Dynamic Multi-Facility Coordination through Rolling Horizon Timeslot Optimisation

Modelling Real-Time Decision-Making for Port Logistics Planning

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Preface

This thesis marks the final step in my journey toward obtaining my Master of Science degree in Transport, Infrastructure, and Logistics at Delft University of Technology.

It has been a long road, full of hard work, persistence, and a lot of learning. Looking back, I'm grateful I chose a path that wasn't always the most straightforward. Taking the road less travelled led to experiences that shaped me far beyond the lecture halls.

As someone who teaches mathematics, it made perfect sense that my thesis ended up being math heavy. Mathematics, being the mother of all sciences and the language of logic, has served as the foundation for this work. It has enabled me to conceptualise, formalise and solve a real-world problem within the complex and dynamic field of port logistics.

This study, in general, and this thesis in particular, have taught me to be patient with results but impatient with action. Results are followed by action, but no positive results should not discourage you from taking action further. It has also taught me the principle of "get it done first, get it right later". This principle applied to both my coding and writing. What has been immensely helpful for me, was to just get something down first, that I can tweak and build off of later.

I am extremely grateful for everyone that has supported me during my study. Alhamdullilah, all praise and thanks are due to Allah. The One who created, measured, and guided. I'm deeply thankful to my family, and especially my parents, for always being there for me. And of course, I want to thank my supervisors for their guidance and support throughout this thesis.

Now that I've closed this chapter, I'm looking ahead to what's next. For me, that's education and entrepreneurship—two areas where I've found my passion. I'm excited to carry everything I've learned into this next stage.

Thank you for reading.

Summary

Introduction: An estimated 90% of all goods are transported by sea, with containerization serving as the primary method of this transportation (Roy et al., 2020). According to UNCAD (2024), this trend of containerization is expected to continue, forecasting that the containerised trade volume is going to increase by 2.7% annually. This implies a significant 30% growth over the next decade, which will lead to a substantial expansion of logistical activities within and around the ports. For ports to remain globally competitive, port infrastructure must be sufficiently developed to facilitate the growth of containerization from the seaport into the hinterland.

Problem description: A key challenge in keeping port operations streamlined is the coordination between the container terminals and the truck operators for scheduling the container pick-up and delivery activities. This challenge can be seen from both perspectives. First, from the truck's perspective, the arrival time at the terminal is becoming increasingly unpredictable, due to delays caused by, for example, road congestion. And from the perspective of the terminal, yard congestion, waiting times, and other terminal-related disruptions are difficult to predict. Thus, good coordination between parties to reduce waiting times is highly relevant but challenging, as delays are often only known at the last minute. In fact, truck-terminal misalignment can cause ripple effects, impacting not only the profitability of the terminal and operations of the carrier but also the overall global competitiveness of the seaport. Besides operational inefficiencies that are caused by idling trucks at the gate, gate congestion is also a significant source of emission problems and air pollution at the port and can lead to dangerous traffic congestion that threatens safety around the port (Chen, Govindan, & Yang, 2013. Sharif et al., 2011). As road congestion is expected to only escalate over the coming years, this problem is becoming increasingly relevant. (Port of Rotterdam, 2024).

Literature review: The problem of truck-terminal misalignment has been addressed to some extent both in practice and in the literature. In practice, Truck Appointment Systems (TAS) have been deployed, in which truck operators book a timeslot to schedule the container pickup or delivery activity (Rijnmond, 2020). This system has proven to be inadequate, as it is incapable of rescheduling appointments for vehicles that miss their time slot due to unforeseen delays. In the literature, various studies have explored more advanced solutions. For example, Prakoso et al. (2022) used a predictive slot management approach, while Da Silva et al. (2023) applied decision trees based on historical data to forecast truck arrivals and determine whether rescheduling was necessary. Additionally, N. Huynh & Walton (2008) developed a simulation-optimisation model to determine the

optimal number of trucks a terminal operator should allow into the terminal within a specific time window.

Research gap: Although the problem of truck-terminal misalignment has been widely tackled in the literature under different terms, several key aspects remain underexplored. Most studies focus primarily on truck-terminal coordination through appointment scheduling but fail to consider the potential for rescheduling due to unforeseeable delays. Furthermore, these studies often follow a one-sided decision-making approach, assuming that a single terminal operator implements the coordination system, while in reality, trucks interact with multiple terminal facilities. Another generation of approaches is collaborative models, which encourage coordination between terminal and truck, for example, by sharing real-time data. Studies that have included this feature, such as Prakoso et al. (2022) and Skoulas (2024), were conducted in the context of petrochemical loading facilities, which differ from container terminals in terms of goods, infrastructure, and disruptions. Another limitation in the existing literature is the focus on operational costs, often overlooking other important objectives such as customer satisfaction and sustainability. These gaps suggest an interesting opportunity for further research by considering multi-terminal, multi-carrier interactions and proposing a solution that aligns the stakeholders that operate in port logistics environments.

Research objective & methodology: This thesis aims to address this critical gap by exploring the potential of integrating real-time data for truck-terminal coordination across multiple container terminals at seaports, while considering the diverse objectives of the involved agents. This is achieved through an in-depth literature review, system analysis, conceptual modelling, mathematical modelling, and performance evaluation. First, the literature review maps the current state-of-the-art and key research gaps. Then, a system analysis will help in understanding the truck-terminal coordination system, after which multiple ways are put forth for improving the system by allowing rescheduling through real-time data sharing. The proposed system innovation is then conceptualised as a conceptual model and formalised as an analytical model. Lastly, the model is evaluated based on the predefined KPIs.

System Analysis: The truck-terminal coordination system in the context of this study consists of a set of facilities (terminals and depots), a set of vehicles that belong to a particular carrier, and a set of activities (pick-up and drop-off) that need to be performed by a particular carrier. The system has time-related constraints (such as facility opening hours and maximum ride time constraints) as well as capacity-related constraints. Of these, the timeslot capacity constraint is the most significant one, which states that a solution is only feasible if, for all timeslots, the number of reservations at a particular facility does not exceed the capacity of that facility. The unique feature of this vehicle-terminal coordination system is that it is characterised by an interdependent set of consecutive activities assigned to a single vehicle, rather than a list of independent appointments between vehicles and terminals. Taking this feature into consideration during conceptualisation allowed for effective rescheduling in the model.

Model Formulation: The truck-terminal coordination system has been formalised by formulating two separate yet related models. The first model is the static scheduling model, which finds an optimal and feasible solution (satisfying all system constraints). The second model, which is the dynamic rescheduling model, then uses as input the real-time vehicle Estimated Times of Arrivals as well as the output of the first model: the initial planning consisting of a list of consecutive appointments per vehicle. Based on these two inputs, the model finds a new optimal planning based on a predefined objective. This re-optimisation is done consistently through a rolling horizon approach. This modelling approach is both collaborative and adaptive. Collaborative because it integrates collaborative efforts through real-time data sharing, and the model is adaptive, dynamically reoptimizing based on latest information gained, thus effectively dealing with the uncertainty of vehicle arrival times.

Model Application: The developed two-layered model framework was applied to investigate the effectiveness of integrating real-time ETA vehicle data into truck scheduling systems. The scenario analysis shows that real-time ETA updates and dynamic rescheduling can greatly reduce total waiting time at the port—up to 96% in some cases—though they increase the number of reschedules that take place. Allowing container reassignment as a technique for dealing with vehicle delays leads to the most efficient results. The scenario analysis has revealed that a clear trade-off exists between minimising waiting times and limiting reschedules, but enabling reassignment can balance both. Lastly, penalising delays fairly among the delayed vehicles does not hurt overall system performance. Besides a scenario analysis, a multi-objective analysis is conducted to study the nature of the identified trade-off. The Pareto Frontier has visualised the trade-off between operational flexibility—such as allowing rescheduling and vehicle reassignments—and overall system performance improvements. Both analysis have highlighted that achieving a system-wide optimum requires balancing the interests of both terminal operators, who prefer stable schedules, and road carriers, who prefer minimal waiting times. Assigning different weight to these objectives results in different system optimums, as the Pareto Frontier in Figure 1 highlights.

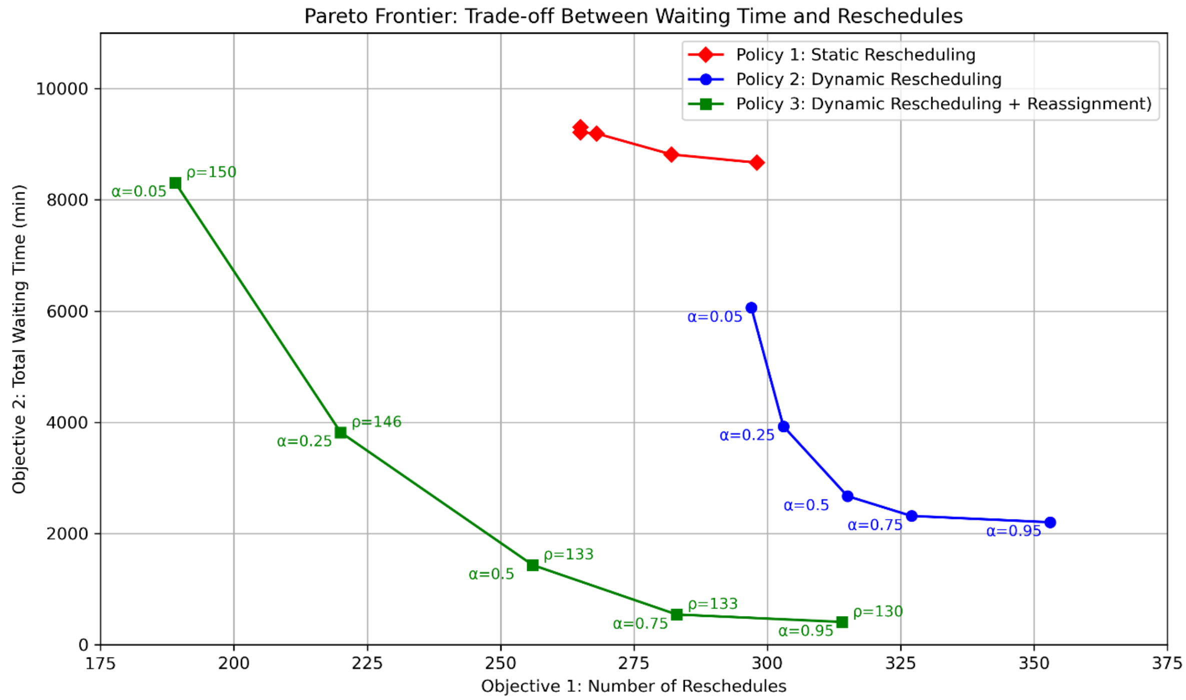

Figure 1. Pareto Frontier for the different coordination policies analysed, including the value of the stakeholder priority α and the number of reassignments ρ.

Conclusion: This study has demonstrated that integrating real-time ETA vehicle data into truck appointment systems combined with dynamic rescheduling mechanisms can dramatically improve coordination performance between trucks and terminals. The proposed two-layered approach—static for initial planning, dynamic for real-time replanning—offers a more realistic and responsive method for managing port logistics as compared to traditional static Truck Appointment Systems. However, for the further development of a Dynamic Port Logistics Planning Decision-Making Model, multiple aspects need to be defined, such as the diverse objective prioritization as well as the degree of management and control passed on to the algorithm. By means of further stakeholder collaboration, interests can be aligned to develop a tailored solution derived from the verified methodology of this study.

Report structure: First, an extensive literature review is conducted, exploring the truck-terminal coordination problem in more detail. Based on this review, a conceptual model for an innovative approach to model this system is proposed. Next, these conceptual models are translated into analytical models for modelling the problem. Finally, these models are evaluated based on predefined KPIs, followed by a discussion of the results and a conclusion of this thesis.

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1. Introduction

1.1. Background

Container transport to and from the port area involves complex coordination between carriers and terminal operators. To better streamline this coordination, many port systems utilise a Truck Appointment System (TAS), which relies on time slot reservations to manage truck arrivals based on the capacity of terminal facilities. The goal of this system is to improve coordination, which leads to reduced congestion, optimised terminal operations, and better overall logistics efficiency.

However, as more facilities implement these appointment systems, the coordination between vehicles and facilities becomes increasingly rigid. This increased rigidity is becoming an issue, as a previous solution aimed at effectively managing truck arrivals has created a problem of reduced flexibility, as the appointment system is not designed to respond to real-time disruptions in the transportation network. The inherent nature of this system, however, involves a high degree of uncertainty on both sides of the coordination. Terminal operators cannot predict future yard conditions or operational delays, while carriers face unpredictable traffic and other external factors that may lead to late arrivals.

A late arrival that causes a missed timeslot negatively impacts all parties involved, as it results in inefficiencies, rescheduling challenges, and financial penalties. Therefore, there is a growing need for a more adaptive and collaborative appointment system. Adaptive in that it is capable of accommodating unexpected delays and uncertainties, and cooperative in that it optimises from the perspective of both the carrier and the terminal operator.

1.2. Research Gap

In the vehicle-facility coordination system, vehicles typically conduct multiple trips. Each trip consists of a pick-up activity and a drop-off activity, in which the origin and destination of the trip can be either a terminal, warehouse or (empty) depot. An effective scheduling and rescheduling system takes into consideration the sequence of these activities. However, most existing research on Truck Appointment Systems (TAS) focuses on optimising individual appointments for a single activity (being either a pick-up or a drop-off), rather than considering the full schedule of a truck’s activities. This narrow focus results in models that fail to accurately reflect operational reality, where trucks often move between multiple terminals and must coordinate several appointments in sequence. As a consequence, current approaches overlook critical interdependencies between activities and fail to account for how delays or constraints at one facility impact subsequent tasks.

There is a clear gap in the literature for system-wide, multi-appointment scheduling models.

This study addresses that gap by proposing an integrated scheduling approach that considers the full schedule of a truck's operations for all trucks involved in the system. Only by considering the interdependent nature of the dynamics between a series of trucks and a series of facilities can a proper adaptive and collaborative truck appointment system be formulated.

1.3. Research Objective & Questions

The objective of this research is to explore the potential of incorporating real-time data for improving the coordination between vehicles and facilities across multiple seaport terminal facilities. This integrated approach is realised by applying dynamic planning, in which real-time data is leveraged to improve the truck-terminal coordination in real-time. This innovation is first conceptualised, then formulated as a mathematical model, and lastly evaluated based on the predefined KPIs and scenarios.

To achieve the research objective, the main research question is defined:

How can real-time data be effectively integrated into a dynamic planning model to improve coordination between trucks and terminal facilities across multiple seaport terminals, thereby enhancing system-wide port logistics performance?

To answer the main research question, multiple sub-questions are defined, which will be answered in the following chronological order:

1. What are the key characteristics and real-time data inputs that influence truck-terminal coordination in a multi-terminal seaport environment?
2. How can the truck-terminal coordination system be formulated into a dynamic planning model that allows for real-time rescheduling?
3. To what extent does the proposed dynamic planning model improve performance?

The first sub-question focuses on analysing the system and conceptualising the problem into a model. The second sub-question addresses the model development, which translates the conceptual model into a mathematical dynamic planning model. The third sub-question concerns the evaluation of the model, assessing its performance based on predefined KPIs.

1.4. Research Method

Several methods are used to answer the research questions and achieve the research objective, as defined in the previous sub-chapter. These methods include a literature review, a system analysis, a conceptual model, a mathematical model, and a scenario analysis. The literature review explores existing truck appointment systems, identifying their strengths and limitations. To better understand the nature of the truck-terminal coordination system, a system analysis is conducted. The insights from the literature review and system analysis will serve as input for the development of a new conceptual dynamic planning model. This conceptual model simplifies the truck-terminal coordination system, translating the real-world system into a concept that can then be computerised. This modelling will be done through mathematical optimisation. Lastly, a scenario analysis is conducted to test the model under various scenarios.

1.5. Research Process

This research is structured into three main phases, which are in accordance with the three research sub-research as defined in the chapter Research Objective & Questions. These three phases are: the Conceptualisation phase, the Model Development phase, and the Evaluation phase. As illustrated in Figure 2, each phase is further broken down into smaller research steps, which are then subdivided into specific tasks. The goal of this step-by-step systematic approach is to address the main research question of this study.

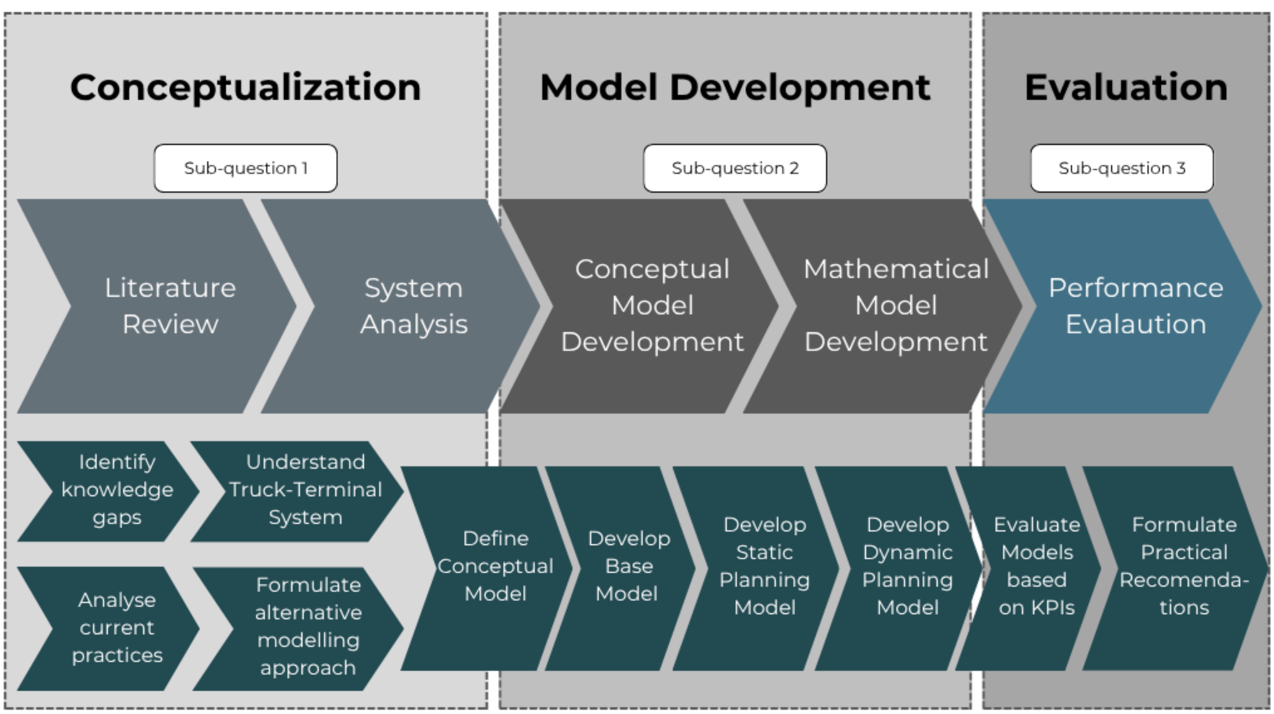

Figure 2. Research Process Breakdown

1.6. Research Impact

Improving truck-terminal coordination that results in better streamlined port logistics has a significant impact on the involved stakeholders. For the port authority, this improves global port competitiveness, which will boost the national economy. Port air quality is also improved with fewer idling trucks at the port. Carriers benefit from a higher service level, as the dynamic system accommodates last-minute delays caused by external factors. Furthermore, truck drivers experience shorter waiting times, reducing stress, improving job satisfaction, and enhancing traffic safety by avoiding rushed and tight time slots. Terminal operators benefit from reduced idle equipment time and less manual rescheduling, leading to higher utilisation, more handled containers, and increased profits without extra costs. Lastly, importers and exporters benefit from faster and more reliable transportation. Although the precise objectives of the involved parties may differ, improving the coordination between trucks and terminals is beneficial for all parties involved.

1.7. Research Scope

The scope of this research has been defined to focus on the key elements relevant to modelling truck-terminal coordination dynamically. Broader and unrelated aspects of the system are therefore excluded. The scope of this study is defined as follows:

1. **Traffic Conditions:** The research will not consider advanced traffic models that include variables such as traffic or weather conditions. Instead, the model will rely on Estimated Time of Arrival (ETA) of the trucks, as well as the uncertainty that is associated with these estimations.
2. **Scheduling optimisation**: The primary objective of this research is to optimise the scheduling component of the system, to reduce congestion and truck waiting times around the port. For that reason, detailed analyses of operational costs or cost breakdowns are excluded. The core focus of this study is the optimisation of the scheduling between vehicles and facilities.
3. **Geographical scope of the model:** This research is limited to the operational area of a single seaport. The model incorporates a set of terminal facilities within a larger single port. The model captures truck movements between facilities within the port as well as between terminals and the hinterland. However, broader external transport networks fall outside the scope of this study.

1.8. Report Structure

This report is organised in such a way that it follows the logical steps towards answering the main research questions.

Chapter 2 presents a literature review on truck appointment systems and real-time coordination. It discusses the different methodologies used in the field as well as the different generations of Truck Appointment Systems identified in the literature. Finally, the chapter is concluded with outlining the existing gaps in the field and describing the relevance of filling these gaps with this study.

Chapter 3 focuses on the problem analysis. This chapter introduces the key actors of the vehicle-facility coordination system, along with their objectives and roles. It also describes and illustrates the operational constraints and requirements of the system.

Chapter 4 builds upon the insights gained from Chapter 3 to develop an integrated conceptual model. This model incorporates the system dynamics as described in the previous chapter. The conceptual model acts as the bridge between the problem analysis and the development of the analytical model in the next chapter.

Chapter 5 translates the conceptual model into two formal models: the static scheduling model and the dynamic rescheduling model. This chapter extensively describes the model formulation, including the required inputs, decision variables and constraints of the model.

Chapter 6 will apply the developed model through an integrated simulation-optimisation approach. First, two simulation models are discussed, after which the model is applied by designing and using different scenarios, based on specific coordination policies and rescheduling objectives. The scenarios are evaluated based on certain KPIs such as total waiting time and the number of rescheduled appointments.

Chapter 8 concludes the thesis by summarising the key findings and offering recommendations for further research.

Figure 3 shows the structure of this report, which aligns with the research questions and methodology outlined in the previous chapters. Each chapter covers a specific part of the research process, with a logical flow from literature review and system analysis to model development and evaluation.

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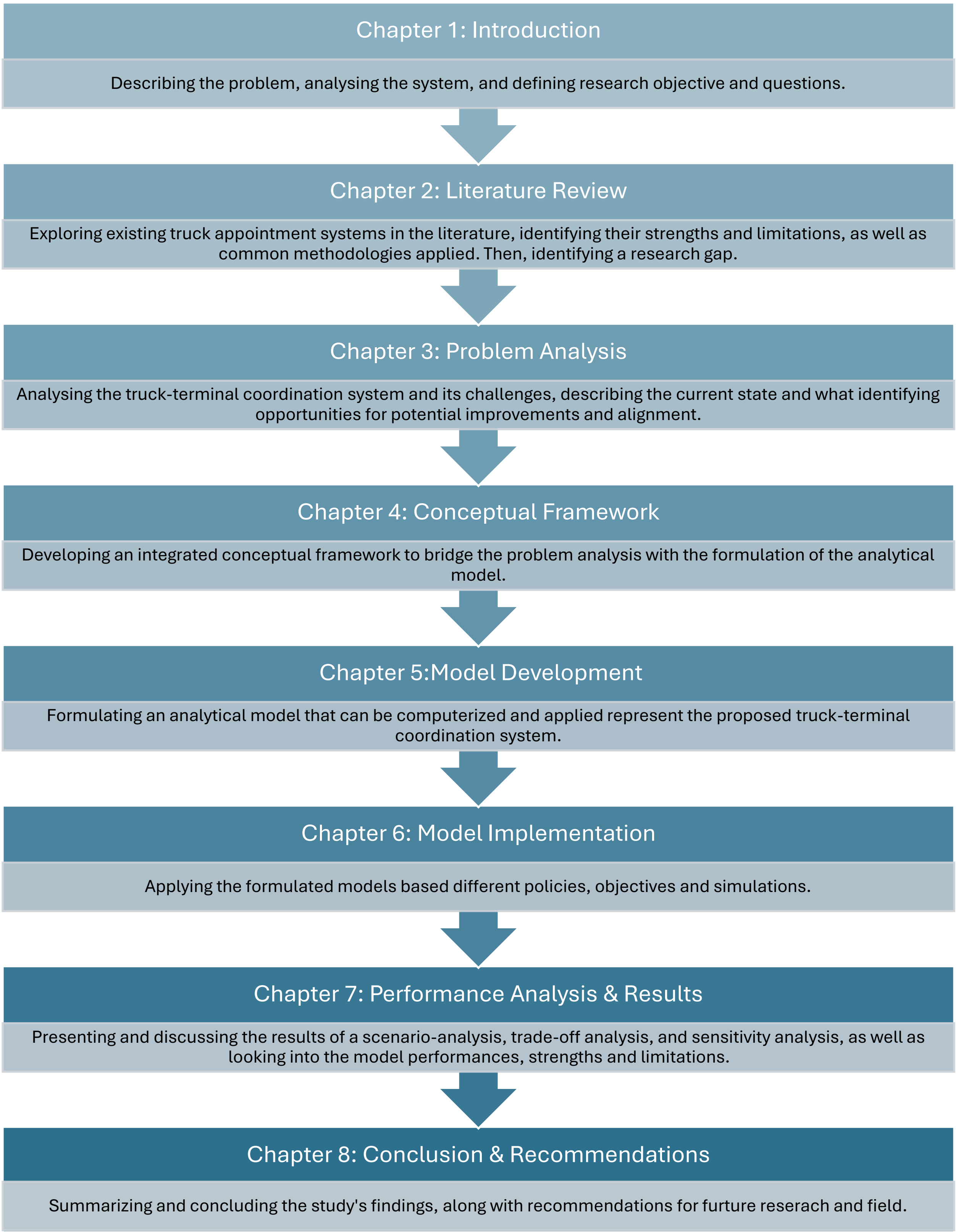

Figure 3. Report Structure Overview

2. Literature Review

For this thesis, a literature review is conducted by exploring and synthesising multiple relevant studies in the literature. The aim is to gain insight into the context of the problem and understand the complex system. The goal is to further understand the existing body of truck appointment systems and to address the strengths and limitations of the appointment systems. Based on these insights, a research gap will be identified that this research will address. This literature review is conducted based on the relevant keywords of this study, and by means of the snowball approach, i.e. by looking at the articles that a particular relevant article is referencing and is referenced by.

2.1. Application of truck appointment systems

The implementation of a truck appointment system for better truck-terminal alignment has been proposed by literature as one of the effective measures to reduce terminal gate congestion and truck turn time; the other measure being the expansion of terminal handling capacity (Chen, Govindan, & Yang, 2013; N. N. Huynh, 2005). The aim of a truck appointment system is to better manage truck arrivals, and to spread more evenly the truck arrivals at the terminal gates throughout the day, especially during peak hours (Azab et al., 2017; Chen, Govindan, & Yang, 2013; N. Huynh & Walton, 2008; Lange et al., 2022; Phan & Kim, 2015; Xu et al., 2022).

2.2. Objectives of truck appointment models

A large body of different truck appointment systems has been formulated in the literature, with each formulation having a specific objective, particular inputs included in the model, and using a certain methodological approach. Some studies aimed at reducing truck churn time, such as the study of Azab et al. (2017) and N. N. Huynh (2005), while Chen et al. (2013) aimed at reducing truck waiting time. Other more complex models, as developed by Guan (2009), aim to optimise the entire system by quantifying multiple costs. Some studies, although extremely limited, have included sustainability in the objective. For instance, Chen et al. (2013) aimed at minimising truck idling emissions, while the prediction-optimisation model of Hoxha et al., (2024) focused on reducing pollutant emissions to prevent critical thresholds that would require redistributing truck arrivals. Other studies accommodate for no-shows by introducing the concept of overbooking, which is a common strategy in the airline industry (N. Huynh & Walton, 2008).

An overarching recurring element of all truck appointment systems is that the result of the model is an optimised number of trucks which are expected to appear at the terminal in a given time window. Each model finds this optimum by incorporating different elements, such as uncertainty related to yard capacity, travel and loading times, no-show probabilities, and truck arrival patterns.

2.3. Classification of TAS models

Gracia et al. (2025) has, based on a systematic literature review, classified TAS models into four distinct generations. The first models were formulated using deterministic inputs. As these models neglected no-shows and late arrivals, they have proven to be unrealistic and impractical. The second generation of models was more collaborative by promoting coordination between terminals and trucking companies but still lacked the ability to respond to real-time changes in truck arrivals or terminal operations. The third generation can be characterised by its dynamic and stochastic approach, for example, by considering dynamic truck arrivals and stochastic travel times. The challenge with these dynamic and stochastic models, however, is the significant computational resources they require. The last generation of models leverages intelligent systems, AI, and advanced optimisation algorithms. The limitation of these models is that they heavily rely on high-quality and real-time data, and a substantial initial investment is required to build the necessary advanced technological infrastructure.

2.4. Commonly used methodologies

TAS models in literature leverage a range of methodologies, but the primary methods used are optimisation models, simulation models, specifically discrete event simulation, data analytics, AI-driven predictive models, and, to a lesser extent, queuing models. Queuing theory is applied to model terminal gate congestion (Guan, 2009). Optimisation models are used to minimise an objective such as waiting times or cost. Lastly, simulation models are used to evaluate system performance under real-world variability (Abdelmagid et al., 2022).

An example of a first-generation model is the framework developed by N. Huynh & Walton (2008). A simulation-optimisation model is formulated to determine the optimal number of trucks a terminal operator should allow into the terminal, given a specific time window. As this framework did not consider the impact of no-shows and is neither dynamic nor stochastic, it can be classified as a first-generation model.

In the literature, second-generation models are often labelled as a collaborative model or a negotiation framework. In these TAS models, the goal is to find the best possible solution for both the container terminals and the trucking companies (Lange et al., 2022), hence the name collaborative models. Azab et al. (2017) developed a collaborative model where the terminal operator receives the preferred arrival times of trucks, simulates the scenario based on this input, sends back adjusted appointments to the trucks, and then, by means of back and forth, arrives at a solution optimised for both actors. This negotiation framework assumes that there is only limited information shared among the actors, and therefore, decentralised decision-making is required to find a solution acceptable to both parties (Phan & Kim, 2015). This approach results in a solution that is acceptable rather than system optimal.

Examples of more recent, fourth-generation models are formulated by Prakoso et al. (2022) and Da Silva et al. (2023). The former has developed a real-time prediction model using an Artificial Neural Network (ANN). The latter created a flexible TAS, by means of a discrete event simulation, with the ability of dynamically rescheduling truck appointments, showing that the use of smart technologies significantly reduces truck waiting times. Xu et al. (2022) has also developed a model that can cope with the uncertain nature of the truck scheduling problem. This study modelled dynamic rescheduling as a scheme where truck drivers can confirm, 30 min before the appointment time, whether they will arrive on time.

Methodologies Comparison

Study	Optimisation Model	Simulation Model	Prediction Model	Input Data	System Disruption	Case study
Prakoso et al., 2022	MIQP	-	ANN	Real-time truck location	Traffic congestion	Petrochemical loading facility
Azab et al., 2017	MIP	DES	-		Terminal congestion	Container terminal
Da Silva et al., 2023	-	DES	DT	Historical terminal data	Terminal congestion	Port terminal
Skoulas, 2024	MILP	DES	-	Historical chemical plant data	Multiple uncertain parameters	Petrochemical loading facility

Table 1. Literature overview of different Dynamic Truck Appointment Systems. (DES: Discrete Event Simulation, DT: Decision Tree, ANN: Artificial Neural Network, MIQP: Mixed-Integer Quadratic Programming, MIP: Mixed Integer Programming, MILP: Mixed Integer Linear Programming).

Optimisation Models

An optimisation model is a mathematical model that optimises a certain predefined objective in a deterministic and static way. In the context of TAS, the mathematical model is often formulated as the scheduling model. The scheduling model decides the schedule for container pickups, considering the preferred timeslots of carriers, and by taking into account certain constraints of the system. The optimisation model then finds an optimal solution, based on a predefined objective function.

Simulation Models

Two main simulation methodologies are used in the context of TAS: Discrete Event Simulation (DES) and Agent Based Modelling. All studies found have used DES for the simulation of the system, as it is regarded by literature as a solid way of simulating this system. The simulation model can be built on top of the optimisation model. This allows testing the optimisation model for different scenarios and circumstances and see how the outcome of the optimisation model influences the other components of the system, such as terminal congestion.

Prediction Models

Prediction models use Machine Learning as an approach to classify and predict behaviours and outcomes, which is based on historical data. Prakoso et al. (2022) has developed an innovative real-time predictive slot management approach, by developing an Artificial Neural Network (ANN) to predict arrival times of trucks. This probabilistic prediction model is based on the real-time location of the truck, and historical data of the chemical facility. The model then assigns probabilities for trucks being on time, too early or too late. This probabilistic prediction model reduced the total rescheduling cost by 42%, compared to the baseline deterministic model, (Prakoso et al., 2022). Da Silva et al. (2023) used decision tree as a methodology for classifying truck arrival in a qualitative way. This algorithm used historical data and real time truck information to predict the truck arrival.

Dynamic-Collaborative Models

In literature, several Dynamic-Collaborative Truck Appointment Systems (DCTAS) have been developed, reflecting a growing interest in the coordination between terminals and trucking companies (Abdelmagid et al., 2022). These systems are typically modelled as decentralized or agent-based frameworks that facilitate real-time communication and data-sharing. For instance, Jin & Kim (2018) studied inter-terminal container transportation and found that collaboration among trucking companies can significantly reduce empty trips. Moreover, studies such as Azab et al. (2017) and Phan & Kim (2015) found that both stakeholders can benefit from the collaboration between terminals and carriers as truck arrival patterns can be smoothened and terminal workload reduced.

While much of the existing research focuses on decentralized coordination among carriers, to the author’s knowledge, no truck appointment systems in the literature integrate planning across multiple terminal facilities.

2.5. Limitations in literature

The above-mentioned studies, as well as a considerable number of other related studies, scope the TAS model to one terminal. This conclusion of the conducted literature review is also supported by findings of structured and more extensive literature reviews about TAS models. For example, Lange et al. (2022) also points out that the individual planning problems of container terminals are usually considered in isolation, while interdependencies are ignored. The assumption is that TAS models are implemented by a single terminal operator, without considering the loading and unloading activities of the truck. The problem with this scoping is that in reality, trucks perform a number of pick-up and drop-off activities in a single day, which often must be done in series. A vehicle might have to drop off a loaded container before picking up the next container, which might be located at a different location or terminal. These models, therefore, do not lead to an integrated system-wide optimal solution as they neglect the interdependence between appointments.

In short, existing TAS models are often rigid time-window-based systems, focused on optimising truck appointments for a single facility rather than optimising the entire truck activities schedule, i.e. a series of activities that need to be performed by a single truck. However, for the transferability of the results of a truck appointment system into practice, it is important to consider delays caused by traffic jams, as well as delays at upstream logistics nodes (Lange et al., 2022).

2.6. Knowledge Gap

The literature review has made evident that the majority of Truck Appointment Systems that are formulated in previous studies are only considering a single perspective from a two-sided problem. The vast majority of prior studies are centred around a single terminal that needs to coordinate with a set of vehicles. In reality, however, the set of vehicles is also coordinating not only with that single terminal but with a set of facilities.

By including this perspective of the problem in the model, a system-wide optimal solution can be found. Such an approach immensely increases the realism of the model as it more accurately reflects the interdependent nature of the vehicle-facility coordination system. It is for this reason that this study will take this holistic approach for the development of the model, allowing it to be adaptive and capable of a system-wide truck-terminal synchronisation, rather than single-sided truck-terminal coordination.

3. Problem Analysis

This chapter analyses the key components and interactions that shape truck-terminal coordination, including container activities, timeslot reservations, and system constraints. Understanding these complexities is essential before moving to a formal model, as they define the design requirements and solution space.

3.1. Current System Description

The current state of vehicle-facility coordination is characterized by a fragmented and inconsistent implementation of appointment systems across the transport chain. While some facilities have developed systems to better align truck arrivals with terminal capacity—most often through Truck Appointment Systems TAS) with a timeslot reservations mechanism—this innovation is not yet embraced by all parties. Deep sea container terminals are the most likely to implement such systems, whereas hinterland facilities, such as warehouses and empty depots, often rely on more manual coordination methods. Even among deep sea terminals, the way that Truck Appointment Systems are applied is not uniform. Some terminal parties enforce strict policies with financial penalties for missed timeslots, while others offer flexible windows with tolerance for early or late arrivals. In contrast, many facilities continue to operate using FIFO (First-In-First-Out) approaches or manual communication to coordinate vehicle arrivals. This variability in coordination mechanisms contributes to inefficiencies and misalignments across the chain, highlighting the need for a more integrated and standardized system-wide approach.

As discussed in Chapter 2, a major shortcoming of Truck Appointment Systems (TAS) is their rigidity, as these systems were not designed to adapt to changes or disruptions that occur in real time. The more facilities implement such a system, the more rigid and less adoptable the whole logistical network becomes. Truck Appointment Systems are therefore incapable of scaling across the entire chain. They were originally implemented to better control truck arrival patterns and can therefore not be treated as non-negotiable appointment systems. The other shortcoming covered in Chapter 2, is that most commonly terminal operators own and run the Truck Appointment Systems, while it is expected from the trucks to book a timeslot in their designed system. In reality, however, coordination does not take place between a single facility and a single vehicle, but rather it takes place between a network of facilities and a network of vehicles. Therefore, Truck Appointment Systems are fit to function as a static communication tool to indicate timeslot availability, but will cause problems once it is regarded as a binding agreement between parties. To enable dynamic synchronization and achieve system-wide efficiency, new innovations are required that support real-time coordination among multiple stakeholders.

3.2. Coordination Dynamics

The interaction between carriers, shippers, and facilities is a core attribute of the vehicle-facility coordination system. The coordination process is triggered when a shipper submits a transport request to a carrier to move a container between facilities. Carriers provide the transportation of containers between facilities as a service to shippers. Once a carrier accepts this request, it can begin with the operational planning. The carrier must coordinate with the origin and destination facilities, after which a vehicle is dispatched, which may or may not be owned by the carrier, to perform the transportation.

The presence of information asymmetry between carriers and facilities is another core attribute of the vehicle-facility coordination system. Each carrier, that belongs to a set of carriers, is coordinating with a network of facilities simultaneously. Similarly, each facility, that belongs to a set of facilities, is coordinating with a network of carriers simultaneously. In this many-to-many relationship, both parties have no visibility in the other's internal planning. The coordination that takes place therefore involves manual planning, leading to a solution that is at most acceptable for each involved actor. Therefore, the system operates below its potential, and achieving anything close to system-wide optimised schedules is impossible to achieve.

Effective data-sharing solutions, such as collaborative platforms that exchange information between facilities and carriers (a fleet of vehicles), can have huge improvements for the optimality of the system. Figure 4 illustrates these two contrasting coordination mechanisms. When parties move beyond their siloed, single-sided optimisation approach and embrace data-enabled collaborative platforms, significantly better solutions can be achieved.

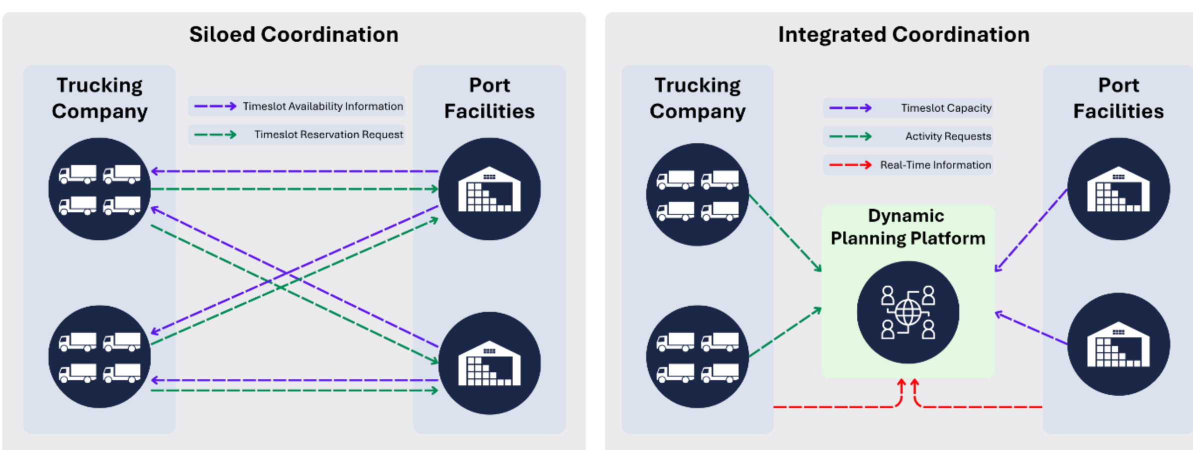

Figure 4. Comparison of Siloed Coordination without information exchange (left) and Integrated Coordination via an Information Exchange Platform (right).

3.3. System Constraints

The vehicle-facility coordination system is characterized by a variety of constraints, which must be satisfied to make a solution feasible. The set of all feasible solutions is then called the solution set of this system. These constraints can be grouped into three main categories, namely the vehicle-container compatibility constraint, the timeslot capacity constraint, and the operational availability constraints. The latter category consists of a set of time-related limitations, namely vehicle working hours, container availability windows and facility operating hours.

The vehicle-container compatibility constraint is a fundamental constraint of the system that states that a specific transportation can only be carried out by a vehicle that belongs to the same carrier who received the request. Thus, the transportation of a container between the two involved facilities can only be assigned to one of the vehicles that belongs to the carrier that is receiving the request for this transportation. This is because carriers profit from executing the transport using their own fleet.

The vehicle-container compatibility constraint may be extended to a vehicle-container matching constraint when additional limitations apply. This is the case when containers that have been assigned to a specific vehicle of the carrier become cannot be changed at a later stage. The reason for this may be due to legislative, operational, or technical constraints, which prohibit the transportation activity to a re-assigned to different vehicle—even if the alternative vehicle belongs to the same carrier. In such cases, once the assignment is communicated with the facilities involved in the transportation, and then confirmed as an appointment, the reassignment of the container to a new vehicle is not allowed anymore—the assignment of vehicles to containers is hence a binding decision.

The second key constraint within the vehicle-facility coordination system, is the timeslot capacity constraint, which determines the number of vehicles that a specific facility can handle within a given timeslot. This constraint is predominantly imposed by the facilities involved in the transportation, as facilities cope with resource availability and operational constraints. It is arguably the most influential constraint in the entire coordination system, as the existence of this limitation caused the necessity to coordinate the entire vehicle-facility interaction in the first place—to reduce truck turnaround times and prevent terminal gate congestion. Academic literature has shown that these two metrices can only be improved either by expanding the handling capacity of the terminal (and thereby increasing the timeslot capacity), or by better coordinating between truck arrivals and terminal operations to make the most of the capacity that is already available.

The final category of constraints consists of operational availability constraints, which consists of three time-related limitations within the coordination system. First, vehicle drivers are not allowed to be on the road for longer than the maximum allowable working hours. Second, container transportations can only begin after the container becomes available for pick-up at the facility, and hence an earliest allowed pick-up time. Containers also have a latest pick-up time, determined by either the shipper or the facilities. Shippers want the container to arrive before a predefined agreed moment, while facilities apply a penalty fee for containers held for longer than the maximum storage duration, as terminals want idle containers to be picked up within a timeframe to make space for new containers. Hence, containers should be picked up after they have been dispatched, but before either a specified time that is agreed with the shipper or otherwise before the facility charges additional storage fees.

The last key constraint of the system is the facility operating hours. Some facilities have fixed opening hours, meaning that any activity that is scheduled outside these windows is not feasible. These time-related constraints may shrink the solution space significantly.

3.4. System Description

To better understand the complexity of the system, a description is given for the types of facilities, the categories of transportation activities, and the three dynamical scheduling mechanisms—reassignment, rescheduling and reshuffling.

In the context of vehicle-facility coordination system at seaports, facilities can broadly be categorized into port-based facilities and hinterland-based facilities. Port-based facilities include deep-sea terminals, empty container depots, and other terminal infrastructure located within a specific perimeter from the port area. In contrast, hinterland-based facilities refer to facilities outside the port area perimeter, which may include dry ports, warehouses, and inland terminals further away from the main port infrastructure. It is currently common to apply truck appointment systems only to port-based facilities, as the problems that it aims to solve are less typical for hinterland-based facilities.

Transportation activities can be categorised into three types: pick-up, drop-off, and inter-terminal transfer. Pick-up activities originate at the port area and are transported to the hinterland, while drop-offs originate at the hinterland and are transported to the port area. The former are include goods that are imported or empty containers ready to be re-utilised, while the latter may include goods that are exported or empty containers transported to an empty depot. The third transportation type, inter-terminal transfers, are transportations between two facilities within the port area. Although each transportation activity must necessarily consist of one loading and one unloading activity, an integrated truck appointment system may or may not include the coordination of activities at hinterland-based facilities, as these are less relevant compared to the congested port-based facilities.

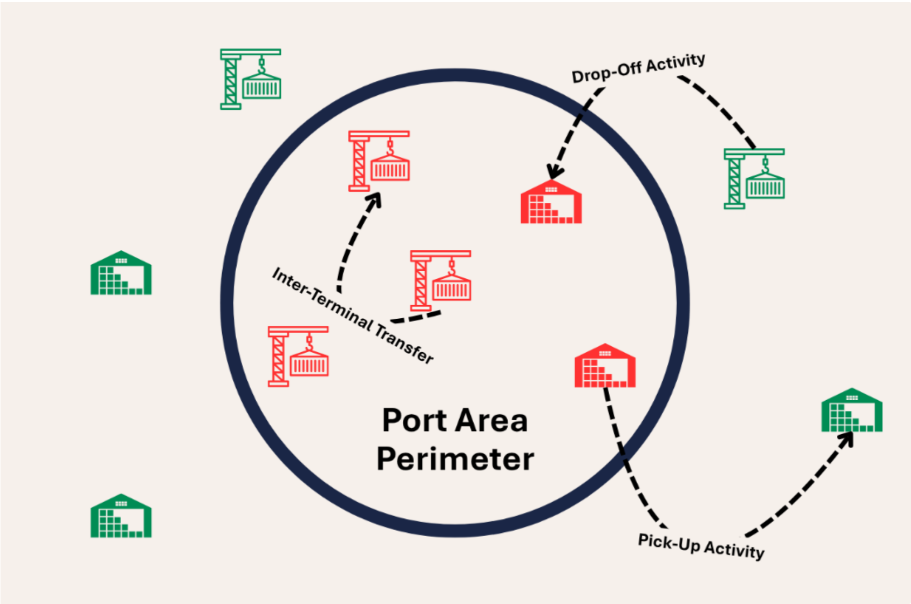

Figure 5. Port Area Perimeter with port-based facilities (red) and hinterland-based facilities (green), illustrating the three categories of container transportation activities: pick-up, drop-off, and (inter-terminal) transfer.

Dynamic scheduling can be achieved by means of three mechanisms: reassignment, rescheduling or reshuffling. Reassignment implies that a new vehicle is assigned to the container, rescheduling means that the same vehicle will handle the container but at a different time, and reshuffling means that the activities on the schedule of a particular vehicle is re-ordered. While activities may or may not be switchable between vehicles—due to the possible vehicle-container matching constraint—the re-scheduling and reshuffling of activities is by definition allowed in an integrated vehicle-facility coordination system. If vehicles are expected to arrive at a facility outside the reserved window of the timeslot— either due to arriving too early or too late—an integrated coordination system might opt for re-scheduling as it aims to achieve a system-wide optimisation within the system constraints. Reshuffling might also be possible, in which case the order in which the vehicle performs the assigned activities changes. By definition, reshuffling implies rescheduling as well. Note that reshuffling can only take place if at the moment of re-optimisation the vehicle is unloaded, as a loaded vehicle must first complete the current transportation. Thus, an integrated vehicle-facility coordination system can dynamically optimise by mechanisms of reassignment, rescheduling or reshuffling.

3.5. System Trade-offs

Although the parties involved in the vehicle-facility coordination system—specifically the carriers and the terminal operators—aim for optimal solution, there are at least three ways in which inefficiency are willingly or unwillingly added into the system: timeslot overbookings, vehicle overutilization, and truck waiting times.

Timeslot overbookings are regulated by the facilities, which might allow more vehicles to book a specific timeslot than it is actually capable of handling, as it already expects that some vehicles will arrive outside the time window belonging to its appointment. The degree of incorporated overbookings may vary between timeslots. However, the effectiveness of overbooking practices is uncertain, and determining the optimal level of overbookings for each timeslot requires empirical analysis based on case-specific data.

Carriers add slack to the coordination system by utilizing more vehicles than the minimum required. Carriers add this strategic buffer because they already foresee delays in the initial schedule, and too highly optimised initial schedules means less resilient on-the-fly reschedules. Carriers must deploy sufficient vehicles to mitigate unforeseeable circumstances, that may have a more fatal consequence—such as not keeping promises made to shippers—than incorporating a safety factor for the amount of trucks utilised. At the same time, however, carriers cope with a limited fleet size availability, which enforces them to coordinate efficiently and utilize vehicles strategically.

Another way slack may be added to the system is through the inclusion of truck waiting times. This makes subsequent activities not too tightly planned after one another. That way, carriers create buffers for vehicles wherever possible in the schedule. Adding waiting times to the schedule essentially means that vehicles arrive earlier than the allowed start time of the reserved timeslot, rather than scheduling vehicles to be arriving exactly on time. This reduces the risk of missing a timeslot, which impacts not only the current reservation but has a cascading effect on all subsequent scheduled appointments. While at first glance this approach may appear as an inefficiency, it is a strategic way to mitigate the risks of uncertainty at a later stage in the planning process.

Although in manual planning, these buffers are incorporated based on experience and gut feeling, an integrated system can keep track of and ultimately optimise the values of these buffers that lead to an optimised trade-off between optimality and resilience. Hence, overbookings, vehicle overutilization and vehicle waiting times can be considered strategic buffers that reduce optimality but increase resilience as they are able to absorb future disruptions in the system.

4. Conceptual Framework

This chapter aims to conceptualise the vehicle-facility coordination system, as described in chapter 3, into an elaborated conceptual coordination framework. This conceptual model will translate the complex real-world problem into a structured and manageable representation that is suitable for analytical and computational development. This conceptual framework, therefore, acts as a foundation for the development of the static scheduling and dynamic rescheduling model that will be developed in chapter 5.

The conceptual framework is a simplified representation of the complex vehicle-facility coordination system and is defined by three key characteristics: it is multi-layered, interdependent, and iterative. The first attribute of the conceptual framework is that it is multi-layered, as the coordination process consists of a sequence of decisions made consecutively. This complexity is managed by decomposing the entire decision-making process into five distinct layers, each having distinct characteristics and constraints. These five layers are: vehicle assignment decision, vehicle routing decision, vehicle scheduling calculation, facility timeslot reservation, and waiting time calculation.

The second attribute is interdependence: decisions made at one layer affect the feasible solution set of the subsequent layers. For example, containers must be assigned to vehicles before vehicle routes can be determined. Only after that can vehicle schedules be. Once routes and schedules are finalised, reservations at facilities can be made, and waiting times can be calculated. This interdependence means that system-wide optimisation cannot be achieved by considering layers in isolation. Instead, it requires algorithms that iteratively optimise through feedback loops, where feedback from later decisions informs earlier decisions, ultimately converging to a system-wide optimal and layer-specific feasible solution.

The third attribute of the framework, iteration, reflects the dynamic and uncertain environment of the vehicle-facility coordination system. Conditions are constantly changing, and this requires previously made decisions to be adjusted on the fly. These dynamically changing conditions necessitate an ongoing cycle of replanning throughout the time horizon of the vehicle-facility coordination process.

In sub-chapter 4.1, the five layers of the framework are discussed in detail, highlighting how the above-mentioned characteristics are integrated into the conceptual coordination framework, and explores the iterative process and represents a visualisation of conceptual coordination framework. Next, sub-chapter 4.2 provides an illustrative example of the mechanisms of the conceptual coordination framework.

4.1. Conceptual Framework Development

This sub-chapter will discuss the five layers of the coordination framework, how these layers are interdependent, as well as how the conceptual framework as a whole is iterative. As chapter 3 has highlighted that the vehicle-facility coordination process consists of a sequence of decisions, each with distinct characteristics and constraints. This complexity is managed by conceptually decomposing the system into five layers. Understanding what these layers encompass as well as their inputs and constraints is essential for accurately conceptualizing the complexity of the system.

The three attributes of the conceptual framework—multi-layered, interdependent, and iterative—are illustrated in a simplified conceptual model in Figure 6. In this visualisation, the blue boxes represent the five layers of the decision-making process, each addressing a specific subproblem within the coordination system. The red arrows illustrate the interdependencies between layers, emphasising that there is a continuous feedback mechanism between all layers. The green arrow models the iterative nature of the system, indicating that the entire model must respond to changing conditions over time. These three attributes together capture how the model handles complexity.

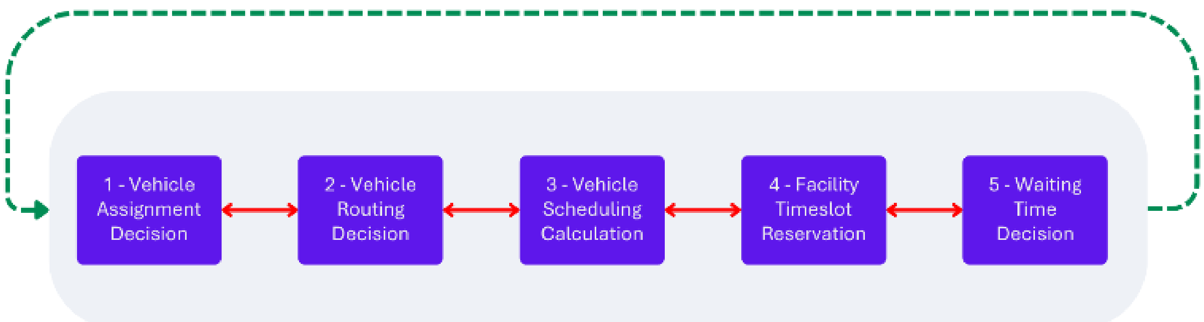

Figure 6. Simplified conceptual model of the vehicle-facility coordination system.

The behaviour of the conceptual model can be understood by examining its three defining attributes. The multi-layered structure ensures that the constraints of each subproblem are satisfied independently, resulting in a set of feasible yet siloed solutions. The interdependence between layers makes the model capable of finding solutions that are holistically feasible, after which an optimal system-wide solution can be selected. Lastly, iteration accounts for the dynamic nature of the coordination environment. As conditions evolve, a previously optimal (and thus by definition feasible) solution may become suboptimal. Iteration makes the model capable of responding to real-time changes across the time horizon. Together, these elements ensure that the model not only generates feasible and optimal solutions but also maintains optimality in a time-sensitive and uncertain environment.

Table 2 provides an overview of the five layers, including a description of its function, the required inputs, the desired outcome, and the feasibility constraints per layer. Building on this, the simplified conceptual model in Figure 6 is extended into a comprehensive conceptual coordination framework in Figure 7. This figure brings together the three key attributes of the framework—multi-layered structure, interdependence, and iteration—into a detailed yet helicopter-viewed representation of the coordination system, forming a bridge to the computerised coordination model in chapter 5.

Layer	Description	Inputs	Outcome	Constraints
1. Vehicle Assignment Decision	Determine which vehicles should handle which containers.	Vehicles & transportation requests: a list of the containers per carrier that need to be transported.	Set of utilised vehicles per carier	Vehicle-container compatibility constraint
2. Vehicle Routing Decision	Determine what route each vehicle should take, by selecting a feasible route for each vehicle to follow to complete all the assigned transportation activities.	Network topology parameters: geospatial data of all facilities and nodes in the network.	Set of activated arcs per vehicle	Deadheading constraint
3. Vehicle Scheduling Calculation	Determine a feasible operational schedule for each vehicle based on the selected route of that vehicle.	Time-related parameters: travel time and handling time.	Operational schedule per vehicle	Time-related operational constraints
4. Facility Timeslot Reservation	Determine the time slots that need to be reserved per vehicle per facility.	Timeslot parameters: timeslot duration, begin-time and end-time per timeslot, arrival allowance.	Timeslot reservations for all activities	Timeslot capacity constraint
5. Waiting Time Calculation	Determine the added waiting time per vehicle per activity	-	Confirmed schedule per vehicle	Waiting time constraints

Table 2. A comprehensive overview of the five layers of the Conceptual Coordination Framework.

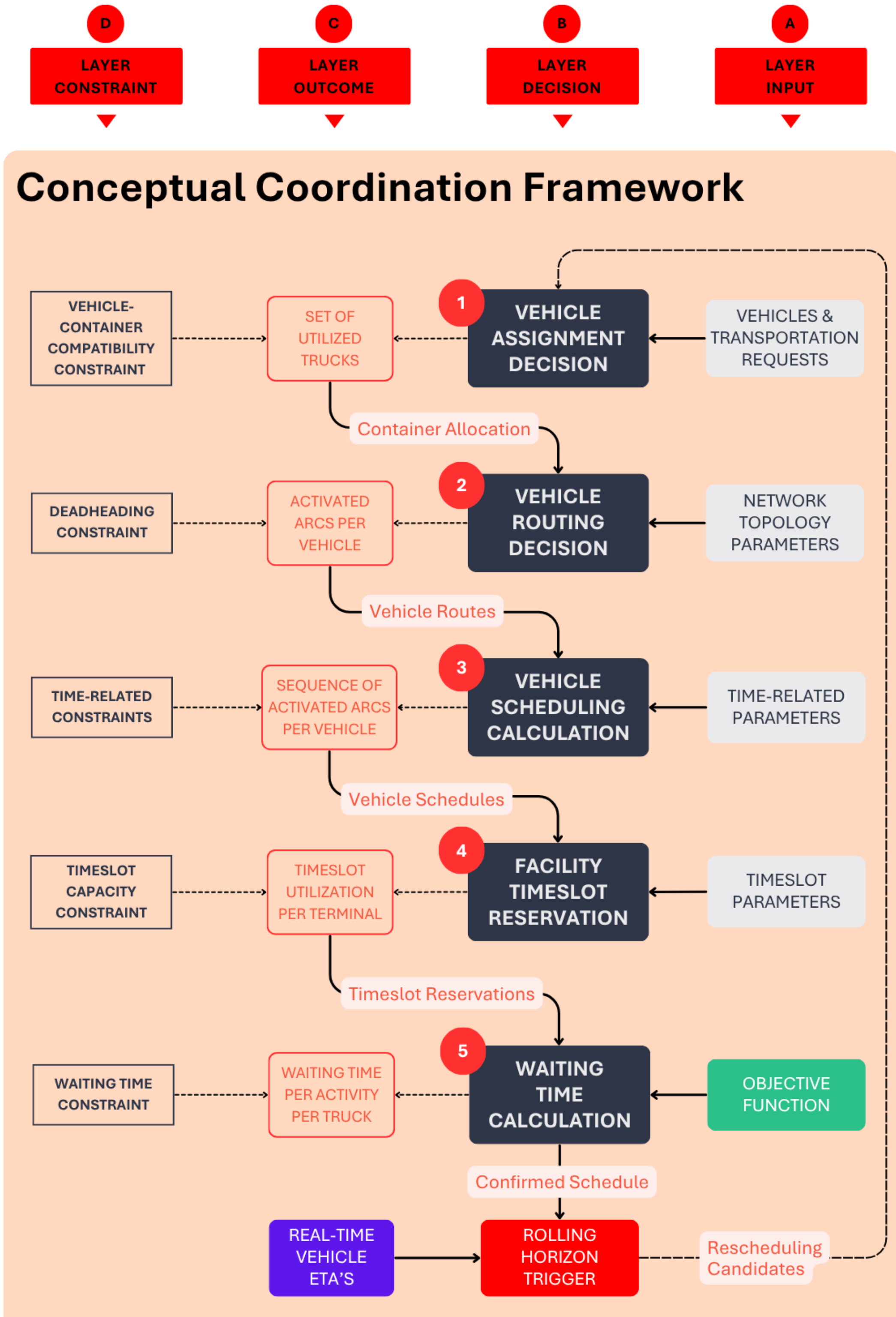

Figure 7. Conceptual Coordination Framework illustrating the multi-layered, interdependent, and iterative nature of the vehicle-facility coordination problem.

4.2. Conceptual Framework Illustration

This subchapter will go through an illustrative example to demonstrate the behaviour and mechanisms of the conceptual coordination framework. This illustration goes through each of the five layers of the framework, and is done based on hypothetical datasets as well as visual representations.

4.2.1. Vehicle Assignment Decision

As discussed in chapter Problem Analysis. The first decisive constraint of the vehicle-facility coordination system is the vehicle-container compatibility constraint. The first layer of the model takes as input all the container transportation requests per carrier as well as a list of all vehicles belonging to each carrier. Then, the vehicle assignment decision determines which container transportations are assigned to which vehicles. Hence, the two datasets that are defined for this decision are:

- C: set of containers, with compatibility attributes such as corresponding carrier.
- V: set of vehicles, with compatibility attributes such as corresponding carrier.

A container can only be assigned to a vehicle if both the vehicle and the transport activity belong to the same carrier. Furthermore, the assignment of a container to a vehicle must respect other vehicle-container compatibility constraints, such as hazardous material restrictions, refrigeration needs, or container and vehicle sizes. The objective of this decision is to comply with operational, organisational, and regulatory constraints. Figure 8 visualises this compatibility constraint, illustrating that each container must be handled by a vehicle with an identical colour due to the restrictions imposed by the system.

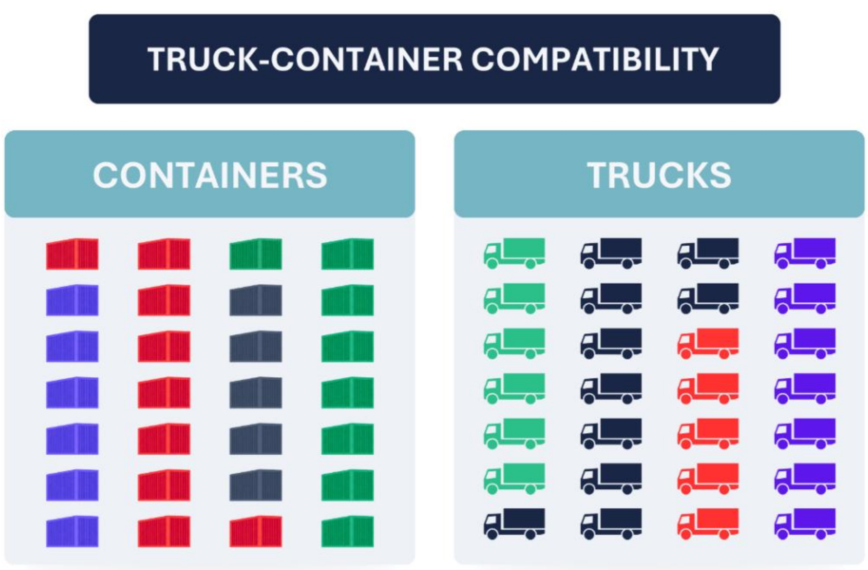

Figure 8. Vehicle-Container Compatibility Visualization

4.2.2. Vehicle Routing Decision

The second layer of the model determines the specific routes that each utilised vehicle can follow to handle the assigned containers of the previous layer. This layer activates the arcs in the transportation network, which are necessitated by both the outcome of the previous layer and this layer's constraints: deadheading and flow conservation.

The deadheading constraint implies that arcs in the network may only be activated if utility is added, such as performing a current activity or travelling to the next activity. Redundant detours are explicitly disallowed as they do not reflect realistic driver behaviour, as drivers follow direct routes without intentional delays or deviations. This constraint can be modelled by not allowing two consecutive empty rides. The flow conservation constraint states that each utilised vehicle must arrive and depart from each activated node in the network, with the exception of the start and end nodes of the route.

Figure 9 is a continuation of Figure 8, illustrating an example of the routes that each utilised vehicle can follow to transport all assigned containers. In this example, four trucks are utilised to handle all container movements, while two vehicles from the fleet remain idle. Unnecessary detours are excluded from the solution, and flow conservation is respected.

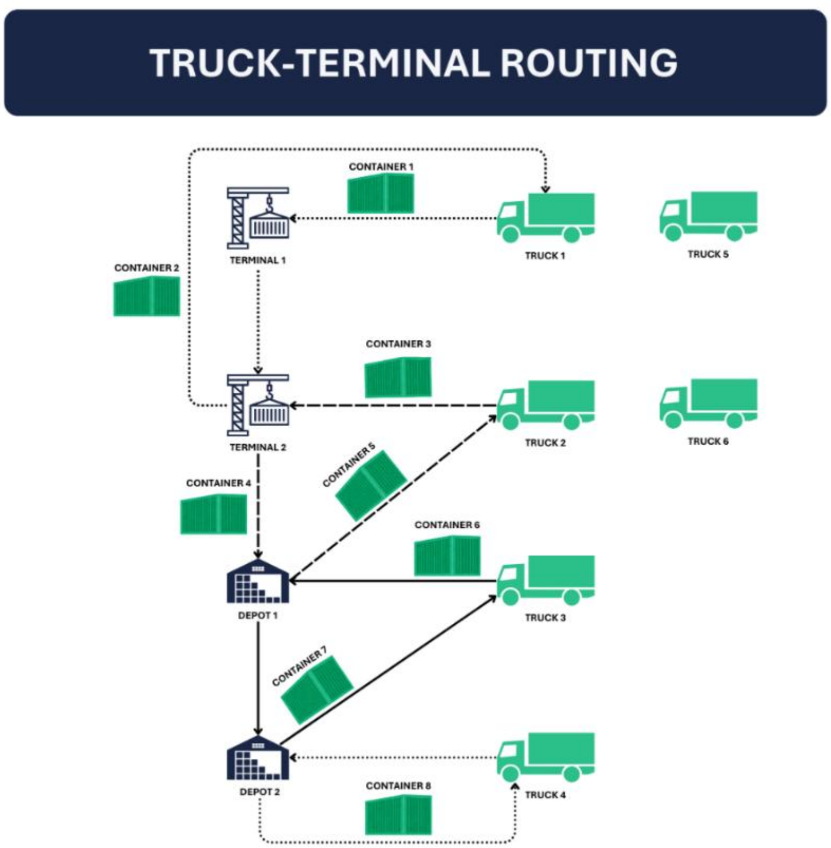

Figure 9. Vehicle-Facility Routing Visualization

4.2.3. Vehicle Scheduling Calculation

Based on the previously determined vehicle routes, the vehicle schedules can be calculated. This calculation is done based on the departure time of the vehicle from its origin node, as well as the travel times and service times in the route. As has been elaborated in chapter 3.3, vehicle schedules need to adhere to multiple time-related limitations: vehicle working hours, container availability windows, and facility operating hours. First, drivers are not allowed to drive for longer than the maximum allowable ride time, and may have an availability time window. Secondly, containers must be picked up and dropped off before a certain time. Lastly, facilities may have opening hours that need to be taken into consideration in the scheduling of the activities.

By taking into consideration all these constraints, there may or may not be a feasible schedule that adheres to the vehicle routes as determined in previously. If there is no feasible solution that can complete the transportation route while satisfying all the time-related constraints, a new route must be found. This new route may or may not adhere to the outcome of the first layer of the model, as it is possible that containers are assigned differently to the vehicles to find a solution that is feasible for the subsequent layers of the framework. This feedback loop captures the interdependent nature of the system.

Figure 10 illustrates that each arc is characterised by two arrival times: the arrival time at the origin and the arrival time at the destination. Furthermore, the calculated schedule must satisfy all time-related constraints to be feasible.

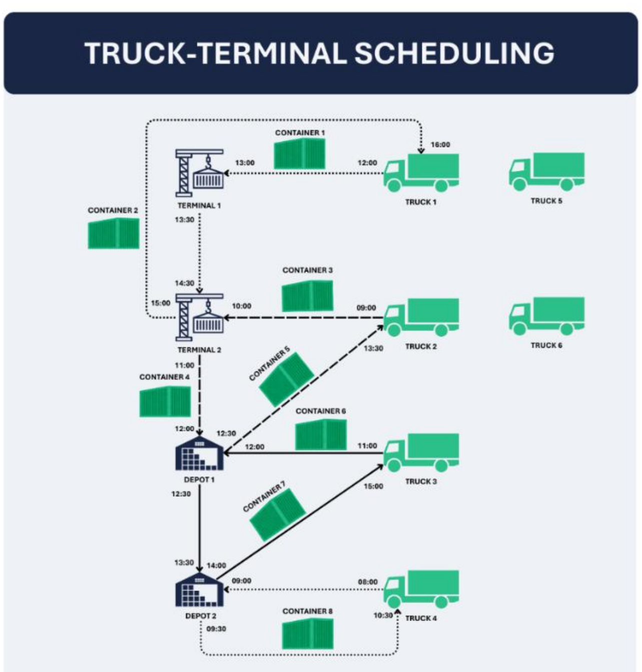

Figure 10. Vehicle Scheduling Visualization

4.2.4. Facility Timeslot Reservation

The forth layer of the framework reserves timeslots based on the calculated vehicle arrival times. However, the system copes with a limited timeslot availability per facility. If the current schedule as determined in the previous step results in exceeding the timeslot reservation constraint, a new vehicle schedule must be found.

Figure 11 shows an example of the timeslot occupancy level per timeslot per facility. The timeslot capacity may differ between facilities. In this illustrative example, the timeslot constraints of terminal 1 and depot 2 are unmet, making the current vehicle schedule infeasible. The interdependent and multi-layered framework will go back to the previous layers to come up with an alternative solution that satisfies all constraints.

FACILITY TIMESLOT RESERVATION

TIMESLOT	TERMINAL 1	TERMINAL 2	DEPOT 1	DEPOT 2
1	4	1	2	1
2	3	1	2	3
3	1	2	3	1
...	2	3	2	4
|T|	1	1	1	4

Figure 11. Facility Timeslot Reservation Illustration

4.2.5. Waiting Time Calculation

The last layer of the modelled coordination framework determines the amount of slack that is added to the schedule of each vehicle. In the model, this is captured as potential waiting time at the origin or destination of each activated arc. Waiting, however, is only to occur prior to a scheduled activity—either a pick-up or a drop-off—meaning that no waiting time is allowed on empty rides. Additionally, the total waiting time per vehicle must not surpass the total waiting time threshold.

If these constraints are satisfied, a feasible solution to the current state of the system is found. After the solution space of all feasible solutions is found, system-wide optimisation can be achieved. At a later moment, when conditions change, this entire process is repeated to ensure optimality across the time horizon.

5. Model Development

In this chapter, the analytical framework of this study is introduced, which is based on and translated from the conceptual framework as has been developed in chapter 4.1 and illustrated in chapter 4.2. The analytical framework consists of two analytical models: a static scheduling model and a dynamic rescheduling model. The static scheduling model gives the initial planning for a predefined planning horizon, while the dynamic model iterates during this planning horizon to re-optimise the initial scheduling based on disruptions that have occurred in the meantime and the rescheduling constraints that have been set. While the two analytical models are similar in their formulation and logic, the exact structure, required inputs, desired outputs, and constraints differ significantly.

Chapter 5.1. discusses the Static Scheduling Model and chapter 5.2. will cover the Dynamic Rescheduling Model. Both chapters will describe the dynamics and intricacies of the model, including its logical structure, objective, and constraints. It also outlines the data requirements for the proposed models, including parameters such as travel times, service times, time windows, and terminal handling capacities. For the static model, Table 3, Table 5, and Table 6 show the model parameters, inputs and formulation of the static scheduling model respectively. For the dynamic model, Table 8 shows the additional parameters and indices, which are used on top of the parameters in Table 3. While Table 9 shows the complete decision variables and formulation of the model, respectively.

Chapter 5.2. explains how the rolling horizon approach has been built on top of the static scheduling model. This model can adapt based on disruptive events, balancing optimality with flexibility.

5.1. Static Scheduling Model

5.1.1. Static Model Inputs

This section discusses the data requirements of the model. Table 3 provides an overview of the indices, sets and parameters used for the Static Scheduling Model. This model requires four primary data components: nodes, vehicles, containers, and timeslots. Each of these data components is further described below the summarised overview in Table 3.

Table 3. Static Scheduling Model: Indices, Sets & Parameters.

Indices	
i, j, f	Node index
v	Vehicle index
c	Container index
t	Timeslot index
Sets	
N	Locations; $N = P \cup \mathrm{L} \cup \mathrm{D}$
P	Port; $P \subset N, P = \{0, \lvert N\rvert\}$
L	Terminals; $L \subset N$
D	Depots; $D \subset N$
F	Facilities; F $= L \cup D$
V	Vehicles
C	Containers
C_{pickup}	The set of all containers that need to be picked up from the port.
$C_{dropoff}$	The set of all containers that need to be dropped off at the port.
$C_{transfer}$	The set of all containers that are transferred within the port (both pick-up and drop-off take place within the port area).
$C_{pickup}(i)$	The set of all containers that need to be picked up from location i.
$C_{dropoff}(j)$	The set of all containers that need to be dropped off at location j.
T	Timeslots
Parameters	
TT_{ij}	Travel Time between location i and j.

ST_c	Service Time for container c.
α_c^v	Container-vehicle compatibility (binary parameter).
δ_v	Maximum allowed port dwell time for vehicle v.
γ_v	Maximum allowed total waiting time per vehicle.
O_c	The origin node of container c.
D_c	The destination node of container c.
$EPUT_c$	Earliest Pick Up Time for container c.
$LPUT_c$	Latest Pick Up Time for container c.
μ_f^t	Time Slot Capacity of facility f during timeslot t.
TSD	Time Slot Duration for each timeslot.
T_{start}^t	Start Time of Time Slot t.
T_{end}^t	End Time of Time Slot t.

1. **Network Nodes (N)**

Three types of network nodes (N) are included in the model: terminals (L), depots (D) and port gates (P). The facilities (F) include both the terminals and depots ($\mathrm{L} \cup \mathrm{D}$). The port gates are represented by the first and last node of the dataset, where {0} marks the vehicle's entry point into the port area, and |N| marks the vehicle's departure point from the port area. While the vehicle still requires travel time ($\mathrm{TT_{ij}}$) from these nodes to its designated facility, the arrival at node {0} signifies its transition from the public road network to the port area. The terms port inbound gate and port outbound gate refer to the vehicle's entry and exit points at the boundary of the port area. Hence, the port gates are modelled as predefined nodes in the network. This abstraction is illustrated in Figure 12.

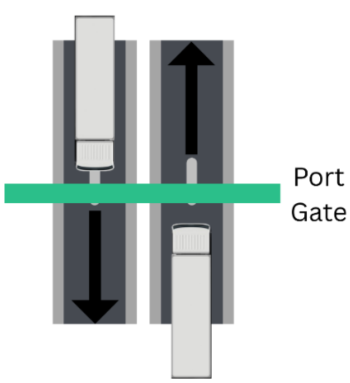

Figure 12. Abstraction of the Port Inbound Gate and Port Outbound Gate.

2. **Fleet of Vehicles (V)**

The fleet of vehicles (V) is a dataset where each element corresponds to a unique vehicle. Every vehicle furthermore belongs to a particular road carrier, and is characterised by a maximum allowable port dwell time (δ_v) and a maximum allowable total waiting time (γ_v). The parameter δ_v should hence be greater than the difference between the vehicle's arrival time at the inbound gate node {0} and the vehicle's departure from the outbound gate node {|N|}. The total waiting time, on the other hand, is the summation of the vehicle's waiting times within the port area before getting serviced for its assigned pick-up and drop-off activities. This must not exceed the total allowable waiting time of a vehicle (γ_v). If a vehicle has multiple activities to perform in the port area, the total dwell time limit becomes leading, while for vehicles with fewer assigned activities, the total waiting time is more significant. In other words, the total dwell time parameter limits the number of activities that can be assigned to a vehicle, while the total waiting time parameter limits the idle time of a vehicle in the port area.

3. **Container Activities (C)**

The containers dataset (C) contains three main attributes: the origin node, the destination node, and the road carrier responsible for the handling and transportation of this container. Hence, both vehicles and containers belong to a particular road carrier, and an activity can only be assigned to a vehicle if both the vehicle and the container belong to the same carrier. This compatibility is modelled by introducing the binary parameter α_c^v, which is equal to 1 if and only if vehicle v is allowed to handle container c.

The containers dataset is further divided into three types of containers: pickup (C_{pickup}), drop-off ($C_{dropoff}$), and inter-terminal transfer ($C_{transfer}$). Pick-ups originate within the port area and should be dropped off at a facility in the hinterland, while drop-offs are picked up at the hinterland and dropped off at a terminal facility. Transfers are containers that are both picked up and dropped off at a facility within the port area, and hence make part of the facilities dataset (F). This distinction has been visualised in Figure 5.

The functions $C_{pickup}(i)$ and $C_{dropoff}(j)$ return all the containers that should be picked up at facility i, or dropped off at facility j, respectively, where i $\subset \mathrm{F}$ and j $\subset \mathrm{F}$, while O_c and D_c Return the origin and destination node of a particular container c, respectively. If a container c is a drop-off, then $O_c = \{0\}$, and if container c is a pick-up, then $D_c = |P|$. As the model scope is limited to the port area, and does not consider all activities that take place in the hinterland, pick-ups at the hinterland originate in the model at the port inbound gate, after which the vehicle enters the port area, and drop-offs end at the port outbound gate, after which the vehicle exits the port area. This notion is illustrated in Figure 5.

Besides sets belonging to containers, there are also parameters which are related to the container dataset. These include the service time ST_c and the operational time window of container c. The operational time window is defined by the earliest (possible) pick-up time ($EPUT_c$) and the latest (allowed) pick-up time ($LPUT_c$). This abstraction derives from the fact that each container first needs to be unloaded from the ship and properly stacked before it becomes available for pickup. The latest pick-up time derives from the fact that facilities set a deadline for containers to be picked up from the facility before a penalty fee is charged. This limitation may also be set by the client at the hinterland, as they may want to receive the container before a certain time. Hence, these time-related parameters ensure that container transportations are executed within the required service windows.

4. Available Timeslots (T)

The timeslot dataset is mainly determined by the terminal operator, and is firstly defined by the Timeslot Duration (TSD), which in turn determines the start and end time of each timeslot. The number of available timeslots (|T|) included in the model depends on the planning horizon (PH) of the model. The total number of timeslots is hence calculated as $|T| = \frac{PH}{TSD}$. For example, if the timeslot duration (TSD) is equal to 60 minutes and the planning horizon (PH) is 24 hours, there will be 24 timeslots in the model. The start- and end-time of each timeslot can then be calculated accordingly, as illustrated in Table 4.

Table 4. Illustration of Timeslot Durations.

Timeslot	T_{start}^t	T_{end}^t
1	00:00	00:59
2	01:00	01:59
⋮	⋮	⋮
24	23:00	23:59

Lastly, the timeslot duration parameter further determines the timeslot capacity of a certain facility during the timeslot (μ_f^t). A smaller timeslot duration implies that the facility can handle less during that timeslot as opposed to a larger timeslot duration. In the model, the handling capacity may vary among facilities as well as among the timeslots, as some facilities might have a larger handling capacity, and certain timeslots during the day may have a larger handling capacity as well. If a facility has certain opening hours, then this can be modelled by setting the handling capacity during those timeslots equal to zero ($\mu_f^t = 0$).

5.1.2. Static Model Variables

This section shows the model outputs, namely the decision variables that result from solving the optimisation model. Table 5 provides an overview of the decision variables of the Static Scheduling Model, followed by an explanation of the role of each variable in the scheduling model.

Table 5. Static Scheduling Model: Decision Variables.

Vehicle Assignment Variables	
$\propto_v$	1 if vehicle v is utilised; 0 otherwise. $\forall v \in V$
y_c^v	1 if container c is assigned to vehicle v; 0 otherwise. $\forall c \in C, \quad \forall v \in V$
β	Total number of utilised vehicles.
Vehicle Routing Variables	
x_{ij}^v	1 if vehicle v travels from node i to node j; 0 otherwise. $\forall i, j \in N, \quad \forall v \in V$
Vehicle Scheduling Variables	
$PUST_i^v$	Pick-Up Start Time of vehicle v at node i. $\forall i \in N, \quad \forall v \in V$
$DOST_j^v$	Drop-Off Start Time of vehicle v from node j. $\forall \mathrm{j} \in N, \quad \forall v \in V$
Z_{ij}^v	Auxiliary variable indicating the arrival time of vehicle v for the trip between node i and j. $\forall i, j \in N, \quad \forall v \in V$
PUT_c	Pick Up Time of container c. $\forall c \in C$
DOT_c	Drop Off Time of container c. $\forall c \in C$
Waiting Time Variables	
WTP_i^v	Waiting Time before Pick-up at node i for vehicle v. $\forall i \in N, \quad \forall v \in V$
WTD_i^v	Waiting Time before Drop-off at node j for vehicle v. $\forall \mathrm{j} \in N, \quad \forall v \in V$
WT^v	Total waiting time of vehicle v.
Slot Reservation Variables	

$z_{pickup}^{c,t}$	1 if container c is assigned to timeslot t for pickup; 0 otherwise. $\forall c \in C, \quad \forall t \in T$
$z_{dropoff}^{c,t}$	1 if container c is assigned to timeslot t for drop-off; 0 otherwise. $\forall c \in C, \quad \forall t \in T$
$g_{pickup}^{f,t}$	Number of pickup activities scheduled at facility f for timeslot t. $\forall \mathrm{f} \in \mathrm{F}, \quad \forall t \in T$
$g_{dropoff}^{f,t}$	Number of drop-off activities scheduled at facility f for timeslot t. $\forall \mathrm{f} \in \mathrm{F}, \quad \forall t \in T$

The static scheduling model has a total of 16 decision variables, as outlined in Table 5. Each layer of the five layers, as described in the conceptual framework in chapter 4, has a distinct set of variables. Each part of the analytical model can therefore be regarded as a sub-mathematical model. A description of the five decision variable categories will follow.

1. Vehicle Assignment Variables

In the model, not all vehicles that are part of the available fleet of vehicles (V) have to be utilised per se. If in the solution found by the model, vehicle v is utilised, the binary variable $\propto_v$ is equal to one. If, however, vehicle v remains idle in the solution, $\propto_v$ is equal to zero. The summation of all utilised vehicles equals β. Lastly, each container must be assigned to exactly one vehicle. If the model assigns container c to vehicle v, the binary variable y_c^v is equal to one. Note that β is not a decision variable in itself, but rather the result of the decision variable $\propto_v$.

2. Vehicle Routing Variables

If vehicle v travels from node i to node j, the binary variable x_{ij}^v is equal to one. Each utilised vehicle must start at the inbound port gate and end at the outbound port gate. The vehicle route is the result of the containers that are assigned to that vehicle, which is found in the previous layer of the model.

3. Vehicle Scheduling Variables

After the vehicle route is determined, a vehicle schedule can be calculated. The $PUST_i^v$ and the $DOST_j^v$ indicate the pick-up start time at node i and the drop-off start time at node j of vehicle v, respectively. To calculate these, the exact route of the vehicle must be known beforehand. The auxiliary variable Z_{ij}^v supports the consistency of calculating these two decision variables. Lastly, PUT_c and DOT_c finds the actual pick-up time and drop-off time of container c. Hence, the variables $PUST_i^v$ and the $DOST_j^v$ link the vehicle schedule to the vehicle route, while the decision variables PUT_c and DOT_c link the container schedule to the next layer of the model, where timeslots are reserved.

Note that each node is hence assigned two scheduling-related variables if vehicle v visits node i: $PUST_i^v$ and the $DOST_j^v$. This model formulation allows two separate times, one for a pick-up and one for a drop-off, to be assigned to one node. The logic and continuity of calculating the scheduling variables are illustrated in Figure 13.

4. **Waiting Time Variables**

The determined schedule in the previous model layer also specifies the waiting times. The waiting time of vehicle v before pick-up at node i, is indicated by the continuous variable WTP_i^v and the waiting time before drop-off at node j, is indicated by WTD_j^v. The total waiting time of vehicle v, WT^v, is the summation of the waiting times at all the nodes visited by that vehicle.

Note that the service time is a model input, while the waiting time is a model output. Waiting time is defined as the how long a vehicle has to wait until the facility will start with handling the activity, while the service time is how long it actually takes the facility to handle the activity.

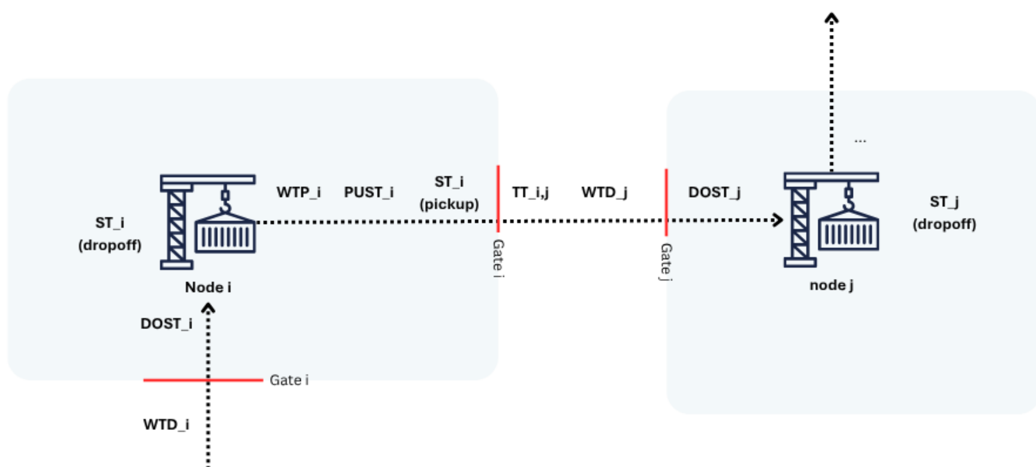

Figure 13. Pickup and drop-off start times variables.

5. **Slot Reservation Variables**

Lastly, the slot reservations are made, which is based on the determined vehicle schedule. The binary variables $z_{pickup}^{c,t}$ and $z_{dropoff}^{c,t}$ are equal to one if the pick-up activity, respectively the drop-off activity, of container c takes place during timeslot t. The continuous variables $g_{pickup}^{f,t}$ and $g_{dropoff}^{f,t}$ indicate the number of scheduled pick-up respectively drop-off activities, during timeslot t at facility f. This may not exceed the timeslot capacity of facility f during timeslot t, which was indicated in Table 3 by the parameter μ_f^t.

5.1.3. Static Model Formulation

This section presents the mathematical formulation of the Static Scheduling Model. The objective function and corresponding constraints are outlined in Table 6, followed by a description of the entire model formulation. The static model makes use of the parameters and decision variables as introduced in Table 3 and Table 5.

Table 6. Static Scheduling Model: Objective Function & Constraints.

Objective Function

$$\min \sum_{v \in V} WT^v$$

A. Container Assignment Constraints

$\sum_{v \in V} y_c^v = 1$	$\forall c \in C$	(1)
$y_c^v \leq b_c^v$	$\forall c \in C, \forall v \in V$	(2)
$\sum_{c \in C:\ i = O_c;\ j = D_c} y_c^v \leq 1$	$\forall i, j \in N, \forall v \in V$	(3)
$y_c^v \leq x_{i,j}^v$	$\forall c \in C: i = O_c, j = D_c, \forall v \in V$	(4)

B. Vehicle Utilization Constraints

$\sum_{i,j \in N} x_{i,j}^v \leq \propto_v \cdot M$	$\forall v \in V$	(5)
$\sum_{c \in C} y_c^v \geq \propto_v$	$\forall v \in V$	(6)
$\beta = \sum_{v \in V} \propto_v$		(7)

C. Vehicle Entry and Exit Constraints

$$\sum_{j \in F} x^{v}_{\{0\},j} = \mathrm{h_v} \qquad \forall \mathrm{v} \in \mathrm{V} \qquad (8)$$

$$\sum_{i \in F} x^{v}_{i,|N|} = \mathrm{h_v} \qquad \forall \mathrm{v} \in \mathrm{V} \qquad (9)$$

$$\sum_{i \in N} x^{v}_{i,\{0\}} = 0 \qquad \forall \mathrm{v} \in \mathrm{V} \qquad (10)$$

$$\sum_{j \in N} x^{v}_{|N|,j} = 0 \qquad \forall \mathrm{v} \in \mathrm{V} \qquad (11)$$

D. Flow Continuity Constraint

$$\sum_{\mathrm{j} \in \mathrm{N} \setminus \{0\}} x^{v}_{i,j} = \sum_{\mathrm{j} \in \mathrm{N} \setminus \{|N|\}} x^{v}_{j,i} \qquad \forall \mathrm{i} \in \mathrm{F}, \forall \mathrm{v} \in V \qquad (12)$$

E. Deadheading Constraint

$$\sum_{\mathrm{j} \in \mathrm{N}} (x^{v}_{i,j} + x^{v}_{j,i}) \leq 2 \cdot \sum_{\mathrm{c} \in C_{pickup}(i) \cup C_{dropoff}(i)} y^{v}_{c} \qquad \forall \mathrm{v} \in \mathrm{V}, \forall \mathrm{i} \in \mathrm{F} \qquad (13)$$

F. Vehicle Scheduling Constraints

$$PUST^{v}_{i} = DOST^{v}_{i} + \sum_{\mathrm{c} \in \mathrm{C_{dropoff}}(i)} y^{v}_{c} \cdot ST_{c} + WTP^{v}_{i} \qquad \forall \mathrm{v} \in \mathrm{V}, \forall \mathrm{i} \in \mathrm{N} \qquad (14)$$

$$Z^{v}_{ij} = \mathrm{PUST}^{v}_{i} + \sum_{c \in C_{pickup(i)}} y^{v}_{c} \cdot ST_{c} + TT_{ij} + WTD^{v}_{j} \qquad \forall v \in V, \forall i \in N, \forall j \in N, i \neq j \qquad (15)$$

$$DOST^{v}_{j} \geq Z^{v}_{ij} - M \cdot \left(1 - x^{v}_{ij}\right) \qquad \forall \mathrm{v} \in \mathrm{V}, \forall \mathrm{i} \in \mathrm{N}, \forall \mathrm{j} \in \mathrm{N}, \mathrm{i} \neq \mathrm{j} \qquad (16)$$

$$DOST^{v}_{j} \leq Z^{v}_{ij} + M \cdot \left(1 - x^{v}_{ij}\right) \qquad \forall v \in V, \forall i \in N, \forall j \in N, i \neq j \qquad (17)$$

G. Dwell Time Constraint		
$DOST_{\|N\|}^{v} - PUST_{0}^{v} \leq \delta_{v}$	$\forall v \in V$	(18)

H. Time Window Constraints		
$\mathrm{PUT_c} = \sum_{\mathrm{v \in V}} y_{c}^{v} \cdot PUST_{i}^{v}$	$\forall c \in C, i = O_{c}$	(19)
$\mathrm{DOT_c} = \sum_{\mathrm{v \in V}} y_{c}^{v} \cdot DOST_{j}^{v}$	$\forall c \in C, j = D_{c}$	(20)
$\mathrm{PUT_c} \geq EPUT_{c}$	$\forall c \in C$	(21)
$\mathrm{PUT_c} \leq LPUT_{c}$	$\forall c \in C$	(22)

I. Timeslot Reservation Constraints		
$\sum_{\mathrm{t \in T}} z_{pickup}^{c,t} = 1$	$\forall c \in \mathrm{C_{pickup}} \cup \mathrm{C_{transfer}}$	(23)
$\sum_{\mathrm{t \in T}} z_{dropoff}^{c,t} = 1$	$\forall c \in \mathrm{C_{dropoff}} \cup \mathrm{C_{transfer}}$	(24)
$\mathrm{PUT_c} \geq \sum_{\mathrm{t \in T}} z_{pickup}^{c,t} \cdot T_{start}^{t}$	$\forall c \in \mathrm{C_{pickup}} \cup \mathrm{C_{transfer}}, \forall t \in T$	(25)
$\mathrm{PUT_c} \leq \sum_{\mathrm{t \in T}} z_{pickup}^{c,t} \cdot T_{end}^{t} + M \cdot \left(1 - z_{pickup}^{c,t}\right)$	$\forall c \in \mathrm{C_{pickup}} \cup \mathrm{C_{transfer}}, \forall t \in T$	(26)
$\mathrm{DOT_c} \geq \sum_{\mathrm{t \in T}} z_{dropoff}^{c,t} \cdot T_{start}^{t}$	$\forall c \in \mathrm{C_{dropoff}} \cup \mathrm{C_{transfer}}, \forall t \in T$	(27)

$$\mathrm{DOT_c} \leq \sum_{\mathrm{t \in T}} z^{c,t}_{dropoff} \cdot T^t_{end} + M \cdot \left(1 - z^{c,t}_{dropoff}\right) \qquad \forall c \in \mathrm{C_{dropoff}} \cup \mathrm{C_{transfer}}, \forall t \in T \qquad (28)$$

J. Timeslot Capacity Constraints

$$g^{f,t}_{pickup} = \sum_{c \in \mathrm{C_{pickup}}(f)} z^{c,t}_{pickup} \qquad \forall t \in T, \forall f \in F \qquad (29)$$

$$g^{f,t}_{dropoff} = \sum_{c \in \mathrm{C}_{dropoff}(f)} z^{c,t}_{dropoff} \qquad \forall t \in T, \forall f \in F \qquad (30)$$

$$g^{f,t}_{pickup} \leq \mu^t_f \qquad \forall f \in F, \forall t \in T \qquad (31)$$

$$g^{f,t}_{dropoff} \leq \mu^t_f \qquad \forall f \in F, \forall t \in T \qquad (32)$$

K. Waiting Time Constraints

$$WT_v = \sum_{\mathrm{i \in N}} WTP^v_i + WTD^v_j \qquad \forall v \in V \qquad (33)$$

$$\widetilde{WT}^h_v \leq \gamma \qquad \forall v \in \tilde{V}, \forall h \in \mathcal{H} \qquad (34)$$

L. Variable Constraints

$$\propto_v \in \{0,1\} \qquad \forall i, j \in N, \forall v \in V \qquad (35)$$

$$y^v_c \in \{0,1\} \qquad \forall \mathrm{c} \in \mathrm{C}, \forall v \in V \qquad (36)$$

$$\beta \geq 0 \qquad (37)$$

$$x_{ij}^{v} \in \{0,1\} \qquad \forall i,j \in N, \forall v \in V \qquad (38)$$

$$\mathrm{PUST_i^v}, \mathrm{DOST_i^v} \geq 0 \qquad \forall i \in N, \forall v \in V \qquad (39)$$

$$Z_{ij}^{v} \geq 0 \qquad \forall i,j \in N, \forall v \in V \qquad (40)$$

$$PUT_c, DOT_c \geq 0 \qquad \forall c \in C \qquad (41)$$

$$\mathrm{WTP_i^v}, \mathrm{WTD_i^v} \geq 0 \qquad \forall i \in N, \forall v \in V \qquad (42)$$

$$\mathrm{WT^v} \geq 0 \qquad \forall v \in V \qquad (43)$$

$$z_{pickup}^{c,t}, z_{dropoff}^{c,t} \in \{0,1\} \qquad \forall \mathrm{c} \in \mathrm{C}, \forall t \in T \qquad (44)$$

$$g_{pickup}^{f,t}, g_{dropoff}^{f,t} \geq 0 \qquad \forall f \in F, \forall t \in T \qquad (45)$$

The model constraints can be divided into multiple categories, and each category can be linked to the five model layers as defined in the Conceptual Framework in Chapter 4.1. This subdivision is shown in Table 7.

Table 7. Static Scheduling Model Constraints per Model Layer.

Model Layer	Model Constraints
1. Vehicle Assignment Decision	A. Container Assignment Constraints B. Vehicle Utilisation Constraints
2. Vehicle Routing Decision	C. Vehicle Entry and Exit Constraints D. Flow Continuity Constraint E. Deadheading Constraint
3. Vehicle Scheduling Calculation	F. Vehicle Scheduling Constraints G. Dwell Time Constraint H. Time Window Constraints

4. Facility Timeslot Reservation	I. Timeslot Reservation Constraints J. Timeslot Capacity Constraints
5. Waiting Time Calculation	K. Waiting Time Constraints

A. Container Assignment Constraints

Constraint (1) ensures that each container is assigned to exactly one vehicle, as each container must be handled during the planning, and can only be handled by one vehicle.

Constraint (2) ensures that containers are only assigned to a vehicle, if the vehicle and container are compatible. That is to say, y_c^v is allowed to become 1 only if b_c^v is equal to one, and the binary parameter b_c^v is 1 if vehicle v is allowed and able to handle container c.

Constraint (3) is the vehicle capacity handling constraint, stating that each vehicle has only the capacity to carry out one activity per trip movement. Hence, a vehicle that travels from i to j can only get assigned at most one container with origin i and destination j.

Constraint (4) enforces that vehicles carry out the required trip to perform the container activity it is assigned to. Hence, if container c is assigned to vehicle v, then this vehicle must travel from the origin to the destination of this container ($from\ \mathrm{O_c}$ to D_c). Hence, this constraint links the vehicle assignment decision, being the first layer of the model, to the vehicle routing decision, which is the second layer of the model.

B. Vehicle Utilisation Constraints

Constraint (5) states that if a vehicle v makes any movement within the network, i.e. $\sum_{\mathrm{I,j \in N}} x_{i,j}^v \geq 1$, then this vehicle must count as a utilised vehicle ($\propto_v = 1$).

Constraint (6) states that if a vehicle is utilised ($\propto_v = 1$), then it must perform at least one activity. That is because a vehicle can only be counted as a utilised vehicle if it has at least one container activity assigned to it, preventing idle vehicles to be utilised in the planning.

Constraint (7) counts the total number of utilised vehicles in the planning.

C. Vehicle Entry And Exit Constraints

Constraints (8) and (9) enforce that all utilised vehicles start their route by departing from the incoming port gate to any facility, and end their route by arriving at the outbound port gate from any facility. This concept has been schematized earlier in Figure 12.

Constraints (10) and (11) state that vehicles cannot travel to the inbound port gate, nor travel from the outbound port gate. Hence, the start and end nodes are one-directional nodes in the network.

D. Flow Continuity Constraint

Constraint (12) ensures that the travel that takes place between the facilities (i.e., within the port area), happens in a closed route. Hence, if vehicle v arrives at a facility, it must also leave that facility.

E. Deadheading Constraint

Constraint (13) ensures that a vehicle cannot perform two consecutive empty trips, as a vehicle is not allowed to drive around redundantly. Hence, a vehicle is allowed to perform at most one empty ride to arrive at the next assigned activity. In other words, vehicle v can only visit node i, if the vehicle is either performing a pick-up or drop-off activity at this node. This constraint prevents the model from including unrealistic redundancy in the schedule.

F. Vehicle Scheduling Constraints

Constraints (14), (15), (16) and (17) calculate the schedule of the vehicle routes as determined in the previous model layer. Specifically, (16) calculates the pick-up start time, while constraints (16) and (17) calculate the drop-off start time. Constraint (15) makes use of the auxiliary variable Z_{ij}^{v} to find the actual route that vehicle v is performing from node i. Figure 10 illustrates the concept that these constraints enforce.

G. Dwell Time Constraint

Constraint (18) calculates the dwell time of vehicle v, which is departure time from the inbound port gate minus the arrival time at the outbound port gate. This should be less than or equal to the maximum allowed dwell time of vehicle v.

H. Time Window Constraints

Constraints (19) and (20) calculate the actual pick-up and drop-off time of container c, respectively. The actual pick-up time of container c (PUT_c) is equal to the pick-up start time $(PUST_i^v)$ at the pick-up node of container c $(i = O_c)$, but only if vehicle v has been assigned to handle this container $(y_c^v = 1)$. Similarly, the actual drop-off time of container c (DOT_c) is equal to the drop-off start time $(DOST_j^v)$ at the drop-off node of container c $(j = D_c)$, but only if vehicle v has been assigned to handle this container $(y_c^v = 1)$. These constraints link the vehicle scheduling layer to the facility timeslot reservation layer of the model.

Constraints (21) and (22) enforce that the pick-up time of container c should fall within the earliest pick-up time and latest pick-up time of container c.

I. Timeslot Reservation Constraints

Constraints (23) and (24) enforce that each container activity gets assigned exactly one timeslot. Constraint (23) states that each container that needs to be picked up from the port (i.e. is either a pick-up or transfer type of container), gets assigned exactly one timeslot of the set of timeslots. Similarly, constraint (24) states that each container that needs to be dropped off within the port area (i.e. is either a drop-off or transfer type of container), gets assigned exactly one timeslot reservation for drop-off. Note that transfer containers hence receive one pick-up and one drop-off reservation, and both activities take place within the port area, which is the scope of the scheduling model.

Constraints (25), (26), (27) and ensure consistency between the reserved timeslots and the actual handling times of container c. Hence, these constraints establish a connection between the previous and current model layers.

Specifically, constraints (25) and (26) enforce that the start and end time of the reserved pick-up timeslot for container c, falls within the scheduled pick-up time of container c. Likewise, constraints (27) and (28) guarantee that the reserved drop-off timeslot aligns with the scheduled drop-off time of container c.

J. Timeslot Capacity Constraints

Constraints (29) and (30) calculate the total number of reserved timeslots for pick-up activities and drop-off activities, respectively, during timeslot t at facility f.

Constraint (31) and (32) ensure that the total number of reserved pick-up and drop-off timeslots during timeslot t at facility f, does not exceed the timeslot capacity of that facility during that timeslot.

K. Waiting Time Constraints

Constraint (33) calculates the total waiting time of vehicle v during the entire planning period.

Constraint (34) enforces that the total waiting time in the planning does not exceed the maximum allowable waiting time of vehicle v.

L. Variable Constraints

Constraints (35), (36), (37), (38), (39), (40), (41), (42), (43), (44) and (45) are variable constraints, enforcing some variables to be binary while others to be non-negative continuous variables.

5.2. Dynamic Rescheduling Model

5.2.1. Dynamic Model Inputs

The inputs of the Dynamic Rescheduling Model are the inputs used for the static model as outlined in 5.1.1, as well as inputs specifically for the dynamic model. This distinction is made clear in Table 8, where the indices, sets and parameters of the dynamic model come after the ones for the static model.

Table 8. Dynamic Rescheduling Model: Indices, Sets & Parameters.

Indices	
Static Model Indices:	
i, j, f	Node index
v	Vehicle index
c	Container index
t	Timeslot index
Dynamic Model Indices:	
h	Horizon index
Sets	
Static Model Sets:	
N	Locations; $N = P \cup \mathrm{L} \cup \mathrm{D}$
P	Port; $P \subset N, P = 0, \lvert N \rvert$
L	Terminals; $L \subset N$
D	Depots; $D \subset N$
F	Facilities; $\mathrm{F} = L \cup D$
V	Vehicles
C	Containers
C_{pickup}	All containers that need to be picked up from the port.
$C_{dropoff}$	All containers that need to be dropped off at the port.
$C_{transfer}$	All containers that are transferred within the port (both pick-up and drop-off take place at a facility within the port area).
$C_{pickup}(i)$	All containers that need to be picked up from location i.

$C_{dropoff}(j)$	All containers that need to be dropped off at location j.
T	Timeslots
Dynamic Model Sets:	
$\mathcal{H}$	Horizons
$\tilde{V}$	All utilised vehicles during the entire planning horizon; $\tilde{V} \subset \mathrm{V}$
$\tilde{V}_{ontime}^{h}$	All on-time vehicles during time horizon h; $\tilde{V}_{ontime}^{h} \subset \tilde{V}$
$\tilde{V}_{delayed}^{h}$	All delayed vehicles during time horizon h; $\tilde{V}_{delayed}^{h} \subset \tilde{V}$
Parameters	
Static Model Parameters:	
TT_{ij}	Travel Time between location i and j.
ST_c	Service Time for container c.
α_c^v	Container-vehicle compatibility (binary parameter).
δ_v	Maximum allowable port dwell time for vehicle v.
O_c	The origin node of container c.
D_c	The destination node of container c.
$EPUT_c$	Earliest Pick Up Time for container c.
$LPUT_c$	Latest Pick Up Time for container c.
μ_f^t	Time Slot Capacity of facility f during timeslot t.
TSD	Time Slot Duration for each timeslot.
T_{start}^t	Start Time of Time Slot t.
T_{end}^t	End Time of Time Slot t.
Dynamic Model Parameters:	
$\mathrm{ETA}_{\mathrm{v}}^{\mathrm{h}}$	Estimated Time of Arrival of vehicle v during time horizon h.
Δ_v^h	Total delay of vehicle v up until time horizon h.
$\delta_{\mathrm{v}}^{\mathrm{h}}$	Additional delay of vehicle v during time horizon h.
$\lambda_{\mathrm{v}}^{\mathrm{h}}$	Penalty weight for waiting time of vehicle v during time horizon h.
τ_{h}	The current time during time horizon h.

Initial Planning Parameters:	
$\hat{y}_c^v$	Equal to 1 if container c is assigned to vehicle v in the initial plan; 0 otherwise.
$\hat{x}_{ij}^v$	Equal to 1 if vehicle v is assigned to travel from node i to node j in the initial plan; 0 otherwise.
$\hat{z}_{pickup}^{c,t}$	Equal to 1 if container c is assigned to timeslot t for pickup during the initial plan; 0 otherwise.
$\hat{z}_{dropoff}^{c,t}$	Equal to 1 if container c is assigned to timeslot t for drop-off during the initial plan; 0 otherwise.
$\widehat{\mathrm{WTP}}_{\mathrm{i}}^{\mathrm{v}}$	Waiting Time before Pick-up at node i for vehicle v during the initial plan.
$\widehat{WTD}_j^v$	Waiting Time before Drop-off at node j for vehicle v during the initial plan.

The overlapping parameters that have been used in both the static scheduling model and dynamic rescheduling model have been previously described (see Chapter 5.1.1). This section will therefore elaborate further on the dynamic model data requirements.

Time Horizons ($\mathcal{H}$)

The introduction of time horizons allows the static model to be extended to a dynamic rolling horizon model, in which the static model output is continuously updated after a fixed duration. This duration is the Horizon Interval (HI), and the number of time horizons of the dynamic model is determined by the entire Planning Horizon (PH) and the Horizon Interval (HI), which can be calculated with the following formula: $|\mathcal{H}| = \frac{PH}{HI}$. For instance, if the planning horizon is 24 hours, and the horizon interval is 1 hour, then $|\mathcal{H}| = 24$.

Utilised Vehicles ($\tilde{V}$)

The set of all utilised vehicles ($\tilde{V}$) is the subset of all available vehicles (V), which have been utilised in the initial planning. The set of utilised vehicles is further subdivided into the delayed and on-time vehicles per horizon. If during a certain horizon h, vehicle v is on-time, then this vehicle is among the set V_{ontime}^h, while vehicles that are delayed during time horizon h are part of the set $V_{delayed}^h$. Hence, for each horizon h, $V_{ontime}^h \cup V_{delayed}^h = \tilde{V}$.

Estimated Times of Arrival ($\mathbf{ETA_v^h}$)

One of the data requirements of the dynamic rescheduling model, is the Estimated Time of Arrival for each vehicle v during each horizon h. Hence, the ETAs used in the model are dynamic and real-time as they are updated at every horizon. Hence, the Horizon Interval

(HI) determines the frequency at which these ETA's should be captured for the dynamic model to be executed.

If the ETA of vehicle v during horizon h is equal to the ETA of the previous horizon, then this vehicle is considered as an on-time vehicle and part of the set V_{ontime}^{h}. If, however, the updated ETA ($\mathrm{ETA}_{\mathrm{v}}^{\mathrm{h}}$) for vehicle v differs from the previous ETA ($\mathrm{ETA}_{\mathrm{v}}^{\mathrm{h}-1}$) of vehicle v, then this vehicle is marked as delayed and part of the set $V_{delayed}^{h}$. The difference between the current and previous ETA is given by $\delta_{\mathrm{v}}^{\mathrm{h}}$, which is thus equal to zero if vehicle v is not delayed between horizon h and h-1. The total delay of vehicle v up until horizon h, is given by Δ_{v}^{h}. Accordingly, this total delay can be calculated using the formula $\Delta_{v}^{h} = \sum_{t=1}^{h} \delta_{v}^{t}$. Note that the delay of all vehicles is equal to zero for h=0, as the solution of the initial horizon is equal to the initial planning as found in the static model. Furthermore, note that if $\delta_{\mathrm{v}}^{\mathrm{h}} > 0$, then $v \subset V_{delayed}^{h}$. This logical consistency between the parameter Δ_{v}^{h} and the set $V_{delayed}^{h}$ is further illustrated in Figure 14.

δ: The Additional Delay per Horizon per Vehicle

	0	60	120	180	240	300	360	420	480	540	600	660	720	780	840	900	960	1020	1080	1140	1200	1260	1320	1380	1440
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	5	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	64	26	10	0	0	0	0	0	0
3	0	0	0	0	0	0	15	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

```
The time horizons in which vehicle v gets delayed:

{0: [1080, 1140],
 2: [900, 960, 1020, 1080],
 3: [360, 420],
 6: [420],
```

Figure 14. Consistency between parameter δ_{v}^{h} and dataset $V_{delayed}^{h}$.

Lastly, the parameter τ_{h} returns the actual time of the day during horizon h, which can be calculated using the formula: $\tau_{\mathrm{h}} = h \cdot \frac{HI}{PH}$. For instance, if the Planning Horizon is 1 day, and the Horizon Interval is 1 hour, the current time for h=3 is 3:00 ($\tau_{\mathrm{h}} = 3 \cdot \frac{24 \cdot 60}{60}$ = 3:00).

Initial Planning Parameters

As mentioned, the dynamic model requires an initial schedule as input, which is used in the dynamic model as the solution for time horizon h = 0. The initial planning parameters used from the initial planning are $\hat{y}_{c}^{v}$, $\hat{x}_{ij}^{v}$, $\hat{z}_{pickup}^{c,t}$, $\hat{z}_{dropoff}^{c,t}$, $\widehat{\mathrm{WTP}}_{\mathrm{i}}^{\mathrm{v}}$, and $\widehat{WTD}_{j}^{v}$. Note that all initial planning parameters are indicated with a hat. The Dynamic Rescheduling Model then re-optimises the planning based on the previous planning (if h=1, the previous planning is the initial planning) combined with the dynamically updated Estimated Times of Arrival.

5.2.2. Dynamic Model Variables

This section outlines all the variables used in the Dynamic Rescheduling Model, which is summarised in Table 9. Some of the variables that are used in the Static Scheduling Model are omitted, while other variables are introduced to model this dynamic behaviour. The variables used in both the static and dynamic models are indicated with a tilde for use in the dynamic model to prevent overlapping. The newly introduced variables for the dynamic model include the rescheduling variables and the reassignment variables.

Table 9. Dynamic Rescheduling Model: Decision Variables.

Vehicle Assignment Variables	
$\tilde{y}_c^{v,h}$	1 if container c is assigned to vehicle v during horizon h; 0 otherwise. $\forall c \in C, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
Vehicle Routing Variables	
$\tilde{x}_{ij}^{v,h}$	1 if vehicle v travels from node i to node j during horizon h; 0 otherwise. $\forall i, j \in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
Vehicle Scheduling Variables	
$\widetilde{PUST}_i^{v,h}$	Pick-Up Start Time of vehicle v at node i during horizon h. $\forall i \in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
$\widetilde{DOST}_j^{v,h}$	Drop-Off Start Time of vehicle v from node j during horizon h. $\forall$j $\in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
$\tilde{Z}_{i,j}^{v,h}$	Auxiliary variable indicating the arrival time of vehicle v for the trip between node i and j during horizon h. $\forall i, j \in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
$\widetilde{PUT}_c^h$	Pick Up Time of container c during horizon h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
$\widetilde{DOT}_c^h$	Drop Off Time of container c during horizon h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
Waiting Time Variables	
$\widetilde{WTP}_i^{v,h}$	Waiting Time before Pick-up at node i for vehicle v during horizon h. $\forall i \in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
$\widetilde{WTD}_i^{v,h}$	Waiting Time before Drop-off at node j for vehicle v during horizon h. $\forall$j $\in N, \quad \forall v \in V, \quad \forall h \in \mathcal{H}$
$\widetilde{WT}^{v,h}$	Total waiting time of vehicle v during horizon h. $\forall v \in V, \quad \forall h \in \mathcal{H}$

Slot Reservation Variables	
$\tilde{z}_{pickup}^{c,t,h}$	1 if container c is assigned to timeslot t for pickup during horizon h; 0 otherwise. $\forall c \in C, \quad \forall t \in T, \quad \forall h \in \mathcal{H}$
$\tilde{z}_{dropoff}^{c,t,h}$	1 if container c is assigned to timeslot t for drop-off during horizon h; 0 otherwise. $\forall c \in C, \quad \forall t \in T, \quad \forall h \in \mathcal{H}$
$\tilde{g}_{pickup}^{f,t,h}$	Number of pickup activities scheduled at facility f for timeslot t during horizon h. $\forall \mathrm{f} \in \mathrm{F}, \quad \forall t \in T, \quad \forall h \in \mathcal{H}$
$\tilde{g}_{dropoff}^{f,t}$	Number of drop-off activities scheduled at facility f for timeslot t during horizon h. $\forall \mathrm{f} \in \mathrm{F}, \quad \forall t \in T, \quad \forall h \in \mathcal{H}$
Rescheduling Variables	
$\emptyset_{pickup}^{c,h}$	The difference between the previous and the current pickup timeslot reservation t for container c during horizon h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
$\emptyset_{dropoff}^{c,h}$	The difference between the previous and the current drop-off timeslot reservation t for container c during horizon h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
$\psi_{pickup}^{c,h}$	Absolute change in pick-up timeslot reservation for container c between horizons h-1 and h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
$\psi_{dropoff}^{c,h}$	Absolute change in drop-off timeslot reservation for container c between horizons h-1 and h. $\forall c \in C, \quad \forall h \in \mathcal{H}$
$\sigma_{pickup}^{c,h}$	Equal to 1 if the pick-up appointment for container c is rescheduled during horizon h; 0 otherwise. $\forall \mathrm{c} \in C, \quad \forall h \in \mathcal{H}$
$\sigma_{dropoff}^{c,h}$	Equal to 1 if the drop-off appointment for container c is rescheduled during horizon h; 0 otherwise. $\forall \mathrm{c} \in C, \quad \forall h \in \mathcal{H}$
Reassignment Variables	
$\rho^{c,h}$	Equal to 1 if container c is re-assigned to a new vehicle during horizon h; 0 otherwise.

The continuous variables $\emptyset_{pickup}^{c,h}$ and $\emptyset_{dropoff}^{c,h}$ equal the difference between the previously and currently reserved timeslot t for container, while the auxiliary continuous variables $\psi_{pickup}^{c,h}$ and $\psi_{dropoff}^{c,h}$ take the absolute value of this difference. The binary variables $\sigma_{\mathrm{pickup}}^{c,\mathrm{h}}$ and $\sigma_{\mathrm{dropoff}}^{c,\mathrm{h}}$ equal one if a new timeslot is reserved for container c during horizon h. The binary variable $\rho^{c,\mathrm{h}}$ equals one if a new vehicle is assigned to container c during horizon h.

5.2.3. Dynamic Model Formulation

This section presents the complete mathematical formulation of the Dynamic Rescheduling Model. Table 10 provides this model formulation, after which a description is given for the newly added constraints. The dynamic model makes use of the parameters and decision variables as outlined in Table 8 and Table 9.

Table 10. Dynamic Rescheduling Model: Objective Function & Constraints.

Objective Function		
$min \sum_{v \in V} WT^{v,h}$	$\forall h \in \mathcal{H}$	
I. Dynamic ETA Constraint		
$\widetilde{PUST}_0^{v,h} = ETA_v^h$	$\forall h \in \mathcal{H}, \forall v \in \tilde{V}$	(46)
II. Initial Horizon Constraints		
$\tilde{y}_c^{v,0} = \hat{y}_c^v$	$\forall c \in C, \forall v \in \tilde{V}$	(47)
$\tilde{x}_{ij}^{v,0} = \hat{x}_{ij}^v$	$\forall i, j \in N, \forall v \in \tilde{V}$	(48)
$\tilde{z}_{pickup}^{c,t,0} = \hat{z}_{pickup}^{c,t}$	$\forall c \in C, \forall t \in T$	(49)
$\tilde{z}_{dropoff}^{c,t,0} = \hat{z}_{dropoff}^{c,t}$	$\forall c \in C, \forall t \in T$	(50)
$\widetilde{WTP}_i^{v,0} = \widehat{WTP}_i^v$	$\forall i \in N, \forall v \in \tilde{V}$	(51)
$\widetilde{WTD}_i^{v,0} = \widehat{WTD}_i^v$	$\forall i \in N, \forall v \in \tilde{V}$	(52)

III.	**Operational Rescheduling Constraints**	
$\sum_{c \in C} \tilde{y}_c^{v,h} \geq 1$	$\forall h \in \mathcal{H}, \forall v \in \tilde{V}$	(53)
$\tilde{y}_c^{v,h} = \hat{y}_c^{v}$	$\forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall c \in C_{dropoff}$	(54)
IV.	**Rescheduling Tracking Constraints**	
$\emptyset_{pickup}^{c,h} = \sum_{t \in T} \left(\tilde{z}_{pickup}^{c,t,h} - \tilde{z}_{pickup}^{c,t,h-1} \right) \cdot t$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{pickup} \cup C_{transfer}$	(55)
$\emptyset_{dropoff}^{c,h} = \sum_{t \in T} \left(\tilde{z}_{dropoff}^{c,t,h} - \tilde{z}_{dropoff}^{c,t,h-1} \right) \cdot t$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{dropoff} \cup C_{transfer}$	(56)
$\psi_{pickup}^{c,h} = \left\| \emptyset_{pickup}^{c,h} \right\|$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{pickup} \cup C_{transfer}$	(57)
$\psi_{dropoff}^{c,h} = \left\| \emptyset_{dropoff}^{c,h} \right\|$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{dropoff} \cup C_{transfer}$	(58)
$\sigma_{pickup}^{c,h} \leq M \cdot \psi_{pickup}^{c,h}$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{pickup} \cup C_{transfer}$	(59)
$\sigma_{pickup}^{c,h} \geq \varepsilon \cdot \psi_{pickup}^{c,h}$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{dropoff} \cup C_{transfer}$	(60)
$\sigma_{dropoff}^{c,h} \leq M \cdot \psi_{dropoff}^{c,h}$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{pickup} \cup C_{transfer}$	(61)
$\sigma_{dropoff}^{c,h} \geq \varepsilon \cdot \psi_{dropoff}^{c,h}$	$\forall h \in \mathcal{H} \setminus \{0\}, \forall c \in C_{dropoff} \cup C_{transfer}$	(62)
V.	**Reassignment Tracking Constraint**	

$$\rho^{c,h} = 1 - \tilde{y}_c^{v,h} \qquad \begin{matrix} \forall h \in \mathcal{H} \setminus \{0\}, \\ \forall v \in \tilde{V}, \\ \forall c \in C, \\ if\ \tilde{y}_c^{v,h-1} = 1: \end{matrix} \tag{63}$$

VI. Rescheduling Requirement Constraints

$$\widetilde{PUT}_c^h \geq \sum_{v \in V} \sigma_{pickup}^{c,h} \cdot \tau_h \qquad \begin{matrix} \forall h \in \mathcal{H}, \\ \forall c \in C_{pickup} \cup C_{transfer} \end{matrix} \tag{64}$$

$$\widetilde{DOT}_c^h \geq \sum_{v \in V} \sigma_{dropoff}^{c,h} \cdot \tau_h \qquad \begin{matrix} \forall h \in \mathcal{H}, \\ \forall c \in C_{dropoff} \cup C_{transfer} \end{matrix} \tag{65}$$

VII. Dynamic Rescheduling Constraints

$$\widetilde{PUT}_c^h = \widetilde{PUT}_c^{h-1} \qquad \begin{matrix} \forall h \in \mathcal{H} \setminus \{0\}, \\ \forall v \in \tilde{V}_{ontime}^h, \\ \forall c \in C_{pickup} \cup C_{transfer}, \\ if\ \tilde{y}_c^{v,h-1} = 1: \end{matrix} \tag{66}$$

$$\widetilde{DOT}_c^h = \widetilde{DOT}_c^{h-1} \qquad \begin{matrix} \forall h \in \mathcal{H} \setminus \{0\}, \\ \forall v \in \tilde{V}_{ontime}^h, \\ \forall c \in C_{dropoff} \cup C_{transfer}, \\ if\ \tilde{y}_c^{v,h-1} = 1: \end{matrix} \tag{67}$$

VIII. Dynamic Reassignment Constraints

$$\tilde{y}_c^{v,h} = \tilde{y}_c^{v,h-1} \qquad \begin{matrix} \forall h \in \mathcal{H} \setminus \{0\}, \\ \forall v \in \tilde{V}_{ontime}^h, \\ \forall c \in C, \\ if\ \tilde{y}_c^{v,h-1} = 1: \end{matrix} \tag{68}$$

IX. Container Assignment Constraints

$$\sum_{v \in \tilde{V}} \tilde{y}_c^{v,h} = 1 \qquad \forall h \in \mathcal{H}, \forall c \in C \tag{69}$$

$$\tilde{y}_c^{v,h} \leq b_c^v \qquad \forall h \in \mathcal{H}, \forall c \in C, \forall v \in \tilde{V} \tag{70}$$

$$\sum_{c \in C:\, i=O_c;\, j=D_c} \tilde{y}_c^{v,h} \leq 1 \qquad \forall h \in \mathcal{H}, \forall i, j \in N, \forall v \in \tilde{V} \qquad (71)$$

$$\tilde{y}_c^{v,h} \leq \tilde{x}_{i,j}^{v,h} \qquad \forall h \in \mathcal{H}, \forall c \in C: i = O_c, j = D_c, \quad \forall v \in \tilde{V} \qquad (72)$$

X. Vehicle Entry and Exit Constraints

$$\sum_{j \in F} \tilde{x}_{\{0\},j}^{v,h} = 1 \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (73)$$

$$\sum_{i \in F} \tilde{x}_{i,|N|}^{v,h} = 1 \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (74)$$

$$\sum_{i \in N} \tilde{x}_{i,\{0\}}^{v,h} = 0 \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (75)$$

$$\sum_{j \in N} \tilde{x}_{|N|,j}^{v,h} = 0 \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (76)$$

XI. Flow Continuity Constraint

$$\sum_{j \in N \setminus \{0\}} \tilde{x}_{i,j}^{v,h} = \sum_{j \in N \setminus \{|N|\}} \tilde{x}_{j,i}^{v,h} \qquad \forall h \in \mathcal{H}, \forall i \in F, \forall v \in \tilde{V} \qquad (77)$$

XII. Deadheading Constraint

$$\sum_{j \in N} (\tilde{x}_{i,j}^{v,h} + \tilde{x}_{j,i}^{v,h}) \leq 2 \cdot \sum_{c \in C_{pickup}(i) \cup C_{dropoff}(i)} \tilde{y}_c^{v,h} \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall i \in F \qquad (78)$$

XIII. Vehicle Scheduling Constraints

$$\widetilde{PUST}_i^{v,h} = \widetilde{DOST}_i^{v,h} + \sum_{c \in C_{dropoff}(i)} \tilde{y}_c^{v,h} \cdot ST_c + \widetilde{WTP}_i^{v,h} \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall i \in N \qquad (79)$$

$$\tilde{Z}_{ij}^{v,h} = \widetilde{PUST}_i^{v,h} + \sum_{c \in C_{pickup(i)}} \tilde{y}_c^{v,h} \cdot ST_c + TT_{ij} + \widetilde{WTD}_j^{v,h} \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall i \in N, \forall j \in N, i \neq j \qquad (80)$$

$$\widetilde{DOST}_j^{v,h} \geq \tilde{Z}_{ij}^{v,h} - M \cdot \left(1 - \tilde{x}_{ij}^{v,h}\right) \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall i \in N, \forall j \in N, i \neq j \tag{81}$$

$$\widetilde{DOST}_j^{v,h} \leq \tilde{Z}_{ij}^{v,h} + M \cdot \left(1 - \tilde{x}_{ij}^{v,h}\right) \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V}, \forall i \in N, \forall j \in N, i \neq j \tag{82}$$

XIV. Time Window Constraints

$$\widetilde{PUT}_c^h = \sum_{v \in \tilde{V}} \tilde{y}_c^{v,h} \cdot \widetilde{PUST}_i^{v,h} \qquad \forall h \in \mathcal{H}, \forall c \in C, i = O_c \tag{83}$$

$$\widetilde{DOT}_c^h = \sum_{v \in \tilde{V}} \tilde{y}_c^{v,h} \cdot \widetilde{DOST}_j^{v,h} \qquad \forall h \in \mathcal{H}, \forall c \in C, j = D_c \tag{84}$$

XV. Timeslot Reservation Constraints

$$\sum_{t \in T} \tilde{z}_{pickup}^{c,t,h} = 1 \qquad \forall h \in \mathcal{H}, \forall c \in C_{pickup} \cup C_{transfer} \tag{85}$$

$$\sum_{t \in T} \tilde{z}_{dropoff}^{c,t,h} = 1 \qquad \forall h \in \mathcal{H}, \forall c \in C_{dropoff} \cup C_{transfer} \tag{86}$$

$$\widetilde{PUT}_c^h \geq \sum_{t \in T} \tilde{z}_{pickup}^{c,t,h} \cdot T_{start}^t \qquad \forall h \in \mathcal{H}, \forall c \in C_{pickup} \cup C_{transfer}, \forall t \in T \tag{87}$$

$$\widetilde{PUT}_c^h \leq \sum_{t \in T} \tilde{z}_{pickup}^{c,t,h} \cdot T_{end}^t + M \cdot \left(1 - \tilde{z}_{pickup}^{c,t}\right) \qquad \forall h \in \mathcal{H}, \forall c \in C_{pickup} \cup C_{transfer}, \forall t \in T \tag{88}$$

$$\widetilde{DOT}_c^h \geq \sum_{t \in T} \tilde{z}_{dropoff}^{c,t,h} \cdot T_{start}^t \qquad \forall h \in \mathcal{H}, \forall c \in C_{dropoff} \cup C_{transfer}, \forall t \in T \tag{89}$$

$$\widetilde{DOT}_c^h \leq \sum_{t \in T} \tilde{z}_{dropoff}^{c,t,h} \cdot T_{end}^t + M \cdot \left(1 - \tilde{z}_{dropoff}^{c,t,h}\right) \qquad \forall h \in \mathcal{H}, \forall c \in C_{dropoff} \cup C_{transfer}, \forall t \in T \tag{90}$$

XVI. Timeslot Capacity Constraints

$$\tilde{g}_{pickup}^{f,t,h} = \sum_{c \in C_{pickup}(f)} \tilde{z}_{pickup}^{c,t,h} \qquad \forall h \in \mathcal{H}, \forall t \in T, \forall f \in F \qquad (91)$$

$$\tilde{g}_{dropoff}^{f,t,h} = \sum_{c \in C_{dropoff}(f)} \tilde{z}_{dropoff}^{c,t,h} \qquad \forall h \in \mathcal{H}, \forall t \in T, \forall f \in F \qquad (92)$$

$$\tilde{g}_{pickup}^{f,t,h} \leq \mu_f^t \qquad \forall h \in \mathcal{H}, \forall f \in F, \forall t \in T \qquad (93)$$

$$\tilde{g}_{dropoff}^{f,t,h} \leq \mu_f^t \qquad \forall h \in \mathcal{H}, \forall f \in F, \forall t \in T \qquad (94)$$

XVII. Waiting Time Constraints

$$\widetilde{WT}_v^h = \sum_{i \in N} \widetilde{WTP}_i^{v,h} + \widetilde{WTD}_j^{v,h} \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (95)$$

$$\widetilde{WT}_v^h \leq \gamma \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (96)$$

XVIII. Variable Constraints

$$\tilde{y}_c^{v,h} \in \{0,1\} \qquad \forall h \in \mathcal{H}, \forall c \in C, \forall v \in \tilde{V} \qquad (97)$$

$$\tilde{x}_{ij}^{v,h} \in \{0,1\} \qquad \forall i,j \in N, \forall v \in \tilde{V}, \forall h \in \mathcal{H} \qquad (98)$$

$$\widetilde{PUST}_i^{v,h}, \widetilde{DOST}_i^{v,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall i \in N, \forall v \in \tilde{V} \qquad (99)$$

$$\tilde{Z}_{ij}^{v,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall i,j \in N, \forall v \in \tilde{V} \qquad (100)$$

$$\widetilde{PUT}_c^h, \widetilde{DOT}_c^h \geq 0 \qquad \forall h \in \mathcal{H}, \forall c \in C \qquad (101)$$

$$\widetilde{WTP}_i^{v,h}, \widetilde{WTD}_i^{v,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall i \in N, \forall v \in \tilde{V} \qquad (102)$$

$$\widetilde{WT}^{v,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall v \in \tilde{V} \qquad (103)$$

$$\tilde{z}_{pickup}^{c,t,h}, \tilde{z}_{dropoff}^{c,t,h} \in \{0,1\} \qquad \forall h \in \mathcal{H}, \forall c \in C, \forall t \in T \qquad (104)$$

$$\tilde{g}_{pickup}^{f,t,h}, \tilde{g}_{dropoff}^{f,t,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall f \in F, \forall t \in T \qquad (105)$$

$$\emptyset_{pickup}^{c,h}, \emptyset_{dropoff}^{c,h} \in R \qquad \forall h \in \mathcal{H}, \forall \in C \qquad (106)$$

$$\psi_{pickup}^{c,h}, \psi_{dropoff}^{c,h} \geq 0 \qquad \forall h \in \mathcal{H}, \forall f \in F, \forall t \in T \qquad (107)$$

$$\sigma_{pickup}^{c,h}, \sigma_{dropoff}^{c,h} \in \{0, 1\} \qquad \forall h \in \mathcal{H}, \forall \in C \qquad (108)$$

$$\rho^{c,h} \in \{0, 1\} \qquad \forall h \in \mathcal{H}, \forall \in C \qquad (109)$$

The Dynamic Rescheduling Model is a model that runs for every horizon h independently. The model is run in real-time, as the new Estimated Times of Arrivals must be known. Based on the model constraints and the previous planning, a new optimal planning is determined. Hence, for $h = 2$, the required inputs for the model are ETA_v^2 for all vehicles v, together with the planning from $h = 1$. Note that for $h = 1$, the required planning is the initial planning ($h = 0$), which can but does not necessarily have to be found using the Static Scheduling Model as described in Chapter 5.1. Hence, the model is run for each horizon interval independently, and the previously found solution is used to find the current solution. This rolling horizon approach enables continuity in planning while introducing flexibility and real-time responsiveness, as determined by the model constraints.

Multiple constraints of the dynamic model are an extension of the constraints used in the static scheduling model. This extension is due to the additional time dimension present in the dynamic model. However, some constraints copied from the static model have been modified, while others have been omitted completely due to their redundancy or irrelevance during the rescheduling process. The dynamic model formulation, as presented in Table 10 starts with the new constraints that are unique for the dynamic rolling horizon model. These constraints include the Dynamic ETA Constraint, Initial Horizon Constraints, Operational Rescheduling Constraints, Rescheduling Tracking Constraints, Reassignment Tracking Constraint, Rescheduling Requirement Constraints, Dynamic Rescheduling Constraints, and Dynamic Reassignment Constraints. A description of these constraints will follow.

I. Dynamic ETA Constraint

Constraint (46) ensures that the arrival time of each vehicle during horizon h is equal to the in real-time updated Estimated Time of Arrival of vehicle v. The new ETAs are the starting point after which the new vehicle schedules are constructed. Consequently, the model can, with the help of this constraint, determine which vehicles are going to miss a previously booked timeslot, and as a result, decide on the rescheduling or reassigning of these appointments.

II. Initial Horizon Constraints

The constraints $(47), (48), (49), (50), (51) \text{ and } (52)$ result in the planning for the initial horizon. These constraints together are sufficient to achieve the exact same initial planning as was determined by the static scheduling model. Constraint (47) sets the container-vehicle mapping constraint (48) the vehicle routes, constraints (49) and (50) the booked timeslots and constraints (51) and (52) the waiting times of the vehicles before the start of each appointment. Hence, these are the core decision variables of the Static Scheduling Model that will determine the value of all other variables in Table 5. Note that all variables are marked with a tilde while initial horizon parameters are marked with a hat. Also note that the initial horizon parameters can be found with the Static Scheduling Model or otherwise.

III. Operational Rescheduling Constraints

Constraint (53) ensures that in every horizon h, each initially utilised vehicle v is assigned at least one container. This reflects the requirement that every vehicle utilised in the initial planning must remain actively utilised in all subsequent time horizons.

Constraint (54) enforces that the vehicle initially assigned to perform a drop-off remains fixed across all subsequent planning horizons. That is because once a vehicle is on the road to carry out a drop-off, the container is already loaded, making it operationally infeasible to reassign it to a different vehicle.

IV. Rescheduling Tracking Constraints

Constraints (55) and (56) calculate the difference between the pick-up respectively drop-off timeslot that was reserved during the previous time horizon and that is reserved during the current time horizon. Hence, $\emptyset_{pickup}^{c,h}$ and $\emptyset_{dropoff}^{c,h}$ are continuous variables, which take a positive value if the timeslot reserved during horizon h is greater than the timeslot reserved during horizon h, and a negative value if the opposite is the case. As $\tilde{z}_{pickup}^{c,t,h}$ and $\tilde{z}_{dropoff}^{c,t,h}$ are binary variables, this is multiplied by the value of the timeslot t, resulting in the actually booked timeslot once the binary variable is equal to one. If in the dynamic planning system timeslots are only to be rescheduled later than the currently scheduled timeslot, a constraint can be added that restricts the values of $\emptyset_{pickup}^{c,h}$ and $\emptyset_{dropoff}^{c,h}$ to be positive only.

Constraints (57) and (58) calculate the value of the non-negative continuous variables $\psi_{pickup}^{c,h}$ and $\psi_{dropoff}^{c,h}$ respectively. These auxiliary variables are introduced to not make a distinction between appointments rescheduled to an earlier or to a later timeslot. Hence, if $\psi_{dropoff}^{c,h} = 3$, then this implies that during time horizon h, the drop-off appointment for container c has been rescheduled to either three timeslots earlier or three timeslots later.

Constraints (59), (60), (61) and (62) determine the values of the binary variables $\sigma_{pickup}^{c,h}$ and $\sigma_{dropoff}^{c,h}$, which is equal to one if the pick-up appointment respectively drop-off appointment for container c has indeed been rescheduled during time horizon h, regardless of how many timeslots is has moved up or down the schedule.

V. Reassignment Tracking Constraints

Constraint (63) keeps track of the container reassignment interferences that the model determines. It states that if container c was assigned to vehicle v during the previous time horizon (i.e., $\tilde{y}_c^{v,h-1} = 1$), then for time horizon h, either the variable $\tilde{y}_c^{v,h}$ is equal to one or the variable $\rho^{c,h}$ is equal to one. If the former is equal to one, then the container is still assigned to the same vehicle during horizon h as it was assigned to during horizon h-1. If the former, however, is not equal to one, then container c has indeed been rescheduled to a different vehicle during horizon h as opposed to horizon h-1, enforcing the binary variable $\rho^{c,h}$ to be set to one.

VI. Rescheduling Requirement Constraints

Constraints (64) and (65) states that if the pick-up respectively drop-off appointment for container c is rescheduled during time horizon h (i.e. $\sigma_{pickup}^{c,h} = 1\ or\ \sigma_{dropoff}^{c,h} = 1$), then the new pick-up respectively drop-off time of container c must be greater than or equal to the current actual time. Hence, this constraint makes sure that appointments that are rescheduled at the time being are only rescheduled into the future, as appointment cannot be rescheduled to the past. If an appointment is not rescheduled (i.e. $\sigma_{pickup}^{c,h} = 0\ or\ \sigma_{dropoff}^{c,h} = 0$), then the new pick-up respectively drop-off time of container c must be greater than or equal to zero, which is always the case. Note that these constraints, however, do not restrict containers to be rescheduled to an earlier timeslot compared to the previously reserved timeslot, as these constraints only limit new reserved timeslot to be greater than or equal to the current actual time.

VII. Dynamic Rescheduling Constraints

Constraint (66) and (67) restrict the rescheduling of appointments for on-time vehicles. It ensures that if vehicle v is on-time during time horizon h, then the pick-up and drop-off times of the containers assigned to it should be equal to the pick-up and drop-off times during the previous horizon. Hence, these constraints prevent vehicles that are on-time to be penalised with waiting time. Note that without these constraints, the model has the flexibility to reschedule any appointment. Constraint (66) and (67) hence enforce a certain rescheduling policy, which in the dynamic rescheduling model is to limit the rescheduling during horizon h only to vehicles that are late during that horizon.

VIII. Dynamic Reassignment Constraints

Constraint (68) restricts the reassignment of containers for which the vehicle is on-time. If vehicle v is on time during horizon h, then any container previously assigned to it should remain assigned to this vehicle. Note that this constraint only restricts containers to be taken away from on-time vehicles, but does not restrict the assignment of additional containers to on-time vehicles. In other words, already assigned containers are not allowed be taken away from on-time vehicles, while new containers are allowed to be assigned to on-time vehicles.

The remaining constraints of the dynamic model are all comparable to the static model in addition to the variable constraints. These remaining constraints ensure that the model runs smoothly and that the new planning after rescheduling and reassignment remains valid. The following tables show a comparison between the constraints used for both models. A description of these constraints, without the addition of the time horizon dimension, can be found in Chapter 5.1.3. It can be concluded that all constraints from the static model are included in the dynamic model, with the exception of the vehicle utilization constraints (5), (6) and (7) due to their irrelevance, as well as the time window constraint (21) and (22) which can cause model infeasibility due to vehicle delays.

IX. Container Assignment Constraints

Table 11. Dynamic vs Static Model: Container Assignment Constraints.

Dynamic Model	(69)	(70)	(71)	(72)
Static Model	(1)	(2)	(3)	(4)

X. Vehicle Entry and Exit Constraints

Table 12. Dynamic vs Static Model: Vehicle Entry and Exit Constraints.

Dynamic Model	(73)	(74)	(75)	(76)
Static Model	(8)	(9)	(10)	(11)

XI. Flow Continuity Constraint

Table 13. Dynamic vs Static Model: Flow Continuity Constraint.

Dynamic Model	(77)
Static Model	(12)

XII. Deadheading Constraint

Table 14. Dynamic vs Static Model: Deadheading Constraint.

Dynamic Model	(78)
Static Model	(13)

XIII. Vehicle Scheduling Constraints

Table 15. Dynamic vs Static Model: Vehicle Scheduling Constraints.

Dynamic Model	(79)	(80)	(81)	(82)
Static Model	(14)	(15)	(16)	(17)

XIV. Time Window Constraints

Table 16. Dynamic vs. Static Model: Time Window Constraints.

Dynamic Model	(83)	(84)	-	-
Static Model	(19)	(20)	(21)	(22)

XV. Timeslot Reservation Constraints

Table 17. Dynamic vs. Static Model: Time Window Constraints.

Dynamic Model	(85)	(86)	(87)	(88)	(89)	(90)
Static Model	(23)	(24)	(25)	(26)	(27)	(28)

XVI. Timeslot Capacity Constraints

Table 18. Dynamic vs. Static Model: Timeslot Capacity Constraints.

Dynamic Model	(91)	(92)	(93)	(94)
Static Model	(29)	(30)	(31)	(32)

XVII. Waiting Time Constraints

Table 19. Dynamic vs. Static Model: Waiting Time Constraints.

Dynamic Model	(95)	(96)
Static Model	(33)	(34)

XVIII. Variable Constraints

Constraints (97), (98), (99), (100), (101), (102), (103), (104), (105), (106), (107), (108) and (109) are variable constraints, enforcing variables to be either binary, non-negative or continuous.

6. Model Implementation

This chapter presents the application of the two models developed in Chapter 5. This application is done by integrating two simulations with the scheduling models. These simulations include a trip simulation and a dynamic ETA simulation. The former simulation serves as the primary input for the Static Scheduling Model, which then results in an initial planning. This together with the Dynamic ETA Simulation are used to run the Dynamic Rescheduling Model, which then provides the optimal planning per time horizon for this specific simulation. This followed approach is illustrated in Figure 15.

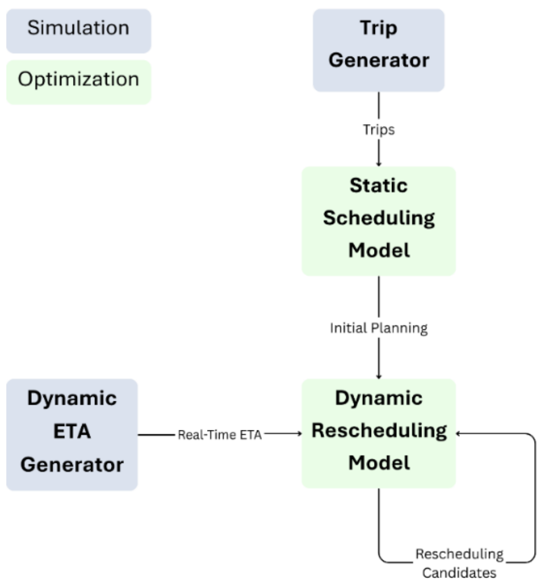

Figure 15. Simulation-Optimisation integration for approaching the model application.

This simulation-optimisation integration approach is highly versatile, as several configurations can be adjusted to explore different system behaviours. These configurations fall into three main categories: the coordination policy applied in the dynamic model, the objective function using during rescheduling optimisation, and the planning parameter that are adjusted for the construction of the simulation. Seven distinct scenarios are developed to analyse the results of different configurations.

Chapter 6.1 covers the two simulations used for the model application. Chapter 6.2 discusses the various model configurations after which Chapter 6.3 77.4covers the scenario design and Chapter 6.4 the scenario analysis. Based on these results, a multi-objective optimisation approach is followed in section 7.3. Chapter 8 concludes the findings of the model application.

6.1. Simulation Framework

Two simulations are developed to create a realistic dataset for applying and evaluating the rolling horizon model. First, the Trip Generator aims to realistically simulate container flows in the port logistics environment, after which the Dynamic ETA Generator creates a realistic progression of the Estimated Times of Arrival. These two simulations are developed in Python and integrated with the two optimisation models that were covered in Chapter 5.

6.1.1. Trip Simulation

One of the data requirements for the static scheduling model is a set of container transportation requests that need to be executed. To simulate realistic container flows in a port logistics environment, a generalised Trip Generator function is developed. This function generates container trips, with each trip characterised by an origin, destination, trip type, and assigned carrier, which all happen based on a weighted random selection.

The assignment of a certain trip to a road carrier is done using an exponential decaying function $(i+1)^{exp}$, in which i is the carrier number, and exp is the parameter that controls the degree of skew, with a high value resulting in a few dominant carriers receiving the majority of trips. This distribution reflects the observation that a relatively small number of carriers are huge players in the market that receive a large number of container transportation requests, while a substantial portion of the players in the market are small carriers that receive a relatively smaller amount of transportation requests. Figure 16 shows the distribution of the 500 trips across the carriers.

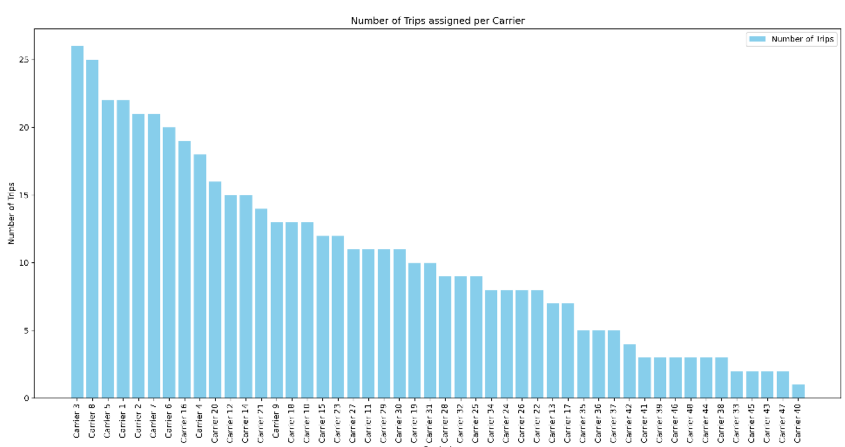

Figure 16. Simulation: Number of trips per carrier.

The generator also probabilistically determines the trip type of each trip, which can either be a pick-up, drop-off, or transfer. The presence probabilities for this simulation are set to be 0.3 for pick-ups, 0.3 for drop-offs, and 0.4 for transfers. The generated dataset consists of 500 trips, with each having an origin (pick-up location), a destination (drop-off location), and an assigned carrier. This dataset is used as the primary input for the Static Scheduling Model to find an initial planning that schedules all container transportations. The generated container trip dataset is partially shown in Figure 17. Furthermore, the resulting initial planning, found by the static scheduling model, is partially shown in Figure 18.

Container ID	Origin	Destination	Trip Type	Carrier
0	Inbound Port Gate	Depot 1	Drop-off	Carrier 9
1	Depot 1	Terminal 2	Transfer	Carrier 2
2	Depot 1	Terminal 1	Transfer	Carrier 18
3	Terminal 1	Outbound Port Gate	Pick-up	Carrier 3
4	Depot 1	Outbound Port Gate	Pick-up	Carrier 3
5	Inbound Port Gate	Depot 1	Drop-off	Carrier 4
6	Inbound Port Gate	Depot 1	Drop-off	Carrier 18
7	Depot 1	Terminal 1	Transfer	Carrier 12
8	Inbound Port Gate	Terminal 1	Drop-off	Carrier 8
9	Depot 1	Outbound Port Gate	Pick-up	Carrier 18
10	Depot 1	Outbound Port Gate	Pick-up	Carrier 5
11	Inbound Port Gate	Depot 1	Drop-off	Carrier 5
12	Inbound Port Gate	Terminal 1	Drop-off	Carrier 2
13	Terminal 2	Outbound Port Gate	Pick-up	Carrier 15
14	Terminal 1	Terminal 2	Transfer	Carrier 14
15	Inbound Port Gate	Terminal 1	Drop-off	Carrier 7
16	Inbound Port Gate	Terminal 2	Drop-off	Carrier 3
17	Terminal 1	Depot 1	Transfer	Carrier 33
18	Terminal 2	Outbound Port Gate	Pick-up	Carrier 4
19	Terminal 1	Outbound Port Gate	Pick-up	Carrier 4
20	Inbound Port Gate	Depot 1	Drop-off	Carrier 41

Figure 17. Generated Container Transportation Requests Dataset (partially).

📋 Truck Schedule

T	Origin	Destination	Con	WTP	**PUST**	ST_P	TT	WTD	**DOST**	ST_D
0	Inbound Port Gate	Terminal 1	375	00:00	07:29	00:00	00:30	00:00	07:59	00:20
0	Terminal 1	Terminal 2	-	00:00	08:19	-	00:30	00:00	08:49	-
0	Terminal 2	Depot 1	77	00:00	08:49	00:00	00:30	00:00	09:19	00:00
0	Depot 1	Outbound Port Gate	-	00:00	09:19	-	00:30	00:00	09:49	-
1	Inbound Port Gate	Depot 1	340	00:00	01:30	00:00	00:30	00:00	02:00	00:20
1	Depot 1	Outbound Port Gate	230	00:00	02:20	00:30	00:30	00:00	03:20	00:00
2	Inbound Port Gate	Depot 1	451	00:00	11:30	00:00	00:30	00:00	12:00	00:20
2	Depot 1	Outbound Port Gate	-	00:00	12:20	-	00:30	00:00	12:50	-
4	Inbound Port Gate	Terminal 1	-	00:00	22:00	-	00:30	00:00	22:30	-
4	Terminal 1	Terminal 2	485	00:00	22:30	00:00	00:30	00:00	23:00	00:00
4	Terminal 2	Depot 1	126	00:00	23:00	00:00	00:30	00:00	23:30	00:00
4	Depot 1	Outbound Port Gate	-	00:00	23:30	-	00:30	00:00	24:00	-
5	Inbound Port Gate	Terminal 1	-	00:00	00:00	-	00:30	00:00	00:30	-
5	Terminal 1	Depot 1	449	00:00	00:30	00:00	00:30	00:00	01:00	00:00
5	Depot 1	Outbound Port Gate	-	00:00	01:00	-	00:30	00:00	01:30	-
7	Inbound Port Gate	Terminal 2	-	00:00	13:29	-	00:30	00:00	13:59	-
7	Terminal 2	Outbound Port Gate	243	00:00	13:59	00:30	00:30	00:00	14:59	00:00
8	Inbound Port Gate	Depot 1	385	00:00	03:29	00:00	00:30	00:00	03:59	00:20
8	Depot 1	Terminal 2	141	00:00	04:19	00:00	00:30	00:00	04:49	00:00
8	Terminal 2	Outbound Port Gate	-	00:00	04:49	-	00:30	00:00	05:19	-
9	Inbound Port Gate	Terminal 2	263	00:00	07:30	00:00	00:30	00:00	08:00	00:20
9	Terminal 2	Outbound Port Gate	-	00:00	08:20	-	00:30	00:00	08:50	-
10	Inbound Port Gate	Depot 1	-	00:00	14:30	-	00:30	00:00	15:00	-
10	Depot 1	Terminal 1	296	00:00	15:00	00:00	00:30	00:00	15:30	00:00
10	Terminal 1	Terminal 2	-	00:00	15:30	-	00:30	00:00	16:00	-
10	Terminal 2	Outbound Port Gate	299	00:00	16:00	00:30	00:30	00:00	17:00	00:00

Figure 18. Initial Planning found by integrating the trip generator simulation with the static scheduling model (partially).

Based on this initial planning, the scheduled arrivals times of each vehicle are determined. These arrival times are then put into the Dynamic ETA Generator to add disruption, generating an Estimated Time of Arrival per utilised vehicle per horizon. This process is covered in the next section.

6.1.2. Dynamic ETA Simulation

The Dynamic ETA Generator is used to simulate a realistic progress of the Estimated Times of Arrival. The initial ETA of each utilised vehicle is equal to the scheduled arrival time in the initial planning, which is determined by the Static Scheduling Model. This initialisation forms the baseline for the progression.

At each subsequent horizon for $\forall h \in \mathcal{H}$, the generator updates vehicle ETAs using certain conditions. There are two conditions in which the updated ETA of the vehicle is equal to the previous ETA:

1. If a vehicle has already arrived at the port, i.e. if the actual time during the current horizon update is greater than the previous Estimated time of Arrival of vehicle v, then the previous horizon ETA is equal to the current horizon ETA for vehicle v as this implies that the vehicle has already arrived at the port. This condition is modelled such that if for vehicle v during horizon h, $ETA_{h-1}^{v} < \tau_h$, then $ETA_h^v = ETA_{h-1}^{v}$.
2. If the vehicle is still too far away from the port, following a certain threshold distance (D), then the previous ETA remains unchanged for the current horizon. In this case, the vehicle is still too far to adjust its estimated time of arrival as it may not have departed yet. This condition is modelled such that if for vehicle v during horizon h, $ETA_{h-1}^{v} - \tau_h > D$, then $ETA_h^v = ETA_{h-1}^{v}$.

These two conditions prevent the simulation of unrealistic updates to the ETAs. If neither of the conditions is satisfied, the ETA_h^v is delayed probabilistically using a Gaussian distribution, which takes into consideration two realistic factors. The first factor is congestion profiles, and the second factor is proximity to the port uncertainty. The congestion profiles divide the day into three profiles. High congestion is introduced during the morning and evening congestion hours, during which the mean and standard deviation of the delays are increased. During working hours, the mean and standard deviation are moderate, while during off-peak hours (early mornings and late nights) these values are low. The second factor that is featured in the formula, the proximity to the port factor, takes into consideration that vehicles far from the port have a less certain Estimated Time of Arrival as opposed to vehicles closer to the port. Therefore, the standard deviation of vehicle v that is still far from the port during horizon h is greater than the standard deviation of its delay when it is approaching the port. The formulas that are used to simulate a probabilistic dynamic ETA formula using a Gaussian distribution are:

$$f(x) = \frac{1}{\sqrt{2 \cdot \pi \cdot \sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{110}$$

Where f(x) is equal to the delay of a certain vehicle during a certain time horizon. Furthermore,

$$\mu = \bar{\mu} \cdot \kappa \tag{111}$$

$$\sigma = \bar{\sigma} \cdot (\kappa + \frac{d_v}{D}) \tag{112}$$

Where $\bar{\mu}$ is the base mean, $\bar{\sigma}$ the base standard deviation, κ the congestion severity parameter, d_v the distance to the port for vehicle v during horizon h, and D the distance threshold. The base mean and base standard deviation are determined based on the time of the day, such that ETA's that are being updated during morning and evening times receive larger delays compared to working hours and off-peak hours. Furthermore, note that the $\frac{d_v}{D}$ models the proximity to the port factor, resulting in a greater standard deviation if the vehicle is further away. Hence, the parameters $\bar{\mu}$ and $\bar{\sigma}$ model the congestion profiles, while the proximity to the port factor is modelled by the parameter $\frac{d_v}{D}$. Lastly, the congestion intensity can be determined by κ.

Figure 19 illustrates the average delay that is added to the Estimated Times of Arrivals of the on-road vehicles throughout the day. For this simulation, a distance threshold (D) of 120 minutes is chosen. Hence, disruptions are added to arrival times only if the remaining travel time of a vehicle is less than 120 minutes.

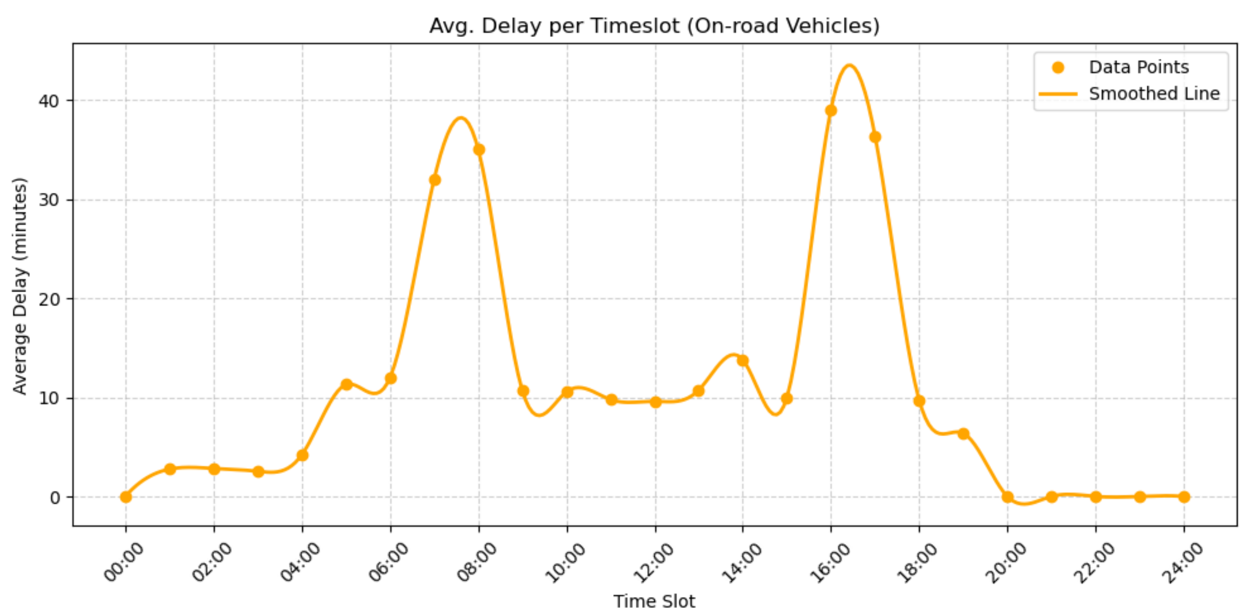

Figure 19. Delay of on-road vehicles during the day.

6.2. Model Configurations

The integrated simulation-optimisation framework as illustrated in Figure 15 is a highly versatile model in which multiple configurations can be adjusted. Three different configurations are identified: the coordination policy, the rescheduling objective, and the planning parameters. Each possible configuration modification will be discussed further.

6.2.1. Coordination Policy

The coordination policy determines who the rescheduling candidates are during the rescheduling process. As explained in Chapter 3.4, there are two possible ways to re-optimise the schedule that has been disrupted by delayed vehicles, which is by either rescheduling or reassigning. The former implies that the previously reserved timeslot is cancelled and replaced with a new appointment. Reassigning an activity means that the reserved appointment is carried over to another vehicle that is still able to make the appointment on time. A combination of rescheduling and reassigning can also take place, for example, due to terminal handling capacity limitations or vehicle-specific constraints.

Three distinct coordination policies are formulated: static rescheduling, dynamic rescheduling, and dynamic rescheduling with reassignment. Table 20 provides an overview of the coordination policies and the constraints that enforce the chosen policy. Note that the Dynamic Rescheduling Model, as formulated in Chapter 5.2.3 corresponds to the last coordination policy, which has the highest degree of coordination flexibility. The constraints that enforce this policy are (66), (67) and (68). Hence, for policies 1 and 2, these constraints must be omitted from the dynamic model and replaced with the constraints as mentioned in Table 20. Furthermore, to be able to model the first coordination policy, the Dynamic ETAs are replaced with Static ETAs.

Table 20. Coordination Policy Constraints per Scenario.

Coordination Policy	**Coordination Mechanisms**		**Vehicle ETAs Dataset**	**Coordination Flexibility Constraints**	
	Rescheduling	Reassignment		Rescheduling Constraints	Reassignment Constraints
Static Rescheduling	Static	Disabled	Static ETAs	(113), (114)	(115)
Dynamic Rescheduling	Dynamic	Disabled	Dynamic ETAs	(66), (67)	(115)
Dynamic Rescheduling & Reassignment	Dynamic	Enabled	Dynamic ETAs	(66), (67)	(68)

Table 21. Formulation of the Static Rescheduling Constraints & Disabled Reassignment Constraints.

Static Rescheduling Constraints		
$\sum_{t \in T} \tilde{z}_{pickup}^{c,t,h} \cdot t = \sum_{t \in T} \tilde{z}_{pickup}^{c,t,h-1} \cdot t$	$\forall h \in \mathcal{H} \setminus \{0\}$, $\forall v \in \tilde{V}_{non-arriving}^{h}$, $\forall c \in C_{pickup} \cup C_{transfer}$, $if\ \hat{y}_c^v = 1$:	(113)
$\sum_{t \in T} \tilde{z}_{dropoff}^{c,t,h} \cdot t = \sum_{t \in T} \tilde{z}_{dropoff}^{c,t,h-1} \cdot t$	$\forall h \in \mathcal{H} \setminus \{0\}$, $\forall v \in \tilde{V}_{non-arriving}^{h}$, $\forall c \in C_{dropoff} \cup C_{transfer}$, $if\ \hat{y}_c^v = 1$:	(114)
Disabled Reassignment Constraint		
$\tilde{y}_c^{v,h} = \hat{y}_c^v$	$\forall h \in \mathcal{H}$, $\forall v \in \tilde{V}$, $\forall c \in C$	(115)

Static Rescheduling Constraints

Constraints (113) and (114) state that all pick-up and drop-off appointments that belong to a vehicle that is not arriving at the port during horizon h, should keep the same pick-up or drop-off timeslot reservations. Hence, $v \notin \tilde{V}_{non-arriving}^{h}$ if vehicle v is not arriving at the port during horizon h. Note that $\tilde{V}_{non-arriving}^{h} \subset \tilde{V}$, and that each vehicle is present in all sets $\tilde{V}_{non-arriving}^{h}$ for all horizons except for one horizon, which is the time horizon in which vehicle v actually arrives at the port. According to Figure 20, vehicle 3 is to be found in every set $\tilde{V}_{non-arriving}^{h}$, except in $\tilde{V}_{non-arriving}^{480}$, as this is the time horizon in which vehicle 3 is arriving at the port. Constraints (113) and (114) therefore only allows rescheduling to take place during the actual arrival of vehicles. Note that these constraints therefore limit rescheduling to take place at most once per vehicle.

Disabled Reassignment Constraint

Constraint (115) enforces that the vehicle-container assignments remain fixed through the entire rolling horizon model. It states that for each time horizon h, the containers assigned to vehicle v ($\tilde{y}_c^{v,h}$) are equal to the containers assigned to vehicle v in the initial planning ($\hat{y}_c^v$). Hence, containers are never reassigned to another vehicle during the entire planning horizon.

Static vs Dynamic ETAs

For the static rescheduling policy, the vehicle ETAs are not known in real-time, but rather remain unknown until the actual arrival of the vehicle. Therefore, upcoming appointments that are going to be missed cannot be cancelled on-time, but lead to after-the-fact no-shows. This policy assumes that there is no information flow between facilities and carriers, as vehicles do not inform facilities of their incapability to make an appointment, nor are facilities able to share updated timeslot availability to the carriers. This policy, therefore inevitably results in the underutilization of the terminal capacity.

The static rescheduling policy is modelled by introducing a new dataset of Static ETAs to be used for constraint (46). This dataset keeps the vehicle ETAs fixed until the Actual Time of Arrival (ATA) of the vehicle is known, i.e. until the vehicle has actually arrived at the port. The Static ETAs dataset is created from the Dynamic ETAs dataset, as illustrated in Figure 20. For instance, the dynamic ETA of vehicle 2 is continuously updated from the moment it departs up until its actual arrival, i.e. from horizon 900 until horizon 1140, while the static ETA of vehicle 2 is only updated once, during its actual arrival at time horizon 1140. Hence, ETAs are updated only once per vehicle, which is during the actual arrival of the vehicle, and consequently, rescheduling can only happen at most once per vehicle.

	0	60	120	180	240	300	360	420	480	540	600	660	720	780	840	900	960	1020	1080	1140	1200
0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1170.0
2	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	1114.0	1114.0
3	430.0	430.0	430.0	430.0	430.0	430.0	430.0	430.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0
5	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0
6	450.0	450.0	450.0	450.0	450.0	450.0	450.0	450.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0
8	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	1008.0	1008.0	1008.0	1008.0
10	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	823.0	823.0	823.0	823.0	823.0	823.0	823.0

	0	60	120	180	240	300	360	420	480	540	600	660	720	780	840	900	960	1020	1080	1140	1200
0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1150.0	1165.0	1170.0	1170.0
2	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	989.0	1014.0	1078.0	1104.0	1114.0	1114.0	1114.0
3	430.0	430.0	430.0	430.0	430.0	430.0	445.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0	455.0
5	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0	1350.0
6	450.0	450.0	450.0	450.0	450.0	450.0	450.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0	473.0
8	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	990.0	998.0	1008.0	1008.0	1008.0	1008.0	1008.0
10	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	810.0	812.0	823.0	823.0	823.0	823.0	823.0	823.0	823.0	823.0

Figure 20. Static (above) vs Dynamic (below) Estimated Times of Arrivals per vehicle per horizon.

Rescheduling Candidates

The rescheduling candidates of horizon h is the set of all vehicles that can potentially be rescheduled during that horizon, while all other vehicles keep the timeslot that was previously reserved. For policy 1, the candidates are the vehicles that actually arrive, while in policy 2 and 3, the set of rescheduling candidates are all the vehicles that are delayed during horizon h. The larger the set of rescheduling candidates during a certain horizon, the higher the degree of flexibility to re-optimise the planning.

6.2.2. Rescheduling Objective

The updated planning at each horizon, which is generated by the dynamic rescheduling model, is strongly influenced by the chosen objective function. Different objectives can be identified, which reflect varying priorities of the stakeholders involved in the process, particularly the terminal operators and the road carriers. To model these diverse perspectives, three primary rescheduling objectives are defined. Each objective represents a different optimisation strategy, prioritising from a different stakeholder perspective.

1. **Port-wide Optimisation**

This approach prioritises overall system efficiency by minimising the total waiting times within the port, and hence preventing port congestion at all costs. This approach does not distinguish between the severity of delays of individual vehicles.

$$min \sum_{v \in V} WT^{v,h} \qquad \forall h \in \mathcal{H} \qquad (116)$$

2. **Balanced Waiting Time Optimisation**

In this objective, the model still minimises total waiting time, but weights are introduced to penalise the waiting time of a vehicle according to its delay. This promotes fairness by prioritising the rescheduling of slightly delayed vehicles before heavily delayed vehicles:

$$min \sum_{v \in V} WT^{v,h} \cdot \lambda_{\mathrm{v}}^{\mathrm{h}} \qquad \forall h \in \mathcal{H} \qquad (117)$$

The parameter $\lambda_{\mathrm{v}}^{\mathrm{h}}$ is the penalty weight for the waiting time of vehicle v during horizon h, which can be calculated using the formula: $\lambda_{\mathrm{v}}^{\mathrm{h}} = \frac{1}{\sqrt{1+\Delta_v^h}}$ Hence, slightly delayed vehicles are less likely to get penalised with waiting times compared to heavily delayed vehicles.

3. **Operator-focused Optimisation**

From the terminal operator's perspective, the goal is to minimise the number of cancelled appointments. Disruption caused by frequent rescheduling has a negative impact on operational stability for terminal operators. This objective, therefore, aims to reduce deviations from the previous schedule by penalising the rescheduled appointments:

$$min \sum_{c \in C} \sigma_{pickup}^{c,h} + \sigma_{dropoff}^{c,h} \qquad \forall h \in \mathcal{H} \qquad (118)$$

6.2.3. Planning Parameters

The final model configuration considered for the model application involves the adjustment of the planning parameters. This makes it possible to test the robustness of the system under different external conditions or parameter tweaks. It can also provide insights into the consequences of certain strategic and operational decisions and their impact on overall system performance. By changing these parameters, an entirely new simulation is conducted, as this will change the foundational input of the model.

The planning parameters that can be adjusted to run different simulations include:

1. **Congestion Severity (κ)**

Changing the congestion severity in Equation (111) and (112) will change the magnitude of delays. By increasing κ, more severe congestion during low and high peaks can be simulated. This allows the testing of the model's ability to handle increased uncertainty.

2. **Number of Containers (C)**

Increasing the number of required container transportations adds complexity to the system but may also increase the flexibility in rescheduling and reassignment, which can potentially lead to more efficient solutions.

3. **Number of Facilities (F)**

Similar to an increased number of containers, by adding more facilities, the system complexity increases. However, this may result in higher flexibility to coordinate between vehicles and timeslot appointments during the rescheduling process.

4. **Timeslot Duration (TSD)**

Shorter timeslot durations make appointments more strict, which increases the likelihood of missing appointments. In contrast, by increasing timeslot durations, the risk that a vehicle misses its reserved timeslot is reduced, hence decreasing the number of required reschedules. This reduction in reschedules means that terminal operators can be more certain that reserved timeslots will be fulfilled as planned.

5. **Facility Capacity (μ_f^t)**

Reducing facility capacity encourages a more uniform distribution of appointments throughout the day, as the system is forced to spread container handling more evenly. Similarly, changing the facility opening hours, which can be enforced in the model by setting the facility capacity to zero (i.e., $\mu_f^t = 0$) for certain timeslots, can also lead to a more even distribution of appointments among the available timeslots.

6. **Fleet Size ($\boldsymbol{\beta}$)**

Lowering the number of utilised vehicles, i.e. the fleet size, in the planning will increase the average number of assigned appointments per vehicle, hence leading to an increased average dwell time. If the average number of assigned appointments per vehicle is increased, then the consequence of the vehicle's delay is more severe, as its delay now affects more appointments. Hence, lowering the number of utilised vehicles leads to a greater vulnerability to delay propagation. Furthermore, by utilizing fewer vehicles, there is less flexibility to reassign during the coordination process, leading to fewer alternative solutions. In contrast, adding slack in the schedule by utilising more vehicles will increase the flexibility during rescheduling and will enable vehicles belonging to the same road carrier to compensate for each other's delays.

7. **Maximum Allowed Turnaround Time ($\boldsymbol{\delta_v}$)**:

Increasing the maximum allowed turnaround time at the port allows more containers to be assigned to a single vehicle during both scheduling and rescheduling, potentially improving efficiency during rescheduling.

By adjusting these parameters, multiple simulations can be performed to analyse the system's sensitivity and behaviour under varying conditions. This enables a deeper understanding of how internal or external factors, such as congestion levels and vehicle availability, impact the performance of the system. It can also help in identifying potential bottlenecks and thresholds beyond which operational efficiency decreases. The insights that can be gained from these simulations are valuable for both strategic planning and real-time decision-making, especially in complex and dynamic environments like port logistics.

Note that the planning parameters influence the entire system setup, including the input structure, initial planning, and truck arrival patterns, while the rescheduling policy and rescheduling objective only define the internal logic of the dynamic model. In other words, changing planning parameters results in an entirely new simulation, while changing the rescheduling policy or objective keeps the same simulation while only changing the desired approach of the rescheduling process. Therefore, caution is necessary when drawing conclusions after changing planning parameters, as differences in outcomes may be caused by input variability rather than the adjustment of the planning parameter, particularly when the sample size is small. In contrast, changes to the rescheduling policy or rescheduling objective are evaluated on the same underlying dataset, meaning that any improvements observed can be directly attributed to enhancements in the dynamic model.

6.3. Scenario Design

By combining different model configurations, a wide range of scenarios can be constructed. For the sake of scoping, seven representative and realistic scenarios have been selected for the scenario analysis. Each scenario consists of a certain coordination policy and rescheduling objective. Each subsequent scenario introduces a change in only one configuration relative to the previous one. This makes a meaningful scenario analysis possible as the impact of each adjustment is analysed in isolation. An overview of the designed scenarios is presented in Table 22.

Table 22. Overview of the scenarios constructed for the Scenario Analysis.

Scenario	Description	Coordination Policy	Rescheduling Objective
1	Static Rescheduling - Flexible Operators	1	1
2	Static Rescheduling - Rigid Operators	1	3
3	Dynamic Rescheduling – Flexible Operators & Cooperative Carriers	2	1
4	Dynamic Rescheduling – Flexible Operators & Competitive Carriers	2	2
5	Dynamic Rescheduling – Rigid Operators	2	3
6	Dynamic Rescheduling + Reassignment - Flexible Operators	3	1
7	Dynamic Rescheduling + Reassignment - Rigid Operators	3	3

1. **Static Rescheduling – Flexible Operators**

This scenario assumes no real-time updates to vehicle ETAs. As discussed in Section 6.2.1, it represents a setup with minimal coordination, and this scenario is therefore acting as the worst-case benchmark to be able to compare to what degree real-time data sharing can improve the coordination system.

2. **Static Rescheduling – Rigid Operators**

Similar to scenario 1, no real-time data sharing is assumed. However, this scenario aims to reduce the number of reschedules rather than the vehicle waiting times.

3. **Dynamic Rescheduling – Flexible Operators & Cooperative Carriers**

In this scenario, real-time data sharing between carriers and terminals is enabled, leading to dynamic rescheduling. Stakeholders collectively aim to minimise overall waiting times to prevent congestion at the port. Reassignment is disabled, for example, due to technological or operational limitations—e.g., carriers are not yet equipped with technology to facilitate reassignment, or facilities are enforcing vehicle-specific handling rules.

4. **Dynamic Rescheduling – Flexible Operators & Competitive Carriers**

This scenario builds on scenario 3 but shifts the focus from cooperative, port-wide optimisation to a fairer distribution of waiting times among delayed vehicles. Carriers now prioritise individual performance over system-wide performance. Note that as rescheduling priority is based on delay severity, the traditional use of grace periods—buffer times after the timeslot's end during which delayed vehicles are not rescheduled—becomes obsolete as priority during the rescheduling process is given to the delayed vehicles based on their delay severity.

5. **Dynamic Rescheduling – Rigid Operators**

In this scenario, terminal flexibility is reduced to facilitate only the necessary reschedules. This reflects the terminal operators' objective to minimise appointment cancellation, due to constraints related to container stacking, hence improving their internal operational planning. In this scenario, cancelling an appointment can be prevented by adding waiting times. Note that while the number of reschedules is minimised, the vehicle waiting time still has an upper limit to prevent excessive delays, as defined by constraint (96).

6. **Dynamic Rescheduling + Reassignment – Flexible Operators & Cooperative Carriers**

This scenario builds on scenario 3 by enabling reassignment. This significantly increases the system's flexibility to coordinate between delayed vehicles and reserved timeslots.

7. **Dynamic Rescheduling + Reassignment – Rigid Operators**

The final scenario is similar to scenario 4 in terms of prioritising the operator's objective, but now introduces reassignment capabilities. Missed appointments can now be resolved not only by adding vehicle waiting times but also by reassigning the appointment to a different vehicle belonging to the same carrier. This allows the analysis of whether the added flexibility of reassignment can compensate for operator rigidity.

6.4. Model Environment

The previously designed scenarios were executed within the developed model environment. The simulation generated 500 trips, which were randomly distributed across 48 trucking companies of varying sizes.

The model setup included three facilities: two terminals and one empty depot. The probability of an inter-terminal transfers was set to 30%. The trip simulation resulted in 182 pick-ups, 178 drop-offs, and 140 inter-terminal transfers, which consists of both a pick-up and drop-off activity. Therefore, the total number of scheduled appointments during scheduling and rescheduling were constantly equal to 640. The static scheduling model—used to generate the initial planning—determined that 388 trucks were required to fulfil all trip demands. For the dynamic ETA simulation, the congestion severity parameter was set to 1, resulting in a total delay of 12,884 minutes across all time horizons and an average delay of 33.2 minutes per vehicle.

The model parameters remained constant across both the scheduling and rescheduling models. The service times were fixed at 30 minutes for pick-up and 20 minutes for drop-offs, applied uniformly across all facilities. Each timeslot was defined as a 60-minute interval, with a timeslot capacity of 10 vehicles per service type (pick-up or drop-off) per facility. Lastly, the intra-port travel time between any two facilities was set to 30 minutes.

The model was implemented in Python and solved using the Gurobi Optimizer. All computational experiments and simulations were carried out on a local computer with the following hardware specifications:

- CPU: 12th Gen Intel(R) Core(TM) i5-12450H
- Cores: 8 physical, 12 logical processors (4 threads used)
- Instruction sets: SSE2, AVX, AVX2
- RAM: 7.7 GB

Across all simulated scenarios, the computation time remained within practical bounds. The total runtime of the entire simulation process was consistently around 1700 seconds. Solving the static model component of the model required approximately 33 seconds, while the dynamic rolling horizon model took around 96 seconds. Both achieved a 0.00% optimality gap. The remaining computational time was primarily due to the time required for parameter initialization, model definition, and constraint formulation, which were all required before the solver can begin optimization.

7. Performance Analysis & Results

7.1. Scenario Analysis

The seven designed scenarios have been executed to assess the effectiveness of different coordination policies and rescheduling objectives. The scenario analysis focuses primarily on two key performance indicators (KPIs): total vehicle waiting time and the number of reschedules. Additional KPIs are tracked to provide a holistic understanding of the system:

1. Total waiting time (in min): The cumulative waiting time of all vehicles.
2. Total number of reschedules: Total number of cancelled appointments—terminal operators aim to minimise this to improve operational stability.
3. Maximum waiting time (in min): The longest waiting time experienced by a single vehicle during the entire planning horizon.
4. Total number of reassignments: Total reassignments made during the entire planning horizon. While this can improve system performance, excessive reassignments may create logistical challenges.

Table 23 summarizes the results of all seven scenarios. The table is sorted by the objective function. Scenarios 1, 3 and 6 minimise the total waiting time while scenarios 2, 5 and 7 aim to minimise the number of reschedules. Scenario 4 also minimises the total waiting time, but aims to achieve this in a more balanced and fair strategy.

Table 23. Results of the Scenario Analysis.

Scenario	Policy	Objective	Total Waiting Time (in min)	# of Reschedules	Max Waiting Time (in min)	# of Reassignments
1	1	1	8783	317	411	-
3	2	1	1556	393	231	-
6	3	1	332	494	218	171
2	1	3	27317	267	458	**-**
5	2	3	33459	282	400	-
7	3	3	17999	184	400	175
4	2	2	1559	369	233	-

7.2. Key Observations

The most immediate conclusion that can be drawn from the results of the scenario analysis is that enabling real-time ETA updates and dynamic rescheduling results in significant performance improvements compared to the static base case (scenario 1).

For example, comparing scenarios 1, 3, and 6—which all aim to minimise the total waiting time—reveals the potential of dynamic coordination. Scenario 6 reduces the total waiting time by over 96% relative to scenario 1 with an increase of 55% in reschedules, while scenario 3 reduces the total waiting time by over 82% with only an increase of 24% in reschedules. The increase in reschedules due to dynamic rescheduling is expected, as real-time vehicle ETA updates necessitate more frequent adjustments to the schedule.

Scenario 6, which allows not only dynamic rescheduling as in scenario 3 but also enables dynamic reassignment, achieves the lowest total waiting time across all scenarios. However, this improvement comes with the cost of a significant rise in the number of reschedules. This observation indicates that the dynamic rescheduling model is able to effectively leverage the added flexibility from reassignments to achieve its objective, the minimisation of the total waiting time, albeit at the cost of other KPIs.

This trade-off between minimising total waiting times and limiting the number of rescheduled appointments is also evident by comparing scenarios 2, 5 and 7. The objective of these scenarios, which is to minimise the number of reschedules, is successfully achieved, but again at the expense of the total waiting time. This illustrates that it is indeed possible to reduce rescheduling frequency, but only by tolerating higher waiting times, shifting the operational burden from terminal operators to road carriers.

Furthermore, comparing scenarios 5 and 7 reveals that by enabling reassignments (Scenario 7), both objectives can be achieved: fewer reschedules as well as a reduced total waiting time compared to scenario 5. Hence, if the vehicle-facility coordination system is capable of handling the reassignment of container appointments to different vehicles, significantly more efficient solutions can be achieved, benefiting both terminals and carriers.

Lastly, penalising waiting time of a vehicle in proportion to the severity of its delay, does not necessarily result in a significantly less optimal solution system-wide, as a comparison between scenario 3 and 4 identifies. Hence, a system-wide optimal solution can still be achieved, even though a more equitable waiting time distribution across the delayed vehicles.

7.3. Trade-Off Analysis

The scenario analysis reveals a clear trade-off between optimizing operations from the carriers' perspective—minimising vehicle waiting time—and from the terminal operators' perspective—minimising the number of cancelled appointments. A decrease in one of the KPIs necessarily results in an increase of the other, which emphasizes the competing priorities of the stakeholders. To zoom in further on this trade-off, a Pareto frontier has been constructed using a weighted sum approach for bi-objective optimisation. The objective function used in this approach is as follows:

$$min\, \alpha \cdot \sum_{v \in V} \frac{WT^{v,h}}{60} + (1-\alpha) \cdot \sum_{c \in C} \left(\sigma_{pickup}^{c,h} + \sigma_{dropoff}^{c,h}\right) \qquad \forall h \in \mathcal{H} \tag{119}$$

In Equation (119), α represents the trade-off parameter which determines the priority assigned to the objective of the stakeholders. An α-value close to 1 prioritises the reduction of waiting times, prioritizing the carriers' objective. While an α-value close to zero shifts the focus toward minimising the number of reschedules, placing a higher importance on the optimization from the perspective of terminal operators.

The results of this analysis are shown in Table 24. The weighted sum approach has been applied to all coordination policies (Policy 1, Policy 2, and Policy 3). Furthermore, the Pareto frontier is visualised in Figure 21, after which a description is given for the key insights that are derived from the multi-objective analysis.

Table 24. Results of the Multi-Objective Analysis for Coordination Policy 1, 2 and 3.

α	Coordination Policy 1		Coordination Policy 2		Coordination Policy 3		
	Total Waiting Time	Number of Reschedules	Total Waiting Time	Number of Reschedules	Total Waiting Time	Number of Reschedules	Number of Reassignments
0.05	9303	265	6060	297	8310	189	150
0.25	9214	265	3928	303	3820	220	146
0.5	9192	268	2673	315	1434	256	133
0.75	8816	282	2316	327	544	283	133
0.95	8668	298	2203	353	410	314	130

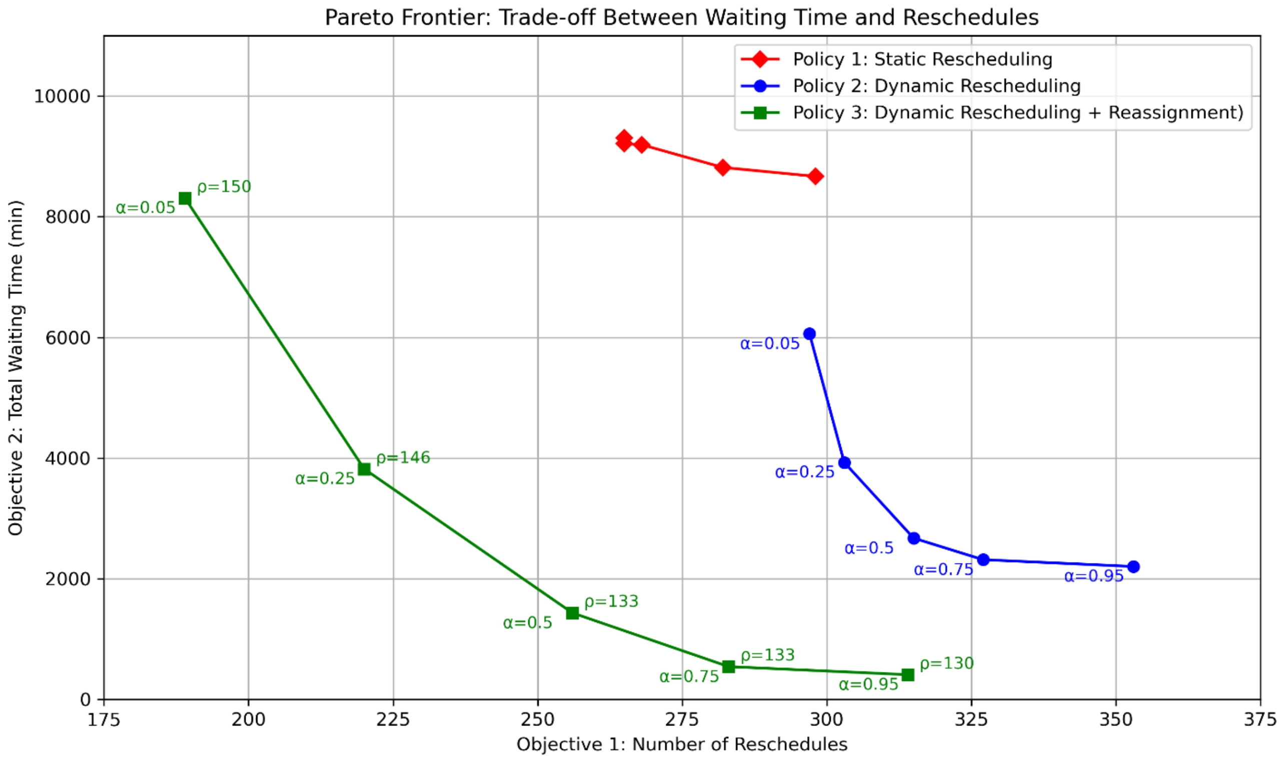

Figure 21. Pareto Frontier for the different coordination policies analysed, including the value of the stakeholder priority α and the number of reassignments ρ.

The Pareto frontier reveals several key insights related to the vehicle-facility coordination system:

- Dynamic rescheduling with reassignment (Policy 2) can already improve performance significantly compared to the static approach (Policy 1). By setting a low value for α, it can even achieve a lower number of required reschedules compared to the base scenario that prioritises waiting times (297 compared to 298 reschedules).
- Policy 3, which also enables reassignments, which has far greater flexibility compared to policy 2, results in a much lower total waiting times when carriers are prioritised. Hence, policy 3 is able to widen the range of possible trade-offs between the two stakeholders, while policy 2 has a far lower variety among the found KPIs.
- The introduction of reassignments enables the system to find better solutions for both stakeholders.
- Port performance can be significantly increased if terminal operators can operate in a real-time fashion, as opposed to a static, pre-planned operational planning. Although facilities may be constrained by stacking and sequencing dependencies, flexibility from both stakeholders is required to achieve a system-wide optimal solution (i.e., the minimisation of total waiting times).

7.4. Sensitivity Analysis

This section presents three sensitivity analyses that have been conducted to evaluate the robustness of the multi-facility planning model under varying operational conditions. Each analysis explores how changes in certain planning parameters influence the performance such as waiting times and the number of cancelled appointments. The tested planning parameters, which are road congestion severity, timeslot duration, and fleet size, are a selection of the planning parameters that have been previously introduced in section 6.2.3.

First, a range of congestion profiles are simulated to in measure the impact of varying road congestion severity on the performance indicators. The hypothesis is that more severe road congestion leads to less optimal planning outcomes, which will be reflected in higher waiting times and more frequent rescheduling. The second tests adjusts the timeslot duration parameter. This will evaluate whether shorter or longer timeslots can improve the system outcome. Lastly, the fleet size is adjusted, which is defined as the number of utilized vehicles by the road carriers to meet the container transportation demand. This analysis examines whether utilizing more or fewer vehicles impacts the performance in the modelled dynamic multi-facility planning system.

It is important to note that the sensitivity tests adjust different components of the model coherence, which has been illustrated in Figure 15. The first sensitivity analysis modifies the Dynamic ETA simulation, while the second and third analyses alter the initial planning. This difference is because changing the timeslot durations or number of utilized vehicles requires a totally new initial planning to be found, whereas congestion severity impacts only the dynamic arrival patterns. For all sensitivity analyses, only coordination policy 3 is applied, as it has consistently outperformed the other policies. As all other planning parameters are held constant, the sensitivity analysis is a valid method to better understand the dynamics and behaviour of the dynamic multi-facility planning system.

Table 25. Overview of Sensitivity Analyses and effects

Sensitivity Analysis	Tested Parameter Values	Trade-off Parameter (α)	Model Component Affected
Congestion Profiles	$\kappa \in \{0.5, 1.0, 1.5\}$	Varying	Dynamic ETA Generator
Timeslot Duration	$\mathrm{TSD} \in \{30, 60, 90, 120, 150\}$	Constant (0.5)	Initial Planning
Fleet Size	$\beta \in \{255, 278, 288, 318, 328, 348, 368, 388, 408, 428, 448, 468, 470, 488, 500\}$	Constant (0.5)	Initial Planning

7.4.1. Congestion Profiles

The first sensitivity analysis is performed by adjusting the congestion intensity parameter (κ) of the dynamic Estimated Time of Arrival simulation. This will simulate an environment with differing traffic conditions. The three distinct congestion profiles that have been simulated are: mild congestion (κ = 0.5), moderate congestion (κ = 1.0) and severe congestion (κ = 1.5). The different congestion profiles have resulted in different delays added to the vehicles. The results of these simulations are summarized in Table 26. The results show that higher congestion severity indeed leads to greater total and average vehicle delays. Furthermore, the number of vehicles arriving without any delay decreases with increasing congestion, as can be expected.

Table 26. Impact of Congestion Profiles (Mild, Moderate and Severe) on Vehicle Delays

Congestion Profile	Congestion Intensity Parameter (κ)	Total Delay (in min)	Average Delay per Vehicle (in min)	Vehicles with zero delay
Mild	0.5	6469	16.7 min	51
Moderate	1.0	12884	33.2 min	45
Severe	1.5	20405	52.6 min	40

The performance of the multi-facility coordination system under each congestion profile is further evaluated by applying a multi-objective analysis on top of the simulation. This will analysis will provide a deeper insight into the trade-offs between total waiting time, number of rescheduled appointments, and number of reassignments across different values of the trade-off parameter α, as has been previously conducted in section 7.3. The outcomes of the multi-objective analysis are summarized in Table 27. The resulting Pareto frontier for each congestion profile is visualized in Figure 22.

Table 27. Sensitivity Analysis – Multi-objective Performance Under Different Congestion Profiles

α	Mild Congestion			Moderate Congestion			Severe Congestion		
	Total Waiting Time	Number of Reschedules	Number of Reassignments	Total Waiting Time	Number of Reschedules	Number of Reassignments	Total Waiting Time	Number of Reschedules	Number of Reassignments
0.05	4461	125	110	8310	189	150	16485	275	173
0.5	1393	153	108	1434	256	133	2981	350	175
0.95	176	208	112	410	314	130	808	471	166

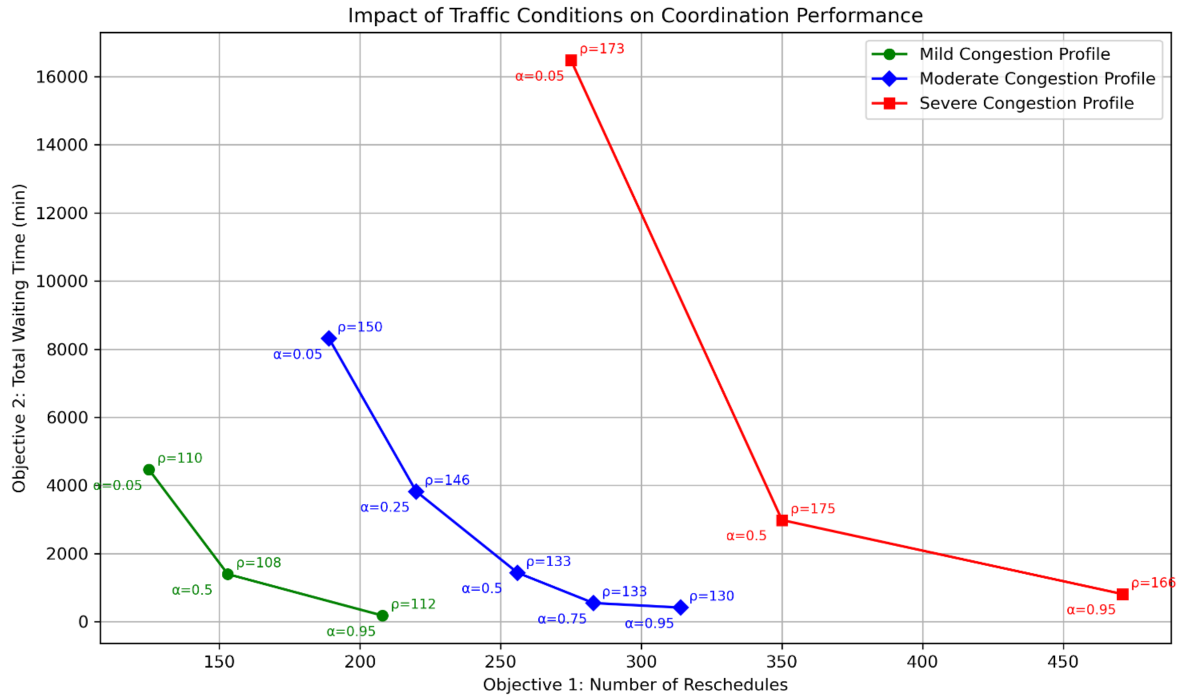

Figure 22. Pareto Frontiers comparing Mild, Moderate, and Severe Congestion Profiles on System Performance.

The results show that the hypothesis can be validated: less severe road congestion leads to more optimal solutions for all stakeholders. Both waiting times and the number of cancelled appointments decrease when road congestion, which is causing vehicle delays, is less severe. Note that the moderate congestion profile in Figure 22 corresponds to the results of coordination policy 3 in the trade-off analysis, as shown in Figure 21.

A quantitative comparison highlights both the severe impact road congestion can have on system performance, as well as the effectiveness of the model in mitigating its impact. If total vehicle delay is increased by 215% (mild: 6469 vs severe: 20405 minutes), the number of cancelled appointments can still be controlled by setting it as the objective (i.e., α = 0.05), leading to a modest increase of 120% (mild:125 vs. severe: 275). However, this performance comes at a significant cost to waiting times (mild: 4461 vs. severe: 16485). On the other hand, if the emphasis is on minimizing waiting times (i.e., α = 0.95), waiting times are almost quadrupled (mild: 176 vs severe: 808) nevertheless. However, by increasing the tolerance for reschedules (i.e., α = 0.95), the model is consistently able to achieve a reduction in waiting time of approximately 95% across all congestion profiles. Specifically, waiting time reductions are 96% for mild (4461 vs. 176 min), 95% for moderate (8310 vs. 410 min), and 95% for severe congestion (16485 vs. 808 min). The results of this sensitivity analysis therefore demonstrate that the model is highly effective at minimizing waiting times by leveraging both rescheduling and reassignment mechanisms, even if road congestion conditions are severe.

7.4.2. Timeslot Duration

The second sensitivity analysis examines the impact of varying timeslot duration on system performance. Its impact is evaluated by measuring the total waiting time, the number of reschedules, and the number of reassignments. Through all simulation runs, the value of the trade-off parameter (α) is fixed at 0.5, which balances the priority between both waiting time and rescheduling frequency. The results of this analysis are shown in Table 28 and visualised in Figure 23.

Table 28. Impact of Timeslot Duration on Dynamic Multi-Facility Coordination Performance

Timeslot Duration (in min)	Total Waiting Time (in min)	Number of Reschedules	Number of Reassignments
30	1896	330	136
60	1434	256	133
90	1080	214	146
120	371	157	128
150	237	120	147

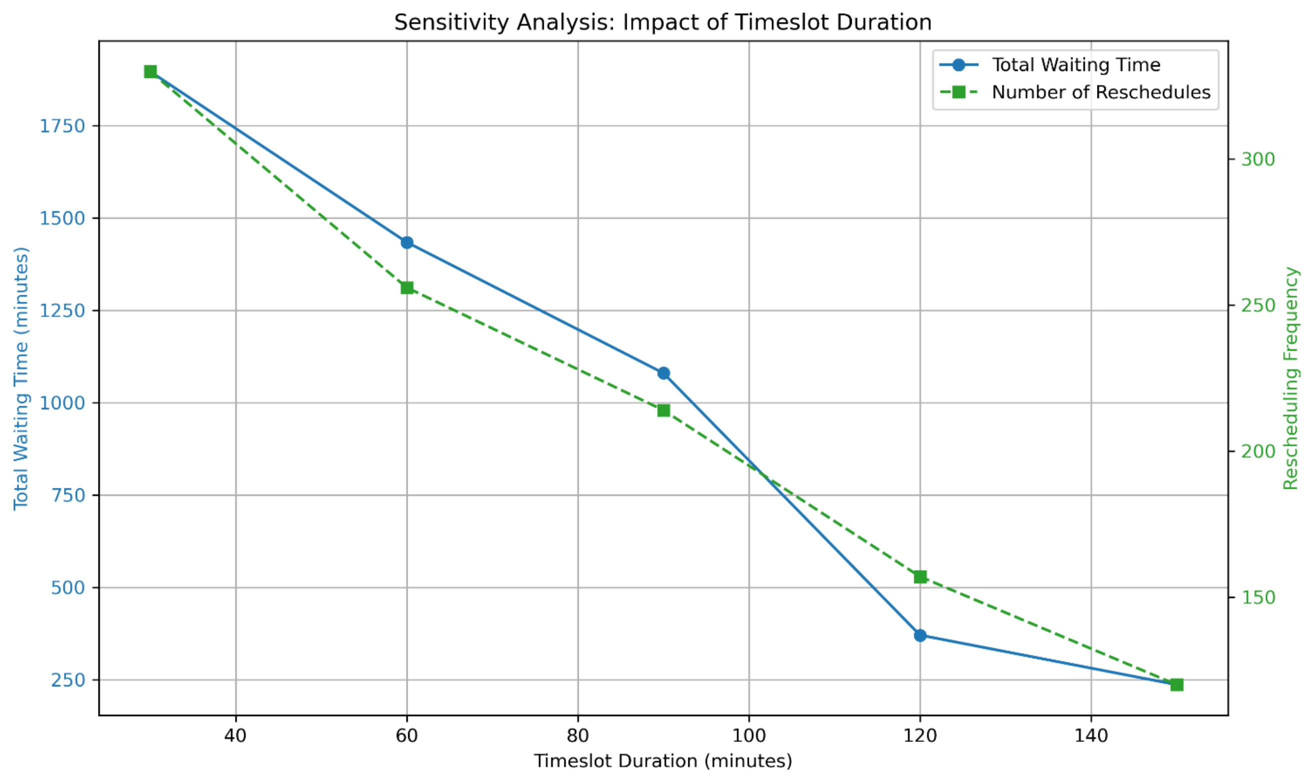

Figure 23. Impact of Timeslot Duration on Waiting Time and Rescheduling Frequency

An initial inspection of the results suggests an evident relationship between timeslot duration and system performance. To validate this statistically, both Pearson and Spearman correlation tests were performed. Both tests show that there is indeed a strong and significant relationship between timeslot duration and both waiting time and rescheduling frequency (Pearson: $r = -0.9936$, $p = 0.0006$ and Spearman: $\rho = -1.000$, $p = 0.000$). This suggests that increasing the timeslot duration consistently leads to improved performance of the dynamic multi-facility coordination system.

The findings of this analysis indicate a clear trade-off: increasing timeslot duration improves overall system efficiency, although this might be at the expense of appointment accurateness of the coordination system. Specifically, the simulation shows that the strongest relative improvement can be observed in total waiting time, which decreases considerably as timeslot durations increase. For example, by broadening the timeslot duration from 30 to 150 minutes, the total waiting times can be reduced by approximately 88% (1896 vs. 237). The number of reschedules also decreases, but at a more moderate rate of around 64% (330 vs. 120). This indicates that some degree of flexibility in rescheduling remains necessary to optimize system performance.

This finding highlights a critical trade-off within the dynamic multi-facility coordination system. Longer timeslot durations provide greater scheduling flexibility, which leads to fewer reschedules and shorter waiting times. However, this advantage comes at the cost of reduced scheduling accuracy. If timeslots become too broad, facilities may not be able to service all vehicles arriving within that timeslot, especially if vehicles arrival are not distributed evenly throughout the timeslot, but rather arrivals occur in clusters. Hence, increasing timeslot duration tends to generalize facility capacity, making the modelled and optimized system less accurate.

The practical implication is that timeslot duration is a crucial operational parameter that must be considered adequately. However, innovations such as the integration of real-time Estimated Time of Arrival (ETA) data into the coordination system have the potential to transform how scheduling is perceived and managed. Real-time ETAs can be applied beyond dynamic rescheduling, for example by incorporating it directly into the workflow of facilities. This allows terminal operations to be dynamically adjusted based on the real-time expected sequence of vehicle arrivals. This will reduce the dependency and reliance on fixed timeslot appointments. In this scenario, terminals know when containers are expected for pick-up or drop-off. This degree of transparency enables an even higher degree of responsiveness as compared to traditional scheduling. In this scenario, Implementing such a collaborative system can be encouraged by incentivizing both parties and can be facilitated by a centralized planning system, as illustrated in Figure 4.

7.4.3. Fleet Size

The third sensitivity analysis aims to understand the impact of varying fleet sizes on overall system performance. Fleet size in this context is defined as the number of vehicles that will be utilized to carry out the container transportation requests. Therefore, a smaller fleet size increases the number of combined trips, where a single truck handles the transportation of multiple containers in sequence. From the perspective of road carriers, this approach is an effective means to reduce operational costs by maximizing vehicle utilization.

This analysis examines whether the minimization of the fleet sizes, which is beneficial from the perspective of a single road carriers, will result in sub-optimal system performance. This will reveal whether a reduction of fleet size will be traded off with longer waiting times and more frequent rescheduling. To explore the effects thoroughly, a wide range of fleet sizes (β) were simulated, using a fixed trade-off parameter (α) of 0.5, which will balance waiting times with rescheduling frequency. For this analysis, coordination policy 3 was applied, which enables reassignment as a strategy to mitigate disruptions caused by vehicle delays. The outcomes of the simulations are summarised in Table 29 and visualised in Figure 24.

Table 29. Sensitivity Analysis – Impact of Fleet Size on System Performance

Fleet Size (β)	Total Waiting Time (in min)	Number of Reschedules	Number of Reassignments	Average Delay
255	1129	254	81	31
278	2482	254	84	30
288	1137	249	83	27
318	1303	251	133	36
328	2051	251	119	35
348	2063	254	118	33
368	1545	257	131	32
388	1434	256	133	33
408	1270	267	159	33
428	1626	263	131	33
448	988	202	117	32
468	1226	261	153	34
470	1412	217	118	33
488	1741	258	133	32
500	1690	267	115	34

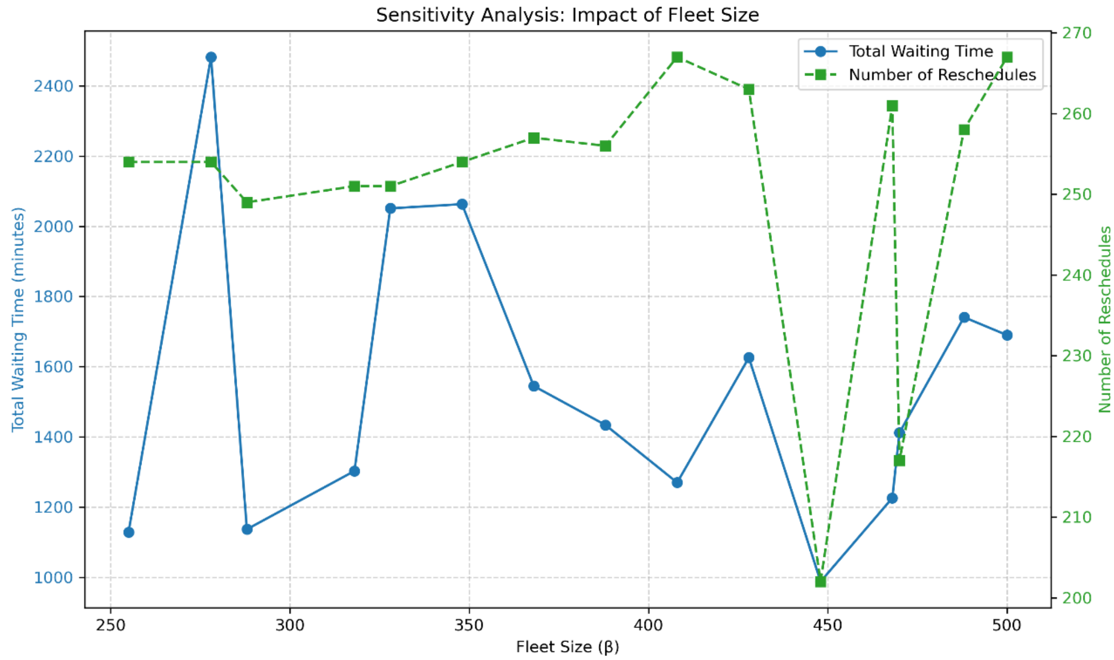

Figure 24. Impact of Fleet Size on Waiting Times and Rescheduling Frequency

The results clearly suggest that there is no direct correlation between the number of utilized vehicles and overall system performance. Statistical testing using both Pearson and Spearman correlations confirm that changes in the number of utilized vehicles do not meaningfully affect waiting times or rescheduling frequency. Hence, under the given congestion and capacity settings, the system performance is not limited by fleet size. Instead, other contributing factors are more dominant, such as timeslot capacity, congestion severity, and timeslot duration.

The reason that there is no direct relationship between fleet size and system performance, is due to the complexity of the system dynamics and the high degree of variability involved in the rescheduling process. For example, by utilizing a different number of vehicles, a totally new initial planning is constructed, in which vehicles are assigned to different containers at different timeslots. And as different times of the day encounter varying levels of congestion, the rescheduling and reassignment that consequently takes place is unpredictable. For instance, increasing the fleet size can improve flexibility in reassignments, as there are more vehicles available to which reassignment can take place. However, more vehicles on the road implies more unexpected delays on arrival times, increasing the disruptions on the system. Similarly, operating with fewer vehicles can also cause more disruption as the delay of one vehicle has a cascading effects of delays on all its subsequent appointments. It is therefore safe to assume that road carriers can optimize the fleet size in siloes without significantly compromising the overall optimality of the dynamic multi-facility coordinated system.

7.5. Discussion

The results of this study have demonstrated the huge potential of integrating real-time Estimated Times of Arrival (ETAs) to improve the coordination between inbound trucks arriving at the port and previously reserved timeslots at terminal facilities. The study found that by means of dynamic planning, which is enabled by rescheduling and reassignment, total waiting times can be reduced by up to 96% compared to the static base scenario.

The findings of this study are in line with prior research. For instance, Prakoso et al. (2022) demonstrated that by implementing a dynamic rolling horizon approach, total rescheduling cost can be reduced by 42%. Similarly, Skoulas (2024) concluded that by integrating real-time vehicle ETAs, the mean waiting time of vehicles can be reduced by up to 94.5%. Vanga et al., (2022) likewise found that the availability of ETA information can cut average truck waiting times by 20% besides improving other performance indicators. These results confirm that dynamic planning, which is made possible by integrating real-time data, is a promising solution for tackling the increasing uncertainty in vehicle-facility systems, which is causing inefficiencies and challenges among all involved stakeholders.

Compared to the previous works, the framework developed in this study is novel. To the author's knowledge, no prior research has developed a similar modelling framework, which jointly plans operations across multiple port facilities in collaboration with multiple trucking companies. The existing literature on Collaborative and Dynamic Truck Appointment Systems (CD-TAS), which is in itself a very limited subset of TAS literature, typically focus on the coordination between a single facility and multiple carriers. This approach opens the door to greater efficiency improvements and more robust and resilient supply chains. For example, this modelling approach allows the investigation of a vast range of operational objectives, such as reducing empty trips, ensuring fairness among stakeholders, and improving KPIs such as truck waiting times and turnaround times.

A unique insight that this holistic approach has uncovered, is the nature of the trade-off between the objective of the terminal operator and those of the trucking companies. The multi-objective analysis has revealed how varying degrees of stakeholder collaboration influence system performance. This has raised a critical question: to what extent should individual objectives be sacrificed in pursuit of system-wide optimality? Hence, for the application of dynamic planning, system-wide optimality needs to be clearly defined.

In summary, this study has advanced the existing literature by introducing multi-facility planning, thereby broadening the scope of collaborative planning frameworks. By integrating real-time data and adopting a rolling-horizon approach, more flexible, efficient, and resilient coordination among the stakeholders in port logistics chains can be realized.

To arrive at these insights, however, several assumptions and limitations related to the model and methodology need to be acknowledged. Three key limitations of the followed approach are outlined below, after which a discussion of how these and other limitations can be addressed by extending the current modelling framework.

1. Terminal simplifications: In the current model, both terminal capacities and terminal service times are constants with no dynamic variability or stochasticity. Hence, terminals are treated as a black box. The service time of a certain facility during a certain timeslot is considered a deterministic parameter. This approach is also followed by a majority of the other Dynamic and Collaborative Truck Appointment Systems developed in literature, such as the ones by Prakoso et al. (2022), Skoulas (2024), Vanga et al., (2022). Hence, disruptions are caused solely due to uncertain truck arrivals rather than by insufficient handling capacity.
2. Fixed inter-port parameters: The model solely focuses on the impacts of road congestion, excluding any variability in inter-port travel times or gate waiting times caused by port congestion. Hence, the travel times between facilities within the port infrastructure are assumed to be constant. Therefore, internal port congestion is excluded from the scope of the model. This simplification aligns with the primary objective of this study, which is to improve vehicle-facility coordination under uncertainty caused by road congestion.
3. Terminal-level scheduling: The model schedules pick-up and drop-off activities on level of the terminal. This is a simplification of the actual operational circumstances. In practice, trucks are assigned to a specific block section within a terminal, each with potentially its own capacity, constraints and schedule. The relevance of scheduling activities on block-level rather than on terminal-level, is due to the physical presence of the container, which generally depends on the location where the crane has unloaded the container from the vessel and additional stacking done by the crane afterwards.

The three limitations outlined above can be addressed by extending the current model framework. Given the model's modular, layered and adaptable structure, multiple model enhancements can be implemented with relatively minor adjustments. This makes the model able to be tailored to multiple practical needs and research goals. It will now be discussed what these possible adjustments are to both the analytical models—namely, the static scheduling and dynamic rescheduling models—as well as to the two supporting simulations: the trip simulation (input for the static model) and the dynamic Estimated Time of Arrival (ETA) simulation (input for the dynamic model).

First, the terminal handling capacity can modelled as a stochastic parameter during the rescheduling process. These fluctuations in handling capacity can be caused by operational disruptions such as a crane malfunctions or unforeseen staff shortages. Introducing this type of stochasticity to the model would naturally lead to increased waiting times and a higher number of reschedules throughout the planning horizon, compared to the current model environment in which terminal capacity is assumed to be reliable.

Second, uncertainty can be introduced in intra-port travel times. Variability in travel times within the port, for example due to internal port congestion, adds uncertainty to truck arrival times later on in their individual operational planning. This means that close to the actual appointment times, rescheduling still occurs. This measurement would also likely result in an increased number of reschedules as well as potentially longer waiting times.

Third, the current assumption of scheduling appointments at the terminal level, can be overcome by reinterpreting the definition of the current scheduling models. In the extended model, each terminal facility, $f \subset \mathrm{F}$, can be redefined as a sub-terminal, rather than an entire terminal. For instance, for terminal-level optimisation, $terminal_1 \subset \mathrm{F}$, while for crane-level optimisation, $terminal_{1.1} \cup terminal_{1.2} \cup terminal_{1.3} \subset \mathrm{F}$, in which each terminal is broken down further into blocks. While incorporating this level of detail adds complexity to the decision-making model, it can hence easily be integrated.

These potential extensions are illustrated in Figure 25. Stage 4 reflects the extension of the model from multi-terminal to multi-crane optimisation, while stage 5 introduces uncertainty and disruption caused by the terminals. Achieving such advanced coordination by such minor adjustments, suggest that there is a significant quick win to be made in enhancing the realism of the currently modelled dynamic rescheduling problem.

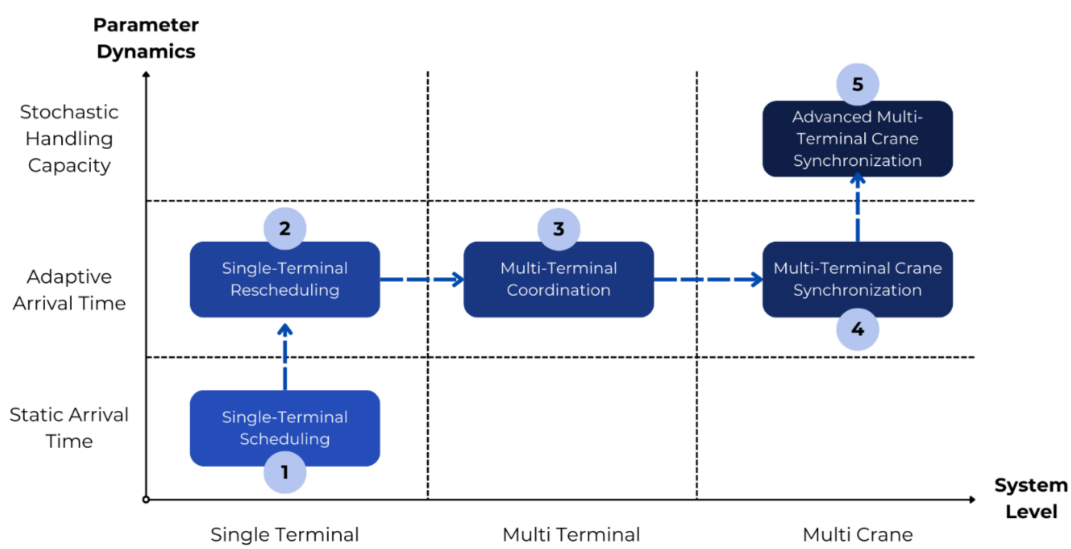

Figure 25. Potential Model Extensions.

8. Conclusion & Recommendations

This chapter concludes the conducted study, after which recommendations for future research are provided.

8.1. Conclusion

The objective of this study was to explore how real-time Estimated Time of Arrival (ETA) data for trucks can be integrated into port planning processes and how this integration can lead to improved coordination between on-the-road vehicles and pre-booked timeslot appointments. The research aimed to achieve this objective while balancing the competing interests of key stakeholders, including road carriers and terminal operators.

The relevance of this research stems from a gap between industry practice and developments in the academic literature. Prior studies on Truck Appointment Systems (TAS) have largely focused on optimising interactions between a single terminal facility and multiple vehicles. However, this approach lacked the sophistication to effectively coordinate across multiple facilities and stakeholders simultaneously.

This study addresses that gap by adopting a holistic and system-wide perspective, which moves beyond isolated optimisation. This approach is followed by first conducting a comprehensive system analysis to understand the underlying system dynamics. Based on this understanding, an integrated conceptual framework was developed, which was then translated into a versatile analytical model. This analytical model consisted of two distinct models: the static scheduling model, which results in the initial planning, and the dynamic rescheduling model, which achieves real-time optimisation. This developed model was applied using a combined simulation-optimisation approach, on which a scenario analysis and multi-objective analysis were conducted.

The study demonstrated that integrating real-time vehicle data can lead to substantial performance improvements. The scenario analysis concluded that waiting time reductions of up to 96% can be achieved compared to the static base scenario, where no real-time data-sharing occurs. The model, besides proving a significant reduction in waiting times, has also shed light on a fundamental trade-off in the vehicle-facility coordination system. Minimising vehicle waiting times—which primarily benefits road carriers—generally leads to an increase in the number of rescheduled appointments, considered one of the key performance indicators for terminal operators. The conducted multi-objective analysis has made evident the extent to which these two objectives are in contradiction with each other. Therefore, the concept of “system-wide optimality” must be carefully defined by engaging the different stakeholders and aligning on the definition of the rescheduling policy.

Another important finding of the study is that enabling vehicle reassignments—which is the ability of carriers to swap booked timeslot appointments among their managed vehicles—can significantly improve the system's performance even further. Hence, there are two ways in which flexibility and, therefore, potential optimality can be introduced into the system:

- Terminal operators enhance rescheduling flexibility by extending the boundaries of allowed dynamic rescheduling, such as last-minute timeslot reservation adjustments.
- Road carriers enhance rescheduling flexibility by allowing reassignments between utilised vehicles.

Results from the Pareto frontier highlight the added value of this flexibility. For instance, when terminal operators allow high rescheduling flexibility, which is modelled by assigning a low priority to the minimisation of reschedules (i.e., a low value for α), the total waiting time drops significantly. Specifically, the total waiting time is reduced to 410 minutes with reassignment enabled, and 2,203 minutes without reassignment. These figures represent a 95% and 75% improvement compared to the base scenario (8,783 minutes).

In conclusion, the proposed two-layered planning approach—where the static model shapes vehicle arrival behaviour and the dynamic rolling-horizon model responds to real-time disruption events—has shown strong potential to enhance the performance of port logistics systems significantly. The findings underscore the importance of flexible, real-time coordination mechanisms and highlight the need for stakeholder-aligned objectives in the implementation of such systems.

Lastly, this study has been evaluated by highlighting its underlying assumptions and limitations. Following this, suggestions were provided to enhance the currently developed rolling-horizon modelling approach. These extensions include advancing terminal-level optimisation to crane-level optimisation, as well as transitioning from deterministic to stochastic facility parameters.

In conclusion, the conducted research has been able to address key gaps in the literature, which resulted in new insights which contribute to a better understanding of multi-stakeholder coordination in port logistics. Moreover, it paves the way for future research which could further expand the decision-making modelling approach and reshape how port logistics operations are optimised in practice.

8.2. Recommendations

Traditional Truck Appointment Systems (TAS) typically treat appointment bookings as binding agreements between a truck and a specific terminal facility for a designated time slot. However, both practical experience and academic literature indicate that this is an oversimplification. Real-world operations are subject to frequent disruptions—many of which are beyond the control of the system actors—which reduce the effectiveness of this rigid and static scheduling framework.

This study has followed a holistic and collaborative approach, in which all actors contribute to a system-wide optimisation. The integration of simulation and optimisation has allowed for a realistic and adaptive scheduling and rescheduling framework. The results demonstrate that a dynamic rescheduling approach outperforms traditional static approaches. Building on this work, future research can explore several directions:

1. **Case-specific parameter optimisation**

Since each port logistics system is distinct, there is no universal solution for real-time coordination between vehicles and facilities. Future research can focus on fine-tuning model parameters to reflect the specific dynamics and preferences of individual port environments.

2. **Stochastic terminal handling modelling**

In this study, terminal operations were treated as deterministic parameters. In practice, however, terminal handling is also subject to variability and disruptions, in addition to vehicle arrival times. Incorporating stochastic modelling of terminal operations could provide a more comprehensive understanding of system resilience and evaluate whether the current or an extended model is robust under this increased uncertainty.

3. **Designing static schedules for dynamic flexibility**

This research treated the static schedule as an idealised initial plan aimed at influencing truck arrival patterns. Hence, this approach considers the static schedule merely as an initial suggestion, while dynamic rescheduling responds to the real-time disruptive events. Future studies can investigate ways to design the static scheduling model such that it is optimised to facilitate more efficient downstream rescheduling. This could be achieved through predictive modelling, machine learning, or historical data analysis.

In summary, this study presents promising opportunities for further research to transition from isolated, static scheduling to dynamic, collaborative, and data-driven coordination.

With regard to the practical application of the methodology followed and model framework developed in this study, three recommendations can be made.

First, while this study confirms the effectiveness of the dynamic rescheduling model, its implementation in practice requires clearly defining the objective of the system. More specifically, stakeholders interests need to be clearly aligned for defining the performance objective, e.g. to what degree is waiting time reduction vs. rescheduling stability predominant. Hence, for successfully adopting an integrated dynamic rescheduling approach, it is important to agree on what the system should optimize for.

Second, the level of control and autonomy passed on to the rescheduling system must be considered. Depending on the degree of trust and willingness to move to an automated system, organizations can collaboratively define to what extent human planners remain in control, and how much flexibility is handed over to the automated decision-making framework.

Finally, it is important to establish robust operational infrastructure to facilitate real-time data sharing and communication between stakeholders. This includes integrating updates of the Estimated Times of Arrivals of the vehicles based on the real-time location.

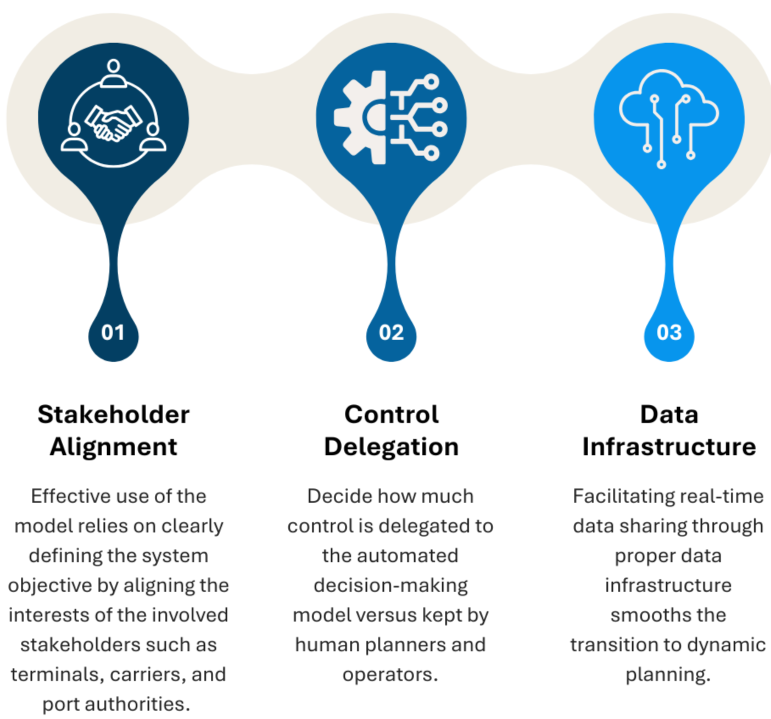

Figure 26. Practical Recommendations for the implementation of a dynamic port logistics decision-making framework.

References

Abdelmagid, A. M., Gheith, M. S., & Eltawil, A. B. (2022). A comprehensive review of the truck appointment scheduling models and directions for future research. *Transport Reviews*, *42*(1), 102–126. https://doi.org/10.1080/01441647.2021.1955034

APMT. (2022). *Operationele Procedures—APM Terminals*. https://www.apmterminals.com/nl/maasvlakte/practical-information/operating-procedures

Azab, A., Karam, A., & Eltawil, A. (2017). A Dynamic and Collaborative Truck Appointment Management System in Container Terminals: *Proceedings of the 6th International Conference on Operations Research and Enterprise Systems*, 85–95. https://doi.org/10.5220/0006188100850095

Chen, G., Govindan, K., & Golias, M. M. (2013). Reducing truck emissions at container terminals in a low carbon economy: Proposal of a queueing-based bi-objective model for optimizing truck arrival pattern. *Transportation Research Part E: Logistics and Transportation Review*, *55*, 3–22. https://doi.org/10.1016/j.tre.2013.03.008

Chen, G., Govindan, K., & Yang, Z. (2013). Managing truck arrivals with time windows to alleviate gate congestion at container terminals. *International Journal of Production Economics*, *141*(1), 179–188. https://doi.org/10.1016/j.ijpe.2012.03.033

Da Silva, M. R. F., Agostino, I. R. S., & Frazzon, E. M. (2023). Integration of machine learning and simulation for dynamic rescheduling in truck appointment systems. *Simulation Modelling Practice and Theory*, *125*, 102747. https://doi.org/10.1016/j.simpat.2023.102747 de Rijcke, J. (2025, January 9). *Port Alert: Betere en snellere doorstroom*. Transport en Logistiek Nederland. https://www.tln.nl/actueel/port-alert-betere-en-snellere-doorstroom

Gracia, M. D., Mar-Ortiz, J., & Vargas, M. (2025). Truck Appointment Scheduling: A Review of Models and Algorithms. *Mathematics*, *13*(3), Article 3. https://doi.org/10.3390/math13030503

Guan, C. Q. (2009). Analysis of marine container terminal gate congestion, truck waiting cost, and system optimization. *New Jersey Institute of Technology*.

Hoxha, R., Cangelosi, S., Sacone, S., & Zero, E. (2024). Reducing Emission Peaks in a Port Terminal through Optimized Truck Arrivals. *IFAC-PapersOnLine*, *58*(10), 321–326. https://doi.org/10.1016/j.ifacol.2024.07.360

Huynh, N. N. (2005). *Methodologies for reducing truck turn time at marine container terminals*. http://hdl.handle.net/2152/1579

Huynh, N., & Walton, C. M. (2008). Robust Scheduling of Truck Arrivals at Marine Container Terminals. *Journal of Transportation Engineering*, *134*(8), 347–353. https://doi.org/10.1061/(ASCE)0733-947X(2008)134:8(347)

Jin, X., & Kim, K. H. (2018). Collaborative Inter-Terminal Transportation of Containers. *Industrial Engineering & Management Systems*, *17*(3), 407–416. https://doi.org/10.7232/iems.2018.17.3.407

Lange, A.-K., Nellen, N., & Jahn, C. (2022). *Truck appointment systems: How can they be improved and what are their limits?* 615–655. https://doi.org/10.15480/882.4706

Nextlogic. (2024). *Release notes—Algemene informatie—Nextlogic Support*. https://nextlogicsupport.refined.site/space/SAI/524484609/Release+notes

Phan, M.-H., & Kim, K. H. (2015). Negotiating truck arrival times among trucking companies and a container terminal. *Transportation Research Part E: Logistics and Transportation Review*, *75*, 132–144. https://doi.org/10.1016/j.tre.2015.01.004

Port of Rotterdam. (2024, August 23). *ROADMAP CONTAINER LOGISTICS EFFICIENCY* [Confidential internal document of the Port of Rotterdam].

Portbase. (2022, August 19). *Terminal tijdsloten*. Portbase Support. https://support.portbase.com/timeslots/

Prakoso, E. F., Maknoon, Y., Pel, A., Tavasszy, L. A., & Vanga, R. (2022). A Predictive–Proactive Approach for Slot Management of a Loading Facility With Truck ETA Information. *Frontiers in Future Transportation*, *3*, 815267. https://doi.org/10.3389/ffutr.2022.815267

Rijnmond (Director). (2020, October 13). *Ook vrachtwagenchauffeurs overwegen actie bij terminals: "Voor ons is het klaar"* [Video recording]. https://www.youtube.com/watch?v=aeOBbtSC2Fs

Roy, D., De Koster, R., & Bekker, R. (2020). Modeling and Design of Container Terminal Operations. *Operations Research*, *68*(3), 686–715. https://doi.org/10.1287/opre.2019.1920

Skoulas, V. (2024). *Time-window based Truck Appointment System with Adaptive Slot management and Real-Time Truck Information* [Delft University of Technology]. https://resolver.tudelft.nl/uuid:e4870113-975f-4fa1-96dd-1e6d0f061e29

Truckstar. (2023, April 28). RWG voert “boete” in op tijdslots tijdens piekuren. *Truckstar*. https://www.truckstar.nl/rwg-voert-boete-in-op-tijdslots-tijdens-piekuren/

UNCAD. (2024). Review of maritime transport 2024: Navigating maritime chokepoints. *Review of Maritime Transport*.

Vanga, R., Maknoon, Y., Tavasszy, L. A., & Gelper, S. (2022). Effect of Real-Time Truck Arrival Information on the Resilience of Slot Management Systems. *2022 Winter Simulation Conference (WSC)*, 1593–1602. https://doi.org/10.1109/WSC57314.2022.10015289

Xu, B., Liu, X., Li, J., Yang, Y., Wu, J., Shen, Y., & Zhou, Y. (2022). Dynamic Appointment Rescheduling of Trucks under Uncertainty of Arrival Time. *Journal of Marine Science and Engineering*, *10*(5), 695. https://doi.org/10.3390/jmse10050695

Appendix

Appendix A: Dynamic Planning Applications at the Port of Rotterdam

This section will highlight 3 case studies where dynamic planning and truck appointment systems are being applied at the port of Rotterdam. These applications will be used as reference projects for the development of a dynamic planning algorithm for this project.

1. **Nextlogic Implementation at the Port of Rotterdam**

One of the applied cases of dynamic planning at the Port of Rotterdam, is Nextlogic. Nextlogic is the integrated planning solution for the handling of inland container shipping in the port of Rotterdam. The development of the technology is taking place in collaboration with the participating stakeholders. Nextlogic makes use of a planning algorithm that continuously recalculates the entire planning, based on the current state of the barge and terminal.

For the optimisation of the appointment planning, three stages are classified, as show in Figure 27. The three optimisation stages defined by Nextlogic are:

1. Necessary optimisation: if the start of the operation is less than 6 hours away, the order of the calls on the quay are fixed based on the way they have been planned. In case of a delay, the order of calls is shifted linearly, which is called "linear shifting".
2. Limited optimisation: if the start of the operation is 6 to 30 hours away, limited optimisation ensures that the order of calls on the quay can still shift, but only until a certain limit.
3. Free optimisation: if the start of the operation is more than 30 hours away, little optimisation takes place.

Figure 27. Optimisation schedule of the Nextlogic algorithm (Nextlogic, 2024).

Linear shifting is an important characteristic of the Nextlogic optimisation algorithm. This rule ensures that calls that are scheduled between now and 4 hours before the appointed timeslot, will keep their order of operation. In case of a delay in operations, all calls will be shifted straight back based on its respective order, with a few exceptions in place. These exceptions are as follows:

1. If the same barge has consecutive appointments at two terminals, and the operation at the first terminal is delayed, then the appointment at the second terminal can be shifted backwards, prioritizing the next call. The aim of this rule is to prevent idle equipment at the quay.
2. In case of a disruption at the terminal side, e.g. because of a crane failure, then all appointments for the coming 4 hours are cancelled and a new planning is designed.
3. If the appointment has a fixed window or is a priority, i.e. it needs to be handled before a fixed end time, then this has priority in case of a delay.

Nextlogic is a currently applied algorithm at the Port of Rotterdam with a proven success application for dynamically planning appointments for inland container shipping, and will be used as a reference project for the development of a dynamic planning algorithm of this project.

2. The Port Alert App

Port Alert is a platform where planners, drivers, terminals and depots can share real-time information about disruptions and lead times at the container terminals of port of Rotterdam (de Rijcke, 2025). Users of the app can find delays and disruptions, create alerts for future incidents and delays, get traffic information for terminal visits, and find details about truck parking occupancy.

Truck drivers can share the real-time location while being on their way to a terminal, and with that information, the app can predict what time the driver will arrive at the terminal, taking into account traffic and lead time. It is not yet possible to book a time slot via the app, but there is a possibility for communication between the driver and the terminal or depot.

This app emphasizes that port of Rotterdam aims to bridge the gap between carriers and terminals as the app is a very recent innovation and is currently still under full development.

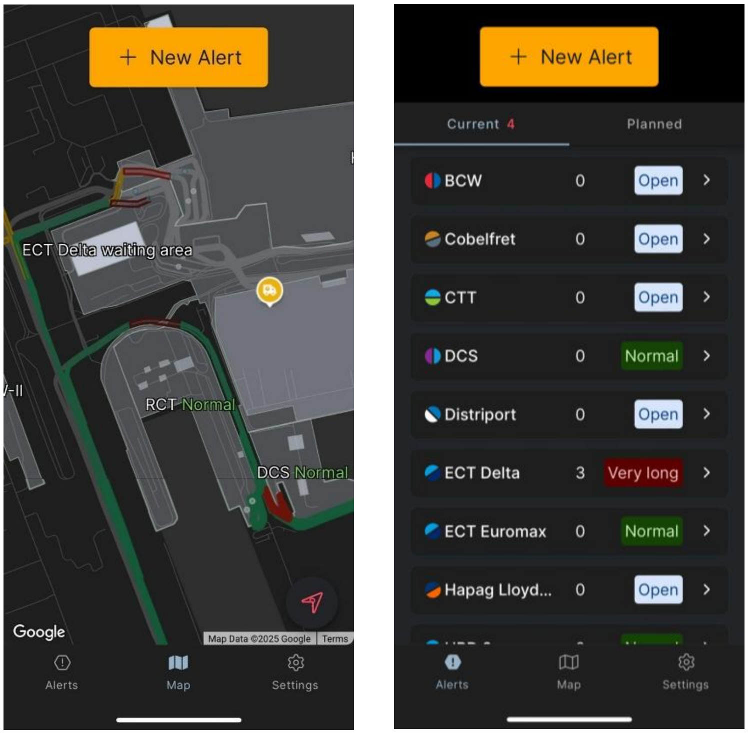

Figure 28. The Port Alert app shows current bottlenecks (left), and the condition of terminals, depots, and parking (right).

3. Applications of TAS at Container Terminals in Rotterdam

Each container terminal at the port of Rotterdam currently has a different method for coordinating between the terminal and the carrier, with some terminals having a TAS in place.

APM Terminals Maasvlakte II has a timeslot duration of 30 minutes, with a tolerance of 45 minutes, meaning that it is possible to arrive at the gate 45 minutes before and 45 minutes after the reserved time slot (APMT, 2022). As the terminal is less busy at night, there is a slot time from 00.01 to 03.45. Different timeslots are also applied during the weekend. APMT also has a Truck Appointment Availability overview, showing the percentage of capacity booked for each timeslot.

Other terminals, such as DCS and RCT follow a 1 hour or more timeslot, with a tolerance of 15 minutes (Portbase, 2022). RWG follows a timeslot of 60 minutes during daytime, with a tolerance of 30 minutes. Furthermore, RWG charges an additional fee for booking a time slot during peak hours, i.e. between 06:00 and 17:59 from Monday to Friday. This measure is taken by RWG to better distribute and streamline the handling process at the terminal (Truckstar, 2023).

ECT and other terminals do not have a TAS in place, and therefore follow the FIFO rule.