed and there are quay cranes available then the service can start. The number of containers that need to be loaded and unloaded is referred to as the call size of the vessel. The call size is dependent on the size of the vessel but is also influenced by a seasonal pattern. Moreover, a vessel needs to be serviced with a certain productivity. This required productivity is the service level on which the terminal has to operate. For example, if a vessel has a required productivity of 100 bx/h and the QC's have a productivity of 25 bx/h, then the vessel would need on average 4 QC's to reach the required service level. Once service is completed the vessel has to unberth. Only when a vessel is done unberthing, a new vessel can start the berthing process to take the unberthed vessel's place.

The sum of all call sizes in a year is the yearly volume of the container terminal and is expressed in Twenty-foot Equivalent Units (TEU). A single container is either one or two TEU which is equivalent to 20 and 40 feet respectively. Therefore, the volume is not only determined by the number of containers but also the size of the containers. The TEU factor of a terminal is the average size of all containers that are handled. For example, a TEU factor of 1.75 means that the average container is Therefore, the number of containers that have to be loaded and unloaded in a year can be calculated by dividing the yearly volume in TEU's by the TEU factor.

The set of vessels expected to arrive at a container terminal is called the vessel mix. Container ships are generally divided into three types: Barge, Feeder, and Deepsea. These differ in size, range, and function. Barges are smaller vessels used for inland waterways and short sea routes, connecting regional ports. Feeder vessels are medium-sized ships transporting containers between smaller regional ports and major hub ports. Deepsea vessels are large ships for long-haul, transoceanic voyages, carrying large quantities of containers between major international ports. For this thesis, only terminals where feeder and deepsea vessels arrive are considered since these operate within the same shore power regulations. The vessel mix also includes specific information such as length, expected call size, and required productivity.

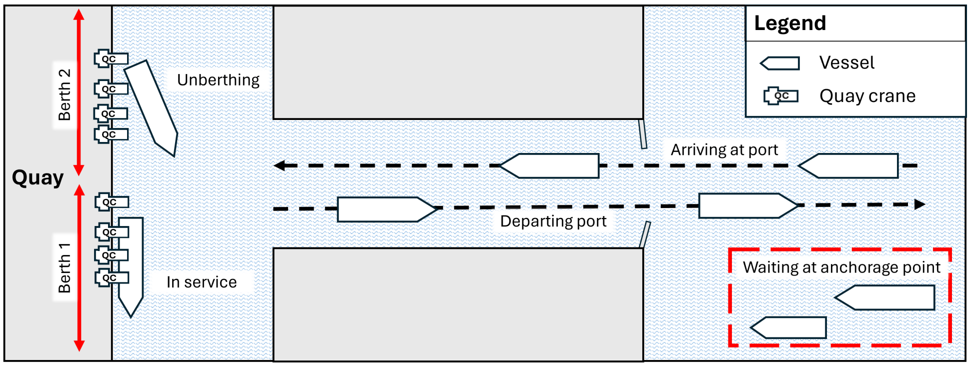

Figure 2.2: Schematic of port operations

2.1.2 A terminal's objective

Container terminals are profit-driven businesses. The revenue of container terminals is mainly generated by terminal handling charges (THC). A THC is a fee that shipping lines pay for the use of a terminal's services and facilities. Therefore, for a container terminal to be successful, it is important to ensure that shipping lines use their services and not move to a competitor.

Maintaining a competitive advantage is therefore one of the main objectives of a container terminal.

The competitiveness of a container terminal is influenced by several factors. Kaliszewski et al., Baştuğ et al and Cruz et al [6, 7, 8] found that the most significant factor for competitiveness in the eyes of shipping lines is the turnaround time of vessels. Turnaround time is the time it takes a vessel to do a round trip from one point to another. For a container terminal, the turnaround time of a vessel is the time between arriving at the port and leaving the port. This means that the turnaround time consists of the journey to the berth, berthing time, service time, unberthing time, journey time out of the port and all waiting times. Since journey time, berthing time and unberthing time are less likely to fluctuate considerably, the turnaround time is mostly impacted by service and waiting times. Thus, a container terminal will strive for efficient operations by reducing waiting and service times. Moreover, due to varying contracts with shipping lines, adhering to agreed service levels is more important for particular vessels which will get service priority.

The service level a container terminal wants to maintain is not the sole reason to minimize waiting times. Waiting times are a source of direct costs for a terminal operator. A terminal can be held responsible for the accrued costs of a shipping line if their vessel must wait at the anchorage due to inefficiencies at the quay. The costs for a waiting vessel usually consist of demurrage fees, fuel expenses and port fees. The demurrage fees are the main source of expenses since these are to be paid per delayed container. Therefore, it is generally more expensive for larger ships to wait at the anchorage point. Who is accountable for what costs is very irregular and often determined in contracts between shipping lines and terminal operators.

2.2 Berth Schedule

Vessels arrive at a container terminal according to a weekly pattern. The week pattern is known by the container terminal and is usually set for a year in advance. Therefore, a container terminal can create a berth schedule which contains the arriving vessels and the berth position they are assigned. The position a vessel can moor is dependent on the water depth and the type of QC at the berths. Another constraint of berthing vessels is the mooring margin. The mooring margin is the space around a berthed vessel required for mooring lines. So if two vessels both have a mooring margin of 15 meters, then the space between the vessels must be larger than 30 meters. The mooring margin also applies to the boundaries of the quay. An example of a berth schedule is shown in Figure 2.3

2.2.1 Proforma

The proforma berth schedule is created before the vessels arrive based on the expected arrival time and call size of the week pattern. A finalised proforma schedule is used to allocate containers to stacks in the yard such that there is an efficient distribution. The distribution of containers throughout the yard is important since the distance between a container and the vessel it is assigned to can affect the productivity of the QCs. If the distance is too large, then trucks carrying the containers have to drive longer distances. Longer distances impact the frequency

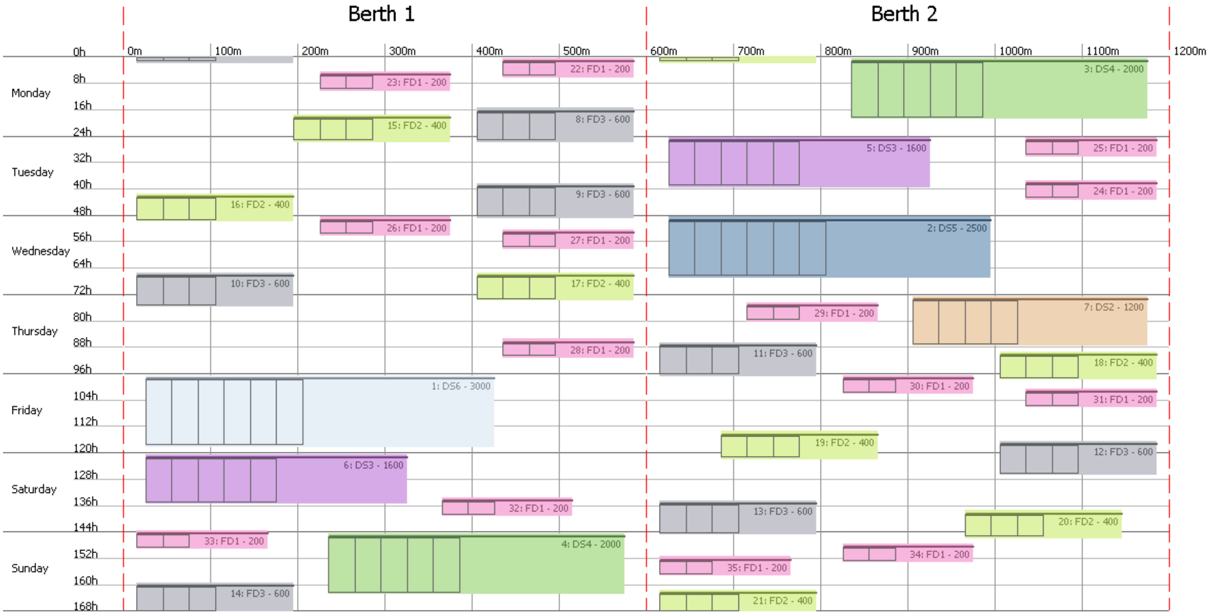

Figure 2.3: Example of a berth schedule for a container terminal with two berths of 600 metres.

with which containers arrive at the QC's which decreases productivity and can harm the service level of the terminal.

The proforma schedule is created with the expected arrival times and call sizes. However, a vessel's arrival is not deterministic but is influenced by uncertainty and the call sizes can change per arrival. Therefore, the proforma schedule must be robust against uncertainties. If the proforma is robust then the likelihood of vessels berthing at, or close to, their planned position increases.

The proforma should ideally be designed to minimize vessel waiting time, efficiently allocate vessels along the quay, and be robust to unpredictability. However, in reality, it's not possible to achieve optimality for all three criteria. Therefore, a trade-off is necessary to optimize the proforma.

2.2.2 Realised

The realised berth schedule is created based on actual arrival times and call sizes. The realised berth schedule is generated and adjusted throughout the operating period since operations are prone to uncertainties. Due to changing arrival times, the berthing schedule has to be altered with each new piece of information such as arrival delays and service time delays. With the realised schedule, the performance depends on how much the terminal values the trade-off between waiting time and berthing close to the planned position.

2.3 On-shore Power Supply

2.3.1 Shore power infrastructure

Shore power designs have to be able to reliably supply large quantities of energy to often multiple container vessels simultaneously. Moreover, the components of the OPS infrastructure are limited to the spatial availability within the terminal. Shore power designs consist of the shoreside components and shipside components as seen in Figure 2.4. In this section, the most important components concerning the quay operations are discussed.

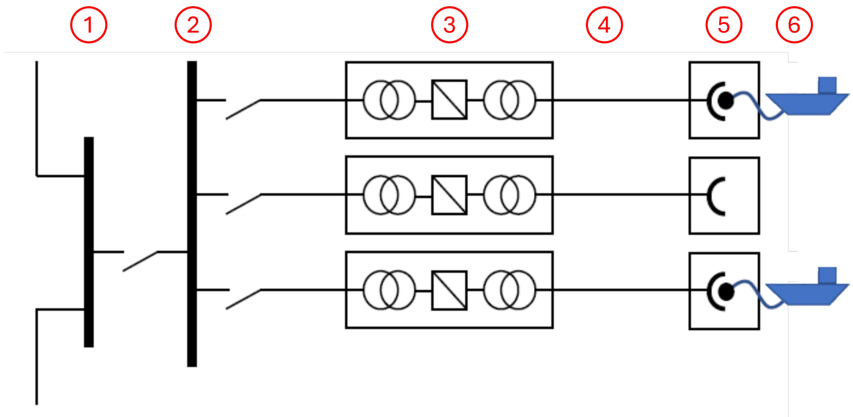

Figure 2.4: Schematic of OPS infrastructure. 1) Connection to power grid. 2) Substation. 3) Converter station. 4) Cabling. 5) Connection points. 6) Cable Management System on board of the vessel.

Shoreside infrastructure. The infrastructure at a container terminal consists of five main parts [9, 10]. First, the connection to the regional electricity grid and the intake station. Secondly, a substation which contains voltage transformers. Thirdly, a converter station which houses frequency converters, transformers and switchgears. A converter module is needed for each vessel that is berthed with OPS simultaneously to supply the right voltage and frequency. Then there is the cabling network from the converter module to the quay and the connection points at the quay.

Shipside infrastructure Ship-to-shore connection for container vessels is made possible with a cable management system (CMS) on board the vessel. For container ships, the international standard for shore power demands that the CMS must be located on the ship side of the operations [11]. The CMS contains a cable reel which can lower the cable to the quay so it can be connected to one of the connection points. The CMS can be built into the vessel or located in a containerised unit and is often near the stern or in the middle of the vessel as shown in Figure 2.5 [10]. The cable can generally extend between 35 and 55 meters which allows approximately 25 meters of horizontal freedom considering the height of the CMS [12].

Figure 2.5: Containerised cable management system at the aft of the vessel.

Figure 2.6: Fixed connection box

Figure 2.7: Mobile connection box [13]

2.3.2 Connection points and Shore power zones

A container terminal quay side operations rely heavily on the berth flexibility of the ships. With the introduction of shore power, the flexibility is affected by the location of the connection points on the quay and the number of vessels that can be berthed simultaneously. To remain competitive, a terminal will want to limit the negative impact on their berth flexibility with the introduction of shore power. To achieve this, vessels must be able to connect to a connection point wherever they are berthed. However, a terminal can't have an unlimited amount of connection points which can be used simultaneously since each simultaneous connection needs a converter station.

Shore power zone. A common solution is the division of the quay into multiple shore power zones. A shore power zone is a section of the quay containing connection points which can supply a single vessel at a time. The length of a zone is typically between 150 and 400 meters. The zone can contain several fixed connection points (Figure 2.6) which are spaced out in such a way that the entire zone is covered. The zone can also be covered by a single mobile connection point (Figure 2.7) which can move along the quay wall towards the CMS of the vessel.

An increase in the number of zones means that more vessels can be berthed at the same time which increases flexibility. However, too many zones mean unnecessary costs for the terminal. Therefore, terminals need to decide on the number of zones and the length of the zones to limit flexibility reduction and minimise costs. Ultimately, the optimal number of zones is dependent on the arrival pattern of vessels and the vessel mix. If a terminal expects five vessels to arrive and be berthed concurrently, there should be at least five zones, possibly more for optimal flexibility.

However, due to arrival delays or operational disruptions, it is difficult to know in advance how many vessels are likely to be berthed simultaneously.

3

Related work

The optimization of berth schedules is a fundamental challenge for container terminals. Scheduling berth positions is a known problem called the Berth Allocation Problem and has been extensively studied in previous literature. This chapter discusses work related to the Berth Allocation Problem and the use of Shore Power at container terminals.

Bierwirth and Meisel determined that the Berth Allocation Problem can be separated into three main categories according to the spatial properties of the quay at a container terminal [14]. The Discrete Berth Allocation Problem (DBAP) involves a single berth where a single vessel can dock. The Continuous Berth Allocation Problem (CBAP) allows multiple vessels to dock at a berth. The Hybrid Berth Allocation Problem (HBAP) permits a single vessel per berth but a ship can occupy multiple berths.

This study focuses on the Continuous Berth Allocation Problem and related work. Lim demonstrated that the CBAP is NP-complete, indicating that there is no known way to find an optimal solution to the problem quickly [15]. As a result, heuristic and approximation algorithms are commonly used to find adequate solutions in a reasonable time frame.

Lee et al. proposed minimizing a weighted waiting time function using a Greedy heuristic combined with a local search algorithm to improve the solutions [16]. Babazadeh et al. found that a Particle Swarm Optimization algorithm was time-efficient and effective for minimizing the total waiting time [17]. However, in the studies by Lee et al. and Babazadeh et al., ship arrivals were assumed to be deterministic, and a single arrival pattern was used to evaluate their algorithm performance.

Frojan et al. extended the formulation of the CBAP to include multiple continuous berths and stochastic arrival times, proposing a Genetic Algorithm (GA) combined with a Local Search algorithm to find good solutions [18]. Lin and Ting compared a Simulated Annealing model to the GA proposed by Frojan et al. and improved waiting time in all problem instances [19]. These problem instances only considered the vessel arrival pattern and did not account for different vessel properties such as priority, waiting costs, and preferred berth positions.

Sheikholeslami and Ilati expanded the CBAP by incorporating preferred berth positions and adding berth deviation into the objective function [20]. Xiang et al. conducted a study in 2017 that included a berth deviation factor in the objective, focusing on service levels per vessel by incorporating vessel-specific weights [21]. However, Xiang et al. used randomly generated berth preferences for each problem instance and did not consider the periodic pattern of arriving vessels using the same proforma schedule. For a single proforma schedule across multiple scenarios prone to uncertainties, a level of robustness is needed to minimize the costs of a schedule.

Zhen and Chang studied the impact of different levels of robustness in the proforma schedule against varying levels of uncertainty [22]. They tested various berth strategies ranging from cost-effective without regard for robustness, to robust with less focus on cost-effectiveness. They concluded that the trade-off between minimizing costs and robustness for the proforma berth schedule depends on the expected level of uncertainty in arrival and handling times. Still, they concluded that a strategy focussed primarily on robustness was never the best, even with very high levels of uncertainty. Zhen and Chang proposed a Squeaky Wheel Optimization heuristic for the proforma schedule and did not change berth positions for the realized arrivals. Therefore, further optimization is possible by optimizing the cost of realized schedules with respect to the proforma schedule.

Xiang et al. expanded their 2017 study in 2021 with a more robust formulation of the CBAP which optimized a proforma schedule considering robustness and re-optimized realized berth schedules subject to uncertainties [23]. They found that re-optimizing the berth schedule is superior at reducing costs at high uncertainty scenarios. Moreover, by re-optimizing, they could lower the level of conservatism in the proforma schedule without an overall cost reduction.

The demand for sustainable initiatives and increasing interest in shore power at container terminals led to many research articles on the environmental benefits and economics of shore power. Winkel et al. assessed the economic and environmental benefits of shore power policies at European container terminals [24]. They concluded that the container terminal, which is responsible for the investment costs of shore power, is often not the party that benefits from the reduced emissions. However, with the reduced emissions, a substantial economic health benefit is anticipated. These investment costs are significantly influenced by the shore power design as mentioned in section 2.3.

Peng et al. recognized this and published a paper in 2019 where they used a simulation-based solution algorithm to optimize shore power allocation and berth allocation for continuous berths. They discussed multiple Shore Power patterns with varying capacities and assumed that a shore power zone can supply multiple berthed ships if there is enough capacity. However, this is not up to current international safety standards which dictate that shore power connections must be 7.5 megawatts and can only supply a single vessel simultaneously. Peng et al. continued their research on the cost of shore power with the DBAP. They proposed a PSO algorithm which schedules berths and allocates shore power to berths to minimize the costs of shore power [25].

Zhang et al. optimized berth allocation with shore power with discrete berths with regards to operational costs and energy costs [26]. Wang et al. considered a continuous berth with shore power zones and formulated a model which optimizes the operational costs, emissions and emission taxes by allocation vessels to berth positions and allocation QC's to moored vessels [27]. Zhang et al. and Wang et al. assumed that shore power for berthed vessels is not mandatory and developed models that can compromise shore power connections to achieve better operational costs.

4

Methodology

4.1 Mathematical formulation

Lim (1998) showed that the Continuous Berth Allocation Problem (CBAP) could be formulated as a modified Strip Packing Problem (SPP) [15]. The Strip Packing problem is a 2-dimensional geometric minimization problem. The idea of the SPP is to fit several geometric shapes into a 2-dimensional strip with limited width and infinite height without overlap between the objects. The objective is to minimize the height of the strip by packing all objects efficiently.

The quay at a container terminal can be pictured as a two-dimensional space as seen in Figure 4.1. The 2D space is defined by the length of the quay on the horizontal axis and time on the vertical axis. If a vessel is berthed at the quay, it takes up a certain length of the quay (the vessel's length including mooring margins) for a certain time (service time of a vessel including the berthing and unberthing time). Therefore, a vessel can be visualised in this space by a rectangular shape. For the CBAP, when multiple vessels are berthed, they can't be berthed at the same location at the same time. In other words, the rectangles representing the vessels in the 2D space cannot overlap. This is similar to an SPP since the width of the space is finite (quay length) and the height of the space is infinite (time).

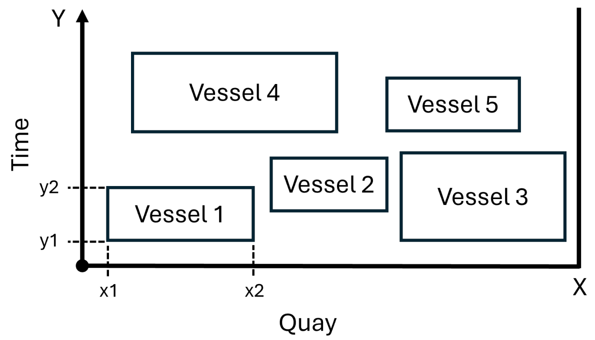

Figure 4.1: The berth allocation problem is visualised as a strip packing problem. For vessel 1, x_1 and x_2 are the stern and bow of the vessel including the mooring margin. The vessel is berthed at time y_1 and unberthed at y_2.

However, the CBAP is more constrained than a traditional SPP since an item (vessel) can only be placed above a certain height (a vessel's arrival time). Consequently, the position of an item along the vertical axis is constrained. Moreover, additional constraints are often present in the CBAP in the case of container terminals — for example, vessel priority, a maximum deviation from a planned position or the limitations of OPS. Another difference between SPP and CBAP is the objective function. In a SPP, the objective is to minimize the height of the strip. For the CBAP, the objective depends on the needs of the container terminal which is generally more complicated as mentioned in section 2.1.2. The parameters and decision variables for the CBAP are shown in table 4.1.

Sets		
V	Set of vessels $\{1, 2, .., I\}$ where I is the number of vessels	
B	Set of berths $\{1, 2, .., N\}$ where N is the number of berths	
Z	Set of shore power zones $\{1, 2, .., K\}$ where K is the number of zones	
Q	Set of sections of the Quay $1, 2, ..., S$ where S is the number of sections	
Parameters		**Domain**
a_i	the arrival time of vessel $i \in V$ at the quay.	$\mathbb{R}_+$
l_i	the length of vessel $i \in V$ including the mooring margins.	$\mathbb{Z}_+$
s_i	the expected time on quay of vessel $i \in V$ including the berth and unberthing time.	$\mathbb{R}_+$
c_i	the cost per time unit that vessel $i \in V$ has to wait.	$\mathbb{R}_+$
l^b_n	is the left boundary of berth $n \in B$	$\mathbb{R}_+$
r^b_n	is the right boundary of berth $n \in B$	$\mathbb{R}_+$
x^p_i	is the planned position of vessel $i \in V$	$\mathbb{R}_+$
p_c	the position of the center of shore power zone $c \in Z$	$\mathbb{R}_+$
r_c	the length of shore power zone $c \in Z$	$\mathbb{R}_+$
w_i	the position of the CMS relative to the aft of vessel $i \in V$	$\mathbb{R}_+$
$\hat{b}^{dev}$	is the maximum berth deviation in meters	$\mathbb{R}_+$
β	is the deviation penalty.	$\mathbb{R}_+$
T	is the length of the berth schedule in hours.	$\mathbb{R}_+$
M_{time}	a big M value concerning time.	$\mathbb{R}_+$
M_{pos}	a big M value with respect to the x position.	$\mathbb{R}_+$
Decision variables		
x_i	the position where vessel $i \in V$ berth.	$\mathbb{R}_+$
y_i	the time vessel $i \in V$ berths	$\mathbb{R}_+$
m_{ij}	binary variable stating if vessel $i \in V$ is berthed left of vessel $j \in V$	$\{0, 1\}$
t_{ij}	is a binary variable stating if vessel $i \in V$ is unberthed before the berth of vessel $j \in V$	$\{0, 1\}$
b_{in}	is a binary variable stating if vessel $i \in V$ is berthed in berth $n \in B$	$\{0, 1\}$
$\gamma_{i\alpha}$	is a binary variable stating if vessel $i \in V$ is berthed along quay section $\alpha \in Q$	$\{0, 1\}$
k_{ic}	is a binary variable stating if vessel $i \in V$ is connected to shore power zone $c \in Z$	$\{0, 1\}$

Table 4.1: Nomenclature for CBAP

4.1.1 Objective function

The berth allocation problem's objective function depends on the type of berth schedule. For a proforma schedule, the goal is to allocate berth positions such that ships can berth close to the planned position even with variations in arrival times, without waiting at the anchorage point. Consequently, a proforma schedule should try to be as robust as possible against uncertainties, minimize waiting costs and ensure that vessels are distributed evenly along the quay. An uneven distribution of calls along the quay can lead to situations where multiple vessels might arrive simultaneously with the same planned position. For a realized schedule, the goal is to minimize waiting costs and to berth ships close to their planned proforma position to minimize driving distances.

Proforma schedule. The objective function of the proforma schedule is given by equation 4.1. The aim is to minimize the waiting costs and ensure that vessels are evenly distributed along the quay. This is done by multiplying the total waiting costs by the maximum occupancy of the quay. The total waiting costs are calculated by summing the waiting costs of all vessels. The waiting cost of a vessel is computed by multiplying the vessel's waiting cost per hour c_i by the difference between the arrival time and the berthing time $y_i - a_i$. The occupancy rate per section is computed to get the maximum occupancy of the quay. The parameter $\hat{o}_\alpha$ is the occupancy of section $\alpha \in Q$ and is expressed by eq. 4.2. The occupancy of section α of the quay is the fraction of time vessels are berthed along that section. The expected service time s_i is used to calculate the occupancy and is divided by the length of the berthing schedule T.

$$\textbf{minimize:} \quad \sum_{i \in V} c_i(y_i - a_i) \cdot \max_{\alpha \in Q} \{\hat{o}_\alpha\} \tag{4.1}$$

$$\text{where,} \quad \hat{o}_\alpha = \frac{1}{T} \sum_{i \in V} s_i \cdot \gamma_{i\alpha} \tag{4.2}$$

Realized schedule. The objective function for a realized berth schedule is defined by Formula 4.3. The objective is the waiting time and a penalty for deviating from the planned position multiplied by the waiting costs per hour for all vessels.

$$\textbf{minimize:} \quad \sum_{i \in V} c_i(y_i - a_i + \frac{|x_i - x_i^p|}{1000} \cdot s_i \cdot \beta) \tag{4.3}$$

The waiting time is expressed by $(y_i - a_i)$. The deviation penalty can be interpreted as the additional service time due to the distance between the planned and actual position. The factor $\frac{|x_i - x_i^p|}{1000}$ expresses the berth deviation in kilometres and is multiplied by the service time s_i and a deviation penalty β. For this study, a deviation penalty $\beta = 0.1$ was used. The deviation penalty β can be explained as the percentual increase in service time for each kilometre the berth position deviates from the planned position. So, with a deviation penalty of 0.1, a vessel with a service time of 10 hours would rather wait 1 hour to berth at the planned position than berth without waiting 1000 metres away from the planned position. The deviation penalty was determined based on a trial and error approach.

4.1.2 Constraints

The constraints of the basic formulation of the berth allocation problem modelled as an adjusted strip packing problem are given by eq. 4.4-4.9. Constraint 4.4 ensures that vessels can only berth after they have arrived at the quay. Constraint 4.5 ensures that berthed vessels are located within the berth that they are assigned to. Constraints 4.7-4.9 ensure the absence of overlap between vessels in the berthing schedule.

$$t_i \geq a_i \qquad \forall\ i \in V \tag{4.4}$$
$$x_i + l_i \leq \sum_{n \in B} b_{in} r_n^b \qquad \forall\ i \in V \tag{4.5}$$
$$x_i \geq \sum_{n \in B} b_{in} l_n^b \qquad \forall\ i \in V \tag{4.6}$$
$$t_{ij} + t_{ji} + m_{ij} + m_{ji} \geq 1 \qquad \forall\ (i,j) \in (V \times V),\ i \neq j \tag{4.7}$$
$$x_i + l_i \leq x_j + (1 - m_{ij}) M_{pos} \qquad \forall\ (i,j) \in (V \times V),\ i \neq j \tag{4.8}$$
$$y_i + s_i \leq y_j + (1 - t_{ij}) M_{time} \qquad \forall\ (i,j) \in (V \times V),\ i \neq j \tag{4.9}$$

The introduction of shore power zones can be modelled with the following constraints. Constraint 4.10 ensures that simultaneously berthed vessels are not connected to the same shore power zone. Constraint 4.11 ensures that vessels connect with a single zone if they require the use of Shore Power. Constraint 4.12 ensures that a vessel can only connect to a zone if the vessel is berthed within reach of the zone.

$$k_{ic} + k_{jc} \leq 1 + t_{ij} + tji \qquad \forall\ (i,j,c) \in (V \times V \times Z),\ i \neq j \tag{4.10}$$
$$\sum_{c \in Z} k_{ic} = 1 \qquad \forall\ i \in V \tag{4.11}$$
$$|p_c - (x_i + w_i)| \leq r_c + (1 - k_{ic}) M_{pos} \qquad \forall\ (i,c) \in (V \times Z) \tag{4.12}$$

In the case of a realized berthing schedule, an additional constraint is introduced to limit the difference between the planned and realized berth position which is expressed by constraint 4.13

$$|x_i - x_i^p| \leq \hat{b}^{dev} \qquad \forall\ i \in V \tag{4.13}$$

Finally, vessel priority is a constraint which can be ensured by carefully choosing the right waiting costs of the vessels such that prioritized vessels don't have to wait unless that can't be realized.

4.2 Algorithms

4.2.1 Greedy heuristic

To efficiently obtain a feasible solution for the CBAP a greedy algorithm is proposed which assigns berthing positions to an ordered set of vessels. The algorithm sequentially selects a vessel from the ordered set and evaluates all possible berth positions. To determine the possible positions, the quay is divided into sections of 5 metres. Then, for every 5 metres of quay, it is evaluated if the vessel can berth without violating any of the constraints in section 4.1.2. If the position does not violate any constraints then the position is given a score. This position score is different for the proforma CBAP and the realized CBAP. The position with the highest score is chosen as the berth position.

In determining parameter values and equations for the greedy algorithm, a trial-and-error approach was employed. This method was chosen because simulations with stochastic parameters made an analytical approach challenging. By iteratively testing and refining the parameters, it was possible to identify values that produced the most reliable and satisfactory results among several experimental setups. This empirical approach helped determine parameters that were appropriate for the specific conditions and constraints of the CBAP.

Proforma schedule. For a possible berth position $\tilde{x}_i$ Let the $\hat{P} \subseteq Q$ denote the subset of sections that vessel i occupies if berthed at position $\tilde{x}_i$. Then the Formula 4.14 represents the score used to evaluate a position for the position.

$$f_p(\tilde{x}_i) = gap \cdot (1 - occupancy)^2 \tag{4.14}$$

$$gap = \max\{r_n^b - (\tilde{x}_i + l_i), \tilde{x}_i l_n^b\} \tag{4.15}$$

$$occupancy = \frac{1}{|\hat{P}|} \sum_{\alpha \in \hat{P}} \hat{o}_\alpha \tag{4.16}$$

The score is the product of two factors. The first factor (4.15) is the score for the largest gap to a berth boundary. Maximizing the distance to one of the boundaries of the berth the position is located in incites to leave ample space for other vessels to dock. The second factor (4.16), is the average occupancy score of the set $\hat{P}$ where $\hat{o}_\alpha$ is described by 4.2. The final occupancy score is obtained by subtracting the average occupancy score from 1 to penalize high occupancy. Lastly, the occupancy score is squared to increase the factor's weight. The emphasis on the occupancy score is necessary to ensure that vessels are distributed evenly among the berths. By multiplying both factors, the final score reflects the two most important aspects of the proforma schedule, leaving space for other vessels to berth to reduce waiting times and distributing vessel calls along the quay.

Realized schedule. For a possible berth position $\tilde{x}_i$ there is a planned position $\tilde{x}_i^p$. Eq. 4.17 gives the score used to evaluate the feasible positions. The score is a trade-off between leaving space for other vessels to berth and deviating from the planned position where λ and μ are the weights. For this study, berthing close to the planned position is seen as a key performance indicator, therefore, weights of 0.1 and 1 are used for λ and μ respectively. With $\mu > \lambda$ priority is given to positions closer to the planned position.

$$f_r(\tilde{x}_i) = \lambda \cdot gap - \mu \cdot deviation \tag{4.17}$$

$$gap = \max\{r_n^b - (\tilde{x}_i + l_i), \tilde{x}_i - l_n^b\} \tag{4.18}$$

$$deviation = |\tilde{x}_i - \tilde{x}_i^p| \tag{4.19}$$

4.2.2 Simulated Annealing

The effectiveness of the greedy heuristic is significantly influenced by the input order of vessels. Since the greedy heuristic is deterministic, it consistently returns the same solution for a given input. Moreover, the number of possible input orderings is finite. This means that there is an optimal order for the greedy algorithm. The number of variations in the input order for a set of n vessels V is $n!$. Evaluating all possible order variations for large sets of vessels, however, is practically impossible due to the factorial growth of combinations. To improve the input order the Simulated Annealing meta-heuristic algorithm is proposed which optimizes the input order for the greedy algorithm discussed in the previous section.

Simulated Annealing (SA) is an iterative and probabilistic method to solve combinatorial optimization problems and was first proposed by Kirkpatrick et al in 1983 [28]. Simulated Annealing is inspired by metallurgical practices where a material is heated to a high temperature and gradually cooled down. Analogously, for combinatorial problems such as the BAP, the SA algorithm begins with a high value for a temperature parameter and an initial solution which could be improved. With a controlled cooling schedule, the algorithm iteratively decreases the temperature and tries to improve the solution.

The SA algorithm starts with an initial solution x_0 with an objective value $f(x_0)$ and an initial temperature t_0. With a permutation function, a neighbour x' to the current solution x is found. The new solution x' is accepted with a certain acceptance probability $p(\Delta E, t)$. The acceptance probability for a minimization problem is given by Formula 4.20. The parameter ΔE denotes the difference in objective values as formulated in 4.21 and t_i is the temperature at iteration i.

$$p(\Delta E, t_i) = \exp\left(\frac{\Delta E}{t_i}\right) \tag{4.20}$$

$$\Delta E = f(x') - f(x) \tag{4.21}$$

From 4.20 it can be verified that for a superior neighbour solution ΔE will be negative and $P(\Delta E, t)$ will be larger than 1. Therefore an improvement will always be accepted. Inferior neighbour solutions are more likely to be accepted if the difference in objectives is small or if the temperature is high. If a neighbour is always accepted because of a too-high temperature parameter, then the algorithm is essentially a Random Walk algorithm. By cooling the temperature with each iteration, the algorithm is guided to better solutions. Guidance is done by decreasing the temperature with each iteration following a cooling schedule. The SA algorithm iterates for an arbitrary number of iterations or until a convergence criterion is met. A single iteration is described by Algorithm 1.

Initial solution The initial solution for the simulated annealing algorithm is crucial for reaching the final best solution, as all future solutions originate from the initial solution. Therefore, a good initial solution increases the chance of finding the optimal order. Wanke examined the impact of different berth allocation policies and queuing priorities on waiting costs in a container terminal [29]. The study simulated various combinations of policies and priorities and considered the demurrage cost ratios between different-sized ships. They found that prioritizing smaller vessels or a FIFO prioritization strategy reduced waiting times but increased the demurrage costs while prioritizing larger vessels reduced demurrage costs at the expense of an overall

Algorithm 1: A single iteration of Simulated Annealing

Data: x, t the current solution and temperature.
Result: updated current solution
$x' \leftarrow$ generate a random new neighbor from x
$\Delta E \leftarrow e(x') - e(x)$
if $\Delta E < 0$ **then**
  $x \leftarrow x'$
else
  $r \leftarrow Unif[0, 1]$
  if $r < \exp(\Delta E/t_i)$ **then**
    $x \leftarrow x'$
  end
  $t_{i+1} \leftarrow$ decrease the temperature parameter following the cooling schedule.
end

higher waiting time. Based on the the findings of Wanke the initial solution order is determined to be a sorted list of V sorted by:

1. **Priority** – vessels with a higher priority will be first in the order
2. **Waiting cost** – If vessels have the same priority level then the order is based on the vessel's waiting cost.
3. **Arrival time** – If vessels have the same priority and waiting cost then the vessel that arrived at the anchorage point first is berthed first.

Simulated Annealing is often observed to find good approximations of the optimal solution for combinatorial problems since it balances exploration and exploitation of the solution space. The cooling schedule and permutation method determine the balance between exploration and exploitation.

Neighbour selection. The permutation method which selects a new neighbour solution is relevant to the size of the steps taken when exploring the solution space. Many changes to a solution to get a neighbour mean large exploratory steps but less exploitation. A solution for the CBAP is a list of vessels where the order is the input for the greedy heuristic. A neighbour solution is created by selecting a random vessel in the current solution and moving it up the order. A ship can't be moved in front of another with a higher priority level to ensure the priority constraint is not violated. A bias can be introduced when selecting a vessel that is moved up in the vessel order to improve the likelihood of finding a better solution. Instead of choosing a ship randomly, the selection method assigns a probability p_i to each vessel $i \in V$ based on the expected waiting costs $c_i^* = c_i(y_i - a_i)$. If in the current solution, a vessel i has to wait, it is because it waits for vessels that are assigned a berth position before vessel i. Therefore, when vessel i is selected to move up in the order, it is more likely that it waits less in the neighbour solution. Therefore, selecting vessels that have high waiting costs in the current solution offers the most likely chance of decreasing their respective costs and therefore decreasing the objective value. Based on this logic three different selection strategies were evaluated.

1. **Random** – Each vessel can selected to be moved up with equal probability.

$$p_i = \frac{1}{|V|} \tag{4.22}$$

2. **Semi-Biased** – All vessels can be selected but vessels which contribute more to the waiting costs have a higher probability of being selected. Probabilities are calculated as follows:

$$p_i = \frac{\log(c_i^* + \delta)}{\sum_{j \in V} \log(c_j^* + \delta)} \tag{4.23}$$

Where, (4.24)

$$\delta = \min_{j \in V} \{c_j^* \mid c_j^* > 1\} \tag{4.25}$$

3. **Biased** – Only waiting vessels can be selected. Vessels with higher waiting costs have a higher probability of being selected. Probabilities are computed as follows:

$$p_v = \frac{\log(c_i^* + 1)}{\sum_{j \in V} \log(c_j^* + 1)} \tag{4.26}$$

With the addition of bias to the selection process, the stochasticity of the SA algorithm is reduced. Therefore, additional stochasticity is introduced by making the selected vessel move up a random number of places. The number of places is randomly drawn from a uniform distribution between 1 and 3.

Cooling schedule The cooling schedule determines how frequently inferior solutions are accepted. At high temperatures, worse solutions are more likely to be accepted to focus on the exploration of the solution space. By cooling the temperature the focus shifts to exploitation of promising areas. Two common cooling schedules, geometric cooling and linear cooling are described by 4.27 and 4.28 where i is the current iteration and I is the total number of iterations.

$$\textbf{Geometric cooling:} \quad t_{i+1} = 0.99 t_i \tag{4.27}$$

$$\textbf{Linear cooling:} \quad t_{i+1} = \left(1 - \frac{i}{I}\right) t_0 \tag{4.28}$$

Linear cooling allows for a more gradual decrease in temperature, accepting larger objective deviations in later iterations. Geometric cooling decreases the temperature more rapidly in the early stages and slows down the decline later on. Thus, with a geometric cooling schedule, large improvements are expected in the earlier iterations after which smaller differences in the objective value are accepted at later stages. Both cooling schedules are visualized in Figure 4.2.

The initial temperature, along with neighbour selection and the cooling schedule, is another crucial parameter that influences the performance of the simulated annealing algorithm. The initial temperature can be expressed by the objective value of the initial solution since the temperature reflects the tolerated increase in the objective value. Because the objective value

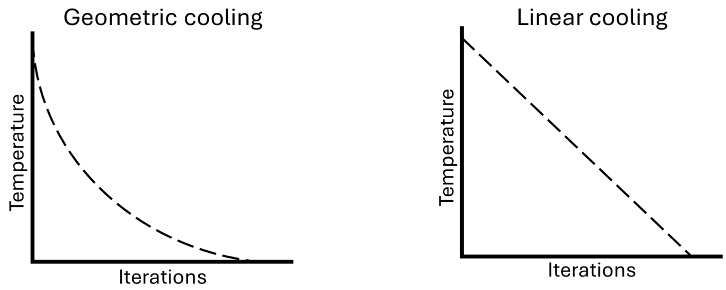

Figure 4.2: Two different cooling schedules

depends on the experiment setup, a different initial temperature is needed for each CBAP. The initial temperature is expressed by 4.29 where α is a scalar such that the initial temperature is relative to the scale of the problem.

$$t_0 = \alpha \cdot e(x_0) \tag{4.29}$$

4.2.3 Parameter Tuning

Parameter tuning for the Simulated Annealing algorithm is done using Python. A berth allocation problem for the proforma schedule is used to evaluate different parameters. Each algorithm configuration is used to solve the CBAP 50 times, with each run being independent. Configurations are evaluated on the percentual improvement over the initial solution. Where 100% improvement is a solution with objective value 0 and at 0% improvement, the best-found solution is the same as the initial solution. A well-configured parameter set demonstrates high average improvement and low variability, indicating consistency. The different sets of parameters are shown in table 4.2. All 18 possible combinations are evaluated.

Parameter	**Values**
Selection strategy	{Random, Semi-Biased, Biased}
Cooling Schedule	{Geometric, Linear}
α	{0.25, 0.5, 1}

Table 4.2: Simulated Annealing parameters used for tuning

Table 4.3 shows the percentual improvement of all 18 parameter sets. The standard deviation of the 50 independent runs per parameter set is shown in brackets behind the improvement percentage. The three parameter sets with the highest average improvement and lowest variance all used a linear cooling schedule. The best overall parameter set had both the highest mean improvement and lowest standard deviation. This set is a combination of a Biased selection strategy, a linear cooling schedule and an initial temperature scalar α of 1. Thus, with $\alpha = 1$, the initial temperature is equal to the objective value of the initial solution.

		Selection strategy		
Cooling schedule	**α**	**Random**	**Semi-Biased**	**Biased**
Geomertic	**0.25**	76% (12)	77% (15)	81% (14)
	0.5	74% (18)	77% (18)	74% (22)
	1	71% (20)	81% (7)	82% (7)
Linear	**0.25**	76% (13)	79% (9)	83% (3)
	0.5	72% (13)	82% (5)	81% (11)
	1	68% (17)	78% (12)	**84% (2)**

Table 4.3: Results parameter tuning. The percentages denote the improvement to the initial greedy solution. The number in between the brackets represents the standard deviation. The best-performing parameter set is coloured green.

4.3 Simulation model

To reliably measure the effects of shore power and evaluate the impact of the berthing strategy under uncertainty, Portwise's simulation model TRAFALQUAR is utilized. With TRAFALQUAR it is possible to configure detailed scenarios and run simulations under uncertainty to assess the performance. A specific simulation configuration is referred to as an experiment. TRAFALQUAR simulates the arrival of vessels at a container terminal and the berthing, servicing and unberthing of ships. It does not simulate the gate and yard operations. For this report, the most important experiment parameters are the length of the quay, the number of berths, the number of QCs, the QC productivity, the weekly arrival pattern, seasonal call size variations and the arrival delay distributions. The scenarios and parameters of importance are specified in chapter 5. To improve the reliability of experimental results under uncertainty, it is recommended to conduct multiple replications of the same experiment.

A simulation run starts with creating the proforma schedule, which will be used for all realized arrivals afterwards. The set of vessels V used to find a solution to the CBAP is the pre-defined week pattern of arriving vessels. With all vessels having a planned position they are assigned berthing locations upon arrival. If vessels can't berth directly at arrival, they must wait at the anchorage point. Due to the delays, the exact arrival time is known just 12 hours in advance. Moreover, service times can vary from the expected service time if more or fewer QCs work on the vessel than required. Therefore, it is necessary to re-evaluate berth positions with every event that could result in a vessel starting the berthing process. Thus, the CBAP is solved at each of the following two events with V consisting of the waiting vessels, new arrivals and vessels that arrive in the next 12 hours.

1. **Arrival of a vessel at the port** – An arriving vessel could berth immediately if there is space on the quay.
2. **A vessel finishes unberthing** – A vacant spot opens up at the quay for a waiting vessel to berth.

TRAFALQUAR already uses algorithms that solve the CBAP but the algorithms do not yet include the added constraints of shore power. In this report, TRAFALQUAR's berth algorithms will be referred to as the base algorithm. The base algorithm will be used as a benchmark to decide if the Greedy and SA algorithms are up to standard. Because the base algorithm is not suited for experiments with shore power, benchmarking is done solely on experiments without OPS with the assumption that performance between algorithms performance will be comparable with or without OPS. A large difference between the base algorithm and the proposed heuristics is the inclusion of waiting costs. The base algorithm does not differentiate the cost of waiting between vessels and treats all vessels as equals. Equal treatment of different vessel's waiting times results in the optimization of waiting time without regard for costs. In the base algorithm, the only method for differentiating the importance of vessels is through prioritization which is a hard constraint and will likely lead to more unnecessary waiting time for unprioritized vessels.

To assess the impact of shore power, new parameters for configuring OPS at a container terminal were incorporated into TRAFALQUAR. Shore power was implemented such that each shore power zone could be specified in length and position at the berths. For each arriving vessel it is possible to set the position of the Cable Management System relative to the aft of the vessel and the horizontal length of the connection cable.

TRAFALQUAR already uses an algorithms that solve the CBAP which will be referred to as the base algorithm. The base algorithm will be used as a benchmark to decide if the Greedy and SA algorithms are up to standard. Originally, the base algorithm was not suited for experiments with shore power. Therefore, the constraints 4.10-4.12 are added to the base algorithm.

A large difference between the base algorithm and the proposed heuristics is the inclusion of vessel-specific waiting costs. The base algorithm does not differentiate the cost of waiting between vessels and treats all vessels as equals. Equal treatment of different vessels waiting times results in the optimization of waiting time without regard for costs. This will likely mean that the waiting costs with the base algorithm will be relatively high but waiting times will be relatively low. In the base algorithm, the only method for differentiating the importance of vessels is through prioritization which is a hard constraint and will likely lead to more unnecessary waiting time for unprioritized vessels. However, using prioritization of certain vessels is a better representation of real-life practice. Therefore, the Simulated Annealing algorithm will be compared to both the base algorithm with and without prioritization.

4.4 Evaluation metrics

During a simulation run, all statistics on the operations get logged and can be used to evaluate the performance. The focus of this report is on analyzing the impact of different berthing strategies and the utilization of shore power on the berthing schedule. Therefore, the metrics used to evaluate performance were the average waiting time at the anchorage point per vessel call, the total yearly waiting costs and the difference between the planned and realized berth position.

However, vessel-specific waiting costs are only used by the simulated annealing algorithm as weights for waiting time. To allow for a fair comparison between algorithms, the waiting costs are expressed in a more general manner. Instead of evaluating performance by the costs used only by the simulated annealing algorithm, costs will be expressed in Waiting Container Hours. The Waiting Container Hours of a vessel call are calculated by multiplying the waiting time in hours by the call size of the vessel. For example, if a vessel has a call size of 1,000 containers and has to wait for 2 hours at the anchorage point, then the vessel has a waiting cost of 2,000 containers.

As mentioned in section 4.3, multiple replications of an experiment will have to be conducted to account for uncertainty. For the results presented in section 6, each experiment consists of 10 replications used to obtain average results and each replication simulates one year of vessel arrivals.

5

Experimental Setup

5.1 Model assumptions

TRAFALQUAR allows for detailed scenario descriptions with many input parameters. Therefore, in developing the experimental setup for this study, several assumptions were made to allow for a controlled environment to analyze and compare shore power configurations. Importantly, while these assumptions simplify certain aspects, they still ensure that the model closely represents real-world conditions. The assumptions are as follows:

1. **Realized arrival times** – Exact arrival times are known 12 hours in advance.
2. **Operational continuity** – No external factors such as tide, wind, or QC breakdowns will interrupt vessel operations.
3. **Constant QC productivity** – The productivity of each QC is constant and unaffected by uncertainty or deviation from a planned position.
4. **Universal QC service** – Any QC can serve any vessel.
5. **Flexible berthing** – Any vessel can berth everywhere along the quay as there are no draught limitations.
6. **Berthing proximity** – A vessel cannot berth more than 1,000 metres from its planned position.
7. **Shore Power Zone Compatibility** – Any shore power zone can supply any vessel.
8. **Vessel Equipment** – All vessels are equipped for shore power and can only berth if a connector is available.
9. **Cable Management System** – The CMS on board the vessel is always at the aft of the vessel.
10. **Cable Length** – The connection cable on the shipside offers 25 metres of horizontal flexibility.
11. **Shore Power Realiability** – Shore power electrical infrastructure never fails or breaks down.

These assumptions provide a structured basis for all experiments, allowing for a focused analysis of the berthing algorithms and shore power designs. The model aims to deliver reliable and consistent results by controlling these parameters while ensuring that the simulations remain a valid representation of real-world quayside operations.

5.2 Stochastic parameters

5.2.1 Arrival distribution

Terminals create the proforma schedule based on the planned arrival times of vessels. The planned arrival times are determined by the weekly schedule and are established before the operational year begins. However, container ships can be delayed or arrive earlier than expected during the year. Arrival time deviations are likely to occur and are difficult to predict. Most deviations occur due to unexpected weather effects, fluctuations in call sizes or disturbances at a previous port call [30, 31]. Arrival deviations in TRAFALQUAR follow a discrete probability distribution where a vessel's actual arrival time deviates between a and b hours from the planned arrival time with probability $p_{a,b}$. The realized deviation is then drawn from a uniform distribution with values between a and b. Figure 5.1 shows the probability and cumulative distribution used for the experiments in this report. Thus, a vessel has a 50% chance of arriving within 1 hour of the planned arrival time and a 20% chance of arriving 1 to 8 hours later. Veenstra and de Waal [32] showed that small changes in the arrival deviation distribution negatively impact operational efficiency. They showed that when deviations are more likely to occur, the waiting time for all vessels will increase. However, the purpose of the experiments in this study is to compare shore power configurations and see if they affect operational efficiency compared to scenarios without shore power. Since more deviations will impact all vessels, it will be assumed that waiting times will increase for all scenarios as long as the same probability distribution is used for all experiments.

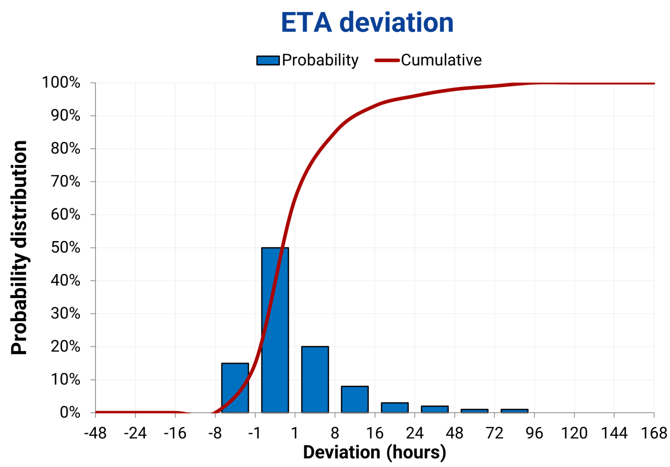

Figure 5.1: Deviation in the expected arrival times.

5.2.2 Callsize variations

The operations of container terminals are dependent on seasonal demand fluctuations. For a certain yearly volume that a container terminal handles, it is unlikely that this volume is distributed evenly over the year. Yin and Shi [33] analysed seasonal patterns in the shipping industry and found that the peak season is generally between September and November as preparation for the holiday season. Moreover, they stated that the off-season for the container industry is generally around March. Therefore, we assume the seasonal call size pattern shown in Figure 5.2 which shows the monthly call size as a percentage of the yearly volume.

In addition to the seasonal effect, The call size of a vessel fluctuates for each port visit. With each port visit the number of containers that have to be loaded and unloaded can vary by 20% from the expected call size of the vessel.

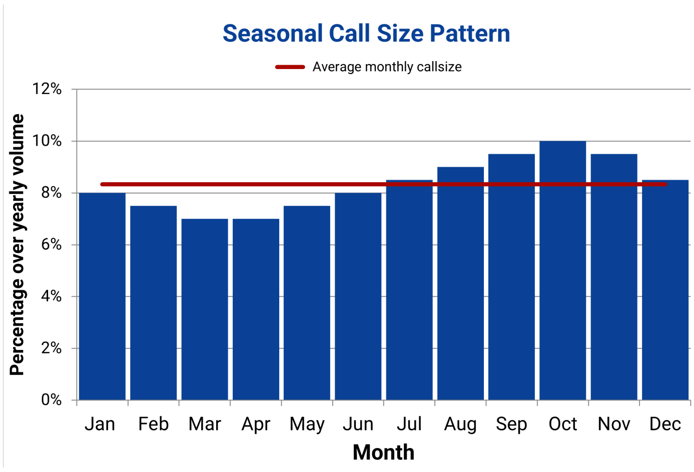

Figure 5.2: Distribution of call sizes throughout the operational year.

5.3 Scenario's

To evaluate the impact of shore power different scenarios will be compared. Four different hypothetical terminals are modelled and simulated with different shore power configurations. An overview of the 4 scenarios is shown in Table5.1. These Scenarios are chosen because the berths are long enough to support multiple shore power designs for comparison. Moreover, the quay configuration and volume are inspired by container terminals found in Europe. For all scenarios, a TEU factor of 1.75 is used and a QC productivity of 25 boxes per hour is assumed. The scenarios are described in more detail in the following sections.

Scenario	**Volume (TEU)**	**Quay length**	**Berths**	# of QC's
1	5,000,000	2,000 m	2,000 m	20
2	4,500,000	2,000 m	1,000 m + 1,000 m	10 + 10
3	2,500,000	1,200 m	1,200 m	12
4	2,200,000	1,200 m	600 m + 600 m	6 + 6

Table 5.1: Scenario overview

5.3.1 Scenario 1: 5.0 M TEU – 1 Berth

The first scenario models a container terminal with a high volume of 5 million TEU and a single long continuous berth of 2,000 metres. The berth has 20 QC in operation which can move along the entire length of the berth. The quay layout is similar to the quay of the ECT Delta terminal in the Port of Rotterdam as seen in Figure 5.3.

In this scenario, the week pattern consists of 30 deepsea or feeder calls. The main contributor to the large volume is the weekly arrival of two vessels with a call size of 10,000 boxes. Moreover, these two large calls get specific prioritization compared to the other vessels. The vessel mix and the weekly arrival pattern for this scenario can be found in Appendix A.1.

Figure 5.3: Berth layout of the ECT Delta terminal in the Port of Rotterdam that can be compared to the quay configuration of Scenario 1.

5.3.2 Scenario 2: 4.5 M TEU – 2 Berths

The second scenario models another high-volume container terminal. However, the modelled terminal has a volume of 4.5 million TEU and two continuous berths of 1,000 metres each. Each berth has 10 QC in operation which can move along the entire length of the berths. The terminal layout is similar to the quay of the Eurogate Terminal in Hamburg as seen in Figure 5.4.

In this scenario, the week pattern consists of 34 deepsea or feeder calls. Compared to the first scenario there are more feeder calls and no vessels with a call size of 10,000 boxes. For Scenario 2, all arriving vessels have the same priority level. The vessel mix and the weekly arrival pattern for Scenario 2 can be found in Appendix A.2.

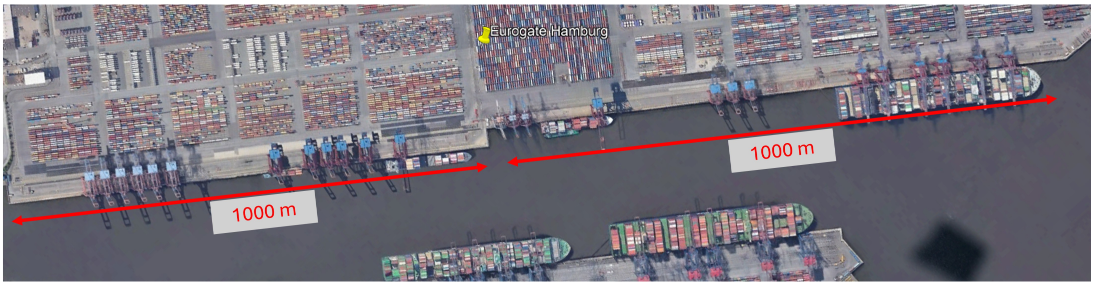

Figure 5.4: The quay configuration in Scenario 2 is inspired by the Eurogate terminal in Hamburg.

5.3.3 Scenario 3: 2.5 M TEU – 1 Berth

The third scenario models a smaller container terminal relative to the first two scenarios. However, with a yearly volume of 2.5 million TEU, it is still a large container terminal. The terminal of Scenario 3 has a single continuous berth of 1,200 metres with 12 QCs. An example of such a terminal layout is the Europa Terminal operated by PSA in Antwerp shown in Figure 5.5.

With the lower volume and shorter quay fewer vessels arrive and the call sizes are smaller compared to the first two scenarios. The vessel mix and the weekly arrival pattern for Scenario 2 can be found in Appendix A.3.

Figure 5.5: The PSA Europa Terminal in Antwerpen is an example of a container terminal modelled by Scenario 3.

5.3.4 Scenario 4: 2.2 M TEU – 2 Berths

The fourth scenario models a container terminal that handles a yearly volume of 2.2 million TEU with 2 continuous berths. Each berth has a length of 600 metres with each 6 QC's. The DCT Baltic Hub terminal in the port of Gdansk shown in Figure 5.6 is a similar terminal with 2 berths of approximately 600 metres.

The vessel mix and the weekly arrival pattern for Scenario 2 can be found in Appendix A.4.

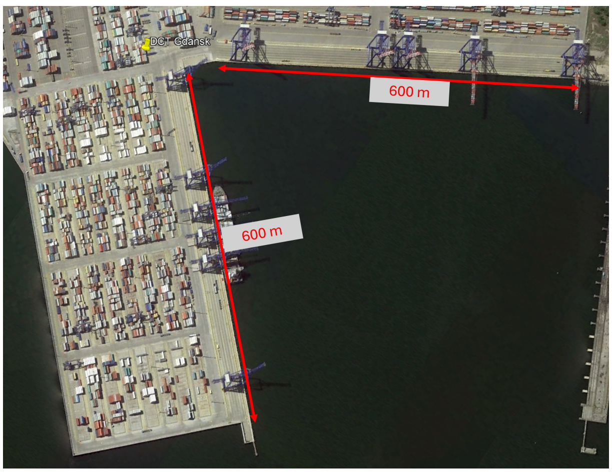

Figure 5.6: Quay layout of the Baltic Hub terminal in Gdansk that is similar to the quay configuration of Scenario 4.

5.4 Shore Power designs

Shore power is implemented by dividing the quay into multiple zones as described in Section 2.3. Six different zone lengths are considered: 150, 200, 250, 300, 350 and 400 metres. The main investment for a shore power zone is the converter station and not the length of the zone. Therefore, to reduce investment costs it is in the interest of the terminal operator to reduce the total number of zones regardless of the length. Moreover, the shore power zones should cover the full quay length to keep berthing flexibility similar to a quay design without shore power.

Table 5.2 shows the shore power designs per scenario used to simulate quayside operations. A shore power design is specified per berth and consists of a combination of zones such that the zones cover the entire berth without overlapping. For example, for Scenario 1 and a design with 7 zones, the quay is divided into 1 zone of 200 metres and 6 zones of 300 metres as shown in Figure 5.7. The shortest zone is used as the first zone in case of any berth division with varying zone lengths. This is because the cable management system on board of the ships is assumed to be at the stern of the vessel and that way, any vessel can connect to the shorter zone regardless of the vessel size.

	Scenario					
	1	**2**		**3**	**4**	
# of zones	2000m	1000m	1000m	1200m	600m	600m
4	–	–	–	4×300m	2×300m	2×300m
5	5×400m	–	–	1×200m, 4×250m	2×300m	3×200m
6	1×250m, 5×350m	1×300m, 2×350m	1×300m, 2×350m	6×200m	3×200m	3×200m
7	1×200m,6×300m	4×250m	1×300m, 2×350m	4×150m, 3×200m	4×150m	3×200m
8	8×250m	4×250m	4×250m	8×150m	4×150m	4×150m
10	10×200m	5×200m	5×200m	–	–	–

Table 5.2: Shore power designs per berth for each scenario.

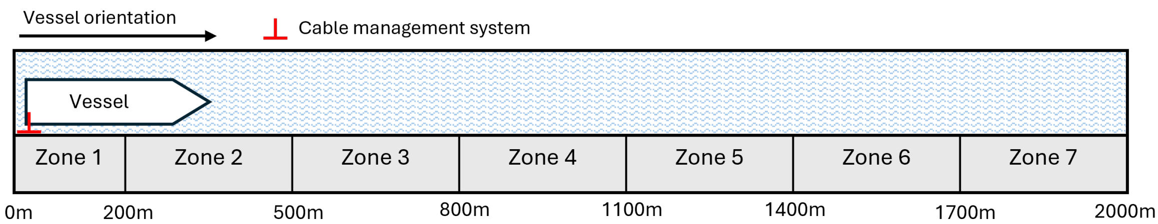

Figure 5.7: Shore power design for Scenario 1 with 7 zones: 1×200m, 6×300m. Vessel orientation determines the direction of the bow of berthed vessels. The cable management system is assumed to be at the stern of the vessel.

6

Results

In this chapter, the most relevant results of the simulations are presented. First, the different algorithms for the berth allocation problem are evaluated and their differences are highlighted. Secondly, the simulations of the experiments described in Chapter 5 are assessed and discussed.

6.1 Algorithm performance

Three different algorithms that were discussed are compared. The Base TRAFALQUAR algorithm will be used as a benchmark for the Greedy algorithm and the Simulated Annealing (SA) approach. The base algorithm without vessel priority is used as the benchmark since it uses the same vessel priority as the Greedy and SA algorithms, meaning that all three algorithms are subject to the same hard priority constraints. First, the differences in berth allocation between the three algorithms are visualized using the average quay occupancy. The Quay Occupancy is part of the objective function of the proforma schedule. Figure 6.1 shows that the Base algorithm distributes most calls evenly along the quay. However, at the 800-metre mark, the occupancy is significantly higher than the rest of the quay. This can result in more congestion around this quay section meaning that vessels will have to deviate more from their planned position and terminal trucks will have to travel greater distances to the stacked containers. The Greedy and SA algorithms showcase a similar occupancy pattern. However, the SA algorithm has slightly less difference in the extremes. This is expected since the SA algorithm optimizes the input of the greedy algorithm concerning the quay occupancy. A noticeable difference between the SA algorithm and the Base algorithm is the location of the low occupancy zones. With SA, there are low occupancy zones in the middle of each berth while the base algorithm has lower occupancy rates near the berth boundaries. This difference is a result of the Greedy algorithm's formula to score the positions. The greedy algorithm favours positions that have low occupancy and maximizes the distance to one of the berth boundaries. Therefore, vessels are more likely to be assigned berthing positions with a preference for positions further from the berth's centre.

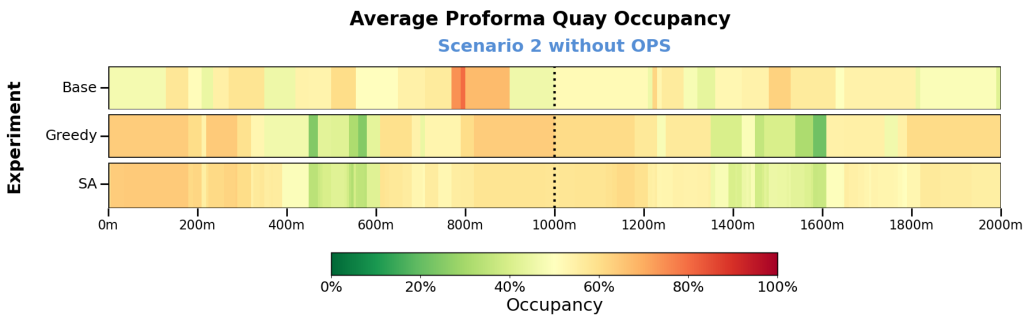

Figure 6.1: Heatmap of the quay occupancy of proforma schedules created by the different algorithms for scenario 2.

Figure 6.2 shows a heatmap of the realized quay occupancy. Comparing the realized occupancy to the proforma quay occupancy in Figure 6.1 makes it apparent that the heatmaps of the Greedy and SA algorithms are very similar. The heatmaps of the Base algorithm proforma and realized schedules appear less similar. This could be a sign that the Base algorithm is not as good at creating a robust proforma which enables vessels to berth at their planned positions under uncertainty. It could also be that the Base algorithm for realized arrivals is not as good at berthing vessels close to their preferred berth position compared to the Greedy and SA algorithms.

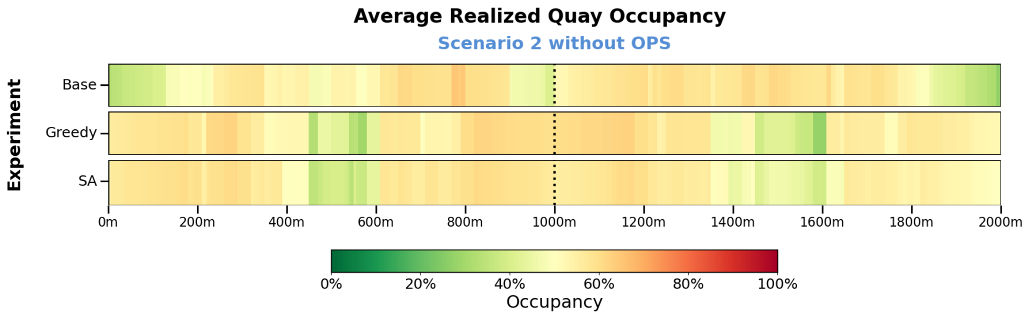

Figure 6.2: Heatmap of the quay occupancy of realized vessel arrivals which are allocated by the different algorithms for scenario 2

To evaluate the performance of the different algorithms concerning the proforma and realized schedule, all nine possible combinations of algorithms for the proforma and realized schedules are simulated for every scenario without OPS. Figure 6.3 shows the average key performance indicators of the nine combinations relative to the base case which uses the Base Algorithm for both the proforma and the realized schedules. The values in the matrices show the percentual increase (positive value – red) or decrease (negative value – green) for each metric relative to the base case.

Across all three metrics, the Simulated Annealing algorithm generally outperforms the Base and Greedy algorithms, especially when used in both proforma and realized scheduling. The Greedy algorithm, while reducing berth deviations and waiting container hours compared to the base case, often results in higher waiting times, particularly when applied in the realized scheduling phase. Moreover, the base algorithm and greedy algorithm for realized planning perform better across all 3 metrics when paired with a proforma schedule generated with SA. Furthermore, if the SA algorithm is used for realized berth allocation, then it can improve performance compared to the greedy algorithm across all three metrics. This shows that the SA optimization of the greedy algorithms input order is effective.

The figure also illustrates the effects of different proforma schedules on the operational efficiency of a container terminal. Different proforma schedules account for substantial variance in performance when combined with the different algorithms for realized scheduling. However, the SA algorithm is generally able to reduce the impact of different proformas and outperforms the Base and Greedy algorithms when these are paired with their proforma counterpart.

All in all, the SA algorithm appears to be the most robust and effective in optimizing operational efficiency in port scheduling, reducing both waiting times and berth deviations, while also improving container handling efficiency. The SA algorithm generally outperforms the base and greedy algorithms when used for the proforma schedule, realized schedules and both combined.

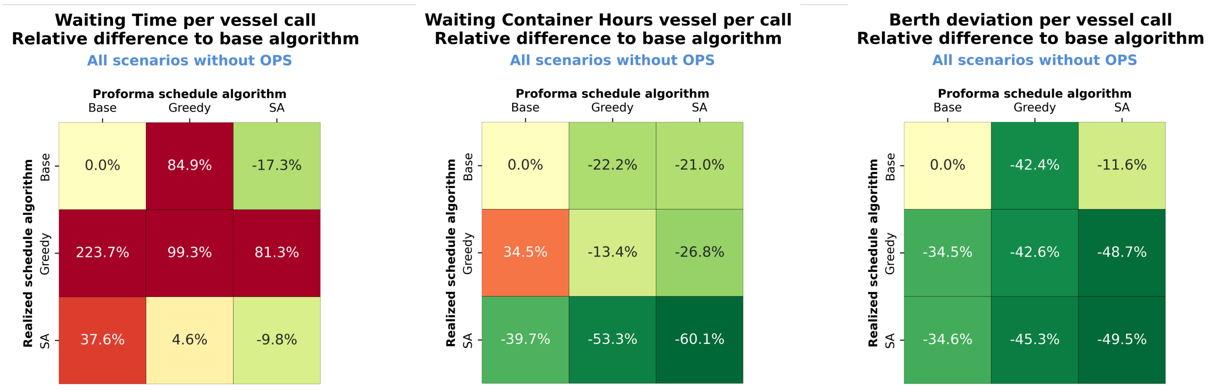

Figure 6.3: Matrices for each evaluation metric showing the performance of the nine possible algorithm combinations relative to the base algorithm. The values are obtained by taking the average of all replications of all scenarios without OPS.

Figure 6.3 showed that the SA algorithm is effective in optimizing the input order of the greedy algorithm. For the SA algorithm, the initial solution is the same as the greedy algorithm. Figure 6.4 shows the frequency of improvement compared to the initial solution for the proforma and realized instances of the CBAP of all 69 experiments described in section 5. The simulated annealing can either improve the initial solution, it can't improve the initial solution because the initial solution is optimal with an objective value of 0 or it can't improve the non-optimal initial solution. Figure 6.5 shows per scenario the average improvement when the initial solution is improved.

Simulated Annealing is able to improve the proforma schedule costs in all 690 simulation runs. The average proforma cost improvement for each scenario is between 76% and 95% relative to the initial solution. For realized planning, the initial solution is improved for 25% of the problem instances while 24% of the time, the initial solution was already optimal. For all scenarios, the average improvement for the realized schedule is between 30% and 40%. This decrease in frequency and average improvement compared to the proforma schedule is most likely due to the size of the problem instance. For the proforma schedule, the number of vessels V that have to be scheduled is larger than for realized arrivals, since the proforma has a planning horizon of a week while for realized arrivals the planning horizon is only 12 hours because of uncertain arrival times. Figure 6.4 supports this by showing the SA performance of the realized schedule for different problem sizes. It can be seen that as V increases, the likelihood that SA can improve the initial solution increases while the likelihood that the initial solution is optimal decreases. Contrary to the frequency of improvement, Figure 6.5 Shows that the average improvement compared to the initial solution reduces as V increases for all scenarios.

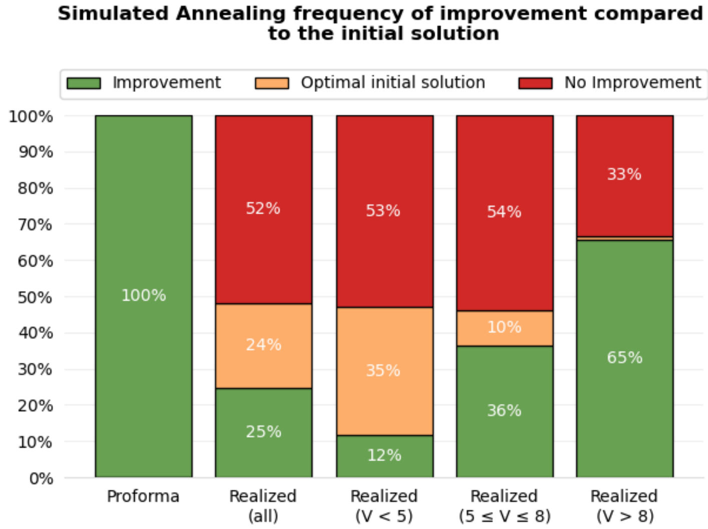

Figure 6.4: Improvement distribution of the SA algorithm compared to the initial greedy solution. V is the number of arriving vessels that have to be scheduled in the planning horizon.

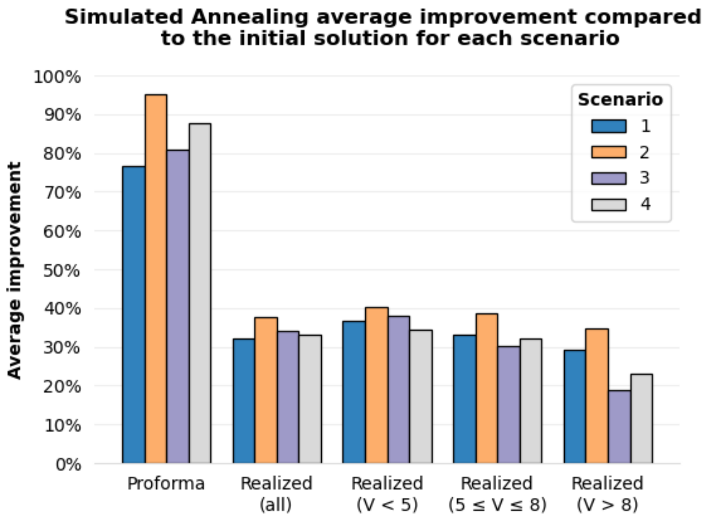

Figure 6.5: Average improvement compared to the initial greedy solution. V is the number of arriving vessels that have to be scheduled in the planning horizon.

From the results in this section, it becomes clear that the Simulated Annealing is an effective way to improve the input order of a greedy algorithm to optimize berth planning. The simulation results with SA show significant improvement over simulations without simulated annealing. To analyse the impact of OPS and evaluate algorithm performance for each scenario individually, only the SA algorithm will be compared to the Base algorithm with and without priority since it outperforms the greedy algorithm across all three evaluation metrics.

6.2 Scenario and Shore Power design simulations

For each scenario, the quayside operations without OPS and with the shore power designs specified in Table 5.2 are simulated with the Base TRAFALQUAR Algorithm without vessel priorities, the Base Algorithm with vessel priorities and with the Simulated Annealing algorithm. The performance of each experiment is evaluated based on three metrics: Average vessel waiting time, Total waiting container hours and Average vessel berth deviation. The error bars that are displayed for each experiment show the 95%-confidence interval. There is a significant difference in performance between experiments when the confidence intervals do not overlap.

6.2.1 Scenario 1: 5.0 M TEU – 1 Berth

Figure 6.6 shows the average waiting time at the anchorage point per arriving vessel for each of the OPS designs specified for Scenario 1. It can be seen that for each algorithm, as the number of zones increases, the waiting times get closer or become similar to the experiments without OPS. This is expected since more zones are expected to facilitate more flexibility.

For each Shore power design, the Base algorithm with priority has higher average waiting times compared to the other two algorithms. With the SA algorithm, the waiting times are significantly higher for the design of 5 and 6 zones in comparison with the Base algorithm. This is likely because the SA algorithm optimizes waiting costs and will often let smaller vessels wait longer with fewer zones. However, for 8 zones, 10 zones and the experiment without OPS, the SA algorithm has significantly lower waiting times. For the base algorithm, there is no significant rise in waiting time with 7 or more zones compared to no shore power. For Base with priority and SA, at least 8 zones are needed to get similar waiting times.

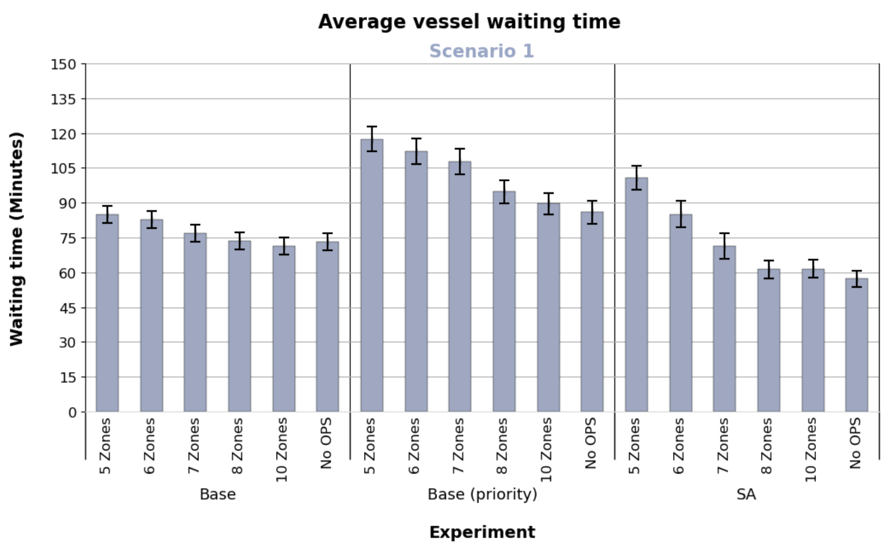

Figure 6.6: Average waiting times of a vessel for each experiment of Scenario 1.

Figure 6.7 displays the total waiting container hours per year. The graph indicates that all experiments using the SA algorithm outperform those using the Base algorithm with priority. Similarly, all experiments with the Base algorithm with priority outperform those with the Base algorithm without priority. There is no significant difference in waiting container hours among the experiments using the Base algorithm without priority, likely because this algorithm does not account for vessel size. However, for the algorithms that do take vessel size into account, fewer zones result in more waiting container hours due to limited flexibility. Both the Base with priority and SA algorithms demonstrate that with 8 or more zones, performance similar to the experiments without OPS is achieved.

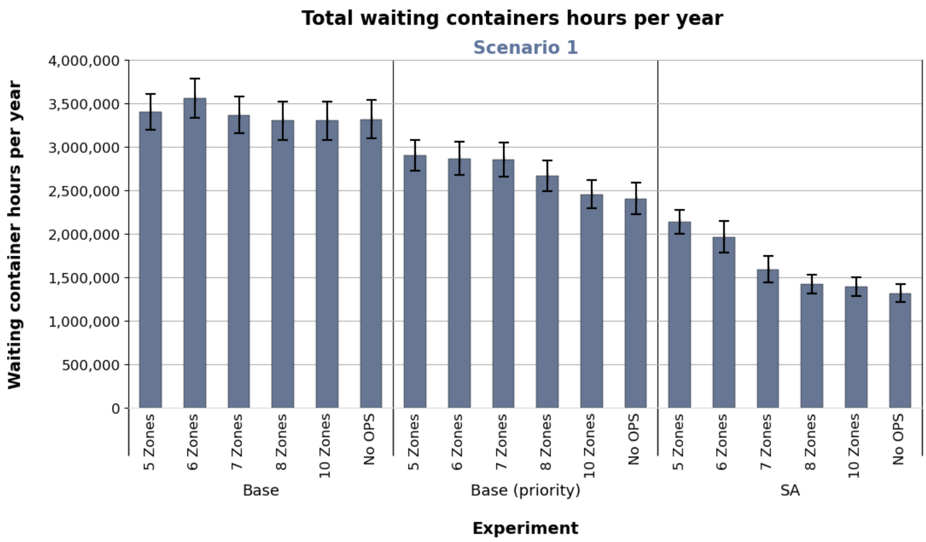

Figure 6.7: Total waiting container hours per experiment of scenario 1.

Figure 6.8 shows the average berth deviation per vessel. It can be seen that the Base algorithm is the worst of the three while the Base algorithm with priority is consistently better than without priority. However, if there are more than 7 zones or if no shore power is required, then the simulated annealing algorithm is best at berthing vessels close to their planned position. With SA, 7 zones or more are required to have a similar average berth deviation to the experiment without shore power.

Across all three metrics, the Simulated Annealing algorithm can improve the terminal's berth planning compared to both Base algorithms. Moreover, the container terminal can achieve similar performance with and without shore power. However, if this terminal wants to operate with shore power without sacrificing any performance, then it will need to install a minimum of 8 zones. This is the case for all three algorithms.

6.2.2 Scenario 2: 4.5 M TEU – 2 Berths

For Scenario 2 there is no significant difference in vessel waiting time between the Base algorithm without priority and the Simulated Annealing algorithm as shown in Figure 6.9. However, the

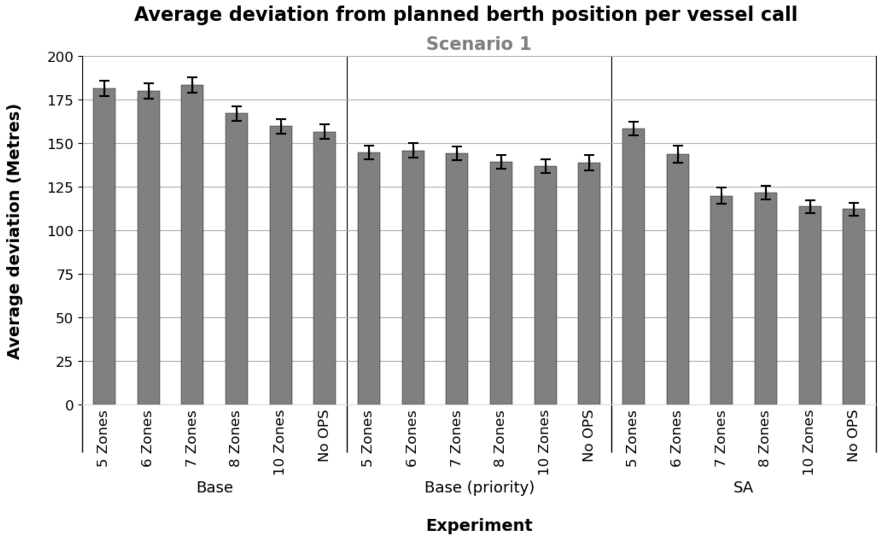

Figure 6.8: Average distance between planned and realized berth position for each experiment of Scenario 1.

average waiting time almost triples without shore power when vessel prioritization is introduced for the Base algorithm. This is because vessel prioritization is a hard constraint which means that feeder calls will always have to wait for deepsea calls. This results in longer average waiting times. The SA algorithm is able to reduce the waiting times since the waiting costs it assigns to vessels are not a hard constraint. For both Base algorithms to maintain the same service level with shore power as without, it is necessary to divide the quay into at least 8 zones. With SA, the difference in waiting time between the 6, 7 and 8 zones is insignificant as the confidence intervals overlap. This could indicate that with SA as an allocation algorithm, the number of necessary shore power zones could be reduced compared to the Base algorithms.

Figure 6.10 shows the total waiting container hours for all experiments of Scenario 2. Notably, the total waiting container hours are significantly lower for the Base algorithm without priority compared to the Base algorithm with vessel priorities. This is in contrast to the results of Scenario 1. It is expected to have lower waiting container hours with priority since the prioritization should make larger vessels wait less. However, for this scenario, the feeder vessels have to wait so much longer due to the priority constraint that, in the end, the total waiting container hours are much higher. This is an example of a scenario where prioritization is not successful in reducing The SA algorithm can reduce the total waiting container hours by more than 50% across all OPS designs compared to both Base algorithms while having similar average waiting times as the Base algorithm without vessel prioritization. This shows that the SA algorithm can reduce the waiting times for larger deepsea vessels and feeder vessels without the need for prioritization.

To remove any negative effect of shore power on the terminal's waiting container hours it is necessary to install at least 7 shore power zones when vessels are scheduled using Simulated Annealing. This is again less than the minimum of 8 zones that are required with the Base algorithms.

The last key performance indicator of the quayside operations is the average berth deviation

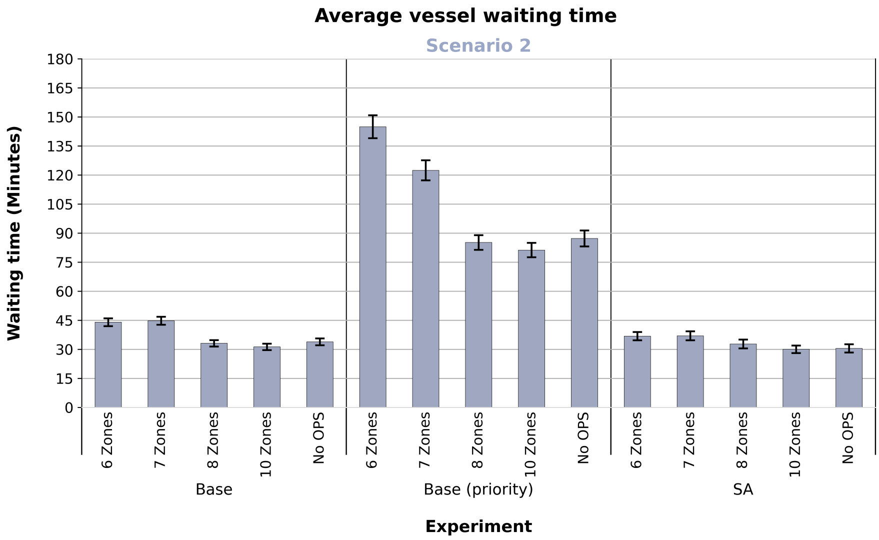

Figure 6.9: Average waiting times of a vessel for each experiment of Scenario 2.

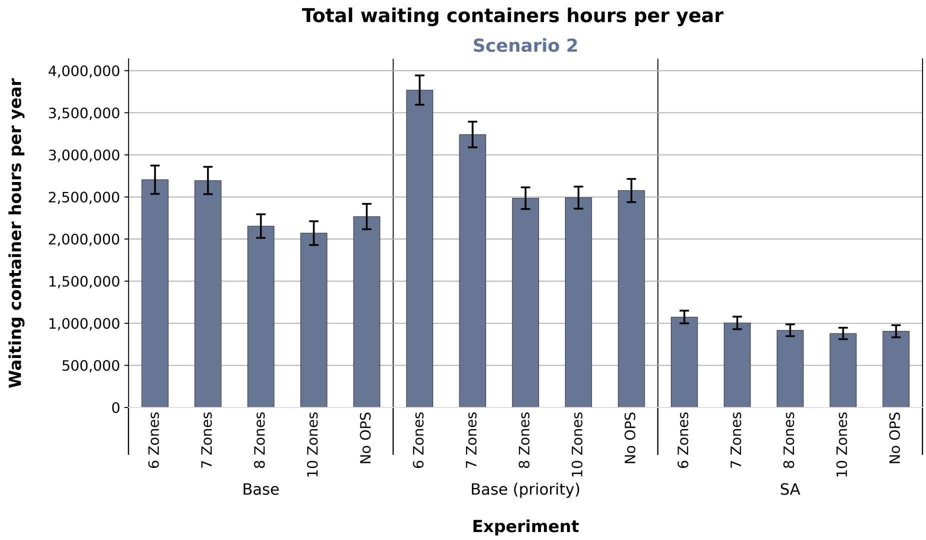

Figure 6.10: Total waiting container hours per experiment of scenario 2.

shown in Figure 6.11. On average, the Base algorithms will allocate vessels further from their planned position compared to the SA algorithm, which is significantly better for all experiments. However, vessel prioritization helps the Base algorithm reduce berth deviations. Again it is noticeable that with both Base algorithms more than 8 zones are required to maintain similar average berth deviation while with SA, there is no significant difference between the experiment with 7 zones and the experiment without shore power.

In short, the SA annealing algorithm improves the berth planning of the container terminal in scenario 2. It outperforms the Base algorithm with and without vessel priorities for all eval-

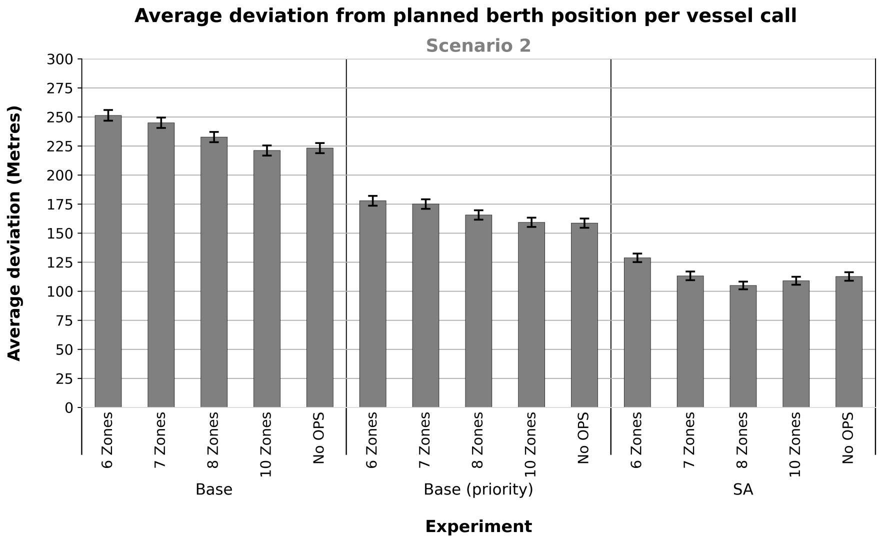

Figure 6.11: Average distance between planned and realized berth position for each experiment of Scenario 2.

uation metrics. Moreover, with SA, fewer shore power zones are required to maintain the same performance level as without shore power compared to the Base algorithms. This indicates that for scenario 2 and improved berth planning, the number of zones and therefore the necessary shore power investments can be reduced to benefit the terminal operator.

6.2.3 Scenario 3: 2.5 M TEU – 1 Berth

The average waiting times in Figure 6.12 for scenario 3 show that the Base algorithm without priority results in the lowest vessel waiting times. Vessel priority will significantly increase the average waiting times while SA will be in the middle of both Base algorithms. For all berth strategies, only a shore power design with 4 zones does not result in similar waiting times as those without shore power.

For the total waiting container hours presented in Figure 6.13, the results are as expected. The Base strategy without priority results in the most waiting container hours since large deepsea vessels are more likely to wait. With prioritization, the total number of container hours can be reduced at the cost of the longer waiting times. However, using vessel-specific waiting costs and SA will significantly decrease the total waiting container hours while still improving the waiting time compared to the Base strategy with priorities. Equivalent to the results in Figure 6.12, at least 5 shore power zones are needed to get similar results to the experiments without shore power.

Even with less quay space, compared to scenarios 1 and 2, the SA algorithm manages to lessen the average distance to the planned berth position compared to the Base strategies. Figure 6.14 shows that, while prioritization helps to berth vessels closer to their planned position, the SA strategy can reduce the average berth deviation. The base algorithm without priority is considerably inferior to the other two algorithms. Moreover, for the Base strategies the berth deviation is slightly higher when less flexibility is available due to fewer shore power zones. For

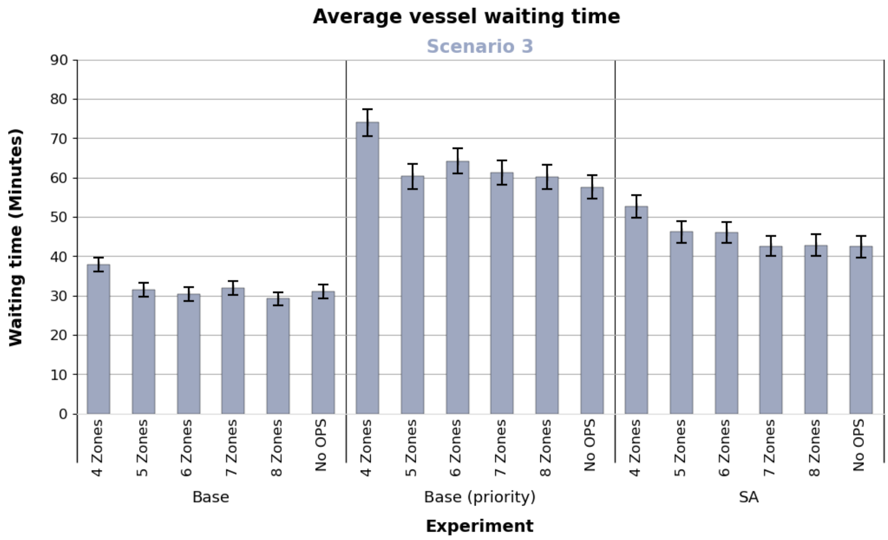

Figure 6.12: Average waiting times of a vessel for each experiment of Scenario 3.

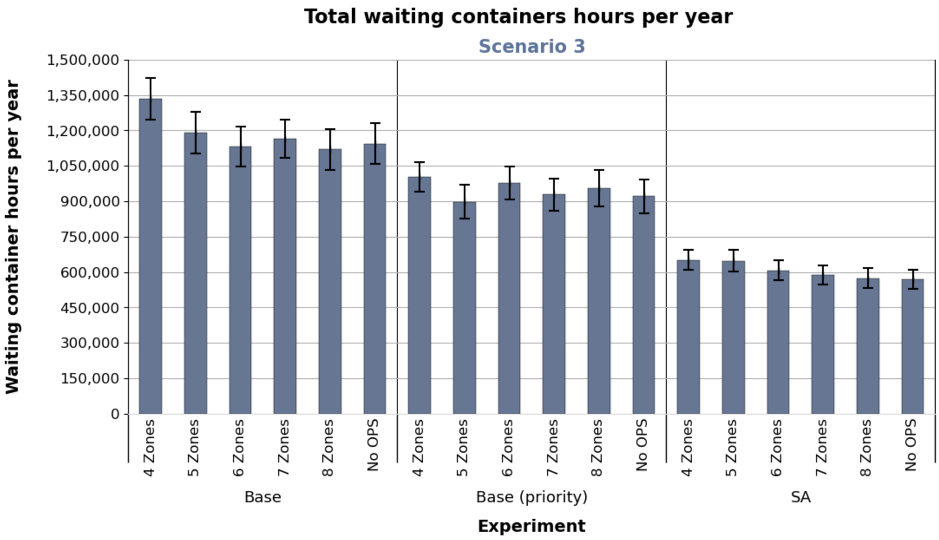

Figure 6.13: Total waiting container hours per experiment of scenario 3.

the SA algorithm, there is no significant difference between any of the Shore Power designs.

In summary, it is still possible to improve berth planning with Simulated Annealing for a terminal with a shorter quay and therefore less space for variability. However, it is also apparent that shore power has less influence on quayside operations in this Scenario compared to the results of Scenarios 1 and 2. For all evaluation metrics and algorithms, the performance between the various Shore Power designs is not significantly different unless there are only 4 zones. This is likely due to the shorter quay length which has space for at most 5 vessels with the vesselmix specified. The slight decrease in performance with 4 zones indicates that sometimes 5 vessels

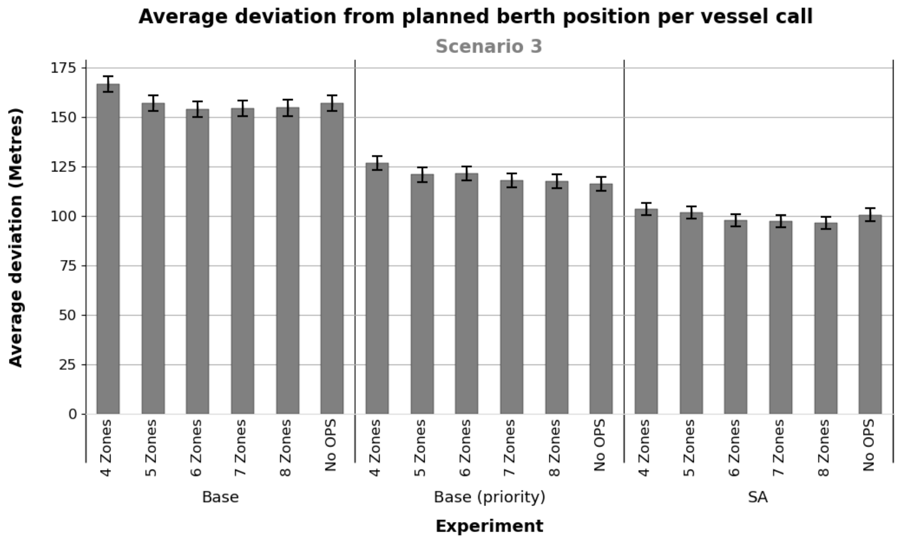

Figure 6.14: Average distance between planned and realized berth position for each experiment of Scenario 3.

need to be berthed simultaneously.

6.2.4 Scenario 4: 2.2 M TEU – 2 Berths

In scenario 4, the quay is separated into 2 berths of 600 metres. This means that per berth there is even less flexibility. Figure 6.15 shows the average vessel waiting times. Again, the average vessel waiting time is the lowest with the base algorithm without priority. However, it is notable that the experiment without shore power has significantly higher waiting times than with 8 zones which contrasts expectations. Since the difference is small, it could still be caused by uncertainty even after the 10 replications. Another reason could be that the additional restrictions help the Base algorithm berth the vessels more efficiently. Nonetheless, the average waiting times without shore power are still significantly less than the other two strategies. Contrary to the previous 4 scenarios, the difference in waiting times between the Base algorithm with priority and SA is insignificant for most experiments. Only with less than 6 zones the performance of SA is substantially better. This implies that the SA and Base with priority are equally capable of limiting waiting times as long as there are 6 or more zones. With 4 or 5 zones, the flexibility is too limited for the Base algorithm while the SA algorithm has significantly less average waiting time. Nevertheless, 6 zones or more are needed to reduce the operational impact of shore power.

Figure 6.16 shows the total waiting container hours for Scenario 4. The Base strategy without priorities again appears to perform better with shore power however in this graph the difference is insignificant due to the larger confidence intervals. The difference in waiting container hours and the larger confidence intervals is because the Base algorithm only optimizes waiting time. The total waiting container hours are directly related to the average vessel waiting time since the algorithm never takes into account the vessel sizes. Moreover, since it does not use vessel sizes, more fluctuations in waiting container hours are expected leading to more uncertainty and larger confidence intervals. In line with previous observations, the addition of vessel priorities to

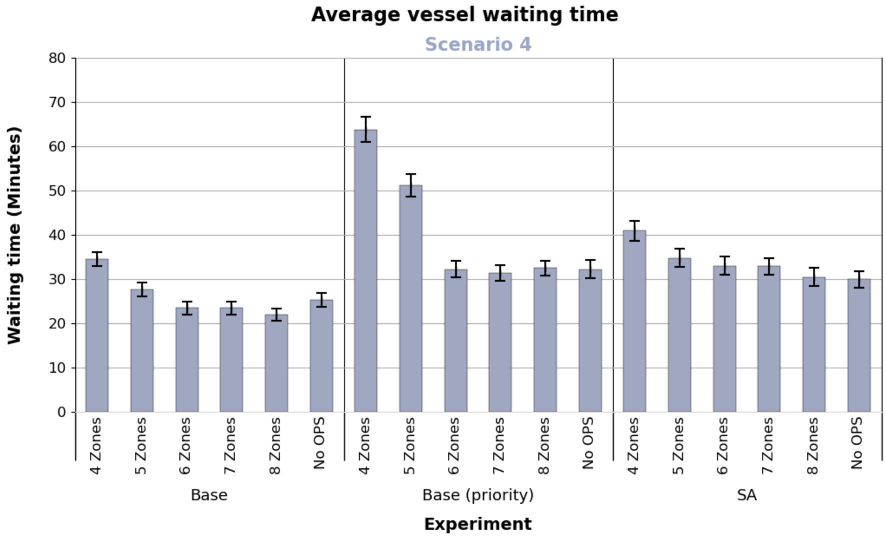

Figure 6.15: Average waiting times of a vessel for each experiment of Scenario 4.

the Base algorithm benefits the total waiting container hours. However, when there is less berth flexibility with 4 zones, The difference is insignificant. The SA algorithm can reduce the total waiting container hours with less flexibility. Yet, the SA performs significantly better with more than 4 zones. Nevertheless, with 6 or more zones, the performance between the SA algorithm and the Base algorithm with priorities is similar. This means that with enough zones there is no difference between the two strategies in terms of average waiting time and total waiting container hours.

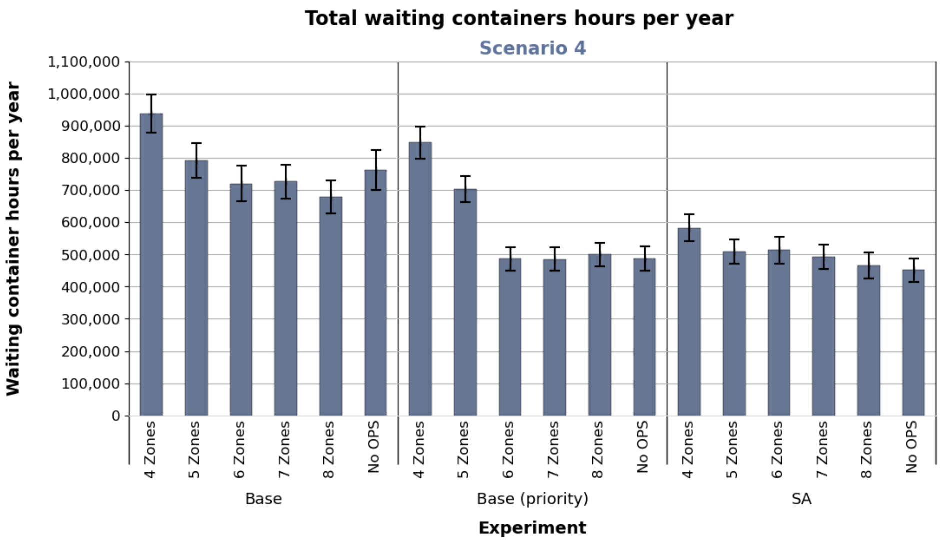

Figure 6.16: Total waiting container hours per experiment of scenario 4.

The previous two figures showed no significant difference between the Base strategy with priority and the SA strategy. However, Figure 6.17 shows that the SA algorithm significantly reduces the average berth deviation compared to both base algorithms. Remarkably, there is no significant difference between the Base strategy with or without priority, unlike the results from the other three scenarios where vessel prioritization benefits berth deviation. With SA, 5 zones are the minimum to require a similar average berth deviation while for both base algorithms, the deviation is significantly worse at 5 zones compared to the design without shore power.

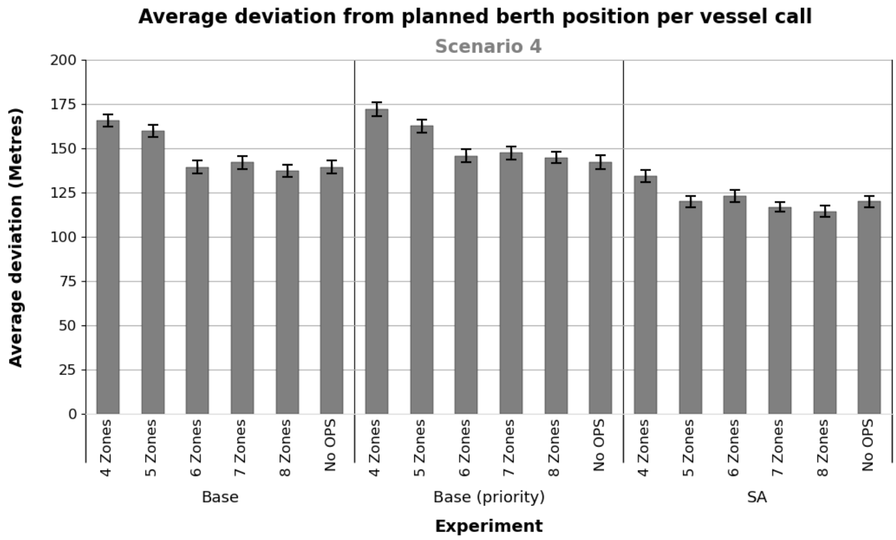

Figure 6.17: Average distance between planned and realized berth position for each experiment of Scenario 4.

Even though the Base strategy without prioritization results in the least vessel waiting time, it is outperformed by SA on the total waiting container hours and average berth deviation. The Base strategy with priority performs similarly to the SA strategy for the first two metrics if the flexibility is not too limited by Shore Power. However, with less flexibility when the quay is divided into 4 or 5 Shore Power zones then SA is superior. Moreover, across all experiments, the lowest berth deviation is achieved with the SA algorithm.

7 Discussion

The primary objective of this thesis was to evaluate whether an allocation algorithm could enhance the efficiency of berth planning in container terminals that utilize shore power. While previous studies have predominantly focused on the environmental benefits of shore power, particularly in reducing emissions, there has been limited research on its potential negative operational impacts, especially on berth planning. To address this gap, Portwise's TRAFALQUAR, a verified simulation model, was employed to simulate the operations of container terminals. The key performance indicators identified for berth planning included waiting time, waiting container hours, and the deviation to the proforma berth position. A simulated annealing algorithm was proposed to optimize the input order of a greedy algorithm, aiming to enhance berth planning beyond the capabilities of existing algorithms offered by TRAFALQUAR. The most prominent change introduced by the Greedy algorithm is the ability to assign vessel-specific waiting costs, allowing for more effective vessel prioritization. To ensure a comprehensive analysis, four scenarios are defined. Each scenario is a different container terminal modelled to represent a typical European terminal, where shore power utilization will become mandatory starting in 2030. Vessel arrival patterns were simulated to compare various berth planning strategies and examine the influence of different shore power designs on quayside operations. Chapter 6 presented the simulation results comparing various planning strategies and showed the impact of shore power on quayside operations under different berth strategies.

First, the difference between TRAFALQUAR's Base algorithm, the Greedy algorithm and the Simulated Annealing algorithm was highlighted for both the proforma and realized berth schedules. In terms of the proforma berth schedule, the schedule generated using the Simulated Annealing algorithm was more robust, leading to improvements in realized berth planning across all algorithms. The Simulated Annealing algorithm proved to be the superior allocation algorithm providing the best results across all three evaluation metrics when used for the proforma and realized berthing schedules. Furthermore, the Simulated Annealing algorithm consistently demonstrated its effectiveness in optimizing the input order of the Greedy algorithm, thereby enhancing its overall performance.

Secondly, the results of the simulation experiments for each of the four scenarios are presented. The operations at each terminal were simulated using both the Simulated Annealing algorithm and the Base TRAFALQUAR algorithm, with and without vessel prioritization, under various Shore Power designs. The Simulated Annealing algorithm outperformed both Base algorithms across all three evaluation metrics for every scenario and shore power design. This shows that vessel-specific waiting costs as a method of vessel prioritization offer more room for optimization than modelling vessel priorities as a hard constraint.

Across all experiments, it was demonstrated with all three berth algorithms that maintaining operational performance is feasible with an appropriately designed shore power system. The primary constraint imposed by shore power on berth planning is the reduced berth flexibility, as vessels must dock within range of an available shore power connection. Increasing the number of connection zones enhances this flexibility, approaching the level seen without shore power. This trend was observed across all scenarios: terminals with fewer zones exhibited the poorest performance, which progressively improved as additional zones were added, ultimately matching the performance of terminals without shore power. Each berth strategy identified a minimal number of zones that eliminated any negative impacts on performance for each scenario. Notably, the Simulated Annealing algorithm showed less sensitivity to the number of connection zones compared to the other algorithms. Specifically, in Scenarios 2 and 4, the Simulated Annealing algorithm maintained unrestricted performance with fewer zones than the Base strategies. This suggests that improved berth planning can mitigate the negative effects of shore power, allowing for higher operational efficiency even with more restrictive shore power designs.

These findings indicate that Shore Power can be a sustainable initiative to reduce the carbon footprint of container terminals without being a burden on container terminals' operational efficiency. For Portwise, this study is particularly valuable as it highlights the operational impact of Shore Power and underscores the importance of effective berth planning for container terminals. As part of this thesis, an improved berth strategy, which allows more control over vessel prioritisation through vessel-specific waiting costs, has been integrated into their berth simulation model, TRAFALQUAR. Additionally, the model now allows for specifying shore power designs to simulate their effects on quayside operations. With these enhancements, Portwise can offer more comprehensive berth studies, aiding customer terminals in making informed decisions regarding Shore Power implementation.

While this study provides valuable insights into the impact of shore power and berth planning on container terminal operations, several limitations must be acknowledged. Firstly, the simulation model, TRAFALQUAR, although robust and well-verified, relies on certain assumptions and simplifications that may not fully capture the complexities of real-world terminal operations. One of these assumptions is the knowledge of exact arrival times 12 hours in advance. However, in real-world situations, arrival times can fluctuate even in the last few hours before expected arrivals. Another assumption that simplified real-world terminals is that there are no equipment breakdowns which can disrupt operations. These assumptions can have an enormous impact on the reliability of berthing schedules and the performance of berthing algorithms. Secondly, the research primarily utilized a simulated annealing algorithm to optimize berth planning. While this algorithm showed superior performance in the study, there may be other optimization techniques or hybrid approaches that could offer comparable or better results. Finally, for each specified number of zones, only a single design was considered per scenario. There may be further opportunities for optimization by exploring various combinations of zone lengths. Furthermore, the vessel mix appears to be a critical factor in the performance of a shore power design. To better assess the generalizability of shore power designs, it would be advisable to test multiple designs and a variety of vessel mixes for each scenario. This would provide a more comprehensive understanding of how different design configurations and vessel compositions impact the effectiveness of shore power integration.

8

Conclusion and future work

To answer the research question-"To what extent can berth planning be optimized to improve the performance of a container terminal with shore power?"—the study demonstrated that optimizing berth planning can significantly enhance terminal performance, even under the constraints of shore power. The Simulated Annealing algorithm consistently outperformed both TRAFALQUAR's Base algorithms, providing the most robust solutions for proforma and realized berth schedules. The Simulated Annealing algorithm achieved superior results across all evaluation metrics by optimizing the input for the Greedy algorithm and incorporating vessel-specific waiting costs. Additionally, it was observed that with the right shore power design, particularly by increasing the number of shore power connection zones, terminals can maintain high levels of operational flexibility and efficiency. The Simulated Annealing algorithm was particularly effective, maintaining optimal performance even with fewer connection zones compared to other algorithms. This highlights the potential for improved berth planning to mitigate the operational constraints imposed by shore power, thereby achieving higher efficiency with more restrictive shore power designs.

Given the limitations identified in this study, there are several possibilities for future research to build on these findings and improve the understanding of shore power and berth planning optimization. Firstly, future studies should aim to model real-world terminal operations more accurately. This includes accounting for the variability in vessel arrival times, especially the deviations that can occur in the final hours before docking. Another improvement would be to incorporate potential equipment breakdowns that can disrupt operations. By addressing these factors, the reliability of berthing schedules and the performance of berthing algorithms can be more rigorously tested.

Additionally, exploring other optimization techniques next to the simulated annealing algorithm could yield further improvements in berth planning. Hybrid approaches or entirely different algorithms might offer comparable or even superior results.

Furthermore, future research should consider multiple designs for each specified number of shore power zones. Investigating various combinations of zone lengths could expose more efficient designs. The vessel mix also plays an important role in the effectiveness of shore power designs, so testing a range of designs with different vessel compositions for each scenario is essential. This approach would provide a better understanding of how design configurations and vessel mixes impact shore power integration, ultimately leading to more generalizable and robust shore power solutions for container terminals.

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A

Appendix

A.1 Scenario 1: 5.0 M TEU – 1 Berth

ID	Vessel Type	Length (m)	Mooring margin (m)	Call size (box)	Priority (Base)	Waiting Cost (SA)
FD1	Feeder	150	15	200	1	1
FD2	Feeder	180	15	600	1	1.4
FD3	Feeder	200	15	900	1	1.7
DS1	Deepsea	240	25	1,200	2	10
DS2	Deepsea	270	25	1,500	2	10
DS3	Deepsea	300	25	2,000	2	12
DS4	Deepsea	340	25	3,000	2	14
DS5	Deepsea	370	25	5,000	2	18
DS6	Deepsea	400	25	10,000	3	25

Table A.1: Vessel mix used for Scenario 1.

ID	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total calls
FD1		1	1	1	1	1	1	**6**
FD2	1		1	1	1	1	1	**6**
FD3		1		1		1	1	**4**
DS1			1				1	**2**
DS2		1		1		1		**3**
DS3		1	1				1	**3**
DS4		1		1		1		**3**
DS5			1					**1**
DS6	1				1			**2**
Total Calls	**2**	**5**	**5**	**5**	**3**	**5**	**5**	**30**

Table A.2: Weekly arrival pattern used for scenario 1.

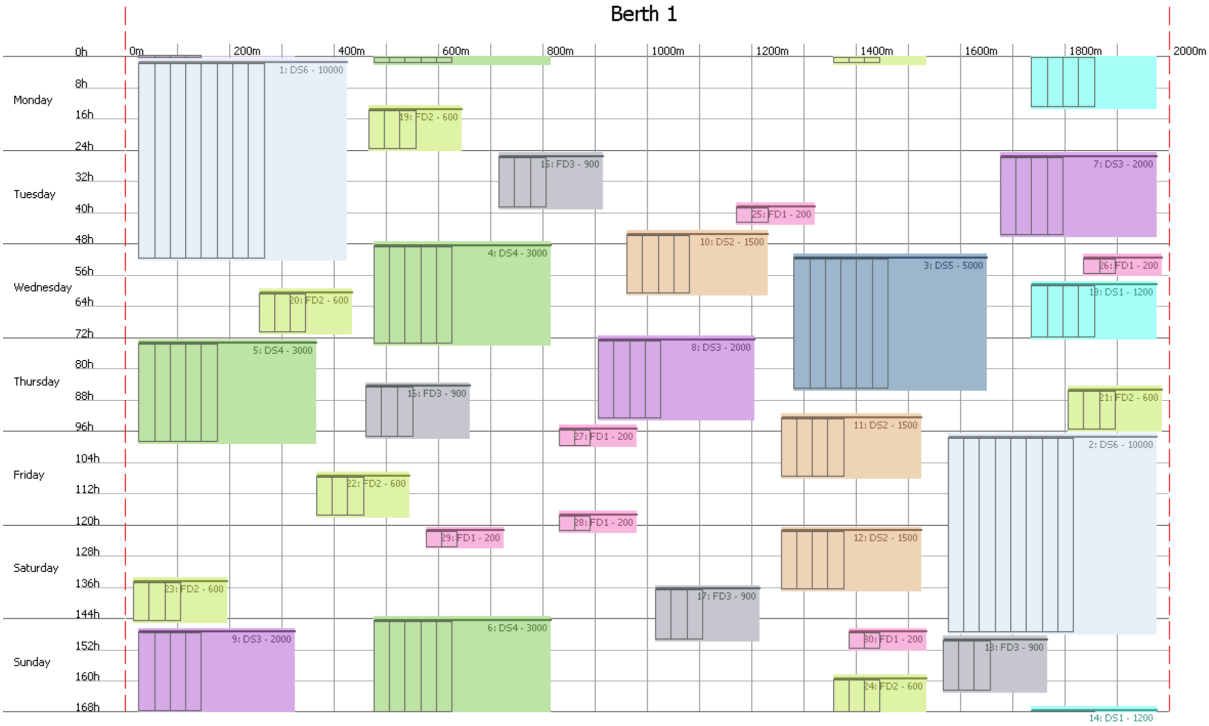

Figure A.1: Visualized week pattern Scenario 1

A.2 Scenario 2: 4.5 M TEU – 2 Berths

ID	Vessel Type	Length (m)	Mooring margin (m)	Call size (box)	Priority (Base)	Waiting Cost (SA)
FD1	Feeder	150	15	200	1	1
FD2	Feeder	180	15	600	1	1.4
FD3	Feeder	200	15	900	1	1.7
DS1	Deepsea	240	25	1200	2	10
DS2	Deepsea	270	25	1500	2	10
DS3	Deepsea	300	25	2000	2	12
DS4	Deepsea	340	25	3000	2	14
DS5	Deepsea	370	25	4000	3	18
DS6	Deepsea	400	25	5000	3	22

Table A.3: Vessel mix used for Scenario 2.

ID	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total calls
FD1	1	1	1	1	1	1	1	**7**
FD2	1		1	1	1	1	1	**6**
FD3	1	1		1		1	1	**5**
DS1	1		1		1		1	**4**
DS2		1		1		1		**3**
DS3		1	1		1		1	**4**
DS4		1		1		1		**3**
DS5			1					**1**
DS6	1				1			**2**
Total Calls	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**35**

Table A.4: Weekly arrival pattern used for scenario 2.

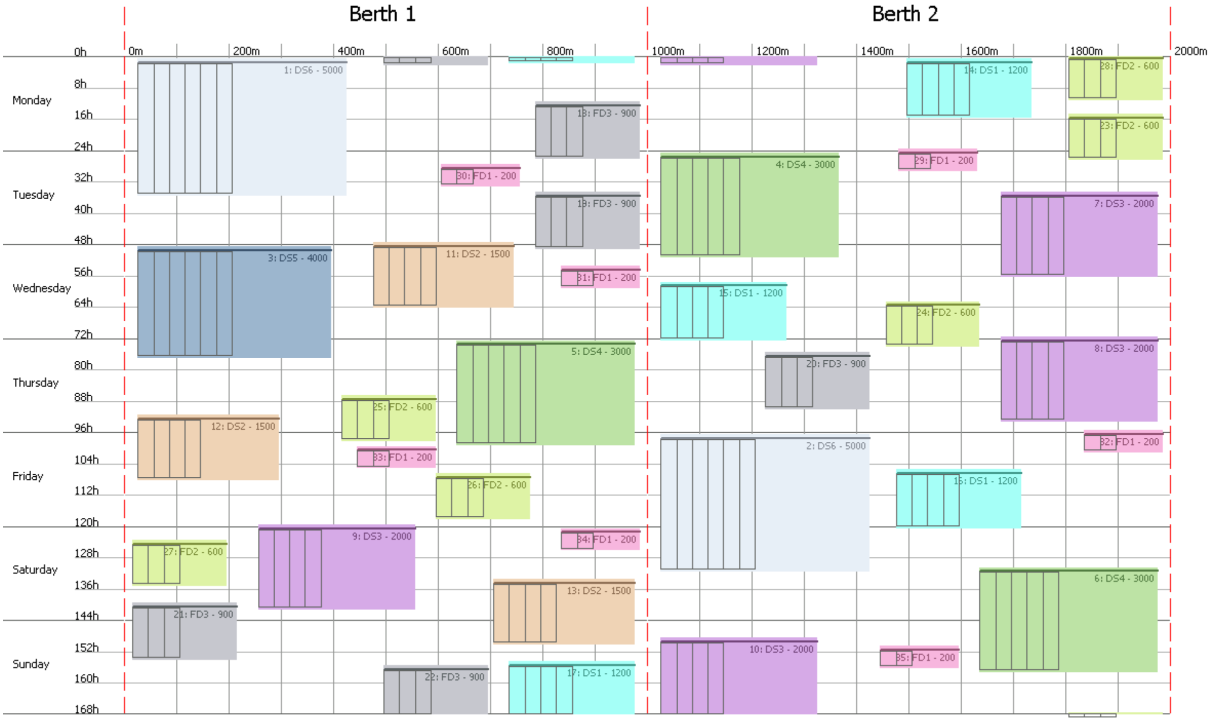

Figure A.2: Visualized week pattern Scenario 2

A.3 Scenario 3: 2.5 M TEU – 2 Berths

ID	Vessel Type	Length (m)	Mooring margin (m)	Call size (box)	Priority (Base)	Waiting Cost (SA)
FD1	Feeder	150	15	200	1	1
FD2	Feeder	180	15	400	1	1.4
FD3	Feeder	200	15	600	1	1.7
DS1	Deepsea	240	25	900	2	5
DS2	Deepsea	270	25	1200	2	7
DS3	Deepsea	300	25	1600	2	10
DS4	Deepsea	340	25	2000	2	12
DS5	Deepsea	370	25	2500	2	14
DS6	Deepsea	400	25	3000	2	16

Table A.5: Vessel mix used for Scenario 3.

ID	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total calls
FD1	1	1	1	1	1	1	1	**7**
FD2	1	1	1	1	1	1	1	**7**
FD3	1			1			1	**3**
DS1		1			1		1	**3**
DS2						1	1	**2**
DS3		1	1					**2**
DS4					1			**1**
DS5			1	1				**2**
DS6	1					1		**2**
Total Calls	**4**	**4**	**4**	**4**	**4**	**4**	**5**	**29**

Table A.6: Weekly arrival pattern used for scenario 3.

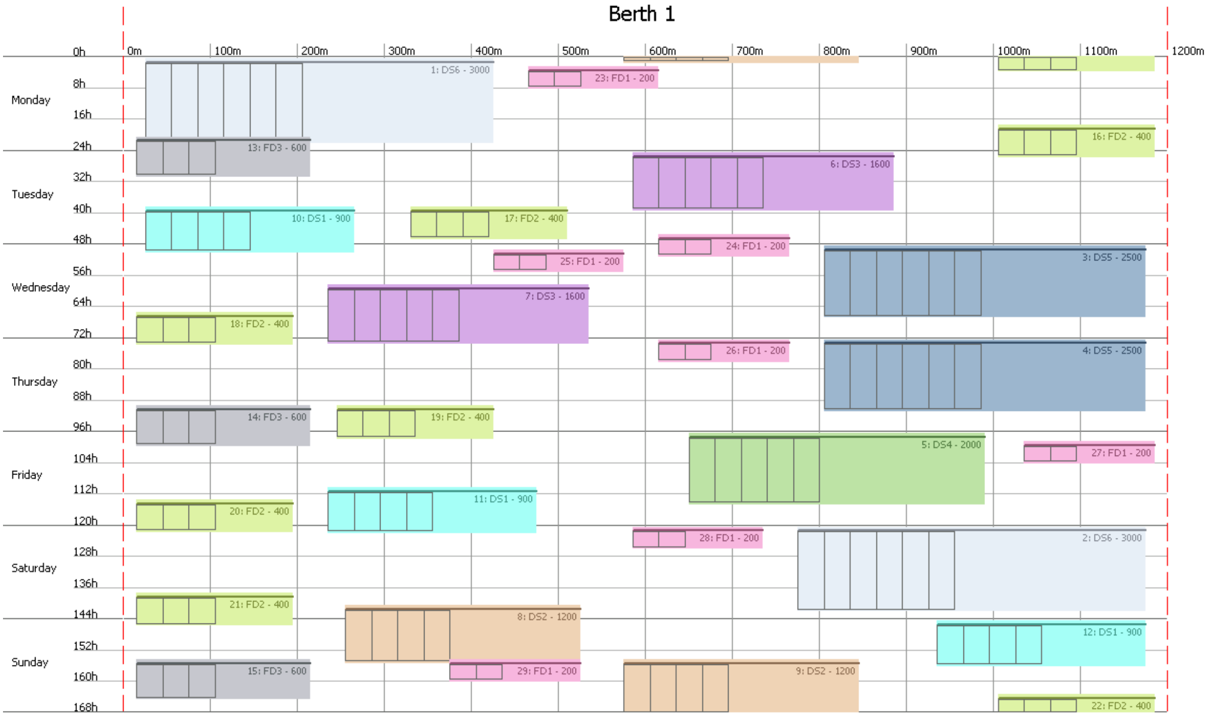

Figure A.3: Visualized week pattern Scenario 3

A.4 Scenario 4: 2.2 M TEU – 2 Berths

ID	Vessel Type	Length (m)	Mooring margin (m)	Call size (box)	Priority (Base)	Waiting Cost (SA)
FD1	Feeder	150	15	200	1	1
FD2	Feeder	180	15	400	1	1.2
FD3	Feeder	200	15	600	1	1.5
DS1	Deepsea	240	25	900	2	10
DS2	Deepsea	270	25	1200	2	10
DS3	Deepsea	300	25	1600	2	12
DS4	Deepsea	340	25	2000	2	14
DS5	Deepsea	370	25	2500	2	16
DS6	Deepsea	400	25	3000	2	20

Table A.7: Vessel mix used for Scenario 4.

ID	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total calls
FD1	2	2	1	2	2	2	2	**13**
FD2	1		1	1	1		1	**5**
FD3	1	1	1	1		1	1	**6**
DS1		1				1		**2**
DS2		1						**1**
DS3				1		1		**2**
DS4							1	**1**
DS5	1		1					**2**
DS6					1			**1**
Total Calls	**5**	**5**	**4**	**5**	**4**	**5**	**5**	**33**

Table A.8: Weekly arrival pattern used for scenario 4.

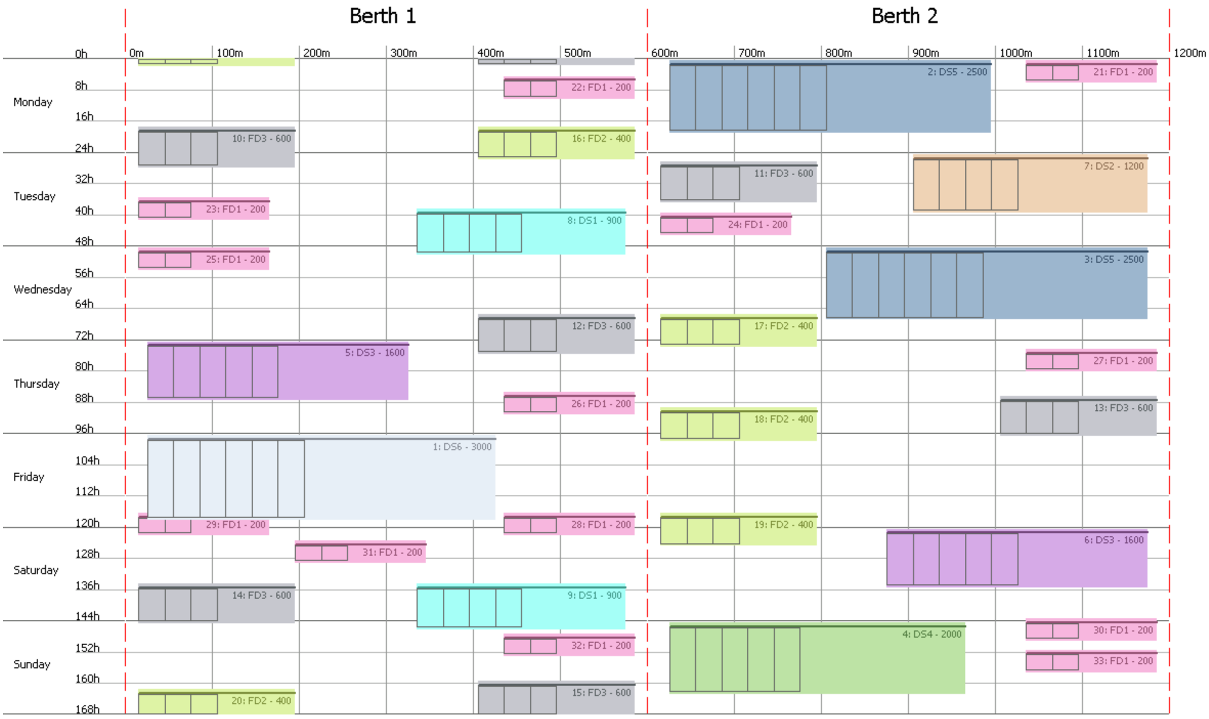

Figure A.4: Visualized week pattern Scenario 4