

Berth Planning and Disruption Recovery: A Sim- ulation Approach

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by

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Abstract

With the increasing amount of container freight transport and the increasing size of container vessels, for the Port of Antwerp, the second largest container port in Europe, a critical task is port planning. A simulation model provides the means to gain proper insight in the effect of future expansions. Macomi, a company specialized in simulation and optimisation, has been working on a simulation model to aid the Port of Antwerp in their port planning. One important issue in this simulation model is how the berth allocation of vessels is handled. Berth allocation is the problem of assigning vessels a time and location at the quay wall where the vessel can be loaded and unloaded. In this thesis, the aim is to develop decision models for both the preliminary berth planning and the real-time recovery of this plan during simulation. For the first part, a cyclic baseline berth allocation plan is created which takes into account the tidal dependencies vessels have when entering the port of Antwerp. This preliminary berth plan is used as a basis for the simulation model as the arrival times are based on this plan. However, during the simulation disruptions might occur; vessels can arrive earlier or later or take longer to load and unload. To deal with these disruptions a real-time disruption management decision model is proposed which aims to solve all disruptions while staying as close to the theoretical berth plan as possible. Using the proposed models, several experiments have been conducted regarding the influence of uncertainty, occupation and robustness on the quality of the solutions that the decision models found. Regarding occupancy rates, results show that a tipping point exists where the recovery model has more difficulty to find a good solution. Results also show that when the expected occupation of a terminal is higher, adding robustness has more effect and is therefore more important. The decision models presented in this thesis have been implemented in the Macomi port simulation model and have been demonstrated to the Port of Antwerp. Both parties have expressed their satisfaction with the models.

Preface

This thesis is the end product of a 9 month graduation project which concludes my M.Sc. Computer Science at the Delft University of Technology. During this time I have had the opportunity to do an internship at Macomi, and work on this very interesting project with Macomi and the Port of Antwerp.

There are many people without whom this project would not have been the same. First of all, I would like to express my gratitude to my supervisor at the TU Delft, Dr. ir. Neil Yorke-Smith. Your expertise, critical feedback and experience in supervising other graduation students have helped me a lot. I would also like to thank Menno Oudshoorn, my daily supervisor at Macomi. I really appreciate how you were always there to help me out, brainstorm and provide valuable input when I needed it. Another special word of thanks to Corne Versteegt and the rest of the Macomi team. Because of you this internship has been a great experience.

Finally, I would like to thank my friends and family for being there for me. Especially my wife, whose moral support means the world to me, and my parents, who I would like to thank for everything they have done for me.

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Introduction

The Port of Antwerp is the second largest container port in Europe handling 11.1 million TEU (Twenty-foot Equivalent Unit) in 2019 alone [30]. With the increasing amount of container freight transport and the increasing size of container vessels, port planning is crucial. To get a feeling of how busy the port will be in ten years for instance, the port can use historical data to forecast how many vessels can be expected in 2030. However, to really grasp how busy the port will be in the future, simulation models are applied. Simulation models provide a means to gain insights into operational plans and future port expansions [4, 8].

Simulation models for port planning can be as detailed as a user wishes. An important issue within these models is the berth allocation for vessels that need to be loaded/unloaded. A berth is a location at the quay wall where the vessel can be moored and loaded/unloaded. The problem of berth allocation in short is the process of assigning each vessel a certain time slot and part of the quay wall such that each vessel will be able to load and unload their containers without interrupting other vessels. Usually, some kind of objective function is used to optimize these berth plans; for instance to minimize the amount of waiting time vessels that enter the port have before they can berth.

However, such a planning can be heavily influenced by all kinds of disruptions. These disruptions can be due to vessels arriving earlier or later than planned or when the loading and unloading time of a vessel takes longer than expected. In this case, the berth planning as it was created can be rendered infeasible. If this happens, the planning needs to be altered such that each vessel still can find a berthing spot. This thesis focuses both on the creation of a berth planning within a simulation model but also on the real-time recovery of these berth plans when disruptions happen.

1.1. Problem background

One important design choice that impacts the simulation process is the generation of vessel arrivals. This is an important design decision because it influences everything from the busyness in the port's entrance waters to the allocation of berths and other terminal-related planning. In many works the generation of vessel arrivals is modelled as a random arrival process [e.g., 42] or is based on historical data [e.g., 19]. In practice, when historical data is not provided, using a random arrival process is usually a decent assumption given that different terminals might schedule vessels differently. Further, external factors, like vessel delays and bad weather might influence these schedules. However, there are drawbacks to modelling vessel arrivals as a random process.

First, the random approach is hindered when simulating a port that has tide restricted entrance and exit windows. As the Port of Antwerp is a sea port that is located 80 kilometers inland, all the vessels that come from sea and wish to enter the port sail through the River Scheldt. The water height of the River Scheldt can differ almost 5 meters depending on the tides. For the port this means that depending on the draught of the vessel and the tide at that moment, a certain vessel may or may not be able to enter or exit the port. In a simulation model this means that if a few deep vessels try to enter the port during a certain low water period they will all need to wait for this low water window to end. As soon as the water raises again all of these vessels that were waiting will want to enter the port at the same time. The result is congestion and vessel waiting time [9].

The second drawback to using a random arrival process is that it disregards how many container shipping companies and terminals work: with cyclically calling vessels from 'loops' [17]. A loop can be seen as a series

of ports that are visited in order. Because of the size of these loops, container shipping companies usually have multiple vessels sailing in the same loop. In reality, a terminal plans the arrivals of these loops using a cyclic baseline berth planning: a schedule for a week, in which every loop gets a certain time and location where it is expected to arrive each week. This baseline plan is modified during the week's execution because, due to external factors and uncertainties, vessels often encounter deviation from the baseline plan.

These drawbacks can be overcome by creating a berth planning for the simulation period. However, as stated before, such a berth planning cannot be a deterministic decision of when a vessel will arrive. In practice one can also note that the planned time according to this theoretical planning is rarely the exact time that a vessel can be berthed. Many different factors play a role in this but from a berth planning perspective three major types of disruptions can be expected. First of all a vessel can be arriving earlier or later than planned. This type of disruption is usually due to earlier disruptions in the travels of a vessel. It might have encountered delays in ports it visited before and therefore be later. Secondly, the handling time of the vessel might be different from the expected handling time. This can be due to a variety of factors including how many quay cranes are available and the call size of the vessel. The call size of a vessel is the amount of containers a vessel needs to load/unload during its stay at the port. The last type of disruption is one that is crucial for the Port of Antwerp, namely the travel time to enter the port. In creating the baseline planning one can only account for a certain expected travel time, but in reality this can be influenced by many factors which mainly have to do with traveling through the River Scheldt. As mentioned before, tidal windows might make that even though the vessel arrived on time it might arrive later at the berth. Also, the river makes for the necessary sailing rules which means that if it is busy, a vessel can take longer to sail through the river and enter the port. All of the disruptions mentioned make that the berth planning in practice needs resolving.

1.2. Problem statement

The problem that this thesis addresses is two-fold: firstly the *creation of a preliminary baseline berth planning* that serves as the input or basis of the simulation model. Secondly, the *real-time recovery of this berth planning* in case disruptions happen during simulation.

To be more exact, the first problem this thesis addresses is that of the creation of a cyclic baseline berth allocation of vessel arrivals in a simulation model. The allocation must respect physical and operational constraints. This baseline berth planning serves as a basis on which the vessel arrival times in the simulation will be based. In addition, this berth planning can be used as the theoretical berth plan during simulation. In practice this means that based on provided data about the total number of expected vessel arrivals in the port, vessels will be generated for the simulation model. Each of these vessels will be allocated a berth at a certain time during the simulation. Thus each vessel will be assigned the combination of a certain time, and a certain position at the quay wall, where the vessel can be loaded and unloaded without interfering with other vessels. Based on the time of this allocation, the actual time the vessel will arrive in the simulation can be decided. Further, in real-life scenarios, if a container shipping company knows that the planned arrival of a vessel is during low water time, they will attempt to load the vessel so that it has a draught as small as possible. This aspect of realistic decision making can also be accommodated by the planning approach presented in this paper.

The second problem addressed in this thesis is that of recovering from disruptions during execution of the simulation. This means that as soon as a vessel arrives at sea it calls the port and provides it with information regarding its arrival and travel time. Based on this information and the theoretical berth planning, a resolution will need to be found such that the vessel can berth without interfering with other vessels. It is of key importance here that the deviation from the theoretical planning is minimized. This is because the re-allocation of resources in the port is very expensive and should therefore be avoided as much as possible. Further, it is important that a disruption is solved as locally as possible within the theoretical plan. This means that if a certain disruption happens, we don't want vessels that are expected to arrive in a week still be disrupted and replaced in the planning.

In this work the optimisation technique of constraint programming is used to automatically derive and to dynamically update the berth allocation plans.

1.3. Contribution

This thesis contributes a novel approach as the basis for the vessel arrival generation and the berth allocation in a simulated environment. This approach focuses on the generation of a cyclic baseline planning on which the vessel arrival times and the actual berth allocation are based. By creating this baseline planning one can



Figure 1.1: Map of the Port of Antwerp

incorporate both the tidal windows of vessels and the cyclic nature of realistic container vessel arrivals.

Further, contributions will be made in the form of a disruption recovery approach for the berth planning that works in real-time and can make decisions on the spot and for every vessel. Moreover, this approach will work in large-scale settings of simulation models with a time horizon of at least one month.

This thesis also contributes with a case study investigating the influence of factors like occupation, chance of disruption and robustness in the theoretical planning on the ability of the disruption recovery approach to find good recovery plans.

1.4. Introduction to Port of Antwerp and Macomi

This thesis was made possible through a position as intern with Macomi. Macomi is a company which has developed its own advanced analysis platform [2]. Using this platform they can help companies get insight in complex issues. They are specialized in artificial intelligence, simulation and algorithms for optimization which form the basis for this platform. Macomi is working together with the Port of Antwerp [1] to provide the port with a simulation platform which can help to get insight into port planning issues like the addition of a new terminal or the extension of an existing quay wall. As stated earlier, the Port of Antwerp is a very large port (see Figure 1.1) which handles millions of containers each year, which makes port planning all the more important. This thesis was done following from an intern position at Macomi and in cooperation with the Port of Antwerp. Macomi now uses the models presented in this thesis as a part of their port simulation model.

1.5. Objectives

1.5.1. Main objective

The first main objective of this thesis is to provide a model for the creation of a berth planning for the entire simulation period of multiple terminals at the Port of Antwerp. On top of that, the second main objective is to provide a model for the real-time disruption recovery of the berth planning during simulation time.

1.5.2. Secondary objectives

From a research perspective there are some interesting topics that can be investigated through the models for the theoretical berth planning and the real-time disruption recovery.

1. The affect of the probability that disruptions happen on how well the disruptions can be resolved by the disruption recovery model. Expected is that the larger the uncertainty of the data available when making the initial planning, the more deviation from the planning will happen. An interesting topic of research would be to see how this deviation increases with increasing uncertainty.
2. How well disruptions can be resolved under the influence of different occupations of the terminal. When the occupation of a terminal is higher, or, in other words, when the terminal is busier, it is expected that disruptions can be solved less efficiently and with that a larger deviation from the theoretical plan. From an expert in the field I received the information that from a certain level of occupancy it will become much harder to find good allocations. Consequently, a certain tipping point in occupation should exist where the recovery suddenly becomes much worse. An additional objective of this work is to investigate if this tipping point indeed exists and if so, at which occupancy percentage this is.
3. Another interesting topic is to see how much influence the addition of making the initial planning more robust helps the recovery of the the berth planning in real-time. Robustness can be added in the form of time slacks after each vessel in which no other vessel will be planned. Expected is the more robust the initial planning is the better the recovery will be but with a higher robustness the baseline planning can be harder to create. Using this model this effect can be quantified.

1.5.3. Research questions

The main research question for this thesis will be:

How can preliminary planning and real-time disruption recovery improve the berth planning for the Port of Antwerp simulation model?

To be able to answer this question a series of sub-questions can be formulated.

1. What is the current state of the research with regard to the subject of berth planning and recovery as provided by literature?
2. How can the specifications and requirements of a preliminary berth planning be combined into one berth schedule model?
3. How can a model be formulated that deals with large-scale and real-time disruption recovery in a berth planning?

With the secondary objectives in mind the following sub-questions are also formulated.

4. How does the probability that disruptions happen affect the ability to find good recovery solutions?
5. How does the average occupancy of a terminal relate to the ability to find good recoveries?
6. How does robustness ('time slacks') in the theoretical plan affect the ability to find good recovery solutions?

1.5.4. Scope

Even though the developed models will be tested in the Macomi simulation platform, they should be generally applicable and the general solution approach should easily be transformed to the needs of a user. Regarding the creation of both the initial berth planning and the real-time recovery the focus is put on the berth allocations. In literature sometimes the berth allocation problem is combined with optimization on land like quay cranes. While this is an interesting research direction the land infrastructure lays beyond the scope of this thesis.

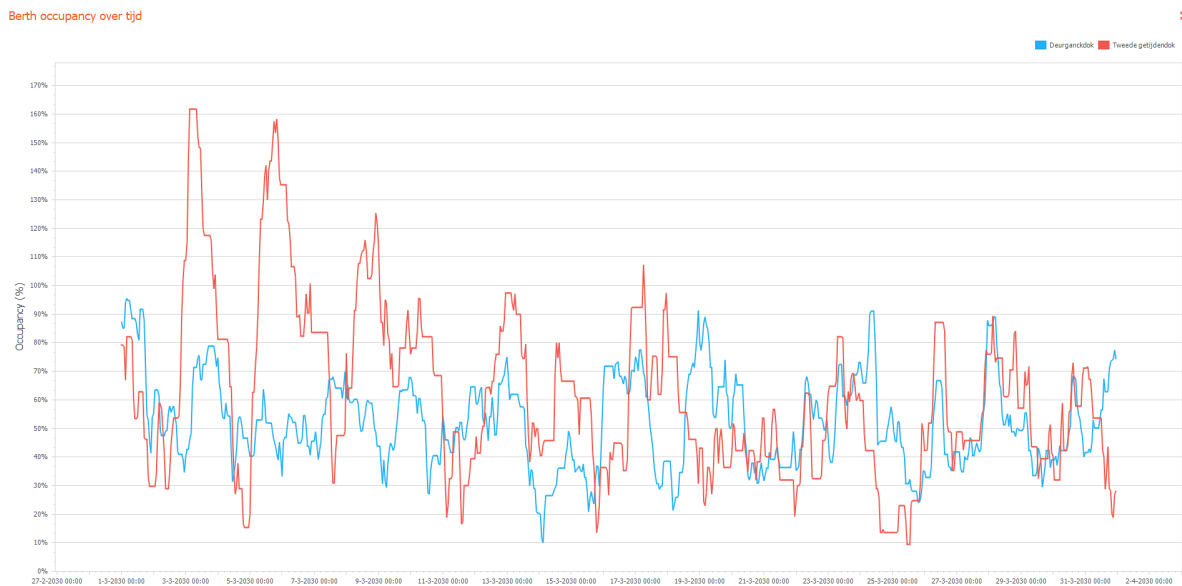


Figure 1.2: Graph showing the berth occupancy over time. This graph is the results of a simulation run before the start of this graduation project. The two lines represent two terminals. The simulation has been run for 1 month in 2030.

1.6. Current situation

The main goal of this thesis is to improve on the port simulation model. To be able to place the improvements presented in this thesis, one needs a bit of background on the status of the berth planning and vessel generation before the start of this project.

When a simulation was done with the former simulation model, before the start of this graduation project, vessels were generated according to a stratified random arrival process. It is stratified because the total arrivals of different classes were counted and matched with the forecast about the number of arrivals that was given to the simulation model. The total arrivals should be representative for the yearly numbers with regard to the division. It should be noted that when sampling the arrival time, no other factors are taken into account like the tidal dependencies of the vessel.

When the vessel arrives at sea calling to be berthed at a terminal, a berth allocation controller looks at the current state of the vessels berthed at the terminal and decides the earliest location at the quay wall that will be free. The vessel is assigned that berthing location and the fastest way to this berthing location is calculated.

There are a few major problems with the way vessel arrival generation and berth allocation was done in the old simulation model. The first problem is that no physical restrictions are placed on the vessels when they have berthed. This means that even though the vessel is berthed at the location that will be free first, it can be that it is berthed at the same location as another vessel. This leads to berth occupancy rates of above 100%. Given that double berthing is not being considered, this is physically impossible and therefore needs adaptation. An early screenshot of the berth occupancy rates can be seen in Figure 1.2. This graph represents a simulation time of one month in 2030 on the horizontal axis and the occupancy in percentages on the vertical axis. Each line represents a terminal. One can immediately notice the peaks over time where the occupancy goes above 100%.

Another major problem is that tidal dependencies of vessels are not taken into account, this leads to vessels having to wait before they can start sailing and consequently all entering at the same time. The consequence hereof can be seen at the big peaks in the graph.

1.7. Anonymity

Real data provided by the Port of Antwerp has been used in this thesis. Because of confidentiality reasons the data and actual results cannot be made public. Details about the datasets used in the experiments are therefore not provided in this thesis. The results presented in this thesis are all representational for the real situation, and should be considered as such.

1.8. Document structure

The structure of the remainder of this document will be laid out in this section. First, Chapter 2 surveys related literature. Chapter 3 will describe the optimisation approach developed for the creation of the initial berthing plan. Subsequently, Chapter 4 will go into the methodology for the real-time disruption recovery. The following Chapter 5 will provide experiments and results that have been done for a case study for the Port of Antwerp. First the influence of hardness, or difficulty, of the problem to be solved on the execution time of the initial berthing time will be investigated and results presented. Next, the experiment regarding uncertainty and its influence on the quality of the found recovery is presented. The experiment and results of the experiments regarding occupation and robustness go hand in hand and are presented last in Chapter 5. The final Chapter 6 draws conclusions, answers the research questions and discusses future research directions.

2

Literature

Now that the problem is introduced and defined, existing approaches to this problem and problems closely related can be considered. First we will take a closer look at other simulation environments in literature and how they consider the vessel arrival generation. Subsequently, the berth allocation problem as researched in literature will be investigated. After that, an overview of disruption recovery and rescheduling of berth schedules will be given. Lastly, a quick view of using a CP approach to solve the berth allocation problem will be given. For all of the subjects in this chapter we will investigate how the problem presented earlier is different from the problems in literature and why different approaches are required.

2.1. Vessel arrival generation

For vessel arrival generation, simulation models either follow a random arrival process or base arrivals on historical data. In the first case, Pachakis and Kiremidjian [31] developed a procedure for modelling ship traffic. The authors propose the use of exponentially distributed inter-arrival times if data is not available. Thiers and Janssens [34], Yeo et al. [42] model the arrival generation with a Poisson process. This allows for varying arrival rates over the course of the simulation.

In the second case, when historical data is available and is relevant, simulation models can use it as a basis for vessel arrival generation [15]. Huang et al. [19], for instance, use the actual arrival historical times in the simulation. This is valid if the historical arrival times are representative of the simulation period; in particular, this assumption can be false when simulating future design options for the port. Cimpeanu et al. [7] assume that a yearly schedule for vessel arrivals are known beforehand. These are based on distributions of inter-arrival times derived from historical data provided by a port terminal company.

van Asperen et al. [36] examine arrival generation for jetty facilities. The data provided in their case was yearly arrival numbers for the vessels, and not information about any kind of specific distributions.

Tidal patterns have been included in some simulation models. The early work of Groenveld [14] presents a port simulation model where tides are included. Here, the tidal conditions are included post hoc as a check whether a vessel is allowed to sail or not; a vessel that is not allowed to sail due to tidal restrictions needs to wait in the anchorage. Similarly, both Hassan [15] and Cimpeanu et al. [7] keep vessels restricted by tidal conditions waiting in a queue. Wadhwa [37] also takes tidal patterns into account when entering and exiting the port. Here, the notion of loading a vessel according to a certain allowable draught is introduced. Thiers and Janssens [34] divide vessels into tide-dependent and not tide-dependent. For vessels that are tide-dependent there are certain threshold locations which the vessel can only pass during a certain time-frame. These tidal windows are defined as the time frame in which the vessel can depart from a certain location and pass all the thresholds without issues.

From these works we can see that, with the exception of Huang et al. [19], all works generate vessels according to inter-arrival times. In cases where historical data is provided these are often based on data. On the other hand, if no data is available, different random arrival processes are incorporated. None of the models have included the cyclic nature of arrivals and only some of them included tidal patterns. The latter, however, are modelled as a check whether or not a vessel is allowed to enter the port or not, rather being taken into account in the arrival generation. By contrast, in reality shipping companies do attempt to take tides into account to reduce waiting time. As van Asperen et al. [36] have shown, random arrival processes not based on

any environmental information leads to the highest vessel delays.

2.2. Berth allocation problem

While berth allocation problems have received extensive attention in literature, to the best of my knowledge, no work uses a baseline berth allocation as a base for a simulation model. In this section the main research directions and development will be investigated. However, for a thorough and complete overview I refer the reader to Bierwirth and Meisel [5], where a thorough survey into the creation of a baseline berth planning is done.

2.2.1. Berth allocation with certainty

The early works on this problem all consider a certain environment. Nishimura et al. [29] for instance consider the berthing spaces to be discrete and propose a model that minimizes the total service time that vessels have. Here the authors assume that the service time depends on the berth that is chosen for a certain vessel. All the arrival times and the handling times at different berths in the model are assumed to be known and certain. A genetic algorithm is proposed as a heuristic to obtain a good solution to the model. Imai et al. [20] also minimizes for the service time but include a minimization of the waiting time as well. A special feature here is that the priority of different vessels is taken into account. Again, a certain environment is expected where all the information is assumed to be known and certain beforehand. Kim and Moon [24] propose a simulated annealing approach to find a good solution to their MIP formulation that minimizes the delay in departure time of the vessel and the cost for not berthing the vessel at its preferred location. Again, this work approaches the BAP from a discrete berth point of view and the information is assumed to be known beforehand. A final example of a BAP in a certain environment is the work of Wang and Lim [39]. Here a stochastic beam search algorithm is developed that aims at minimizing the cost of not berthing a vessel at its preferred location and the cost for delays. Literature has also focussed its attention on the fact that there is a relationship between scheduling berths and scheduling quay cranes. One example can be found in the work by Meisel and Bierwirth [28] where different heuristics are presented that deal with the integration of quay crane scheduling in the berth scheduling problem. Here the possible assignment of quay cranes to vessels depend on their berthing location and the amount of assigned quay cranes influence the handling time required to load and unload the vessel.

2.2.2. Berth allocation with uncertainty

The certainty as assumed in the works in the previous subsection can in practice turn out to be very influenced by all kinds of external factors. Researchers started to include uncertainty of these unknown factors into their approaches. One way to include uncertainty is presented by Zhen et al. [47]. Here uncertainty is modeled as a finite set of discrete scenarios. Each scenario presents the actual arrival time and service time of each vessel and the probability of that scenario happening. The authors model this problem as a MIP minimizing the cost with respect to berthing time and location but also including the cost of each scenario happening. A similar approach is used by Xiang et al. [40]. Here scenarios are prepared based on historical data and again the chance of each of these scenarios happening is included. The prepared baseline schedule should deviate as little as possible under each of these scenarios happening. The proposed model is bi-objective searching for a solution with both a good economic performance and high customer satisfaction.

Another approach for taking uncertainty into account is through making the baseline planning as robust as possible. Zhen and Chang [45] for instance add robustness to their baseline planning by adding time buffers in between vessels. A bi-objective optimization approach is presented that both maximizes the bufferspace while minimizing a cost function regarding vessel berthing time and location. A different approach is presented by [13]. The arrival times of vessels in this approach are given as a time window. Through this, robustness is defined as the variability in the total service time of all vessels together. The proposed model minimizes this variability by minimizing the average service time and the range of the service time that is expected by berthing the vessel at a certain time and location.

Du et al. [11] combines the use of robustness and scenarios through a feedback procedure that creates a robust baseline berth planning. Through a set of delay scenarios the planning is resolved multiple times where the time buffers for different vessels are adjusted each loop. The idea behind these adjustments is that a good buffer for each vessel lowers the possible delay propagation in case of delays.

2.2.3. Inclusion of tides

Most studies do not consider the fact of tidal dependencies when entering and leaving the port. However, this is very relevant for the case of the port of Antwerp. Some works however do include a notion of tides in their model. Qin et al. [33] consider a river port where water depths at the berths themselves are deciding factors on whether vessels can berth. Both integer programming and constraint programming approaches are proposed to minimize the total weighted service time for all vessels. Du et al. [12] assume tidal levels to restrict the entrance and exit possibilities of vessels. In this formulation the expected arrival time of the vessel is known and with this the first possible arrival in the port is calculated by taking the tidal levels into account. Only after this moment of entering the port the vessel is allowed to be berthed. A few important assumptions are made here. Until the moment it is berthed it is assumed the vessel can wait in an anchorage which is infinitely large. The tidal windows are assumed to be static 12-hour windows. Also incoming and outgoing drafts of vessels are assumed to be identical. Both Ding et al. [10] and Zhen et al. [48] address the problem of daily berth planning and quay crane allocation. When considering the daily planning it is assumed that the information about the arrival and departure times are known. Based on this the berth and berthing times are provided to the shipping lines. Because this is the case of daily planning a lot of information is available and relatively certain. When considering tidal windows the decision is made on how many tide cycles vessel will stay in the port. If the vessel stays for one cycle it needs a lot of quay cranes, and with multiple cycles the assigned quay cranes can be lower and more vessels can be served simultaneously.

2.2.4. Cyclic nature of arrivals

In the most generic case of berth allocation, as explored in the previous subsections, one tries to find an allocation that plans vessels as close to their expected arrival time as possible. Often also some preferred berthing location of a vessel is taken into account. One of the main directions indicated by Bierwirth and Meisel [5]'s survey is the incorporation of the cyclic nature of a berth schedule. Hendriks et al. [17] are one of the few authors who incorporated the cyclic nature of a berth planning into a model. Here a cyclic period is divided into discrete time periods and it is assumed that vessels that berth simultaneously are known. Based on this a combined berth allocation and yard planning model is presented. Similarly, Zhen et al. [46] also present an integrated berth allocation and yard template model. In this work the planning horizon is divided into discrete time periods. The planning horizon can be repeated without issues which is why the resulting berth plan can also be considered cyclic.

These works all follow the assumption outlined by Hendriks et al. [16]: namely that strategic-level decisions have been made about the time of arrival and departure which are used to create the cyclic berth allocations. As these times are not known in a simulated environment and need to be generated from yearly arrival numbers these models cannot be used as such. However, the same mindset of rectangle packing on a cylinder instead of a plane, as well explained by Zhen et al. [46], is adopted in this work.

2.2.5. Strategic berth template problem

Relevant to this last made point there is a different problem in the literature that is also closely related to the problem tackled in this thesis, namely the strategic berth template problem. Recent works by e.g. Imai et al. [21], Huang et al. [18] and Iris et al. [23] consider this problem. The berth template problem focusses on the creation of a repeating schedule for a longer period of time in which different vessel lines have the same arrival time each cyclic period. While the end goal of creating a cyclic plan for a longer period of time is very relevant to this study, some major differences are detected in how this end goal can be reached. The goal in these papers can also be defined as, given a set of vessels with corresponding arrival and handling times, how can these be planned in a given time horizon such that the deviation from their arrival times is minimized. Additionally, constraints are added that ensure that if the resulting berth planning is repeated, no overlap will arise. This redefinition shows why the berth template problem as addressed in literature is not applicable in this thesis. This is because when working in a simulated environment, a yearly number of arrivals is provided and consequently the arrival times are not known. Also, one particular requirement of importance in the current situation is that tidal influences are not considered. However, the idea behind the strategic berth template problem comes closest to the first part of what is attempted in this thesis, namely the creation of a cyclic berth planning for a longer period of time.

2.2.6. Conclusions

From this overview on works that tackle berth allocation problems a few important conclusions can be drawn. First of all, to the best of my knowledge, no work has used the baseline planning as a basis or input for a

simulation model. Secondly, there is a crucial difference between the berth allocation papers in the literature and actually using the allocation as a base for a simulation: in the former the expected arrival time is usually assumed to be known. Even papers that incorporate uncertainty into the creation of a schedule always assume some information is given about the expected arrival time of a vessel. Thirdly, only a few works have investigated the inclusion of tides into their modeling which is a very relevant topic for the case of the Port of Antwerp. Lastly, as also indicated by Bierwirth and Meisel [5]'s survey, the incorporation of the cyclic nature of a berth schedule is something that has not been done often and is something that will be considered in this thesis.

2.3. Disruption recovery

The last important point regarding berth allocation is how to do it in real time. A good and robust berth schedule might be very useful, but in reality there is a lot of deviation and uncertainty about the arrivals and handling times of vessels. If a vessel arrives later than planned, the berth schedule will change and often even become infeasible. When disruptions happen there are two main ways to solve these problems. First there is rescheduling. Rescheduling is the act of creating a completely new schedule while optimizing the original performance measure. Carette [6] solves the berth allocation problem from a rescheduling approach. Here, the optimal plan is recalculated at given time intervals. At each interval, new information is collected and based on this information an optimization method is used to create entirely new schedule. However, in practice, and also in this thesis, a different way of solving disruptions is preferred. This approach is called disruption management and it is the act of adjusting the original berthing plan to fit potential disruptions while keeping as close as possible to the original berthing plan. This is preferred over rescheduling since this minimizes actual relocation of equipment and resources which is prepared according to the original plan. Furthermore, in cases where there are many incoming vessels an updated plan can usually be achieved faster.

Zhang et al. [44] use a disruption management strategy to reschedule in case of disruptions. A lexicographic optimization approach is used to add a hierarchical structure to different types of vessels. Meaning that the updated berthing plan is first optimized for key line vessels, then for trunk line vessels and lastly for feeder line vessels. The authors assume that the baseline planning is known and propose a model that aims to stay close to the original plan given new expected arrival times for each vessel. Yang et al. [41] propose a disruption management approach which makes use of simulation to simulate disruptions and based on this extract stable states for vessels. Multiple simulation runs are done which result in these stable states. Based on these stable states a rescheduling is done where these vessels are influenced as little as possible. Similarly, Zeng et al. [43] disruption management is done with a simulation optimization approach. This means that an optimal berth allocation is found through repeated simulation runs and solving disruptions that arise. In this paper both berth allocation and quay crane scheduling is done simultaneously. The performance measure in this case is two-fold: one one hand the original optimization function is optimized and on the other hand the deviation from the original problem is minimized. The authors propose the idea of local rescheduling which only considers a limited time and space window to solve the disruption. The authors show that the local rescheduling approach can improve the computation efficiency over a full rescheduling approach. Iris and Lam [22] propose to do the berth and quay crane planning in a recoverable robust way. The authors assume a finite set of scenarios that give the value of different uncertain variables. For the baseline planning a vessel specific buffer is added which acts as robustness. The authors also generate recovery plans for each scenario. For each scenario a plan is created which subsequently are used to create the baseline plan.

The approaches mentioned above are all not real-time recovery approaches. They aim at optimizing the schedule given a series of simulation runs and corresponding disruptions. Umang et al. [35] do present a real-time approach for disruption recovery in a bulk port. The authors assume a baseline schedule and aim to stay as close to that as possible when disruption happen. During a run, the model expects vessels to update their arrival time and handling time. Each hour, a check is done and with all of the updated values a recovery is done. The authors do rescheduling through both an greedy algorithm and an optimization algorithm which are later compared. The greedy algorithm places vessels at berthing locations where the total cost of reassignment is minimal. The optimization algorithm minimizes the objective function through reformulating the optimization function as a set-partitioning problem where all the feasible assignments are investigated. They find that the optimization algorithm outperforms the others based on objective value while the greedy algorithm stays closer to the original baseline plan.

Concluding, very few works have focused on recovery of a berth schedule given disruptions that appear, especially when looking at recovery in real-time. However, in this thesis, the real-time aspect is very important.

When comparing with the work of Umang et al. [35] there are a few aspects that this thesis will improve on. First of all, the simulation model for the port of Antwerp are very large scale. Simulation periods of at least one month are typical time horizons for this application. Therefore, a model is needed that can deal with these large scale settings. Umang et al. work only with test scenarios of 10-25 vessels and a time horizon of 5 days. Also, they only update their planning each hour. Ideally we would want to respond as soon as new information becomes available. Lastly, Umang et al. assume fixed (hybrid) berthing positions whereas in the container terminal case of Antwerp, continuous quays are required, which means that vessels can be berthed anywhere along the quay wall.

2.4. Constraint programming for the Berth Allocation Problem

Constraint Programming (CP) is a flexible Artificial Intelligence approach to modelling and solving combinatorial optimisation problems [38]. Kizilay et al. [25], for instance, use CP to address a decision problem in integrated port container terminal operations. Li et al. [26] use CP to plan vessel rotations (loops) among terminals within a port. In solving a berth allocation problem, Qin et al. [33] show that CP outperforms integer programming in three instances, namely when using dynamic arrivals over static arrivals, when using fine time granularity, and when the restriction of the objective towards the decision variables is not tight. Since the optimisation problem we will formulate has no tight restriction towards the decision variables (only to be close to a preferred location) and uses a very fine time granularity (that of 1 minute), CP is adopted for which a compact and understandable optimisation model is formulated.

3

Methodology of theoretical berth plan

In this chapter the proposed methodology for the creation of the theoretical baseline berth planning is presented in detail. The proposed approach centres around the generation of a projection plan. The simulation model will be provided with yearly arrival numbers for different vessel classes based on which vessels will be generated. These vessels will be divided over cyclic periods, and consequently, the arrivals of every period are transformed into a projection plan. This is a berth allocation for one cyclic period. This projection plan serves as an outline for each period's arrivals, which will be 'projected' on this plan. In this phase the vessels, as generated at the start, will receive an arrival time according to the berth allocation in the projection plan. Through this approach, vessels that are assumed to be from the same loop are planned at the same time each cyclic period. In the remainder of this chapter, first the data that is used in this approach is explored. Next, a step-wise explanation of the proposed approach is given.

3.1. Problem Data

In this thesis, a typical situation is considered in which historical data about vessel arrivals is either not available or not applicable. There can be multiple reasons why data about past arrivals are not applicable for a simulation model. First, inter-arrival times based on historical arrivals can be inaccurate when simulating future scenarios. The further in the future one is interested to simulate, the more likely it is that changes arise regarding amount of arrivals and arrivals from different vessel classes. Second, past arrivals are of limited value when the simulation is used for analysing possible port expansions. An instance of a possible port expansion, adding a new terminal, is taken up in the case study provided by the Port of Antwerp (see Chapter 5). Third, aggregated inter-arrival time distributions from historical data do not take account particular tidal windows nor the cyclic behaviour of arrivals. As discussed in Section 1.1, this omission leads to no cyclic behaviour and increased waiting times because of the tidal pattern.

On top of this, from a more practical point of view, since terminals are usually independently operating from the port, the port does not have detailed information about every vessel arrival at each terminal. They have a good estimation of the total amount of arrivals, but exact information about arrival and handling times are not available without receiving them from the terminals.

In order to develop a realistic data-based simulation, we take advantage of the following commonly-available data.

1. First, a yearly forecast for the simulation period. That is, for each class of container vessels, the port manager provides an expected yearly number of arrivals. To make these arrivals more realistic, the division of these vessel classes over different approach routes to the port can be used. What vessels belong to what vessel classes can be specific to the application. In the data provided by the Port of Antwerp, vessel classes are defined by their size, amount of Twenty-foot Equivalent Unit (TEU) that can be carried, and the handling time distributions. Hence each vessel from the same class has the same size, TEU and handling time distribution.
2. For each class it is also important to know the division of draught. That is, how many vessels are expected yearly with what draught. The draught of a vessel is essential knowledge since it determines whether or not a vessel can sail given the tidal situation.

3. Next, for each draught the tidal windows need to be known. These are required in a similar fashion as in Thiers and Janssens [34]. The tidal window at a certain location represents the first and last moment a vessel with a specific draught is allowed to pass that location, such that it will not encounter any tidal issues over the course of the journey to or from the port. To make a good estimation about the berthing times after a vessel can pass through the tidal window, data about travel times in and around the port are used.
4. Lastly, for each vessel class there is additional information regarding, for instance, the length of the vessel and the distribution of the handling time for that class.

For the subsequent parts of a port simulation, in which berth planning is incorporated, more data could be necessary. For example, information about traffic rules, tug boat assistance and external conditions like weather. Chapter 4 discusses the data required for the disruption recovery.

3.2. Proposed Methodology

The six steps are illustrated in Figure 3.1. Each of these are described in turn.

Step 1: Determine simulation period and cyclic period

Any simulation design requires some foundational decisions regarding the simulated period and the cyclic loop period. The decision for the simulation period is important as the tidal windows depend on this. The cyclic period determines how often the cyclical berth allocation pattern repeats itself. In practice this period is usually 7, 10 or 14 days [17]. The combination of this simulation period and cyclic period determine how often the cyclic pattern is repeated. The cycle period can be chosen to the user's needs.

Step 2: Generate vessels for the simulation period

The second step concerns the generation of all the vessels that will arrive in the simulated period. This is done through a repeated random selection with stratification. A list of vessel arrivals is generated that represents the total amount of arrivals that is expected in the simulation period according to the provided number of yearly arrivals for each class and draught within that class.

Step 3: Divide arrivals over cyclic periods

One important assumption that is made regarding the cyclic nature of the arrivals is that vessels from the same vessel class can belong to the same loop. Consequently, for each instance where a vessel class has arrivals in every cyclic period we may assume there is one loop for that vessel class. In this step the division of vessels

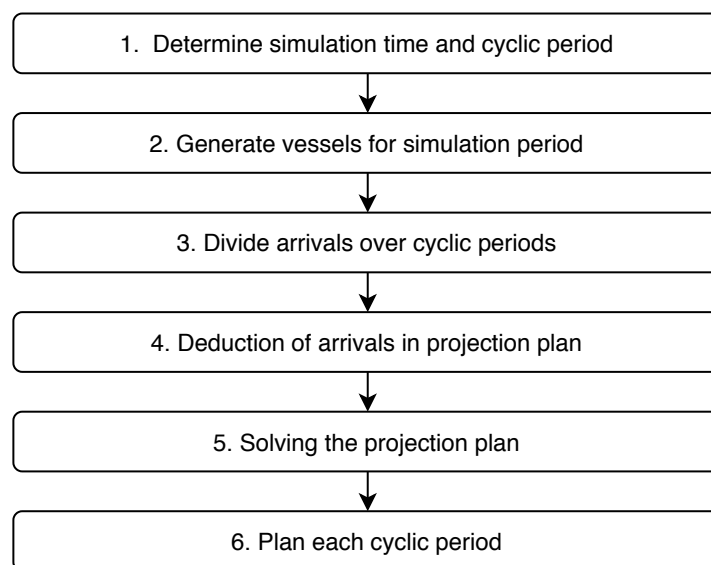


Figure 3.1: Six steps of the berth allocation approach.

over the cyclic periods is being made. The goal is to divide the arrivals from each vessel class as evenly as possible over the cyclic periods.

For example, suppose that the cyclic period is one week and the simulation period covers five weeks, then the vessel arrivals are divided over five periods. Now, if from a certain class 13 arrivals are expected in the simulation period we will assign two arrivals to each week and these will be considered cyclic arrivals. The remaining three arrivals that cannot cover each cyclic period will be assigned to random periods where the same period is not chosen twice. These remaining arrivals are considered non cyclic arrivals.

Step 4: Deduction of arrivals in projection plan

Now that the arrivals of each class per cyclic period is known, the next step is to deduce a projection plan. A projection plan is a berth allocation for one period on which the arrivals for each cyclic period are projected. The arrivals of the projection plan can be deduced as follows. First, for each cyclic loop that has an arrival each period, one vessel from that class is added to the projection plan. These loops will be planned at the same time and place each period. Secondly, since the projection plan is the berthing plan on which every period's arrivals will be projected, room for non cyclic arrivals needs to be incorporated as well. This is done by adding the number of non cyclic vessels of the period that has the most non cyclic arrivals. This way, the projection plan will have enough planned spaces such that each period can fit all their planned arrivals.

Step 5: Solve the projection plan

In this step the goal is to reserve a time slot and location for all the vessel class arrivals that are expected in the projection period. As explained earlier, the arrivals in the projection period are not actual arrivals but placeholders on which the actual arrivals for each period will be projected. This means that a decision needs to be made on how much space and how much time needs to be reserved for each arrival. The cases of cyclic and non-cyclic arrivals are treated separately.

For the cyclic arrivals this means that each arrival is from the same class which means that the vessel length and estimated handling time are likely rather similar. In any case, for each of the cyclic arrivals the longest vessel length and the longest estimated handling time for that vessel class needs to be reserved. In our case study, vessels from the same class all have the same vessel length and handling time distribution, which means that this length and expected handling time from this class can be used. This is to make sure that when planning the actual arrivals and projecting it on this space that the arrival will stay within the reserved boundaries.

The non-cyclic arrivals are more difficult, since each period different vessels from different classes might use this spot. It is necessary to make sure that the spaces that are reserved are large enough such that every cyclic period each non-cyclic vessel fits in a space that is large enough to prevent overlap. To do this, we check the non-cyclic arrivals and find the arrival each period which takes the longest handling time and has the largest vessel length. This is the time and space that is reserved for the longest non cyclic arrival each period and by reserving this space we ensure that the largest non-cyclic arrival each period will have enough space. Next we check each period for the second-to-longest handling time and vessel length and reserve that space and so forth. This way it is guaranteed that all the spaces reserved in the projection plan are boundaries for the actual arrivals and no vessel will be outside its planned spot.

To solve the berth allocation for the projection plan an optimisation approach is adopted. A compact constraint programming model is formulated.

The parameters, decision variables, objective function and the constraints are:

Parameters

V = set of vessels to be served in time horizon

l_i = length of vessel i

t_i = estimated handling time of vessel i

L = quay length

T = cyclic period planning time horizon

b_{ip} = a score for vessel i to be placed at location p

Decision variables

x_i = start berthing time vessel i

y_i = berthing position vessel i , where the front of the vessel is located

$yObj_i$ = the objective score value for vessel i

$xInterval_i$ = an interval variable covering the interval $\{x_i, x_i + t_i\}$

$yInterval_i$ = an interval variable covering the interval $\{y_i, y_i + l_i\}$

Objective and constraints

$$\max \sum_{i \in V} yObj_i \quad (3.1)$$

$$\text{NoOverlap2D}(xInterval, yInterval) \quad (3.2)$$

$$0 \leq x_i \leq T - t_i \quad \forall i \in V \quad (3.3)$$

$$0 \leq y_i \leq L - l_i \quad \forall i \in V \quad (3.4)$$

$$\text{Element}(y_i, b_i, yObj_i) \quad \forall i \in V \quad (3.5)$$

$$yObj_i \geq 1 \quad \forall i \in V \quad (3.6)$$

The objective function (3.1) is to maximise the score given to each vessel regarding a certain preferred berthing location for that vessel. Constraint 3.2 is a CP-specific constraint which constrains each pair of $xIntervals$ and $yIntervals$, which form rectangles, to be non-overlapping rectangles (also known as the *diffn* constraint [3]). Constraints 3.3 and 3.4 ensure that the values x and y can take on such that they remain within the boundaries of the berthing plan. Constraint 3.5 ensures that the value taken up by $yObj_i$ equals the score for vessel i to be berthed at location y_i .

The final constraint (3.6) constrains the minimum score that each vessel must have. This last constraint is optional; the minimum score depends on the application. This can be used if certain vessels need to be guaranteed at a certain location. In our case study a value of 1 was chosen to be able to deal with the situation of discontinuous quays (see also Ma et al. [27]). Namely, in this situation the discontinuous quay can be treated as a continuous quay but on the split a score of 0 is assigned. This way vessels can never be located over the split. One should note that a value of 1 is considered small as the parameter b_{ip} has scores scaled between 0-100.

The parameter b_{ip} allows for a lot of flexibility regarding scoring vessels for their berthing position. In the case study presented in Chapter 5 the scoring rule is based on the size of the vessel, namely that large vessels should be located as much as possible in the center of the quay wall while smaller vessels should be located to the sides of the quay wall. The parameter also provides options to exclude a certain part of the quay wall for a certain loop, by just adding score 0 for that location, if these vessels are supposed to be berthed at a specific section of the quay wall. If in practice this definition leads to problems and only a preferred berthing location is known one can manipulate this parameter to show for each location a score based on how close this point is to the preferred location. If, in practice, no location is preferred, one could just add maximal score for each location.

Note that the constraints used in this model follow the naming as implemented in the OR-Tools CP solver [32] used in the case study (Chapter 5).

It should also be noted that uncertainty can be managed through adding robustness to the berth plan. This can be done in a proactive manner by increasing t_i , that is the expected handling time, of each vessel. If the expected handling time considered in this part is higher, a time slack will appear after the vessel. This leads to the fact that when disruptions happen during the simulation, the vessel has some buffer space to move, giving it space to either take longer handling or arrive later without disrupting other vessels. For a detailed study on adding robustness to the preliminary berthing plan the reader is referred to Section 5.4.

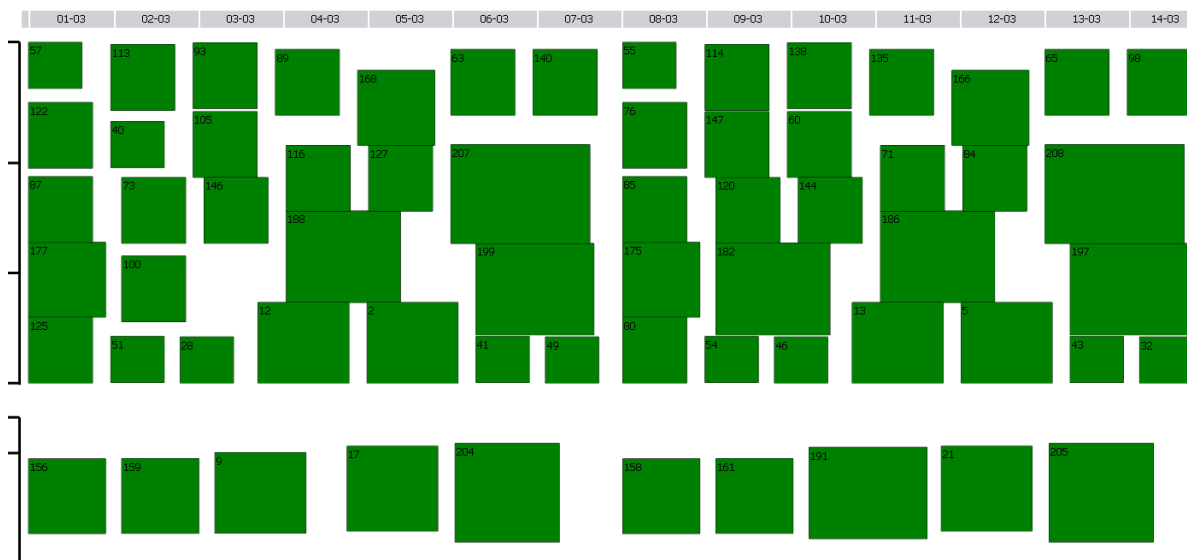


Figure 3.2: Example berth allocation: simulation period 2 weeks, cyclic period 1 week. The horizontal axis is the time factor of the berth allocation and the vertical axis shows the quay wall. One can see by the split in the vertical axis that this terminal has a discontinuous quay wall and consists of two sections of quay. The green boxes in this image all represent vessels planned in this time frame. Note that in the length of the vessels as visualised (the vertical length of the boxes) also a necessary safety distance is incorporated. Thus, boxes that touch do not touch in real life.

Step 6: Plan each cyclic period

The final step is to project each period's arrivals on the projection berth allocation as created in the previous step. In this procedure the tidal windows will have an important role in deciding which vessel from a loop will arrive in which period. This can be optimised under the assumption that when planning arrivals a shipping line will not plan a very deep vessel during a low water period but rather have the vessel arrive less heavily laden. Hence for each cyclic loop for which a time and place is reserved in the projection plan, vessels will be planned in such a way that, if the vessel arrives exactly at the time that is planned, the vessel will not have any issues with entering the port due to tidal restrictions. Further, when the expected handling time is over, the vessel should be able to leave as soon as possible.

In practice, this means that when planning the vessels from a loop, first the vessel with the largest draught will be planned. For each period one can use the estimated travel time from the tidal window threshold point to the berth to find the time the vessel would pass that point if it would arrive exactly on time at the planned berth that period. With this time it is possible to check if the vessel would be able to enter the port at that time according to the tidal patterns. Every period in which the vessel can enter immediately will be selected as a potential period that the vessel will arrive. If the vessel can not enter immediately in any of the periods, the period with the shortest time to high water will be selected. Now, for each of the selected periods the time after handling is done until the time it can exit the port because of the tides is calculated using the exit draught for each period. Since this is the preliminary planning phase, no information is known yet about the actual exit draught. It can happen that the draught changes because of loading and unloading. Because this can only be known a short time in advance, it is assumed here that the exit draught is the same as the draught with which the vessel enters. The period in which this is shortest is selected as the period in which the vessel will arrive. If multiple periods have the same time until exit, a random one is selected. The remainder of the vessels in the loop are planned in similar fashion in descending order of draught. This process is repeated for each loop, or spot in the projection plan.

An example output berth allocation from our approach can be seen in Figure 3.2. The figure shows a simulation period of 2 weeks with a cyclic period of 1 week. Arrivals are randomly generated; the terminal has discontinuous quay walls. One can note the cyclic behaviour of the planning for instance when looking at vessel 207 and 208. An example of a space reserved for non cyclic arrivals can be seen with the vessels 100 and 182. These vessels are clearly different size and handling time, and thus from a different vessel class, but are planned at the same location.

4

Methodology of disruption management

In the previous chapter an approach to create a preliminary berth planning was presented. This theoretical berth planning can serve as input for the simulation model. However, during simulation, disruptions might occur. This chapter gives a detailed explanation of the proposed disruption management approach. It first explores the simulation model where it is implemented because this gives some insight in some of the design decisions made. Then the disruption management approach itself is explained in detail, as the different methods used are discussed and the decision making strategy is presented.

4.1. Simulation model

4.1.1. Simulation controller models

Within the simulation model there are two controller models that are of interest for the disruption recovery, namely the vessel controller and the berth controller. The vessel controller controls the vessels: it calculates the routes that the vessel will take, generates motion plans and makes sure that the vessel complies to all sailing rules. The inner workings of how routes are chosen and how sailing rules and other traffic are included into the sailing behaviour of the vessel is being handled by the vessel controller and beyond the scope of this thesis. The berth controller controls the berths for the terminals: it has knowledge about the most recent berth schedule and determines where and when a vessel can berth.

4.1.2. Communication between controllers

To be able to incorporate the disruption recovery the communications between the vessel controller and the berth controller need to be modified. The new flow is visualised with a communication diagram in Figure 4.1.

When a vessel arrives at sea, the Vessel Controller (VC) will start handling the vessel. The first step that is taken is asking the Berth Controller (BC) to provide the VC with the planned berthing location of the vessel in question. After receiving this information the VC will calculate the vessel's route and corresponding travel time and respond with all the information the BC needs to properly plan the vessel. This information contains the minimum arrival time at the berth, the actual handling time, the travel time to the berth and the change in draught after handling. It is assumed that this information is accurate and correct at that point which is based on the fact that in reality planners can give a good estimation of the handling time and change in draught based on the call size of the vessel. Also, planners can make a good estimation of the travel time a vessel needs to get to the berth given the current tidal situation and other traffic on the water.

As soon as the BC receives this information from the VC it is able to use this information to determine a berth location and berthing time for the arriving vessel. Until this point, the BC only had information about the estimated arrival time and estimated handling time of the vessel. Now that the vessel made a terminal call the actual arrival time and handling time are known. The BC will use this to determine a berthing time and location by manipulating the current berth schedule to make all the vessels fit into the schedule again. The details of how this works will be provided in the next section of this chapter.

In response to receiving the berthing time and location of the vessel from the BC, the VC will calculate the route to the berth and start the simulation of that specific vessel. It will also send one last message to the BC with the actual arrival time at the berth. This is necessary because in the case where a vessel is not berthed at exactly the location that it was originally planned to, the actual arrival time might differ with a few

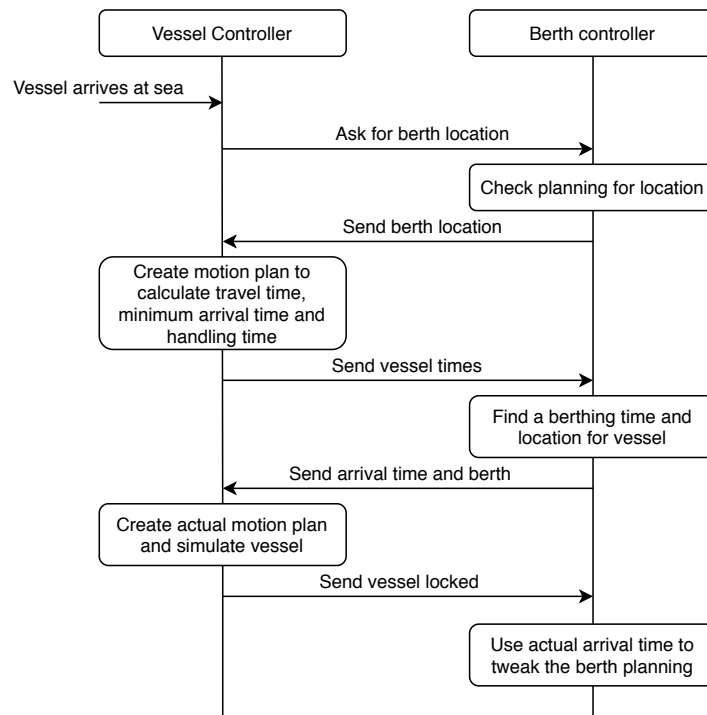


Figure 4.1: Visualisation of the communication between the Vessel Controller and Berth Controller

minutes depending on how much it changed. The BC will use this to tweak the arrival time of the vessel in its berthing plan and lock it in place. When a vessel is locked, it is not allowed to be moved in the berth schedule anymore. This is a design decision made based on the fact that as soon as a vessel starts its simulation process, its behaviour, route and travel time (the so-called motion plan) is decided until it leaves the port again. Only when a vessel is done with its loading and unloading a new motion plan is calculated for leaving the port. This means that when a vessel starts its travels, its route or speed cannot be changed and it is essentially locked. This means that when a vessel starts simulating the BC will lock that specific vessel so that it knows that it cannot change that vessel in the berth schedule.

4.2. Real-time disruption recovery

When the BC receives all the information necessary, the first step will be to check if the proposed berth is free at the minimum arrival time of the vessel and if planning the vessel at that point will result in any collisions. If this is not the case, the vessel can be planned at that location and at its minimum arrival time and the BC will report this back to the VC.

If disruptions happen the BC needs to recover the berth schedule in such a way that every vessel fits in the planning again. This has to happen in real-time and for every vessel so it needs to be relatively fast. If finding a good recovered berth plan takes one hour per vessel, running the simulation would become infeasible for the large-scale setting that the Port of Antwerp has provided. Also, as discussed in Section 2.3, the aim is to stay as close to the original berth planning as possible. To do this, first a formula will be introduced that evaluates the quality of the realised berth planning after the simulation is complete in comparison with the theoretical baseline planning. Subsequently, three important approaches and methods are explained that will be used in the disruption management method. The final part of this section will be on decision making. That is, how these different approaches and methods are deployed, work together and how decisions are made based on their output.

4.2.1. Quality measure

It is important to have a sense of when a recovery is good and when it is not. Therefore, a formula for the quality of a realised berthing plan in comparison with the theoretical planning was formulated in consultation with an expert with experience in berthing vessels in real life. There are two important factors when deciding

on the quality of a recovery; namely the deviation in berthing time for a vessel, and the deviation in berthing location for a vessel. The formula is formulated as a penalty for a single vessel:

$$p = c_1 * (x - t) + c_2 * ((1 - \delta) * |y - b| + \delta * L) \quad (4.1)$$

Here, p is the penalty for berthing a vessel at time x and location y . The lower p is, the better the recovery has planned the vessel. One can note that the berthing time of a vessel x is compared with its theoretical berthing time t , where the same berthing time would lead to no added penalty. Likewise is the berthing location of a vessel y compared with b , the planned location of the vessel in the theoretical plan.

Because in the case study presented by the Port of Antwerp there are multiple terminals with two quay walls instead of just one, this is something that has also been adopted in this thesis. Terminals can have more than one quay wall. In the case of disruption recovery, it might be that a good solution in case of some disruption is that a vessel needs to be berthed at a different quay wall than at its originally planned quay wall. This has been incorporated in the quality formula with the variable δ , which is 1 if the vessel is moved to a different quay wall, and 0 otherwise. If the vessel is moved to a different quay wall it is impossible to decide how large the displacement is and therefore the decision has been made to add a large penalty L which is the length of all the quay walls in the terminal combined. This large penalty also makes sense in real life because moving resources to a different quay wall is a costly operation. Lastly, c_1 and c_2 are cost parameters, regarding the deviation in time and space respectively. In consultation with the expert mentioned earlier, for c_1 the value of 1 is chosen and for c_2 the value of 0.2 is chosen. With this penalty function in mind, the quality of a complete realised berthing plan would be the average penalty over all the vessels:

$$P = \frac{1}{n} \sum_i^n p_i \quad (4.2)$$

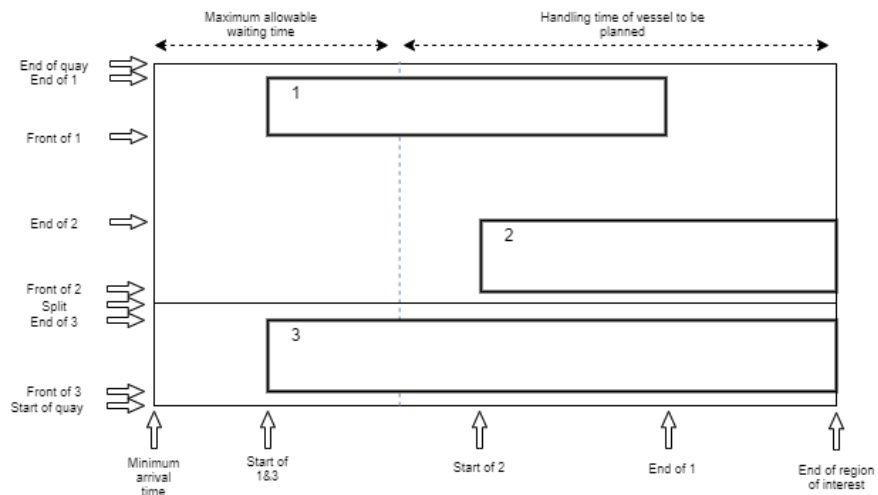
4.2.2. Distinct point method

The first method that will be used in the disruption management is a novel method called the distinct point method. The distinct point method is a more efficient method (compared to brute-force checking each (x, y) -pair) to determine the empty spaces in a berthing plan. These boxes are of interest because each of these empty spaces represents a potential berthing place and time for the vessel to be planned. In the remainder of this subsection the workings and details of this method are explained.

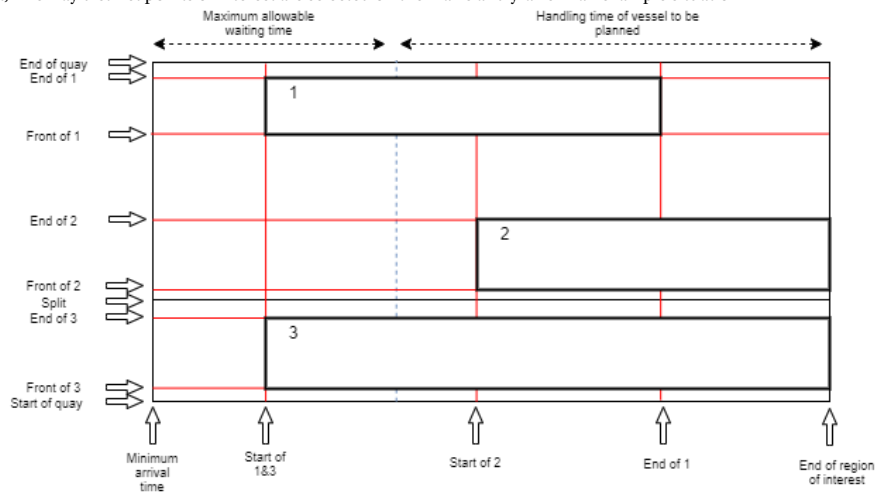
Before one can start determining the empty spaces in the berthing plan first the region of interest needs to be determined. For each vessel to be planned, only a small portion of the berthing plan is of interest since this gives the potential berthing locations after its arrival time and within its maximum allowable waiting time. The region of interest therefore starts with the minimum arrival time of the vessel. The end time of the region of interest is the minimum arrival time of the vessel with the addition of the minimum allowable waiting time and the handling time of the vessel. The maximum allowable waiting time can be decided based on the user's requirements. In the case study in Chapter 5 this maximum allowable waiting time is 16 hours. For the region of interest the complete quay length is considered.

To determine the empty boxes in a berth planning first the distinct points of interest will be determined for both the x-axis and the y-axis. The distinct points of interest on the x-axis are the start and end times of all the vessels within the region of interest in the planning, the start time of the region of interest, and the end time of the region of interest. The distinct points of interest on the y-axis are the begin and end location of the vessels on the quay within the region of interest, the first point at the quay (at 0 meter) and the last point at the quay (the length of the quay). In the case that the terminal is split into multiple quays, the split is also added as a point of interest. In Figure 4.2a the selection of distinct points of interest are shown for an example situation.

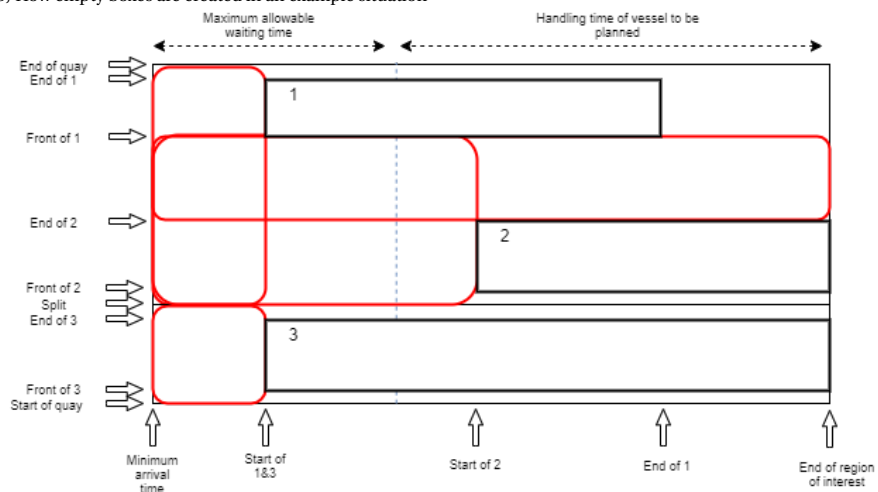
Now that the distinct points of interest are known, we can use each combination of two x points and two y points to form boxes. These boxes are known as the potential empty boxes. The creation of empty boxes is shown in an example situation in Figure 4.2b. To determine the actual empty boxes, each of these boxes are checked for collisions with the vessels in the region of interest. After that, each of the boxes that do not collide with vessels in the region of interest is checked with the other empty boxes. If a box has a 100% intersection with another box it is completely surrounded by the other box. In this case, the bigger box is kept and the smaller box is removed. After doing this, only the largest possible boxes which completely fill up the empty space are kept. Lastly, only the boxes that start within the first 16 hours are kept, because these are the boxes that can actually be used as potential berthing locations for the vessel to be planned when adhering the the maximum allowable waiting time. How the final set of boxes are chosen in the example situation is depicted in Figure 4.2c. It should be noted that in light of clarity and visibility some of the selected boxes are left out.



(a) The way distinct points of interest are selected on the x-axis and y-axis in an example situation



(b) How empty boxes are created in an example situation



(c) How the largest empty boxes are selected that do not intersect with the vessels

Figure 4.2: Example situation of a berth planning and how empty boxes are selected. NOTE. In light of clarity and visibility 4 empty boxes have been left out of figure c. These boxes are the narrow boxes that reach along the whole x-axis and on the y-axis are between 'End of quay' and 'End of 1', between 'Front of 2' and 'Split', between 'Split' and 'End of 3' and between 'Front of 3' and 'Start of Quay'.

These boxes are the narrow boxes that reach along the whole x-axis and on the y-axis are between 'End of quay' and 'End of 1', between 'Front of 2' and 'Split', between 'Split' and 'End of 3' and between 'Front of 3' and 'Start of Quay'.

4.2.3. Chain recovery

The next method that is used in the disruption management approach is called chain recovery. The chain recovery approach has gotten its name because of the 'chain' in which the vessels are pushed back in time to solve the disruptions. This chain starts with the vessel to be planned, or the vessel of interest. When a berthing location is chosen for this vessel, the collisions it makes with other vessels in the berthing plan can be calculated. The vessels that it collides with are pushed back until the two vessels do not collide anymore. However, since these vessels have been pushed backwards, they might have caused new collisions. These collisions are solved repeatedly, in which the time slacks that have been planned after each vessels act as sponges to absorb the collisions. How and when this approach is applied will be further discussed in the decision making part at the end of this chapter.

4.2.4. Local CP recovery

There might be situation in which heuristics to recover the berth planning do not give satisfactory results. This might be in the situation of the Port of Antwerp when the recovery for a specific vessel is not allowed to influence the planned berthing time and location of vessels that are expected to arrive in a set amount of days. When this happens a backup recovery approach is proposed which makes use of a local CP model to locally reschedule the berth planning. This is still considered disruption management and not rescheduling because of the fact that the CP model aims to fit all the vessels in while staying as close to their original location and time as possible. The CP model is called local because it aims to keep the region of interest that will be replanned as local as possible and thereby influencing as little other vessels as possible. This region of interest consists of the entire quay in the y direction, and an expanding time span in the x direction. Expanding means that a increasing time span is used until the model is able to find a feasible solution.

The parameters, decision variables, objective function and the constraints for the local CP model are:

Parameters

V = set of vessels to be served in time horizon

$xOriginal_i$ = original x position for vessel i

$yOriginal_i$ = original y position for vessel i

l_i = length of vessel i

t_i = handling time of vessel i

$Locked_i$ = 1 if the vessel cannot be moved, 0 otherwise

L = Quay length

$Split$ = split location of quay

T = Planning time horizon

Decision variables

x_i = start berthing time vessel i

y_i = berthing position vessel i

$yObj_i$ = berthing position penalty for deviation from y

s_i = 1 if vessel i is located above the split, 0 otherwise

$xInterval_i$ = an interval variable covering the interval $\{x_i, x_i + t_i\}$

$yInterval_i$ = an interval variable covering the interval $\{y_i, y_i + l_i\}$

Objective and constraints

$$\min \sum_{i \in V} (x_i + 0.2 * yObj_i) \quad (4.3)$$

$$\text{NoOverlap2D}(xInterval, yInterval) \quad (4.4)$$

$$xOriginal_i \leq x_i \leq T - t_i \quad \forall i \in V \quad (4.5)$$

$$0 \leq y_i \leq L - l_i \quad \forall i \in V \quad (4.6)$$

$$x_i = xOriginal_i \quad \text{if } Locked_i = 1 \quad \forall i \in V \quad (4.7)$$

$$y_i = yOriginal_i \quad \text{if } Locked_i = 1 \quad \forall i \in V \quad (4.8)$$

$$y_i \geq Split \quad \text{if } s_i = 1 \quad \forall i \in V \quad (4.9)$$

$$y_i + l_i \leq Split \quad \text{if } s_i = 0 \quad \forall i \in V \quad (4.10)$$

$$yObj_i \geq y_i - yOriginal_i \quad \forall i \in V \quad (4.11)$$

$$yObj_i \geq yOriginal_i - y_i \quad \forall i \in V \quad (4.12)$$

$$yObj_i = L \quad \text{if } (s_i = 1 \wedge yOriginal_i \leq Split) \vee (s_i = 0 \wedge yOriginal_i \geq Split) \quad \forall i \in V \quad (4.13)$$

The objective function (4.3) minimizes the difference with the vessels original berthing time and position by minimizing their arrival time and penalty for deviation in berthing position. Constraint 4.4 is a CP-specific constraint which constrains each pair of $xIntervals$ and $yIntervals$, which form rectangles, to be non-overlapping rectangles (also known as the *diffn* constraint [3]). Constraints 4.5 and 4.6 ensure the boundaries of the values that x and y can take on are being held. The main point of interest here is that x can only be put after $xOriginal$ because vessels cannot be forced to come earlier. Constraints 4.7 and 4.8 ensure that if a vessel is locked it cannot be moved. Constraints 4.9 and 4.10 ensure that a vessel cannot be positioned on a split. The final three constraints (4.11), (4.12) and (4.13) are concerned with setting the right value for $yObj$. The first two ensure that the value taken up by $yObj$ is the absolute difference between the original location and the actual location. The last constraint has a relatively difficult if clause which basically checks whether or not the vessel is put at the other side of the split. If this is the case $yObj$ takes on the value for the total length. These constraints will never lead to infeasible results because by definition we know that L is always larger than the absolute difference between the original location and the actual location.

4.2.5. Decision making

Now that the different approaches and models have been introduced the decision making can be investigated. That is, when are the different methods applied and why. A visualisation of this decision making process is presented in Figure 4.3.

As stated before, the first check done by the BC is whether the vessel fits at its minimum arrival time at its planned location. If this fits and no disruptions happen one can know for certain that this is the optimal location and time for the vessel because it does not have to wait to be handled and it is positioned at its planned location. However, if this is not the case the distinct point method will be applied to the region of interest in the berth planning for this vessel. When the empty boxes of interest are determined for the vessel to be planned they can be used to determine the most promising berthing location and time for the vessel. Whether an empty box is considered promising is determined by checking the width of the box. If the vessel fits with regards to the vessel length the box is wide enough for the vessel and is therefore considered promising. How promising this box is is based on the the time span the box covers. The longer this time span the more promising the box.

Now that all the promising boxes are known we will check the solutions corresponding to the empty boxes and choose the best recovery regarding the quality measure as introduced in Section 4.2.1. The recovery that has the lowest sum of penalties over all the vessels is chosen as the best recovery. The recovery corresponding to an empty box is made through positioning the vessel in that box and applying the chain recovery method. The vessel to be planned is positioned in the empty box with its berthing time equal to the start time of the box and its berthing position as much as possible to the side of the box. This is to make sure that the empty space is used as efficient as possible. There is one exception, if the original planned berthing position of the vessel is contained in the empty box, this will be the berthing position of the vessel. When the vessel is positioned correctly chain recovery is applied. If all the disruptions are recovered, the penalties for each vessel is calculated and summed and compared with the recoveries corresponding to the other empty boxes. Finally,

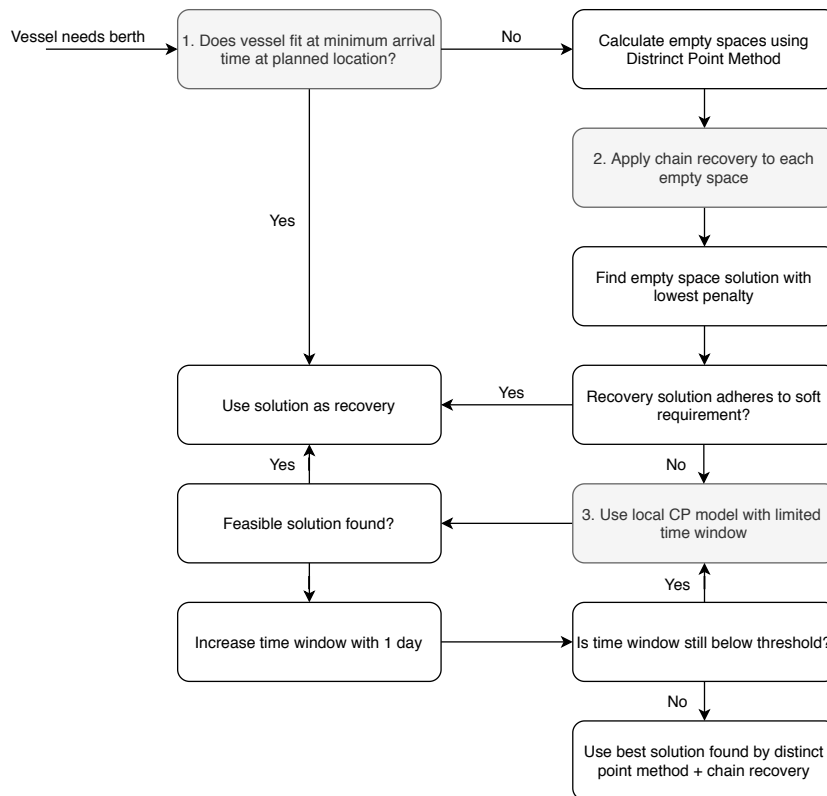


Figure 4.3: Flow chart visualising the decision making process for the disruption recovery model.

the best recovery is also compared to the situation where the vessel is just put at its originally planned location and chain recovery is applied from there. This last step is done because of the fact that even if there is no empty box, not changing the location of the vessel might give good results. The best recovery from here is selected as the recovery for the vessel and the BC will update the berth plan.

However, there is one important exception. It might be that the recovery found in the previous step conflicts with other soft requirements. One soft requirement set in the case of the Port of Antwerp is that a recovery at this moment is not allowed to change the berthing time and location of other vessels that are expected to arrive in four days. In this case the local CP is applied with an expanding time window. First only one day is tried and each time the CP model is not able to find a feasible solution, this time window is extended with one day and the local CP model will try again. This is repeated until the time window also hits the four day mark. In this situation, no good solution can be found within the required time and the best recovery from the previous step is applied anyway.

The approaches as listed above show step wise how disruptions will be solved. However, there are certain important considerations which need attention as well. One of these considerations is that although vessels ideally are planned as short after each other as possible to keep the terminal as efficient as possible, it is important to still keep some time, e.g. half an hour after each vessel, to deal with unforeseen trouble when exiting the harbour and so that vessels have some space to pass each other.

Another consideration is that the draught of the vessel can change during handling. This change can result in unforeseen extra time when a vessel needs to wait for its tidal window. When the vessel arrives on sea, a good estimation of the exit draught can be made which can be used to calculate the extra time required before the vessel can leave the port. This is added to the total duration that the vessel is at the berth.

5

Case Study and results

In light of the secondary objectives and testing the proposed methods for preliminary berth planning and real-time berth plan recovery in this chapter a case study will be conducted. The Port of Antwerp has provided Macomi with a detailed forecast and data regarding a future scenario in 2030. The interesting part for the Port is that it also includes a new terminal that does not exist at the moment. The approaches presented in this thesis are used in a simulation model that will give the port more insight into the effect of the addition of this extra terminal under various uncertainty scenarios. With the provided data many experiments have been conducted of which the results will be presented in the remainder of this chapter. First, the experimental setup will be discussed. After that the susceptibility of the preliminary berth planning approach to the hardness of the problem is investigated. Subsequently the effect of uncertainty on the recovery outcomes will be tested and lastly the trade off between occupancy and robustness is investigated.

5.1. Experimental setup

All the experiments that will be presented in this chapter have been done within the simulation platform of Macomi.

5.1.1. Data

The platform requires a lot of data about vessel arrivals, vessel types and specifications, location information, tidal windows for different vessel draughts and sailing rules. These datasets have been provided by the Port of Antwerp and are confidential; the exact numbers cannot be made public. The data required to generate the vessels and make the preliminary berth plan is explained in detail in Section 3.1. The data required for the disruption recovery is mainly the data generated by the preliminary berth planner, namely the berth schedules for each terminal. Also, to be able to keep track of potential waiting time, the data on tidal windows is required. Information about for instance travel times to and from the berths are generated by the simulation model's motion plan generator. This generator takes much of the data mentioned earlier to calculate a vessels move path and travel time, all while taking other traffic and sailing rules into account.

5.1.2. Simulation environment

For each of the experiments, most the settings for the simulation environment are kept constant. Each run is for the simulation period of one month, March, in 2030 with a cyclic period of one week. There is other traffic present like RoRo-vessels (Roll-on-roll-off vessel), liquid bulk tankers and general cargo vessels which can lead to busy periods while attempting to enter or leave the port. The main type of vessel of this thesis, the container vessel, has one of three possible terminals as destination. The terminals in this case study have the following specifications:

DP is relatively short with one quay wall of about 1700 metres.

MPET is a large terminal with two quay walls: one of about 2500 metres and a smaller one of about 600 metres.

Tweede getijdendok (2GTD) is a new terminal in design. In this case study the terminal consists of two quay walls: one of about 1500 meters and one of about 600 metres.

Since these terminals will be handled separately by the berth planning approaches as presented in this thesis. In practice they only influence each other through traffic since all vessels that enter the port come through the same water way. So, even though they are all present in a single simulation run, the results of these runs can be seen as three separate readings. Therefore, each experiment will present the data of these three terminals separately. This means that even though the simulation is tested for just the situation of the Port of Antwerp, having multiple terminals with very different specifications speaks a bit to the generalisability of this case study.

Further information on the exact specifications of each experiment will be given with that experiment as these differ for the different experiments. Experiments were run on a computer with 8GB RAM and an Intel i7 2.80GHz CPU (4 cores). For solving the CP models the state-of-the-art hybrid OR-Tools CP solver [32], version 7.5, is used running with 4 cores.

5.2. Problem hardness

The first experiment is conducted to test the performance of just the preliminary berth planning approach. Especially interesting are the cases where the port is very busy and thus the performance of the algorithm under a lot of stress.

5.2.1. Experiment specifications

Here we face a typical situation in which historical data about vessel arrivals is available but not applicable. First, a new terminal will be simulated of which no historical data is available. Second, we are simulating ten years in the future, and vessel arrivals (both the amount and the distribution over the classes) in the forecast provided by the port management are very different from the historical arrivals. Third, the river port is highly tide dependent, meaning that vessels with a large draught can have very long waiting times due to tidal restrictions and sometimes even have a tidal window of mere minutes.

The main time consuming part in the creation of the initial berth planning, is the time that the CP model needs to find a solution to a berth allocation for the projection week. It would be interesting to see how the run time of the CP model increases with the difficulty of the problem. In this case difficulty is measured as the expected occupancy of a terminal. Basically, if the terminal has more vessels to handle in the simulation period, we want to measure how well the CP model can handle this stress.

In order to establish the feasibility and potential optimality of this approach to berth generation, the problem hardness is investigated. The average occupancy of the terminals is investigated and the time it takes for the CP model to obtain a solution is measured. The solution time of the CP model is of interest because it is the most time consuming part of this approach described in Chapter 3. In this stress test, vessels will be added or removed with regard to the forecast for 2030, while keeping the original ratios between classes similar, until a certain expected occupancy is reached. Then, the approach for the creation of an initial berth plan is run. In this run the time is measured that the CP model needs to find the optimal solution, or when the solution does not improve for more than 2 hours. To really stress test the CP model, no additional buffer time was reserved for the vessel, ensuring that an occupancy as high as physically possible can be reached.

The experimental setup consists of the three mentioned terminals in Section 5.1 and their respective yearly forecast as provided by the port. Each run is for the simulation period of one month in 2030 with a cyclic period of one week. The CP solver is stopped when it has found and proved the optimal solution, or when it has made no solution improvement for two hours. The latter occurs when, for instance, the model has difficulty proving (in)feasibility. For each occupation, starting from 5% up to 95% with 5% increments, the average runtimes of five runs are reported. The differences between the five runs for each occupancy are found in the random generation of vessel arrivals from the yearly forecast and the division over the cyclic periods.

5.2.2. Results

The results are presented in Figure 5.1 and its corresponding exact numerical values in Tables 5.1 and 5.2. From these results one can note that, even though the speed with which the runtimes increase differs per terminal, the general trend is the same. At first, until about 50% occupation, the CP solver is able to find a good solution easily and is also able to prove its optimality. This changes in the region from 50% to 60%: here the runtimes start increasing and the solver is not able to prove the optimality without timing out after two hours of no improvement. From the 65% mark, none of the runs are able to prove optimality anymore within the set timeout. As soon as we reach the extremely busy cases (above 80% and higher) we start seeing runtimes of more than 90 minutes and occasional proven infeasible results. At 90% and higher most results are proven

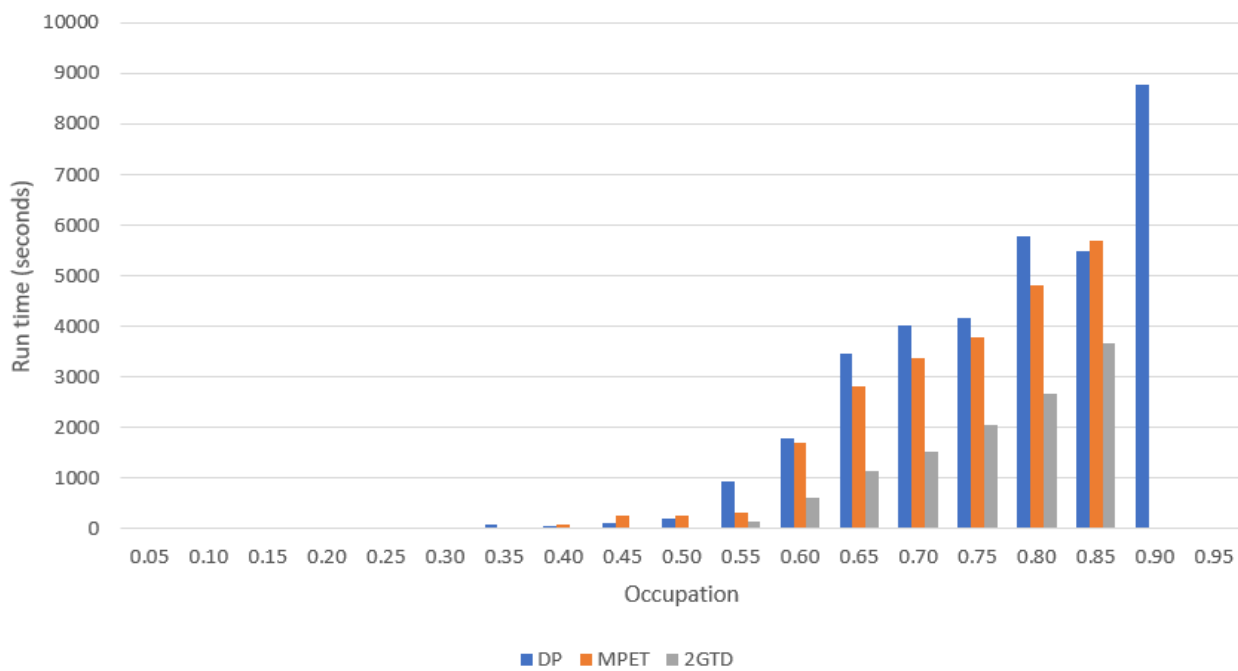


Figure 5.1: Bar graph representing the runtime of the CP model for different occupations

Table 5.1: Runtime in seconds of the CP model for three terminals. Occupancies up to 50%. For each terminal both the runtime and the percentage of runs that yield infeasible results are provided.

		0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
DP	Time (s)	5.21	5.99	5.68	6.39	7.38	25.54	89.49	45.78	109.87	200.33
	Infeas. %	0	0	0	0	0	0	0	0	0	0
MPET	Time (s)	7.92	10.31	11.49	13.03	15.58	13.78	17.86	70.84	251.49	252.04
	Infeas. %	0	0	0	0	0	0	0	0	0	0
2GTD	Time (s)	4.92	6.23	7.24	8.69	8.58	10.12	11.23	12.06	12.1	16.51
	Infeas. %	0	0	0	0	0	0	0	0	0	0

infeasible within two hours. The consequence of these findings are that for normal occupancy of between 50–70% runtimes of above an hour are very unusual.

5.2.3. Discussion

For the cases where the set timeout is reached, optimality is not proven. However, multiple experiments have been conducted investigating different solver timeouts and how the solution changes. From these experiments it can be concluded that solutions that do not change in 2 hours, also do not change in 12 hours. In this case study the goal was to place large vessels in the centre of the quay wall while smaller vessels should be positioned as much to the sides of the quay as possible. This made it relatively easy to manually check, in a qualitative way, the visual results whether solutions not proved optimal are good. We also have experimented with a short 5 minute timeout. While the solver does not find feasible solutions in this time for cases above 75% occupation, 70% and below it usually does. Here, the solution quality between a run with a timeout of 5 minutes and a timeout of 12 hours are compared. These results can be compared because the experiments have the same seed, guaranteeing the same optimisation setting. The results show that solutions found in 5 minutes are very close in quality to the ones that timeout after 12 hours.

An example of one of the test runs where a short timeout is compared with a long timeout can be found in Figure 5.2. Here the objective value after the 5 minutes timeout was 1890 while the timeout after 12 hours has an objective value of 1892. The visuals look identical to the naked eye and as one can notice, the large vessels are all positioned in the center of the quay wall and the smaller vessels all to the sides. More tests like this have

Table 5.2: Continuation of Table 5.1. Runtime in seconds of the CP model for three terminals, and percentage of infeasible runs. Occupancies above 50%.

	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
DP	924.52 0	1778.04 0	3461.22 0	4009.1 0	4158.97 0	5772.3 20	5487.1 20	8772.91 60	0 100
MPET	313.48 0	1699.62 0	2803.3 0	3378.02 0	3774.64 0	4822.1 20	5680.25 40	0 100	0 100
2GTD	136.17 0	612.28 0	1146.91 0	1534.25 0	2058.14 0	2659.1 0	3669.27 20	0 100	0 100

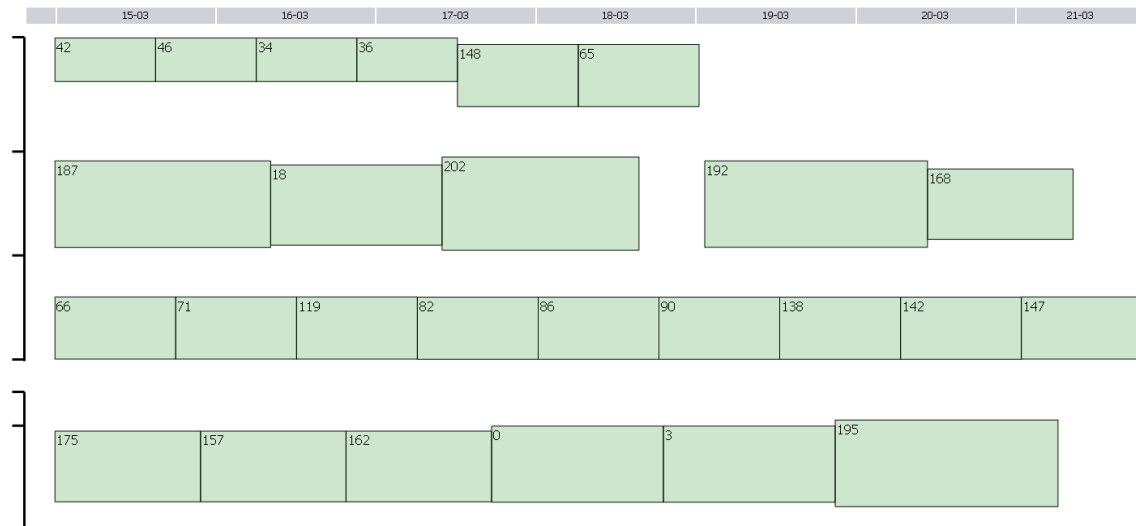


Figure 5.2: Example of the preliminary planning for 2GTD with 0.5 occupancy. This is an example where the plan looks the same when the solver has a timeout of 5 minutes and 12 hours of no improvement. The visual results show us that even though optimality is not proven, the result is very good. Note that since no robustness was added in this experiment, the actual berth plan is not at all realistic.

been done with different occupations and the same trend could be found. Based on this it can be concluded that even though the solver was not able to prove optimality, we can be relatively certain that after 2 hours of no improvement, the resulting solution is very good.

5.3. Uncertainty

Now that the performance of just the preliminary berth planner has been tested experiments have been conducted where the two parts are working together. First a baseline berth planning is created for the entire simulation period, then the simulation is run where the disruption management approach plays its role. In this specific experiment the main goal is to investigate the affect of uncertainty surrounding vessel arrivals in the simulation model on the quality of the recovered berth plan. However, also the run time and division over the different solution steps are measured. The quality is tested against a baseline recovery approach and the approach where no CP model is included.

5.3.1. Experiment specifications

In this experiment the effect of uncertainty on the ability of the disruption management model to find good recovery berth schedules. This experiment is run for the same month in 2030 for the same three terminals with the yearly forecasts for 2030 provided by the Port of Antwerp.

As introduced in the introduction of this thesis there are three main sources of disruptions. The first one, regarding handling time, is based on a distribution which is based on data provided by the Port of Antwerp. The second one, travelling time, is included in the simulation model and varies based on busyness on the water with other traffic and corresponding sailing rules. The third source of disruptions can be seen in the arrival times of vessels. The first two sources are already included in the simulation but the third, the arrival

Table 5.3: The quality of the realised berth plan and the standard deviation over 10 runs for the different recovery methods for different levels of uncertainty for the DP terminal. Lower scores are better.

		0	6	12	18	24	30	36	42	48
DRCP	avg	102.67	172.76	317.56	448.65	536.83	590.22	760.94	806.09	926.05
	std	14.31	47.48	61.34	98	73.44	186.3	189.87	181.63	176.22
DRnCP	avg	114.89	192.19	327.32	476.5	611.35	681.25	716.03	785.68	986.7
	std	22.88	41.61	54.71	123.88	118.2	312.02	211.41	260.26	240.08
Baseline	avg	382.3	373.25	815.82	1323.85	1590.65	1737.69	1875.11	1990.62	2247.75
	std	229.03	40.73	295.65	707.39	468.23	317.91	341.06	529.03	765.36

Table 5.4: The quality of the realised berth plan and the standard deviation over 10 runs for the different recovery methods for different levels of uncertainty for the MPET terminal. Lower scores are better.

		0	6	12	18	24	30	36	42	48
DRCP	avg	83.66	139.55	210.55	336.05	464.46	546.17	579.59	649.38	695.03
	std	8.15	19.17	36.69	61	73.09	32.07	81.16	91.46	99.08
DRnCP	avg	79.8	143.11	216.95	366.51	503.95	575.13	589.25	637.96	727.36
	std	10.56	24.76	45.11	75.17	80.94	89.33	149.71	123.99	177.78
Baseline	avg	135.04	342.53	719.98	1217.71	1794.16	1974.04	2044.14	2415.56	2502.77
	std	30.99	81.86	157.61	229.3	509.89	635.82	719.54	574.72	627.16

time disruption, can be altered and serve as a measure of uncertainty. To formalize this, if we model the arrival time as a normal distribution with the planned arrival time as mean, uncertainty is defined as the standard deviation in hours in this normal distribution. As an example, say that the uncertainty is 6 hours, the actual vessel arrival will be sampled from a normal distribution with its planned arrival time as mean and 6 hours as standard deviation. In this example, following the standard rules of statistics, about 68% of the vessels in this simulation run will arrive within one standard deviation, 6 hours before or after the planned arrival time, and about 95% of the vessels will arrive within two standard deviations, 12 hours before or after the planned arrival time.

With the increasing uncertainty it is interesting to see how many of the vessel arrivals are solved by which recovery technique. As explained in Section 4.2.5 there are different steps towards deciding on a good recovery. The first step is to check if the vessels fits directly at its arrival time at its planned location. The second step is the application of the distinct point method and chain recovery to find the best recovery from there. The third step concerns the application of the local CP model in case the recoveries from the previous steps are unsatisfactory. With more uncertainty one would expect that step 1 would be applicable less and step 3 would be necessary more, which is why, to test this, the deviation between recovery techniques are counted.

To be able to say something about the quality of the proposed method (Disruption Recovery with CP, DRCP) it was compared with a baseline recovery approach and the same approach but where the local CP model as backup is excluded (Disruption Recovery no CP, DRnCP). The baseline recovery approach always plans the vessel at its planned location and if disruptions appear it just performs chain recovery to make sure that the planning is physically possible again. This approach can serve as a baseline to see how well the proposed methodology compares with it. It is also interesting to compare this with the same approach but where the soft requirements are ignored and the output from the second step, the distinct point method and chain recovery, is always used as recovery.

For be able to reliably compare these three methods well they have all been conducted with the same seed. The average over 10 runs is taken as an indication for the quality of the resulting recovered berth plan under a certain level of uncertainty. Also, the run time for each method has been measured. However, because of the fact that each simulation run simulates three terminals at once, the presented run time is the average resulting time over all three of the terminals.

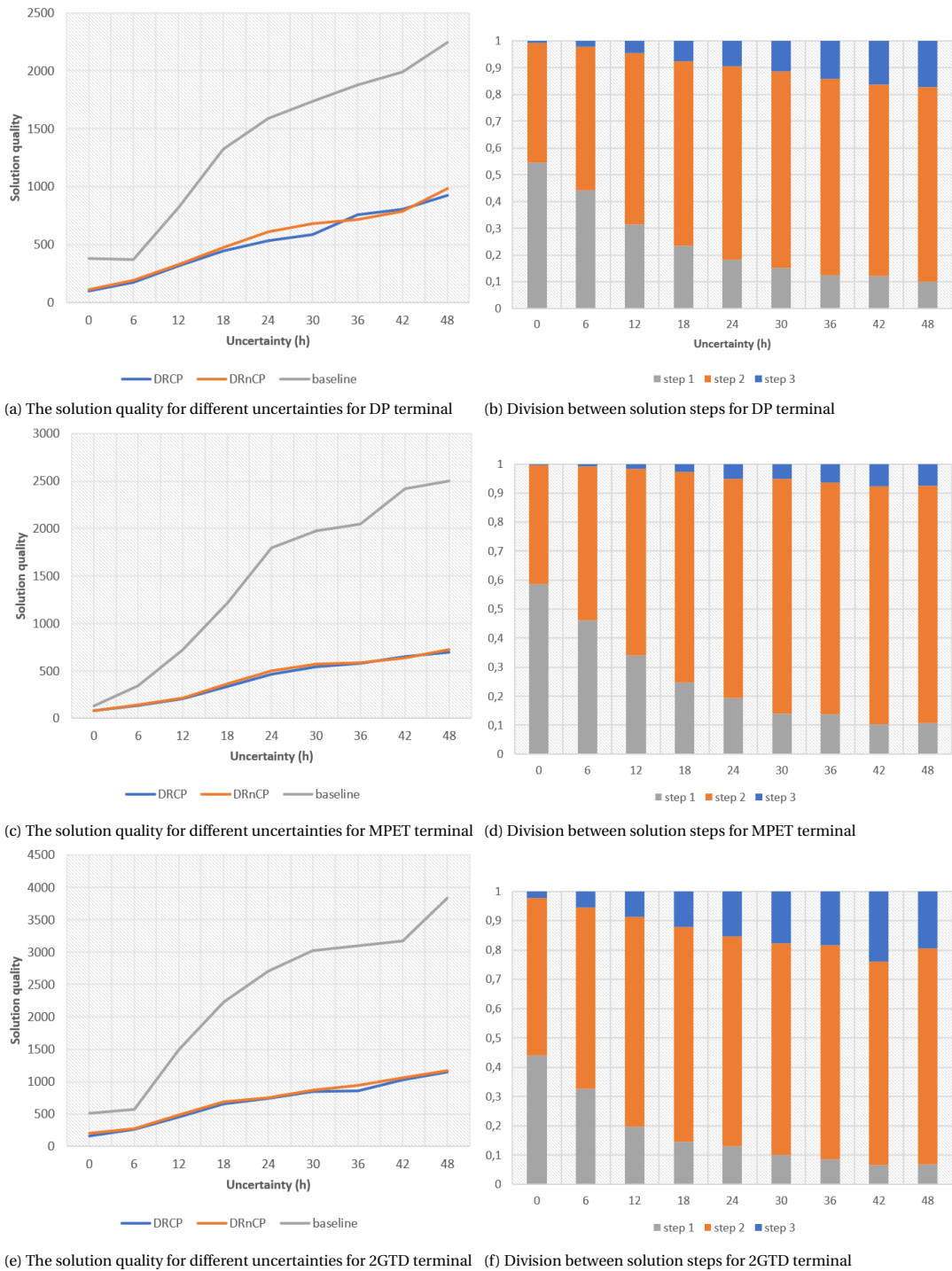


Figure 5.3: This figure shows for each of the three terminals, DP, MPET and 2GTD, the solution quality for the different recovery approaches for different uncertainties and how the division between different solution steps is for different uncertainties.

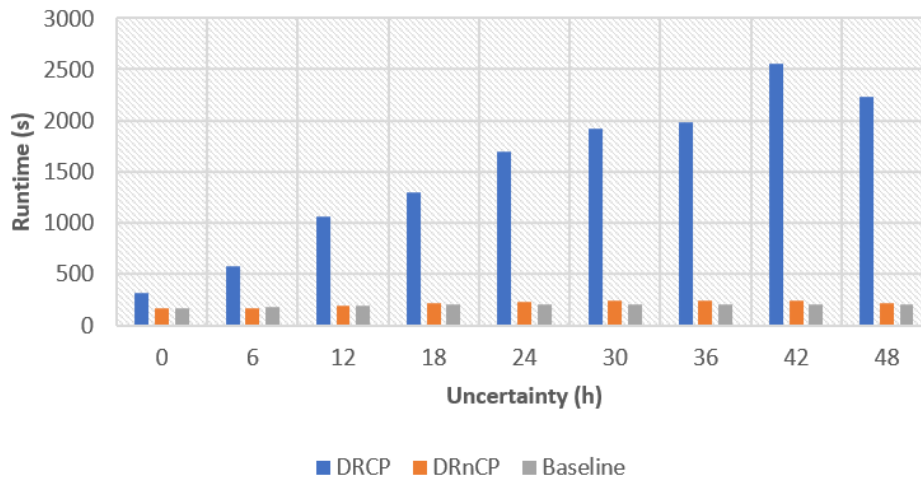


Figure 5.4: Run time in seconds for the different recovery approaches for the different uncertainties

Table 5.5: The quality of the realised berth plan and the standard deviation over 10 runs for the different recovery methods and different levels of uncertainty for the 2GTD terminal. Lower scores are better.

		0	6	12	18	24	30	36	42	48
DRCP	avg	159.15	268.03	453.55	661.01	739.74	849.58	854.97	1028.13	1150.06
	std	47.22	41.42	59.34	93.74	120.68	143.25	174.43	170.38	160.67
DRnCP	avg	205.86	278.43	489.4	689.75	747.07	866.22	945.54	1064.8	1165.45
	std	66.51	56.95	67.32	140.61	134.95	183.76	194.86	215.77	241.9
Baseline	avg	511.68	571.22	1492.8	2227.56	2701.32	3020.28	3098.68	3170.95	3834.59
	std	314.25	230.58	541.73	649.47	390.35	283.2	533.01	370.61	618.98

Table 5.6: The run time in seconds for the three terminals combined for the different recovery methods and different levels of uncertainty.

	0	6	12	18	24	30	36	42	48	48
DRCP	313.24	570.97	1062.82	1300.54	1693.32	1925.96	1977.42	2558.88	2228.53	926.04
DRnCP	172.02	171.34	188.92	218.46	226.63	244.82	237.80	237.52	221.01	176.21
Baseline	165.16	174.83	187.71	200.46	199.70	202.78	209.52	199.62	201.02	986.70

5.3.2. Results

The results of all the experiments regarding uncertainty have been presented in Figures 5.3 and 5.4. For more details and the exact numbers the reader is referred to the presented Table 5.3, 5.4, 5.5 and 5.6.

5.3.3. Discussion

Figure 5.3 gives for each terminal the solution quality for the three different recovery algorithms, DRCP, DRnCP and the baseline. One can immediately note that the presented approaches in this paper perform a lot better than the baseline approach which shows the effectiveness of these approaches. Also, when combining the graphs of the division of the steps with Figure 5.4, one can see how the run time scales directly with how often step 3 (the local CP model) is necessary. From this we can conclude that the CP model is the most time consuming part of the DRCP approach.

One can also note that the difference between the averages DRCP and DRnCP is often rather small. This would mean that the addition of a local CP model does not necessarily improve the solution quality of the recovered berth schedule. With this in mind, and looking at Figure 5.4, one could easily conclude that that DRnCP much more efficient than DRCP, given that the solution quality looks similar while the run time of DRnCP is a lot lower, especially for the higher uncertainties, and is also less affected by the uncertainty.

This raises the question why the local CP model is applied so often while it seems like using just the distinct point method and chain recovery works fine. What happens in the process is that the CP model replans everything, and likely more close together, in an attempt to solve the disruption within as little days as possible. This means that locally the berth plan might be changed a bit more while the distinct point method with chain recovery might be changing things further in the future. As a result, at the time the recovery decision is made and the CP is applied, the solution found by the CP often has a much lower intermediate penalty than the solution found by the distinct point method with chain recovery. This of course raises the question how the final quality measure can still be similar.

I believe that the answer to that question lies in the fact that the planning is updated every time a new vessel arrives. This means that even though the distinct point method with chain recovery can push back the berthing time of a vessel in the berth plan, it still arrives following its planned arrival time in the baseline berth plan. This means that as soon as the vessel actually arrives it might be planned at the berthing time and location as indicated before, but it is also likely that the distinct point method with chain recovery might find a new time and location for this vessel that is not as far in the future. To conclude, even though the intermediate solutions are worse, there is a good chance that the problems are solved again when more vessels arrive and more information is available.

However, it is important to note that this is not guaranteed and completely dependant on the current situation in the port, the arrival times of other vessels and the handling time of other vessels. This is why we can see in Tables 5.3a, 5.3c and 5.3e that often the standard deviation between the 10 runs are higher for DRnCP than for DRCP. From this one can conclude that even though the averages seem similar, the DRnCP approach is more susceptible to random initialisation and therefor less trustworthy. Also, DRCP is able to guarantee that the soft requirements can be held, while for DRnCP this is left completely to chance.

5.4. Occupancy and Robustness

In this section the influence of the occupancy rate of berth occupation and the value of adding robustness in the preliminary planning is explored. The goals of these final experiments are to investigate these influences and also the trade off that exists between the occupancy rate and robustness. First a baseline berth planning is created based on a certain expected occupation and while ensuring a certain robustness in the planning. Subsequently, the simulation will be run and the quality of the realised berth schedule is measured.

5.4.1. Experiment specifications

The average occupation of the berths in a terminal is a very important measurement to grasp the busyness in the terminal. An expert in the field of berth allocation expressed his interest in the affect of occupancy on how well the disruption recovery would work. This is because in real life, from a certain occupancy rate, it becomes very difficult to keep the terminal running. There should be a certain tipping point from where it becomes very difficult to keep the waiting times low and stay close to the theoretical planning. One of the main goals in this experiment is to investigate if indeed such a tipping point exists and if so, at what occupancy rate this is.

Adding robustness to the preliminary berth planning can be done in a proactive manner by adding a time slack after each vessel. By guaranteeing this time slack after each vessel in the plan, the planning is less

susceptible to disruptions because the smaller disruptions can be captured within this time buffer. However, when more vessels are expected the potential length these time slacks can take on decreases. This is because more vessels are required to be fit in the same space, which obviously results in less empty space in the planning. This leads to two additional goals of these experiments. First of all to investigate how important the addition of robustness is to the quality of the realised berth schedule. Secondly, to investigate how this trade off between robustness and occupancy rate expresses itself in practice and whether this can lead to additional findings.

For each vessel it is expected that some kind of distribution is known about the handling times of the vessels. This is necessary in creating the preliminary berth planning because the expected value from this distribution is used as handling time that is reserved in the berth planning. However, in the simulation the actual handling time is sampled from this distribution and thus can easily differ a lot from this expected value. This will not be a problem if the sampled time is shorter, but when its longer, it can lead to disruptions and overlap in the planning. Therefore robustness is added to the planning. Robustness is added with regard to the standard deviation of the handling time distribution. To be exact, in this experiment, robustness is defined as a certain percentage of the standard deviation of the handling time of the vessel that is added as time buffer in the preliminary berth planning. The longer this time slack is, the longer the vessel can stay handling, if needed, before it results in disruptions.

This experimental environment is similar as the previous ones as it is run in the same month in 2030 for the three terminals with the yearly forecasts for 2030 provided by the Port of Antwerp. Experiments are run for increasing occupancy rates and for increasing robustness levels. For each combination of occupancy rate and robustness level, 10 runs are done of which the average solution quality is reported. To stay true to the soft requirements set by the Port of Antwerp the DRCP approach is used and a disruption standard deviation of 12 hours is assumed in every run. This means that following the rules of statistics, 95% of the vessels in these runs will arrive in the time window of one day before and after their planned arrival time.

5.4.2. Results

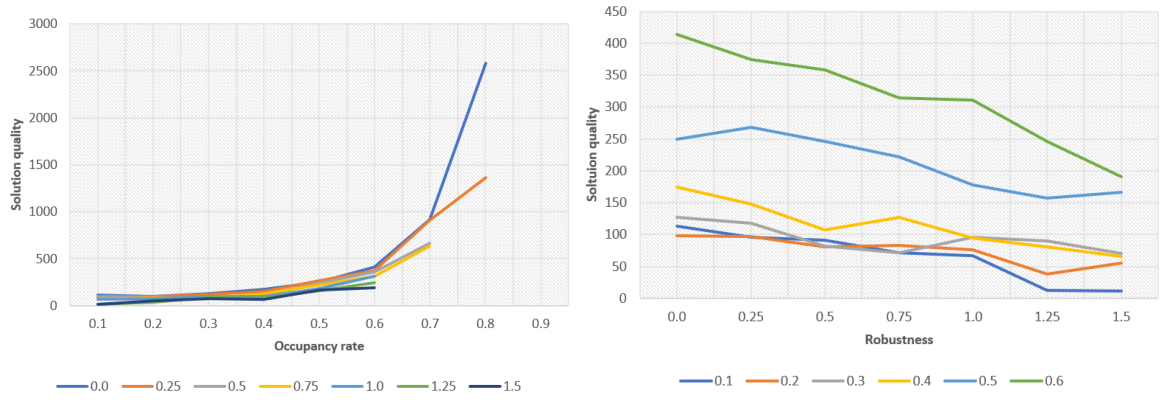
Table 5.7: Numerical results for the quality of the realised berth plan given different occupancy rates and robustness levels for the DP terminal. Lower score is better and an empty field represent the value where the initial baseline planning found no feasible plan.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0	113,59	98,61	126,75	174,53	249,71	414,42	915,52	2578,49	
0.25	95,66	97,2	117,76	148,02	268,57	374,73	906,84	1366,18	
0.5	91,28	80,6	81,55	107,64	245,87	358,45	662,49		
0.75	71,21	82,8	71,24	126,99	222	314,51	638,31		
1.0	66,78	76,57	95,79	94,53	177,71	310,89			
1.25	12,09	38,28	89,51	80,78	157,6	246,18			
1.5	10,89	54,71	70,91	66,09	166,76	190,14			

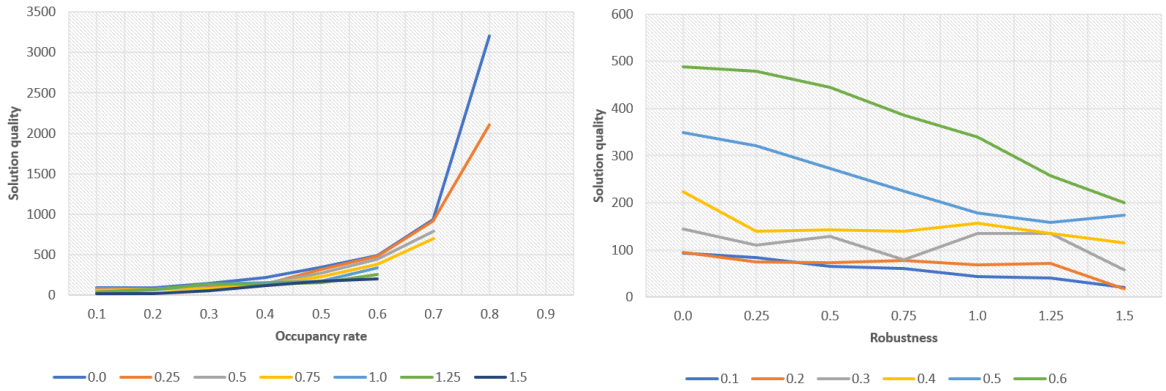
Table 5.8: Numerical results for the quality of the realised berth plan given different occupancy rates and robustness levels for the MPET terminal. Lower score is better and an empty field represent the value where the initial baseline planning found no feasible plan.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0	92,97	95,81	144,51	223,53	348,91	488,36	933,19	3206,22	
0.25	84,25	75,53	109,83	139,81	320,08	479,39	915,31	2101,55	
0.5	65,43	73,8	129,36	143,65	273,52	444,35	793,67		
0.75	60,2	77,81	79,58	139,74	225,21	385,73	701,81		
1.0	43,87	69,27	135,52	156,68	177,77	339,63			
1.25	41,22	70,95	135,12	134,39	158,98	257,01			
1.5	20,71	18,07	57,88	115,98	174,16	200,99			

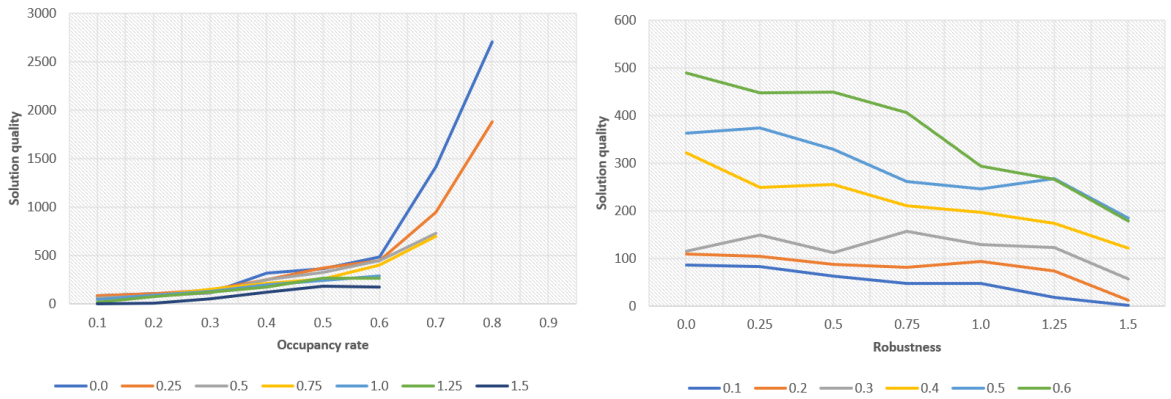
The results of the experiment regarding occupancy rates and robustness are presented in Figure 5.5. For the exact numbers behind these graphs the reader is referred to Tables 5.7, 5.8 and 5.9. In the cases where there are empty values in these tables, the preliminary planner was not able to find a feasible berth planning. In this



(a) The solution quality for different robustness levels with increasing occupancy rates for DP terminal (b) The solution quality for different occupancy rates with increasing robustness levels for DP terminal



(c) The solution quality for different robustness levels with increasing occupancy rates for MPET terminal (d) The solution quality for different occupancy rates with increasing robustness levels for MPET terminal



(e) The solution quality for different robustness levels with increasing occupancy rates for 2GTD terminal (f) The solution quality for different occupancy rates with increasing robustness levels for 2GTD terminal

Figure 5.5: This figure shows for each of the three terminals, DP, MPET and 2GTD, the solution quality for different occupancy rates and different robustness levels. Every right graph is the same as the left graph but with occupancy rate and robustness inverted.

Table 5.9: Numerical results for the quality of the realised berth plan given different occupancy rates and robustness levels for the 2GTD terminal. Lower score is better and an empty field represent the value where the initial baseline planning found no feasible plan.

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.0	86,6	108,84	114,67	322,18	362,81	489,49	1419,93	2708,56	
0.25	82,64	104,22	148,93	249,67	374,47	448,13	945,01	1878,1	
0.5	62,35	87,77	112,04	254,46	329,85	449,96	728,77		
0.75	47,95	81,84	156,36	210,7	261,25	406,2	697,84		
1.0	47,59	92,99	129,46	196,11	245,88	294,09			
1.25	18,28	74,27	122,07	173,57	267,88	265,69			
1.5	1,12	12,48	57,23	121,25	185,04	178,48			

case the recovery algorithm would still work but since there is no initial plan, the returned quality values have no meaning and have therefore been omitted.

5.4.3. Discussion

If one compares Subfigures 5.5a, 5.5c and 5.5e, which show the effect of occupancy on the solution quality for the different terminals, it can be seen that, as expected, the quality becomes worse the higher the occupancy rate. This is expected because the more vessels are expected in the same time frame, the more disruptions will happen and therefore higher penalties will be made. What can also be noted is that the tipping point, as discussed in Section 5.4.1 does indeed exist. For every terminal a sudden increase in penalty can be seen at 70% occupation and this trend increases very fast when 80% occupation is reached. This confirms the prediction that a tipping point exists from where the recovery approach has much more difficulty to find good solutions.

The right graphs, Subfigures 5.5b, 5.5d and 5.5f, show the same graph but with robustness and occupancy inverted. From these graphs can be seen how the solution quality improves when the robustness increases. It can also be seen that for higher occupancy rates, the addition of robustness has more effect. It should be noted that the lines for the occupancy rates of 0.7 and 0.8 were omitted to better show the effect of robustness at the lower levels. If however these would have been added, one would see that they show the same downward trend, but with a lot steeper fall the higher the robustness becomes. From this the conclusion can be drawn that the higher the expected occupation, the more important it is to include robustness in the preliminary berth planner.

However, as noted before, it is not possible to add endless time slacks to a berth schedule. Depending on the occupancy more or less robustness can be added before the plan becomes infeasible. The effect of this can be seen best in the tables (5.7, 5.8 and 5.9) where the empty spaces represent problems that are infeasible. In Figure 5.6 for each occupancy the points have been drawn where the first infeasible runs were detected. Interestingly enough these points seem to form a linear trend. This information can be used in simulation models to proactively and dynamically add robustness to a berth plan based on the estimated occupancy for that simulation period.

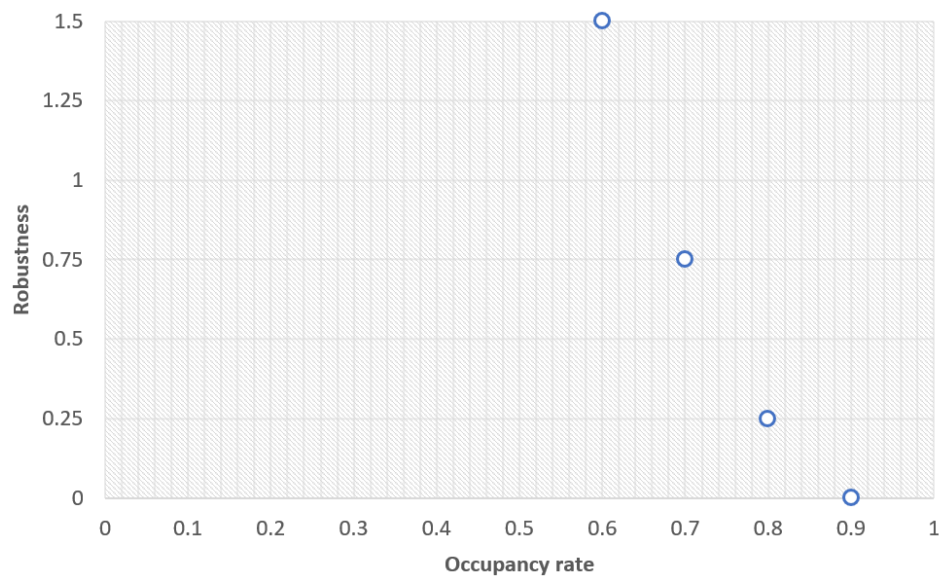


Figure 5.6: Trade off between occupancy rate and robustness

6

Conclusion

In this thesis the problems of creating a preliminary berth plan and real-time recovery of the berth plan within a simulated environment are tackled. These two problems required solving for a simulation model which the Port of Antwerp will use for future port-planning. For the creation of the preliminary berth plan a 6-step decision model is proposed that ensures the cyclic behaviour of vessel arrivals and incorporates tidal dependencies of vessels. The resulting berth plan is used as a theoretical berth plan on which the vessel arrivals in the simulation model are based. Real-time recovery is necessary when disruptions in the berth plan occur while simulating. To deal with these disruptions a second decision model is proposed in this thesis. The main goal of this disruption management model is to give every vessel a berthing time and location without any of them colliding while staying as close to the theoretical berthing plan as possible.

In the remainder of this chapter this thesis is concluded by first answering the sub research questions posed in Section 1.5.3 and finally the main research question. After the research questions are answered, some potential future research directions are proposed which could further validate and improve the models presented in this thesis.

6.1. Research questions

In this section the research questions are answered. First the sub-questions:

1. What is the current state of the research with regard to the subject of berth planning and recovery as provided by literature?

In Chapter 2 the main literature surrounding the topic of berth planning and recovery is set out. Regarding the baseline berthing plan it was concluded that none of the approaches in literature consider the use of a berth planning as a basis for a simulation model. It was found that within the creation of a berth schedule the strategic berth template problem exists which attempts to create a cyclic planning regarding vessels that call the port every period. The main deviation with the problem considered in this thesis and the problems considered in literature is that in the basis for a simulation model only a yearly number of arrivals is known. However, in literature it is always assumed that for each vessel some arrival time is known based on which a minimisation can be done. Hence the gap in literature that this thesis addressed.

Regarding disruption recovery some approaches have been proposed many of which are not real-time and require for instance multiple simulation runs to determine an optimal recovered berthing plan given that for each vessel the actual arrival time is known. Of the discovered works that do (semi-) real-time recovery there were three main points that this thesis attempted to improve on: namely to create a model that

- can deal with large scale settings
- can respond as soon as new information becomes available
- can deal with continuous quays

2. How can the specifications and requirements of an preliminary berth planning be combined into one berth schedule model?

Chapter 3 presents a model that incorporates the specifications and requirements to create a preliminary berth schedule. The model revolves around the creation of a projection plan, which is a berth planning in which spots have been reserved for each cyclically calling loop. When this projection plan has been created, all the generated vessels are projected onto this plan taking into account their draught, and thereby their tidal windows. The berthing time for each vessel that follows from this projection serves as the arrival time in the actual simulation. The complete generated berthing plan, which contains the berthing time and location for each vessel, is used as the theoretical berth schedule for the simulation period.

3. How can a model be formulated that deals with large-scale and real-time disruption recovery in a berth planning?

When the simulation begins many types of disruption can occur which can lead to changes in the berth plan or even turn the berth schedule infeasible. This is due to the fact that when creating a baseline schedule one can only work with expected handling times and expected travel times. Chapter 4 proposes a real-time disruption management approach that attempts to solve these problems as soon as they come up. Three methods are given, the distinct point method, chain recovery and the local CP model, which are combined into a decision model that helps recovering from disruptions. The main goal of this decision model is to stay as close to the theoretical berth schedule as possible.

4. How does the probability that disruptions happen affect the ability to find good recovery solutions?

The level of uncertainty can make a lot of difference for the proposed models in this thesis. When there is a lot of uncertainty the expected values that are worked with in the creation of the theoretical berth planning are less certain. Therefore, when the simulation is running, disruptions will happen more frequent and might be of larger impact when the uncertainty is higher. In Section 5.3 results are presented for the experiments regarding uncertainty. The results of these experiments show how the model reacts to increasing levels of uncertainty. It can be noted that the quality does worsen when the uncertainty increases, which is as expected, but it is important to see that this increase is linear and no tipping point exists where the quality suddenly becomes much worse.

5. How does the average occupancy of a terminal relate to the ability to find good recoveries?

As explained in Section 5.4 it is expected that at a certain occupation level of the terminal it becomes much harder to find a good recovery since it is just too busy at the terminal. In the same section experiments are set up and executed which determine the affect of occupation on the quality of the realised berthing plan. As expected, if the terminal has to handle more vessels, and therefore has a larger occupation, the quality of the realised plan goes down. However, this decrease in quality is relatively small and is therefore not a problem. On the other hand, the predicted tipping point from which the solutions suddenly become much worse does exist and is found around 70-80%.

6. How does robustness ('time slacks') in the theoretical plan affect the ability to find good recovery solutions?

Regarding robustness the experiment in Section 5.4 has shown that more robustness leads to higher quality recovered berthing plans. However, the same experiment has also shown a trade-off with occupation of the terminal, where the addition of robustness becomes more important with higher occupations. When a terminal is not as busy the influence of robustness is rather small, while with a higher occupancy the quality of the realised berthing plan increases a lot with more robustness.

Lastly, the main research question can be answered:

How can preliminary planning and real-time disruption recovery improve the berth planning for the Port of Antwerp simulation model?

This thesis presents a novel approach for preliminary planning and real-time disruption recovery in a simulated environment. Where before the simulation model would just generate vessels according to a random

Berth occupancy over tijd

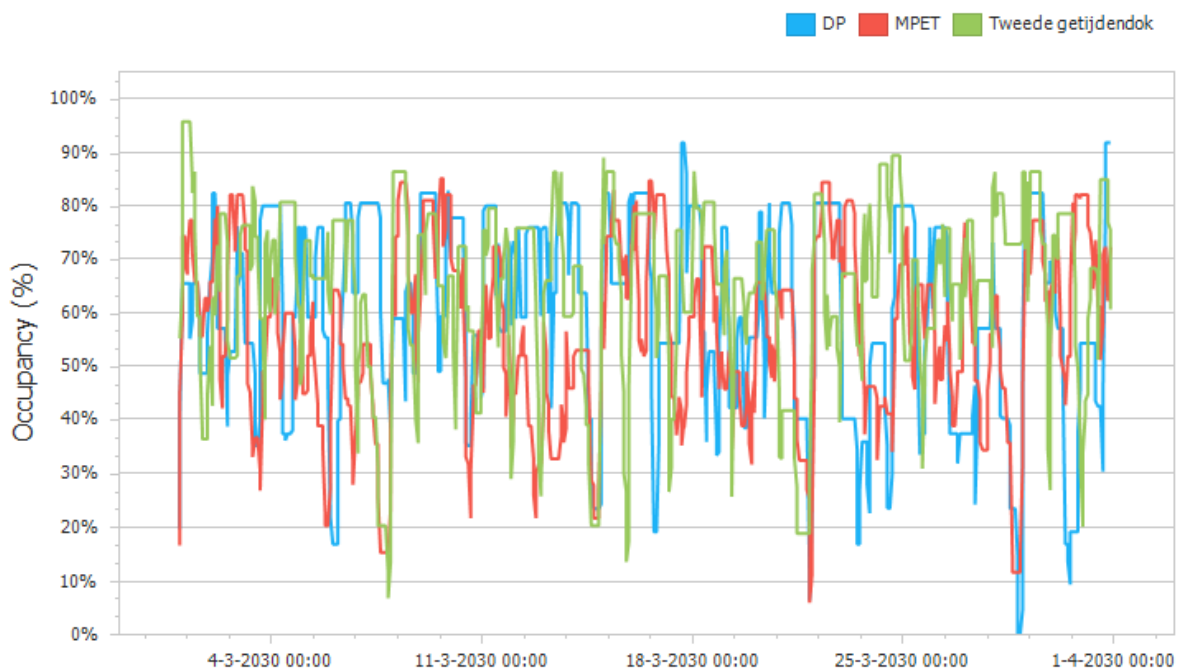


Figure 6.1: Graph showing the berth occupancy over time. This graph is the results of a simulation run with the new models included. The three lines represent the three terminals. The simulation has been run for 1 month in 2030. Note that over the course of this graduation project the data has been updated, which is why there are more terminals in this graphs in comparison with Figure 1.2.

distribution and allow it to berth at the location that would be freed the first, this new approach creates a preliminary baseline berthing schedule based on which the simulation is run. When comparing Figure 6.1 with Figure 1.2 at the start of this thesis, one can see a big difference in the graphs. The occupation at the port no longer has peaks over 100%, hardly any over 90%, and the occupations seems to be more balanced over time. During the simulation, in real-time decisions are being made regarding vessels and where and at what time they have to berth. The experiments in Section 5.3 show that the quality of the realised berthing plan of the approach methods outperforms the baseline recovery model. The models presented in this thesis have been implemented in the Macomi port simulation model and has been demonstrated to the Port of Antwerp. Both parties have expressed their satisfaction with the models.

6.2. Future work

In this section some potential future research directions are given.

- Decision framework for pro-actively and dynamically adding robustness to the preliminary berth planner. Section 5.4.3 discusses the trade off between the expected occupation of the terminal and the possible robustness that can be added to the baseline plan. With more focused experiments I believe the trend as seen in Figure 5.6 can be made more detailed. This could be used in some kind of decision framework in which the expected occupation can be calculated beforehand and based on this a certain amount of robustness can be added proactively to the vessels in the preliminary berth planner.
- Performance of models under different uncertainty scenarios. The uncertainty experiment results presented in Section 5.3 are run under the assumption that the uncertainty regarding arrival times can be captured in a normal distribution. It would be an interesting future work direction to investigate the effect of different uncertainty scenarios on the performance of the presented models. Different distributions could be interesting, but even more interesting would be to base this on historical data concerning deviation from planned arrival time.
- Further validation of results and additional testing. Due to pragmatic reasons mainly concerning time limitations the experiments presented in Chapter 5 have only been replicated for a set number of time.

Though I am confident that the presented results are a close representation of the actual values, more replications of the same experiment should be run to further validate the results. This should especially be done for the runs where the standard deviation between the runs are relatively high. Another test that would be interesting for future research is to see the influence of early stopping the local CP model. In most cases when the local CP model is called during a recovery run the solver is able to prove optimality or infeasibility within mere seconds. However, in some cases the solver has difficulty proving optimality, which is why a time limit was introduced. If the solver hit the time limit, the best found solution is used and if no solution has been found yet, the time windows are increased. It would be interesting to investigate how much effect this has on the quality of the realised berth schedule and how much the quality would improve if no time limit was introduced and unlimited time was given to the simulation run.

Bibliography

- [1] Port of Antwerp. <https://www.portofantwerp.com/en>. Accessed: 2020-06-26.
- [2] Macomi. <https://macomi.nl/>. Accessed: 2020-06-26.
- [3] N. Beldiceanu and E. Contejean. Introducing global constraints in CHIP. *Mathematical and Computer Modelling*, 20(20):97–123, 1994.
- [4] M. A. Izaskun Benedicto, Rafael M. Garcia Morales, Javier Marino, and Francisco de los Santos. A decision support tool for port planning based on monte carlo simulation. In *Proceedings of the 2018 Winter Simulation Conf. (WSC'18)*, pages 2885–2896, 2018.
- [5] Christian Bierwirth and Frank Meisel. A follow-up survey of berth allocation and quay crane scheduling problems in container terminals. *European Journal of Operational Research*, 244(3):675–689, 2015.
- [6] Benonie Carette. Berth allocation in a stochastic environment. Master's thesis, Vrije Universiteit Amsterdam, 2016.
- [7] Radu Cimpanu, Mel T Devine, and Conor O'Brien. A simulation model for the management and expansion of extended port terminal operations. *Transportation Research Part E: Logistics and Transportation Review*, 98:105–131, 2017.
- [8] Uwe Clausen and Jan Kaffka. Development of priority rules for handlings in inland port container terminals with simulation. *Journal of Simulation*, 10(2):95–102, 2016.
- [9] Paul Corry and Christian Bierwirth. The berth allocation problem with channel restrictions. *Transportation Science*, 53(3):708–727, 2019.
- [10] Yi Ding, Shuai Jia, Tianyi Gu, and Chung-Lun Li. Sgict builds an optimization-based system for daily berth planning. *Interfaces*, 46(4):281–296, 2016.
- [11] Yuquan Du, Ya Xu, and Qiushuang Chen. A feedback procedure for robust berth allocation with stochastic vessel delays. In *2010 8th World Congress on Intelligent Control and Automation*, pages 2210–2215. IEEE, 2010.
- [12] Yuquan Du, Qiushuang Chen, Jasmine Siu Lee Lam, Ya Xu, and Jin Xin Cao. Modeling the impacts of tides and the virtual arrival policy in berth allocation. *Transportation Science*, 49(4):939–956, 2015.
- [13] Mihalis Golias, Isabel Portal, Dinçer Konur, Evangelos Kaisar, and Georgios Kolomvos. Robust berth scheduling at marine container terminals via hierarchical optimization. *Computers & Operations Research*, 41:412–422, 2014.
- [14] R Groenveld. Harborsim, a generally applicable harbour simulation model. Technical Report Internal report 1983-1, TU Delft, Section Hydraulic Engineering, 1983.
- [15] Said Ali Hassan. Port activity simulation: An overview. *ACM SIGSIM Simulation Digest*, 23(2):17–36, 1993.
- [16] MPM Hendriks, D Armbruster, M Laumanns, E Lefeber, and JT Udding. Strategic allocation of cyclically calling vessels for multi-terminal container operators. *Flexible Services and Manufacturing Journal*, 24(3): 248–273, 2012.
- [17] MPM Hendriks, Erjen Lefeber, and Jan Tijmen Udding. Simultaneous berth allocation and yard planning at tactical level. *OR Spectrum*, 35(2):441–456, 2013.
- [18] Kuancheng Huang, Suprayogi, and Ariantini. A continuous berth template design model with multiple wharfs. *Maritime Policy & Management*, 43(6):763–775, 2016.

- [19] Shell Ying Huang, Wen Jing Hsu, Hui Fang, and Tiancheng Song. A marine traffic simulation system for hub ports. In *Proceedings of 1st ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*, pages 295–304, 2013.
- [20] Akio Imai, Etsuko Nishimura, and Stratos Papadimitriou. Berth allocation with service priority. *Transportation Research Part B: Methodological*, 37(5):437–457, 2003.
- [21] Akio Imai, Yukiko Yamakawa, and Kuancheng Huang. The strategic berth template problem. *Transportation Research Part E: Logistics and Transportation Review*, 72:77–100, 2014.
- [22] Çağatay Iris and Jasmine Siu Lee Lam. Recoverable robustness in weekly berth and quay crane planning. *Transportation Research Part B: Methodological*, 122:365–389, 2019.
- [23] Çağatay Iris, Eduardo Lalla-Ruiz, Jasmine Siu Lee Lam, and Stefan Voß. Mathematical programming formulations for the strategic berth template problem. *Computers & Industrial Engineering*, 124:167–179, 2018.
- [24] Kap Hwan Kim and Kyung Chan Moon. Berth scheduling by simulated annealing. *Transportation Research Part B: Methodological*, 37(6):541–560, 2003.
- [25] Damla Kizilay, Deniz Türsel Eliyi, and Pascal Van Hentenryck. Constraint and mathematical programming models for integrated port container terminal operations. In *Proceedings of 15th International Conf. on Integration of Constraint Programming, Artificial Intelligence, and Operations Research (CPAIOR'18)*, volume 10848 of *Lecture Notes in Computer Science*, pages 344–360. Springer, 2018.
- [26] Shijie Li, Rudy R. Negenborn, and Gabriël Lodewijks. A distributed constraint optimization approach for vessel rotation planning. In *Proceedings of 5th International Conf. on Computational Logistics (ICCL'14)*, volume 8760 of *Lecture Notes in Computer Science*, pages 61–80. Springer, 2014.
- [27] H. L. Ma, Sai Ho Chung, Hing Kai Chan, and Li Cui. An integrated model for berth and yard planning in container terminals with multi-continuous berth layout. *Annals of Operations Research*, 273(1-2):409–431, 2019.
- [28] Frank Meisel and Christian Bierwirth. Heuristics for the integration of crane productivity in the berth allocation problem. *Transportation Research Part E: Logistics and Transportation Review*, 45(1):196–209, 2009.
- [29] Etsuko Nishimura, Akio Imai, and Stratos Papadimitriou. Berth allocation planning in the public berth system by genetic algorithms. *European Journal of Operational Research*, 131(2):282–292, 2001.
- [30] Theo Notteboom. The european container port scene 2019 and outlook for 2020. *Port Technology International*, (92):8–10, 2019.
- [31] Dimitris Pachakis and Anne S Kiremidjian. Ship traffic modeling methodology for ports. *Journal of Waterway, Port, Coastal, and Ocean Engineering*, 129(5):193–202, 2003.
- [32] Laurent Perron and Vincent Furnon. OR-Tools, 2019. URL <https://developers.google.com/optimization/>.
- [33] Tianbao Qin, Yuquan Du, and Mei Sha. Evaluating the solution performance of ip and cp for berth allocation with time-varying water depth. *Transportation Research Part E: Logistics and Transportation Review*, 87:167–185, 2016.
- [34] Geert F Thiers and Gerrit K Janssens. A port simulation model as a permanent decision instrument. *Simulation*, 71(2):117–125, 1998.
- [35] Nitish Umang, Michel Bierlaire, and Alan L Erera. Real-time management of berth allocation with stochastic arrival and handling times. *Journal of Scheduling*, 20(1):67–83, 2017.
- [36] Eelco van Asperen, Rommert Dekker, Mark Polman, and Henk de Swaan Arons. Modeling ship arrivals in ports. In *Proceedings of 2003 Winter Simulation Conf. (WSC'03)*, volume 2, pages 1737–1744, 2003.

- [37] Lal C Wadhwa. Planning operations of bulk loading terminals by simulation. *Journal of Waterway, Port, Coastal, and Ocean Engineering*, 118(3):300–315, 1992.
- [38] Mark Wallace. *Building Decision Support Systems – using MiniZinc*. Springer, Cham, Switzerland, 2020.
- [39] Fan Wang and Andrew Lim. A stochastic beam search for the berth allocation problem. *Decision support systems*, 42(4):2186–2196, 2007.
- [40] Xi Xiang, Changchun Liu, and Lixin Miao. A bi-objective robust model for berth allocation scheduling under uncertainty. *Transportation Research Part E: Logistics and Transportation Review*, 106:294–319, 2017.
- [41] Jie Yang, Hong Gao, Wei Liu, and Tao Liu. A novel strategy for berth and quay crane allocation under disruption in container terminal. *International Journal of Innovative Computing Information and Control*, 12(5):1535–1551, 2016.
- [42] Gi-Tae Yeo, Michael Roe, and Sang-Moon Soak. Evaluation of the marine traffic congestion of north harbor in Busan port. *Journal of Waterway, Port, Coastal, and Ocean engineering*, 133(2):87–93, 2007.
- [43] Qingcheng Zeng, Xiangpei Hu, W Wang, and Yan Fang. Disruption management model and its algorithms for berth allocation problem in container terminals. *International Journal of Innovative Computing, Information and Control*, 7(5):2130–2142, 2011.
- [44] Qian Zhang, Qingcheng Zeng, and Hualong Yang. A lexicographic optimization approach for berth schedule recovery problem in container terminals. *Transport*, 31(1):76–83, 2016.
- [45] Lu Zhen and Dao-Fang Chang. A bi-objective model for robust berth allocation scheduling. *Computers & Industrial Engineering*, 63(1):262–273, 2012.
- [46] Lu Zhen, Ek Peng Chew, and Loo Hay Lee. An integrated model for berth template and yard template planning in transshipment hubs. *Transportation Science*, 45(4):483–504, 2011.
- [47] Lu Zhen, Loo Hay Lee, and Ek Peng Chew. A decision model for berth allocation under uncertainty. *European Journal of Operational Research*, 212(1):54–68, 2011.
- [48] Lu Zhen, Zhe Liang, Dan Zhuge, Loo Hay Lee, and Ek Peng Chew. Daily berth planning in a tidal port with channel flow control. *Transportation Research Part B: Methodological*, 106:193–217, 2017.

A

Paper

Berth Planning under Uncertainty for Tidal Freight Port Simulation

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Abstract. A crucial aspect of berth planning for container ports located in tidal water is to take into account the vessel arrivals and tidal windows. When historical data is not available or relevant for simulation, the typical approach is to generate vessel arrivals randomly. By contrast, this paper develops an optimisation-based approach that allows incorporation of realistic aspects – cyclic vessel arrivals, tidal windows, and minimisation of vessel draught during low water periods – in order to develop a cyclic baseline berth allocation plan for simulation. We develop a mathematical model from which, using an AI-based solver, we can obtain optimal or satisficing solutions for a year’s operation of a large port. The baseline plan can be incrementally modified to handle real-time uncertainties and disruptions. The approach is implemented for a major European inland tidal port, forming the basis of a simulation-based decision support tool for operational planning and exploring port expansion options.

Keywords: berth allocation · simulation · arrival generation · tidal ports · constraint programming

1 Introduction

With the increasing volume of container freight transport and the increasing size of container vessels, port planning is crucial. Simulation models provide a means to gain insights into operational plans and future port expansions [3, 6].

One important design choice that impacts the simulation process is the generation of vessel arrivals. This is an important design decision because it influences everything from the busyness in the port’s entrance waters to the allocation of berths and other terminal-related planning. In many works the generation of vessel arrivals is modelled as a random arrival process [e.g., 25] or is based on historical data [e.g., 12]. In practice, when historical data is not provided, using a random arrival process is usually a decent assumption given that different terminals might schedule vessels differently. Further, external factors, like vessel delays and bad weather might influence these schedules. However, there are drawbacks to modelling vessel arrivals as a random process.

First, the random approach is hindered when simulating a port that has tide restricted entrance and exit windows. This means that depending on the draught of the vessel and the tide at that moment, a certain vessel may or may not be able to enter or exit the port. If a few deep vessels try to enter the port during a certain low water period they will all need to wait for this low water window to end. As soon as the water raises again all of these vessels that were waiting will want to enter the port at the same time. The result is congestion and vessel waiting time [7]. Our work is motivated by a major European inland tidal port where these aspects are critical upon port utilisation and vessel throughput.

The second drawback to using a random arrival process is that it disregards how many container shipping companies and terminals work: with cyclically calling vessels from ‘loops’ [11]. A loop can be seen as a series of ports that are visited in order. Because of the size of these loops, container shipping companies usually have multiple vessels sailing in the same loop. In reality, a terminal plans the arrivals of these loops using a cyclic baseline berth planning: a schedule for a week, in which every loop gets a certain time when and location where it is expected to arrive each week. This baseline plan is modified during the week’s execution because, due to external factors and uncertainties, vessels often encounter deviation from the baseline plan.

This paper contributes a novel approach as the basis for the vessel arrival generation and the berth allocation in a simulated environment. Our approach focuses on the generation of cyclic baseline planning on which the vessel arrival times and the actual berth allocation are based. By creating this baseline planning one can incorporate both the tidal windows of vessels and the cyclic nature of realistic container vessel arrivals. Further, in real-life scenarios, if a container shipping company knows that the planned arrival of a vessel is during low water time, they will attempt to load the vessel so that it has a draught as small as possible. This aspect of realistic decision making can also be accommodated by our planning approach. We use the optimisation technique of constraint programming to automatically derive, and in ongoing work, to dynamically update (compare e.g., Nishi et al. [16]), the berth allocation plans. Our work is implemented as part of a bespoke commercial simulation platform in use for decision support.

The next section surveys related literature. Section 3 describes the problem addressed and the optimisation approach developed. Section 4 presents an analysis on data from a major European tidal port. Section 5 draws our conclusions and discusses future directions.

2 Background and Related Work

For vessel arrival generation, simulation models either follow a random arrival process or base arrivals on historical data. In the first case, Pachakis and Kiremidjian [17] developed a procedure for modelling ship traffic. The authors propose the use of exponentially distributed inter-arrival times if data is not available. Thiers and Janssens [21], Yeo et al. [25] model the arrival generation with a Poisson process. This allows for varying arrival rates over the course of the simulation.

In the second case, when historical data is available and is relevant, simulation models can use it as a basis for vessel arrival generation [9]. Huang et al. [12], for instance, use the actual arrival historical times in the simulation. This is valid if the historical arrival times are representative of the simulation period; in particular, this assumption can be false when simulating future design options for the port. Cimpeanu et al. [5] assume that a yearly schedule for vessel arrivals are known beforehand. These are based on distributions of inter-arrival times derived from historical data provided by a port terminal company. van Asperen et al. [1] examine arrival generation for jetty facilities. The data provided in their case was yearly arrival numbers for the vessels, and not information about any kind of specific distributions.

Tidal patterns have been included in some simulation models. The early work of Groenveld [8] presents a port simulation model where tides are included. Here, the tidal conditions are included post hoc as a check whether a vessel is allowed to sail or not; a vessel that is not allowed to sail due to tidal restrictions needs to wait in the anchorage. Similarly, both Hassan [9] and Cimpeanu et al. [5] keep vessels restricted by tidal conditions waiting in a queue. Wadhwa [22] also takes tidal patterns into account when entering and exiting the port. Here, the notion of loading a vessel according to a certain allowable draught is introduced. Thiers and Janssens [21] divide vessels into tide-dependent and not tide-dependent. For vessels that are tide-dependent there are certain threshold locations which the vessel can only pass during a certain time-frame. These tidal windows are defined as the time frame in which the vessel can depart from a certain location and pass all the thresholds without issues.

From these works we can see that, with the exception of Huang et al. [12], all works generate vessels according to inter-arrival times. In cases where historical data is provided these are often based on data. On the other hand, if no data is available, different random arrival processes are incorporated. None of the models have included the cyclic nature of arrivals and only some of them included tidal patterns. The latter, however, are modelled as a check whether or not a vessel is allowed to enter the port or not, rather being taken into account in the arrival generation. By contrast, in reality shipping companies do attempt to take tides into account to reduce waiting time. As van Asperen et al. [1] have shown, random arrival processes not based on any environmental information leads to the highest vessel delays.

While berth allocation problems have received extensive attention in the literature (Wawrzyniak et al. [24] being a recent example), to the best of our knowledge, no work uses a baseline berth allocation as a base for a simulation model. The creation of a baseline berth planning itself is found in the literature: for a thorough overview we refer to Bierwirth and Meisel [4]. However, there is a crucial difference between the berth allocation papers in the literature and actually using the allocation as a base for a simulation: in the former the expected arrival time is usually assumed to be known.

In the most generic case of berth allocation, one tries to find an allocation that plans vessels as close to their expected arrival time as possible. Often also

some preferred berthing location of a vessel is taken into account. One of the main directions indicated by Bierwirth and Meisel [4]’s survey is the incorporation of the cyclic nature of a berth schedule. Hendriks et al. [11] are one of the few authors who incorporated the cyclic nature of a berth planning into a model. Here a cyclic period is divided into discrete time periods and it is assumed that vessels that berth simultaneously are known. Based on this a combined berth allocation and yard planning model is presented. Similarly, Zhen et al. [26] also present an integrated berth allocation and yard template model. In this work the planning horizon is divided into discrete time periods. The planning horizon can be repeated without issues which is why the resulting berth plan can also be considered cyclic.

These works all follow the assumption outlined by Hendriks et al. [10]: namely that strategic-level decisions have been made about the time of arrival and departure which are used to create the cyclic berth allocations. As these times are not known in a simulated environment and need to be generated from yearly arrival numbers these models cannot be used as such. However, the same mindset of rectangle packing on a cylinder instead of a plane, as well explained by Zhen et al. [26], is adopted in our work.

Constraint programming (CP) is a flexible Artificial Intelligence approach to modelling and solving combinatorial optimisation problems [23]. Kizilay et al. [13], for instance, use CP to address a decision problem in integrated port container terminal operations. Li et al. [14] use CP to plan vessel rotations (loops) among terminals within a port. In solving a berth allocation problem, Qin et al. [19] show that CP outperforms integer programming in three instances, namely when using dynamic arrivals over static arrivals, when using fine time granularity, and when the restriction of the objective towards the decision variables is not tight. Since the optimisation problem we will formulate has no tight restriction towards the decision variables (only to be close to a preferred location) and uses a very fine time granularity (that of 1 minute), we adopt CP and formulate a compact and understandable optimisation model.

3 Berth Planning Problem and Approach

3.1 Problem Summary

The problem this paper addresses is that of the creation of a cyclic baseline berth allocation of vessel arrivals in a simulation model. The allocation must respect physical and operational constraints. This baseline berth planning serves as a basis on which the vessel arrival times in the simulation will be based. In addition, this berth planning can be used as the theoretical berth plan during simulation. In practice this means that based on provided data about expected vessel arrivals in the port, vessels will be generated for the simulation model. Each of these vessels will be allocated a berth at a certain time during the simulation. Thus each vessel will be assigned the combination of a certain time, and a certain position at the quay wall, where the vessel can be loaded and unloaded without

interfering with other vessels. Based on the time of this allocation, the actual time the vessel will arrive in the simulation can be decided.

Hence we treat uncertainty by means of the simulation paradigm rather than through formulating, for instance, a stochastic programming model [20]. We also note the ability of simulation to capture behavioural factors, although this is not the focus of the current paper.

3.2 Problem Data

We consider a situation in which historical data about vessel arrivals is either not available or not applicable. There can be multiple reasons why data about past arrivals are not applicable for a simulation model. First, inter-arrival times based on historical arrivals can be inaccurate when simulating future scenarios. The further in the future one is interested to simulate the more likely it is that changes arise regarding amount of arrivals and arrivals from different vessel classes. Second, past arrivals are of limited value when the simulation is used for analysing possible port expansions. An instance of this, adding a new terminal, is taken up in the case study in Section 4. Third, aggregated inter-arrival time distributions from historical data do not take account particular tidal windows nor the cyclic behaviour of arrivals. As discussed in Section 1, this omission leads to no cyclic behaviour and increased waiting times because of the tidal pattern.

In order to develop a realistic data-based simulation, we take advantage of the following commonly-available data.

1. First, a yearly forecast for the simulation period. That is, for each class of container vessels, the port manager provides an expected yearly number of arrivals. To make these arrivals more realistic, the division of these vessel classes over different approach routes to the port can be used. What vessels belong to what vessel classes can be specific to the application. In the case study that we conducted (see Section 4) vessel classes are defined by their size, amount of Twenty-foot Equivalent Unit (TEU) that can be carried, and the handling time distributions. Hence each vessel from the same class has the same size, TEU and handling time distribution.
2. For each class it is also important to know the division of draught. That is, how many vessels are expected yearly with what draught. The draught of a vessel is essential knowledge since it determines whether or not a vessel can sail given the tidal situation.
3. Next, for each draught the tidal windows need to be known. These are required in a similar fashion as in Thiers and Janssens [21]. The tidal window at a certain location represents the first and last moment a vessel with a specific draught is allowed to pass that location, such that it will not encounter any tidal issues over the course of the journey to or from the port. To make a good estimation about the berthing times after a vessel can pass through the tidal window, data about travel times in and around the port are used.
4. Lastly, for each vessel class there is additional information regarding, for instance, the length of the vessel and the distribution of the handling time for that class.

For the subsequent parts of a port simulation, in which berth planning is incorporated, more data could be necessary. For example, information about traffic rules, tug boat assistance and external conditions like weather. We discuss the subsequent use of our approach in Section 5.

3.3 Proposed Methodology

The six steps are illustrated in Figure 1. We describe each in turn.

Step 1: Determine simulation period and cyclic period

Any simulation design requires some foundational decisions regarding the simulated period and the cyclic loop period. The decision for the simulation period is important as the tidal windows depend on this. The cyclic period determines how often the cyclical berth allocation pattern repeats itself. In practice this period is usually 7, 10 or 14 days [11]. The combination of this simulation period and cyclic period determine how often the cyclic pattern is repeated. The cycle period can be chosen to the user's needs.

Step 2: Generate vessels for the simulation period

The second step concerns the generation of all the vessels that will arrive in the simulated period. This is done through a repeated random selection with stratification. A list of vessel arrivals is generated that represents the total amount of arrivals that is expected in the simulation period according to the provided number of yearly arrivals for each class and draught within that class.

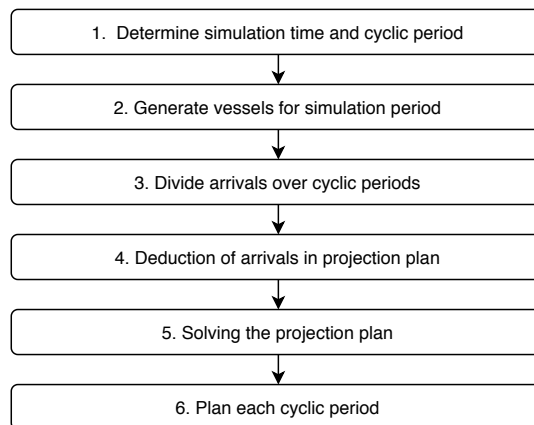


Fig. 1. Six steps of the berth allocation approach.

Step 3: Divide arrivals over cyclic periods

One important assumption that is made regarding the cyclic nature of the arrivals is that vessels from the same vessel class can belong to the same loop. Consequently, for each instance where a vessel class has arrivals in every cyclic period we may assume there is one loop for that vessel class. In this step the division of vessels over the cyclic periods is being made. The goal is to divide the arrivals from each vessel class as evenly as possible over the cyclic periods.

For example, suppose that the cyclic period is one week and the simulation period covers five weeks, then the vessel arrivals are divided over five periods. Now, if from a certain class 13 arrivals are expected in the simulation period we will assign two arrivals to each week and these will be considered cyclic arrivals. The remaining three arrivals that cannot cover each cyclic period will be assigned to random periods where the same period is not chosen twice. These remaining arrivals are considered non cyclic arrivals.

Step 4: Deduce of arrivals in projection plan

Now that the arrivals of each class per cyclic period is known, the next step is to deduce a projection plan. A projection plan is a berth allocation for one period on which the arrivals for each cyclic period are projected. The arrivals of the projection plan can be deduced as follows. First, for each cyclic loop that has an arrival each period, one vessel from that class is added to the projection plan. These loops will be planned at the same time and place each period. Secondly, since the projection plan is the berthing plan on which every period's arrivals will be projected, room for non cyclic arrivals needs to be incorporated as well. This is done by adding the number of non cyclic vessels of the period that has the most non cyclic arrivals. This way, the projection plan will have enough planned spaces such that each period can fit all their planned arrivals.

Step 5: Solve the projection plan

In this step the goal is to reserve a time slot and location for all the vessel class arrivals that are expected in the projection period. As explained earlier, the arrivals in the projection period are not actual arrivals but placeholders on which the actual arrivals for each period will be projected. This means that a decision needs to be made on how much space and how much time needs to be reserved for each arrival. We treat the cases of cyclic and non-cyclic arrivals separately.

For the cyclic arrivals this means that each arrival is from the same class which means that the vessel length and estimated handling time are likely rather similar. In any case, for each of the cyclic arrivals the longest vessel length and the longest estimated handling time for that vessel class needs to be reserved. In our case study, vessels from the same class all have the same vessel length and handling time distribution, which means that this length and expected handling time from this class can be used. This is to make sure that when planning the

actual arrivals and projecting it on this space that the arrival will stay within the reserved boundaries.

The non-cyclic arrivals are more difficult, since each period different vessels from different classes might use this spot. It is necessary to make sure that the spaces that are reserved are large enough such that every cyclic period each non-cyclic vessel fits in a space that is large enough to prevent overlap. To do this, we check the non-cyclic arrivals and find the arrival each period which takes the longest handling time and has the largest vessel length. This is the time and space that is reserved for the longest non cyclic arrival each period and by reserving this space we ensure that the largest non-cyclic arrival each period will have enough space. Next we check each period for the second-to-longest handling time and vessel length and reserve that space and so forth. This way it is guaranteed that all the spaces reserved in the projection plan are boundaries for the actual arrivals and no vessel will be outside its planned spot.

To solve the berth allocation for the projection plan we adopt an optimisation approach. We formulate a compact constraint programming model. The parameters, decision variables, objective function and the constraints are:

Parameters

V = set of vessels to be served in time horizon
 l_i = length of vessel i
 t_i = estimated handling time of vessel i
 L = quay length
 T = cyclic period planning time horizon
 b_{ip} = a score for vessel i to be placed at location p

Decision variables

x_i = start berthing time vessel i
 y_i = berthing position vessel i
 $yObj_i$ = the objective score value for vessel i
 $xInterval_i$ = an interval variable covering the interval $\{x_i, x_i + t_i\}$
 $yInterval_i$ = an interval variable covering the interval $\{y_i, y_i + l_i\}$

Objective and constraints

$$\max \sum_{i \in V} yObj_i \quad (1)$$

$$\text{NoOverlap2D}(xInterval, yInterval) \quad (2)$$

$$0 \leq x_i \leq T - t_i \quad \forall i \in V \quad (3)$$

$$0 \leq y_i \leq L - l_i \quad \forall i \in V \quad (4)$$

$$\text{Element}(y_i, b_i, yObj_i) \quad \forall i \in V \quad (5)$$

$$yObj_i \geq 1 \quad \forall i \in V \quad (6)$$

The objective function (1) is to maximise the score given to each vessel regarding a certain preferred berthing location for that vessel. Constraint 2 is a CP-specific constraint which constrains each pair of $xIntervals$ and $yIntervals$, which form rectangles, to be non-overlapping rectangles (also known as the *diffn* constraint [2]). Constraints 3 and 4 ensure that the values x and y can take on such that they remain within the boundaries of the berthing plan. Constraint 5 ensures that the value taken up by $yObj_i$ equals the score for vessel i to be berthed at location y_i .

The final constraint (6) constrains the minimum score that each vessel must have. This last constraint is optional; the minimum score depends on the application. This can be used if certain vessels need to be guaranteed at a certain location. In our case study a value of 1 was chosen to be able to deal with the situation of discontinuous quays (see also Ma et al. [15]). Namely, in this situation the discontinuous quay can be treated as a continuous quay but on the split a score of 0 is assigned. This way vessels can never be located over the split.

Note that the constraints used in this model follow the naming as implemented in the OR-Tools CP solver [18] used in our empirical case study (Section 4).

Step 6: Plan each cyclic period

The final step is to project each period's arrivals on the projection berth allocation as created in the previous step. In this procedure the tidal windows will have an important role in deciding which vessel from a loop will arrive in which period. This can be optimised under the assumption that when planning arrivals a shipping line will not plan a very deep vessel during a low water period but rather have the vessel arrive less heavily laden. Hence for each cyclic loop for which a time and place is reserved in the projection plan, vessels will be planned in such a way that, if the vessel arrives exactly at the time that is planned, the vessel will not have any issues with entering the port due to tidal restrictions. Further, when the expected handling time is over, the vessel should be able to leave as soon as possible.

In practice, this means that when planning the vessels from a loop, first the vessel with the largest draught will be planned. For each period one can use the estimated travel time from the tidal window threshold point to the berth to find the time the vessel would pass that point if it would arrive exactly on time at the planned berth that period. With this time we can check if the vessel would be able to enter the port at that time according to the tidal patterns. Every period in which the vessel can enter immediately will be selected as a potential period that the vessel will arrive. If the vessel can not enter immediately in any of the periods, the period with the shortest time to high water will be selected. Now, for each of the selected periods the time after handling is done until the time it can exit the port because of the tides is calculated for each period. The period in which this is shortest is selected as the period in which the vessel will arrive. If multiple periods have the same time until exit, a random one is selected.

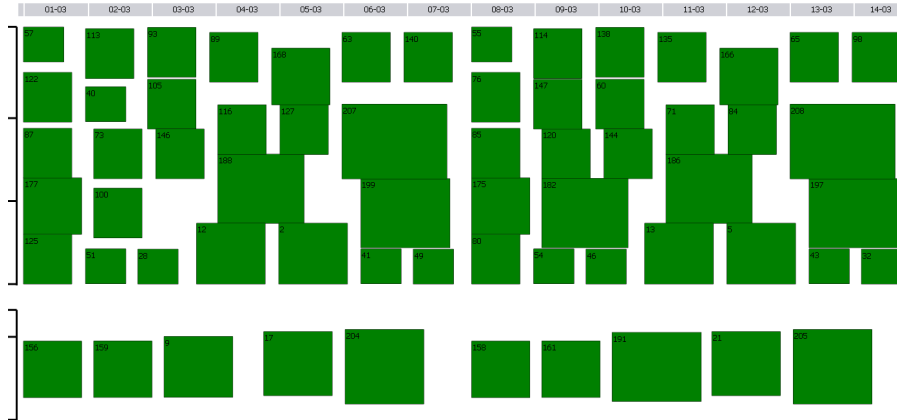


Fig. 2. Example berth allocation: simulation period 2 weeks, cyclic period 1 week. The horizontal axis is the time factor of the berth allocation and the vertical axis shows the quay wall. One can see by the split in the vertical axis that this terminal has a discontinuous quay wall and consists of two sections of quay. The green boxes in this image all represent vessels planned in this time frame. Note that in the length of the vessels as visualised (the vertical length of the boxes) also a necessary safety distance is incorporated. Thus, boxes that touch do not touch in real life.

An example output berth allocation from our approach can be seen in Figure 2. The figure shows a simulation period of 2 weeks with a cyclic period of 1 week. Arrivals are randomly generated; the terminal has discontinuous quay walls.

4 Case Study and Discussion

We examine a case study for a major tide-dependent inland river port in Europe. The goal is to create the baseline berth allocations for three terminals in this inland port; one terminal is in design and does not exist yet. These baseline berth allocations are used in a simulation model that will give the port more insight into the effect of the addition of this extra terminal under various uncertainty scenarios. The port provided a yearly vessel arrival forecast for the year 2030. Our work is implemented as part of a bespoke commercial simulation platform in use at several ports, and in this case, being used to analyse and plan the port expansion and future operations.

We face a typical situation in which historical data about vessel arrivals is available but not applicable. First, a new terminal will be simulated of which no historical data is available. Second, we are simulating ten years in the future, and vessel arrivals (both the amount and the distribution over the classes) in the forecast provided by the port management are very different from the historical arrivals. Third, the river port is highly tide dependent, meaning that vessels with a large draught can have very long waiting times due to tidal restrictions and sometimes even have a tidal window of mere minutes.

The terminals have the following specifications:

- Terminal 1** is relatively short with one quay wall of about 1500 metres.
Terminal 2 is a large terminal with two quay walls: one of about 2500 metres and a smaller one of about 800 metres.
Terminal 3 is a new terminal in design. In this case study the terminal consists of two quay walls: one of about 1500 meters and one of about 600 metres.

In order to establish the feasibility and potential optimality of our approach to berth generation, we investigate the problem hardness. We vary the average occupancy of the terminals and measure the time it takes for the CP model to obtain a (first) solution. The solution time of the CP model is of interest because it is the most time consuming part of this approach described in Section 3.

The hardness of the problem in this study is defined by increasing the occupancy through inflating or deflating the yearly forecasts, thus keeping the ratios in terms of classes and terminals the same, while keeping all other variables the same (e.g., the terminal specifications, the simulation period and the basis of the yearly forecasts per terminal). The theory is that the higher the occupancy, the more vessels will be arriving in the simulation, and the more difficult it will be to allocate berths.

The experimental setup consists of the above three mentioned terminals and their respective yearly forecast as provided by the port. Each run is for the simulation period of one month in 2030 with a cyclic period of one week. We stop the CP solver when it has found and proved the optimal solution, or when it has made no solution improvement for two hours. The latter occurs when, for instance, the projection week is too large and the model proves infeasibility. For each occupation, starting from 5% up to 95% with 5% increments, we report the average runtimes of five runs. The differences between the five runs for each occupancy are found in the random generation of vessel arrivals from the yearly forecast and the division over the cyclic periods. Experiments were run on a computer with 8GB RAM and an Intel i7 2.80GHz CPU (4 cores). For solving the model we used the state-of-the-art hybrid OR-Tools CP solver [18], version 7.5, running with 4 cores.

The results are presented in Tables 1 and 2. We see that, even though the speed with which the runtimes increase differs per terminal, the general trend is the same. At first, until about 50% occupation, the CP solver is able to find a good solution easily and is also able to prove its optimality. This changes in the region from 50% to 60%: here the runtimes start increasing and the solver is not able to prove the optimality without timing out after two hours of no improvement. From the 65% mark, none of the runs are able to prove optimality anymore within the set timeout. As soon as we reach the extremely busy cases (above 80% and higher) we start seeing runtimes of more than 90 minutes and occasional proven infeasible results. At 90% and higher most results are proven infeasible within two hours. The consequence of these findings are that for normal occupancy of between 50–70% runtimes of above an hour are very unusual.

Although for the cases where we reach the set timeout, optimality is not proven, we have conducted multiple experiments investigating different solver

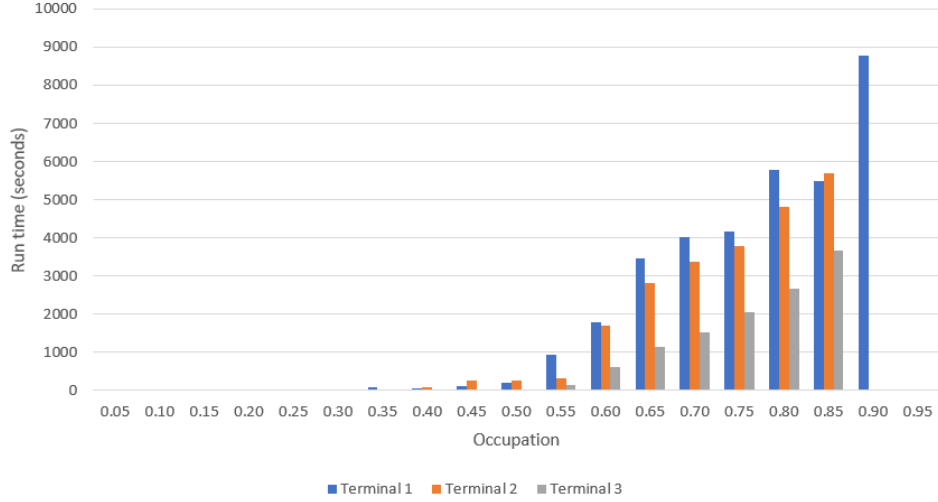


Fig. 3. Bar graph representing the runtime of the CP model for different occupations

Table 1. Runtime in seconds of the CP model for three terminals. Occupancies up to 50%. For each terminal both the runtime and the percentage of runs that yield infeasible results are provided.

	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Terminal 1 Time (s)	5.21	5.99	5.68	6.39	7.38	25.54	89.49	45.78	109.87	200.33
Infeas. %	0	0	0	0	0	0	0	0	0	0
Terminal 2 Time (s)	7.92	10.31	11.49	13.03	15.58	13.78	17.86	70.84	251.49	252.04
Infeas. %	0	0	0	0	0	0	0	0	0	0
Terminal 3 Time (s)	4.92	6.23	7.24	8.69	8.58	10.12	11.23	12.06	12.1	16.51
Infeas. %	0	0	0	0	0	0	0	0	0	0

timeouts and how the solution changes. From these experiments we conclude that solutions that do not change in 2 hours, also do not change in 12 hours. In this case study the goal was to place large vessels in the centre of the quay wall while smaller vessels should be positioned as much to the sides of the quay as possible. This made it relatively easy to manually check, in a qualitative way, the visual results whether solutions not proved optimal are good. We also have experimented with a short 5 minute timeout. While the solver does not find feasible solutions in this time for cases above 75% occupation, until 70% it usually does. We compared here the solution quality between a run with a timeout of 5 minutes and a timeout of 12 hours. We can compare these results because the experiments have the same seed guaranteeing us of the same optimisation setting. These results show that solutions found in 5 minutes are very close in quality to the ones that timeout after 12 hours.

Table 2. Continuation of Table 1. Runtime in seconds of the CP model for three terminals, and percentage of infeasible runs. Occupancies above 50%.

	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95
Terminal 1	924.52	1778.04	3461.22	4009.1	4158.97	5772.3	5487.1	8772.91	0
	0	0	0	0	0	20	20	60	100
Terminal 2	313.48	1699.62	2803.3	3378.02	3774.64	4822.1	5680.25	0	0
	0	0	0	0	0	20	40	100	100
Terminal 3	136.17	612.28	1146.91	1534.25	2058.14	2659.1	3669.27	0	0
	0	0	0	0	0	0	20	100	100

We have presented our results to the management team of the case study port. The management is well satisfied with the speed of our approach and the quality of the berth plans created.

5 Conclusion

In tidal ports, a crucial aspect of berth planning is to take into account the tidal windows. In order to develop a simulation model, berth planning requires an approach to generate vessel arrivals. This paper identifies that when historical data is not available or relevant, the typical approach to arrival generation – that of random generation from a distribution – disregards both tidal windows and cyclic vessel loops.

Our approach focuses on the generation of a cyclic baseline planning on which the vessel arrival times and the actual berth allocation are based. We incorporate realistic aspects of the problem: 1) the tidal windows of vessels, 2) the cyclic nature of certain container vessel arrivals, and 3) the minimisation of vessel draught during low water periods. We obtain the baseline plan using a constraint programming model. By adopting CP, we can formulate a compact and understandable declarative model, while decoupling the modelling from the solving. We employ our approach for a case study of a large tide-dependent river port in Europe. With increasing terminal occupancy we examine the effect of busyness on the runtime of the CP model using a state-of-the-art solver, and show that we can either obtain the optimal berth plan or a good approximation of it, within one hour for a large port.

As noted in the paper, our approach serves as a basis for the vessel arrival times and the actual berth allocation. When the simulation is run, most vessels will not arrive exactly according to this plan; further, the departure time is an expected time from which the simulation can deviate. Hence the times planned for each vessel act as the theoretical planned arrival time of that vessel. The actual arrival time in the simulation will be this theoretical time with a deviation that is based on a distribution. This distribution can be learned from historical data where one compares real arrivals with their theoretical planned counterparts.

Further, the baseline plan is generated based on expected handling times and expected travel times. In the actual simulation, it is also likely that there will be deviation from these expected values. This, plus the deviation from the planned arrival time, requires a disruption recovery module that manages the berth planning in real time. Hence our current work addresses the next step in the simulation: replanning the berth allocation when vessels arrive early or late, or their (un)loading takes longer or shorter than expected. We accommodate this uncertainty by formulating a modified CP model which repairs the plan while minimising perturbation. Our ongoing work is part of a simulation-based decision support tool for operational planning and for exploring port expansion options, in use at several major container terminals.

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References

- [1] van Asperen, E., Dekker, R., Polman, M., de Swaan Arons, H.: Modeling ship arrivals in ports. In: Proceedings of 2003 Winter Simulation Conf. (WSC'03), vol. 2, pp. 1737–1744 (2003)
- [2] Beldiceanu, N., Contejean, E.: Introducing global constraints in CHIP. *Mathematical and Computer Modelling* **20**(20), 97–123 (1994)
- [3] Benedicto, M.A.I., Morales, R.M.G., Marino, J., de los Santos, F.: A decision support tool for port planning based on monte carlo simulation. In: Proceedings of the 2018 Winter Simulation Conf. (WSC'18), pp. 2885–2896 (2018)
- [4] Bierwirth, C., Meisel, F.: A follow-up survey of berth allocation and quay crane scheduling problems in container terminals. *European Journal of Operational Research* **244**(3), 675–689 (2015)
- [5] Cimpeanu, R., Devine, M.T., O'Brien, C.: A simulation model for the management and expansion of extended port terminal operations. *Transportation Research Part E: Logistics and Transportation Review* **98**, 105–131 (2017)
- [6] Clausen, U., Kaffka, J.: Development of priority rules for handlings in inland port container terminals with simulation. *Journal of Simulation* **10**(2), 95–102 (2016)
- [7] Corry, P., Bierwirth, C.: The berth allocation problem with channel restrictions. *Transportation Science* **53**(3), 708–727 (2019)
- [8] Groenveld, R.: Harborsim, a generally applicable harbour simulation model. Tech. Rep. Internal report 1983-1, TU Delft, Section Hydraulic Engineering (1983)
- [9] Hassan, S.A.: Port activity simulation: An overview. *ACM SIGSIM Simulation Digest* **23**(2), 17–36 (1993)
- [10] Hendriks, M., Armbruster, D., Laumanns, M., Lefeber, E., Udding, J.: Strategic allocation of cyclically calling vessels for multi-terminal container operators. *Flexible Services and Manufacturing Journal* **24**(3), 248–273 (2012)

- [11] Hendriks, M., Lefeber, E., Udding, J.T.: Simultaneous berth allocation and yard planning at tactical level. *OR Spectrum* **35**(2), 441–456 (2013)
- [12] Huang, S.Y., Hsu, W.J., Fang, H., Song, T.: A marine traffic simulation system for hub ports. In: *Proceedings of 1st ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*, pp. 295–304 (2013)
- [13] Kizilay, D., Eliiyi, D.T., Hentenryck, P.V.: Constraint and mathematical programming models for integrated port container terminal operations. In: *Proceedings of 15th International Conf. on Integration of Constraint Programming, Artificial Intelligence, and Operations Research (CPAIOR'18)*, *Lecture Notes in Computer Science*, vol. 10848, pp. 344–360, Springer (2018)
- [14] Li, S., Negenborn, R.R., Lodewijks, G.: A distributed constraint optimization approach for vessel rotation planning. In: *Proceedings of 5th International Conf. on Computational Logistics (ICCL'14)*, *Lecture Notes in Computer Science*, vol. 8760, pp. 61–80, Springer (2014)
- [15] Ma, H.L., Chung, S.H., Chan, H.K., Cui, L.: An integrated model for berth and yard planning in container terminals with multi-continuous berth layout. *Annals of Operations Research* **273**(1-2), 409–431 (2019)
- [16] Nishi, T., Okura, T., Lalla-Ruiz, E., Voß, S.: A dynamic programming-based matheuristic for the dynamic berth allocation problem. *Annals of Operations Research* **286**(1), 391–410 (2020)
- [17] Pachakis, D., Kiremidjian, A.S.: Ship traffic modeling methodology for ports. *Journal of Waterway, Port, Coastal, and Ocean Engineering* **129**(5), 193–202 (2003)
- [18] Perron, L., Furnon, V.: *OR-Tools* (2019), URL <https://developers.google.com/optimization/>
- [19] Qin, T., Du, Y., Sha, M.: Evaluating the solution performance of IP and CP for berth allocation with time-varying water depth. *Transportation Research Part E: Logistics and Transportation Review* **87**, 167–185 (2016)
- [20] Schepler, X., Absi, N., Feillet, D., Sanlaville, E.: The stochastic discrete berth allocation problem. *EURO Journal on Transportation and Logistics* **8**(4), 363–396 (2019)
- [21] Thiers, G.F., Janssens, G.K.: A port simulation model as a permanent decision instrument. *Simulation* **71**(2), 117–125 (1998)
- [22] Wadhwa, L.C.: Planning operations of bulk loading terminals by simulation. *Journal of Waterway, Port, Coastal, and Ocean Engineering* **118**(3), 300–315 (1992)
- [23] Wallace, M.: *Building Decision Support Systems – using MiniZinc*. Springer, Cham, Switzerland (2020)
- [24] Wawrzyniak, J., Drozdowski, M., Sanlaville, E.: Selecting algorithms for large berth allocation problems. *European Journal of Operations Research* **283**(3), 844–862 (2020)
- [25] Yeo, G.T., Roe, M., Soak, S.M.: Evaluation of the marine traffic congestion of north harbor in Busan port. *Journal of Waterway, Port, Coastal, and Ocean engineering* **133**(2), 87–93 (2007)
- [26] Zhen, L., Chew, E.P., Lee, L.H.: An integrated model for berth template and yard template planning in transshipment hubs. *Transportation Science* **45**(4), 483–504 (2011)