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Truck Arrival Shift Policy for Port-Hinterland Alignment at the port of Rotterdam

Design, Modelling, and Simulation Approach

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Design, Modelling, and Simulation Approach

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Yours sincerely,
Alex

SUMMARY

High waiting times for trucks at the terminal gates of seaports are an issue that is increasingly receiving more attention. Long queues of idling trucks in front of the terminal waiting to pick up or deliver a container create congestion, and induce emissions, costs and delays. Container terminals in the port of Rotterdam, the largest European port, are no exception to these issues. The waiting times for trucks at the terminal gates are rapidly increasing the past 6 years. The high waiting time at the terminal is an indicator for misalignment between port and its hinterland. With this research it is sought to develop a method to reduce truck waiting time in the port of Rotterdam area taking the port and hinterland system into account, and, hence, to improve the port-hinterland alignment. The main research question is formulated as follows:

How can port-hinterland alignment at the port of Rotterdam be improved such that the waiting time at container terminals is reduced?

This main question is supported by the following sub-questions:

1. What are the main causes of misalignment between port and hinterland which result in waiting time at the container terminals?

2. How can an intervention be designed to reduce the waiting time at the container terminals?

3. What is the potential gain of the intervention in terms of waiting time at the container terminals?

A seaport, as a node in a transport network, functions as a connector of two legs of transportation. These two legs are seaside and landside transport. These two legs overlap at the terminal gates. This indicates that the activities at the terminal gates cater the alignment of the port and its hinterland. In Figure 0.1 a conceptual overview of the port system and the focus of this research is provided.

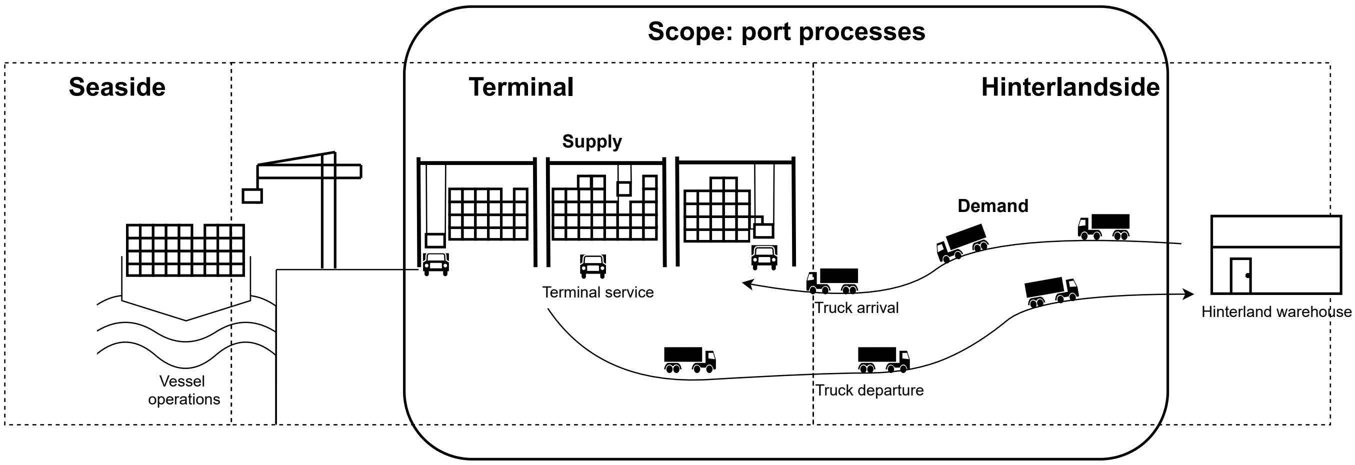


Figure 0.1: Conceptual overview of the port system and the focus of this research

The alignment between a port and its hinterland is indicated by the ability to integrate the port effectively into the transport, logistic and supply chains and fully exploit synergies with transport nodes, logistic networks, and various stakeholders. The synergies relate to efficient utilisation of capacity and operations. Establishing these synergies goes beyond port boundaries and across various stakeholders, and is highly related to hinterland connections.

Consequently, misalignment is caused by the lack of connectivity between port and hinterland. Improving port-hinterland alignment requires both long- and medium-term strategies (e.g. expanding terminal capacity, intermodal freight corridors, dry ports or extended gates), and short-term traffic management solutions (e.g. real-time traffic information sharing or time slot management).

In general, port-hinterland connectivity can be viewed from two perspectives. The first of which is the physical connectivity. From this perspective the connection of the port to the hinterland can be improved through the expansion of physical infrastructures. The physical connectivity perspective predominantly captures long-term strategies. The second perspective is digital connectivity where multiple stakeholders can communicate and exchange information for better cooperation and coordination. Additionally, digital connectivity comprehends the control of demand patterns. This form of connectivity largely requires short-term strategies as well as medium-term strategies. Physical connectivity is considered a precondition to achieve port-hinterland alignment at all. Digital connectivity in addition to physical connectivity ensures efficient use of physical infrastructure.

The alignment port and hinterland can be approached as a matter of matching demand and supply (Figure 0.1). The demand is represented by the trucks that arrive at the terminal to pick up or deliver a container. The terminal operational capacity represents the supply. Ideally, the demand and supply match perfectly, without a surplus or scarcity from any of the two sides. There are two relevant types of bottlenecks that can cause the mismatch of demand and supply. These bottlenecks can arise in port-hinterland physical or digital connectivity. The bottleneck can originate from either the demand or supply side. The combinations of the bottleneck type and origin capture the causes of misalignment between port and hinterland.

From the supply side, scarcity of capacity can cause misalignment. From demand side, misalignment can be caused by demand patterns. Physical bottlenecks are caused by scarcity of physical (infrastructural) capacity. For example, a lack of cranes, manpower or container storage. The digital bottlenecks are caused by inefficient operations or poor demand prediction, predominantly due to a lack of information exchange, communication, cooperation and coordination between stakeholders.

Opposed to physical connectivity, there is limited research towards digital connectivity because the exchange of data and information have always been critical due to privacy issues and fear of potential competitive advantages for other stakeholders. Moreover, the present research field lacks short-term traffic management strategies to mitigate truck traffic at terminal gates. Previous research is predominantly focused on reducing truck traffic congestion via physical infrastructure solutions. Nevertheless, there is potential to reduce waiting times using digital solutions for connectivity by controlling traffic demand patterns. Furthermore, the root of misalignment at the port of Rotterdam lies within inadequate control of truck arrival. Consequently, a digital solution is proposed to reduce waiting time at the terminals and accordingly improve port-hinterland alignment. This solution is found within traffic management strategies to control demand inflow at the terminals. An overarching strategy to control truck arrivals and reduce waiting time, is by shifting truck arrivals to other time periods. By implementing a Truck Arrival Shift control strategy, trucks can be shifted from peak periods to quieter time periods. Hence, peaks in demand can be reduced.

A design, modelling and simulation approach is taken for the design and evaluation of the Truck Arrival Shift policy. In this approach various methods are applied. These include a literature review, data analysis, discrete choice modelling, discrete-event simulation and the development of a heuristic. A suitable and well-known measure to instigate the truck arrival shift is the implementation of a truck appointment system. A truck appointment system is optimised through a time slot management system. Therefore, insight in a methodology for the design of time slot management systems is used to consequently design and evaluate the Truck Arrival Shift policy.

In the light of this research, there are two components in the development of a time slot management system and thus for the Truck Arrival Shift policy. The first component is a simulation platform that can accurately mimic the real world. The second component is an allocation framework to guarantee the best match between demand and supply and hence an optimum design. These two components must be integrated to obtain a complete design for the time slot management system.

In the field of time slot management system design, most researchers aim to optimise the time slot management system from a terminal's perspective. By doing this, many studies fail to recognise the impact of such a system on other stakeholders among which truck operating companies. Therefore, the truckers' perspective in the design and evaluating of the Truck Arrival Shift policy is included in this research by exploring the behaviour of truck operating companies. Behaviour modelling in the form of discrete choice modelling allows to explore trucker behaviour and is a suitable way to include preferences of truckers for container pick up time in the research.

Based on the components required for the design of a time slot management system and shortcomings of previous research, a modelling framework is defined to design and evaluate the Truck

Arrival Shift policy in this research. The modelling framework captures the methodology of this research and is presented in Figure 0.2.

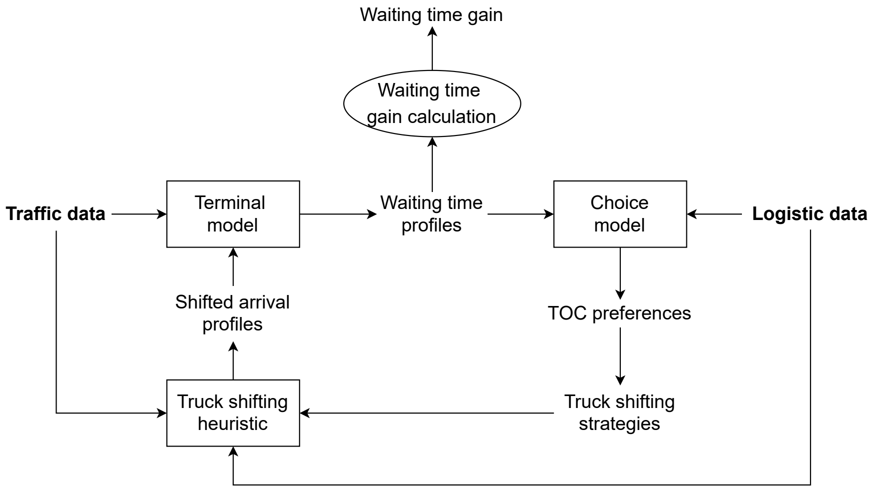


Figure 0.2: Modelling framework

A terminal model is developed to simulate the processes at the terminal. With the terminal model, a waiting time profile can be simulated from an arrival profile. The terminal model is set up using historic traffic data. The terminal model is formulated as a queueing model and discrete-event simulation is used to represent the port system. The terminal model includes three components, namely the truck generator, the trucks and the server. Together these three components make up three processes in the terminal model. The three processes in the model are the arrival process, the server process, and the departure process.

A choice model is developed to gain insight in the behaviour of the truck operating companies regarding time period choice for container pick up. Based on this insight, a truck shifting strategy can be formulated to control truck arrivals at the terminals. The choice model is based on discrete choice theory. The definition of the choice problem in this research is the choice of a trucker to pick up a certain container at a certain time. The probability of choosing a certain time is computed from the attractiveness of the alternatives. The attractiveness is measured from the utility function for each alternative. The utility function captures the influence of an attribute from the data. The choice model is set up using logistic data of container type and commodity type and the expected arrival time of the trucker.

Based on the truck shifting strategies that result from the choice model, the truck shifting heuristic is developed. The purpose of the truck shifting heuristic is to compute new arrival profiles based on the truck shifting strategies that resulted from the choice models. There are various steps involved to shift trucks and compute new arrival profiles. These steps are visualised in Figure 0.3.

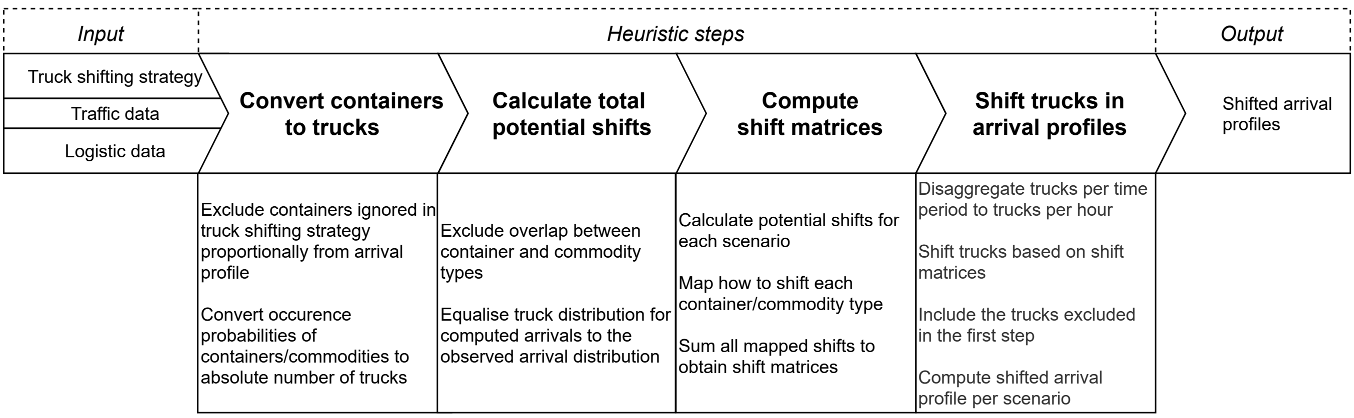


Figure 0.3: Overview of the truck shifting heuristic

Lastly, the waiting time gain calculation provides the results for evaluating the effect of controlling truck arrivals. With the terminal model, the waiting time profiles corresponding to the scenario arrival profiles from the truck shifting heuristic, can be simulated. By comparing the simulated waiting time profiles from the scenarios with the base case a waiting time gain can be calculated. The scenarios are displayed in Table 0.1.

Table 0.1: Overview of scenarios and corresponding application rates. *Scenario 16 represents a reference scenario indicating an equal spread of truck arrivals along the day

Scenario	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Application rate	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	60%	70%	80%	90%	100%	Equal*

The simulated waiting time profiles provide insight in the effect of the Truck Arrival Shift policy on the waiting time. Consequently, the waiting time profiles are analysed statistically to evaluate the potential significant reduction of waiting time. The results show that the truck shifting strategies are capable to reduce waiting time significantly compared to the current situation at the terminals, at small application rates. The implementation of a Truck Arrival Shift policy is found to be an effective measure to spread truck arrivals along the day. Additionally, the Truck Arrival Shift is a control policy with low effort high reward due to the significant reduction at small application rates.

In addition to a statistical analysis to explore significant effects on waiting time, the waiting time gain is analysed. By subtracting for each hour the total waiting time (for all truck and for the entire day) for each scenario from the base case, the waiting time gain profile can be computed.

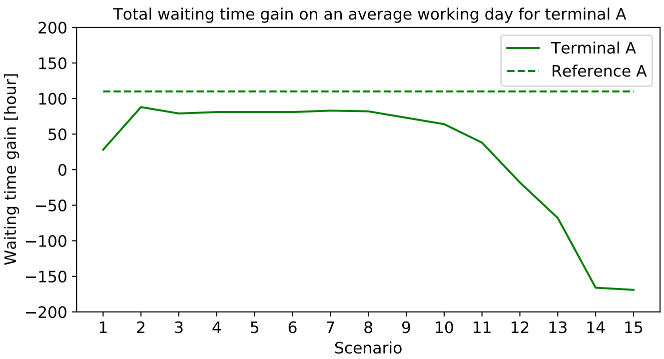
The development of waiting time gain under various application rates (scenarios) is displayed in Figure 0.4. The solid lines represent the development of the waiting time gain under various application rate scenarios. The dotted lines represent the waiting time gain in the 16th scenario. The 16th scenario, represents the scenario in which an entirely equal spread of trucks along the day is simulated. The scenario is used as reference scenario as an entirely equal spread of trucks is considered the perfect situation at the terminal for truck arrival. The number of trucks arriving will always stay below the terminal capacity and there will not be any waiting time. Consequently, the waiting time gain in the 16th scenario is the largest possible. It can be concluded that this largest possible waiting time gain at the terminal can almost be achieved with the shift strategies.

The development of the waiting time gain (Figure 0.4) shows that there is an optimal percentage for shifting trucks to reduce waiting time. It can be observed that the gain under small application rates (5% - 10%) is already quite close to this optimum.

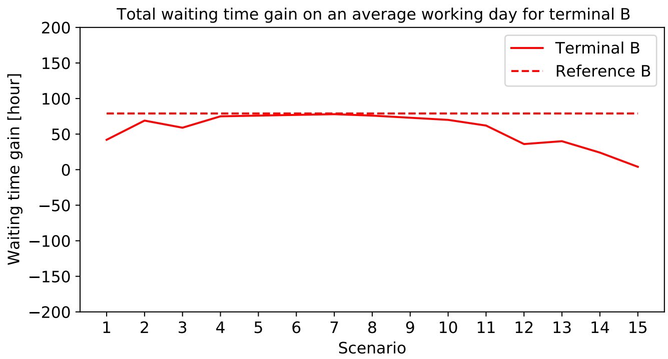
Moreover, it is found that under high application rates of truckers to the control of truck arrivals, there is no waiting time gain, but a loss. This means that under high application rates of truckers, the Truck Arrival Shift policy is not beneficial.

The optimal waiting time gain would be achieved with a shift around 40% of truck arrivals. However, the ideal situation is not solely represented by achieving the highest possible waiting time gain. In the ideal situation the effort must also be considered as a shift of trucks does not naturally happen, it requires effort. The effort required is expected to increase with higher shift percentages. Therefore, the optimal waiting time gain achieved under 35%-45% shift percentage, might not reflect the ideal situation for shifting trucks. The ideal situation is represented by low effort high reward. In other words, achieve high waiting time gain with small shift percentages.

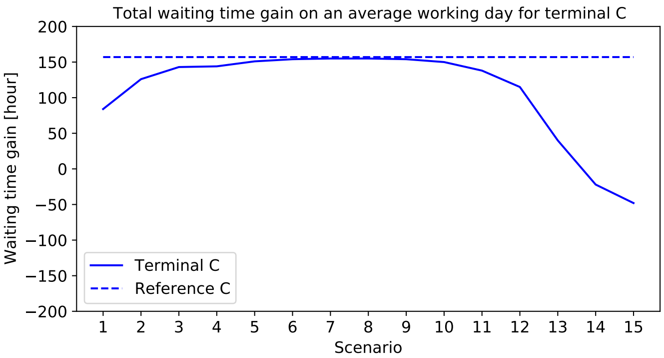
In Table 0.2 the waiting time gain in hours is converted to a monetary gain in euro and a productivity gain in hours for truck operating companies. The monetary gain indicates the cost saved by the truck operating company as the truck does not have to wait at the terminal. The cost of waiting at the terminal are estimated to 38 euro per hour. The cost of transporting a container are 62 euro per hour. The second to right column in Table 0.2 (productivity gain) presents how many hours of transporting a container via road can be gained from not waiting at the terminal, hence a gain in road container transport productivity. This is calculated by dividing the total waiting time gain (terminal wide) by the cost of transporting a container on the road (62€/h). The Truck Arrival Shift policy allows for around 200 hours of productivity gain with the saved costs for waiting at the terminals, on a daily basis. In other words, the waiting time gain for truck operating companies equals the transportation of around 200 containers for one hour. If an average transportation time



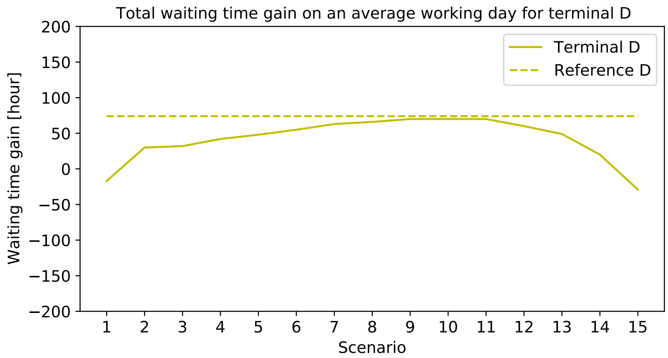
(a) Terminal A



(b) Terminal B



(c) Terminal C



(d) Terminal D

Figure 0.4: Development of the waiting time gain along the scenarios, in comparison with the reference scenario

of one hour is assumed for the Netherlands, this productivity gain equals almost 10% of the entire production in the system on a daily basis.

The most right column (gain/truck) provides insight in the ratio benefit of shifting versus number of trucks that have to shift. As said, low effort high reward is desired. It can be observed that a shift percentage of 10% will terminal wide provide the highest value in terms of effort and reward. This gain per trucks does not only indicate a ratio of effort and reward. Additionally, the most right column indicates a so called social gain. The social gain refers to contribution of a shift made by one single truck to the entire system. Not only the portion of trucks that is shifted benefits from the shift. Rather all trucks benefit of a shift made by another truck. The trucks that are shifted do not only save waiting time in the peak periods, which would cost 38 euro per hour. Additionally, the truck that is shifted contributes to a social benefit because the trucks that are not shifted, will also experience a waiting time reduction even though they still arrive in the original peak period.

Table 0.2: Waiting time gain in monetary value [€] and road container transport [hour] for TOC on an average working day

Share shifted	Trucks shifted (terminal wide)	Gain at each terminal				Total gain (terminal wide)	Productivity gain [hours]	Gain/ truck
		Terminal A	Terminal B	Terminal C	Terminal D			
5%	114	€ 1.061	€ 1.582	€ 3.176	€ -638	€ 5.181	83	€ 45
10%	230	€ 3.356	€ 2.627	€ 4.802	€ 1.144	€ 11.929	192	€ 52
15%	344	€ 3.014	€ 2.253	€ 5.447	€ 1.203	€ 11.916	192	€ 35
20%	459	€ 3.069	€ 2.867	€ 5.477	€ 1.604	€ 13.017	210	€ 28
25%	537	€ 3.073	€ 2.879	€ 5.742	€ 1.811	€ 13.505	218	€ 25
30%	687	€ 3.093	€ 2.914	€ 5.855	€ 2.105	€ 13.967	225	€ 20
35%	803	€ 3.152	€ 2.948	€ 5.876	€ 2.410	€ 14.386	232	€ 18
40%	917	€ 3.112	€ 2.900	€ 5.872	€ 2.521	€ 14.405	232	€ 16
45%	1030	€ 2.775	€ 2.770	€ 5.838	€ 2.647	€ 14.029	226	€ 14
50%	1146	€ 2.431	€ 2.651	€ 5.706	€ 2.667	€ 13.456	217	€ 12

The potential waiting time gain, productivity gain and social gain by controlling truck arrivals by means of a Truck Arrival Shift policy are striking results from this research. Since a system is as efficient as the weakest link, improving the performance of the weakest link, improves the entire system. Hence, controlling truck arrivals does not only cause a gain at the terminal gates, it actually solves costs in the entire system. The root of misalignment at the port of Rotterdam lies within inadequate control of truck arrival. Truck shifting is found to improve the performance of this weakest link and thus of the entire container transport system. Consequently, every minute of gain at the terminals is gain for the entire container transport system. Therefore, the shift of truck arrivals is expected to be beneficial for most stakeholders in the port system. For some stakeholders more than others, but for all a measurable reduction of costs along with the waiting time reduction for the trucks at the terminal gates is expected.

There are three things crucial to implement the Truck Arrival Shift policy effectively in practice and consequently improve port-hinterland alignment at the port of Rotterdam. First and foremost, data sharing between stakeholders is important as this allows to shift the trucks and increases digital connectivity. Fortunately, the proposed framework for the Truck Arrival Shift policy allows for sharing information and data safely, without violation of privacy or creating competitive advantages. Secondly, the shippers and forwarders should relax the constraints regarding container pick up time. This can be accomplished by data sharing to control truck arrivals. Lastly, the opening hours in the hinterland must be extended. The Truck Arrival Shift policy requires that the truck operating companies can operate outside the traditional hinterland operating hours.

All in all, to implement an effective Truck Arrival Shift policy and realise a waiting time reduction in practice to successfully improve port-hinterland alignment, the Port of Rotterdam can pull two strings. First, the Port of Rotterdam should manage safe data sharing between stakeholders so that the truck arrivals can be controlled. Moreover, the Port of Rotterdam should take the lead in extending hinterland opening hours.

Even when the waiting time reduction in practice is less than the reduction found in this research, the Truck Arrival Shift policy is still valuable for improving port-hinterland alignment as the implementation of the Truck Arrival Shift policy increases digital connectivity.

There were some limitations in the research regarding data availability, limitations in methodology and neglecting changing environment in the port area. However, these limitations are not expected to have had significant impact on the results because all choices are sustained with valid argumentation or checked with statistical analysis.

Lastly, various implications for future research arise. The recommendations relate to the developed models and the implementation of the Truck Arrival Shift policy in practice.

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ACRONYMS

PoR Port of Rotterdam . . . 1
TLN The Dutch Association for Transport and Logistics . . . 1
TAS Truck Arrival Shift . . . 2
TSMS Time Slot Management System . . . 2
TOC truck operating companies . . . 1
ITS Intelligent Transportation System . . . 15
FIFO First In First Out . . . 25
LIFO Last In First Out . . . 25
PSFFA Point-wise Stationary Fluid Flow Approximation . . . 21
B-PSFFA Bisection Point-wise Stationary Fluid Flow Approximation . . . 21
WB-PSFFA Wibowo Bisection Point-wise Stationary Fluid Flow Approximation . . . 21
GA Genetic Algorithm . . . 27
DES discrete-event simulation . . . 4
DCM discrete choice modelling . . . 4
MVII Maasvlakte II . . . 33
i.i.d independently and identically distributed . . . 20
ASC alternative specific constant . . . 28
MNL Multinomial Logit . . . 41
MSE mean square error . . . 34
ETA estimated time of arrival . . . 11
MAPE mean absolute percentage error . . . 36
KiM Netherlands Institute for Transport Policy Analysis . . . 57

1 INTRODUCTION

High waiting times for trucks at the terminal gates of seaports are an issue that is increasingly receiving more attention. Long queues of idling trucks in front of the terminal gate waiting to pick up or deliver a container create congestion, and induce emissions, costs and delays [Sharif et al., 2011; van Asperen et al., 2013; Merk and Notteboom, 2015; Li et al., 2018].

Container terminals in the port of Rotterdam, the largest European port [World Shipping Council, 2020], are no exception to these issues. The waiting times for trucks at the terminal gates have been rapidly increasing the past 6 years [Drewes and Gorter, 2017]. In 2014 the maximum waiting time at the terminals for container pick up or delivery in the Rotterdam port area was around 40 minutes. In 2016 this increased to around one hour and 40 minutes. In 2020, reports show that there has been an increase in waiting time, up to three hours, at the port of Rotterdam container terminals [Rijnmond, 2020].

The Dutch Association for Transport and Logistics (TLN), representative of the truck operating companies (TOC), has expressed great concern regarding the waiting time at the Rotterdam terminals [TLN, 2020], as these directly affect the turnaround time for trucks. Turnaround time can be defined as the total time spent by a truck in the port area, the duration from the arrival of a truck at the terminal to the moment of exit [Chen et al., 2013a], thus service time plus the waiting time. Minimal turnaround times ensure that TOC can engage in more transport activities, and accordingly increase their economic value. Additionally, the Port of Rotterdam (PoR) (the port authority in Rotterdam) does not desire the current situation with long queues and waiting time as this can eventually affect their competitive position [Martinho, 2008] and sustainability goals [Port of Rotterdam, 2020a]. The terminals operating in the Rotterdam port area acknowledge the long queues during the day, however they note that there is no congestion during the evening and night [Stroosman, 2020].

1.1 PROBLEM AND BACKGROUND

High waiting time and therefore non-optimal turnaround times for trucks are a problem that the terminals, TOC and PoR face regularly. This problem is a result of misalignment which is due to the lack of connectivity between port and hinterland. Many factors, among which are port accessibility, competitiveness and reliability, play a role in or are (in)directly affected by the problem of misalignment [Notteboom, 2006; Ducruet et al., 2014]. Improving port-hinterland alignment requires both long-term strategies (e.g. intermodal freight corridors, dry ports or extended gates) and short-term traffic management solutions (e.g. real-time traffic information sharing or time slot management).

One of the most important reasons for truck traffic congestion at the terminals and therefore waiting time at terminal gates, is a lack of port-hinterland alignment [Merk and Notteboom, 2015]. The alignment is indicated by the ability to integrate the port effectively into the transport, logistic and supply chains and fully exploit synergies with transport nodes, logistic networks, and various stakeholders [Notteboom, 2009]. The synergies relate to efficient utilisation of capacity and operations. Establishing these synergies goes beyond port boundaries and across various stakeholders, and is highly related to hinterland connections. Many studies have been conducted towards the alignment of port and hinterland in the context of port-hinterland connectivity [Martinho, 2008; Notteboom, 2009; Franc and Van der Horst, 2010; Wan et al., 2018]. In general, this connectivity can be viewed from two perspectives.

The first of which is the physical connectivity. From this perspective the connection of the port to the hinterland can be improved through the expansion of physical infrastructures. Examples are expanding capacity by crane purchases, the development of intermodal freight corridors [Monios and Lambert, 2013], extending port activities to inland terminals like dry ports [Roso et al., 2009] or extended gates [Veenstra et al., 2012], and night time storage facilities for containers near hinterland warehouses. Previous research [Roso and Leveque, 2002; Roso et al., 2009; Veenstra et al., 2012; Monios and Lambert, 2013; Merk and Notteboom, 2015; ITF, 2016] has proved the effectiveness of improved physical connectivity in the reduction of truck traffic at terminal gates. However, the solutions from this perspective require a lot of time and costs to implement and can therefore be categorised as more long-term strategic solutions.

The second connectivity perspective is digital connectivity where multiple stakeholders can communicate and exchange information for better cooperation and coordination. Additionally, digital connectivity comprehends the control of demand patterns. As opposed to physical connectivity, there is limited research towards digital connectivity because the exchange of data and information have always been critical due to privacy issues and fear of potential competitive advantages for other stakeholders. In contrast to physical connectivity solutions, advancements from the digital connectivity perspective may have the potential to be implemented more rapidly as no large physical infrastructure is required. Therefore, some solutions from this perspective can also be categorised as more short-term solutions.

De Langen and van der Horst [2008] propose a framework with four types of solutions to solve coordination problems in the transportation chain. From their research, they concluded that poor coordination of stakeholders along the transportation chain can cause misalignment of port and its hinterland. Additionally, in the context of digital connectivity, De Langen and van der Horst [2008] and other scholars indicate the lack of information sharing between stakeholders as a crucial problem in transportation chains. Examples of other studies towards stakeholder coordination in transport chains and how this affects the efficiency of container transport are Franc and Van der Horst [2010], van der Horst and van der Lugt [2011], Bergqvist and Egels-Zandén [2012] and Bergqvist [2012]. Nevertheless, stakeholder coordination, as proposed in previous studies, suggests a considerable time horizon.

Additionally, digital connectivity can help managers to apply more short-term traffic management solutions for congestion at terminal gates. A strategy to reduce congestion at terminal gates is by controlling demand inflow by application of a Truck Arrival Shift (TAS) policy. The application of a TAS policy has the potential to allow for effectively allocating truck demand to terminal capacity and vice versa. Examples of practical solutions to instigate a TAS policy are time-varying tolls [Chen et al., 2011], sharing of real-time traffic information [Sharif et al., 2011], and the implementation of a Time Slot Management System (TSMS) [Chen et al., 2011, 2013a; Wibowo and Fransoo, 2020].

Few attempts have been made to explore the application of a TAS policy. Sharif et al. [2011] conduct a research in the context of information sharing between stakeholders using a traffic management solution in the form of a live view of the terminal gates. The result of this study is promising as they show that providing real-time gate congestion information and some simple logic for estimating the expected truck waiting time can minimise congestion at terminals gates as TOC shift their arrival to another time. This shows there is potential for a TAS policy to reduce congestion and waiting time at terminals, and consequently improve port-hinterland alignment.

On the port side, applying a TAS policy allows terminal operators to improve their operational efficiency at terminal gates and consequently reduce truck waiting time [Chen and Yang, 2010; Zhang et al., 2013; Chen et al., 2013b; Phan and Kim, 2015; Zhang et al., 2019]. On the hinterland side, TOC can benefit from a TAS policy as it can improve their turnaround time. Nevertheless, the operations of the TOC are largely affected by the application of a TAS policy as they might have to shift their arrival time. Previous studies predominantly ignore the hinterland side i.e. neglecting the roadside or user perspective. The studies from Chen et al. [2011, 2013a] and Wibowo and Fransoo [2020] come closest as they limit the deviation from the preferred time slot of a TOC and include the objectives of the TOC in the optimisation of a TSMS, respectively. However, in this approach the behavioural perspective is not included. It is strongly believed that it is essential to consider both the port and hinterland side, taking multiple stakeholders in the transportation chain into account, to improve port-hinterland alignment and hence the interest.

In sum, poor developments in either physical or digital connectivity deteriorate alignment between port and hinterland. The misalignment increases truck traffic congestion and waiting time at terminal gates and consequently pose various problems, including congestion, emissions, costs and delays to the transportation chain. Although improving physical connectivity enhances truck traffic in the long-term, the improvement of digital connectivity proposes more short-term traffic management solutions on a daily basis. Nevertheless, the presence of minimal physical connectivity must be considered as a constraint for providing alignment between port and hinterland at all. Yet, physical alignment alone is not sufficient, digital connectivity can enhance the overall connectivity complementing physical connectivity.

1.2 RESEARCH APPROACH

The research in the thesis follows from the problem and background discussed in the previous section. In the approach for this research a gap is highlighted, objectives are defined, the scope is determined, research questions are formulated and a method is decided upon.

1.2.1 Gap

Despite the efforts of many scholars, not all aspects of port-hinterland alignment are yet explored. The present research field lacks short-term traffic management strategies to mitigate truck traffic at the gates. Previous research is predominantly focused on reducing truck traffic congestion by physical infrastructure solutions. Nevertheless, previous research indicates the potential of digital connectivity by controlling traffic demand patterns to reduce congestion at the terminal gates.

The traffic management control strategy that is increasingly receiving attention is the application of a TAS policy. Several studies have been conducted towards implementing a TAS policy to reduce truck congestion at terminal gates. However, the vast majority of these studies are from the perspective of the terminal. These truck shifting strategies consider how many trucks can be served at once at the terminal, consequently the shifting the other arrivals. This way of shifting truck arrival is predetermined by the terminal potential, neglecting the roadside or user behavioural perspective.

Moreover, previous research towards TAS design lacks inclusion of all relevant intricacies associated with the system in the design. Inaccurate assumptions or unjustified simplifications have been made for the design components of a TAS policy. Especially in the arrival and queueing process there is a gap regarding the reality.

1.2.2 Objectives

This research seeks to develop a method to reduce truck waiting time in the Rotterdam port area taking the port and hinterland systems into account, and, hence, to improve the port-hinterland alignment. This is the main research objective.

In this research a TAS policy for TSMS is studied as a solution for the waiting time at the terminal gates, since the result of this research and others (Section 1.1) indicate that a TAS policy is indeed effective to reduce the waiting times. However, to thoroughly grasp the issue of port-hinterland alignment and improve this, knowledge of TAS alone is not sufficient. Rather the bigger picture regarding port-hinterland alignment must be explored.

Consequently, to achieve the main objective, insight in the misalignment issue is required. Various possibilities to solve the misalignment should be reviewed. Subsequently, a method should be designed and evaluated on the ability to solve the problem of waiting time at the gates. Lastly, the designed method should be linked to practice.

1.2.3 Scope

At the heart of this research is the focus on landside transportation, as the alignment between port and hinterland is studied. Cargo handling at the seaside and the transshipment of cargo are out of scope. Therefore, the port processes referred to in this research comprehend the arrival of a truck at the terminal, the handling of a truck in the terminal, and the departure of a truck from the terminal.

Even more so, the focus is on container transportation and more specifically on closed containers, open top containers are out of scope. Hence, dry and liquid bulk, and break bulk are not included in the scope of this research. Therefore, the term 'terminal' used in this research always refers to a container terminal.

Subsequently, pipelines as transport mode are left out of scope, as well as the rail and barge transport modes. This research focuses solely on the truck transport mode via road. Road transport contains the largest share of container transport in the port of Rotterdam, and this share has been growing recently [Port of Rotterdam, 2020b]. Moreover, in the last few years initiatives, Nextlogic [Nextlogic, nd] and OnTrack [Port of Rotterdam, nd], have successfully emerged to optimise the rail and barge modalities, respectively. For the trucking mode such a successful project is still missing.

The consequences of misalignment, namely affected port attractiveness and competition [Martinho, 2008], are mentioned occasionally but will not be elaborated extensively as this research is not towards that matter. However these are evidently related to the port-hinterland alignment and can therefore not be left entirely unmentioned.

Lastly, the focal point of this research is on exploring short-term solutions to solve day-to-day traffic issues at the terminals by controlling truck arrivals rather than to solve the underlying causes of the misalignment issue. The causes of misalignment are explored to allow for a realistic solution design. Nevertheless, entirely eliminating the cause of misalignment is expected to require another approach, more time and different measures than are available for this research [Stroosman, 2020].

1.2.4 Questions

To fill the identified knowledge gaps (Section 1.2.1) and achieve the research objectives (Section 1.2.2), a main research question is formulated. Prior to answering the main research question, several other questions should be answer. These questions are formulated as sub-questions in the research.

The main research question is formulated as follows:
How can port-hinterland alignment at the port of Rotterdam be improved such that the waiting time at container terminals is reduced?

The following sub-questions are formulated to answer the main research question:
1. *What are the main causes of misalignment between port and hinterland which result in waiting time at the container terminals?*
2. *How can an intervention be designed to reduce the waiting time at the container terminals?*
3. *What is the potential gain of the intervention in terms of waiting time at the container terminals?*

1.2.5 Method

In this research a design, modelling and simulation approach will be used to study the misalignment issue regarding waiting time at the terminals in the Rotterdam port area.

Several methods are applied to answer the formulated research questions in Section 1.2.4. These methods include a literature review, data analysis, discrete choice modelling (DCM), discrete-event simulation (DES) and the development of a heuristic.

By means of a literature review, the causes and potential solutions for misalignment are explored. Moreover, a literature review is used to gain insight in how to design an intervention to reduce waiting time at the terminals. To include the TOC perspective in the designed intervention, DCM is used. Logistic data of import containers in the year 2017 is input for this choice model.

To evaluate the performance of the intervention, a novel framework is introduced in this research. This framework consists of two components. These are a simulation platform and allocation framework. In the simulation platform, DES is applied to simulate the port processes and consequently to allow for evaluating the effect of the designed intervention. The input for the DES model is traffic data of 2017, obtained from loop detectors in the port area. The allocation framework heuristically applies a set of rules to control the truck arrivals. Consequently, with the allocation framework input for the DES model is generated to evaluate the intervention under various scenarios.

1.3 RESEARCH IMPACT

It is expected that this research has scientific impact as well as social impact. The contribution and the beneficiaries are highlighted in this section.

1.3.1 Contribution

With this research several contributions will be made to the academic field.

First of all, this research will provide an insight in the issue of misalignment in the light of the daily operations at the terminal and digital connectivity. This is complement to previous research that is mainly focused on analysing the port-hinterland alignment from the physical connectivity perspective.

Another contribution is that this research will provide an insight in several approaches, this will provide other scholars with knowledge of possibilities to solve misalignment.

Furthermore, in this research, a TAS policy is designed which will respond to research gaps found in TAS design. To evaluate the performance of this policy, a novel framework is introduced in this research.

1.3.2 Beneficiaries

This research is conducted in cooperation with the port authority of Rotterdam (PoR). As they desire to improve the port-hinterland alignment and reduce waiting time in Rotterdam they will benefit from this research.

Additionally, TOC will benefit from this research as they are in particular confronted with the long queues and suffer the consequences of high waiting time at the terminal in the Rotterdam port area.

Furthermore, the Rotterdam terminals will have advantages from this research, as peak loads of truck arrivals can demote the terminal operation efficiency.

Other beneficiaries may be stakeholders in the port system (e.g. shippers, forwarders, shipping lines and hinterland warehouses) as misalignment affects the efficiency in the entire chain.

Lastly, several actors in the public sector, such as governmental parties, municipalities and road authorities, can benefit from this research as the long queues at the terminal gates induce costs and emissions for society. Moreover, improved alignment can relief pressure from the main road network.

1.4 THESIS OUTLINE

The outline of this thesis follows a chronological order. With chronological order it is meant that first the problem will be analysed, then a possible solution is explored, subsequently a solution is designed, lastly the designed solution is evaluated. A visual representation of the thesis outline is provided in Figure 1.1.

To draw the bigger picture and gain insight in the problem, causes and potential solutions regarding port-hinterland alignment, this is discussed in the second chapter (Chapter 2). In Chapter 2, an answer to the first sub-question is provided.

In the third chapter, Chapter 3, an extensive literature review is conducted to gain insight in the potential methodologies to design an intervention to reduce waiting time at the terminals. Consequently, in Chapter 4 the design, modelling and simulation approach for the intervention is elaborated. In Chapter 3 and Chapter 4 an answer to the second sub-question is provided.

The results of the research are presented and discussed in Chapter 5. In this fifth chapter the answer to the last sub-question is provided.

Lastly, in the sixth chapter, Chapter 6, a discussion and conclusion for the research are presented. Consequently, an answer to the main research question is provided. Additionally, implications for future research are recommended in this last chapter.

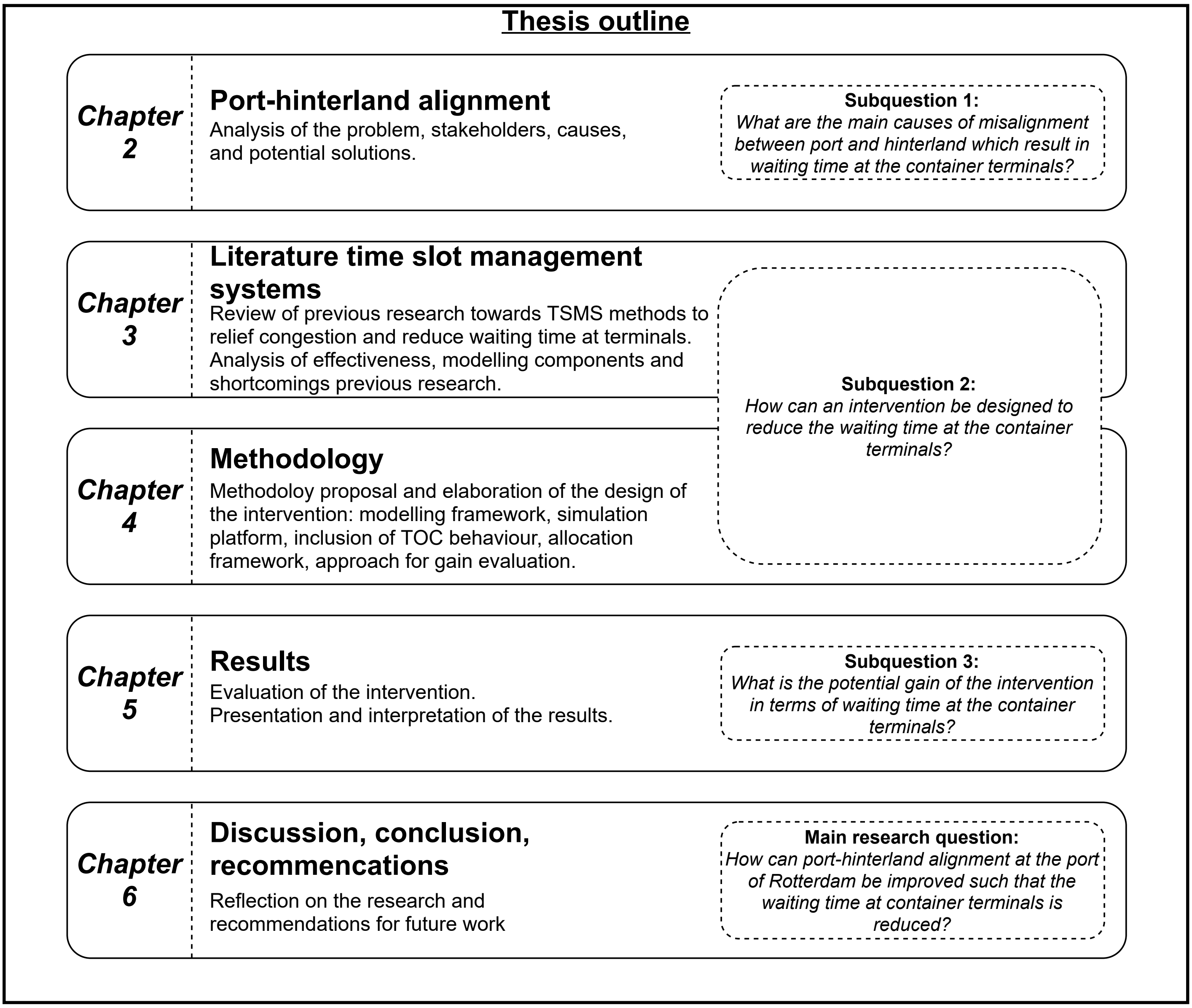


Figure 1.1: Structure of the thesis, overview of chapters, content and research questions

2 PORT-HINTERLAND ALIGNMENT

In this chapter, the alignment between port and hinterland is elaborated. This chapter aims draw the bigger picture regarding port-hinterland alignment by to provide an understanding of where misalignment originates from and the possibilities to improve the alignment. First, some definitions are introduced in Section 2.1 which help to understand the terminology of port-hinterland alignment. Then, the role of a seaport in a network is discussed in Section 2.2. Thirdly, the misalignment problem is illustrated in Section 2.3 by the concept of matching demand and supply. Subsequently, the stakeholder playing field is described in Section 2.4. Thereafter, in Section 2.5 the causes of misalignment are discussed. Lastly, an overview of options for matching demand and supply is provided in Section 2.6.

Figure 2.1 provides an overview of the story line in this research. This represents the advancement from the bigger picture regarding alignment towards the specific focus on TAS.

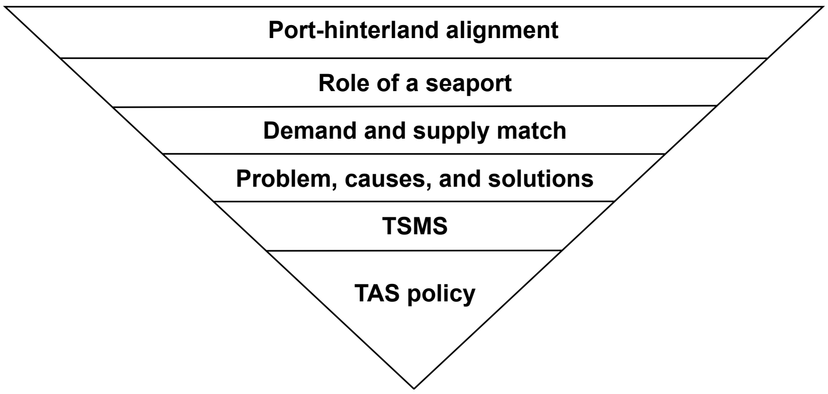


Figure 2.1: Pyramid overview of story line from port-hinterland alignment to TSMS and TAS

2.1 DEFINITIONS

A seaport is part of the supply chain, logistics chain, and transport chain. These three terms are often used interchangeably. However, it is essential to differentiate these terms and chains as they are similar but not the same.

Firstly, a supply chain can be defined as *"a set of three or more entities (organisations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer"* [Mentzer et al., 2001].

Secondly, a logistics chain can be defined as *"the part of the supply chain process that plans, implements and controls the efficient, effective flow and storage of goods, services and related information from the point-of-origin to the point-of-consumption for the purpose of conforming to customers' requirements"* [de Jong and Ben-Akiva, 2010].

Lastly, a transport chain can be defined as *"series of one or more transport legs between the sender and receiver, each with its own mode or vehicle type"* [de Jong and Ben-Akiva, 2010].

By these definitions, it can be deduced that there is a hierarchical structure as the transport chain is included in the logistical chain and the logistical chain is part of the supply chain. The transport chain comprises the physical flow of goods from one place to another. Logistics involves the physical flow of goods (the transport chain); and adds service flow, information flow and inventory to meet the customer requirements. The supply chain includes the logistics chain and links many companies together by adding all the activities, processes and actors, that are required from the raw product to the final product for the end-user.

Additionally, it is important to define precisely and make a distinction between "effectiveness" and "efficiency" in the context of the supply chain, logistics, and transportation.

Drucker [1995] introduces the term 'effectiveness' as *"the extent to which the desired result is realised"* and the term 'efficiency' as *"output divided by input, or the extent to which the result produced was produced at least cost"*.

By rephrasing these definitions, effectiveness indicates doing the right thing, and efficiency indicates doing the things right. Efficiency is often measured in time and costs and implies that processes or activities should use as little time or costs as possible.

Lastly, throughout this research the term 'congestion' is used to describe the problem at the terminal gates. Congestion can have alternate definitions. For this research the definition of Rothenberg (1985) cited in Aftabuzzaman [2007], is used and slightly adapted to reflect the meaning of congestion in this research. *"Congestion is a condition in which the number of vehicles attempting to use terminal services at any time exceeds the ability of the terminal to carry the load at generally acceptable service levels."*

2.2 THE ROLE OF A SEAPORT

A seaport can simply be regarded as a node in a transport network connecting two legs of transportation, namely seaside transport and landside transport. Jakomin [2003] identifies a seaport as *"the area where the traffic/transport routes on sea and land meet"*.

A port acts as a logistics hub in the transport network and plays a crucial role in connecting these legs: combining the processes of transport between the sea and the mainland [Montwiłł, 2014]. A seaport provides connecting services for these transport legs [Branch, 1986]. As the processes between the sea and land legs are interpenetrating, interdependent and interrelated [Montwiłł, 2014], the sea and land transport must be aligned to achieve the optimal potential of a seaport [Jakomin, 2003].

For this research, the seaside leg is out of scope (Section 1.2.3). Nevertheless, for a general understanding of the entire system it adds value to mention this leg. According to Ligteringen and Velsink [2012]; Rijsenbrij [2018b] the seaside leg can be divided into several processes. These include the mooring of a vessel; (un)loading of a vessel from/to internal transport means; transporting containers from/to the stacking yard; (un)loading containers from the stacking yard from/to external transport means.

The landside leg of a port can be demarcated by the transport of goods between the port and a hinterland location. Rijsenbrij [2018a] outlines the landside service activities for trucks. These activities are largely part of the gate process. The process at the gate involves identifying the container, checking the container, entering the port, (un)loading the container at the stacking yard. Landside transportation is often referred to as hinterland transport. There are several options for hinterland transport, namely via road (truck), rail (train), inland waterways (barge), and pipelines. In this thesis, the latter three transport modes are out of scope (Section 1.2.3).

As mentioned, the processes between the seaside and landside legs are connected at the seaport. More precisely the legs overlap at the terminal gates. This indicates that the activities at the terminal gate cater the alignment of the port and its hinterland. In Figure 2.2 an overview of the port system and the focus of this research is provided.

2.3 MATCHING DEMAND AND SUPPLY

The alignment sea and land transport at a seaport is a matter of matching demand and supply at the terminal gates [Guan and Liu, 2009].

Generally in transportation research, the users of the transport mode, for example traveler or goods, represents the demand. Whilst the transport mode, for example truck, train, barge, is considered to represent the supply.

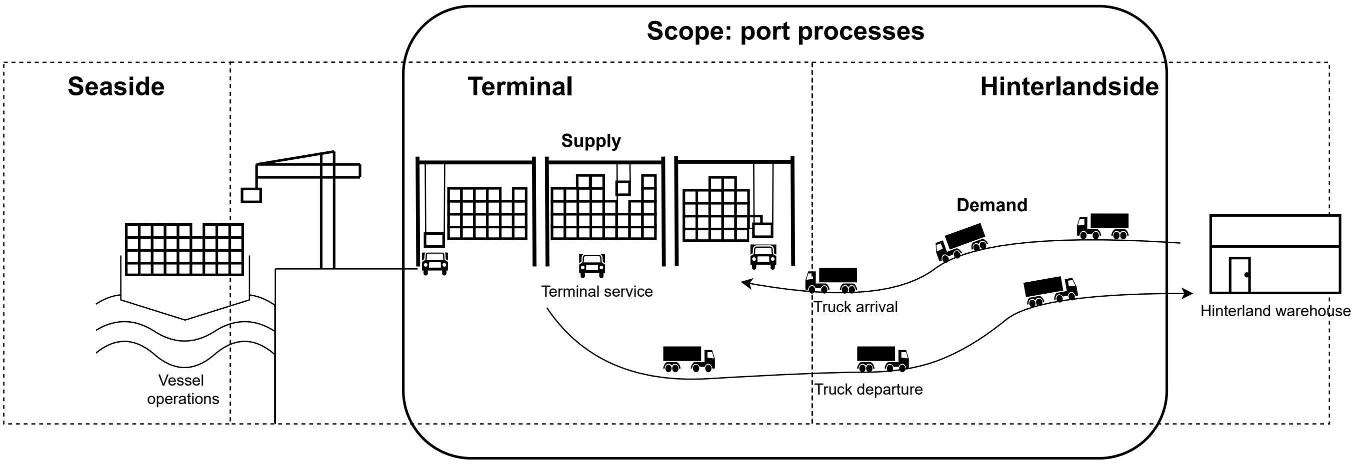


Figure 2.2: Overview of the port system and the focus of this research

However, in the scope of this research and similar to Guan and Liu [2009], the demand is considered to be the number of trucks for container pick up or delivery at time t, as these represent the users in the system. Whereas the supply is regarded as the terminal operational capacity at time t. Hence, terminals supply the demand of trucks at the hinterlandside to handle a container.

In events where the terminal is unable to serve the demand of trucks, the demand exceeds the supply. When the demand exceeds the supply, waiting times are the result. This affects the turnaround times of trucks at the terminal. In these events there is a misalignment between port and hinterland. For example, when there are peak loads in truck arrival, the surplus of trucks queue at the terminal gates, consequently congestion develops.

Matching demand and supply can be understood as the allocation of resources to an agent in a system. Resource allocation is widely discussed in the academic field across several disciplines, often in the context of decision making. For example in the distribution of energy [Naz et al., 2017; Iqbal et al., 2014; Li et al., 2016], health care [e Oliveira et al., 2020; Withanachchi et al., 2007; Stinnett and Paltiel, 1996], air traffic management [Kim and Hansen, 2015; Murça, 2018], transportation [Bhattarai et al., 2020; Zargayouna et al., 2016; Wang, 2016; Mathew et al., 2010], and logistics [Li et al., 2020; Liu et al., 2014; Morariu et al., 2020].

From these examples, the agents in the systems are found to represent the demand. The resources represent the supply. Too many resources for the agents at time t cause a surplus of supply. Moreover, too many agents for the available resources at time t cause a surplus of demand. Both situations are undesirable as a surplus indicates that the system is not exploited to the best of its abilities. The system is as efficient as the weakest link, therefore a mismatch of demand and supply affects the efficiency of the entire system.

Several bottlenecks can be indicated from which the mismatch between demand and supply originates [Merk and Notteboom, 2015]. These are regulatory/political, physical, and digital bottlenecks. In light of this research two main perspectives are relevant, these are captured by the latter two.

First, there are physical bottlenecks. Physical bottlenecks can be the result of demand that exceeds the available capacity of infrastructure. This indicates poor physical connectivity of the seaside and landside leg. The capacity of a terminal to handle containers might not be sufficient, for example a lack of cranes, stacking yard, or terminal gates.

Second, there are digital bottlenecks. These bottlenecks can be the result of inefficient operations of terminals or TOC due to poor demand predictions. These bottlenecks originate from a lack of communication, cooperation, and coordination between stakeholders. This indicates poor digital connectivity between the seaside and landside. For example, there is no information exchange between terminals and TOC. This can cause a poor prediction of demand and therefore insufficient resource allocation.

Physical connectivity can be considered to be a precondition to achieve port-hinterland alignment at all. In addition, digital connectivity ensures efficient use of physical connectivity and improves port-hinterland alignment. In other words, physical connectivity is required but not sufficient for port-hinterland alignment. Even when sufficient infrastructure is present in the port-hinterland alignment, poor digital connectivity could largely deteriorate the port-hinterland alignment [Merk and Notteboom, 2015].

Despite the physical bottlenecks, which are more straightforward and imaginable, their digital counterparts are rather more difficult to identify. To ensure a proper understanding of the digital connectivity between port and hinterland, the stakeholder playing field is described in the next section (Section 2.4).

2.4 STAKEHOLDER PLAYING FIELD

A variety of different firms, such as shipping lines, terminal operators, forwarders, hinterland transport providers and inland terminal operators are involved in container transport [De Langen and van der Horst, 2008]. Besides private companies, different public actors, such as the port authority, customs and infrastructure managers, are involved as well. The relevant stakeholders are categorised into seven groups. These groups are the port authority, shippers, freight forwarders, terminal operators, TOC, hinterland warehouses, and the port community system. For each category, their role, objective, and potential influence are defined.

Port authority

The port authority can be regarded as the party that manages, operates and develops the port area. Often the port authority is a (quasi-)governmental institution.

The most common port exploitation is a 'landlord port'. In this type of exploitation, the port authority acts as a landlord and is responsible for necessary port infrastructure. This port infrastructure includes quays, locks, docks and yards [Notteboom and Winkelmans, 2001].

The main objective of a port authority is to strengthen the competitive position of the port. The performance measure of a port authority is volume-driven [Rijsenbrij, 2018b]. They desire high throughput, optimal utilisation of the area, and minimal environmental impact. The port authority acts as an objective player, aiming for overall efficiency in general instead of the performance of a specific stakeholder or sector [Notteboom and Winkelmans, 2001].

Moreover, the port authority can act as a facilitator in the transport chain. However, a rising trend is that port authorities work together with other stakeholders to improve digital connectivity [Notteboom and Winkelmans, 2001]. De Langen and van der Horst [2008] argue that port authorities can and should become more strongly involved with hinterland access infrastructure and operations to improve port-hinterland alignment. The reason is that port authorities control decision margins that affect the efficiency of hinterland access.

Specifically, port authorities can enhance physical connectivity by providing infrastructure inside and outside of ports. For example, through the creation of inland terminals. Additionally, in the context of digital connectivity, they can manage port accessibility to improve the port and hinterland capacity utilisation. Furthermore, they can improve data exchange among the various agents involved in moving a container from ship to hinterland. De Langen and van der Horst [2008] argue that port authorities should lead the improvements for digital connectivity by introducing coordination between stakeholders in the port and hinterland because other private and public parties have weaker incentives to do so.

Shippers

A shipper is often the owner of goods that should be transported from origin to destination.

The shipper pays for the transport and therefore also decides on many aspects of the transport from origin to destination. These decisions include choice for port of call and transport mode. In practice, a shipper often employs a freight forwarder to arrange the transport and make these choices. Nevertheless, the shipper provides one important constraint for the forwarder. That constraint is the moment the goods should arrive at the destination. Moreover, the shipper desires to transport their goods with maximum efficiency related to costs and time. Additionally, the shipper desires great service quality and reliability for goods transport [Martinho, 2008].

The time constraint for the arrival of goods on their destination posed by the shipper, can influence the port-hinterland alignment. Specifically, digital connectivity can be largely improved when this information is shared with other stakeholders. It might be used to match demand and supply more precisely, preventing any kind of surplus. However, the shipper, as a private stakeholder, is merely focused on increasing its own worth.

Freight forwarders
Freight forwarders, also referred to as forwarders, organise the transport from origin to destination on behave of the shipper. This includes arranging the land and sea transportation via TOC and shipping line, respectively. Often shipping lines sail to a specific port where a terminal is located that is owned by the shipping line or where they have agreements. The choice of shipping line, therefore, often depends on the destination of the goods. However, in shared hinterlands, as is the case in the Le Havre-Hamburg range located in west of Europe, this choice depends merely on the performance and accessibility of the port and terminal. Therefore, port-hinterland alignment is crucial for freight forwarders.

A forwarder is often employed by multiple shippers and can therefore increase the cost efficiency of transporting goods. By bundling the goods of several shippers, the forwarder can achieve economies of scales.

Due to the time constraint from the shipper, the forwarder desires to ensure that the transported goods are in time on their destination. To be sure of this, the forwarder forces the TOC to pick up the container as soon as it is unloaded from the vessel. This affects the connectivity of port and hinterland since this might cause a surplus of demand at the terminal. The forwarders do not influence physical connectivity. However, they can coordinate container pick ups by communicating with other stakeholders in the port and hinterland. This prevents misalignment by increasing digital connectivity which helps the process to take place more smoothly.

Terminal operators
At a terminal the transshipment of goods between the seaside and landside is facilitated. Therefore, terminals are central in port-hinterland alignment. Terminals can be owned by carriers or by a private company specialised in terminal operations. The terminal operator rents land in the port area from the port authority. In the port area of Rotterdam, terminals operate 24 hours a day, 7 days a week.

The objective of a terminal operator is to operate as effective and efficient as possible. This implies that the terminal operator aims to have short dwell times and turnaround times, against low cost. To achieve this, the terminal operator desires to utilise the yard, crane and gate capacity to the best of their abilities. Consequently, terminal operations are demoted by peak loads of truck arrivals as this affects the degree of resource utilisation due to demand surplus at certain times t. Matching terminal supply to truck demand is important for a terminal operator to ensure a continued level of resource utilisation.

Terminal operators use financial incentives, demurrage and detention charges, for container pick up to ensure that the capacity of the storage yard is utilised well. However, this could cause peaks in demand as this encourages container pick up shortly after the container is unloaded. Due to the increasing call sizes many containers may be picked up at once, disturbing the smooth terminal processes [Merk, 2018].

Physical connectivity can be influenced by terminal operators, as terminal operators are responsible for crane and gate operations [Ligteringen and Velsink, 2012]. Port-hinterland alignment can be improved by terminal operators by creating more capacity to handle containers. Hence, terminal operators can increase the supply to match demand. However, when peak loads cause the mismatch of supply and demand, it is very costly and hardly beneficial for terminal operators to invest in physical connectivity.

Moreover, terminal operators can affect the port-hinterland alignment by imposing operational applications [Rodrigue and Notteboom, 2009]. This is in the context of digital connectivity as operational applications can comprehend the sharing of information from other stakeholders or the control of demand inflow. For example, terminal operators could pose an obligatory announcement of estimated time of arrival (ETA) of a truck to allocate resources accordingly or restrict the number of arrivals.

Truck operating companies (TOC)
TOC are responsible for the transportation of containers in the landside leg of the seaport. TOC are employed by freight forwarders to transport goods between port and hinterland locations. The TOC are ordered by the forwarder to pick up or deliver a container at a certain moment. There are many self-employed truckers, and a few larger TOC. As many of the TOC are self-employed, it is complex to achieve alignment between port and hinterland via road.

Usually, TOC operate from the early morning until the evening, and not during the night. Previous research shows clear preferences for truck arrivals at seaports [De Langen and van der Horst, 2008; Phan and Kim, 2015; Zomer et al., 2019]. These preference for arrival times lead to peak demand for terminal services. This causes a demand surplus that results in waiting time, hence an affected port-hinterland alignment.

Nevertheless, the desire of the TOC is to have minimal turnaround times at the terminal for container pick up or delivery [Rijsenbrij, 2018b], in other words no waiting time. Minimal turnaround times allow the TOC to plan more trips on one day and accordingly increase their economic value. Therefore, a smooth match of truck demand with supply at the terminal benefits the TOC. Costs for delay of containers are generally charged to the TOC. Moreover, due to the competitive character of the truck transport market, the TOC do not have much leverage. As a consequence, TOC are often the ones that pay for time inefficiencies in the container transportation chain.

TOC do not have the means to invest in physical infrastructure nor the power to improve it. Hence, TOC have no ability to improve port-hinterland alignment from a physical perspective. However, TOC benefit from physical connectivity. Sufficient supply for their demand ensures that TOC do not have to change their processes and have little to no costs to improve port-hinterland alignment. Opposed to their lack of influence on physical connectivity, TOC play an essential role in digital connectivity. TOC have the information the terminals need to make a valuable demand prediction over time and subsequently enable efficient utilisation of terminal capacity.

Hinterland warehouses
Hinterland warehouses are the origin or destination in the landside leg for export or import containers, respectively. In this research the hinterland warehouses are considered to be the boundary of the landside leg of a seaport. Certainly, the transport of goods in the container does usually not end here as the goods are further distributed from the warehouses to other parties, including supermarkets or retail companies. However, the further distribution of goods to secondary locations is left out of scope in this research.

Hinterland warehouses often operate from morning until late afternoon. They desire to have the containers delivered within these operating hours. This poses a constraint for the TOC.

In the context of physical connectivity, hinterland warehouses have the potential to improve the port-hinterland alignment. Hinterland warehouses could invest in locations to deliver containers outside of operating hours. Additionally, they could relax the operation hour constraint for container delivery by investing in more workforce.

In the context of digital connectivity, the hinterland warehouses also have the potential to improve port-hinterland alignment. The working hours of the warehouses pose a time constraint to TOC tour planning. Since most TOC intend to plan as many trips within a day as possible, they plan their first and last arrivals to warehouses close to their opening and closing hours, respectively. This causes two peaks in demand at terminals, one in the morning and the other in the afternoon. By communication and information exchange of hinterland warehouses with other stakeholders, the container pick up and delivery at the terminals could be planned to utilise the capacity to its full potential.

Port community system
A port community system is a neutral and open digital platform for information exchange between public and private stakeholders [United Nations, nd]. This is a relatively new stakeholder in the port system, however most major ports have such a system. Additionally, the port community system is an important platform for customs as declarations of goods are processed via this platform.

As a neutral player in the port system, the port community system does not have many objectives. The main objective is to ensure information exchange in order to improve the competitive position of the entire seaport community [United Nations, nd].

The port community system has no influence on improving port-hinterland alignment through physical connectivity. Nevertheless, the influence of this stakeholder on digital connectivity is tremendous as it has the function to facilitate information exchange between stakeholders. Therefore, there is an incentive for port community systems to improve port-hinterland alignment through digital connectivity.

2.5 CAUSES FOR MISALIGNMENT

Misalignment can come from two sides in matching demand and supply. Moreover, two types of bottlenecks are relevant in the light of this research (Section 2.3). With the overview of the port system and the boundaries (Figure 2.2) in mind, four quadrants of causes can be identified. A visual overview of the causes is provided in Figure 2.3.

On the one side, scarcity of (infrastructural) capacity, e.g. too little excess roads, cranes, terminal gates, or manpower to supply the demand, can cause misalignment. This kind of misalignment originates from the supply side and is often caused by poor physical connectivity. However, digital connectivity can also influence this kind of misalignment due to the insufficient ability to allocate the existing capacity to supply the demand.

On the other side, misalignment can be caused by demand patterns, e.g. peak loads in truck arrival at the terminals. Inadequate control of truck arrivals can cause a demand surplus, which can cause misalignment. This kind of misalignment stems from the demand side and is often caused by poor digital connectivity. Nevertheless, physical connectivity also impacts the peak loads at the terminal as there are limited options to deliver containers outside operating hours of hinterland warehouses.

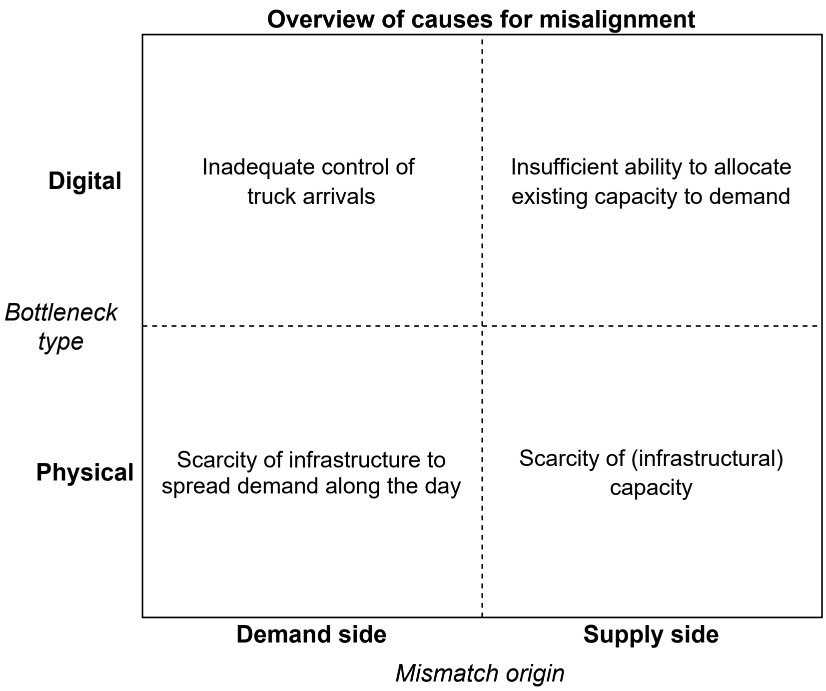


Figure 2.3: Overview of causes for misalignment

The analysis of the several stakeholders in the port system, their role, objectives and potential influence on port-hinterland alignment (Section 2.4), shines a light on the complexity of port-hinterland alignment. The alignment of port and hinterland is especially complex from the perspective of digital connectivity.

The stakeholders are able to influence the alignment with their actions. Though, the actions of one stakeholder can also affect others. Due to unevenly distributed benefits and costs among the port and hinterland stakeholders, a power imbalance exists in the port system. For example, the shippers, forwarders and hinterland warehouses pose time constraints for the TOC regarding container pick up and delivery. The first mentioned three stakeholders benefit from these constraints as they can improve their processes and economic value. Nevertheless, the TOC mainly encounter the costs from these constraints [Merk and Notteboom, 2015].

The unevenly distributed costs and benefits discourage large investments to improve infrastructural capacity [De Langen and van der Horst, 2008]. For example, the terminals must pay for capacity expansion at the terminal. However, the terminals do not necessarily encounter the effects of non-optimal turnaround times to the same extent as the TOC do. Therefore there might be limited incentive for terminals to solve the issue for the TOC.

Moreover, this imbalance of power impedes adequate coordination of stakeholders. Many scholars that studied port-hinterland alignment in the context of connectivity, find that poor coordination of stakeholders in the port system is one of the main issue to deteriorate the alignment [Bergqvist, 2012; De Langen and van der Horst, 2008; van der Horst and van der Lugt, 2011; Franc and Van der Horst, 2010; Merk and Notteboom, 2015].

In sum, misalignment can emerge from scarcity of capacity or the insufficient ability to allocate the existing capacity, and from inadequate control of the demand patterns. However, the improving the alignment between port and hinterland is rather complex. The unevenly distributed benefits and cost cause a power imbalance between stakeholders which affects the port-hinterland alignment. The question that remains is who, on both supply and demand sides, should adapt to improve the port-hinterland alignment. The answer to this question depends on the root of the mismatch, whether there is scarcity of capacity, or an issue in demand patterns.

2.6 OPTIONS FOR PORT-HINTERLAND ALIGNMENT

To improve port-hinterland alignment demand and supply should be matched. Based on the roots of the mismatch, three categories of potential practical solutions to improve the alignment of port and hinterland can be identified. These categories are improving port-hinterland alignment with pure physical connectivity solutions, pure digital solutions, or combined solutions. A visual overview of the solutions is provided in Figure 2.4. In the following subsection, the solutions are elaborated in more detail.

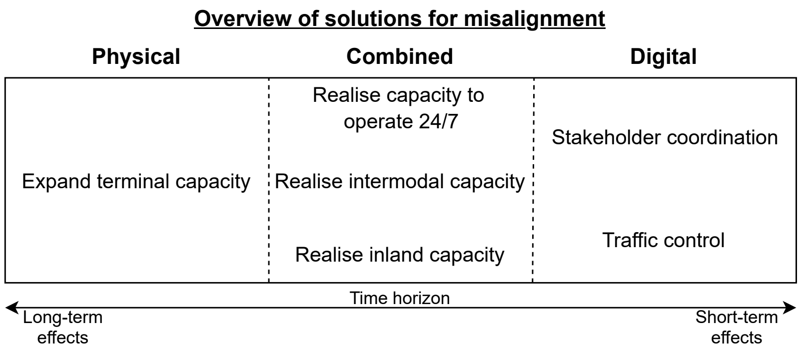


Figure 2.4: Overview of solutions for misalignment

2.6.1 Solutions for physical connectivity

From the physical connectivity perspective, the alignment of port and hinterland could be achieved by expanding capacity, hence increasing the supply. However, for terminals that experience peak loads of truck demand along the day, it is questionable whether expanding capacity at the terminal could solve the misalignment problem.

From the previous section (Section 2.5), it is understood that the peak loads are mostly a consequence of a time constraint that stems from different operating hours of terminals, TOC, and hinterland warehouses [Merk and Notteboom, 2015]. Therefore, it is expected that the preferences for container pick up or delivery time would not change when the terminal capacity is expanded.

Expanding capacity at the terminal does not eliminate the different operating hours of stakeholders along the chain. Therefore, the peak demand would not disappear. It might even cause higher demand peaks at certain times. The reason for this is that some TOC, that are currently planning their arrival outside the peaks, might shift their preference to peak hours due to higher capacity at the terminal.

Improving the port-hinterland alignment through physical connectivity would only be beneficial in cases where huge truck arrivals are expected on a long-term base, or when it flattens the demand peaks. When the misalignment occurs due to scarcity of capacity and there are no peak loads, the misalignment can naturally be solved by expanding capacity at the terminal. For example, by purchasing new handling equipment or increasing the storage yard.

When peak loads are an issue in the system, solutions that flatten the demand peaks are needed. However, peak demands are caused by the constraints posed by several stakeholders for container pick up or delivery. An option to flatten the demand peaks could be to realise a physical infrastructure near hinterland warehouses to deliver or pick up containers outside of operating hours. However, such a solution additionally requires digital connectivity as stakeholder coordination is crucial in such an approach to improve misalignment.

There are no methods to flatten demand peaks and subsequently improve port-hinterland alignment by solely implementing a physical infrastructural solution. To flatten the demand peaks there are solutions that require physical infrastructure, yet these solutions additionally require digital connectivity.

2.6.2 Digital solutions

From the digital connectivity perspective, the alignment could be improved by coordination and information exchange among stakeholders. This provides insight into demand patterns and allows to organise supply accordingly, or to adapt the demand patterns according to the existing capacity. Port community systems play a major role in achieving such solutions. Digital solutions have much potential to be effective when terminals are experiencing peak loads. Opposed to many capacity increasing measures in the physical context, the digital solutions can flatten the demand peaks by coordinating stakeholders or introducing control strategies for demand inflow.

Many of the explored digital solutions are focused on solving the stakeholder imbalance. De Langen and van der Horst [2008] introduce a framework including four types of solutions to solve coordination problems, and consequently achieve more balance in stakeholder power. The solution categories that De Langen and van der Horst [2008] define, are introduction of incentives, creation of an interfirm alliance, changing scope, and creating collective action. Such solutions require a lot of stakeholder discussion, collaboration and concession making. This going back and forth is very time consuming.

Other digital solutions are traffic management strategies to control the inflow of demand, for example via Intelligent Transportation System (ITS). These are solutions that can flatten the demand peaks of truck arrival and could be applied more short-term. An overarching strategy to flatten the demand peaks by controlling demand inflow is by application of a TAS policy. In a TAS policy it is aimed to shift truck arrivals from one time period to another, to ensure a more evenly spread of trucks along the day. Examples of practical solutions to instigate a TAS policy are the introduction of time-varying tolls, sharing real-time traffic information, and implementation of a TSMS.

Time-varying tolls

Time-varying tolls are comparable to road pricing, a traffic management strategy to relieve the road network from peak hour congestion by giving price incentives to travel outside of peak hours [Mattsson, 2008]. With time varying tolls it is aimed to distribute the truck arrivals more evenly along the day, flattening the demand peaks.

This solution fits in the framework of De Langen and van der Horst [2008] in the category of introducing incentives. The height of the toll prices should be distributed along the day in such a manner that it is discouraged to arrive at peak moments. Chen et al. [2011] conducted a study towards finding a pattern of time-varying tolls to accordingly lead to optimal arrival patterns. Even when an optimum is found it is difficult to implement time-varying tolls in real systems because this plays into the hands of unevenly distributed costs and benefits among the stakeholders in the port and hinterland.

Sharing real-time traffic information

This traffic management strategy aims to control truck arrivals by communicating the traffic states at the terminal. The data of trucks on the road and amount of traffic at the container terminal is tracked. Algorithms use this data to predict information on waiting time and congestion for the next hours [TNO, 2016]. The idea is that providing real-time traffic information of the situation near or at the terminal can manage truck arrivals as TOC might change their arrival time due to the available information.

An early research towards the effectiveness of this solution is by Sharif et al. [2011]. They find that providing real-time gate congestion information and some simple logic for estimating the expected truck waiting time, can minimise congestion at terminals gates.

Sharing real-time information, however, is difficult to arrange due to privacy issues. Furthermore, with sharing real-time traffic information the flattening of demand peaks becomes self-regulating.

Time Slot Management Systems

A truck appointment system is a well-known measure by many scholars, port authorities and terminal operators to spread truck arrivals along the day, and consequently improve the port hinterland alignment. A truck appointment system requires to be optimised through a TSMS. There are several methods to optimise a TSMS. For example, Zhang et al. [2019] develop a method to decrease external trucks' waiting time, at the gate and yard, and internal trucks' waiting time at the yard. The opening hours of a terminal are broken down into several time slots. Consequently, a truck capacity is predetermined for the time slots. Several aspects are considered by Zhang et al. [2019] for predetermining the maximum number of trucks per time slot, also called the appointment quota plan. These aspects include the container yard capacity, resource utilisation, and equipment availability.

The central idea of a truck appointment system is that the time slot to arrive at the terminal can be reserved by the TOC. When the determined appointment quota is reached, hence the capacity of the time slot is fully utilised, other TOC cannot claim that specific time slot. This prevents peak loads at the terminal gates, and allows a well spread of truck arrivals along the day. Consequently, the queues and waiting time at the terminal are reduced, the number of idling trucks is decreased, and the environmental impact is less [Li et al., 2018; van Asperen et al., 2013]. Additionally, the terminals are aware of the arrival patterns of trucks, this allows the terminals to plan their operations efficiently. Nonetheless, a truck appointment system is difficult to implement successfully. The problem with implementing a truck appointment system, optimised through a TSMS, is that there is a hard restriction on the number of truck arrivals in a certain time slot. As the TOC have time constraints for container pick up and delivery, a truck appointment can only be implemented successfully when these constraints are taken into account.

2.6.3 Combined solutions

To flatten the demand peaks at a terminal, there are some solutions that require physical infrastructure as well as digital connectivity. Combined solutions can be applied to support a TAS policy. Examples are intermodal freight corridors, dry ports, extended gates, and night time storage facilities for container near a hinterland warehouse. The importance of stakeholder coordination, hence digital connectivity, cannot be neglected in these solutions as these can only be successfully implemented if the stakeholders are aligned. Brief explanations about these solutions are presented in the following paragraphs.

Intermodal freight corridors

Intermodal freight corridors are freight corridors in which several modes are used for the transportation of goods. In the context of container transport, truck, train and barge are suitable modes for transport. To successfully create such corridors, it is crucial that the terminal and hinterland locations are well connected through all transport modes. When the connection via all modes is reliable, and time and cost efficient, it is expected that there will no longer be a preference for a certain mode over the other. This could flatten the peaks for truck demand as forwarders may shift the transport of the container to another mode.

The development of intermodal freight corridors, however, is very costly and time-consuming due to the large number of involved stakeholders. Monios and Lambert [2013] study the development of intermodal freight corridors in the United States. Through many interviews and site visits, they find that aligning stakeholder objectives with funding sources and planning schedules complicate the development of successfully creating intermodal freight corridors.

Dry ports

Roso and Leveque [2002] define a dry port as *"an inland intermodal terminal directly connected to seaport(s) with high capacity transport mean(s), where customers can leave/pick up their standardised units as if directly to a seaport"*. The concept of dry ports reflects the belief that it is not necessary that all activities, industrial or economic, happen near the seaport. The presence of good infrastructure and inland nodes can relieve the seaport of some activities and congestion by providing services for trade and accordingly accommodate growth. Roso et al. [2009] state that dry port concepts can help to identify methods to shift freight volumes from trucks to other modes. This potential to achieve modal shift, can flatten the demand peaks in truck traffic at terminal gates and consequently improve port-hinterland alignment.

For exact implementation of dry ports one is referred to Bergqvist and Cullinane [2013]. Bergqvist and Cullinane [2013] study the development of dry ports in various countries of the world with different economic, social, institutional and environmental characteristics. They report various case studies and state-of-the-art examples that show the complexity and different approaches to the development of dry ports.

Extended gates

This concept is an extension to the dry port concept. According to Veenstra et al. [2012] the definition of Roso and Leveque [2002] for dry ports can be extended with *"... if directly with a seaport, and where the seaport terminal can choose to control the flow of containers to and from the inland terminal"*. Subsequently, the idea of extended gates is to influence the flow of containers to and from the hinterland. The pick up and delivery of containers is moved from the seaport to an inland terminal, literally extending the gates of the seaport.

Although this is very similar to dry ports, there are features that distinguish the extended gate concept from the dry port concept. These features are mainly in the coordination and control of container flows, the legal responsibility, and the role of information.

Night time container storage facilities near hinterland warehouses

This solution addresses the time constraint posed by the hinterland warehouses' operational hours. The idea is similar to dry ports and extended gates, yet it is different as this solution does not move activities from the seaport to the hinterland.

This solution can flatten the demand peaks for truck container transport by enabling the TOC to transport containers to hinterland warehouses outside of operational hours. A parking area to store containers overnight near the warehouse is sufficient. The TOC can deliver or pick up the container at night near the warehouse. Another (automated) vehicle (truck or cart), can transport the stored containers to the warehouse during operational hours.

Opposed to dry ports and extended gates, the container flow in this solution is not handled or controlled by the seaport. Additionally, it has nothing to do with modal shift or intermodality. It is merely an arrangement between TOC and specific hinterland warehouses, supported by other stakeholders, to allow truck arrivals at the terminals outside of peak hours. Moreover, this solution stimulates night time driving.

2.7 CONCLUSION

The alignment between port and hinterland was studied in this chapter. Misalignment between port and hinterland induces waiting time for trucks at the terminal gates. The root cause for misalignment between port and hinterland can emerge from (a combination of) two sources, namely the supply side and the demand side. Misalignment from the supply side can come from scarce capacity to handle the demand, or insufficient ability to allocate the existing capacity. Misalignment from the demand side can come from inadequate control of the demand patterns which cause peaks in demand. Based on these origins of misalignment there are several options for improving alignment. For both sources of misalignment solutions from a physical, digital and combination perspective are presented in this chapter.

Physical solutions are all predominantly time-consuming and costly as these are large infrastructural projects. An example is the expansion of terminal capacity. However, terminal capacity does not always constraint container handling. Moreover, solely applying physical solutions is only beneficial when huge truck arrivals are expected on a long-term base. Therefore, temporary problems, such as long waiting time at the terminals in the Rotterdam port area, cannot be addressed effectively and efficiently by physical solutions, since waiting time in Rotterdam is the result of short-term demand peaks that changes over a day [Zomer et al., 2019].

The remaining options to improve port-hinterland alignment at the port of Rotterdam are pure digital solutions, or combined physical and digital solutions.

Pure digital solutions are attractive to port authorities due to their ease of implementation, reliability, short-term impacts, and cost-time efficiency. In this approach, stakeholder coordination is important as information must be shared to achieve digital solutions. Other digital solutions consider traffic management strategies to control inflow of demand.

Combined physical and digital solutions have the potential to flatten the peak loads. Combined solutions require a lot of stakeholder coordination, which takes time. Furthermore, combined solutions require purchase and development of land across port boundaries and connections to the hinterland. This is costly and has an extended time horizon.

This research is conducted on behalf of the PoR and a solution for misalignment is sought to distribute the peak loads along the day. With this approach it is aimed to solve the congestion problems and reduce waiting time in the Rotterdam port area.

Among digital and combined solutions that fit the desires of PoR, traffic management strategies to control demand inflow are most appealing to improve port-hinterland alignment in Rotterdam. Due to the constraints in the container transportation system, it is of interest to explore a solution in which the preferences of TOC are met. Lastly, the solution must be able to reduce the peaks in demand.

An overarching strategy to control truck arrivals and reduce waiting time, is by shifting truck arrivals to other time periods. By implementing a TAS control strategy trucks can be shifted from peak periods to quieter time periods. Consequently, peaks in demand can be reduced. A well-known measure to instigate the TAS is the implementation of a truck appointment system.

To conclude, in the remainder of this research, the control of truck arrivals via the implementation of a TAS policy, based on TOC preferences, is explored to match demand and supply at the terminals, and consequently improve port-hinterland alignment. The control by means of a TAS policy, aims to flatten the demand peaks and evaluates the effect on truck waiting time at the terminals. The interest of this research lies within gaining insight in the potential to improve alignment by shifting truck arrivals. Therefore, the effect of truck shifting based on trucker preferences is explored.

3 LITERATURE: TIME SLOT MANAGEMENT SYSTEMS

A truck appointment system is believed to be one of the important traffic management tools that are designed to support the shift in truck arrivals (TAS) that is required to match demand and supply at terminal gates (Chapter 2). The aim of TAS is to decrease the waiting time at terminals' gates, and consequently improve port-hinterland alignment. A truck appointment system is very suitable to instigate a TAS policy. A truck appointment system, however, needs to be optimised through a TSMS.

The first implementation of truck appointments at ports dates back to 1999 in Vancouver [Morais and Lord, 2006]. Ever since this first implementation, various scholars have studied the potential benefits and implications of TSMS. Many of these studies have shown that TSMS is capable of reducing truck congestion at terminal gates.

For example, Huynh and Walton [2008] study the effect of limiting truck arrivals on truck turnaround time by introducing TSMS. They found that the implementation of TSMS can reduce truck turnaround time if the appointment quotas are set correctly based on terminal capacity. Moreover, the results of Guan and Liu [2009] show that the use of TSMS seems to be the most viable way, among several congestion mitigation alternatives, to reduce gate congestion and increase system efficiency. Likewise, the research of Zhao and Goodchild [2010] towards the impact of TSMS shows the ability of TSMS to reduce congestion and thus waiting time at terminals.

To the author's knowledge, only one study obtains contradictory results of TSMS implementation. This is a study conducted by Giuliano and O'Brien [2007] in the ports of Los Angeles and Long Beach. Their results shows that a TSMS has little effect on terminal congestion, and consequently on truck emissions. However, these results can partly be explained as the design policies for implementing the TSMS were not complete.

Above are a few examples from research in the academic field towards the benefits of a TSMS. One can refer to the more extensive literature review of Lange et al. [2017] on trends and classifications of reducing truck congestion at terminals for more examples of TSMS research.

All in all, it can be concluded that implementation of a TSMS at a terminal is an effective, suitable and successful solution to reduce truck congestion at terminals, provided that the TSMS is implemented properly. To guarantee a proper implementation of TSMS, the methodology for TSMS development is elaborated in this chapter. This comprehends reviewing methodologies for designing and evaluating a TSMS.

This chapter, first, aims to conceptualise the real world problem in Section 3.1. Thereafter, the development methodologies and optimisation are explored in Section 3.2 and Section 3.3. Lastly, the shortcomings from previous research are identified, and the method to fill gaps is introduced in Section 3.4.

3.1 CONCEPTUALISATION

As the objective of this research is to improve port-hinterland alignment by reducing waiting time at the terminal, the first thing to do is to conceptualise the real world situation. Consequently, various options in the approach for designing and evaluating a TSMS can be explored.

An overview of the real world situation in the port system was provided in Figure 2.2. The focus of this research is on the arrival of trucks (the demand) and serving the trucks at the terminal (the supply), consequently the trucks depart from the terminal. Conceptually this process looks like

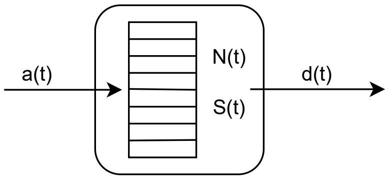


Figure 3.1: High level conceptualisation of the port processes

where $a(t)$ is the arrival of trucks at time t, $N(t)$ denotes the queue length at time t, $S(t)$ represents the service capacity at time t, and $d(t)$ is the departure of trucks at time t. The queue length containers the number of truck arriving minus the trucks being served and the trucks departing. This is simply calculated by

$$\frac{\partial N(t)}{\partial t} = a(t) - S(t) - d(t) \tag{3.1}$$

The queue of trucks is not limited in terms of space in the port area of Rotterdam, therefore the exact length of the queue is irrelevant to the research. Moreover, the focus of this research is on waiting time, not the number of trucks in the queue. The waiting time can be computed from the queue length using queueing theory.

There are two approaches for this, either the trucks are treated as particles, so discrete units, or as fluid, which treats traffic as a viscous fluid. Both methods are based on the idea that the waiting time is directly dependent on the number of trucks that arrive in the system compared to the number of trucks the system can serve. However, the exact calculation for approximating the waiting time differs between the two methods. Both methods can be applied for stationary as well as for non-stationary queueing processes (Section 3.2.2).

Particle-based

The foundation of queueing theory is Little's Law [Hillier and Lieberman, 2015]. Little's Law allows to relate the number of customers in the system, the average time spent in the system, and the arrival rate. Accordingly, the queue length and average waiting time can be estimated based on the service rate. For example, the queueing process could be formulated as a $M/M/s$ model [Hillier and Lieberman, 2015]. Here it is assumed that both the inter arrival time and the service time are independently and identically distributed (i.i.d) with an exponential distribution. Additionally, the number of servers is an integer value. Consequently, by means of Little's Law the queue length and waiting time can be estimated. In this method trucks are treated as particles, so discrete units in time. An example of the particle-based approximation method is provided for a stationary queueing model in Equation 3.2a through Equation 3.2d. Nevertheless, the same equations can be applied to a non-stationary queueing model by including time (e.g. mean arrival rate per hour).

$$L = \lambda W \tag{3.2a}$$

$$L_q = \lambda W_q \tag{3.2b}$$

$$W = W_q + \frac{1}{\mu} \tag{3.2c}$$

$$W_q = \frac{L_q}{\lambda}, \tag{3.2d}$$

where the expected number of trucks in the queueing system, hence in the queue and in the servers, is denoted by L. The mean arrival rate is denoted by λ. The waiting time including service time, hence turnaround time, is represented by W (min). The mean service time is presented by μ (min). Moreover, with L_q the expected queue length, thus excluding the trucks in the servers, is indicated. Lastly, the waiting time in the queue is denoted with W_q (min).

Fluid-based

Throughout the years, the mathematical foundation of queueing theory (Equation 3.2a through Equation 3.2d) is extended from particle to fluid-based. For the fluid-based queueing models several approximation methods are developed and used to estimate queue lengths [Chen et al., 2013c]. Most approximation methods used in the queueing process in TSMS design, are fluid-based. Compared to particle-based methods, fluid-based approximation methods increase the estimation accuracy, whilst maintaining computational efficiency [Chen et al., 2013b].

The Point-wise Stationary Fluid Flow Approximation (PSFFA) method for estimating queue lengths and waiting time developed by Chen et al. [2011], is often used in TSMS design. For example, Phan and Kim [2015] use this PSFFA method in their research. Likewise, Zhang et al. [2013] use a PSFFA to calculate the truck waiting time, they found that the approximation method was capable of estimating the queue length and waiting time accurately. More recently, Zhang et al. [2019] used the PSFFA method to estimate queue lengths.

Chen et al. [2013a] develop the PSFFA method further by integrating it with the bisection method and a correction factor, resulting in Bisection Point-wise Stationary Fluid Flow Approximation (B-PSFFA). They note that their B-PSFFA method is simple to apply and capable of accurate estimations of the non-stationary queueing process in their TSMS design. Wibowo and Fransoo [2020] expand the B-PSFFA method of Chen et al. [2013a] and propose a new method Wibowo Bisection Point-wise Stationary Fluid Flow Approximation (WB-PSFFA). This method does not require the correction factor from the B-PSFFA method to accurately estimate queue lengths and waiting time. The performance approximation method proposed by Wibowo and Fransoo [2020], WB-PSFFA is provided below. In this method period T is divided into n number of small intervals t. The method is based on fluid flow theory, according to the fluid flow conversation principle, $change\ in\ mass = inflow - outflow$. Therefore, the rate of change in the number of trucks in the system L_t should be equal to the difference between the average arrival rates λ_t and the average departure rates v_t. The following formulas (Equation 3.3a to Equation 3.3c) provide the fluid approximation for a non-stationary queueing model

$$\frac{\partial L}{\partial t} = \lambda_t - v_t \tag{3.3a}$$

$$v_t = m_t \mu_t \rho_t \tag{3.3b}$$

$$L_{t+1} = L_t + \lambda_t - v_t \tag{3.3c}$$

where L_t indicates the average number of trucks in the system at time t ($\{t = 1, ..., n\}$), λ_t denotes the average truck arrival rate, v_t is the average truck departure rate, m_t represents the number of identical servers available, μ_t denotes the average service rate of identical servers, and ρ_t is the average capacity utilisation. Equation 3.3a indicates the fluid flow balance function of the queueing model. Equation 3.3b indicates the exit flow function for departure rate v_t. Equation 3.3c indicates the transition rule to update the number of trucks in the system for the time interval of interest.

To determine the number of trucks in the system, Equation 3.4 can be used

$$L_t = \left[\frac{(1+c_e^2)(c_a^2+\rho_t^2 c_e^2)}{2(1+\rho_t^2 c_e^2)}\right]\left[\frac{\rho_t^{\sqrt{2(m_t+1)}}}{m_t(1-\rho_t)}\right] \tag{3.4}$$

where c_e represents the coefficient of the variation of the service time distribution, and c_a is the coefficient of the variation of the inter-arrival distribution.

Lastly, to obtain the average time spent in the system W and average waiting time W_q, the concept of Little's law can be used. This is shown in Equation 3.5a and Equation 3.5b

$$W = \frac{1}{n}\sum_{t=0}^{n} \frac{L_t}{m_t \mu_t \rho_t} \tag{3.5a}$$

$$W_q = \frac{1}{n}\sum_{t=0}^{n}\left(\frac{L_t}{m_t\mu_t\rho_t} - \frac{1}{\mu_t}\right) \tag{3.5b}$$

where W is the average truck time spent in the system, and W_q denotes the average truck time spent in the queue (waiting time).

The cause of waiting time at the port of Rotterdam terminals is found within the demand side, where too many trucks arrive at the terminal demanding service compared to the number of trucks the terminal can serve. Therefore, this research tries to control the truck arrivals in such a way that the waiting time at the terminals is reduced. This can be translated to an optimisation problem. In this optimisation problem it is aimed to find the optimal arrival profile of trucks ($a(t)$) so that the queue ($N(t)$) is minimal. TSMS is a platform with which control policies can be applied to optimise truck arrival through a truck appointment system. On an high level the formulation of the optimisation problem in this research is

$$\begin{aligned} a^*(t) &= arg \min_{a(t)} f(W_q(t), a(t)) \\ \text{s.t.} \quad & a(t) \geq 0, \\ & W_q(t) \geq 0 \end{aligned} \tag{3.6}$$

where f represents the simulation for waiting time for the entire system and all entries of $a(t)$ must be integer values.

There are various ways to formulate this optimisation problem more specifically. Moreover, there are various approaches to design a TSMS. For example, Guan and Liu [2009] and Chen et al. [2013b] introduce a bi-level approach to tackle the TSMS control problem. In this research, a similar line of thinking is employed to propose a control framework for truck arrival time in TSMS. This framework includes two components which are required to design and test policies before implementation. The first component is a simulation platform that can accurately mimic the real word. The advantage of having a simulation platform is that designers can test their design at almost no cost before the actual implementation. The second component is an allocation framework (the controller) which is required to guarantee the best match between demand and supply and hence an optimal arrival of trucks at the terminal. A schematic overview of the procedure for TSMS design and evaluation is provided in Figure 3.2 on the next page.

Within the two components there are various steps required to ensure effective control of truck arrivals at the terminals. These steps are discussed in the following sections.

3.2 SIMULATION PLATFORM

Simulation is used to mimic real-life situations and evaluate the effect of different scenarios on the optimisation problem or explore 'what-if' questions [de Sousa Junior et al., 2019]. Simulation can support experiments that are too costly or impossible to carry out in a real-life situation. Hence, simulation can help decision making in resource allocation, like allocating trucks to terminal resources.

In TSMS research, the simulation method aims to reflect the real-life situation at the terminal. Additionally, it allows for strategy testing in the system and assessing the impacts of shifting truck arrivals due to the TSMS.

In practice, there are two types of simulation approaches, namely continuous simulation and DES. A continuous simulation is a pertinent approach for systems with states that vary continuously over time. One example is the temperature of a liquid inside a tank. In contrast, a DES applies best to model real-word systems that can be decomposed to a series of processes that progress chronologically and autonomously [Banks, 1998].

The DES approach has been extensively used to evaluate assignments, scheduling jobs, and resource allocations. Two examples of studies that use DES to optimise resource allocation are conducted by Li et al. [2020] and e Oliveira et al. [2020].

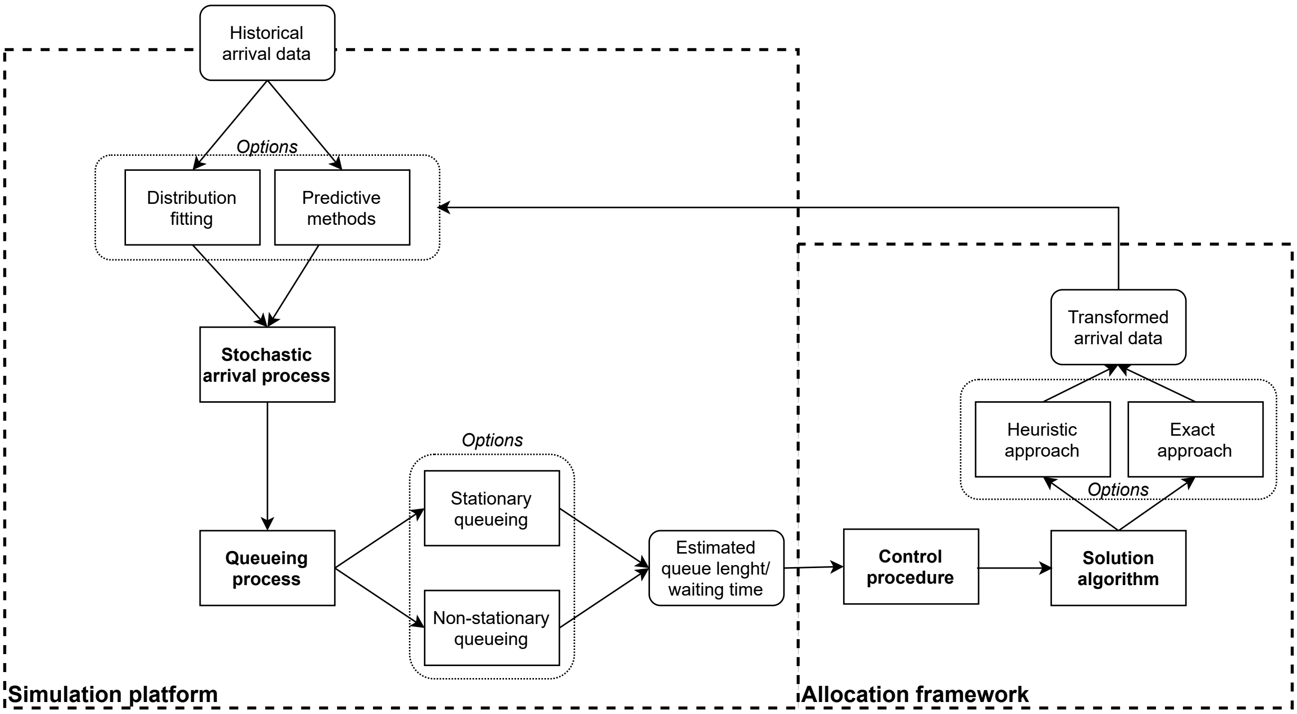


Figure 3.2: Schematic overview of the procedure for Time Slot Management System design and evaluation

Li et al. [2020] study how to develop and assess a simulation model for resource allocation in manufacturing. e Oliveira et al. [2020] use a simulation-optimisation approach to solve an hospital bed allocation problem.

Regarding TSMS research, Huynh and Walton [2008] use a DES model to analyse the truck turnaround time. The model simulates the truck arrival, truck movements, gate service processes and operations of yard cranes. Subsequently, Huynh and Walton [2008] assess the effect of limiting truck arrivals on truck turnaround time and crane utilisation. Furthermore, they proposed a simulation-optimisation method to find the maximum number of trucks in a specific area of the yard for each time window, within the optimisation boundaries, whilst meeting the specified desired truck turnaround time.

From a methodology perspective, queueing theory is a paradigm that supports DES to make the simulation sufficiently close to the real-world system. Additionally, queueing theory makes sure that the physics of the simulated system is interpretable.

In general, a queueing model is based on a stochastic process that models random events (e.g. arrivals and departures) in the system. Below, more details about the stochastic process and different types of queueing models are discussed.

3.2.1 Stochastic arrival process

The arrival process in a queueing model is a stochastic process that can be regarded as the demand side of the system. It indicates the number of trucks that come to pick up or deliver containers at the terminal, ergo the mean arrival rate denoted by λ in Equation 3.2a through Equation 3.2d. The arrival process is crucial for the development of a TSMS, since the introduction of TSMS predominantly aims to reduce congestion by spreading the arrival of trucks evenly along the day. With a TSMS this can be achieved by controlling the truck arrivals at the terminal.

The arrival process is also used for resource allocation in other research fields. An example of this is to replicate patient arrivals in health care research [e Oliveira et al., 2020; Stinnett and Paltiel, 1996] or flight arrivals in air traffic management [Murça, 2018].

An accurate arrival process is essential as the distributions for inter arrival rate influence the queueing model with λ (Equation 3.2a to 3.2d) [Chen et al., 2013a; Hillier and Lieberman, 2015]. Traditionally, a static or historical average was used to estimate the inter arrival time (IAT). However, many researchers such as Morariu et al. [2020] argue the importance of the prediction of inter arrivals for the optimisation of a random process. They state that prediction based solutions provide better results than traditional planning based on static, historical data.

Therefore, predictive methods like regression, advanced machine learning, and artificial intelligence techniques are increasingly used to model inter arrival processes in various applications, including resource allocation [Morariu et al., 2020] and TSMS [Hill and Böse, 2017].

In many TSMS development studies, however, the arrival process is assumed to follow a probability distribution. This approach has been used extensively in the literature [Guan and Liu, 2009; Chen et al., 2013a; Hillier and Lieberman, 2015]. The following subsections outline the two approaches.

Distribution fitting

In this approach, historical data or measurements are analysed and aimed to fit a probability distribution to observed data. Examples of probability distributions are exponential, Erlang, and Poisson. Guan and Liu [2009] debate that truck inter arrival times typically follow an exponential distribution. However, for the truck arrival at the terminal in their TSMS design, Chen et al. [2013a] assume a non-homogeneous Poisson process in which the average arrival rate for each time period can be controlled.

Hillier and Lieberman [2015] sustain that the most commonly used approach for simulating the arrival process in a queueing model, is to assume that the inter arrival times are i.i.d with an exponential distribution. This assumption is valid for truck arrivals at a terminal if the trucks stem from the same generative process when arriving at the terminal, and if the arrival of one truck at the terminal is independent of the arrival of another truck (there is no memory of trucks arriving in the past).

Equation 3.7 provides an example of fitting historical data of mean arrival rate to an exponential distribution to obtain inter arrival time between trucks in minutes.

$$IAT = exp\left(\frac{60}{\lambda}\right) \tag{3.7}$$

Consequently, in Equation 3.8, $f(IAT)$ indicates the probability of a truck arriving with a certain inter arrival time (IAT) at the terminal and ranges between 0 and 1. Logically, the inter arrival time between trucks is expected to decrease when more trucks arrive in an hour.

$$f(IAT, \lambda) = \lambda e^{-\lambda IAT} \tag{3.8}$$

Predictive methods

Regression analysis assumes the desired variable to be dependent on the relation with other, independent, variables. This allows estimating the value of the desired variable based on the relation with the other variables [Huynh, 2005]. It is a statistical method that can be used to evaluate the extent of the relationship between variables, and, more importantly, to make predictions for future events based on the relation between variables.

Examples of regression analysis are linear regression, multivariate regression, and nonlinear regression. Regression analysis uses historical data, in the case of TSMS the historical arrival pattern of trucks, and defines the parameters that have a statistical correlation with the arrival pattern. For example, container size, transported goods, or day-of-week. Chen et al. [2013b] use regression analysis as a method for the arrival process in their TSMS design.

Another predictive method is machine learning. Mohri et al. [2018] define machine learning as *"computational methods using experience to improve performance or make accurate predictions"*. In machine learning, a sample of historical data is used to train a computer algorithm to make predictions. After the computer algorithm is trained, it is fed a new sample of the historic data to test the predictive power. Consequently, the machine learning algorithm is able to make accurate predictions based on data.

Examples of machine learning are random forest, artificial neural networks, and Bayesian networks. Hill and Böse [2017] apply artificial neural networks to incorporate relevant features in their development of a TSMS and forecast the truck waiting time.

3.2.2 Queueing process

The queueing process is extensively discussed in TSMS research, for example by Guan and Liu [2009]; Chen et al. [2013a,c], as the design of the queueing model directly influences the research outcome. If an inaccurate queueing process is used, it provides poor estimations of queue lengths and waiting time which might result in a faulty study.

Discussions on queueing models are not limited to TSMS research. Also in the broader context of resource allocation, the importance of an accurate queueing process is emphasised. For example, in air traffic management [Murça, 2018] or energy distribution [Li et al., 2016].

Besides the arrival process, the inclusion of certain terminal operations, service policies and activity sequences are discussed in the design of the queueing process. These determine where the queues arise, and influence the queue lengths and waiting time.

The inclusion of certain terminal operations comprehends the design decision for including berth side or yard operations in addition to gate operations. Cranes may be utilised by both internal trucks for vessel operations and external trucks for hinterland operations. For example, Zhang et al. [2019] use a vacation model for the queueing process in their TSMS design. In this model, temporary breaks in service, hence vacation, can be described. This is helpful when a crane temporarily cannot serve external truck due to the need of serving internal trucks.

Service policies indicate the method of handling arrival, options include First In First Out (FIFO), Last In First Out (LIFO), and priority. The activity sequence is a design choice that indicates the timely order of processes.

Various queueing models are used and proposed in TSMS research. A distinction can be made in the use of stationary queueing, or non-stationary queueing models. These are different in terms of assuming a constant (stationary) or varying (non-stationary) arrival and service rate.

Stationary queueing models

In stationary queueing models, a stationary arrival process and terminal service is assumed. This means that the arrival and service rates do not vary over time [Green and Kolesar, 1991]. Due to the assumption of a stationary process, one can question the applicability of stationary queueing models for TSMS. As mentioned in the previous Chapter 2, peak loads of truck arrival are an issue that induce waiting time in container terminals. This indicates that it might be incorrect to assume a steady state queue in a terminal. Guan and Liu [2009] estimate the queue length and waiting time in their TSMS design with a stationary $M/E_k/c$ multi-server queueing model. Therefore, Chen et al. [2013c] note that the study of Guan and Liu [2009] resulted in an inaccurate estimation of queue lengths.

The limitation of a stationary queueing model to neglect transient behaviour and only analyse the steady state of a queue [Chen et al., 2013a], can influence the design of a TSMS. Adopting a stationary queueing model, however, highly simplifies the design of TSMS and eases the optimisation. Moreover, when the amplitude of the arrival process is small, e.g. 10%, a stationary queueing model may be used and provide accurate results [Green and Kolesar, 1991].

Non-stationary queueing models

Non-stationary queueing models overcome the limitations of a stationary queueing model by assuming a time-varying arrival and service process. Most researchers adopt non-stationary queueing models to estimate queue lengths and waiting time in TSMS design.

For example, Chen et al. [2013a] design their TSMS as a multi-server non-stationary $M(t)/E_k/c(t)$ queueing model with a FIFO service policy. Likewise, Chen et al. [2013c] adopt a non-stationary $M(t)/E_k/c(t)$ queueing model for the queueing process in TSMS design. Other studies in which the queueing process is described by a non-stationary queueing model are Chen et al. [2011], Chen et al. [2013b], Zhang et al. [2019], and Wibowo and Fransoo [2020]. Overall, non-stationary queueing models for the queueing process seem to be preferred by scholars in the design of TSMS.

3.3 ALLOCATION FRAMEWORK

The allocation framework is the second component required to develop a TSMS. The allocation framework is used to ensure the match between demand and supply. There are two approaches to ensure this match. Firstly, the match can come from the supply side, by using a decision variable to determine the optimal appointment quota [Chen et al., 2013a; Zhang et al., 2013; Chen et al., 2013c; Zehendner and Feillet, 2014; Zhang et al., 2019] or time slot duration [Chen et al., 2013b; Wibowo and Fransoo, 2020] at the terminal.

Secondly, the match can also come from the demand side. The allocation framework can be used to shift truck arrivals based on a control strategy. In this approach trucks are shifted from one time slot to another. Using scenarios, the effect of different arrival profiles can be evaluated with the simulation platform. In this method, the exact number of trucks per time slot (appointment quota) is not computed directly. However, the number of trucks per time slot can be determined based on the arrival profiles scenario results.

3.3.1 Control procedure

The vast amount of studies use mathematical optimisation to address the match between demand and supply. In mathematical optimisation, a problem is formulated with an objective function, decision variable(s) and constraints. Based on the formulated optimisation problem an optimal solution is sought within the given boundaries, called the feasible set. An optimisation is maximising or minimising the value of the objective function, often in an iterative process.

From literature, three categories of optimisation problems in resource allocation can be distinguished. These are single objective, bi-objective and multi-objective. Several models and algorithms are used throughout the literature to solve optimisation problems.

In the TSMS research field, studies predominantly use the formulation of a single objective problem, or bi-objective formulation. Perhaps, that is because most of the objectives needed for optimising truck appointment systems have no conflict and can be unified into one single objective. Whereas, in other fields of resource allocation, for example energy distribution, multi-objective problems are more common Naz et al. [2017]. Nevertheless, multi-objective formulations are rather complex and hard to solve due to conflicting objectives [Iqbal et al., 2014].

For bi-objective optimisation problems, more than one single optimum solution can be found. The set of optimum solutions found by solving a bi-objective problem is called Pareto optimum. An example of a bi-objective problem formulation in TSMS research is by Chen et al. [2013a]. They aim to minimise both truck waiting time and shifted truck arrival times. An example of a multi-objective problem formulation in the transportation field is from Liu et al. [2014] where they aim to solve a very complex resource allocation and activity scheduling problem for fourth party logistics. The work of Wibowo and Fransoo [2020] is another example of a multi-objective problem formulation as they aim to minimise truck waiting time, site overtime cost, space rental cost, and emissions in a joint-optimisation with multiple stakeholders.

Various solution approaches for optimisation problems can be identified from previous literature. Some approaches seek to find a solution using collaboration between involved parties. In this context Zargayouna et al. [2016] use multi-agent system to solve the parking allocation problem. Phan and Kim [2016] study collaborative truck scheduling for TOC and terminals. They proposed an iterative collaboration process based on a decomposed mathematical formulation with sub-problems. Schulte et al. [2017] propose an optimisation model based on the multiple traveling salesman problem with time windows with the aim to reduce empty truck emissions. Other researchers seek to find a solution without collaboration.

Iqbal et al. [2014] distinguish two types of mathematical formulations of optimisation models, namely linear and non-linear models. Within these models a distinction can be made by a continuous, integer, or mix-integer model. In TSMS design a similar formulation is often used. For example, Zehendner and Feillet [2014] develop a mixed-integer linear programming model to find the optimal amount of appointment quota in their TSMS design. Another formulation for the optimisation is a non-linear model. This formulation is used by Phan and Kim [2015] for reallocation of truck arrivals in TSMS design, and by Li et al. [2016] in the allocation of renewable energy. Chen et al.

[2011] develop a convex non-linear programming model for their TSMS design to minimise truck turnaround times and shifted arrival times.

3.3.2 Solution algorithm

e Oliveira et al. [2020] note that mixed-integer programming is the basis of almost all developed models regarding resource allocation. Nevertheless, most of the resource allocation optimisation problems are NP-hard. According to e Oliveira et al. [2020] factors that make it difficult to solve the optimisation problem with one exact solution are non-linear constraints or objectives, or large number of integer decision variables. Therefore, heuristic approaches are often used in resource allocation problems.

Heuristics are iterative search mechanisms that try to search solution space to find an optimum or at least a near-optimum solution. It can be a very complex algorithm that uses computational intelligence, or it can be simply a set of expert-defined rules to generate and evaluate feasible solutions for a practical problem and find the best policy. These methods might not guarantee an optimal solution but can assure efficient solutions within reasonable computational time.

Examples for well-known heuristics are Particle Swarm Optimisation, Genetic Algorithms and Simulated Annealing. Iqbal et al. [2014] find that many researchers use Genetic Algorithm (GA) for resource allocation problems.

The use of GA has several advantages [Chen et al., 2013a]. The GA is very flexible and can therefore be used for every kind of mathematical formulation of the optimisation problem, whether that is linear or non-linear, continuous or mixed-integer, or single or multi-objective. Moreover, GA can easily be combined with other heuristics.

Nevertheless, there is also a weakness in using GA [Chen et al., 2013a]. The main pitfall when using heuristics is that it is not guaranteed that optimality will be found, neither is there a formal selection of search direction for optimality.

Despite the weaknesses, many researchers apply GA in resource allocation problems. For example, Mathew et al. [2010] apply GA in resource allocation for transit agencies fleet management. Chen et al. [2013b] and Zhang et al. [2013] use GA to solve the formulated optimisation problem in their TSMS design to minimise total costs and truck turnaround time, respectively. Chen et al. [2013c] used a GA based on a chromosome in which the code length of the chromosome equals the number of time slots. This way they aimed to optimise the appointment quota for the time slots. In some studies, the weaknesses of GA are tackled by aiming to find a Pareto front solution using GA, for example by Chen et al. [2013a] in their TSMS design.

Heuristics can also be used as strategies for decision making and finding a solution to complex problems. Additionally, heuristics are used in the energy research field to distribute resources [Martín and Gil, 2008]. Moreover, Mingers and O'Brien [1995] develop a heuristic to allocate students to groups based on their characteristics.

In TSMS design, a heuristic similar to Mingers and O'Brien [1995] could be used in an approach to distribute truck arrivals along the day based on a control strategy and scenarios. The control strategy might comprehend the base on which the trucks are allocated. The scenarios might be used to evaluate effects of changes in the control strategy or number of trucks shifted. Additionally, the researcher obtains insight in the effects of non optimal solutions.

A heuristic approach is very suitable to evaluate a TSMS based control strategy for reallocating, or rather shifting, trucks.

3.4 SHORTCOMINGS PREVIOUS RESEARCH

Even though there are valuable studies towards the development of TSMS, there are also some shortcomings. These shortcomings can be divided into two categories. The first category is neglecting stakeholder's perspectives, the second is the lack of including relevant intricacies in TSMS design.

3.4.1 Neglecting stakeholder's perspectives

The first shortcoming identified in the field of TSMS design is that most researchers aim to optimise the TSMS from a terminal's perspective. By doing this, many studies fail to recognise the impact of TSMS on TOC, for example on their scheduling operations [Huynh et al., 2016].

Some researchers recommend the optimisation of TSMS including several stakeholders. For example, Chen et al. [2013b] and Chen et al. [2013a] recommend doing a multi-objective optimisation to accommodate the interests of related parties and to reflect realistic trade-offs, respectively. Wibowo and Fransoo [2020] attempted to include other stakeholder interests by proposing a joint optimisation model for TSMS at a chemical plant. In the field of air traffic management, Murça [2018] incorporates other stakeholders' interests by including disutility of rerouting for the flight operators. However, in this approach the behavioural perspective is not included.

Another approach for including the TOC' perspective in the development of a TSMS is by exploring the behaviour of TOC. Behaviour modelling in the form of DCM allows for exploring trucker behaviour.

In DCM, data is analysed and relations between independent variables and dependent variables are used to explain or predict an event [Bierlaire, 1998]. An event can be considered as a choice in the context of DCM. Moreover, DCM can provide insight in the preferences for arrival time at the terminal.

Generally, DCM in transportation research assumes that demand comes from decisions made by individuals in the population [Bierlaire, 1998]. The decisions comprehend a choice made based on a finite set of alternatives. The attractiveness of an alternative can be captured by the utility function.

There are various models for DCM. These are binomial and multinomial, these can be specified as logit or probit models. Multinomial models can additionally be classified in uncorrelated or nested model and mixed models.

There are two types of choice data, namely stated preference and revealed preference. Stated preference data is obtained from questionnaires in which hypothetical scenarios are presented to the choice maker. Revealed preference data is historical data from past choices. In both types of choice data, the data includes attributes that might be included in the utility function.

Several behavioural assumptions are made in the specification of the choice model [Bierlaire, 1998]. With the inclusion of an attribute in the utility function, it is assumed that the attribute actually impacts the choice for a certain alternative. Choice modelling is build on the concept of the alternatives being attractive relative to each other. Consequently, preferences for certain alternatives can be explored.

Another behavioural assumption made in choice modelling is that the decision maker is rational and a perfect optimiser. Therefore, in theory the alternative with the highest utility is always chosen. Nonetheless, humans tend to behave random and may choose an alternative that does not seem to provide the highest utility. This is due to the fact that it is impossible to capture all factors in the choice model that influence the choice. The utility function, therefore, consists of two parts. The first part is the deterministic part, which includes the attributes that are found to influence the choice of a certain alternative. The second part of the utility function contains an error term. This error term represents the unobserved behaviour that influence the choice. The error term is assumed to be i.i.d and follow an Extreme Value distribution ($EV(0, \mu)$) in which μ is the scale parameter. In general, the scale parameter is normalised to 1. Another method that can be used to capture the unobserved behaviour, is by the formulation of an alternative specific constant (ASC). By the formulation of an ASC the mean of the error term is moved to the deterministic part of the utility function. The ASC is a parameter in deterministic part that can be estimated from data.

DCM is a method that is, to the author's knowledge, never used in TSMS research. However, it is believed that DCM adds a behavioural understanding to the TSMS development. A TSMS development that includes the perspective of TOC, is of interest in this research. DCM using revealed preference data, might be a suitable method to obtain insight in TOC preferences for arrival.

3.4.2 Lack of including relevant intricacies in TSMS design

Another shortcoming that is found from previous research is that not all complexities in the system are taken into account. Even though, this is required to make the study realistic and the proposed TSMS designs usable in practice. For example, the study of Guan and Liu [2009] obtains significantly inaccurate results because they highly simplified the queueing process by applying a stationary queueing model.

Moreover, some researchers claim that not taking into account yard queues will provide faulty results. This is what happened in the research of Giuliano and O'Brien [2007]. Therefore Zhang et al. [2013], Chen et al. [2013a], Phan and Kim [2016], and Zhang et al. [2019] include these operations and queues specifically. However, it depends on the container handling and gate operation policy in the terminal whether the approach of including separate yard queues is necessary. Nevertheless, a lack of including the relevant intricacies associated with the system can deteriorate the value of the study.

Huynh et al. [2016] provide an overview of elements that should be considered for actual or studied TSMS. Among these elements are mandatory appointments for all transaction types; standby provision to fill empty, missed, or cancelled appointments; guaranteed appointments for committed container moves; sufficient and separate gate capacity; rational and flexible quotas; flexibility; reset provision; transaction screening and verification; port-wide, real-time system visibility; fees and penalties. During the design of TSMS in this research, these elements identified by Huynh et al. [2016] should be kept in mind to ensure a valuable study.

Table 3.1 provides an overview of the most related literature towards TSMS and the placement of this research.

Table 3.1: Overview of literature towards Time Slot Management Systems

	Simulation platform		Allocation framework		Behavioural
Author	**Arrival process**	**Queueing process**	**Control procedure**	**Solution algorithm**	**perspective**
Chen et al. [2013a]	Distribution fitting: Poisson distribution	Non-stationary	Bi-objective	Genetic Algorithm	-
Chen et al. [2013b]	Predictive method: Regression analysis	Non-stationary	Single-objective	GA, MSGA and Hybrid GA–SA	-
Chen et al. [2013c]	Distribution fitting: Poisson distribution	Non-stationary	Bi-objective	Genetic Algorithm	-
Zhang et al. [2013]	Distribution fitting: Exponential distribution	Non-stationary	Single objective	Genetic Algorithm	-
Zhang et al. [2019]	Distribution fitting: Exponential distribution	Non-stationary	Single-objective	Strategy-based allocation algorithm	-
Wibowo and Fransoo [2020]	Distribution fitting: General distribution	Non-stationary	Multi-objective	Branch-and-bound algorithm	-
This thesis research	**Distribution fitting: Exponential distribution**	**Non-stationary**	**Single objective**	**Strategy-based allocation algorithm**	✓

3.5 CONCLUSION

It can be concluded that TSMS has the potential to be a very effective, suitable and successful solution to reduce truck congestion at a terminal, provided that the TSMS is implemented properly. Therefore, the methodologies for TSMS design were explored in this chapter.

There are two main components required in TSMS development, namely a simulation platform and an allocation framework. These two components must be integrated to obtain a complete TSMS design.

The simulation platform includes the stochastic arrival process and queue process. For the arrival process there are two methodologies discussed. In most studies fitting to a probability distribution is the method used for the arrival process. However, predictive methods like regression analysis and machine learning, have the potential to make predictions of the arrival rate.

The queueing process comprehends some very important design decision for TSMS. The choices made for the arrival process, the inclusion of certain terminal operations, service policies and activity sequence to comprehend the situation at the terminal directly affect whether the designed TSMS is realistic and usable in practice.

There are two types of queueing models distinguished. Stationary queueing models assume constant rates for arrival and service at the terminal. This is rather unrealistic and might cause inaccurate results and faulty TSMS design. However, it does allow for a more simple estimation of waiting time. Non-stationary queueing models provide more accurate results and allow a more realistic TSMS design. Nevertheless, these models are more difficult and require complex approximation methods to estimate queue lengths and waiting time.

Depending on the assumptions made for the modelling approach, a suitable queueing model, that implements the assumptions, can be chosen.

For the allocation framework component, several mathematical formulations can be used for the optimisation problem. The most common formulation in resource allocation is (non-)linear mixed-integer. These optimisation problems are complex and difficult to solve with the optimal solution within reasonable computational time.

Therefore, heuristics are often used to solve the optimisation problem. The GA is predominantly used in TSMS design. Furthermore, a heuristic approach for reallocating, or rather shifting, trucks is very suitable to evaluate a TSMS based control strategy for truck arrival at terminals.

There are two categories of shortcomings identified from the present research of TSMS. These come down to neglecting stakeholders' perspectives in the design, especially the perspective of TOC. By developing a choice model, using DCM, the behaviour and preferences of TOC can be included in the development of TSMS. Consequently, this shortcoming can be tackled.

Another shortcoming is the lack of including relevant intricacies associated with the system. This lack of including relevant intricacies can happen in the several components of TSMS design. For example, an inaccurate assumption about the arrival or queueing process, or unjustified simplifications in the optimisation model. To tackle this shortcoming, a clear understanding of how the terminal operates is important.

4 METHODOLOGY

In this chapter, the modelling approach for the implementation of a TAS policy is laid out. The approach is based on the insight in methodologies for TSMS development, discussed in Chapter 3. Two models and one heuristic are developed based on two sets of data. First, the interaction between the models and heuristic is outlined in Section 4.1. Thereafter, both models and the heuristic are elaborated individually in Section 4.2, 4.3, and 4.4. Lastly, the approach for calculating the waiting time gain is discussed in Section 4.5.

4.1 MODELLING FRAMEWORK

From the literature review of the methodologies for TSMS development in Chapter 3, it is found that the development of the TAS policy requires two steps. These steps are the development of a simulation platform and an allocation framework. Additionally, it is concluded that choice modelling is a suitable way to include TOC preferences in the design of the TAS. Consequently, a modelling framework is defined to design the TAS in this research. The modelling framework is depicted in Figure 4.1. For this research, four terminals, labeled A through D, in the port of Rotterdam area are examined for TAS policy development. The models are developed based on data of these four terminals. Consequently, the results indicate the effect of truck shifting at these terminals in the Rotterdam port area.

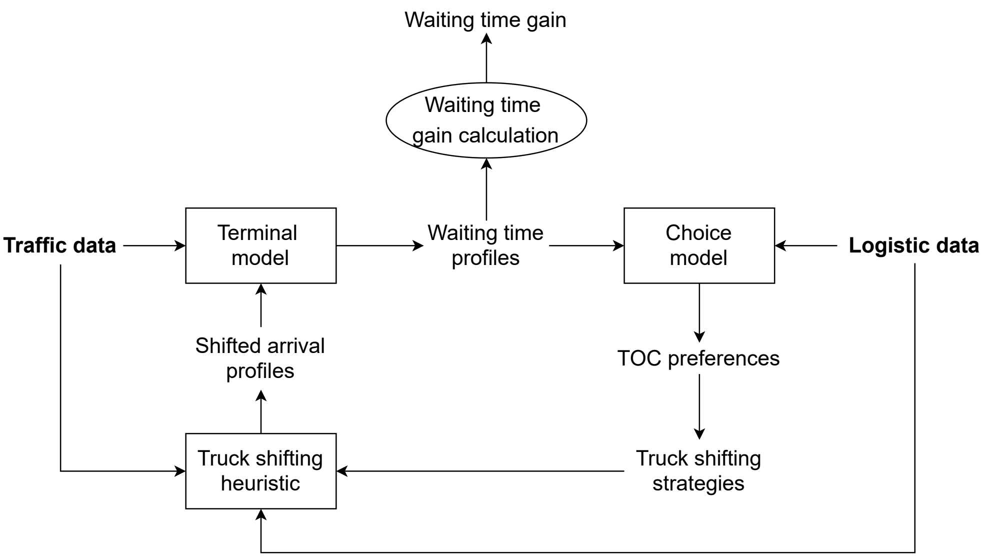


Figure 4.1: Modelling framework

The terminal model represents the simulation platform. Traffic data about truck arrivals at the terminals are the input for the terminal model. The output is waiting time at the terminals.

The choice model indicates the choice modelling step. The data used for the choice model is logistic data of import containers at the terminals. The waiting time profiles from the terminal model are additionally included in the choice model. The output of the choice model is the preferences of TOC for container pick up at certain time periods.

Subsequently, from the TOC preferences truck shifting strategies can be formulated. These indicate the strategy for controlling the truck arrivals at the terminals. The truck shifting strategy is input for the truck shifting heuristic. The truck shifting heuristic represents the allocation framework. In this heuristic, new truck arrival profiles are computed from the historic traffic data, based on the truck shifting strategy and what-if scenarios.

The output of the truck shifting heuristic, the shifted arrival profiles, is the new input for the terminal model. In the terminal model the shifted arrival profiles can be simulated to obtain waiting time profiles for the shifted arrivals.

Lastly, the waiting time profiles simulated from the shifted arrival profiles are compared with the waiting time profiles in the base case year 2017. Consequently, a waiting time gain for the truck shifting strategy and scenarios can be calculated. This results in insight in the effect of controlling the truck arrivals at the terminals. Hence, the potential of the TAS policy to reduce waiting time in the port of Rotterdam.

4.2 TERMINAL MODEL

A terminal model is developed to simulate the processes at the terminal. With the terminal model, a waiting time profile can be simulated from an arrival profile. The terminal model is set up using historic traffic data. One is referred to Appendix A for details of the traffic data.

In this section, the terminal model will be elaborated regarding the model components, the calibration, the verification and the validation. For exact details of the complete terminal model development one is referred to Appendix B.

4.2.1 Model description

The terminal model is formulated as a queueing model and DES is used to represent the port system. The terminal model is formulated as a $M/M/s$ queueing model as it is assumed that both the inter arrival time and the service time are i.i.d with an exponential distribution and the number of servers is an integer value.

With the terminal model, one day is simulated. The terminal model includes three components, namely the truck generator, the trucks and the server. Together these three components make up three processes in the terminal model. The three processes in the model are the arrival process, the server process, and the departure process. In Figure 4.2 a graphical representation of the terminal model, the components and processes is provided. Details of the model components and processes are extensively elaborated in Section B.1.1.

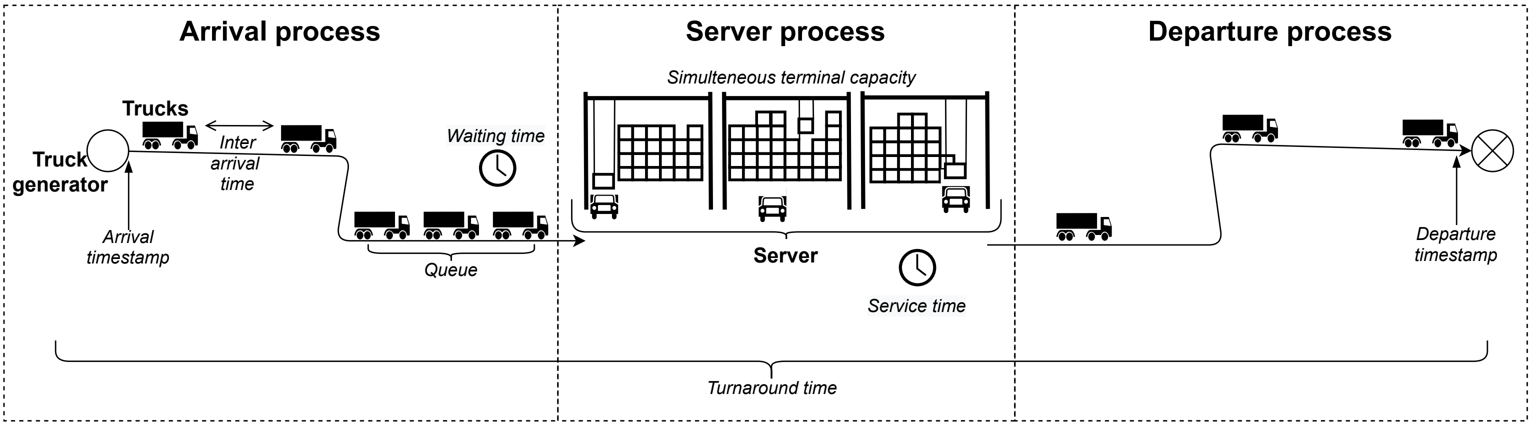


Figure 4.2: Graphical representation of the terminal model, the components and the simulated processes

Truck arrival

The arrival process simulates the truck arrivals at the terminal. Historic traffic data from the year 2017 is obtained from loop detectors in the port of Rotterdam area. This traffic data contains aggregated data for number of trucks arriving or departing from the terminal for each hour of the day. The arrival profile is non-stationary as the number of trucks arriving per hour varies along the day.

The truck generator component in the terminal model generates trucks with an inter arrival time (IAT_h in min). The inter arrival time is determined from the average historic arrival profile representing trucks per hour (λ_h), and fitted to a random probability distribution to account for stochasticity in arrivals. For the stochastic arrival process simulated in this research, it is assumed that the inter arrival times are i.i.d with an exponential distribution. This assumption is valid since the trucks stem from the same generative process and the arrival of one truck is independent of another truck (Section 3.2.1). Equation 4.1 presents the inter arrival time calculation used in the terminal model.

$$IAT_h = exp\left(\frac{60}{\lambda_h}\right) \tag{4.1}$$

A statistical analysis is carried out for the arrival profile obtained from the historic traffic data (Section A.1). By means of an ANOVA test, a monthly trend in truck arrivals is explored (Section A.1.2). It is concluded that there are no significant differences between months of the year ($p > 0.05$).

Moreover, based on a two sided t-test, weekend days are excluded from further research as these are found to be significantly different from working days ($p < 0.05$), and do not represent the situation that cause waiting time due to little truck arrivals on Saturday and Sunday.

To assess a potential daily trend in truck arrivals (Section A.1.3), an ANOVA test is used to compare the arrival profiles of the five working days. It is concluded that the working days do not differ significantly ($p > 0.05$). Hence, the working day average is sufficient to calibrate the simulation model regarding the arrival pattern.

However, the average working day arrival profiles are found to be significantly different ($p < 0.05$) among the terminals at Maasvlakte II (MVII) (Section A.1.1). For the four terminals a simulation model must be defined individually.

Terminal operations

The server component represents the terminal operations. From literature, modelling the terminal operations was found to be a complex task (Section 3.4). Nevertheless, a proper formulation of the server is crucial to make the study realistic and the developed TAS policy usable in practice. A lack of including the relevant intricacies associated with the system can deteriorate the value of the study.

As the four terminals, that are examined in this research, have dedicated cranes for serving external trucks, it is fair to neglect the vessel operations in the model. However, other relevant intricacies should be accounted for in the terminal model. Terminal operations typically include trucks entering the terminal yards, positioning of trucks in a container stack, loading/unloading the container, and driving back to the exit gate. Limited information is available to allow for simulating these terminal operations in detail. Therefore, the terminal operations are all captured by a single server component with the capacity to serve multiple trucks simultaneously in the terminal.

This might seem like a simplification of the model, because the details of the operations are not modelled. However, this is not quite true. The trucks spend a certain time in the terminal to be served. The information of this time spend in the server component, allows to represent all activities in the terminal. Additionally, multiple trucks can enter the server component. This information allows to represent the terminal capacity. Despite that the details of the terminal operations are not modelled, the relevant intricacies are included in the terminal model.

All relevant intricacies for simulating the terminal operations with the server component are thus captured by two parameters with an unknown value. These are the capacity to serve trucks simultaneous and the service time per truck. An optimisation algorithm, Bayesian optimisation [Bergstra et al., 2013], is used to estimate the parameter values based on the historic departure profile. The service time is estimated as a mean with integer value. The service of trucks is modelled as a stationary process, this means that the mean service time does not vary along the day. This is a valid assumption since the terminal in Rotterdam operate at a constant utilisation rate and the container (un)loading is a standardised and highly automated process. Consequently, the mean service time is distributed exponentially to account for stochasticity [Hillier and Lieberman, 2015]. This is similar to the distribution of the arrival process (Equation 4.1, however λ_h is replaced by μ for the constant mean service time. The capacity to serve trucks simultaneously is a constant integer value since no half trucks can be served.

In the optimisation approach to estimate the parameters for the server component, an objective function is formulated. The objective function is to minimise the difference between simulated departure profile and the observed departure profile. For the formulation of the objective function, the mean square error (MSE) method is used Equation 4.2. This method squares the difference between the simulated ($\hat{Y}_i$) and observed (Y_i) departure profile for each data point (n), in this case the hourly time periods, and computes the mean of over all data points. A larger difference results in a larger impact of the difference on the objective function. Therefore, the parameter values are tuned such that the deviation from the historic departure profile is minimised.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{4.2}$$

Simulation
The simulation model is set up with the DES package salabim [van der Ham, 2018]. Since the inter arrival time and service time are assumed to be i.i.d from an exponential distribution, the terminal model is formulated as a $M/M/s$ queueing model [Hillier and Lieberman, 2015].

In the simulation trucks enter the model with a certain inter arrival time. Subsequently, multiple trucks are served in the server component with a certain service time and capacity. When too many trucks arrive for the server component to process, a queue emerges. The trucks spend a certain time waiting in the queue until terminal capacity becomes available. After being served, the trucks leave the system (Figure 4.2).

In the simulation, the trucks obtain an arrival timestamp and departure timestamp upon arrival and departure, respectively. Hence, the total time spent by each truck individually, also referred to as the turnaround time, can be calculated. Moreover, each truck individually encounters a specific service time. By subtracting the service time from the turnaround time for individual truck, the time spent in the queue, also referred to as waiting time, is obtained for each truck.

From literature it was found that estimating the queue lengths and waiting time in a queueing model require a certain approximation method. In this research the approximation method applied is particle-based and for a non-stationary queueing process. Mathematically this is denoted with the following equations

$$L = \lambda_h W \tag{4.3a}$$

$$L_q = \lambda_h W_q \tag{4.3b}$$

$$W = W_q + \frac{1}{\mu} \tag{4.3c}$$

$$W_q = \frac{L_q}{\lambda_h} \tag{4.3d}$$

where the expected number of trucks in the queueing system, hence in the queue and in the servers, is denoted by L. The mean arrival rate for each hour is denoted by λ_h. The waiting time including service time, hence turnaround time, is represented by W (min). The mean service time is presented by μ (min), μ is i.i.d with an exponential distribution ($exp(\mu)$). Moreover, with L_q the expected queue length, thus excluding the trucks in the servers, is indicated. Lastly, the waiting time in the queue is denoted with W_q (min).

The DES salabim package used for the simulation set up provides queues and 'states' [van der Ham, 2018]. These ensure the trucks enter the queue and wait until the server component is ready to serve the trucks. Consequently, the waiting time for each individual truck is tracked throughout the simulation and logged in the results.

The resulting data from the simulation is transformed to provide the number of trucks arriving and departing for each time slot. Equivalent to the historical data profiles from the loop detectors, the simulated data is aggregated to hourly time periods. This provides the arrival and departure profiles along the day as simulated with the terminal model. By comparing these simulated arrival and departure profiles with the observed arrival and departure profiles from the loop detectors, the terminal model is calibrated, verified and validated.

Other results that are obtained from the terminal model, are profiles of hourly averages along the day for the turnaround time, the service time, the waiting time, and the queue length. These results can be used to analyse the simulated system.

4.2.2 Model calibration

To ensure that the terminal model is close to reality and can simulate the arrival, service and departure of trucks accurately, the terminal model requires calibration. For the specific terminal models, the design of the terminal model remains the same. Yet, the arrival and departure profiles in each terminal model correspond to the specific terminals A through D. Hence, the models for individual terminals are set up and calibrated separately. In each specific model, the parameters in the arrival and service process are tuned to a specific terminal. The parameters are tuned based on the traffic data (Appendix A) arrival profile and departure profile obtained from the loop detectors located at the specific terminal.

Arrival process

The parameters in the arrival process are the exponentially distributed inter arrival times from the average arrivals of trucks per hour, see Equation 4.1. The calibrated model simulates an arrival profile based on the tuned parameters. To ensure that the simulated arrival profile is similar to the observed profile a statistical analysis is carried out.

In the statistical analysis a two sided t-test is applied to compare the observed and simulated arrival profile. The results of the statistical analysis indicate that the simulated arrival profile is significantly similar to the observed arrival profile ($p > 0.05$). Additionally, polynomial regression is done to analyse the correlation between the observed and simulated arrival profile. The statistical measure in this analysis is the R-square. The R-square ranges between 0 and 1, this number indicates the extent to which the simulated data matches the observed data. The results of this statistical analysis are depicted in Table 4.1.

Table 4.1: Results for comparing the observed and simulated arrival profiles to check for correlation and significant differences in observed and simulated arrival profiles for several terminals

Terminal	**t-value**	**p-value**	**R-square**
Terminal A	0.025	0.98	0.995
Terminal B	0.014	0.989	0.989
Terminal C	0.025	0.981	0.996
Terminal D	0.031	0.975	0.994

Based on the results of the statistical analysis, the arrival process is calibrated and provides accurate results. In Section B.2.1 the extensive calibration and statistical analysis of the arrival process is elaborated.

Service process

The parameters in the service process are the simultaneous terminal capacity and the mean service time. The service process is, similar to the arrival process, calibrated based on historic traffic data. The historic data used to calibrate the service process is the departure profile.

Similarly to the arrival profiles, the departure profiles from the traffic data are statistically analysed with an identical approach and results (Section A.1). The results show that the departure profiles are significantly different among the four terminals ($p < 0.05$). There are no monthly trends in truck departures ($p > 0.05$). After excluding the significantly different ($p < 0.05$) weekend days from the week, the working days are found to be similar in departure profile ($p > 0.05$). Consequently, the average working day profile for each terminal can be used to calibrate the parameters for the individual models.

The parameters for the service process are tuned by means of the Bayesian optimisation algorithm (Section B.1.2). By the formulation of an optimisation problem, the missing information (the simultaneous terminal capacity and mean service time) can be captured by the model. Therefore, the simulation model can accurately simulate the service process. To tune the parameters to the optimal value, the algorithm iterates until it finds the parameter values that minimise the loss. This minimised loss is considered to be the best loss found by the optimisation algorithm. As aforementioned, the loss is calculated with the MSE method (Equation 4.2) and indicates the deviation from the observed departure profile. This results in the estimated parameter values depicted in Table 4.2.

Table 4.2: Overview of estimated parameter values for the service process and the corresponding loss

Terminal	Simultaneous terminal capacity	Mean service time	Best loss (MSE)	MAPE score
Terminal A	17	17	64.396	23%
Terminal B	16	17	37.15	13.8%
Terminal C	20	12	93.804	13%
Terminal D	20	14	70.05	10.9%

The parameter estimation results are considered to be realistic. Based on the number of stacks and cranes observed in the terminals using Google Maps satellite view [Google, 2017], and earlier research by the PoR [Drewes and Gorter, 2017], the magnitude of the parameters in combination is as expected.

Interpreting the absolute value of the best loss is rather difficult, as the MSE result is always dependent on the data. As a rule of thumb the best loss can be interpreted as the closer to zero, the better. Nonetheless, the absolute value of the MSE is relative to the magnitude of the values in each data point. As the MSE takes the square of the deviation in a data point, a factor 10 larger magnitude of values in a data point can result in a factor 100 larger MSE loss value. Therefore, the mean absolute percentage error (MAPE) score is additionally calculated using Equation 4.4. The calculation of the MAPE score is similar to the MSE (Equation 4.2), though a percentage value is obtained. This percentage value indicates the difference between observed and simulated profile. For interpreting the MAPE the rule of thumb is that a smaller value indicates that the simulated profile is closer to the observed profile.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{4.4}$$

All in all, the loss is found to be reasonable, based on the MSE results and the additional MAPE score results (Table B.4). Nevertheless, some difference between the observed and simulated departure profile is found. Therefore, two additional statistical analysis are applied to assess the power of the calibrated model to simulate the observed profiles.

Similar as to the statistical analysis for the arrival process calibration, the two sided t-test and R-square are used as statistical measures. The results of these analysis are depicted in Table 4.3.

Table 4.3: Results for comparing the observed and simulated arrival profiles to check for correlation and significant differences in observed and simulated departure profiles for several terminals

Terminal	t-value	p-value	R-square
Terminal A	-0.077	0.939	0.934
Terminal B	-0.044	0.965	0.979
Terminal C	-0.195	0.846	0.969
Terminal D	-0.018	0.985	0.977

The results of the statistical analysis indicate that the simulated departure profile is significantly similar to the observed departure profile. From the t-test, p-values larger than 0.05 are obtained. The R-square results are very close to 1, with a maximum deviation of 0.154. In Section B.2.2, the complete and detailed calibration of the service process is elaborated, and a reflection on the estimated parameter results is provided. Additionally, the statistical analysis is discussed extensively in Section B.2.2.

4.2.3 Model verification and validation

In the verification, it is checked whether the terminal simulation model operates as it is supposed to do. In validation, the simulation model is assessed on the capability to provide results that are close to reality.

Verification
The extensive model verification is discussed in Section B.3. In the verification, various checks and tests are executed. Each model for the specific terminals A through D, is verified in a stepwise approach. From the model verification checks, the model is found to operate as it is supposed to do. The components are implemented correctly, the flow conserve is zero, and the chronological order of processes is correct.

Validation
The extensive model validation is discussed in Section B.4. The approach for validating the model is to compare the simulation results with historic traffic data (Appendix A) using a train and a test set of the data. By splitting the historic data set of 2017 traffic data into two parts, the train and test set are created. The train set comprehends traffic data of 11 months of the year 2017. The test set includes the data of the remaining month, which is October.

The model is calibrated and the parameters are tuned using the train data set. Consequently, the calibrated model is validated by means of a test data set. This test set allows for an unbiased evaluation of the model, hence it allows to validate the model. The test set is independent of the train set. Yet, the test set and train set come from the same probability distribution.

The validation exist of three steps. First is visual validation by comparing the observed and simulated profiles visually. Second is polynomial regression with the R-squared as statistical measure. Last is the two sided t-test. The results of these validation steps indicate that the terminal model is validated. The observed and simulated arrival profiles are very similar looking at it with the eye. The results of the statistical analysis are shown in Table 4.4. The t-test results indicate a very high p-value, hence no significant differences between observed and simulated profiles ($p > 0.05$). Moreover, the R-squared results are very close to 1.

Table 4.4: Results for comparing the observed and simulated departure profiles of test set data to check for correlation and significant differences for several terminals

Terminal	t-value	p-value	R-square
Terminal A	-0.055	0.956	0.914
Terminal B	-0.059	0.954	0.956
Terminal C	-0.273	0.786	0.909
Terminal D	-0.033	0.974	0.964

The simulation model for each terminal is proven to be accurately calibrated, verified and validated. Using the simulation model, various results can be obtained. These results reflect the situation at the terminals in 2017. The results comprehend the simulated arrival and departure profiles, the average turnaround time profile, the average waiting time profile and the average queue length profile along a working day. In Section B.5 the results for the base year 2017, are presented for each terminal.

4.3 TIME PERIOD CHOICE MODEL

A choice model is developed to gain insight in the behaviour of the TOC regarding time period choice for container pick up. Based on this insight, a truck shifting strategy can be formulated to control truck arrivals at the terminals. The choice model is set up using logistic data collected from Portbase, the port community system at the port of Rotterdam. The logistic data captures details on import containers in 2017 for the same four terminals considered in the terminal model (Section 4.2). The logistic data required pre-processing and analysis before it could be used as input for the choice model. For details on the pre-processing, analysis and results of the logistic data one is referred to Appendix C.

In this section, the choice model will be elaborated regarding the steps required to set up a choice model [Bierlaire, 1998]. These steps are the problem definition, data, model specification, parameter estimation and model application. For the exact details of the complete time period choice model development and results, one is referred to Appendix D.

4.3.1 Problem definition

The goal of the choice model is to gain insight in the preferences of the TOC to pick up a container at a certain time. The choice model is based on discrete choice theory [Bierlaire, 1998]. The definition of the choice problem in this research is the choice of a TOC to pick up a certain container at a certain time. The probability of choosing a certain time is computed from the attractiveness of the alternatives. The attractiveness is measured from the utility function for each alternative. The utility function captures the influence of an attribute from the data.

4.3.2 Data

As mentioned, the choice model is based on logistic data of import containers. This is revealed preference data of TOC for container pick up. The data set contains information of transaction data on arrival of container vessels, containers discharges and the estimated pick up time (ETA) of these containers by hinterland transport trucks. Moreover, the data set includes container characteristics (type, dimensions, weight, and temperature) and information about the transported commodity. Additionally, the waiting time at the terminals obtained from the terminal models (Section 4.2) is included in the data set.

Data analysis
The logistic data is analysed with the aim to identify the attributes in the data that influence the choice of a TOC to pick up a container. Based on this information the choice model can be formulated. To obtain insight in which attributes impact the choice of the TOC a machine learning technique named random forest is used [Koehrsen, 2017]. This method aims to predict the preferred time slot for container pick up, based on the attributes in the data set.

As a result, the importance of the attributes for the prediction is indicated. Container type and commodity type are found to be important attributes to predict the preferred pick up time. The other attributes are excluded from further research, as these will not explain trucking behaviour. These excluded attributes might be correlated with the other attributes. It is desired to prevent this as collinearity might deteriorate the value of the data.

Additionally, a result of the random forest analysis is that the model is not very accurate in predicting the correct preferred pick up time in hours. The accuracy increases when the pick up time is categorised in four periods instead of hourly slots (Section C.2). Consequently, to obtain better results from the choice model, the hourly pick up time preference is aggregated to four time periods. The time periods are formulated as night (from 21:00 until 3:00), morning (from 4:00 until 9:00), midday (from 10:00 until 14:00), and afternoon (from 15:00 until 20:00). These periods are based on observed arrival patterns and categories used in practice at the terminals.

Moreover, it can be concluded from the data analysis that a separate choice model must be specified for each terminal as the terminals differ from each other considering container types and commodity types handled. This could result in different preferences of the TOC for pick up time (the ETA) based on the terminal the container must be picked up.

Attributes
Container type is an attribute with four levels. Therefore, the container type variable in the choice model is a discrete and categorical variable. The levels are general purpose container, reefer container, chemical container, and tank container. Commodity type is also a discrete and categorical variable. Commodity type is an attribute with eleven levels (Section C.3). However, in the choice model not all levels are included in the commodity type attribute. Solely the levels that are expected to be most influential are included, this is determined by how often the type occurs (Section C.3). Additionally, commodity types that are incompatible for formulation of a truck shifting are excluded. Two examples of this are 'miscellaneous' and 'unknown'.

Opposed to the container type and commodity type, the waiting time is a continuous variable. The waiting time is simulated with the terminal model. For each container in the logistic data set, an averaged waiting time for one hour in each time period is randomly assigned. Hence, the waiting time that could potentially be encountered by the TOC in each of the time periods, is included in the choice model. Therefore, the levels for waiting time are waiting time for morning, midday or afternoon. This allows to capture the effect of waiting time along the entire day, on the pick up period preference of the TOC.

4.3.3 Model specification

A mathematical model is specified for the choice model and contains several attributes. The details of the specification of the choice model for each terminal is elaborated in Section D.3.

In discrete choice modelling there are two types of attributes, dependent and independent attributes. A dependent, or endogenous, attribute is the choice variable, in this research that is time period. An independent, or exogenous, attribute is the explanatory variable. Based on the logistic data, the container type, commodity type and waiting time at the terminal are identified as independent attributes.

In the specified choice model, four alternatives make up the discrete choice set for the choice of pick up period. These alternatives are night, morning, midday, and afternoon. For each decision maker (the TOC), the choice set is the same. The attractiveness of the alternatives is determined by the underlying distribution of utility for the alternatives, as discrete choice modelling is built on the concepts of the alternatives being attractive relative to each other. Consequently, the probability that a TOC chooses time period t ($P(t|T)$), can be computed from the underlying distributions of utility. The utility (U) is calculated with the independent variables.

In theory, the alternative with the highest utility is always chosen (Equation 4.5), due to the behavioural assumption that the decision maker is rational and a perfect optimiser.

$$P(t|T) = Pr(U_t \geq U_j, \forall j \in T) \tag{4.5}$$

Nonetheless, humans tend to behave random and may choose an alternative that does not seem to provide the highest utility. This is due to unobserved behaviour of the decision maker. The utility function (U_t), therefore, consists of two parts (Equation 4.6). The first part is the deterministic part (V_t), which includes the attributes that are found to influence the choice of a certain alternative. The second part of the utility function contains an error term (ε_t).

$$U_t = V_t + \varepsilon_t \tag{4.6}$$

Utility function formulation

As introduced in Section 3.4, there are several behavioural assumptions made in choice modelling. Firstly, with the inclusion of an attribute in the utility function it is assumed that the attribute actually impacts the choice for a certain alternative. Hence, the utility functions are formulated based on insight from the logistic data (Section C.2, C.3 and C.4).

The deterministic part of the utility function (V_t), where V_1 represents the night, V_2 the morning, V_3 the midday, and V_4 the afternoon alternative, captures the attribute levels of container type (x_{type}), commodity types (y_{type}) and waiting time (w_{alt}). The prior two attributes are formulated as dummy variables (0 or 1) as these are discrete and categorical. The latter is a continuous variable, and formulated as the waiting time in minutes.

The utility functions are unique for each alternative and for each terminal. It depends on the terminal which levels of the attribute are included in the choice model. Levels are included or excluded based on the share of containers the level captures. Moreover, the spread of the levels along the day is considered, as this could indicate that for certain attribute levels, TOC prefer a specific time period. This information is obtained from the data analysis (Section C.3 and C.4).

To capture these unobserved behaviour of the TOC, an error term is included in the utility functions by the formulation of an ASC. The ASC is included in the utility functions for the night and morning alternative (ASC_{alt}). These are found to be least attractive (Section C.3). With the ASC in the utility for night and morning, it is aimed to capture the unobserved factors that decrease the preference for these alternatives.

To capture the influence of the independent variables on the choice, several parameters (β) are formulated. The value of these parameters can be estimated from data by the choice model. The parameters represent the preference for a certain alternative based on the container type, commodity type and waiting time as the parameters interact with the independent variables.

The mathematical formulation of the utility functions in the choice model for each terminal is presented in Equation 4.7a through Equation 4.10d. For more details, one is referred to Section D.3.2.

Utility functions for terminal A:

$$V_1 = ASC_{Night} + \beta_{RE} \cdot x_{RE} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{4.7a}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{Chem} \cdot y_{Chem} \tag{4.7b}$$

$$V_3 = \beta_{WT,Morning} \cdot w_{Morning} + \beta_{TC} \cdot x_{TC} + \beta_{CC} \cdot x_{CC} \tag{4.7c}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{GP} \cdot x_{GP} \tag{4.7d}$$

Utility functions for terminal B:

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{Chem} \cdot y_{Chem} + \beta_{RawMin} \cdot y_{RawMin} \tag{4.8a}$$

$$\begin{aligned} V_2 =& ASC_{Morning} + \beta_{WT,Morning} \cdot w_{Morning} + \beta_{CC} \cdot x_{CC} + \beta_{Agr} \cdot y_{Agr} \\ &+ \beta_{SolMinFu} \cdot y_{SolMinFu} \end{aligned} \tag{4.8b}$$

$$V_3 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{WT,Afternoon} \cdot w_{Afternoon} \tag{4.8c}$$

$$V_4 = \beta_{RE} \cdot x_{RE} + \beta_{Petro} \cdot y_{Petro} \tag{4.8d}$$

Utility functions for terminal C:

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{CC} \cdot x_{CC} + \beta_{TC} \cdot x_{TC} \tag{4.9a}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{4.9b}$$

$$\begin{aligned} V_3 =& \beta_{WT,Morning} \cdot w_{Morning} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{TC} \cdot x_{TC} \\ &+ \beta_{Fert} \cdot y_{Fert} + \beta_{RawMin} \cdot y_{RawMin} \end{aligned} \tag{4.9c}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + +\beta_{Chem} \cdot y_{Chem} + \beta_{Ores} \cdot y_{Ores} + \beta_{Petro} \cdot y_{Petro} \tag{4.9d}$$

Utility functions for terminal D:

$$V_1 = ASC_{Night} + \beta_{CC} \cdot x_{CC} + \beta_{Chem} \cdot y_{Chem} \tag{4.10a}$$

$$V_2 = ASC_{Morning} + \beta_{GP} \cdot x_{GP} + \beta_{RawMin} \cdot y_{RawMin} + \beta_{Agr} \cdot y_{Agr} \tag{4.10b}$$

$$V_3 = \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Petro} \cdot y_{Petro} \tag{4.10c}$$

$$V_4 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{CC} \cdot x_{CC} + \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Ores} \cdot y_{Ores} \tag{4.10d}$$

4.3.4 Parameter estimation

Based on the logistic data, the value of the parameters can be estimated by means of an optimisation algorithm. With the estimated parameters, the choice model serves to interpret the preferences of the TOC.

Optimisation algorithm
The optimisation algorithm to estimate the parameter values for ASC and β, is maximum log-likelihood estimation. Maximum likelihood is the probability that the model correctly fits the observations from data. In the maximum log-likelihood estimation, the model aims to estimate the parameters in such a way that the model has the highest probability of fitting the observed data. Hence, the parameter values are estimated as such that these maximise the log-likelihood calculated by

$$\max \mathcal{L}(\hat{\beta}_1, ..., \hat{\beta}_K) = \sum_{n=1}^{N} \left(\sum_{t \in T_n} y_{tn} \ln P_n(t|T_n) \right) \tag{4.11}$$

where $\mathcal{L}$ indicates the log-likelihood. If an individual chooses alternative t, $y_{tn} = 1$, otherwise $y_{tn} = 0$. $P_n(t|T_n)$ represent the logit model (Equation 4.12). The specified model is estimated using Biogeme software [Bierlaire, nd]. For further details of the optimisation algorithm for parameter estimation, one is referred to Section D.4.1.

In the model set-up, the model specifications (Section 4.3.3) are defined. Consequently, the model is estimated using the Multinomial Logit (MNL) model. The MNL model is used because the choice set is not binary but multinomial, there are multiple alternatives to choose from. Since the decision makers are assumed to be homogeneous the MNL model is very suited for the parameter estimation. Moreover, thanks to the closed form of the MNL model, there is less complexity involved. In the MNL model the probability of choosing an alternative compared to the other alternatives in the choice set is calculated by

$$P_n(t|T_n) = \frac{e^{V_{tn}}}{\sum_{j \in T_n} e^{V_{jn}}} \tag{4.12}$$

where, the deterministic part of the utility function (V_{tn}), indicates the utility of individual n for alternative t. Consequently, $P_n(t|T_n)$ represents the probability that individual n chooses alternative t from choice set T_n.

Model output
Several results are obtained from estimating the specified model with the optimisation algorithm, these are provided in Table 4.5. The estimated parameter values represent the preferences of the TOC. Additionally, output for statistical analysis of the model and the estimated parameters is obtained. Note that for some container and commodity types no parameter value is shown as it was found that only these, represented in Table 4.5, significantly ($p < 0.05$) impact the preference of a trucker for pick up time.

For assessing the model accuracy, the goodness of fit of the estimated model to the data can be observed from the likelihood ratio statistic (asymptotically distributed as χ^2). This is calculated with

$$-2(\mathcal{L}(0) - \mathcal{L}(\hat{\beta})) \tag{4.13}$$

The likelihood ratio statistic compares the a model where all parameters are set to zero ($\mathcal{L}(0)$, equal probabilities) with a model where all parameters obtain the estimated values ($\mathcal{L}(\hat{\beta})$. If the model with equal probabilities provides a statistically significant loss of fit compared to the estimated model, the estimated model fits the observed data well. Hence, the estimated model is accurate. The likelihood ratio reported by the estimated models (LR in Table 4.5), indicate a statistically significant loss of fit of the models with equal probabilities ($\chi^2 > 79.08$). Therefore, it can be concluded that the estimated model provides accurate results.

Table 4.5: Results of the time period choice models for each terminal

	Terminal A, $LR = 13326.87$			**Terminal B,** $LR = 26640.73$			**Terminal C,** $LR = 46274.5$			**Terminal D,** $LR = 118682.2$		
	Estimated parameter value	**t-value**	**p-value**	**Estimated parameter value**	**t-value**	**p-value**	**Estimated parameter value**	**t-value**	**p-value**	**Estimated parameter value**	**t-value**	**p-value**
ASC_{Night}	-1.52	-78.9	0	-2.13	-75	0	-2.01	-50.4	0	-1.68	-244	0
$ASC_{Morning}$	-0.601	-36.2	0	-0.407	-33.9	0	-0.338	-40.4	0	-0.333	-46.2	0
β_{GP}	-0.265	-15.1	0	0.325	10.2	0	0.245	5.89	0	-0.107	-13.2	0
β_{RE}	0.288	15.6	0	-0.906	-37.4	0	0.418	14.7	0			
β_{CC}	0.187	6.01	0	-0.096	-4.67	0	0.196	3.31	0.000932	-0.0374	-4.28	0
β_{TC}	0.0855	2.83	0.00462				0.0801	3.24	0.0012			
β_{Agr}	0.177	5.57	0	0.548	14.6	0	0.344	11.7	0	0.322	21.3	0
β_{Chem}	0.27	5.64	0	0.287	5.61	0	0.124	9.31	0	0.265	17.9	0
$\beta_{SolMinFu}$	1.18	26.1	0	0.0967	2.29	0.0223	0.297	16.8	0	-0.088	-7.66	0
β_{RawMin}				0.333	4.48	0	-0.217	-9.77	0	-0.0569	-3.91	0
β_{Petro}				0.175	4.2	0	0.134	7.26	0	0.0532	4.37	0
β_{Ores}							0.108	4.87	0	-0.0378	-2.78	0.00548
β_{Fert}							-0.0656	-2.94	0.00331			
$\beta_{WT,Morning}$	0.079	2.36	0.0185	0.0688	2.25	0.0248	-0.173	-2.93	0.00338			
$\beta_{WT,Midday}$	-0.00386	-3.01	0.00264	-0.0222	-13.7	0	-0.0173	-8.94	0	-0.0139	-8.17	0
$\beta_{WT,Afternoon}$	-0.00193	-2.24	0.0253	-0.0177	-15.5	0	0.00806	14.8	0			

For assessing the estimated parameters value accuracy, t-values and p-values are obtained for each estimated parameter. The t-value is calculated by

$$t_k = \frac{\hat{\beta}_k}{\sigma_k}, \tag{4.14}$$

where $\hat{\beta}$ is the estimate of parameter β and σ_k is the standard error of the parameter. From the t-value the p-value can be computed. This is done with Equation 4.15, where $\Phi(\cdot)$ indicates the cumulative density function of the univariate standard normal distribution.

$$p_k = 2(1 - \Phi(t_k)) \tag{4.15}$$

The obtained t- and p-values in Table 4.5 indicate that each parameter is estimated correctly at a 95% confidence level ($p < 0.05$). Furthermore, each parameter is proven to influence the alternative attractiveness based on the formulated utility functions. Hence, the estimated parameter provides insight in the behaviour of the TOC. Lastly, no significant correlation between estimated parameters in the specified models are observed in the model results ($p < 0.05$). Consequently, it can be concluded that the specified choice model for each terminal is statistically proven to provide accurate results. Thereupon, the estimated parameter values for each terminal can be interpreted.

Results interpretation

The parameters for container type and commodity type are unitless since these are formulated as dummy variables. Therefore, it is not possible to interpret the parameter values, depicted in Table 4.5 based on trade-offs or value-of-time. However, the parameter can be interpret based on two indicators. The first indicator is the parameter sign. The parameter sign provides insight in the taste of the decision maker for an alternative. A negative sign $(-)$ generally indicates a decrease in utility for an alternative, a positive sign $(+)$ generally indicates an increase in utility. This information helps to interpret the choice model. The second indicator is the magnitude of the parameter value. The magnitude of the parameter value indicates the impact of the parameter on the utility, thus on the attractiveness of an alternative.

The interpretation of the waiting time parameters is a bit different. Opposed to the container and commodity type variable, the waiting time is a continuous variable. Hence, the parameter value for waiting time is not unitless and can be interpreted considering trade-offs or value-of-time as the effect of one minute waiting time extra is represented by the parameter value.

Even though the impact of waiting time on the TOC is not further explored regarding the control strategies, the findings are interesting to share. The TOC seem to perceive morning waiting time as more impactful compared to midday and afternoon. Additionally, the TOC value one minute of the waiting time more heavily at one terminal compared to another. Especially for terminals B and C the waiting time impacts in the midday and afternoon are noticeable. One minute of waiting time in the midday and afternoon is rated more valuable for these two terminals compared to the terminals A and D.

These findings can be explained by the expectation of the TOC. In the morning the TOC do not expect long waiting time, therefore encountering waiting time in the morning can feel more costly compared to the midday or afternoon. Moreover, terminal B and C operate with a time slot management policy, terminal A and D with an open door policy. Hence, TOC do not expect waiting time at terminal B and C, but do expect waiting time at A and D. Consequently, the waiting time at the terminals with time slot management might feel more costly compared to terminals with open door policy.

In the interpretation of the parameters values, depicted in Table 4.5, several explanations for the parameters are provided. The thorough interpretation and explanation for each estimated parameter, is provided in Section D.4.2. The preferences or dislikes found from the estimated parameters can be explained by various factors among which are the traffic states on access roads, the type of goods in the containers, the clients of the goods, the industry where the goods are used, and assumptions for combining trips.

Two other factors that might explain the parameter value, hence the preference of the TOC, are not included in the interpretation of the parameter. These factors are the details of the vessel that transported the container, and the exact origin and destination of the containers. As there is no data explored in this research that could provide insight in these factors, therefore these are not further explored in the result interpretation.

As the results of the choice model are used for the formulation of truck shifting strategies, the specific individual results are not further discussed here. For the complete and detailed discussion of the results from the choice model, one is referred to Section D.4.2. An overview of the found preferences is depicted in Table 4.6 on the next page. In this table, the x indicate the found preference for the container type or commodity type.

Another important note is that these preferences are estimated based on import container data. It might be that exploring export data would lead to different arrival time preferences. For some types this might provided inaccurate preferences since the import type might not be dominant for the preference of a TOC. For example, for chemical containers the time period of delivery of an export container is more important, consequently the import chemical container is picked up to avoid an empty trip. On the other hand, for agricultural products or reefer containers the choice for import container pick up is more relevant. However, this impact of export data is not further explored in this research.

For the remainder of this chapter, solely the preferences that allow truck shifting are relevant, these are made bolt in the table. The resulting strategies are mentioned in the next subsection (Section 4.3.5).

4.3.5 Model application

From the choice model results various opportunities can be identified to spread the arrival of trucks more evenly along the day. These opportunities stem from the observed preferences and dislikes of TOC (Table 4.6) and the choice probability distribution for container and commodity types (Table D.11 through Table D.14). The tendency of a TOC to pick up a container in another time period than currently chosen, allows to shift truck arrivals from one time period to another.

Truck shifting strategies

The insight in TOC' behaviour from the choice model is used to formulate strategies for controlling truck arrivals at the terminals. The general strategy for the TAS policy is an approach in which the truck arrivals during peak periods are shifted towards quieter moments. This approach is referred to as peak shaving. The results of the choice model are applied to define a more specific shift strategy for each of the terminals. The shift strategy for each terminal indicates precisely which trucks can be shifted from the peak periods to the quieter time periods. The elaboration of the shift strategies

Table 4.6: Overview of preferences of TOC to pick up certain container or commodity type in a time period. The preference is indicated by x

	Type	Time period preference (indicated by x)			
		Night (21:00-3:00)	Morning (4:00-9:00)	Midday (10:00-14:00)	Afternoon (15:00-20:00)
Terminal A	**General purpose container**	x	x	x	
	Reefer container	x	x		
	Chemical container			x	
	Tank container			x	
	Agricultural products		x		
	Chemical products		x		
	Solid mineral fuels	x			
Terminal B	**General purpose container**	x			
	Reefer container	x	x	x	
	Chemical container	x		x	x
	Agricultural products		x		
	Chemical products	x			
	Solid mineral fuels		x		
	Raw minerals	x			
	Petroleum				x
Terminal C	**General purpose containers**	x			
	Reefer containers		x		
	Chemical containers	x			
	Tank containers	x		x	
	Agricultural products		x		
	Chemical products				x
	Solid mineral fuels		x		
	Raw minerals	x	x		x
	Petroleum				x
	Ores				x
	Fertilizers	x	x		x
Terminal D	**General purpose container**	x		x	x
	Chemical container		x	x	
	Agricultural products		x		
	Chemical products	x			
	Solid mineral fuels	x	x		
	Raw minerals	x		x	x
	Petroleum			x	
	Ores	x	x	x	

can be found in Section D.5. Below, a recapitulation of the truck shifting strategy per terminal is provided.

- Terminal A: agricultural products to the morning, chemical products to the morning, solid mineral fuels to the night, general purpose containers away from the afternoon, reefer containers to the night and the morning.
- Terminal B: agricultural products to the morning, chemical products to the night, raw minerals to the night, solid mineral fuels to the night, chemical containers not to the morning, general purpose containers to the night, reefer containers away from the afternoon.
- Terminal C: agricultural products to the morning, raw minerals away from the midday, solid mineral fuels to the morning, chemical containers to the night, reefer containers to the morning, general purpose containers to the night.
- Terminal D: chemical products to the night, agricultural products to the morning, ores away from the afternoon, raw minerals away from the morning, solid mineral fuels to the morning and the night, chemical containers to the morning, general purpose containers away from the morning.

Experimental plan
By shifting the truck arrivals, new arrival profiles are obtained. How this is done this is explained in Section 4.4. The shifted arrival profiles are input for the terminal model (Section 4.2) to generate new simulated arrival and departure profiles and the corresponding waiting time profiles based on shifted trucks. Together the new arrival and waiting time profiles ensure insight in the potential gain from the truck shifting strategies (Section 4.5).

Various what-if scenarios are formulated to evaluate the effect of application rates of TOC on the spread of truck arrival along the day. The terminal model allows for evaluating the effect of truck shifting under certain TOC application rates by using various arrival profiles. Additionally, the formulation of what-if scenarios allows to gain insight in the percentage of TOC that should apply to the truck shifting strategy to achieve a waiting time gain.

Furthermore, the scenarios provide insight in the drawback of shifting truck arrival. When too many trucks are shifted away from the peak, a new peak might occur during other time periods. This will cause waiting time in other time periods. This is basically moving the current waiting time issue in the midday and afternoon to another time. Hence, simply shifting as many trucks as possible is not the right approach to the problem. The what-if scenarios provide insight in the turning point of truck shifting, from which application rate a waiting time loss instead of gain is encountered.

4.4 TRUCK SHIFTING HEURISTIC

Based on the truck shifting strategies and experimental plan (Section 4.3.5) that result from the choice model, the truck shifting heuristic is developed. The purpose of the truck shifting heuristic is to compute new arrival profiles based on the truck shifting strategies that resulted from the choice models. There are various steps involved to shift trucks and compute new arrival profiles. These steps are visualised in Figure 4.3. First of all, the logistic data (Appendix C) and traffic data (Appendix A) are combined to convert containers to trucks. Secondly, the total potential shifts is calculated. Thereafter, a shift matrix for each scenario is computed. Lastly, the shift matrices are transformed to an arrival profile that matches each scenario. Each step is briefly discussed in this section. The details of the truck shifting heuristic are provided in Appendix E.

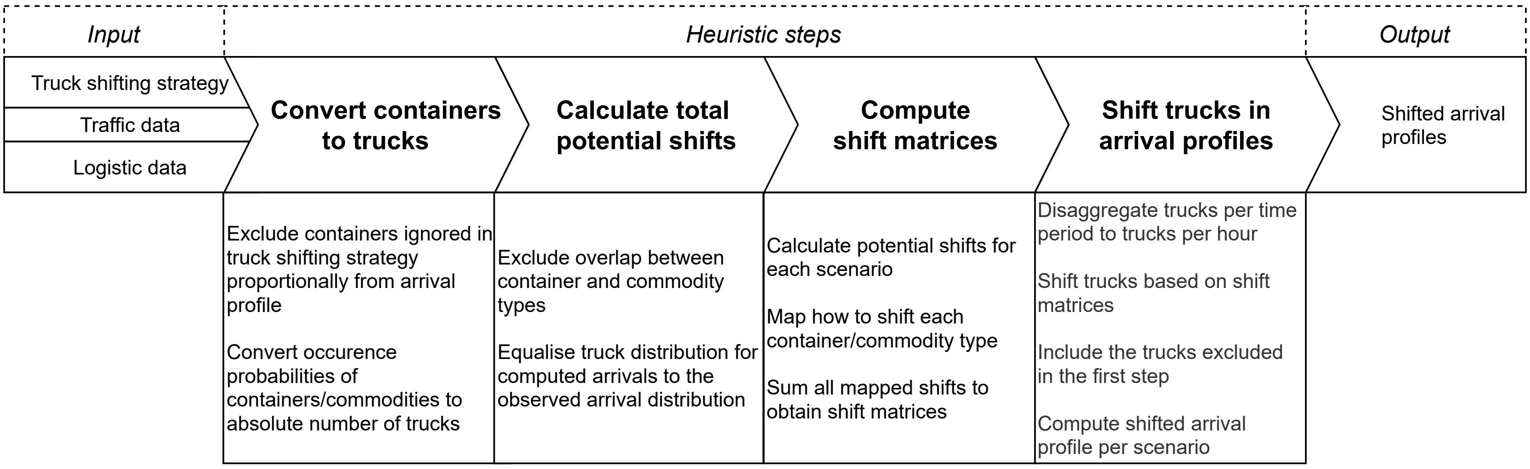


Figure 4.3: Overview of the truck shifting heuristic

4.4.1 Convert containers to trucks

This step comprehends the coupling of traffic and logistic data. The logistic data is summarised in occurrence probability percentages (Section C.3). Hence, these can be converted to absolute numbers of trucks transporting the specific container type or commodity type.

Before converting the logistic data to absolute number of truck arrivals, some trucks are excluded as these will not be shifted based on the strategy. These trucks transport container or commodity types that are not included in the choice model specification, or the TOC has a preferences for pick up of these containers in the peak periods, midday and afternoon. As these trucks are not captured in the truck shifting strategy, these cannot be shifted and remain stationary in the new arrival profiles. Consequently, a parameter r is formulated that represents the rate of trucks that can be shifted in the strategy.

To convert the container data to trucks, the occurrence probability (Table E.1 through Table E.4) is multiplied by the absolute number of trucks arriving at the terminal on an average working day. Hence, there is insight in the number of trucks that arrive in each time period to pick up a certain container type or commodity type. The spread of truck arrival for an average working day based on specific container and commodity types are provided in Table E.5 through Table E.8.

Note that in this approach the container dimensions are ignored. As the translation from container to truck is done based on percentages, the fact that a truck might arrive to pick two containers at once, is captured. Nevertheless, the assumption is made that a truck will only transport one type of container or commodity.

4.4.2 Total potential shifts

With the container data converted to trucks, there is information obtained about the distribution of container types and commodity types along the day. However, this does not yet represent the total potential shifts. The total potential shifts indicate the number of trucks on an average working day that can be shifted per time period, and per container and commodity type.

Occasionally, the containers that are shifted based on container type, contain a commodity type that is also shifted in the truck shifting strategy. A typical example is a reefer container transporting agricultural products. However, it is not necessarily true that the reefer containers always transports agricultural products, nor that agricultural products are always transported in reefer containers. The overlap is accounted for to obtain the potential shifts. The overlap percentage, the probability that a specific container type contains a specific commodity, is summarised in Section C.3. For consistency, the overlap is always excluded from the containers that are shifted based on container type.

Moreover, the distribution of trucks along the day computed from the logistic data is not always similar to the distribution of trucks per time slot from the observed traffic data of truck arrivals. This can be explained due to the fact that the logistic data captures the ETA, the expected arrival time, of the TOC and not the actual arrival time. However, the observed arrival profile should match with the TOC behaviour.

The total potential shifts are in the form of a matrix N_{TxC} with the choice alternatives (night, morning, midday and afternoon) $T = \{1, 2, 3, 4\}$ and the container and commodity types $C = \{1, 2, 3, ..., c\}$.

$$N_{TxC} = \begin{bmatrix} N_{11} & \dots & N_{1c} \\ \vdots & \ddots & \vdots \\ N_{t1} & \dots & N_{tc} \end{bmatrix}_{TxC} \quad \forall t \in T, c \in C \tag{4.16}$$

The matrix with potential shifts (N_{TxC}) is filled with N_{pq} calculated by

$$N_{pq} = P(t|c) \cdot r \cdot \sum_{t}^{T} a(t), \quad \forall p \in T, q \in C, \tag{4.17}$$

where $P(t,c)$ denotes the joint probability of a certain container or commodity type (c) occurring in a certain time period (t), r represents the rate of trucks that can be shifted, and $a(t)$ indicates the base case arrival profile. Finally, the potential shifts for trucks at each terminal is represented in Table E.11 through Table E.14. For the details for obtaining the potential shifts, one is referred to Section E.1.2.

4.4.3 Shift matrices

From the total potential shifts, shift matrices for each what-if scenario can be computed. With the what-if scenarios various application rates of TOC to the truck shifting strategy are evaluated. These shift matrices indicate how many trucks are shifted from a certain time period to another certain time period for each what-if scenario. One is referred to Section E.1.3 for the detailed description of scenario formulation and computation steps of the shift matrices.

Scenario formulation
In total, 16 what-if scenarios are formulated. The first scenarios vary from application rates between 5% and 50%, each scenario is increased with steps of 5%. Scenario 1 indicates a 5% shift of truck arrivals, scenario 2 a 10% shift, and so forth until scenario 10 in which an application rate of 50% is evaluated. Scenario 11 until 15 correspond to an application rate of 60% until 100%, respectively. For these scenarios, the application rates are subsequently increased in steps of 10%. Lastly, a 16th scenario is formulated in which the truck arrivals are spread perfectly equal along the day.

This approach allows to assess the effect of small changes (in steps of 5%) in arrivals more closely. Hence, to approximate the minimal application rate of TOC, that is required to shift for a waiting time gain, more precisely. Additionally, the higher application rates are increased with steps of 10%. Even though the high application rates are less realistic, it is important to understand what would happen with the waiting time profile if these high application rates where to be experienced. The higher application rate scenarios allow to study the potential turning point of truck shifting and the consequences. Moreover, the 16th scenario is used as a reference scenario as the perfect arrival profile would be an equal spread of trucks along the day. The waiting time gain for each scenario is compared with this reference scenario, to review the effectiveness of shifting of trucks under various application rates.

Consequently, the PoR and terminals gain insight in the effect of controlling truck arrivals. The advantages encountered with small application rates, as well as the risks of too high application rates are evaluated with the scenarios.

Shift matrix computation steps
Based on the application rates from the what-if scenarios and the truck shifting strategies, shift matrices (X_{TxT}) can be computed.

$$X_{TxT} = \begin{bmatrix} X_{11} & \dots & X_{1t} \\ \vdots & \ddots & \vdots \\ X_{t1} & \dots & X_{tt} \end{bmatrix}_{TxT} \quad \forall t \in T \tag{4.18}$$

These shift matrices indicate how many trucks are shifted from a certain time period (origin) to another certain time period (destination) for each what-if scenario. X_{TxT} is filled with

$$x_{ij} = N_{TxC} \cdot \gamma, \quad i, j \in T, \tag{4.19}$$

where γ denotes the application rate in the what-if scenario and

$$J = arg \max_t (P(t|c)) \tag{4.20}$$

is used as a rule to shift the potential of specific container from a specific time period to another time period based on the preferences of the TOC. $P(t|c)$ denotes the probability that a TOC arrives in a certain time period (t) to pick up a certain container or commodity type (c). This is based on the MNL model (Equation D.20). The computed shift matrices for each scenarios and each terminal are provided in Table E.15 through Table E.21.

4.4.4 Shifted arrival profiles

The last step in the truck shifting heuristic is to convert the shift matrices to new arrival profiles. The arrival profile obtained from historic traffic data (Section A.2) serves as the base case. Consequently, for each scenario, the trucks in this base case are shifted as indicated by the shift matrices. This results in new arrival profiles for each scenario. However, the data in the shift matrices is aggregated to trucks per time period ($t \in T = \{1, 2, 3, 4\}$). Therefore, the data requires to be disaggregated to hours, resulting in $t' \in T' = \{1, 2, 3, ..., 24\}$. Computing the new arrival profile starts from the base case arrival profile. The trucks taken out of the origin hours are subtracted from the base case arrival profile and the trucks added to the destination hours are summed to the base case arrival profile. Mathematically, for each scenario a corresponding arrival profile is computed with

$$a'(t') = a(t') + \sum_{t}^{T} s(t') \cdot x_{tj} - s(t') \cdot x_{pj} \quad \forall j \in T, t' \in T', p \in T, \tag{4.21}$$

where $a'(t')$ indicates the new arrival profile, $a(t')$ denotes the base case profile. $s(t')$ represents the proportion of trucks in an hour in the base case. Lastly, x_{tj} and x_{pj} indicate the trucks in the shift matrix that require to be shifted to and from a certain time, respectively. Note that this is a recursive function. Some details and extra explanation of this step is provided in Section E.1.4.

An exception in the approach for computing the shift matrices is the 16th scenario. In this scenario trucks are not shifted based on application rates. The total number of trucks arriving in a day is divided by 24, this results in an equal spread of trucks in the arrival profile.

4.4.5 Truck shifting heuristic results

The shifted arrival profiles are displayed in Figure E.3 through Figure E.6). In these figures, the arrival profiles from the truck shifting heuristic for various scenarios are presented per terminal. The shifted arrival profiles will be used as input for the terminal model. In Section E.2, observations from the arrival profiles are discussed in detail.

The most important observation is the occurrence of large dips and peaks in the arrival profiles. These occur around the transition of the different time periods when the application rate increases. That these peaks and dips arise instead of a rather equal spread around the transition of the different time periods is a limitation of the truck shifting heuristic caused by aggregating and subsequently disaggregating the traffic data.

Nevertheless, the large dips and peaks that arise at more extreme application rates, are not inaccurate. The dips and peaks logically increase when the application rates are higher, since more trucks are shifted. In reality, it is expected that the number of truck arrivals at the transition time slots is more comparable to the surrounding hours. Therefore, computed arrival profiles in the scenarios with smaller application rates are more realistic. Yet, the extreme application rates are evaluated to provide insight in the risks of truck shifting.

4.5 WAITING TIME GAIN CALCULATION

The waiting time gain calculation provides the results for evaluating the effect of controlling truck arrivals. With the terminal model, the waiting time profiles corresponding to the scenario arrival profiles, can be simulated. By comparing the simulated waiting time profiles from the scenarios with the base case a waiting time gain can be calculated. This process is elaborated in detail in Appendix F. The results are discussed in the next chapter (Chapter 5).

The waiting time profile simulated by the terminal model indicates the waiting time on average per hour that is encountered by one truck. The waiting time is at maximum 10 to 25 minutes in the base case. This might not seem much, however, it should be noted that this waiting time is encountered by every truck that arrives in the specific hour. Therefore, it is valuable to analyse the waiting time in relation with the arrival profile. By multiplying the waiting time profile with the arrival profile, the total waiting time profile along the day can be calculated.

Ultimately, the aim is to reduce the waiting time for the entire system and for the entire day. By subtracting the total waiting time for each scenario from the base case for each hour, and consequently summing the difference per hour, the waiting time gain can be calculated. This provides insight in whether the waiting time in the scenarios have reduced compared to the base case.

The total waiting time gain for the entire day indicates the impact of truck shifting under a certain application rate of TOC. If a positive value is obtained, the truck shifting strategy leads to a waiting time gain under the application rate scenario. If negative value is obtained, this implies that the truck shifting strategy is not successful to reduce waiting time under a certain application rate.

Furthermore, hourly waiting time gains are difficult to interpret for the entire system as it is not immediately clear what one hour of waiting time gain means and for who this gain is beneficial. For the interpretation of the results, the waiting time gains in hours are converted to monetary values. By doing so, the gain can be interpreted more easily.

4.6 CONCLUSION

In this chapter, the approach for controlling truck arrivals and evaluating the effects on waiting time is laid out. It can be concluded that the developed models and the heuristic are able to evaluate the effect of controlling truck arrivals on waiting time.

The modelling framework indicates the interaction between the data, models, and heuristic, and how these are used to evaluate the effect on waiting time. The foundation for the approach is the literature review in Chapter 3.

The data used for the research are traffic data and logistic data. These are combined to control truck arrivals. From the traffic data, observed arrival and departure profiles at the terminals are obtained. These are used to develop, calibrate and validate the terminal model. Moreover, the traffic data is used as input for the truck shifting heuristic.

From the logistic data, information of import containers and estimated pick up time (ETA) of the containers is obtained. Based on this data insight is gained considering the attributes that impact the preference of TOC for container pick up time. Consequently, the logistic data is applied to estimate the specified choice model. This allows to capture trucker behaviour.

The insight in preferences of TOC for container pick up are used to formulate truck shifting strategies. Based on these strategies, the truck shifting heuristic computes shifted arrival profiles for various scenarios of TOC application rates.

The shifted arrival profiles are simulated with the terminal model. Thereupon corresponding waiting time profiles are obtained. These are compared with the waiting time profile from the observed arrivals. This allows to calculate the waiting time gain and evaluate the effect of controlling the truck arrivals on waiting time at the terminals.

In the next chapter (Chapter 5), the results of the research are provided and discussed.

5 RESULTS

In the previous chapter (Chapter 4), the methodology for the TAS policy design, modelling and simulation approach in this research is laid out. The experimental plan and scenario formulation is discussed. As mentioned, from the truck shifting heuristic, shifted arrival profiles are computed under various what-if scenarios. These what-if scenarios represent application rates of TOC to the formulated truck shifting strategy. One is referred to Section 4.4.3 or Section E.1.3, for details of the scenario formulation. With the formulated scenarios it is possible to evaluate the effect the truck shifting strategies under various TOC application rates.

As a result of the truck shifting heuristic (Section 4.4), shifted arrival profiles for each scenario and for each of the four terminals are obtained. The shifted arrival profiles are based on the truck shifting strategies and application rates. These are input for the terminal model (Section 4.2). The terminal model simulates arrival and departure profiles based on these shifted arrival profiles. These simulated arrival and departure profiles are depicted in Figure F.2 through Figure F.5 in Section F.1.1. In addition to the simulated arrival and departure profile, an average waiting time profile is simulated for each scenario.

The simulated waiting time profiles provide insight in the effect of the TAS policy on the waiting time. Consequently, the waiting time profiles are thoroughly analysed to evaluate the potential reduction of waiting time. The results of the research are presented and discussed in this chapter. First, the results of the analysis for waiting time reduction are discussed in Section 5.1. Thereafter, the total waiting time gain is explored in Section 5.2. Lastly, the results are interpreted in Section 5.3 for the various stakeholders in the port system.

5.1 ANALYSIS OF WAITING TIME REDUCTION

The simulated arrival, departure and waiting time profiles are analysed to gain insight in the potential waiting time reduction. This is done visually and statistically.

5.1.1 Visual analysis

From the simulated arrival and departure profiles under various scenarios (depicted in Figure F.2 through Figure F.5), some initial conclusions can be drawn for the waiting time profiles that result from the different application rate scenarios. These conclusions are based on the difference between the departure profile and the arrival profile. If the arrival and departure profile overlap more closely, thus a smaller offset for the departure profile, less waiting time is expected (Section B.5).

Consequently, it can be observed that with only small application rates, already a large reduction of waiting time is obtained. As the application rates increase, larger differences between arrival and departure profiles are observed. Therefore, it is expected that with higher application rates, waiting time increases again.

From an initial grasp of the simulated profiles, it is expected that, in general, the waiting time decrease starting from a 5% application rate until an application rate of about 40% or 50%. From an application rate of about 50% or 60% the waiting time is expected to increase again. However, the exact shift percentage causing a decrease or increase of waiting time, differs per terminal.

These initial conclusions the waiting time profiles are explored more closely. The simulated waiting time profiles represent the average waiting time for one truck for each hour of the day. In other words, the waiting time that is encountered by one truck if it arrives in a certain time slot. The waiting time profiles of each scenario are plotted against the base case waiting time profile in Figure F.6 through Figure F.9.

From these graphs it can be concluded that the initial conclusions based on the simulated arrival and departure profile are correct. It can be observed that from only small application rates (5%-10%) the waiting time is decreased considerably. Whereas with higher application rates the waiting time increases.

5.1.2 Statistical analysis

In addition to the visual analysis of the waiting time profile, a statistical analysis provides much insight in the effect of shifting trucks on waiting time. With the statistical analysis it is checked whether the observed waiting time reduction is significant ($|t| > 1.96$, $p \leq 0.05$). The statistical measure used for the analysis is the two sided t-test to compare the waiting time profiles from each scenario with the base case waiting profile. In Table F.1 the exact t-values and p-values are depicted. Table 5.1 provides an overview of which shift percentages achieve a significant reduction of waiting time.

In Table 5.1 all the scenarios are presented. Empty cells indicate that the waiting time is not significantly reduced compared to the base case. Cells with x indicate that the waiting time in the corresponding scenario is reduced significantly. An empty cell can indicate that the application rate is not high enough (5%-10%) to reduce waiting time significantly. However, this does not mean that the waiting time does not decrease at all. The empty cell can also imply that waiting time may have appeared somewhere else during the day, this happens when the shift percentages become very large (60%-70%).

The results are different for each terminal due to the different preferences of the TOC for container pick up, the specific shift strategy at each terminal, and the shares of specific container and commodity types handled at each terminal. For example, at some terminals, more often preference for pick up during quiet periods was observed from the choice model. Another reason might be that some container or commodity types with high shares, are preferred for pick up in a night or morning period. Hence, a higher number of absolute trucks is shifted.

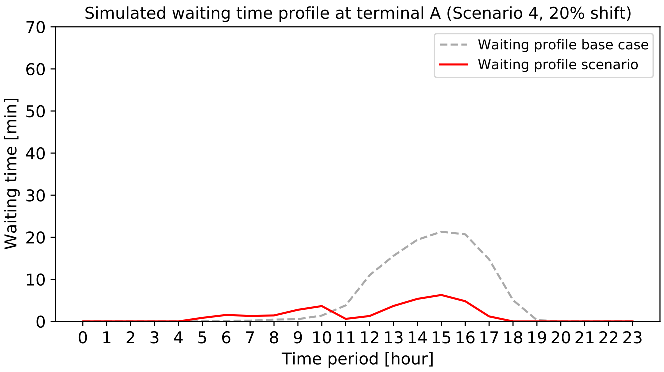
Table 5.1: Overview of which shift percentages provide a significant reduction of waiting time. The x indicate that waiting time is significantly reduced under the shift percentage compared to the base case ($|t| > 1.96$, $p \leq 0.05$)

	Terminal A	**Terminal B**	**Terminal C**	**Terminal D**
5% shift				
10% shift	x	x	x	
15% shift	x	x	x	
20% shift	x	x	x	
25% shift	x	x	x	
30% shift	x	x	x	
35% shift	x	x	x	x
40% shift	x	x	x	x
45% shift		x	x	x
50% shift		x	x	x
60% shift		x	x	x
70% shift				x
80% shift				
90% shift				
100% shift				
Equal	x	x	x	x

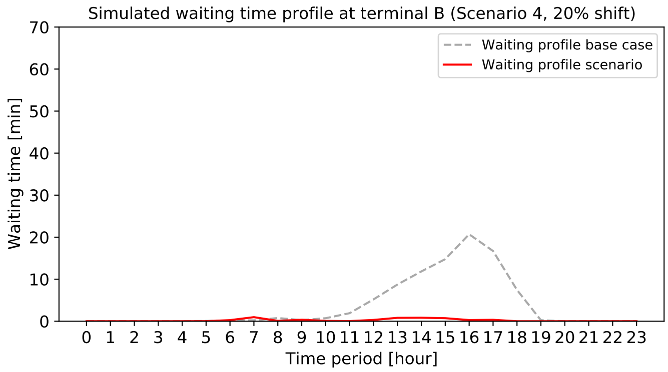
A shift of trucks does not naturally happen. Effort, for example in the form of lobby among the TOC, is required to achieve a certain shift percentage. It is expected that for higher application rates, more effort is required. From Table 5.1, it can be concluded that for three of the four terminals, the waiting time is reduced significantly with a TOC application rate of only 10%. This shows that the TAS is a policy with the potential to have much impact with minimal effort.

However, for terminal D, higher shift percentages are required to achieve a significant reduction of waiting time. This does not mean that at smaller application rates, the waiting time does not decrease. Nonetheless, the reduction is not significant. Moreover, to achieve a significant reduction of waiting time more effort is required to shift the truck arrivals at terminal D.

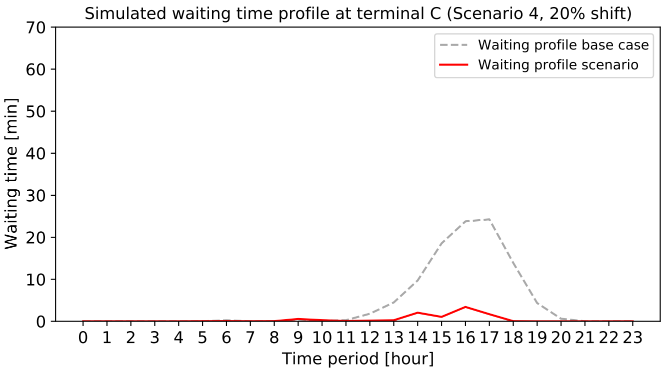
In Figure 5.1, the waiting time profile of a 20% shift scenario is provided for each terminal. The gray dotted line is the waiting time profile for the base case, the red line is the waiting time profile for the second scenario representing a 20% shift. These graphs indicate the average waiting time for each hour of the day encountered by one truck.



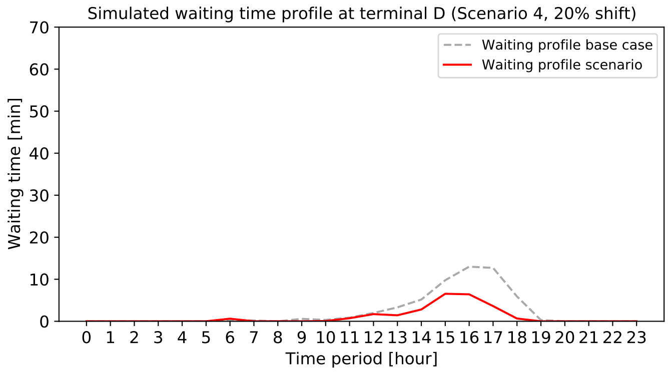
(a) Terminal A



(b) Terminal B



(c) Terminal C



(d) Terminal D

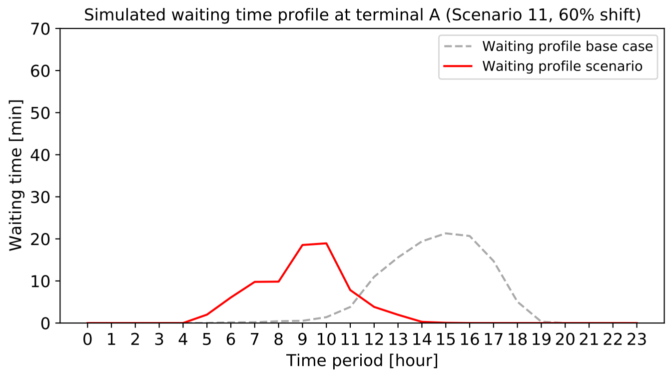
Figure 5.1: Simulated average waiting time profiles for the base case and scenario 2 (10% shift), obtained from the terminal model (Appendix B)

From Table 5.1, the insight is obtained that terminal A, B and C all have significantly reduced waiting time at an application rate of 20%. Terminal D does not have a significant waiting time reduction at 20% shift. However, from Figure 5.1 it can be observed that there is a small reduction at terminal D as well.

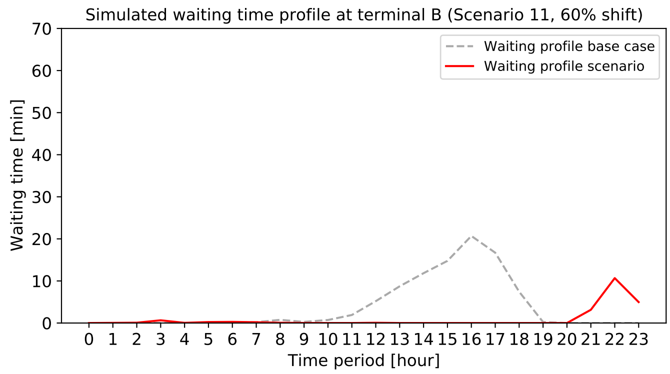
Another interesting observation from Figure 5.1 is that at terminal A, a small waiting time develops in another time period in the shift scenario compared to the base case. This happens due to the trucks shifted towards the morning. At a shift rate of 10% the waiting time arising in the morning period can be ignored. The impact is not critical since the overall waiting time is significantly reduced. Nevertheless, this is an interesting pattern that might become a problem when the shift rates become higher.

To illustrate what happens when the application rates become higher, Figure 5.2 displays the average waiting time profiles for the 11th scenario, which is a 60% application rate to the TAS policy, compared with the base case for each terminal. Again the gray dotted line represents the base case waiting profile, the red line represents the scenario.

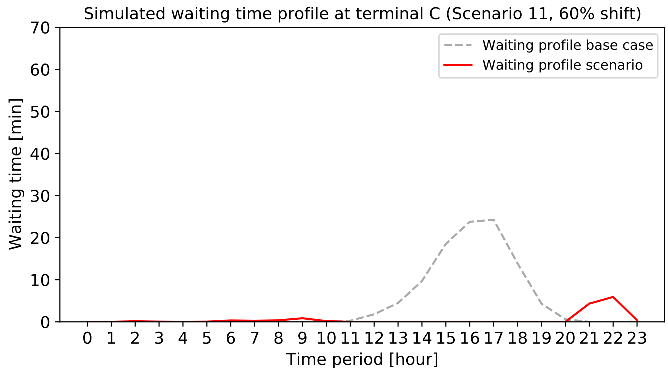
The small increase of waiting time in the morning period at terminal A observed in Figure 5.1, has become much higher under an application rate of 60% (Figure 5.2). It can be observed that the waiting time is more or less moved from the midday and afternoon to the morning. This means that the peak of truck arrival is moved from the midday and afternoon to the morning. Consequently, under high application rate the problem is simply reallocated.



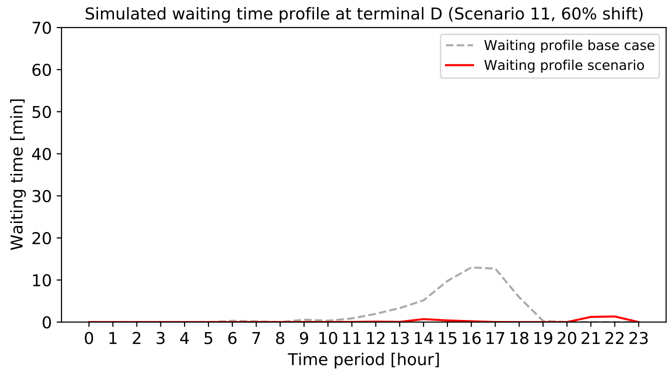
(a) Terminal A



(b) Terminal B



(c) Terminal C



(d) Terminal D

Figure 5.2: Simulated average waiting time profiles for the base case and scenario 11 (60% shift), obtained from the terminal model (Appendix B)

For terminal B, C and D, it can be observed that a 60% application rate does decrease the waiting time. Even though, some waiting time arises in another time period for terminal B and C, the truck shifting strategies manage to reduce the waiting time in general.

From analysis of the average waiting time profiles, it can be concluded that the TAS can significantly reduce waiting time at the terminals by controlling truck arrivals based on what the trucks transport. However, it has not been established yet what the value of this is. Therefore, another measure is valuable to explore regarding the reduction of waiting time. This measure is the waiting time gain.

5.2 TOTAL WAITING TIME GAIN

The waiting time gain considers the total waiting time profile. The total waiting time profile comprehends the total waiting time for the entire system, so for all trucks for an entire day, instead of for only one truck. The total waiting time profile can be computed by multiplying the average waiting time profile with the simulated arrival profile. The total waiting time profiles are presented in Figure F.12 through Figure F.15 in Section F.2.

From the total waiting time, more insight is obtained regarding the impact of the waiting time. Furthermore, the total waiting time for each scenario can be compared with total waiting time in the base case. By subtracting for each hour the total waiting time for each scenario from the base case, the waiting time gain profile can be computed. The waiting time gain profiles for each scenario and for each terminal are presented in Section F.2 (Figure F.16 through Figure F.19).

These graphs indicate for which hours a waiting time reduction is achieved with the scenario compared to the base case. This provides insight in where waiting time is reduced and where new waiting time arises due to shifting the trucks. A negative gain or waiting time loss indicates that the total waiting time in the scenario is higher in the corresponding hour than the total waiting time in the base case. This does not necessarily mean that the application rate in the scenario does not lead to a reduced waiting time. As mentioned, it might happen that waiting time appears in other time periods due to shifting trucks. Since it was found from the choice model that TOC rate one minute of waiting time more costly in the morning compared to the midday and afternoon (Section 4.3.4), it is valuable to obtain insight in where new waiting time arise due to truck shifting.

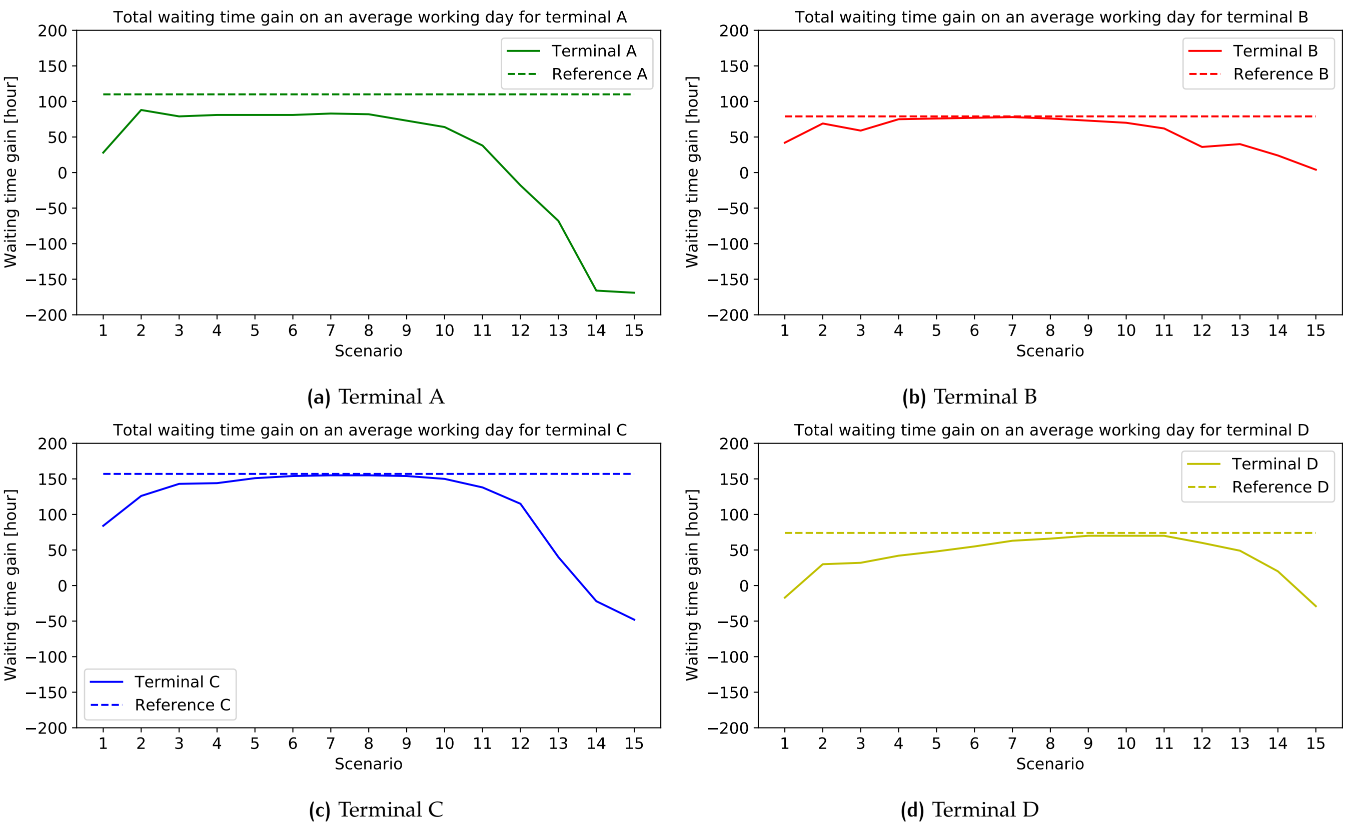
Eventually the aim is to reduce the waiting time for the entire system and for the entire day. Therefore, it is more interesting is to know whether the waiting time is reduced as a whole.

The waiting time reduction for the entire system for the entire day is obtained from the waiting time gain. By summing the difference per hour found from the waiting time gain profiles, the total waiting time gain can be calculated. The total waiting time gain provides insight in the value of shifting trucks.

In Table F.2 (Section F.2), the total waiting time gain (or loss) in minutes and hours, is depicted for each scenario and for each terminal. To provide a visual overview, the waiting time gain is plotted against the scenarios for each terminal in Figure 5.3.

Note that the y-axis ranges between negative and positive values. A positive value indicates that in the shift scenario the total waiting time has been reduced compared to the base case, this is referred to as a waiting time gain. A negative value indicates an increase of waiting time, this is considered to be a waiting time loss. On the x-axis the scenarios are shown. Scenario 1 to 10 are the shift scenarios from 5% to 50%, with an increasing step of 5%. Scenario 11 to 15 are the shift scenarios from 60% to 100%, with an increasing step of 10%.

The solid lines in Figure 5.3 represent the development of the waiting time gain under various application rate scenarios. The dotted lines represent the waiting time gain in the 16th scenario. The 16th scenario, represents the scenario in which an entirely equal spread of trucks along the day is simulated. The scenario is used as reference scenario as an entirely equal spread of trucks is considered the perfect situation at the terminal for truck arrival. The number of trucks arriving will always stay below the terminal capacity and there will not be any waiting time. Consequently, the waiting time gain in the 16th scenario is the largest possible compared to the base case.



(a) Terminal A

(b) Terminal B

(c) Terminal C

(d) Terminal D

Figure 5.3: Development of the waiting time gain along the scenarios, in comparison with the reference scenario

From the shape of the graph can be concluded that there is not a linear relation between application rates and waiting time gain. An increase of 5% for shifting trucks does not cause a 5% increase in waiting time gain.

A general observation from Figure 5.3 is that for most terminals an increase of the waiting time gain can be observed from the first scenario (5% shift) until the seventh scenario (35% shift). Thereafter, for each terminal, the waiting time gain decreases and eventually becomes negative for some terminals. This insight indicates that there is an optimum for shifting trucks to reduce waiting time. Additionally, it can be observed that the gain with small application rates (5% - 10%) is already very close to this optimum.

There are two exceptions. First of all, at terminal A the highest waiting time gain is achieved at a 10% application rate. Additionally, terminal D is an exception, here the increase of the waiting time gain occurs from scenario 2 (10%) until scenario 9 (45%).

As mentioned in Section 4.3.5, there is a turning point or risk of shifting truck arrivals. Figure 5.3 provides insight in this turning point. It can be observed that, under high application rates of truckers to the control of truck arrivals, there is no waiting time gain, but a loss. This means that under high application rates of truckers, the TAS policy is not beneficial.

This is expected since shifting high shares of trucks from peak periods to quiet periods means that the peak periods will almost be empty, and the quiet periods are filled with almost all trucks from the peak periods. Hence, the problem is simply reallocated from one period to the other, as was observed from the 60% shift scenario for terminal A (Figure 5.2).

Even though, the waiting time loss under high application rates is expected, the insight is valuable. It is important to keep in mind that there is at some point, a turning point. For some terminals this turning point is encountered earlier with lower application rates compared to other terminals. Nevertheless, the high application rates will no further be discussed since these high application rates are not realistic.

In Figure 5.3, the waiting time gain for each scenario is compared with the ideal situation, scenario 16. This provides insight in how large the waiting time gain in each scenario is. For example, a waiting time gain of 28 hours might seem very good, however, if the best possible waiting time is 110, this the 28 hour gain is placed in perspective.

From the waiting time gain overview in Figure 5.3, it can be concluded that ideal situation at the terminals can almost be achieved with the shift strategies. For some terminals, the optimum gain obtained from truck shifting under an application ratio of 35%, 35% and 45%, for terminal B, C and D, respectively, is very close to the gain in the reference scenario. At terminal B, C and D the optimum gain deviates only 1, 2 and 4 hours respectively. For terminal A, the difference between the optimum for shift strategy and the ideal scenario, is larger, namely 22 hours.

The ideal situation is not solely represented by achieving the highest possible waiting time gain. In the ideal situation the effort must also be considered. Based on the results in Figure 5.3, the optimum waiting time gain would be achieved with a shift between 35% and 45% of truck arrivals. However, as discussed in the previous section (Section 5.1), achieving a shift of trucks requires effort. The effort required is expected to increase with higher the shift percentages. Therefore, the optimum waiting time gain achieved under 35%-45% shift percentage, might not reflect the ideal situation for shifting trucks. The ideal situation is represented by low effort high reward. In other words, achieve high waiting time gain with small shift percentages.

The results are promising as it can be concluded that the truck shifting strategies are capable to reduce waiting time, at small application rates. However, this requires more discussion. In Section 5.3, it is elaborated how the results can be interpreted and what this means for practice.

5.3 RESULT INTERPRETATION

The truck shifting strategies for peak shaving based on what container or commodity type the trucks transport, are found to be capable of reducing waiting time at the terminals. However, the effect of reduced waiting time in the entire system must be explored to draw conclusions for practice.

Hourly waiting time gains are difficult to interpret for the entire system as it is not immediately clear what one hour of waiting time gain means and for who this gain is beneficial. For the interpretation of the results, the waiting time gains in hours are converted to monetary values (euro) for TOC. By doing so, the gain can be interpreted more easily.

5.3.1 Monetary and productivity gain TOC

Converting the hourly waiting time gain to monetary values is possible using cost figures. The Netherlands Institute for Transport Policy Analysis (KiM) publishes these for freight transport [KiM, 2020]. The cost figures are based on research towards the economic costs of freight transporters. In the year 2017, the cost for transporting a container are approximated to 62 euro per hour. The costs for waiting in container transport are approximated to 38 euro per hour. These waiting costs from KiM [2020] for the TOC do not include the cost for fuel consumption of an idling truck. For a rough estimate of the idling costs for a TOC, one is referred to Table F.5.

Even though fuel consumption due to idling is costly for the TOC, these cost are not further explored since these fuel cost do not have much impact on the entire system. Idling trucks, however, do impact the entire system due to the emissions that are induced by idling. This will be discussed in Section 5.3.2.

In Table 5.2 on the next page, the waiting time gain in hours is converted to cost savings for TOC, based on the cost figures obtained from KiM [2020]. The total waiting time gain in euro for the TOC on an average day is presented. Moreover, Table 5.2 provides insight in the gain in road container transport productivity resulted from not waiting at the terminals.

The gain terminal wide is interesting since this provides insight for the PoR to formulate a target shifting percentage. In Section 2.4, the port authority was discussed as a stakeholder in the port system. It was found that the port authority acts as an objective player, aiming for overall efficiency in general instead of the performance of a specific stakeholder or sector. Therefore, it is valuable to see the impact of a certain shift percentage regarding the overall gain.

In the most left column the percentage of shift is depicted. In the second column the percentage is converted to total of trucks shifted terminal wide. In the four middle columns the waiting time gain in euro for each terminal is presented. This is calculated by multiplying the waiting time gain in hours by the waiting costs (38€/h). Consequently, the total gain in euro among all terminals is represented.

The second to right column depicts how many hours of transporting a container via road can be gained from not waiting at the terminal, hence a gain in road container transport productivity. This is calculated by dividing the total waiting time gain (terminal wide) by the cost of transporting a container on the road (62€/h). This column can be regarded as the increase in road container transport productivity (in hours) that the shift induces. The TAS policy allows for a productivity gain of almost 200 hours at a 10% shift, on a daily basis. In other words, the waiting time gain for TOC equals the transportation of almost 200 containers for one hour. To illustrate the impact of this, on a daily basis around 2300 trucks arrive to transport a container. If you were to assume that on average the transportation time of a container is about an hour in the Netherlands, the waiting time gain equals almost 10% of the entire production in the system.

In the most right column the gain terminal wide is divided by the number of trucks shifted terminal wide in the corresponding scenario. This provides insight in the ratio benefit of shifting versus number of trucks that have to shift. As said, low effort high reward is desired. It can be observed that a shift percentage of 10% will terminal wide provide the highest value in terms of effort and reward.

This gain per trucks does not only indicate a ratio of effort and reward. Additionally, the most right column indicates a so called social gain. The social gain refers to contribution of a shift made by one single truck to the entire system. Not only the portion of trucks that is shifted benefits from the shift. Rather all trucks benefit of a shift made by another truck. The trucks that are shifted do not only save waiting time in the peak periods, which would cost 38 euro per hour. Additionally, the truck that is shifted contributes to a social benefit because the trucks that are not shifted, will also experience a waiting time reduction even though they still arrive in the original peak period.

Table 5.2: Waiting time gain in monetary value [€] and road container transport [hour] for TOC on an average working day

Share shifted	Trucks shifted (terminal wide)	Gain at each terminal: Terminal A	Terminal B	Terminal C	Terminal D	Total gain (terminal wide)	Productivity gain [hours]	Gain/ truck
5%	114	€ 1.061	€ 1.582	€ 3.176	€ -638	€ 5.181	83	€ 45
10%	230	€ 3.356	€ 2.627	€ 4.802	€ 1.144	€ 11.929	192	€ 52
15%	344	€ 3.014	€ 2.253	€ 5.447	€ 1.203	€ 11.916	192	€ 35
20%	459	€ 3.069	€ 2.867	€ 5.477	€ 1.604	€ 13.017	210	€ 28
25%	537	€ 3.073	€ 2.879	€ 5.742	€ 1.811	€ 13.505	218	€ 25
30%	687	€ 3.093	€ 2.914	€ 5.855	€ 2.105	€ 13.967	225	€ 20
35%	803	€ 3.152	€ 2.948	€ 5.876	€ 2.410	€ 14.386	232	€ 18
40%	917	€ 3.112	€ 2.900	€ 5.872	€ 2.521	€ 14.405	232	€ 16
45%	1030	€ 2.775	€ 2.770	€ 5.838	€ 2.647	€ 14.029	226	€ 14
50%	1146	€ 2.431	€ 2.651	€ 5.706	€ 2.667	€ 13.456	217	€ 12

This analysis solely presents the gain from the TAS policy. It should be noted that there are also cost required to achieve the shift in reality. Nevertheless, since the proposed TAS policy shows large gain at only small shift percentages, it is expected that for TOC these benefits outweigh the costs. The question remains whether the waiting time gain is only beneficial for truck companies or that other stakeholders in the port system would also benefit from a truck arrival shift.

5.3.2 Implications for other stakeholders

Besides the benefit of shifting truck arrivals for the TOC, insight in the potential impact of a waiting time reduction for other stakeholders is relevant. Since a system is as efficient as the weakest link, improving the performance of the weakest link, improves the entire system. Hence, controlling truck arrivals does not only cause a gain at the terminal gates, it actually solves costs in the entire system. Even though obtaining and interpreting the results is mainly from the TOC perspective, every minute of gain at the terminals is gain for the entire container transport system. Therefore, the shift of truck arrivals is expected to be beneficial for most stakeholders in the port system. Nevertheless, the port-hinterland alignment is a multi-stakeholder problem and other stakeholders are affected by the TAS policy as they might need to change behaviour or invest to obtain the results from the shift. Therefore, the other stakeholders in the system might encounter benefits as well as costs from the TAS policy.

Port authority and terminals

For the terminals and the port authority, the decrease of waiting time due to truck shifting is directly beneficial as the misalignment of port and hinterland directly impacts the port area. For example, through the accessibly, reliability and competitiveness of the port. Additionally, trucks waiting at the terminal gates occupy terminal space. Space in the port area is costly, consequently waiting trucks that occupy space are expected to induces costs for the terminals. Moreover, the TOC leave their trucks idling. Idling trucks induce CO2 emissions in the port area. A rough estimate of CO_2 emissions in kg spared by shifting trucks under various application rates is provided in Table F.9. CO_2 emissions push cost to the port authority and terminals. Therefore, a reduction of waiting time is also desirable. However, the exact costs are not explored in detail and need more study.

It is expected that along with the TOC, a measurable reduction in cost for the terminals and the PoR results from the application of a TAS policy. However, to achieve the shift they should invest as well. Both the terminals and PoR can undertake actions to realise the shift.

The terminals can largely influence the shift of truck arrivals by designing their system in such a way that a portion of the TOC must apply to a shift. For example, the terminal could operate with a compulsory reservation of a time slot. In this TSMS the hourly arrival quota can be tuned to the computed arrival profile corresponding to the desired shift percentage. Nevertheless, this requires costs from the terminals' side.

For the PoR it is more complex to directly influence the shift with their means since they can not pose similar restrictions as an objective player. However, as discussed in Section 2.4, De Langen and van der Horst [2008] argue that port authorities should lead the improvements for digital connectivity by introducing coordination between stakeholders in the port and hinterland because other private and public parties have weaker incentives to do so. Introducing this coordination and improving data exchange among the stakeholders is rather complex due to the many privacy issues and fear for competitive advantages that arise. The PoR must somehow affect the actions of other stakeholders in the system to ensure the reduction of waiting time by implementing the TAS policy. Nevertheless, the framework for the TAS policy proposed in this research can assist the PoR in improving data exchange, and consequently improving port-hinterland alignment, without the privacy issues and fear for competitive advantages. In this framework the data can be processed via the port community system. The stakeholders do not have to share data directly with each other. The port community system processes the data anonymously. Consequently, the preferences for pick up period can be inferred for container or commodity type after which the truck arrivals can be shifted fairly. Therefore, the stakeholders do not have to fear violation of privacy or competitive advantages, whilst the benefits of the TAS policy can still be encountered.

Shippers and forwarders

It is more difficult to assess the direct benefit of shifting truck arrivals for shippers and forwarders. It might be expected that the TOC charge the shipper or forwarder for the waiting time they experience at the terminal gates. Therefore, are waiting time reduction could have direct economic value for shippers and forwarders. Nevertheless, often the shippers and forwarders have cost arrangements with the TOC which make it difficult to charge extra waiting time to the shipper or forwarder. Moreover, due to the competitive character of the truck transport market, the TOC do not have much leverage to charge extra costs to the shippers or forwarders.

However, the waiting time reduction is considered to be beneficial for the shippers and forwards. The reasoning for this is that the waiting time reduction improves port-hinterland alignment. For shippers and forwarders the accessibility of the port and terminal is important (Section 2.4). Consequently, the waiting time reduction is beneficial for these stakeholders. Yet, the exact benefit and potential costs for shippers and forwarders requires more research.

The shippers and forwarders play an important role in achieving shifted truck arrivals as the shippers and forwarders pose time constraints on the TOC for container pick up (Section 2.4). They pose these constraints due to the potential risk of a container being delivered too late at the hinterland location. Therefore, they want the containers be picked up as soon as possible when the container arrives in at the terminal. However, with the large call sizes this causes that many trucks arrive at once at the terminal which causes waiting times. If the truck arrivals are controlled, the terminal processes are more smooth and the waiting times are reduced (as this research shows). Hence, if the constraints were to be relaxed, the TOC might have the opportunity to shift their arrival without increasing risks for the shippers and forwarders regarding delivery in the hinterland. However, shippers and forwarders should adapt behaviour, which can consequently induce costs on their side. Therefore, shippers and forwarders must recognise the benefit of shifting truck arrivals to accept the required change in their behaviour.

Hinterland warehouses

Lastly, there is one stakeholder that is not expected to directly benefit from the TAS policy. This stakeholder is the warehouse in the hinterland. In Section 2.4, it was discussed that hinterland warehouses often operate with very traditionally working hours (9 to 5). Most hinterland warehouses do not necessarily see the value of extending these operating hours as this induces their costs. Therefore, the benefit for the hinterland warehouses should be explored. This benefit might come from more reliable transport of containers in the night period. However, the exact benefit for hinterland warehouses requires more research.

The hinterland warehouse' operating hours pose timely constraints to the TOC. Therefore, it is important to explore the possibilities to extend opening hours in the hinterland to ensure a TAS policy will work in practice. For example, by creating night time storage facilities. Yet, this will induce costs for the hinterland warehouses. Ultimately, the benefit of shifting the trucks should outweigh the costs for the hinterland warehouses to ensure the shift in practice.

5.4 CONCLUSION

The potential waiting time gain, productivity gain and social gain by controlling truck arrivals by means of a TAS policy are striking results from this research. The truck arrival shift leads to significant reduction of waiting time compared to the current situation at the terminals. The implementation of a TAS policy is found to be an effective measure to spread truck arrivals along the day.

Moreover, the waiting time gain is found to be quite high under only small shift percentages. Therefore, the application of TAS is a control policy with low effort high reward.

Furthermore, the shift of truck arrivals is expected to be beneficial for most stakeholders in the port system. For some stakeholders more than others, but for all a measurable reduction of costs along with the waiting time reduction for the TOC at the terminal gates is expected. However, the exact benefits for all stakeholders and costs to achieve the shift require more study.

To shift truck arrivals along the day and achieve the waiting time reduction requires actions and costs of multiple stakeholders since additional measures are required. Therefore, it is important that the port authority, terminals and other stakeholders in the system work together. There are three things crucial to implement the TAS policy and achieve the shift of truck arrivals to quieter time periods.

First and foremost, data sharing between stakeholders is most important. If the data of containers and truck arrivals are not shared, hence no insight in TOC behaviour, it is impossible to fairly shift truck arrivals along the day. If trucks are not shifted based on the insight of TOC behaviour, it will be difficult to get application rates that ensure the potential gains. Fortunately, the proposed framework for the TAS policy allows for sharing information and data safely, without violation of privacy or creating competitive advantages. A complementary measure to allow for data sharing, is by obliging TOC to announce their container and a compulsory reservation of a time slot. Consequently, in such a TSMS the hourly arrival quota can be tuned by the terminal to the computed arrival profile corresponding to the desired shift percentage. This poses a hard constraint for the TOC to comply with the TAS policy and ensures that a portion of the TOC must apply to shifting.

Secondly, the shippers and forwarders should relax the constraints regarding container pick up time. This can be accomplished by data sharing to control truck arrivals. The shippers and forwarders pose strict constraints because they do not want to risk the container to be delivered too late at the hinterland location. By controlling truck arrivals, the processes at the terminal are more smooth which minimises the risk of the container being delayed.

Lastly, the opening hours in the hinterland must be extended. The developed TAS policy in this research is based on peak shaving. To allow for peak shaving in practice, the trucks must be able to shift towards morning and night time periods. However, this requires that the TOC can operate during those periods. The opening hours at hinterland warehouse location currently limit the possibilities for container delivery. A potential solution to extend opening hours is by creating night time facilities. As the hinterland warehouses do not necessarily see the value of extending opening hours, the PoR should consider bearing part of the costs for this.

All in all, to implement the TAS policy and realise a waiting time reduction to successfully improve port-hinterland alignment the PoR can pull two strings. First, the PoR should manage safe data sharing between stakeholders so that the truck arrivals can be controlled. Moreover, the PoR should take the lead in extending hinterland opening hours, for example by investing in infrastructure in the hinterland to allow for night time distribution of containers.

6 DISCUSSION, CONCLUSION AND RECOMMENDATIONS

In this last chapter, the discussion and conclusion of the research is elaborated. Additionally, possibilities for future research are recommended. A reflection of the methodology and results is provided in Section 6.1. The research questions are answered in Section 6.2, together with an overall conclusion of the research. Lastly, various recommendations for future research are proposed in Section 6.3.

6.1 DISCUSSION

The results presented in Chapter 5 are promising. It was found that the implementation of a TAS policy can successfully flatten peaks in demand. A significant reduction of waiting time under various shift percentage has been found, together with an overall gain for the stakeholders in the port system. Consequently, port-hinterland alignment can be improved by implementing a TAS policy in the port of Rotterdam. Even though the results of this research are reliable due to thorough analysis, the results should be interpreted with caution. There are some points of discussion regarding the results and limitations.

The conducted research is mainly from a TOC and PoR perspective. From this perspective, a benefit is found for all stakeholders in the system. Nevertheless, the collective perspective of all stakeholders in the port system, might provide somewhat different results, and different benefits and costs for the stakeholders. This collective perspective could be captured by a multi-stakeholder analysis.

Furthermore, this research focuses predominantly on the potential gains from the TAS policy. With the proposed framework for the TAS policy it seems to be possible to achieve the shift of trucks and the corresponding gains. Even though, the framework for the TAS policy is in place and it is expected that there are incentives for stakeholders support the TAS policy, it does not necessarily ensure that the TAS implementation is a success. The reason for this is that there are also costs involved to achieve the truck arrival shift. This shines a light on all sorts of real life problems that are encountered to achieve the shift of truck arrivals in practice. Examples of these real life problems are information sharing, compliance, and distribution of cost among stakeholders. In Section 5.4, it was concluded that the PoR has two strings to pull to successfully improve port-hinterland alignment by implementing a TAS policy.

Lastly, it should be noted that even when the implementation of TAS in practice does not lead to the same gains as found from this research, the implementation of the TAS policy is still of added value. This is because the TAS policy ensures data and information sharing between stakeholders. This is an important aspect to improve digital connectivity. An increase of digital connectivity positively influences the port-hinterland alignment directly.

6.1.1 Limitations

There are some points of discussion for the limitations in this research. These are organised in three categories and discussed in the following subsections. The categories are limitations from data, limitations in the methodology, and limitations regarding the changing environment in the port area.

Limitations from data

Two sets of data have been explored and applied to develop the methodology in this research. These sets of data are traffic data and logistic data. The traffic data is obtained from loop detectors at the terminals. The logistic data comprehends information of import containers. Despite that the data is from the same year (2017), the loop detectors represent trucks arriving at the terminals for both import and export containers, whilst the logistic data solely captures data of import containers.

From the traffic data it is not possible to derive for which kind of container the truck arrives at the terminals. Nevertheless, since TOC aim to always combine container trips, it is not expected that this has had serious impact on the research. Moreover, the ratio import and export containers in 2017 across all container terminals was 52% and 48%, respectively [Port of Rotterdam, 2020b]. Nevertheless, the fact that only import container data has been explored in the research does pose another limitation.

Solely handling import container data impacts the outcome of the choice model, and consequently impacts the formulated truck shifting strategies. As the truck arrivals are shifted from one period to another based on the truck shifting strategy, this might have had impact on the exact results.

Since only import container data was available for this research, an assumption is made that the truck arrival time preference is dominated by the pick up of an import container. However, the import container data might capture different preferences compared to export data. This is true for some types of containers or goods, yet not for every type. It is generally known, that for chemical containers the export container is dominant for arrival time preference, whilst for agricultural products the import container is dominant. However, more detailed information was not available and therefore, this is not explored in much.

As a results, some preferences of TOC observed from the choice model are difficult to explain. Additionally, the truck shift might not be entirely realistic because the preference for arrival time is not always based on the pick up container. For some container or commodity types, the export container might dominate the arrival time preference. Therefore, the choice model outcome might not capture the true preference of a TOC for all containers or commodity types.

Nevertheless, solely using import data has led to an accurate research. If export data would have been used, preferences for night or morning pick up time of certain container or commodity types would have been found by all probability. Consequently, it would have been possible to shift trucks from peak periods to quiet period. Even though, the exact trucks transporting a certain type of container of commodity might have been different, the trucks could still be shifted based on a formulated strategy.

Merely the effect from only including import data on the results might be that the exact reduction of waiting time under a certain TOC application rate are different. This difference could be explained by the exact same reasons why the results among terminals are different. If export data would have been included in the research, the preference for night or morning pick up might have been a bit less, or the preference for quiet periods is for container or commodity types that have small shares at the terminal. Therefore, if export data would have been included, the exact shift percentages that result in a certain waiting time reduction might have been somewhat different. The difference could have been both positive or negative. This implies that for smaller application rates, higher waiting time reduction could have been achieved, or the other way around.

Therefore, the limitations from data have not largely impacted the results of the research. Nevertheless, it is important to keep in mind that there were some data limitations. The TAS policy is found to be effective to flatten peaks of demand. However, the exact formulation of the shift strategies might have been influenced by the fact only import data is explored. It is relevant to consider TOC preferences for both import and export when the TAS policy would be implemented in practice.

Limitations in methodology

There are some limitations regarding the method proposed in this research. Some fair assumptions are made to tackle these limitations. First of all, there was little information available to simulate the exact terminal operations with the server process in the terminal model. This is a common issue found in literature in which terminal processes are simulated (Section 3.4). The problem is overcome in this research by using Bayesian optimisation to estimate the missing information. The parameters in the server process are tuned to the value under which the deviation from the observed departure profile is minimised. This resulted in a calibrated model that was validated by statistical analysis. Hence, the terminal model was found to be capable to simulate the situation at the terminal accurately. However, still some deviation from the observed departure profiles was found. For some terminals the deviation was larger than for others. Therefore, the simulated waiting time profile might be slightly impacted due to sensitivity of the terminal model. Nevertheless, since the terminal model was validated the impact on the results is expected to be minimal.

Also in the choice model some simplifications are made. As it was found that the model was not able to predict preferred pick up time of a container to the exact hour, the hourly pick up time was aggregated to time periods. This ensured more accurate choice model results. Nevertheless, in the truck shifting heuristic the time periods required to be disaggregated to hourly slots again. Since the trucks are shifted proportionally in the heuristic, aggregating the time slots to time periods in the choice model caused that the trucks are not spread smoothly surrounding the transition hours of the time periods. Yet, this is found to only affect the results slightly under very high application rates. Application rates to the TAS policy higher than 50% are unrealistic. Therefore, the use of time periods instead of hours in not of significant impact on the research. However, it should be kept in mind when interpreting the research results.

Moreover, the choice model in the research is formulated as a MNL model. This is a very suitable model for this research. Nevertheless, the formulation of a Nested Logit model might provide additionally insight in the behaviour of TOC. In such a model the time periods could be formulated as nests in the model and the hourly slots as the alternatives.

Lastly, in the first step of the truck shifting heuristic containers are converted to trucks. In this conversation, it was not account for whether the container is 20ft or 40ft. The container and commodity type occurrence probability is simply converted to a truck. However, a truck can transport two 20ft container, or one 40ft container. Consequently, the size of the container could impact the number of trucks that arrive for the specific container and thus number of trucks that is shifted. It was not studied what the ratio 20ft and 40ft is among specific container or commodity types. Nevertheless, it was explored in the analysis of the logistic data what the ratio 20ft and 40ft containers was per terminal. This ratio was found to be very stationary along the day. Therefore, it is expected that the effect of container size on the number of trucks shifted is largely cancelled out.

Despite the limitations in the methodology, it is not believed that these limitations have led to different results, bias or noise in the research. The simplifications are all considered to be legitimate as they are sustained by valid argumentation or checked with statistical analysis. Hence, the limitations in the method do not lead to systematic errors in the models.

Changing environment in the port area

The final point of discussion in this research regards the changing environment in the port area. The data and, therefore, the methodology is entirely based on the year 2017. The MVII port area is only operative since 2013, and most container terminals were not yet operating at full capacity in 2017. Since 2017, several developments followed, which are not included in this research. Nevertheless, it should be noted that the container transport through these terminals was also not exploited to the full potential in 2017. Therefore, it is not expected that the waiting time profiles obtained for the year 2017 are extreme. In fact, recent findings indicate that the waiting time at the terminals have only increased the past years.

When it is attempted to apply the methodology from this research to more recent year data, it must be kept in mind that there have been developments in the port area that might impact the results. The developments at the terminal can be included in the methodology by calibrating the terminal model to the recent data. If the parameter values based on the year 2017 are used, this would potentially provide inaccurate results.

6.2 CONCLUSION

This research sought to develop a method to reduce truck waiting time in the Rotterdam port area taking the port and hinterland systems into account, and, hence, to improve the port-hinterland alignment. This was the main research objective. To achieve this objective, the misalignment issue was studied. Various possibilities to solve the misalignment were reviewed. A method was designed and evaluated on the ability to solve the problem of waiting time at the gates. Consequently, the designed method can be linked to practice to improve port-hinterland alignment at the port of Rotterdam.

6.2.1 Main causes of misalignment between port and hinterland

The sub-question answered in this section is:
1. What are the main causes of misalignment between port and hinterland which result in waiting time at the container terminals?

In Chapter 2 an extensive analysis of port-hinterland alignment was discussed. A seaport, as a node in a transport network, functions as a connector of two legs of transportation. These two legs are seaside transport and landside transport. These two legs overlap at the terminal gates. This indicates that the activities at the terminal gate cater the alignment of port and its hinterland. Therefore, waiting time at terminal gates is a clear indicator of misalignment.

The alignment of port and hinterland can be approached as a matter of matching demand and supply. The demand is represented by the trucks that arrive at the terminal to pick up or deliver a container. The terminal operational capacity represents the supply. Ideally, the demand and supply match perfectly, without a surplus or scarcity from any of the two sides.

There are two relevant types of bottlenecks that can cause the mismatch of demand and supply. The first type is caused by scarcity of infrastructural capacity. The scarcity of physical capacity can deteriorate the physical connectivity between port and hinterland, and consequently cause misalignment. For example, due to a lack of cranes, manpower or container storage. Physical connectivity is considered a precondition to achieve port-hinterland alignment at all.

The other type of bottlenecks are caused by inefficient operations or poor demand prediction. These bottlenecks predominantly originate from a lack of digital connectivity. For example, due to information exchange, communication, cooperation and coordination between stakeholders. Digital connectivity in addition to physical connectivity ensures efficient use of capacity. Consequently, digital connectivity is of great importance to improve port-hinterland alignment.

The bottlenecks in port-hinterland physical or digital connectivity can originate from both two sides of matching demand and supply. From one side, scarcity of (infrastructural) capacity can cause misalignment. This originates from the supply side and is often caused by poor physical connectivity. However, digital connectivity can also influence this kind of misalignment due to the insufficient ability to allocate the existing capacity to supply the demand.

From the other side, misalignment can be caused by demand patterns. Inadequate control of truck arrivals can cause a demand surplus, which can cause misalignment. This kind of misalignment stems from the demand side and is often caused by poor digital connectivity. Nevertheless, physical connectivity also impacts the peak loads at the terminal as there are limited options to deliver containers outside operating hours of hinterland warehouses.

The root of the misalignment at the port of Rotterdam emerges from the demand side due to short-term peak loads of demand inflow at the terminals. Due to inadequate control of truck arrivals, a digital bottleneck stems from the demand side. This induces waiting time at the terminal gates and indicates room from the improvement of port-hinterland alignment.

The stakeholders are able to influence the alignment with their actions. Though, the actions of one stakeholder can also affect others. From previous research it is known that poor coordination of stakeholders in the port system is one of the main issue to deteriorate the alignment. Due to unevenly distributed benefits and costs among the port and hinterland stakeholders, a power imbalance exists in the port system. This impedes to solve misalignment easily.

6.2.2 Design of intervention

The sub-question answered in this section is:
2. How can an intervention be designed to reduce the waiting time at the container terminals?

Despite that port-hinterland alignment is a complex issue, there are various options to solve misalignment. The options can be categorised as pure physical solutions, pure digital solutions, and combined physical and digital solutions. As the root of misalignment at the port of Rotterdam lies within inadequate control of truck arrival, a digital solution is proposed to reduce waiting time at the terminals and accordingly improve port-hinterland alignment. This solution is found within traffic management strategies to control demand inflow at the terminals.

An overarching strategy to control truck arrivals and reduce waiting time, is by shifting truck arrivals to other time periods. By implementing a TAS control strategy trucks can be shifted from peak periods to quieter time periods. Consequently, peaks in demand can be reduced. A suitable and well-known measure to instigate the TAS is the implementation of a truck appointment system. A truck appointment system is optimised through a TSMS.

Succeeding the analysis of port-hinterland alignment, literature was reviewed in Chapter 3 to gain insight in methodologies to design a TSMS to reduce waiting time at the container terminals. A TSMS is a platform with which control policies can be applied to optimise truck appointment systems. The implementation of a TSMS is found very effective, suitable and successful to reduce congestion at terminals.

There are two components in the development of a TSMS. First is a simulation platform that can accurately synthesis the real word. The second component is an allocation framework which is required to guarantee the best match between demand and supply and hence an optimum design. These two components must be integrated to obtain a complete design for TSMS.

There are various options in the design of the two components. The simulation platform includes the stochastic arrival process and queue process. For the arrival process, two methodologies were discussed. In most studies fitting to a probability distribution is the method used for the arrival process. However, predictive methods like regression analysis and machine learning, have the potential to make predictions of the arrival rate. There are two types of queueing models distinguished. Stationary queueing models assume constant rates for arrival and service at the terminal. A stationary queueing model allows for a more simple estimation of waiting time. Non-stationary queueing models provide more accurate results but are also more difficult and require complex approximation methods to estimate queue lengths and waiting time.

For the allocation framework component, several control procedure can be used for the optimisation problem. Moreover, heuristics are often used to solve the optimisation problem. A heuristic approach for shifting trucks is very suitable to evaluate a TSMS based control strategy for truck arrival at terminals.

Based on shortcomings from previous research it is found that developing a choice model, using DCM, the behaviour and preferences of TOC can be included in the TAS development.

With the insight from previous research to develop a TSMS, the methodology for the design of the TAS policy for this research is proposed in Chapter 4. The approach for controlling truck arrivals and evaluating the effects on waiting time is presented in a modelling framework.

A terminal model is developed to simulate the processes at the terminal. The terminal model represents the simulation platform. With the terminal model, a waiting time profile can be simulated from an arrival profile. The terminal model is set up using historic traffic data.

A choice model is developed to gain insight in the behaviour of the TOC regarding time period choice for container pick up. Based on this insight, a truck shifting strategy can be formulated to control truck arrivals at the terminals. The choice model indicates the DCM step.

Subsequently, the truck shifting strategy is input for the truck shifting heuristic. The truck shifting heuristic represents the allocation framework. In this heuristic, new truck arrival profiles are computed from the historic traffic data, based on the truck shifting strategy and what-if scenarios. The output of the truck shifting heuristic, the shifted arrival profiles, is the new input for the terminal model. In the terminal model the shifted arrival profiles can be simulated to obtain waiting time profiles for the shifted arrivals.

Lastly, the waiting time profiles simulated from the shifted arrival profiles are compared with the waiting time profiles in the base case year. Consequently, a waiting time gain for the truck shifting strategy and scenarios can be calculated. This results in insight in the effect of controlling the truck arrivals at the terminals. Hence, the potential of the TAS policy to reduce waiting time in the port of Rotterdam and improve port-hinterland alignment.

6.2.3 Potential gain in terms of waiting time

The sub-question answered in this section is:
3. What is the potential gain of the intervention in terms of waiting time at the container terminals?

The design for the TAS policy is evaluated in Chapter 5. There is no linear relation between application rates and waiting time gain. An increase of 5% for shifting trucks does not cause a 5% increase in waiting time gain. A general observation is that for most terminals an increase of the waiting time gain can be observed from a 5% shift until a 35% shift. Thereafter, for each terminal, the waiting time gain decreases and eventually becomes negative for some terminals. This insight indicates that there is an optimum for shifting trucks to reduce waiting time. Additionally, it can be observed that the gain with small application rates (5% - 10% truck shifts) is already very close to this optimum.

Moreover, there is a turning point or risk of shifting truck arrivals. It was found that under high application rates (> 70%) of truckers to the control of truck arrivals, there is no waiting time gain, but a loss. This means that under high application rates of truckers, the TAS policy is not beneficial. This is due to the fact that the problem is simply reallocated from one period to the other when high percentages of trucks are shifted from peak periods to quiet periods.

The waiting time gain for each scenario is compared with the perfect situation in which trucks are equally spread along the day. It can be concluded that perfect situation at the terminal can almost be achieved with the shift strategies. For some terminals, the optimum gain obtained from truck shifting under an application ratio of about 40%, is very close to the gain in the reference scenario. The optimum gain deviates just about 4 hours based on the waiting time for all trucks on an entire day.

The ideal situation is not solely represented by achieving the highest possible waiting time gain. In the ideal situation the effort must also be considered. Based on the results, the optimum waiting time gain would be achieved with about a 40% shift of truck arrivals. However, achieving a shift of trucks requires effort. The effort required is expected to increase with higher the shift percentages. Therefore, the optimum waiting time gain achieved under about 40% shift percentage, might not reflect the ideal situation for shifting trucks. The ideal situation is represented by low effort high reward. In other words, achieve high waiting time gain with small shift percentages. It was found that a shift percentage of 10% for the entire port ares, will provide the highest value in terms of effort and reward.

The waiting time gain is considerable as it induces an increase in road container transport productivity. The TAS policy allows for a productivity gain of almost 200 hours at a 10% shift, on a daily basis. Depending on average the transportation time of a container (e.g. one hour), the waiting time gain equals almost 10% of the entire production in the system.

Beside a waiting time reduction, the corresponding waiting time gain and the productivity gain, the TAS policy allows for a social gain. The social gain refers to contribution of a shift made by one single truck to the entire system. Not only the portion of trucks that is shifted benefits from the shift. Rather all trucks benefit of a shift made by another truck. The trucks that are shifted do not only save waiting time in the peak periods. Additionally, the truck that is shifted contributes to a social benefit because the trucks that are not shifted, will also experience a waiting time reduction even though they still arrive in the original peak period.

The potential waiting time gain, productivity gain and social gain by controlling truck arrivals by means of a TAS policy are striking results from this research. The results are promising as it can be concluded that the truck shifting strategies are capable to reduce waiting time significantly, at small application rates. The implementation of a TAS policy is found to be an effective measure to spread truck arrivals along the day. Additionally, the application of TAS is a control policy with low effort high reward. Moreover, every minute of gain at the terminals is gain for the entire container transport system as a system is as efficient as the weakest link. The root of misalignment at the port of Rotterdam lies within inadequate control of truck arrival. Truck shifting is found to improve the performance of this weakest link and thus of the entire container transport system.

Consequently, the shift of truck arrivals is expected to be beneficial for most stakeholders in the port system. For some stakeholders more than others, but for all a measurable reduction of costs along with the waiting time reduction for the TOC at the terminal gates is expected.

6.2.4 Improving port-hinterland alignment at the port of Rotterdam

In this section the main research question is answered. The main research question was:
How can port-hinterland alignment at the port of Rotterdam be improved such that the waiting time at container terminals is reduced?

From this research it can be concluded that the waiting times at the terminals can be reduced by the implementation of a TAS policy. However, to shift truck arrivals along the day and achieve the waiting time reduction requires actions and costs of multiple stakeholders as additional measures are required. Therefore, it is important that the port authority, terminals and other stakeholders in the system work together. There are three things crucial to implement the TAS policy effectively and achieve the shift of truck arrivals to quieter time periods.

First and foremost, data sharing between stakeholders is most important. If the data of containers and truck arrivals is not shared, hence no insight in TOC behaviour, it is impossible to fairly shift truck arrivals along the day. If trucks are not shifted based on the insight of TOC behaviour, it will be difficult to get application rates that ensure the potential gains. Fortunately, the proposed framework for the TAS policy allows for sharing information and data safely, without violation of privacy or creating competitive advantages.

Secondly, the shippers and forwarders should relax the constraints regarding container pick up time. This can be accomplished by data sharing to control truck arrivals.

Lastly, the opening hours in the hinterland must be extended. The developed TAS policy in this research is based on peak shaving. To allow for peak shaving in practice, the trucks must be able to shift towards morning and night time periods. However, this requires that the TOC can operate during those periods. The opening hours at hinterland warehouse location currently limit the possibilities for container delivery.

All in all, to implement an effective TAS policy and realise a waiting time reduction to successfully improve port-hinterland alignment the PoR can pull two strings. First, the PoR should manage safe data sharing between stakeholders so that the truck arrivals can be controlled. Secondly, the PoR should take the lead in extending hinterland opening hours.

Even when the waiting time reduction in practice is less than the reduction found in this research, the TAS policy is still valuable for improving port-hinterland alignment as the implementation of the TAS policy increases digital connectivity.

6.3 RECOMMENDATIONS FOR FUTURE RESEARCH

Based on the research elaborated in this thesis, various implication for future research arise. These are captured by the following recommendations for future research. The recommendations relate to the developed models and the implementation of the TAS policy in practice.

To begin with, it would be interesting to expand components in the terminal model with more details. Currently there is only one class of trucks, in future research the arrival process could be formulated with multiple truck classes. For example, the trucks can be categorised based on the container or commodity type transported, or by the container size. This can be done with the findings from the logistic data analysis.

Additionally, the arrival process could be formulated with more specific inter arrival times. For example, inter arrival times per 15 minutes instead of per hour.

Moreover, for future research it could be valuable to explore the possibilities to formulate the server process more detailed based on the exact terminal operations.

Lastly regarding the terminal model, it would be interesting to explore the potential of the model to predict future waiting time profiles. By expanding the terminal model with more detail and linking it to real time data, it is expected that can be applied to very accurately predict future waiting time profiles. Especially at terminals that operate with a time slot management policy, this could definitely be possible. Since TOC must reserve a time slot of arrival at the terminal in advance, an arrival profile can be computed from the reservations. Consequently, the terminal model can be used to predict the exact waiting time profile for that day.

Furthermore, it would be valuable in future research to explore a more detailed and extensive discrete choice model. For example, the choice model can be formulated as a Nested Logit model.

Moreover, it would be compelling to include more attributes that might effect the pick up time preference. The travel time of a truck is not captured in this research, nor are the origin and destination of a container. Nevertheless, the factors are expected to have impact on the arrival time preference. Therefore, it is valuable to study this in future work.

Including the export data of containers together with the import data would be a interesting topic for future research. It is expected that this would provide a more complete grasp of TOC preferences for arrival time.

In addition, the shift in arrival of trucks to terminals may have negative impact on the congestion in surrounding road network. This could be explored by coupling the developed simulation framework in this study with a traffic simulation model.

Along with the recommendations for the models, more practical recommendations are identified. For example, this research can serve as a starting point for future research to determine the truck arrival quota per hour at a terminal with a TSMS.

Exploration of the implementation of night time distribution possibilities can additionally follow from this research. This research provides insight in the waiting time gain by shifting trucks under various application rates. Consequently, this insight can be used to design the implementation for night time distributions.

The misalignment of port and hinterland is a multi-stakeholder problem. This research includes perspectives of various stakeholders, however, the main analysis are from the perspective of TOC and the port authority. Therefore, a multi-stakeholder analysis is recommended for future research to obtain results based on a collective perspective.

Finally, the exact (economic) benefits and implications for all stakeholders in the port system should be studied. This is important future research since the container transport market stakeholders must be aligned to successfully implement the TAS policy.

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A TRAFFIC DATA

In this research, traffic data is used to simulate and analyse the arrival and departure profiles at several terminals in the port of Rotterdam. Data of actual arrivals and departures, hence historical profiles, is collected from loop detectors in the port area for the year 2017. Not every terminal in the port area has a loop detector located directly at the gate. Therefore, a selection of terminals is made to avoid noise in the loop detector data of trucks with another destination than the analysed terminal. At these selected terminals, the loop detectors are located such that the trucks arriving or departing correspond to the pick up or delivery of containers at that terminal, see Figure A.1. Subsequently, it is assumed that there is no noise in the data obtained from these loop detectors.

The terminals with a loop detector at the gates are terminals A through D. Note that in Figure A.1 only "terminal" is indicated and not whether the terminal is A, B, C or D. This is to ensure that the terminals remain anonymous throughout the research. Moreover, not specifically labeling the terminals on the map will not deteriorate the value of the research, nor will it lead to missing information for the research.

The red "*X*" in Figure A.1, indicate the locations of the loop detectors for each terminal. The yellow lines and arrows indicate the route of an arriving truck from the A15 highway to the terminal, logically the departure route is the opposite of the arrival route.

Figure A.1: Map to indicate the locations of the loop detectors (Image from Google [2017])

The traffic data, obtained from the loop detectors in the port area, is used for the terminal model which simulates the port processes. Moreover, the traffic data is used in the truck shifting model (Appendix E), which formulates the truck shifting scenarios to evaluate the TAS. Statistical testing is done to check whether there are differences between the arrival and departure profiles for the four terminals. Additionally, the arrival and departure profiles for each month are compared to explore potential monthly trends. Lastly, the profiles for each day of the week are analysed statistically.

The result of this extensive statistical testing will give insight in whether the averages of truck arrival and departure are sufficient to analyse the profiles, and calibrate and validate the simulation model. Additionally, with no differences in arrival and departure profiles, a terminal model with one arrival data input and one departure data input is sufficient to simulate the port processes.

However, with differences between the profiles, the terminal model should account for different traffic data input.

A.1 STATISTICAL ANALYSIS

The obtained traffic data for the arrival and departure profile is aggregated to weekly average profiles for months and daily average profiles for a year. It is not possible to disaggregate this data, therefore the statistical analysis makes use of the aggregated data.

Moreover, the traffic data is aggregated to hourly counts of trucks. Hence, the data samples have a size of 24, corresponding to each hour of the day.

For the statistical analysis of the traffic data, two statistic tests are used. Which test is applied to which analysis depends on whether two or more data samples are compared with each other. If two data samples are compared, a two sided t-test is applied for the statistical analysis. If three or more data samples are compared, the ANOVA analysis is used. The t-test is a parametric test to check if the means of two data sets are significantly different from each other. It is assumed that the data sets have an equal size. Moreover, it is assumed that the data samples come from a normal distribution. The ANOVA analysis (analysis of variance) is a parametric test used in statistical analysis. In the ANOVA test it is assumed that all data samples come from a normal distribution. However, it is unknown whether the data samples have the an equal mean and variance. This is tested with the ANOVA test.

Note that the arrival profiles and departure profiles are not compared with one another but the arrival profiles among the terminals, months and days are compared, and the departure profiles among the terminals, months and days are compared.

In statistical testing two hypothesis are formulated, a null hypothesis ($H0$) and an alternative hypothesis ($H1$). The null hypothesis throughout the statistical analysis in this appendix, is that the data samples come from the same distribution, hence the traffic data samples are the same and an average can accurately represent the actual arrival and departure profiles. The alternative hypothesis states that the data samples are not from the same distribution, hence the traffic data profiles are different and an average is not sufficient to represent the arrival and departure profile. Consequently, when the null hypothesis is accepted, it can be concluded that there are no significant differences between the data samples in terms of mean and variance for the arrival and departure profiles. When the null hypothesis must be rejected and the alternative hypothesis accepted, it can be concluded that the data samples are significantly different from each other.

$H0$: The traffic data samples (arrival profile or departure profile) are the same
$H1$: The traffic data samples (arrival profile or departure profile) are different

The level of significance for the statistical analysis in this appendix is 0.05. This means that the null hypothesis is accepted when the p-value is larger than 0.05. If the p-value is smaller than 0.05 the null hypothesis must be rejected and the alternative hypothesis is accepted.

In the t-test, the p-value is computed from the t-value. With a significance level of 0.05, the t-value must be in the part of the t-distribution that contains only 5% of the probability mass. For the two sided t-test with a significance level of 0.05 the t-value must be between -1.96 and 1.96 for the null hypothesis to be accepted. If the t-value is smaller than -1.96 or larger than 1.96, the null hypothesis must be rejected and the alternative hypothesis is accepted.

In the ANOVA analysis, the p-value is computed from the f-statistics, which is the ratio of mean squares. With a significance level of 0.05, the f-statistics must be in the part of the f-distribution that contains only 5% of the probability mass. The f-statistics must be smaller than 1 to accept the null hypothesis. If the f-statistic is larger than 1, the null hypothesis must be rejected and the alternative hypothesis is accepted.

The critical values for the t-value and f-statistic corresponding to the level of significance (0.05), depend on the degrees of freedom. To ensure that the statistical tests have a high certainty, a infinitive number for the degrees of freedom is assumed, resulting in the exact values for the t-value ($-1.96 \wedge 1.96$) and f-statistic (1).

Accept $H0$: t-value $\geq -1.96 \wedge$ t-value ≤ 1.96, $\vee$ f-statistic < 1, p-value > 0.05
Reject $H0$ and accept $H1$: t-value $\leq -1.96 \vee$ t-value ≥ 1.96, $\vee$ f-statistic > 1, p-value < 0.05

A.1.1 Terminal comparison

The first step in the statistical analysis is to compare the profiles for arrival and to compare the profiles for departure of trucks among the four different terminals. The ANOVA analysis is applied to compare four data samples, corresponding to the four terminals. The result of the statistical test is summarised in Table A.1.

Table A.1: ANOVA analysis results for comparing arrival and departure profiles among the four terminals

	Arrival	Departure
F-statistic	4.110	3.864
p-value	0.009	0.012

Based on these results, the null hypothesis must be rejected and the alternative hypothesis is accepted. This means that the the arrival and departure profiles are different among the terminals. In other words, one data sample does not represent the arrival and departure profile at each of the terminals. Therefore, different traffic data input must be used for the terminal model to simulate the processes at different terminals. These traffic data correspond to the arrivals and departures of a specific terminal, A through D.

A.1.2 Monthly comparison

In the monthly comparison it is checked whether the average arrival profile and departure profile vary across the twelve months in a year. As mentioned, the obtained traffic data is aggregated to weekly average profiles for months. Hence, to check whether there is a monthly trend to account for, the weekly average profile of each month is compared with each other. The ANOVA analysis is used since more than 2 data sets must be compared for this analysis. The ANOVA analysis is obtains the f-statistic and the p-values to conclude whether there are monthly trends that should be accounted for, or whether a yearly average can be used to represent the arrival and departure profiles during the entire year. Since the arrival and departure profiles differ among the terminals, this analysis is done for each of the terminals.

Table A.2: ANOVA analysis results for comparing months to check for monthly trends in arrival and departure profiles for several terminals

	Arrival		Departure	
Terminal	**F-statistic**	**p-value**	**F-statistic**	**p-value**
Terminal A	0.462	0.925	0.477	0.917
Terminal B	0.452	0.931	0.472	0.919
Terminal C	0.659	0.777	0.662	0.774
Terminal D	0.095	1.0	0.103	1.0

The middle columns in Table A.2 summarise the ANOVA analysis results for the comparison of the arrival profile for all months at the several terminals. The two right columns summarise the results for the departure profile.

The results in Table A.2, show that there are no significant differences between different months in terms of mean and variance of arrival or departure profile for each of the four terminals. Consequently, it can be concluded that there is no monthly trend that should be accounted for. Therefore, a weekly average from the entire year can represent the arrival and departure profiles throughout the year since, based on the results, the null-hypothesis must be accepted.

A.1.3 Daily comparison

Since the statistical analysis of the monthly profiles resulted in no significant differences between months, the weekly average of a year is used. However, it might be that there are significant differences between days of the week and hence that the weekly average of a year cannot accurately represent the arrival and departure profiles at the four terminals. In the daily comparison, it is checked whether the average arrival profile and departure profile vary across the days of the week. As mentioned, the obtained traffic data is aggregated to daily averages for a yearly profile. Therefore, the different days of the week can be compared with one another.

The first part of this statistical analysis on daily profiles is comparing the weekday average (the average of Monday throughout Sunday) with the weekend day average. This is necessary because the traffic data indicates that, for each terminal, weekend days have much less truck arrivals and departures on a day compared to the average of all weekdays. Therefore, including the weekend day truck arrivals and departures in the input for the terminal model might cause inaccurate model results. To be sure that the weekend days are indeed very different from the weekday average, the two sided t-test is used as only two data samples are compared.

In Table A.3 the results obtained using the two sided t-test for statistical analysis are summarised. For the arrival and departure profile of several terminals in the port area of Rotterdam, the t-test analysed whether the arrival and departure profiles in the weekend are the same as the weekday average. The results indicate that the null hypothesis must be rejected and the alternative hypothesis accepted. Therefore, it can be concluded that the weekend day arrival and departure profiles are significantly different from the weekday average. This means that the weekday average does not represent the profiles in the weekend.

Table A.3: T-test results for comparing the weekday average and weekend day average to check for significant differences in daily arrival and departure profiles for several terminals

	Arrival		Departure	
Terminal	**t-value**	**p-value**	**t-value**	**p-value**
Terminal A	5.940	0.000	5.928	0.000
Terminal B	5.857	0.000	5.968	0.000
Terminal C	5.502	0.000	5.666	0.000
Terminal D	6.298	0.000	6.198	0.000

As a consequence of the prior statistical analysis, the terminal model is focused on working days (Monday through Friday) and weekend arrivals and departures are excluded. In the weekend the number of truck arrivals is never above the terminal capacity, hence there is no waiting time issue in the weekend. Moreover, the weekend day arrival and departure profiles differ significantly from the weekday average (Table A.3). Therefore, Saturday and Sunday are excluded. Weekend days differ significantly from the working days, therefore these are unable to represent the real life situation that causes issues at the terminals in terms of waiting time. Moreover, by excluding the weekend days, the working day average instead of the total week average can be used to test more precisely whether a daily trend in arrival and departure profiles for working days should be accounted for.

The second part of the statistical analysis on daily profiles to check for daily trends, is to compare the five working days with each other to check whether working day (Monday through Friday) profiles are significantly different from each other. For this, the ANOVA analysis is used as this allows to compare multiple data sets at once.

In Table A.4, the middle columns summarise the results from the ANOVA analysis. The arrival profile of each workday is compared with the other workdays. The two right columns summarise the results for the departure profile.

The results in Table A.4 indicate that there are no significant differences between different working days in terms of mean and variance of arrival or departure pattern. Consequently, there are no daily trends that should be accounted for. The working day average for each of the four terminals can be used as input for the terminal model.

Table A.4: ANOVA analysis results for comparing working days to check for daily trends in arrival and departure patterns for several terminals

Terminal	Arrival F-statistic	Arrival p-value	Departure F-statistic	Departure p-value
Terminal A	0.521	0.720	0.579	0.679
Terminal B	0.653	0.626	0.644	0.632
Terminal C	0.021	0.999	0.029	0.998
Terminal D	0.393	0.813	0.395	0.812

All in all, from the extensive statistical analysis it can be concluded that each terminal should be modelled separately as the arrival and departure profiles differ significantly among the four terminals. Moreover, there is no significant difference between months of the year, thus a yearly average can be used to analyse the arrival and departure profiles at several terminals. The consequence of the prior is that the terminal simulation model does not need to take monthly trends into account. The weekend days, however, are excluded because these differ significantly from the other days in the week and have much less arrivals and departures of trucks. Lastly, the working day averages for the arrival and departure can represent the working days as the arrival and departure rate of the working days is stationary for all terminals, hence it is not necessary to make a separate terminal model for different days.

A.2 DATA SUMMARY

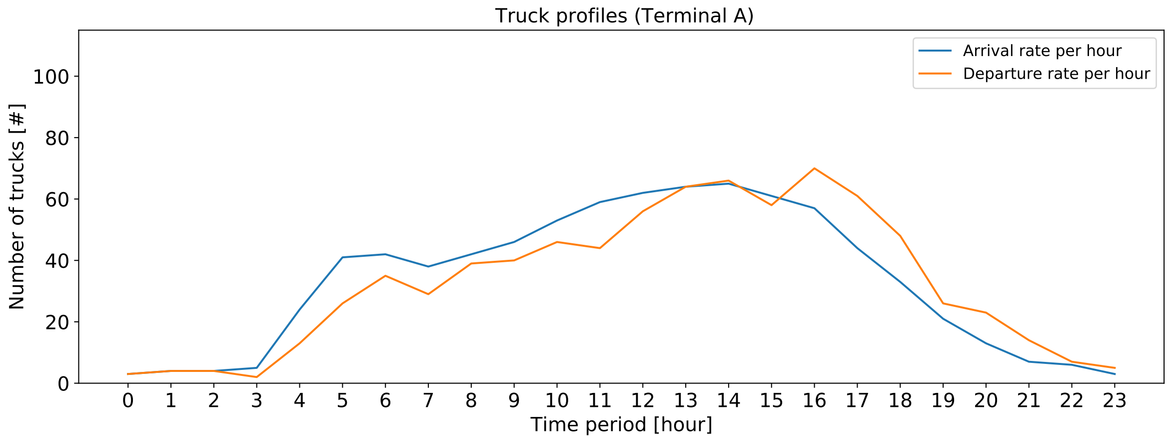
Four different arrival profiles and four different departure profiles are the result of the traffic data after the statistical analysis. The data that is used as an input for the terminal model and truck shifting model is summarised in this section.

The data is shown in Figure A.2. In each sub-figure Figure A.2a through Figure A.2d, the arrival and departure profile is plotted per terminal in the blue and orange line respectively. Each profile represents the working day average at the terminals.

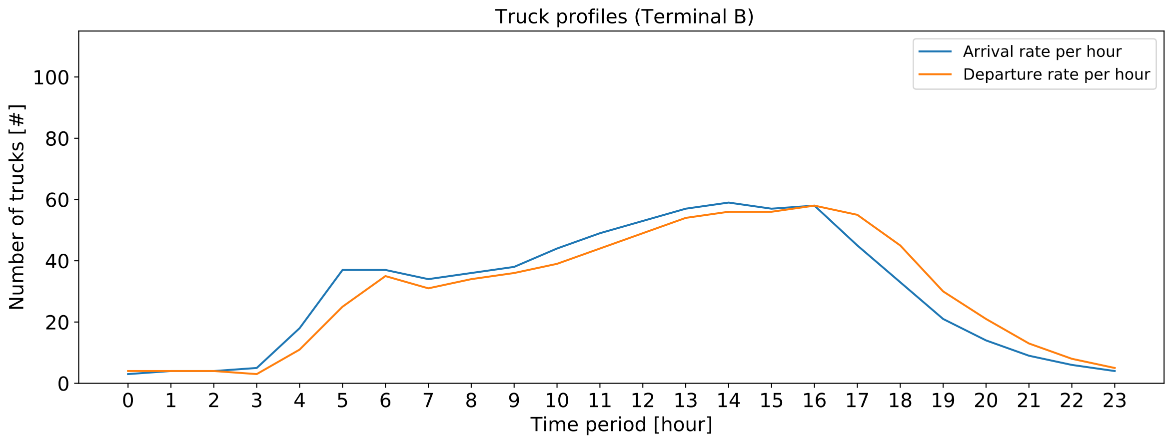
From these figures it can be observed that for each terminal there is a small peak in the morning hours, and a large and more wide spread peak in the midday and afternoon. This peak of trucks arriving at the same time is what causes the issues at the terminal regarding the waiting time.

Moreover, it an be observed from Figure A.2 that the departure profile follows a pattern similar to the arrival profile with a delayed offset. This is because the arrival profile represents the number of trucks entering the terminal during a certain hour, and the departure profile represents the number of trucks leaving the terminal during a certain hour. The difference between the two lines is due to the time a truck spends at the terminal waiting or being served. At the peaks of truck arrival it can be observed in Figure A.2, that the difference between the blue and orange line increases. This shows that the turnaround times of trucks during the peaks is larger, hence this indicates waiting time. The exact waiting time is unknown, and will be simulated by means of the terminal model.

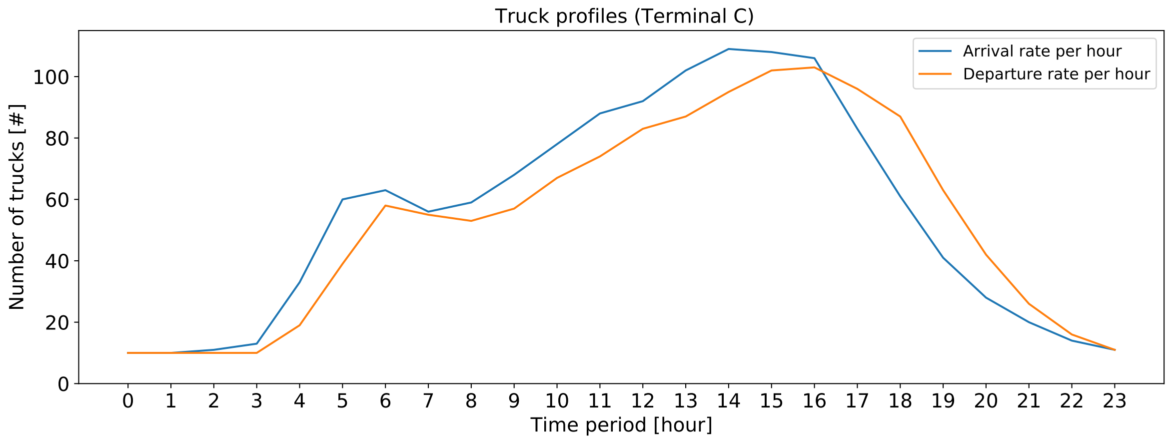
Even though, the traffic data does not contain information, such as exact time of arrival and departure per individual vehicle, the traffic data, aggregated to number of trucks per hour, allows to simulate this information with the terminal model. The way in which the traffic data is used in the terminal model is elaborated in Appendix B. Moreover, the hourly aggregated data is valuable for the truck shifting model. For the traffic data as input for the truck shifting model, one is referred to Appendix E.



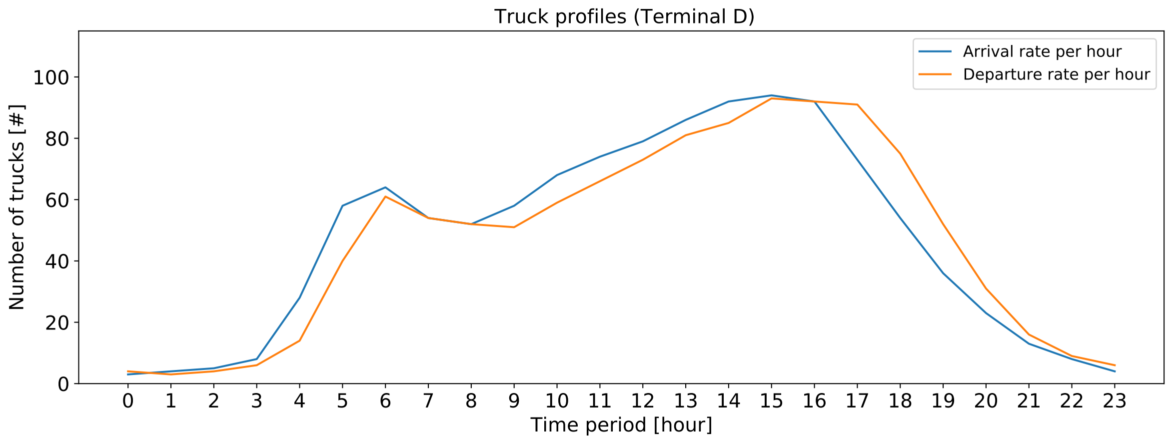
(a) Profiles terminal A



(b) Profiles terminal B



(c) Profiles terminal C



(d) Profiles terminal D

Figure A.2: Arrival and departure profiles of an average working day from historical traffic data (2017) obtained from loop detectors for all terminals

B TERMINAL MODEL

For this research a terminal model is developed to simulate the processes at the terminal. The terminal model is formulated as a queueing model and a DES is used to represent the port system. With the terminal model, a waiting time profile can be simulated from an arrival profile. Consequently, the terminal model allows for evaluating the effect of truck shifting under certain TOC application rates by using various arrival profiles. How these various arrival profiles are computed is elaborated in Appendix E.

In this appendix the development of the terminal model is elaborated. The components in the terminal model and the simulation are described. Moreover, the terminal model is verified, calibrated and validated. Lastly, the results for the base case year 2017 are provided.

From the statistical analysis on traffic data in Appendix A, it was found that the four terminals, located at the MVII in the Rotterdam port area, are significantly different in terms of arrival and departure profile. Therefore, four separate models are created to simulate the processes at the different terminals. The model set up is the same for each terminal, hence the model described in general. The calibration, verification and validation, however, is done for each model individually as different results are obtained.

B.1 MODEL DESCRIPTION

The terminal model consists of three components. Each of the components will be elaborated. Additionally, the simulation itself will be elaborated to provide insight in the developed discrete event simulation.

B.1.1 Model components

The proposed terminal model includes three components, namely the truck generator, the trucks and the server. Together these three components make up three processes in the terminal model. The three processes in the model are the arrival process, the server process, and the departure process. In Figure B.1 a graphical representation of the terminal model, the components and processes is provided. Below the figure, an extensive elaboration of the model components is given.

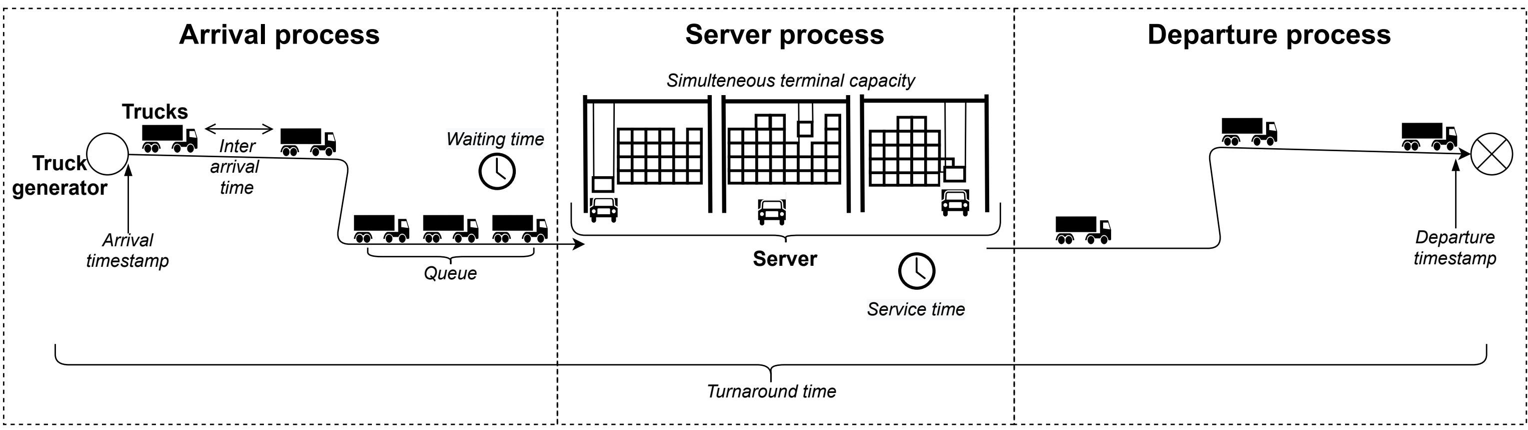


Figure B.1: Graphical representation of the terminal model, the components and the simulated processes

Truck generator

The truck generator generates trucks with a certain inter arrival time. The inter arrival time depends on the time of day. The day is split up in 24 periods, corresponding to a time period of one hour. To set up the model, historical data of arrivals per hour in 2017 at the terminals is used (see Appendix A for the arrival profile per terminal).

Since these arrival profiles are averages and in reality there is stochasticity in arrival, the inter arrival time is assumed to follow an exponential distribution [Hillier and Lieberman, 2015]. An exponential distribution can be used to specify the amount of time until a specific event occurs, in this model that specific event is the arrival of a truck at the terminal. Each hour of the day, the truck generator generates the trucks based on the historic arrival profile and samples the inter arrival time between the trucks from the exponential distribution associated with the hourly average.

The mathematical formulation of the exponential distribution is depicted in Equation B.1. Denoted by X is the time (in minutes) between truck arrival, which is the inter arrival time. This X is a continuous random variable.

$$\lambda_h = E(X) \tag{B.1}$$

The inter arrival time is assumed to have an exponential distribution with rate parameter λ_h for each hour. As denoted in Equation B.2, λ_h is the inverse of the average inter arrival time (IAT_h) for each hour.

$$\lambda_h = \frac{1}{IAT_h} \tag{B.2}$$

The average inter arrival time (IAT_h) is the hourly average inter arrival time between trucks. The model time steps represent minutes, one hour contains 60 minutes. Hence, IAT_h is calculated by dividing 60 by the average number of arriving trucks for each hour (λ_h), as denoted in Equation B.3. The input of λ_h comes from the historical data of arrivals per hour in 2017 (Appendix A).

$$IAT_h = \frac{60}{\lambda_h} \tag{B.3}$$

Lastly, in Equation B.4 $f(x)$ indicates the probability of a truck arriving with a certain inter arrival time (x) at the terminal and ranges between 0 and 1. Consequently, the inter arrival time between trucks is expected to decrease when more trucks arrive in an hour.

$$f(x) = \lambda_h e^{-\lambda_h x} \tag{B.4}$$

After a truck is generated, the truck generator yields hold for the sampled inter arrival time before generating a new truck.

Each truck that is generated by the truck generator is equipped with a 'TruckID'. With this ID the truck can be traced throughout the simulation for verification purposes and result representation.

Trucks

This component represents every instant of trucks in the system. Its main functionality is to control and track trucks in the system. As previously mentioned, the generated trucks have a unique ID. When a truck is generated and enters the system, the truck obtains a timestamp 'arrival time'.

Subsequently, the truck enters the queue. The queue is where the trucks wait before being served. The queue is infinite, there is no maximum number of trucks that can wait in the queue. While waiting in the queue to be served in the terminal the truck is passive. The queueing discipline used in the terminal model is FIFO hence the server picks the first truck in the queue and serves it. During this process the truck remains passive.

After being served the truck becomes active again and leaves the system. When the truck leaves the system it gets a timestamp 'departure time'. Using the timestamps, the turnaround time, hence the time spent in the system, is calculated for each truck.

Server

The server represents the terminal operations. Terminal operations include trucks entering the terminal yards, positioning of trucks in a container stack, loading/unloading the container, and driving back to the exit gate. Since limited information is available to allow for simulating these terminal operations in detail, these are all captured by a single server with the capacity to serve multiple trucks simultaneously in the terminal.

There are two parameters with an unknown value for simulating the terminal operations with the server component. These are the capacity to serve trucks simultaneous and the service time per truck.

The simultaneous terminal capacity represents the number of trucks that can be served in the terminal at the same time. This capacity is, for example, determined by the number of gates to enter the terminal, the number of container stacks, and number of cranes in the yard.

The service time per truck is the required time to serve a truck. In the context of this model, serving a truck refers to unloading and/or loading the truck with one or more containers. The time required for serving a truck is not equal for each truck. The service time is, in the real world situation, determined by whether the truck is at the terminal for container delivery and/or pick up, the number of containers that the truck desires, the number of stacks the truck has to go by, and the driving distance. The stochasticity that is present in reality while serving trucks at a terminal, should be embedded in the server component. Therefore, it is assumed that the service time follows an exponential distribution with a mean service time [Hillier and Lieberman, 2015]. The mathematical formulation for the service time along an exponential distribution is similar to that of the inter arrival time (see Equation B.1 through Equation B.4), in which IAT_h represents the mean service time.

As the specific terminal information for these two parameters is limited, an optimisation approach is proposed (see Section B.1.2) to overcome this problem and calibrate the server component. Consequently, an optimisation algorithm is used to estimated this simultaneous serving capacity of the terminal and the mean service time.

As mentioned, the server picks the trucks from the queue to serve them. The terminal can serve multiple trucks at ones. If there are no trucks in the queue, the unused simultaneous terminal capacity is standby until this service capacity is required. The server have a certain service time.

B.1.2 Simulation

Running the model

To run the model, a simulation is defined. The simulation model is set up with the discrete event simulation package salabim [van der Ham, 2018]. The simulation is equipped with a certain run time, a number of seeds, model parameters, and the model components.

The simulation time is in minutes. The model is set up to simulate one day, 24 hours, at a terminal. Nevertheless, to include warm-up time in the beginning and to ensure that the system is empty at the end of the simulation (flow conserve = 0), the simulation is run for 25 hours. The generated trucks from the first 30 time steps (minutes) and last 30 time steps (minutes) are excluded from the results.

Moreover, to avoid simulation bias, the simulation is run several times with random seeds. Subsequently, the results obtained with the different seeds are averaged. For this research the number of seeds is set to 10, thus the seeds used are 0 through 9. The seeds are used to initialise the randomness in the model via the pseudorandom number generator. For example, the way the stochasticity in the inter arrival time and service time is incorporated.

Since two parameters, the simultaneous terminal capacity and mean service time, are unknown, it is necessary to estimate these parameters before running the definitive simulation for results. The estimation of these parameters is done with simulation based optimisation using a machine learning technique. The optimisation algorithm finds the correct values for these parameters to simulate the terminal model. Subsequently, the found values are used as input for the two parameters in the final terminal model. Thereafter, the simulation can be run to obtain the results.

Optimisation algorithm

As mentioned, the server component of the model has some unknown parameters. These parameters are the simultaneous terminal capacity and the mean service time. By means of Bayesian optimisation [Bergstra et al., 2013], these two parameters are estimated.

Bayesian optimisation considers the problem of finding a combination of optimal Bayesians for fine tuning the machine learning algorithm or calibration of simulation based experiments. The simultaneous terminal capacity and mean service time are regarded as hyper-parameters. A hyper-parameter can be explained as a parameter of which the value controls the learning process. The algorithm finds the value of these parameters from data by minimising the formulated objective over the search space.

The objective function takes a tuple of the hyper-parameters and returns the corresponding loss [Claesen and De Moor, 2015]. The problem is optimised when the hyper-parameter values, under which the loss is minimised, are found by the algorithm.

A simulation based optimisation is used for minimisation of the objective function. The simulation is the terminal model, in which trucks arrive, are served and depart from the system. From the loop detectors at the terminal gates, a historic data for the departure profile in 2017 is obtained (Appendix A). The objective function is to minimise the difference between simulated departure profile and the observed departure profile.

For the formulation of the objective function, the MSE method is used, denoted in Equation B.5. This method squares the difference between the simulated ($\hat{Y}_i$) and observed (Y_i) departure profile for each data point (n), in this case the hourly time periods, and computes the mean of over all data points.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{B.5}$$

A larger difference results in a larger impact of the difference on the objective function. Therefore, the hyper-parameter values are tuned such that the deviation from the historic departure profile is minimised.

Result representation

After the simulation is run, the results are captured in a table in which the rows indicate the unique truck ID's and the data for each truck in the corresponding columns. The columns provide the information for truck ID, arrival time, departure time, turn around time, queue length at the time the truck enters the system, the service time each truck experienced, and the waiting time for each truck.

The arrival and departure time are reported by the truck by means of timestamps obtained by the truck when entering and leaving the system. The difference between arrival and departure time provides the turnaround time of each truck. By subtracting the individual service time from the turnaround time, the waiting time is calculated.

The queueing process is formulated as a $M/M/s$ model as it is assumed that both the inter arrival time and the service time are independently and identically distributed with an exponential distribution and the number of servers is an integer value. The mathematical formulation for calculating the waiting time is provided by Equation B.6 through Equation B.9 [Hillier and Lieberman, 2015],

$$L = \lambda_h W \tag{B.6}$$

$$L_q = \lambda_h W_q \tag{B.7}$$

$$W = W_q + \frac{1}{\mu} \tag{B.8}$$

$$W_q = \frac{L_q}{\lambda_h} \tag{B.9}$$

where the expected number of trucks in the queueing system, hence in the queue and in the servers, is denoted by L. The mean arrival rate per hour is denoted by λ_h. The waiting time including service time, hence turnaround time, is represented by W. The mean service time is presented by μ. Moreover, with L_q the expected queue length, thus excluding the trucks in the servers, is indicated. Lastly, the waiting time in the queue is denoted with W_q.

The resulting data from the simulation is transformed to provide the number of trucks arriving and departing for each time slot. Equivalent to the historical data profiles from the loop detectors, the simulated data is aggregated to hourly time periods. The transformed data shows the arrival and departure profiles along the day as simulated with the terminal model.

By comparing these simulated arrival and departure profiles with the observed arrival and departure profiles found from the loop detectors, the terminal model is calibrated, verified and validated.

Other results that are obtained from the terminal model, are profiles of hourly averages along the day for the turnaround time, the service time, the waiting time, and the queue length. These results can be used to analyse the simulated system.

B.2 MODEL CALIBRATION

To ensure that the terminal model is close to reality and can simulate the arrival, service and departure of trucks accurately, the terminal model requires calibration.

For the specific terminal models, the design of the terminal model remains the same. Yet, the arrival and departure profiles in each terminal model correspond to the specific terminals A through D. To obtain accurate and realistic results for each terminal, a separate terminal model is set up and calibrated.

In each specific model, the parameters in the arrival and service process are tuned to a specific terminal. These parameters are tuned based on the traffic data (Appendix A) arrival profile and departure profile obtained from the loop detectors located at the specific terminal.

B.2.1 Truck arrival process

The simulation model is calibrated, in regard to the arrival process, with the average observed arrival profile. The observed arrival profile is traffic data obtained from loop detectors. The loop detectors are located at the terminal gates of the terminals at MVII (Figure A.1 in Appendix A). To make sure the average arrival profiles are stationary, a statistical analysis is done. The statistical analysis is elaborated in more detail in Section A.1. In this subsection solely the conclusion from the statistical analysis are provided.

For the model calibration the parameters for the arrival process are tuned. Thereafter, reflection on the outcome of the calibrated process, based on the tuned parameters, is provided.

Traffic data

In Section A.1 a statistical analysis is carried out for the arrival profiles. The statistical analysis aims to gain insight in three aspects to be able to calibrate the simulation model. Traffic data, providing the arrival profile of several terminals in the port area, is checked for differences between terminals, monthly trends and daily trends.

In the statistical analysis for terminal comparison (Section A.1.1) it is checked whether the arrival profiles varies among the four different terminals. With the ANOVA analysis the four terminals are

compared with each other. From the statistical analysis it can be concluded that the terminals have significant differences in arrival profile ($p < 0.05$).
For the monthly trend analysis (Section A.1.2), it is checked whether the average arrival rate distribution varies across the twelve months in a year. Using the ANOVA analysis the twelve months are compared with each other. The statistical analysis for monthly trends shows that there are no significant differences in truck arrival between the months in a year ($p > 0.05$).

For the daily trend analysis (Section A.1.3), it is checked whether the average arrival rate distribution changes over the days of the week. This analysis is done in two steps.

First the weekly average is compared with the weekend average. Using the two sided t-test, it was found that the weekend days differ significantly from the weekly average ($p < 0.05$). Moreover, the number of arrivals in the weekend is always far below terminal capacity for each terminal. The weekend days do not represent the weekly profiles and can have undesirable impacts on the research outcome if included. Therefore, the weekend days are excluded from further research.

Therefore, in the second step, the weekend days are excluded and it is checked whether there are significant differences between working days. Using the ANOVA test the five working days are compared with each other. The statistical analysis for daily trends indicates that there are no significant differences between working days ($p > 0.05$).

All in all, from the statistical analysis elaborated in Section A.1, the average working day arrival profiles are found to be significantly different among the terminals at MVII. For these terminals a simulation model must be defined. Moreover, it can be concluded that there are no monthly or daily trends to account for in the simulation model. The arrival profiles are stationary for all terminals. Hence, the working day average is sufficient to calibrate the simulation model regarding the arrival pattern. Therefore, it is not necessary to make a separate simulation model for different days.

Parameter tuning

The parameters defined for the truck generator process are tuned based on the outcome of the statistical analysis. The parameters used for the arrival process are the inter arrival times for each hourly time period. The inter arrival times are based on historical traffic data obtained from loop detectors at the terminal gates (Section A.2). This traffic data of arrivals is aggregated per hourly time periods. The inter arrival time is in minutes.

The inter arrival time between trucks for each hour is approximated by an exponential distribution of the mean inter arrival time (Section B.1.1). The mean inter arrival time for each hour is calculated by dividing one hour (60 minutes) by the average arrivals in that hour. For example, the mean inter arrival time between trucks is 1.36 minutes if on average 44 trucks arrive. In reality trucks do not arrive with an equal inter arrival time, the exponential distribution captures this stochasticity.

Reflection

The calibrated model simulates an arrival profile based on the tuned parameters. To ensure that the simulated arrival profile is similar to the observed profile a statistical analysis is carried out. In the statistical analysis a two sided t-test is applied to compare the observed and simulated arrival profile. The t-test is a parametric test to check if the means of two data sets are significantly different from each other. It is assumed that the data sets have an equal size. Moreover, it is assumed that the data samples come from a normal distribution.

In statistical testing two hypothesis are formulated, a null hypothesis ($H0$) and an alternative hypothesis ($H1$). The null hypothesis, is that the data samples come from the same distribution, hence the observed and simulated samples are similar and the simulated profile accurately represent the actual arrival profile. The alternative hypothesis states that the data samples are not from the same distribution, hence the observed and simulated profiles are different and the simulated profile is not sufficient to represent the actual arrival profile. Consequently, when the null hypothesis is accepted, it can be concluded that there are no significant differences between the data samples in terms of mean and variance for the observed and simulated profiles. When the null hypothesis must be rejected and the alternative hypothesis accepted, it can be concluded that the data samples are significantly different from each other.

$H0$: The observed and simulated arrival profile are similar
$H1$: The observed and simulated arrival profile are different

The level of significance for the statistical analysis is 0.05. This means that the null hypothesis is accepted when the p-value is larger than 0.05. If the p-value is smaller than 0.05 the null hypothesis must be rejected and the alternative hypothesis is accepted.

In the t-test, the p-value is computed from the t-value. With a significance level of 0.05, the t-value must be in the part of the t-distribution that contains only 5% of the probability mass. For the two sided t-test with a significance level of 0.05 the t-value must be between -1.96 and 1.96 for the null hypothesis to be accepted. If the t-value is smaller than -1.96 or larger than 1.96, the null hypothesis must be rejected and the alternative hypothesis is accepted.

Accept $H0$: t-value $\geq -1.96 \wedge$ t-value ≤ 1.96, p-value > 0.05
Reject $H0$ and accept $H1$: t-value $\leq -1.96 \vee$ t-value ≥ 1.96, p-value < 0.05

The resulting values from the statistical analysis are depicted in Table B.1. From these results it can be concluded that the null hypotheses should be accepted. Hence, the tuned parameters in the calibrated model can simulate the arrival process accurately.

Table B.1: T-test results for comparing the observed and simulated arrival profiles to check for significant differences in observed and simulated arrival profiles for several terminals

Terminal	t-value	p-value
Terminal A	0.025	0.98
Terminal B	0.014	0.989
Terminal C	0.025	0.981
Terminal D	0.031	0.975

In addition to the t-test in the statistical analysis, a polynomial regression is done to analyse the correlation between the observed and simulated arrival profile. The statistical measure in this analysis is the R-square. The R-square ranges between 0 and 1, this number indicates the extent to which the simulated data matches the observed data.

The results from the polynomial regression are depicted in Table B.2. It can be observed that the R-square values are very close to 1. This indicates that the observed and simulated arrival profiles are highly correlated. Hence, the simulated values in the arrival profile are very close to the observed values.

Table B.2: R-square results for comparing the observed and simulated arrival profiles using polynomial regression to analyse the correlation between the observed and simulated arrival profiles

Terminal	R-square
Terminal A	0.995
Terminal B	0.989
Terminal C	0.996
Terminal D	0.994

Based on the statistical analysis and polynomial regression results, it can be concluded that all terminal models are accurately calibrated regarding the arrival process.

B.2.2 Service process

The service process is, similar to the arrival process, calibrated based on historic traffic data. The historic data used to calibrate the service process is the departure profile. To make sure the average departure profiles are stationary, a statistical analysis is done. The statistical analysis for the departure profile is identical to the statistical analysis for the arrival process. For more details on the statistical analysis, one is referred to Section A.1.

For the model calibration the parameters for the service process are tuned using a optimisation algorithm (Section B.1.2). Thereafter, reflection on the outcome of the calibrated process, based on the tuned parameters, is provided.

Traffic data

In Section A.1 a statistical analysis is carried out for the departure profiles. Similar to the statistical analysis for the arrival process, the statistical analysis aims to capture differences between terminals, and potential monthly and daily trends. An identical approach is applied for the analysis of the departure profile. The comparable p-values, similar hypotheses, and the same statistic tests (the ANOVA and t-test) are used.

From the statistical analysis, it can be concluded that the departure profile is stationary for all terminals. No monthly trends, nor daily trends are found in the data. Hence, the average working day departure profile is sufficient to calibrate the terminal service process.

Nonetheless, similar to the outcome of the statistical analysis for the arrival profile, the average working day departure profiles are significantly different among the terminals at MVII. Again, this demonstrates the need for separate models for specific terminals.

Parameter tuning

The parameters for the service process are tuned by means of the Bayesian optimisation algorithm (see Section B.1.2). By the formulation of an optimisation problem, the missing information (the simultaneous terminal capacity and mean service time) can be captured by the model. Therefore, the simulation model can accurately simulate the service process. To tune the parameters to the optimal value, the algorithm iterates until it finds the parameter values that minimise the loss. This minimised loss is considered to be the best loss found by the optimisation algorithm. As aforementioned in Section B.1.2, the loss is calculated with the MSE method (Equation B.5).

The estimated parameter values are depicted in Table B.3. These estimated parameters are used as the final settings for the simulation model of each terminal.

Table B.3: Overview of estimated parameter values for the service process and the corresponding loss

Terminal	Simultaneous terminal capacity	Mean service time	Best loss
Terminal A	17	17	64.396
Terminal B	16	17	37.15
Terminal C	20	12	93.804
Terminal D	20	14	70.05

Reflection

This section provides some reflection on the parameter values and best loss. Regarding the estimated parameters it is discussed whether the values are likely. Additionally, the best loss values are discussed. Thereafter, statistical analysis and polynomial regression are done to sustain the power of the calibrated model to reflect the observed data.

The simultaneous terminal capacity indicates how many trucks can be served in the terminal at the same time. The mean service time indicates how long it takes to serve a truck on average. As mentioned in Section B.1.1, in reality this depends on various factors in the terminal. Despite that the exact values of the estimated parameters can not be verified, the order of magnitude of the values for the estimated parameters can.

Based on the number of stacks and cranes observed in the terminals using Google Maps satellite view [Google, 2017], the estimated parameters for simultaneous terminal capacity are quite realistic.

Based on a earlier research executed by the PoR [Drewes and Gorter, 2017], the estimated mean service time seems to be a bit optimistic for all terminals. However, the estimated parameter values are obtained by optimising the objective function based on the two parameters. As a consequence, it might be that the mean service time is estimated a bit lower and the simultaneous terminal capacity a bit higher.

Interpreting the absolute value of the best loss is difficult, as the MSE result is always dependent on the data. As a rule of thumb the best loss can be interpreted as the closer to zero, the better. Nonetheless, the absolute value of the MSE is relative to the magnitude of the values in each data point. As the MSE takes the square of the deviation in a data point, a factor 10 larger magnitude of values in a data point can result in a factor 100 larger MSE loss value.

This can be illustrated with an example in which the magnitude in a data point is increased with a factor 10. If there are 100 trucks observed in one data point, and 120 simulated, the difference is 20 trucks. The square error in this data point is $20^2 = 400$. In the situation that 1000 trucks are observed, and 1200 are simulated, the square error is $200^2 = 40.000$. This example indicates that a 20% deviation between observed and simulated trucks results in a much larger (factor 100) MSE loss value.

The best loss values shown in Table B.3 indicate that there is some difference between the observed and simulated departure profile. However, the magnitude of the deviation appears to be within reason considering the magnitude of the values in the data point. In Table B.4 the minimal, maximal and average values for the observed profile in the data points are depicted to indicate the magnitude of the values in the data point. Additionally, the minimal, maximal and average deviation between the observed and simulated values in the data point are provided.

Table B.4: Overview of magnitude of values in the data point of observed data, the deviation between the observed and simulated profile, and the MAPE score

Terminal	Minimal value in data points	Maximal value in data points	Average value in data points	Minimal deviation	Maximal deviation	Average deviation	MAPE score
Terminal A	2	70	32.6	0	12	4.4	23%
Terminal B	3	58	30	0	6	2.2	13.8%
Terminal C	10	103	53	1	14	4.9	13%
Terminal D	3	93	46.6	0	13	3.3	10.9%

In the most right column of Table B.4 the MAPE score is depicted. The calculation of the MAPE score, given by Equation B.10, is similar to the MSE though a percentage value is obtained. The observed profile is indicated by Y_i, the simulated profile is indicated by $\hat{Y}_i$, and the data points are indicated by n. This MAPE score helps to reflect on the accuracy of the simulated departure profile. It indicates the difference between observed and simulated profile in a percentage value. For interpreting the MAPE the rule of thumb is that a smaller value indicates that the simulated profile is closer to the observed profile. The MAPE values for the terminals range between 10% and 23%. In general, such MAPE scores indicate a good simulated profile [Lewis, 1982].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \tag{B.10}$$

The discussion of the estimated parameter values and the corresponding best loss (depicted in Table B.3) shows that the model is nicely calibrated with regard to the service process. Nevertheless, some difference between the observed and simulated departure profile is found. Therefore, two additional analysis are applied to assess the power of the calibrated model to simulate the observed profiles.

The t-test is used in statistical analysis to compare the observed and simulated departure profiles. If the observed and simulated departure profiles are not significantly different, it can be concluded that the estimated parameter values (Table B.3) can simulate the terminal processes accurately. The statistical analysis using the t-test is similar to the statistical analysis for the arrival process (Section B.2.1). The hypothesis are formulated for the departure profile.

$H0$: The observed and simulated departure profile are similar
$H1$: The observed and simulated departure profile are different

The significance level is the same, namely 0.05, this results in the same approach for hypothesis testing.

Accept $H0$: t-value $\geq -1.96 \wedge$ t-value ≤ 1.96, p-value > 0.05
Reject $H0$ and accept $H1$: t-value $\leq -1.96 \vee$ t-value ≥ 1.96, p-value < 0.05

Table B.5: T-test results for comparing the observed and simulated departure profiles to check for significant differences in observed and simulated departure profiles for several terminals

Terminal	t-value	p-value
Terminal A	-0.077	0.939
Terminal B	-0.044	0.965
Terminal C	-0.195	0.846
Terminal D	-0.018	0.985

In addition to the t-test in the statistical analysis, a polynomial regression is done to analyse the correlation between the observed and simulated departure profile. The statistical measure in this analysis is the R-square. The R-square ranges between 0 and 1, this number indicates the extent to which the simulated data matches the observed data..

The results from the polynomial regression are depicted in Table B.6. It can be observed that the R-square values are very close to 1. This indicates that the observed and simulated departure profiles are highly correlated. Hence, the simulated values in the departure profile are very close to the observed values.

Table B.6: R-square results for comparing the observed and simulated departure profiles using polynomial regression to analyse the correlation between the observed and simulated departure profiles

Terminal	R-square
Terminal A	0.934
Terminal B	0.979
Terminal C	0.969
Terminal D	0.977

Based on the statistical analysis and polynomial regression results, it can be concluded that all terminal models are accurately calibrated regarding the service process.

B.3 MODEL VERIFICATION

To ensure that the terminal simulation model operates as it is supposed to do, verification checks and tests are executed. The each model for the specific terminals A through D, is verified in a stepwise approach. First, the verification is done for smaller parts of the model by a separate evaluation of the model components. This approach allows for clear insight in potential model flaws, errors or bugs. If no problems are encountered, the terminal model is verified as a whole by balance checks and evaluation of expected model results.

B.3.1 Component verification

Truck generator

The truck generator simulates the arrival process of truck at the terminal. Each hour of the day a different input is used to obtain the inter arrival time between trucks. For verification purposes, it is checked whether the truck generator indeed simulates the arrival of trucks with a different inter arrival time in each time interval. Figure B.2 displays the simulated arrival process along the day. As the number of trucks simulated varies over time, it can be observed that the truck generator indeed simulates the arrival process with a different inter arrival time.

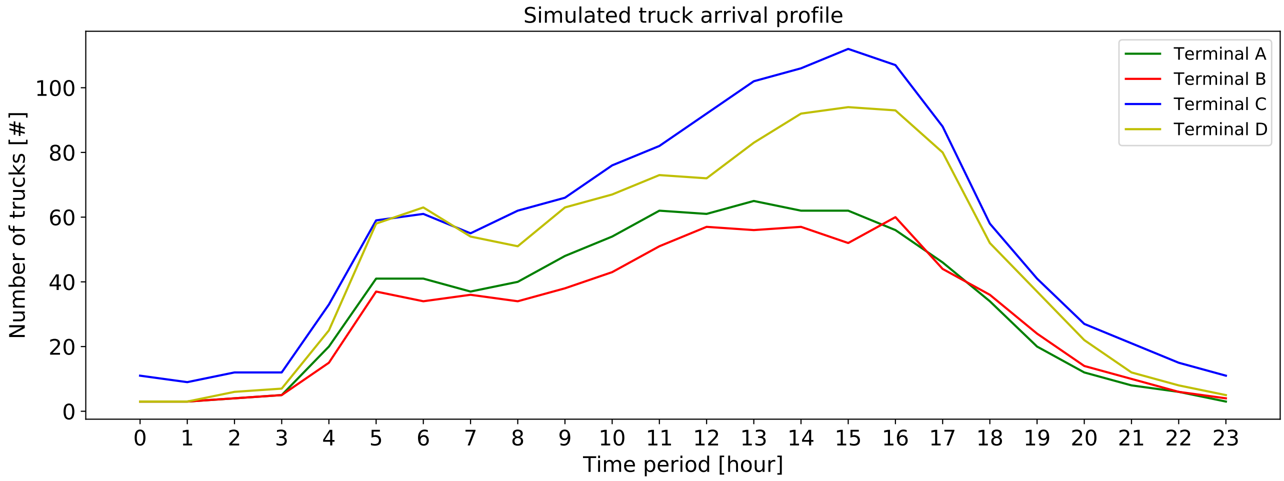


Figure B.2: Simulated arrival profile for all terminals

Each generated truck receives a unique truck ID from the truck generator. This is crucial as this ID is used to track the truck throughout the system. If two trucks obtain the same ID or a trucks fails to receive an ID, this could cause faulty results. Therefore, for verification of the truck generator it is checked whether each generated truck has received a unique truck ID. It can be concluded that each generated truck successfully receives a unique ID from the truck generator.

Hence, the truck generator component is verified based on the arrival profile check and truck ID check.

Truck

The truck component represents the trucks (n). The truck component ensures that progress of the truck throughout the terminal model can be traced. Each truck obtains a timestamp upon arrival (t_a) and departure (t_d). It is crucial that the time stamps are obtained at the correct moment. If this process is implemented wrongly in the simulation, the results will be highly affected. The arrival and departure timestamps are used to calculate turnaround time (t_t).

To check whether the time stamps are correct, the results are analysed. First, it is checked whether any truck obtained a departure timestamp before an arrival timestamp. This would indicate that the chronological order of the simulation is incorrect. It was found that no truck obtained a departure timestamp with an earlier time than the arrival time, each truck satisfies the rule formulated in Equation B.11. The set of generated trucks is denoted by N.

$$t_a(n) < t_d(n), \qquad \forall n \in N \tag{B.11}$$

The turnaround time is subsequently used to compute the waiting time (t_w), by subtracting the service time (t_s) from the turnaround time. Each truck encounters a certain service time. This service time varies per truck and is a main determinant for the turnaround time of a truck. Therefore, it is important that the service time encountered by an individual truck, is logged correctly. If the truck fails to log the specific service time it encountered, the waiting time calculation is incorrect. This causes faulty results of the model.

To check the truck component, a few simple calculations can be made (Equation B.12). If each truck satisfies the formulated rules for arrival time, departure time, service time, turnaround time and waiting time, the truck component can be verified. Each generated truck was proven to satisfy the formulated rules (Equation B.12).

$$\left.\begin{aligned} t_t(n) &= t_d(n) - t_a(n) \\ t_t(n) &= t_s(n) + t_w(n) \\ t_d(n) &= t_a(n) + t_s(n) + t_w(n) \\ t_d(n) &= t_a(n) + t_t(n) \end{aligned}\right\} \quad \forall n \in N \tag{B.12}$$

The formulated rules in Equation B.11 and Equation B.12 are satisfied by each generated truck. Therefore, the truck component is verified.

Server

The server component represents the terminal operations. The details of the terminal operations are not modelled. Instead, a Bayesian optimisation algorithm is used to estimate the parameters that serve as input for the server component (Section B.1.2). A few verification test are executed to check whether the server process is modelled as intended.

A crucial check is whether the server creates the terminal capacity to serve trucks simultaneously. From the simulation trace it can be observed that this is done correctly.

Moreover, it is checked whether the server component executes its main process, picking trucks out of the queue and serving them. In the simulation trace it can be observed that the server picks trucks from the queue and holds the truck for the sampled service time.

By adding a measure in the model, the number of trucks served can be tracked. This measure counts the number of trucks served and only increases after a truck is served. During the simulation run it can be observed that the count increases along the simulation time. This indicates that the server process is modelled as intended.

As mentioned, each truck encounters a specific service time. This service time is exponentially distributed from the mean service time. From Figure B.3 it can be observed that the mean service time varies per hour. Note this graph represents the service time on average per hour.

Even though the information in Figure B.3 is aggregated, the fluctuating average indicates that there is indeed stochasticity in the service time. Moreover, in the obtained results of individual trucks, it can be observed that the service time encountered by the individual trucks varies among the trucks.

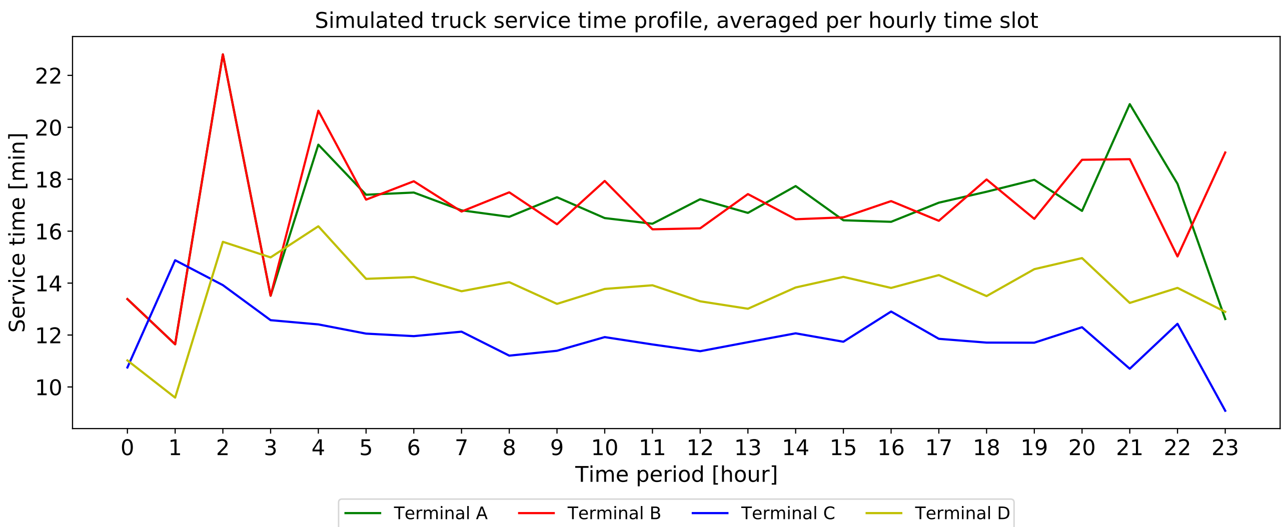


Figure B.3: Simulated service time profile for all terminals

From the executed checks it can be concluded that the server is modelled as intended. Consequently, the server component is verified.

B.3.2 Simulation verification

Flow conserve

Each generated truck should eventually leave the system. A balance check is preformed to check the flow conserve of the model. This balance check is formulated in Equation B.13, where t indicates the time steps (in minutes), T indicates the simulation run time (one day), N_a indicates the number of arriving trucks at time t, and N_d indicates the number of departing trucks at time t.

$$\begin{aligned} \sum_{t=0}^{T} N_a(t) &= \sum_{t=0}^{T} N_d(t) \\ \sum_{t=0}^{T} N_d(t) - \sum_{t=0}^{T} N_a(t) &= 0 \end{aligned} \tag{B.13}$$

After the day is simulated the truck generator yields hold to ensure that the trucks still in the system, can leave the system. Consequently, a flow conserve of zero is obtained. If this balance check (Equation B.13) is not satisfied, hence the flow conserve is not zero, this indicates that there are still some trucks in the system. The trucks are, for example, still in the server component or in the queue.

To ensure a flow conserve of zero, ergo satisfying Equation B.13, a cool down time is added to the simulation time. During this cool down time trucks that are still in the system, can leave the terminal. The terminal model simulates only one day, in reality, when a truck enters the terminal just before midnight, the truck leaves the terminal the next day (just after midnight). To account for this the cool down time is added in the simulation. With this cool down time, the model satisfies this balance check in Equation B.13, the flow conserve is 0.

Chronological order processes

To verify the model as a whole, the simulation results are analysed for chronological order. Although, the chronological order has been verified for the model components separately, the chronological order of the model as a whole should additionally be checked.

Tracing various trucks throughout the simulation trace allows for checking whether the processes in the model are subsequent to each other and as intended with the model design.

The trucks should first be generated. Subsequently, the trucks should enter the queue. From the queue the server should pick the trucks and hold it for a certain service time. Consequently, the trucks should leave the system after being served.

From observations of the simulation results it becomes clear that no truck leaves the system before entering the queue and being held by the server. Moreover, it is observed that the truck always enters the queue before being served. Moreover, before entering the queue, the truck is generated.

Therefore, from observations of the simulation run, it can be concluded that the chronological order of the model as a whole is correct.

All in all, it can be concluded that the terminal model as a whole is implemented as intended. This is the case for the specific models for each of the terminals, A through D. Consequently. each terminal model is verified.

B.4 MODEL VALIDATION

In the validation the simulation model is reviewed on its capability to provide results that are close to reality. A validated model is necessary as it ensures that the model is able to simulate the real world situation. If not, the model and the results are not very valuable. The approach for validating the model is to compare the simulation results with historic traffic data using a train and a test set of data. The available historic data is the traffic data for arrival and departure obtained from loop detectors in the year 2017 discussed in Appendix A.

As mentioned, the validation of the terminal models is done using a train and a test set. This means that the model is calibrated and the parameters are tuned using a certain data set, the train set. Consequently, the calibrated model is validated by means of a test data set. This test set allows for an unbiased evaluation of the model, hence it allows to validate the model. The test set is independent of the train set. Yet, the test set and train set come from the same probability distribution.

By splitting the historic data set of 2017 traffic data into two parts, the train and test set are created. The train set consists of the traffic data for 11 months of the year 2017. To calibrate the model on the data, the average arrival and departure profile for the 11 months is used. The test set encompasses the remaining month, in this case the month of October. To validate the model the average arrival and departure profile for October is used.

The estimated parameter results for the model calibration on the average profiles for 11 months are displayed in Table B.7. To calibrate the model for the 11 months, the same method is applied as for the entire data set (explained in Section B.2).

Note that these values in Table B.7 are slightly different from the estimated parameter values when the model is calibrated on the entire year (Table B.3). This is because less data is used for the train set, resulting in a slightly different average arrival and departure profile. However, statistical analysis (Section A.1) proves that the months in the year do not differ significantly. Therefore, this slightly different average arrival and departure profile is not significantly different and the validation of the terminal model can proceed.

Table B.7: Overview of estimated parameter values for the calibrated model for 11 months and the corresponding loss

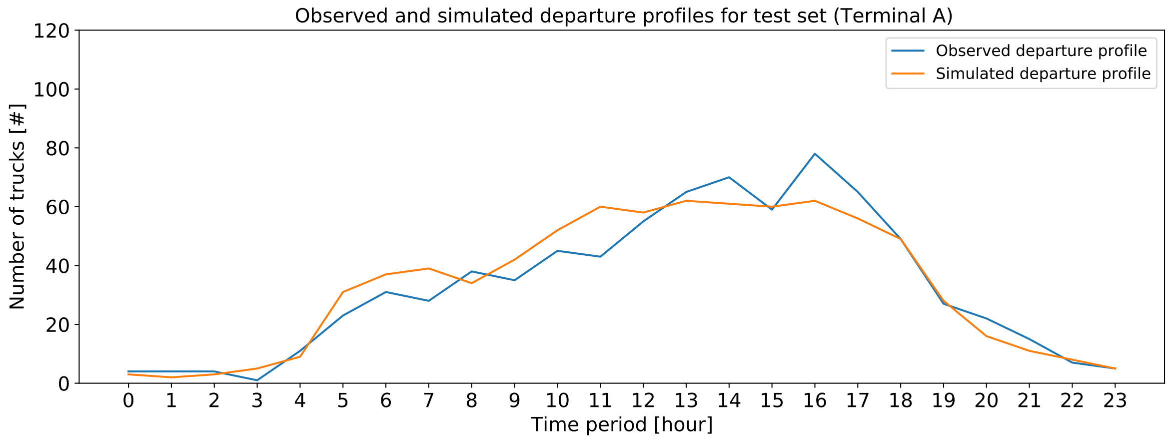
Terminal	**Simultaneous terminal capacity**	**Mean service time**	**Best loss**
Terminal A	20	19	60.938
Terminal B	18	19	34.467
Terminal C	18	11	91.858
Terminal D	14	10	66.10

B.4.1 Visual validation

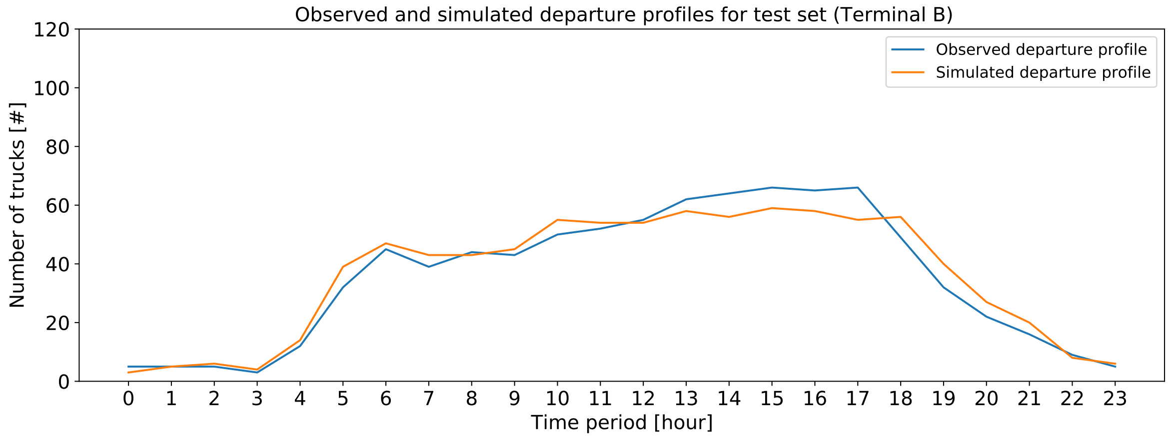
With the terminal model calibrated on the train data set, the arrival profile from the test data set is used as input for validation of the terminal model. The parameters in the model are set to the estimated values in Table B.7 calibrated based on the train data set of 11 months.

The departure profile of the test set of October is used as a measure for validation. The simulated departure profile is determined by the simulation model and parameter settings. In Figure B.4, the observed departure profile in the test data is compared with the simulated departure profile for the test set.

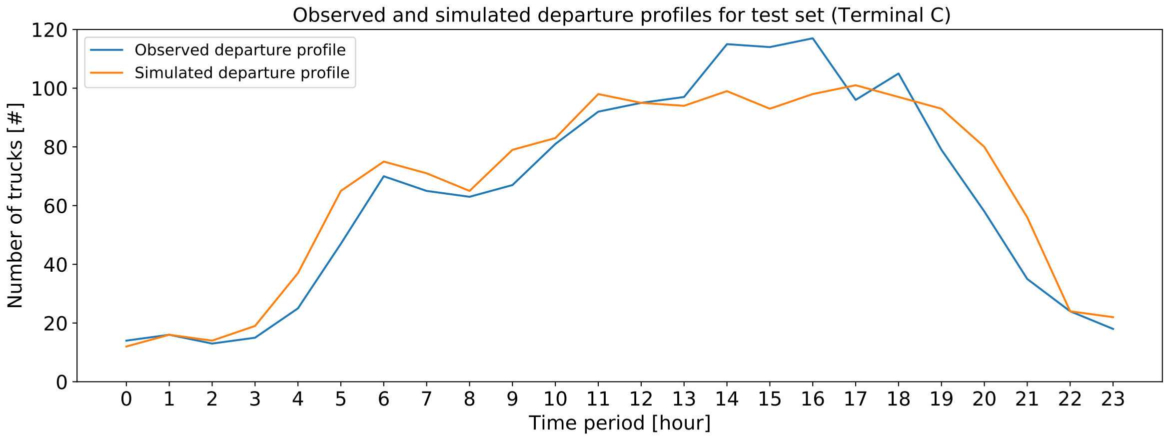
At a first glance, it can be observed that the simulated profiles in Figure B.4 follow a similar trend as the observed profiles. This shows that the simulation model has the potential to simulate close to reality as the simulation output is similar to the actual data. As this visual validation is somewhat subjective judgement, it is valuable for validation purposes to explore this in more detail using quantifiable measures.



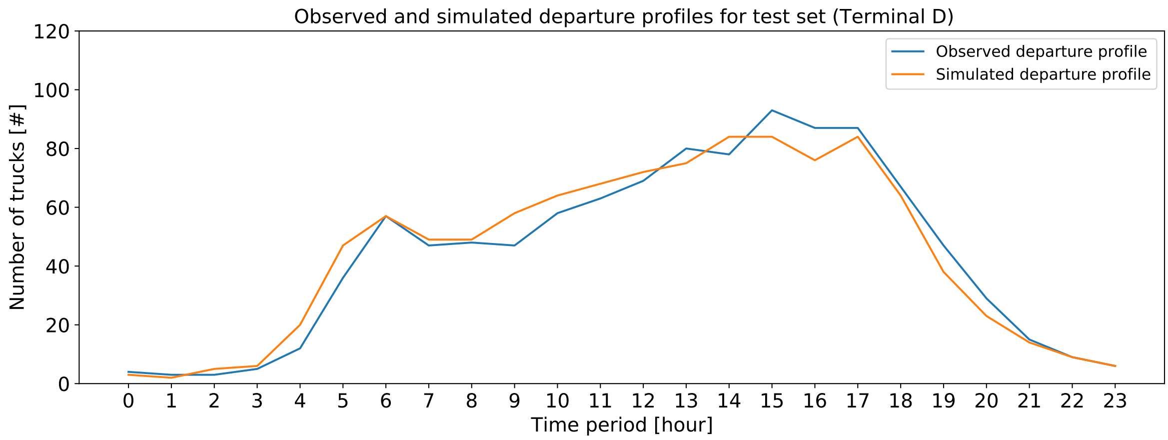
(a) Departure profiles terminal A



(b) Departure profiles terminal B



(c) Departure profiles terminal C



(d) Departure profiles terminal D

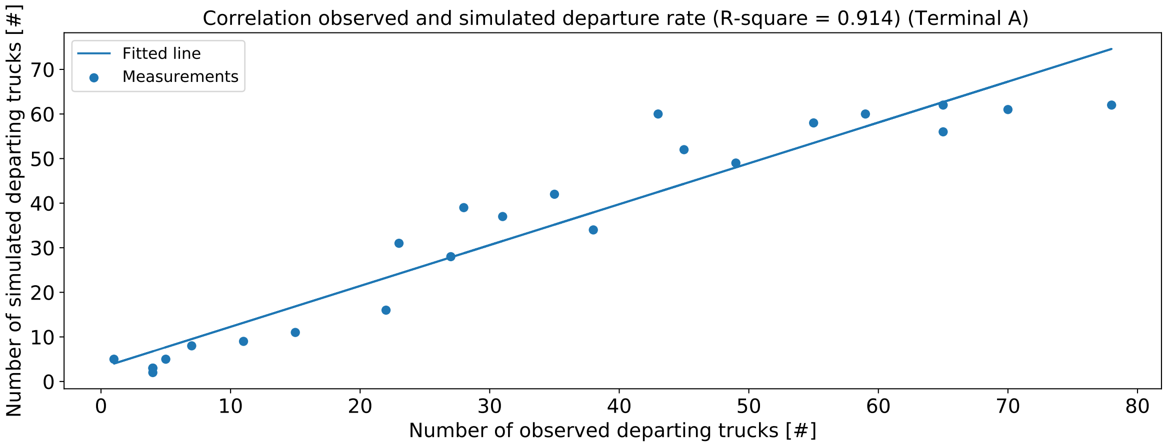
Figure B.4: Observed and simulated departure profiles from the test data set, month of October

B.4.2 Polynomial regression

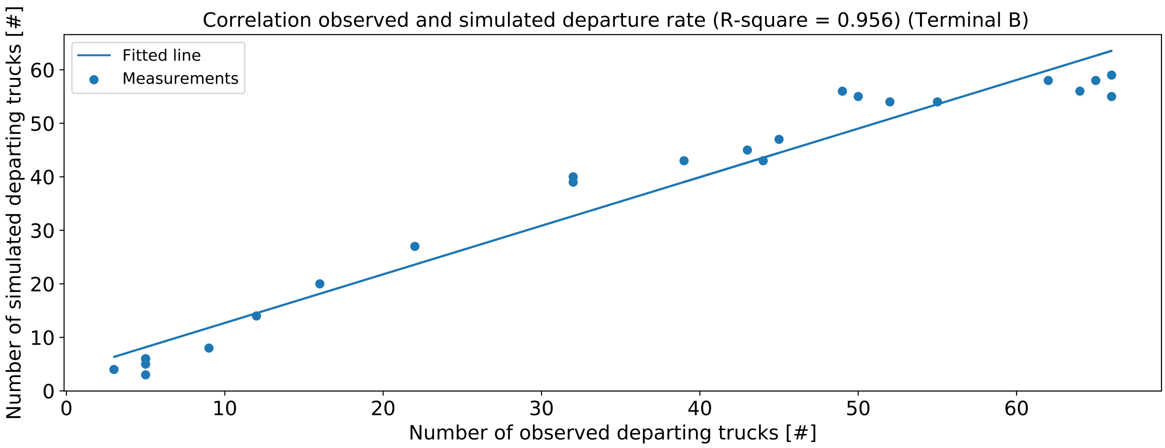
A quantitative method for validation of the terminal model is to analyse the correlation between the observed and simulated departure profiles. This is done with a polynomial regression. Using the R-square as statistical measure, the comparison of the observed and simulated profiles can be expressed. The R-square ranges between 0 and 1, this number indicates the extent to which the simulated data matches the observed data, hence to which extent the simulation model is capable to reflect the reality.

Figure B.5 represents the polynomial regression for the departure profiles at each terminal. There are 24 dots in the graph, each representing the data point for one hourly time slot. The dots indicate the intersect of the observed and simulated departures per hourly time period. Hence, if during a certain time period 21 trucks were observed, and 26 trucks were simulated, the dot is located at the intersect of where the x-axis (observed data) is 21 and the y-axis (simulated data) is 26.

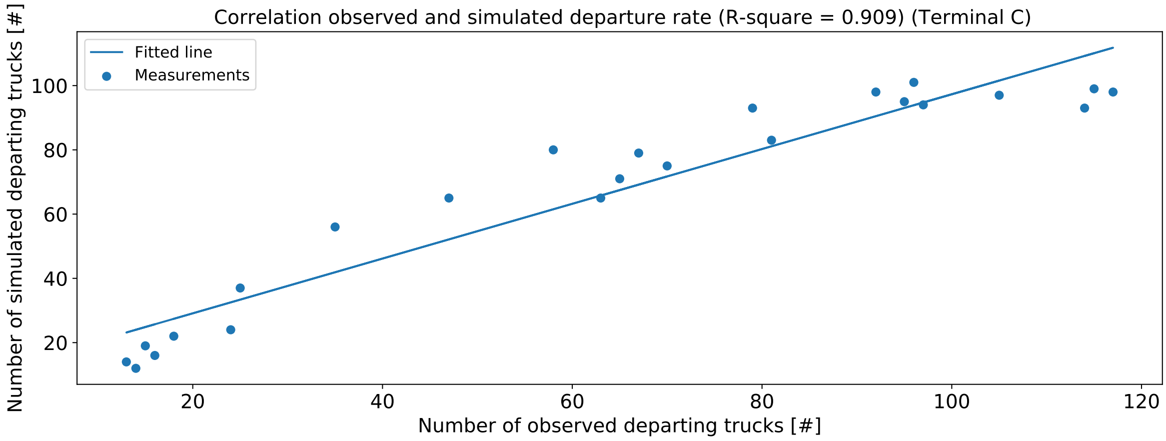
The fitted line indicates the correlation between observed and simulated data. In theory, if the R-square value would be 1, the simulated values would be equal to the observed values for each hourly time period. With a R-square of 1 the dots would always overlap with the fitted regression line.



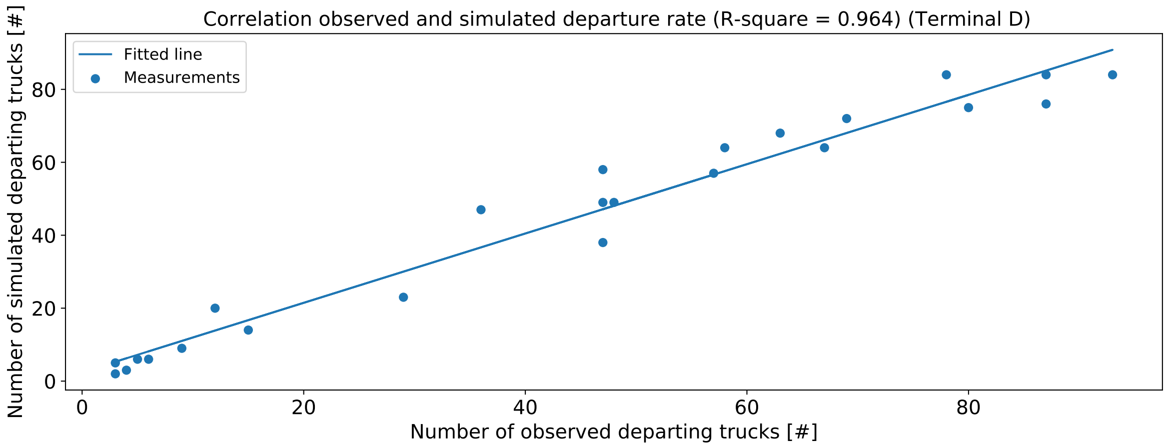
(a) Terminal A



(b) Terminal B



(c) Terminal C



(d) Terminal D

Figure B.5: Correlation between observed and simulated departure profiles from the test data set, for an average working day in the month of October

The R-square value for the departure profiles are depicted in Table B.8. The computed R-square values for the simulated departure profile of the test data are very close to 1. Therefore, it can be concluded that the simulation model has the capability to provide simulation results that are very close to reality.

Table B.8: R-square results for comparing the observed and simulated departure profiles obtained from the test data, using polynomial regression to analyse the correlation between the observed and simulated profiles

Terminal	R-square
Terminal A	0.914
Terminal B	0.956
Terminal C	0.909
Terminal D	0.964

B.4.3 Statistical analysis

The last check for validation of the terminal model is a statistical analysis. Using the two sided t-test, the observed and simulated departure profile from the test data set are compared. In Table B.9 the results of the statistical analysis are shown.

Table B.9: T-test results for comparing the observed and simulated departure profiles of test set data to check for significant differences for several terminals

Terminal	t-value	p-value
Terminal A	-0.055	0.956
Terminal B	-0.059	0.954
Terminal C	-0.273	0.786
Terminal D	-0.033	0.974

All in all, based on the visual validation, polynomial regression and statistical analysis it can be concluded that the terminal model for each terminal is validated using a train and test set.

Consequently, the entire data set, providing an average arrival and departure profile based on 12 months, is used again to obtain results for the base year 2017. For each terminal the estimated parameter values (shown in Table B.3) are set in the model.

B.5 MODEL RESULTS

The simulation model for each terminal is proven to be accurately calibrated, verified and validated. Using the simulation model, various results can be obtained. These results reflect the situation at the terminals in 2017. The results comprehend the simulated arrival and departure profiles, the average turnaround time profile, the average waiting time profile and the average queue length profile along a working day.

Note that these results are based on a yearly working day average. The results presented here do not reflect individual days, extreme outliers of busy days are evened out in the yearly average. Nevertheless, since the model is validated, it is able to reflect an individual day if the estimated parameters are kept constant and the arrival profile for a individual day is used as input.

The presentation of the results is structured on terminal level. Hence, first the results for terminal A are presented, lastly the results for terminal D. The results provide interesting insight in the situation at the terminal.

For each terminal the simulated arrival and departure profiles, the average turnaround time profile, the average waiting time profile and the average queue length profile are depicted in Figure B.6 through Figure B.9. In the subsections below the specific results per terminal can be found. Here some general findings are mentioned.

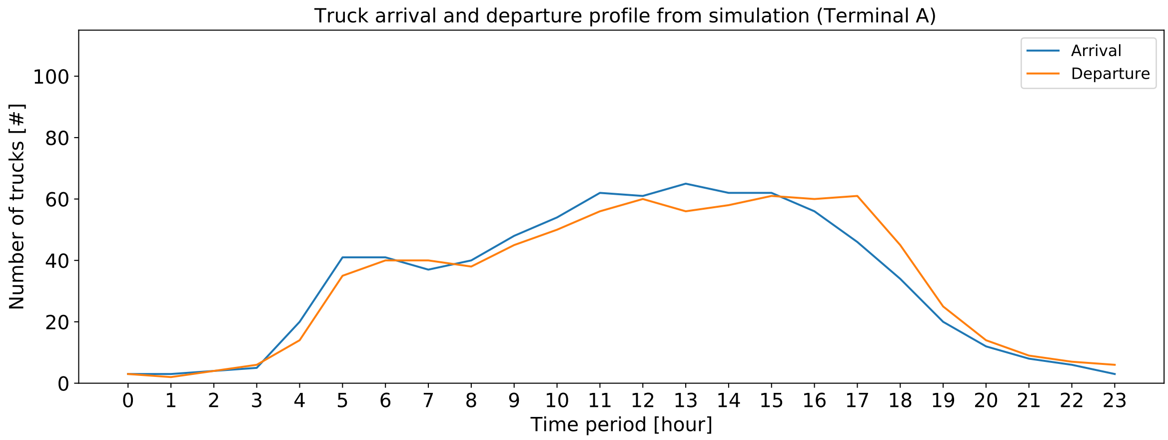
Note that the y-axis is the same for all graphs. This is to allow for easy comparison between the graphs. The y-axis value is chosen based on the most extreme profile among the terminals. However, it might give a distorted image for some graphs as some terminals have a much lower number of truck arrivals on an average working day. Therefore, for terminal A and B, the spread seems more equal along the day in the base case compared to terminals C and D. It can be observed from the graphs for terminal A and B (Figure B.6a, Figure B.7a), that the peak is less extreme. Yet, the spread in the base case is certainly not equal. The relative difference in percentage of truck arrivals between the morning and midday hours is approximately 75% and 50% increase of trucks for terminal A and B, respectively. For terminal C and D the difference between morning and midday is 100% and 80% increase, respectively.

From Figure B.6a, Figure B.7a, Figure B.8a, and Figure B.9a it can be observed what the arrival and departure profile per terminal is. The difference between the arrival and departure profile indicates longer turnaround times. Longer turnaround time are mostly caused by waiting time. Consequently, it can be observed that around the hours where the offset is larger, higher waiting time arise.

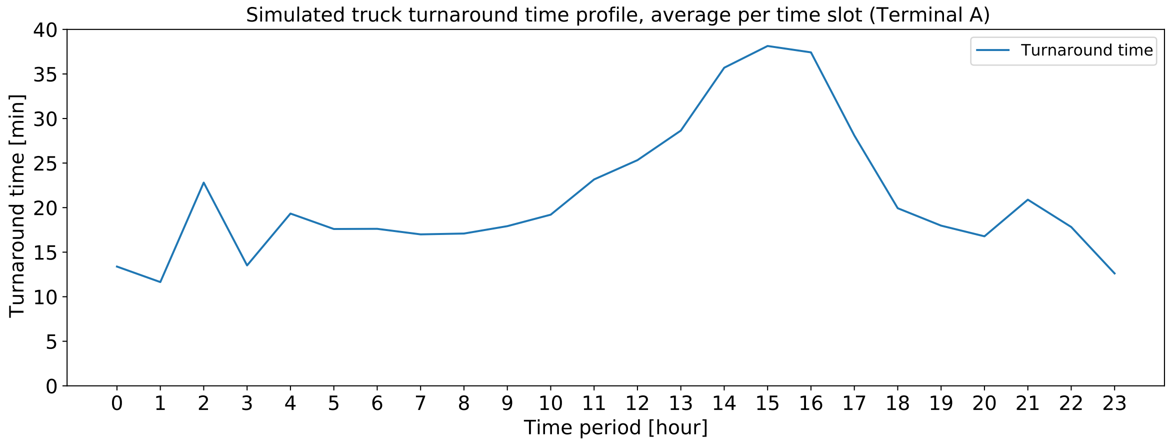
The turnaround time profile, depicted in Figure B.6b, Figure B.7b, Figure B.8b, and Figure B.9b, represents the average service time profile plus the waiting time profile. The turnaround profile represents the average turnaround time for one truck in each hour. This turnaround time profile indicates that trucks have a rather short time spent in the terminal during low peak hours.

From Figure B.6c, Figure B.7c, Figure B.8c, and Figure B.9c it can be concluded that waiting time is indeed experienced on a daily basis. The waiting time profile represents the average waiting time for one truck in each hour. This sustains that there is a misalignment issue at the terminals in the Rotterdam area and the hinterland. This waiting time profile is an average, for individual days the waiting time may be much higher or lower. Striking is that the waiting time at all terminals develop after the morning hours.

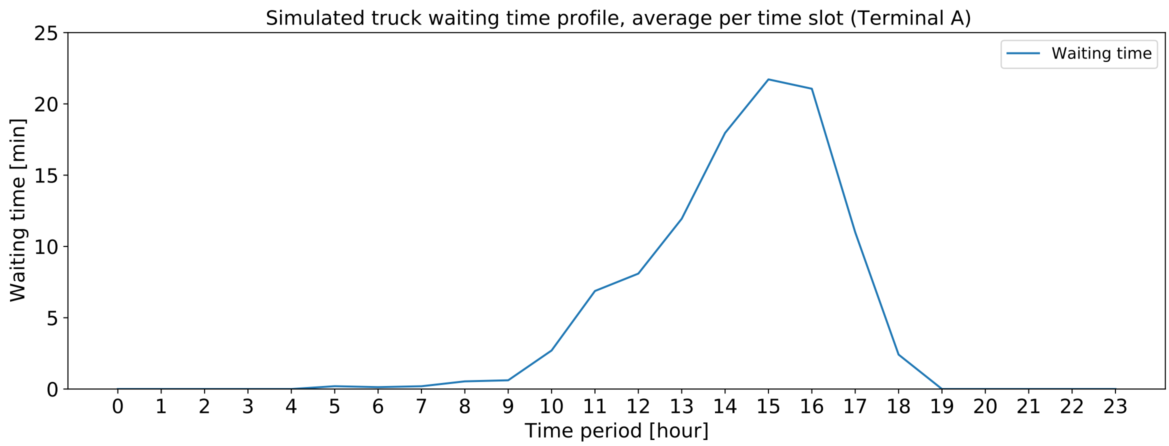
In Figure B.6d, Figure B.7d, Figure B.8d, and Figure B.9d the development of a queue at the terminal gates during the days is shown. The development of the queue follows a similar pattern as the waiting time profile. It can be observed that a queue arises in the late morning hours. Subsequently, the queue grows until the late afternoon hours. Around 17:00 the queue decreases at rapid pace. This is expected as this hour is close to the end of the daily operating hours of hinterland warehouses. Even though it is expected, it is very valuable to see that this is reflected by the simulation model. This sustains the analysis of the misalignment issue between the port and its hinterland (Chapter 2).



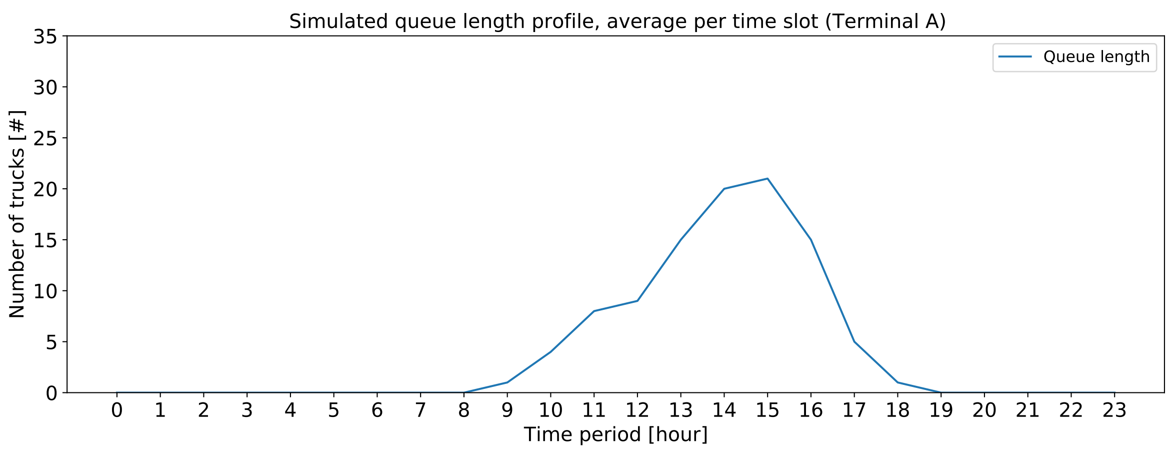
(a) Simulated average arrival and departure profile



(b) Turnaround time profile, averaged per hour

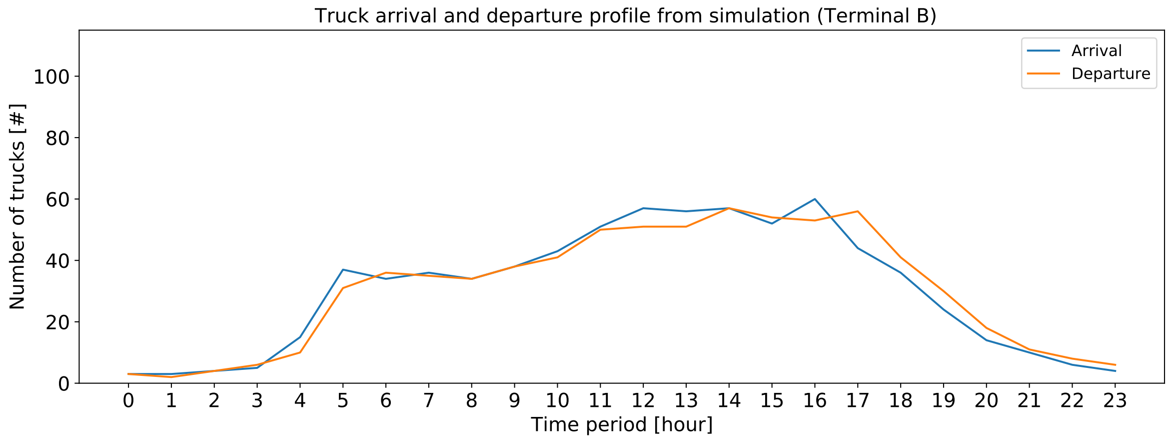


(c) Waiting time profile, averaged per hour

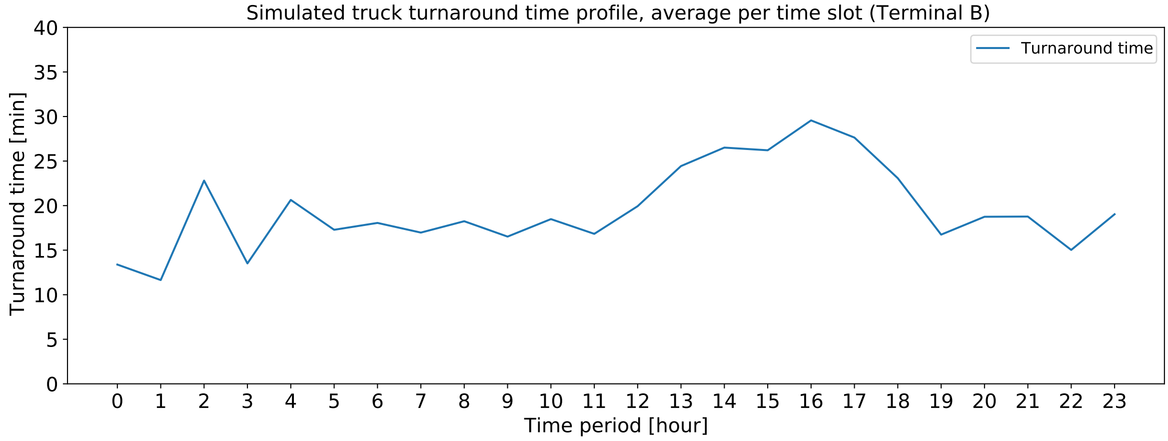


(d) Queue length profile, averaged per hour

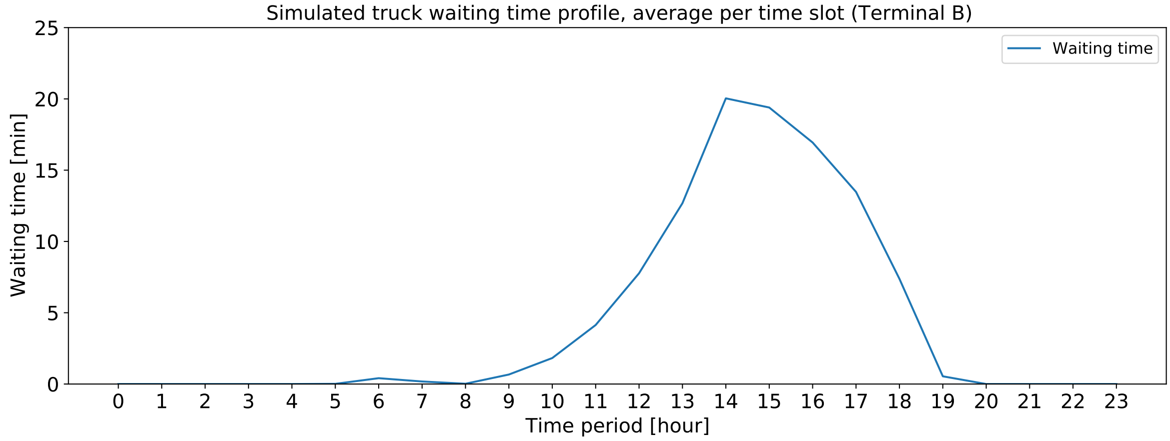
Figure B.6: Results obtained from the simulation model for terminal A



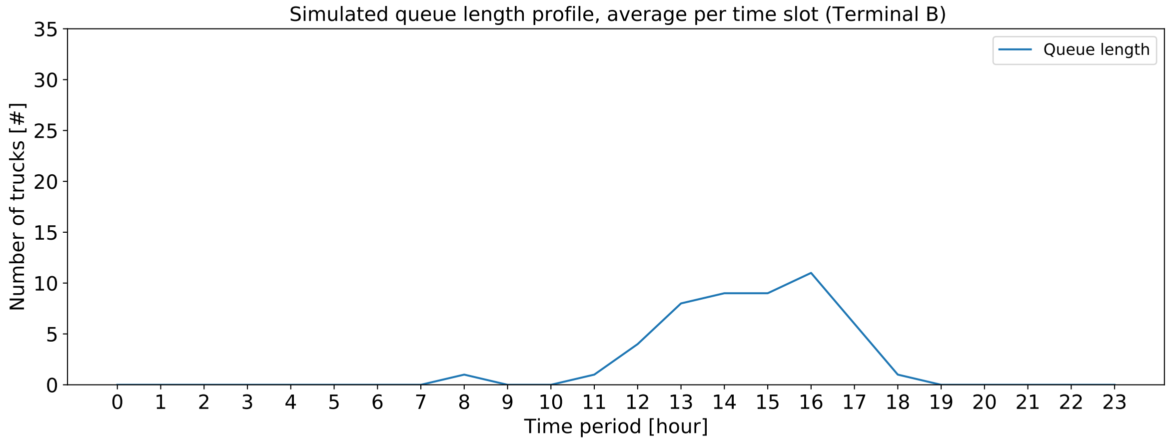
(a) Simulated average arrival and departure profile



(b) Turnaround time profile, averaged per hour

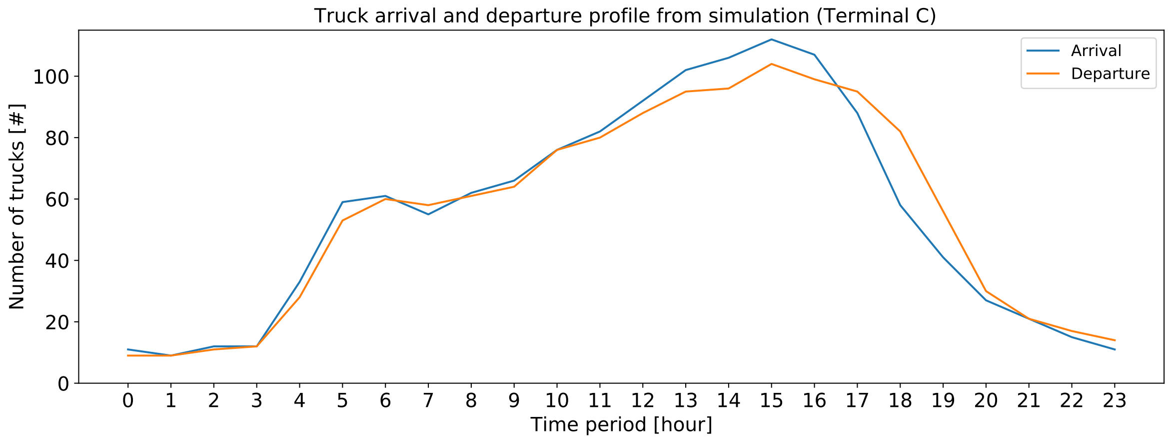


(c) Waiting time profile, averaged per hour

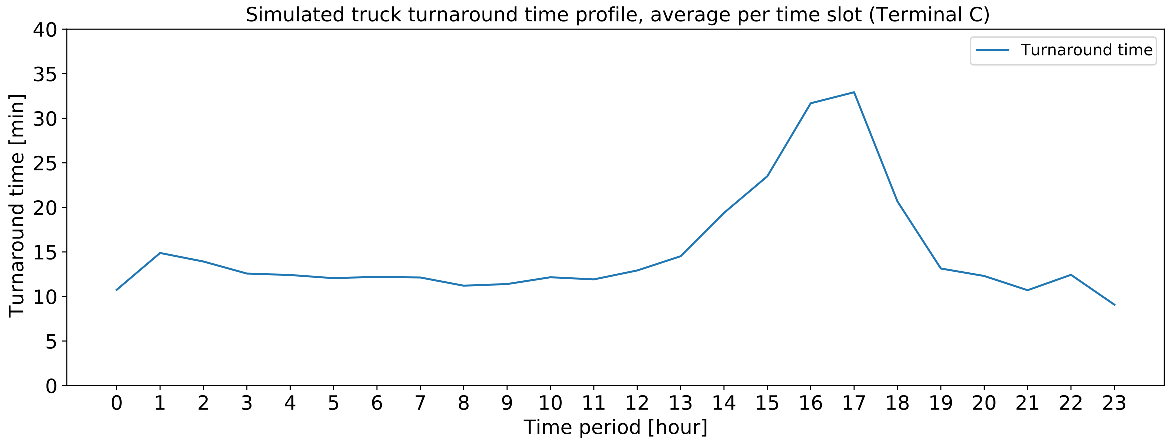


(d) Queue length profile, averaged per hour

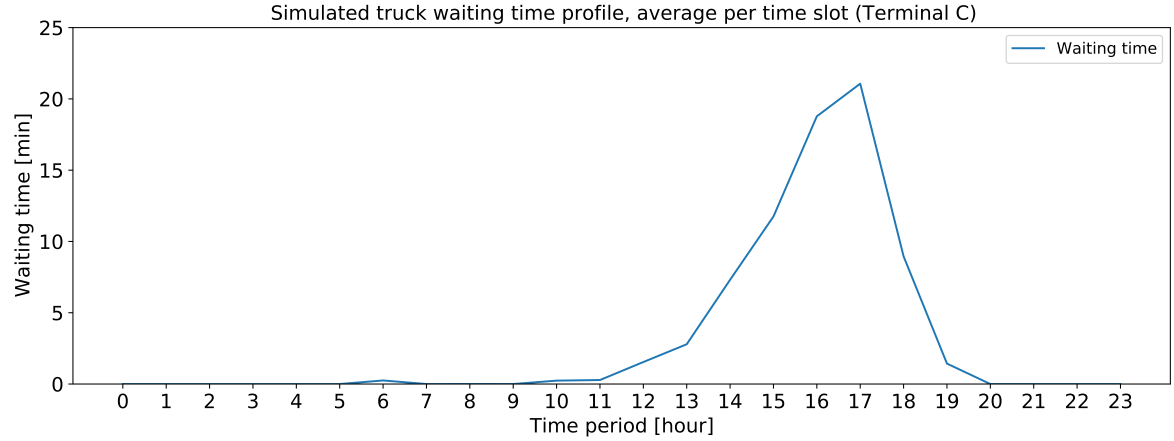
Figure B.7: Results obtained from the simulation model for terminal B



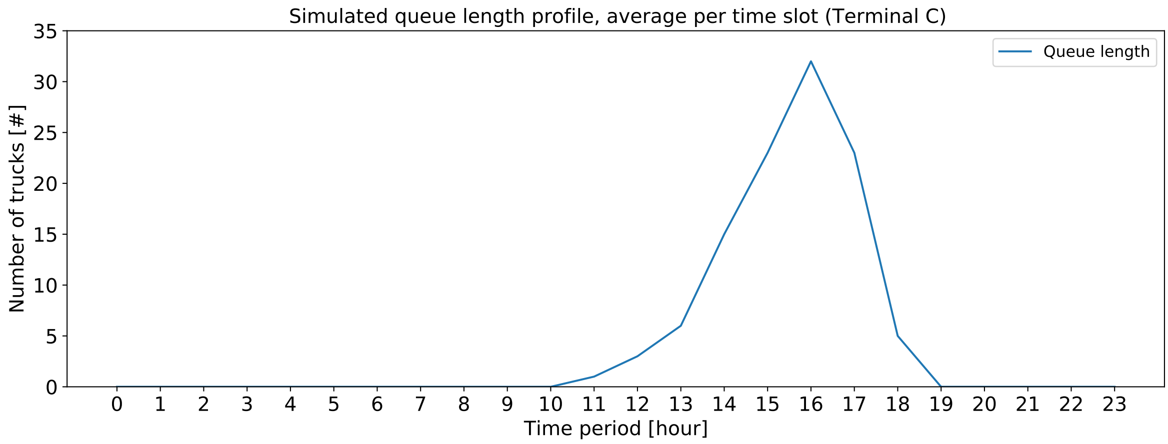
(a) Simulated average arrival and departure profile



(b) Turnaround time profile, averaged per hour

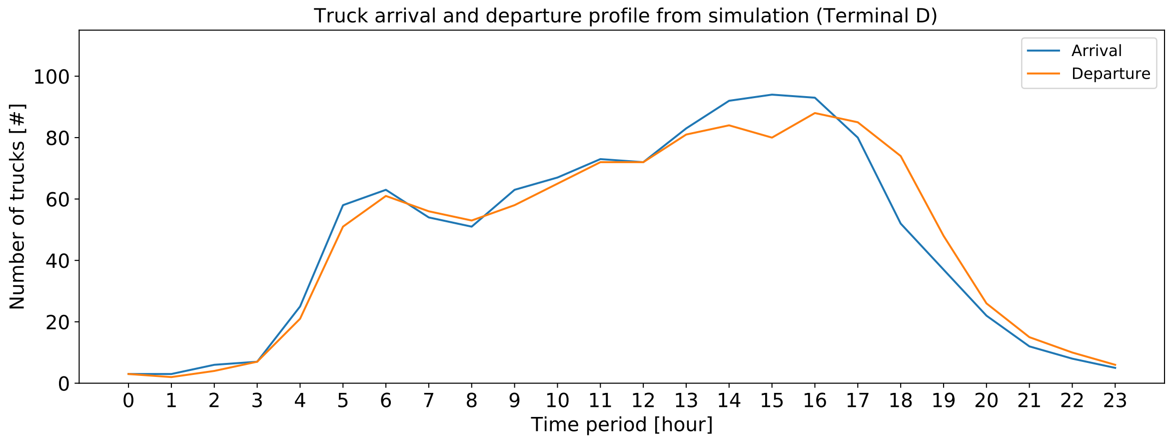


(c) Waiting time profile, averaged per hour

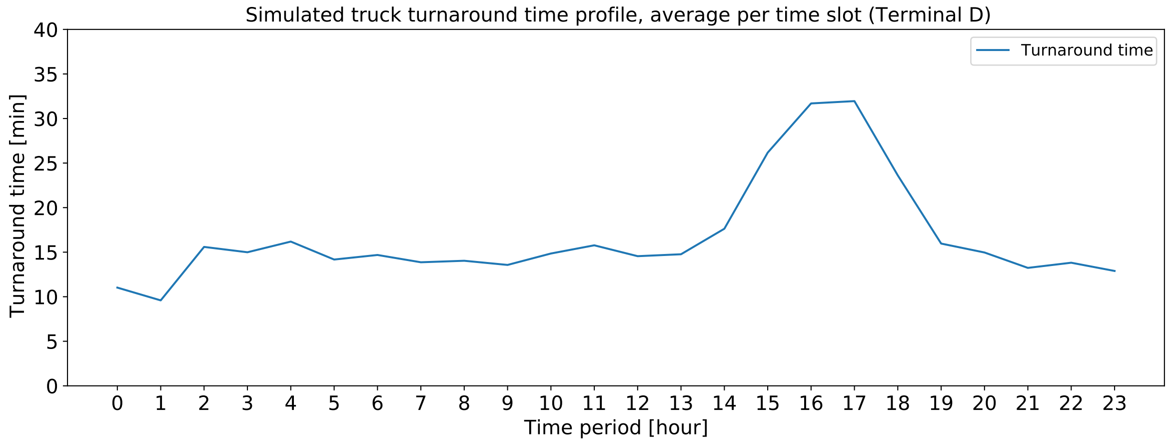


(d) Queue length profile, averaged per hour

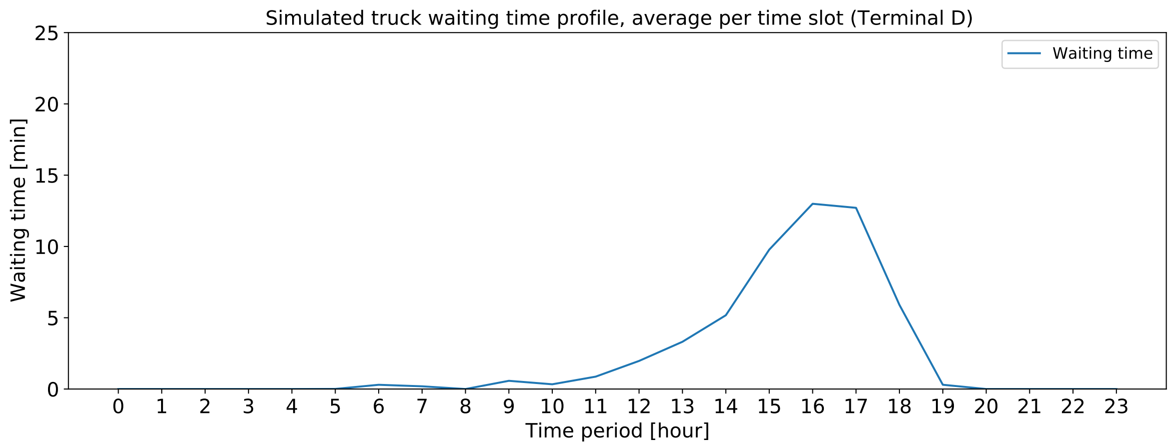
Figure B.8: Results obtained from the simulation model for terminal C



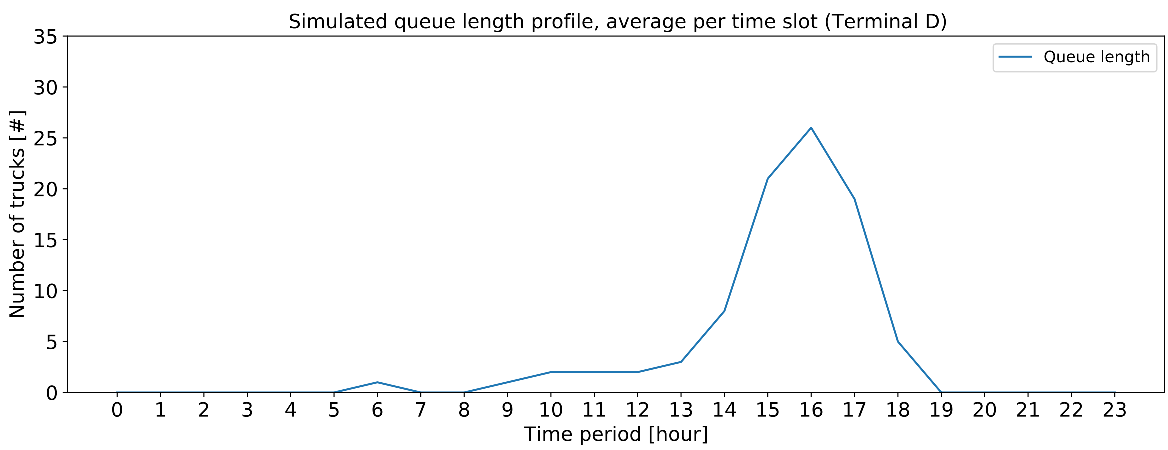
(a) Simulated average arrival and departure profile



(b) Turnaround time profile, averaged per hour



(c) Waiting time profile, averaged per hour



(d) Queue length profile, averaged per hour

Figure B.9: Results obtained from the simulation model for terminal D

C LOGISTIC DATA

In this research logistic data is used to gain insight in the container pick up time preferences of TOC, hence the preferred arrival time at the terminal. The logistic data that is explored in this appendix is historical data collected from Portbase, the port community system at the port of Rotterdam. The logistic data is from the same year, thus 2017, as the traffic data (Appendix A). This way a relation between the data is ensured.

The logistic data is the data from all import containers (>1M transported via road) in the year 2017. The findings from this data analysis are used as an input for the choice model.

The data set contains information of transaction data on arrival of container vessels, containers discharges and the estimated pick up time of these containers by hinterland transport trucks. Moreover, the data set includes container characteristics (type, dimensions, weight, and temperature) and information about the transported commodity. Lastly, the containers in the data set are transported through the same four container terminals as the terminals of which the traffic data is obtained. Again, the terminals are labeled A through D, each terminal corresponds to the same label as in the analysis of traffic data in Appendix A.

For each import container information about the ETA of the TOC to pick up the container, is provided. This estimated time of container pick up is considered to be the preference of a TOC. Two of the four analysed terminals at MVII, operate based on a time slot management policy. The ETA for container pick up by the TOC at these two terminals is directly the reservation of that time slot. Therefore, the ETA at the terminals with time slot management is quite reliable to be the definitive arrival time as there are consequences for the TOC if the reserved time slot is missed.

For the other terminals operating based on an open door policy, ergo without time slot management, the ETA for container pick up by the TOC is an approximation. There will be no consequences if the ETA is not met by the TOC. As a result, the ETA for container pick up at the terminals with an open door policy, may be less reliable to be the actual time of arrival. Nevertheless, the ETA can provide insight into the preference of the TOC. Therefore, these terminals are kept in the analysis.

Furthermore, the majority of the data in the data set is generated manually as the TOC fill in a form with the container characteristics, commodities and estimated time of container pick up. Hence, to prepare the data for model specification and parameter estimation, the data set requires preprocessing.

C.1 DATA PRE-PROCESSING

Some of the pre-processing steps are filtering, regrouping, categorising, column splitting, or renaming. These techniques are applied to the mode of transport, vessel arrival information, container discharge information, terminal information, and the hinterland arrival information (the ETA) attributes in the data set. Additionally, similar to the traffic data, containers with an ETA on a weekend day, Saturday or Sunday, are excluded from the logistic data set.

Other pre-processing steps are more advanced and might have an impact on the eventual outcome of the research. Therefore, the choices and assumptions made in these influential pre-processing steps are described in more detail.

In the original data, a peak of estimated pick up time at 0:00 and 12:00 can be observed, see Figure C.1. Especially for terminal A and D, which are the open door policy terminals, indicated by the green and yellow lines respectively. However, these peaks do not reflect the reality. If no value for estimated pick up time is specified by the TOC, the system automatically logs 0:00 or 12:00 as default value. This is an issue that mostly occurs for containers that are picked up at a terminal with an open door policy. As the estimated pick up time of a container is the reservation for a time slot at the terminals with a time slot management policy, the default settings occurs less at these terminals.

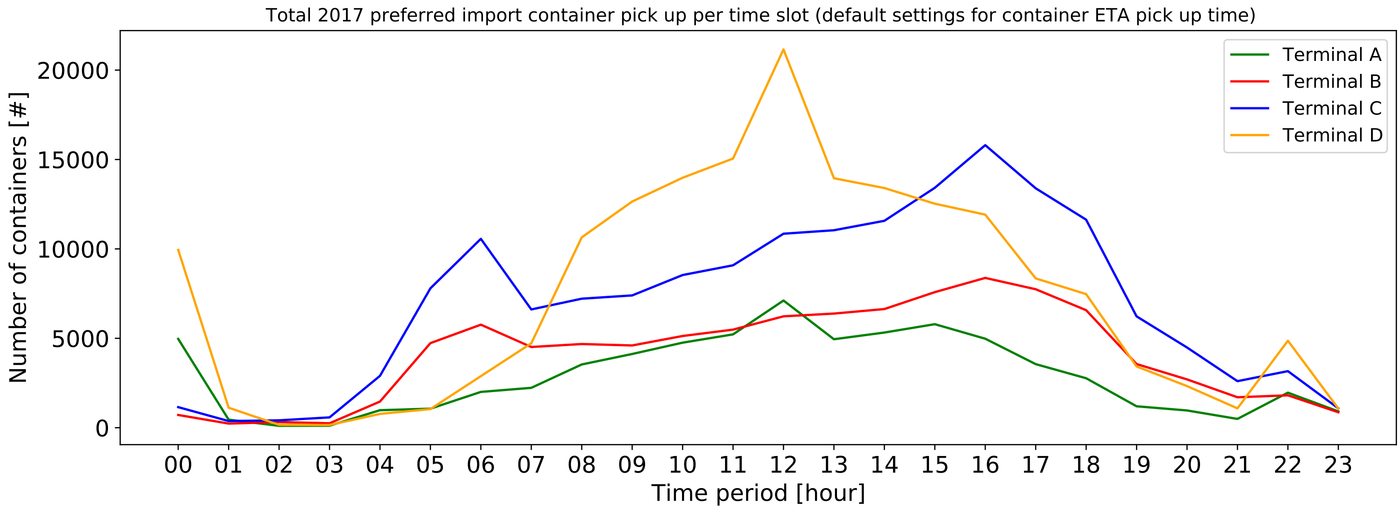


Figure C.1: Total of import containers in 2017 distribution profile along the day based on the ETA of the TOC for the four terminals, before data pre-processing

Monte Carlo simulation is used to properly distribute the containers, that are logged at 0:00 and 12:00 by default, along the day. Yet, there are also containers that are correctly assigned to 0:00 and 12:00. It is expected that the container pick up frequencies at 0:00 and 12:00 are in reality similar to the surrounding hours. Therefore, the share of correctly assigned containers to 0:00 and 12:00 is calculated based on the surrounding hours. The surplus of containers, causing the peaks, at 0:00 and 12:00 is distributed along the other time slots using Monte Carlo simulation. This provides a smoothed graph of import containers along the day based on the ETA of the TOC.

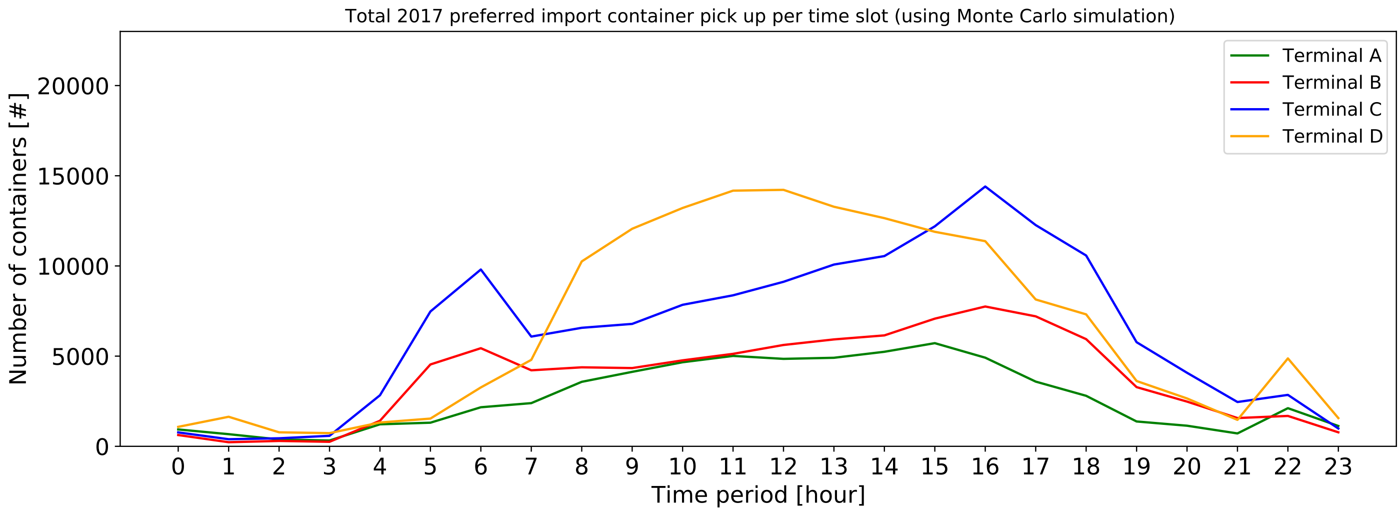


Figure C.2: Total of import containers in 2017 distribution profile along the day based on the ETA of the TOC for the four terminals, after Monte Carlo simulation

Since much of the logistic data is generated manually, several mistakes can be found in the data. For example, non existing container types. In the original data, 21 types of containers are reported, however, 97.1% of all containers in the data is captured by only four container types. These four container types are general purpose containers, reefer containers, chemical containers, and tank containers. The other 17 reported container types are unknown as these are not in the list of ISO type containers, which is a globally used standard for identification of shipping containers [Parsons

Containers, nd]. As these non existing types capture 2.9% of the containers spread over 17 types, these containers are excluded from the logistic data set.

A similar issue occurs with the reported container dimensions. Container dimensions are also standardised with the ISO type [Parsons Containers, nd]. However, because this data is entered manually by the TOC, mistakes are made. The dimension code of a container consists of two digits, the first digit indicates the container length, the second the container height. The ISO code standards have four options for length, and two options for height:

Length: 2 = 20ft, 4 = 40 ft, L = 45ft, M = 48 ft

Height: 2 = 8 ft/6 inches, 5 = 9 ft/6 inches high cube

However, in the original data 6 types of length and 14 types of height are reported. The non existing container dimension codes capture only 0.8% of the containers in the data set. Therefore, these are excluded.

Moreover, there is no container with a reported length of $48ft$ in the data. The remaining containers are are categorised in two types of lengths, namely $20ft$ and $40/45ft$. This is done because many errors are found in the report of the container dimensions. This makes it impossible to distinguish whether a $40ft$ or $45ft$ container is meant. Since there is no difference in number of trucks required to transport a $40ft$ and $45ft$ containers, these are combined into one category. Between $20ft$ and $40/45ft$ containers there is some difference in terms of trucks required for transportation. One truck can transport two or three $20ft$ containers, whilst it can not transport more than one $40/45ft$ container.

The commodities transported in the containers are also captured in the data set. These commodities are indicated by the NSTR code, a standard goods classification in transport of goods [Eurostat, nd]. This is a two digit code, ranging from 00 to 99, thus 100 options. The first digit is the higher level overlapping category, the second digit provides more detail. The commodity type codes are aggregated to the higher level overlapping category, hence category 0 to 9.

0: Agricultural products and live animals, 1: Other food products and animal feed, 2: Solid mineral fuels, 3: Petroleum oils and petroleum products, 4: Ores, metal waste, roasted iron picks, 5: Iron, steel and non-ferrous metals (incl. Semi-finished products), 6: Raw minerals and products; construction materials, 7: Fertilizers, 8: Chemical products, 9: Miscellaneous

For some containers no commodity type is reported. These are not excluded from the data as this corresponds to 36.45% of all data. Therefore these are categorised in an $11th$ category.

10: Unknown commodity.

For a number of containers in the data, a container temperature setting is reported. These temperatures are mainly in Celsius, however, some containers have a temperature setting reported in Fahrenheit.

To divide the containers in temperature categories, the temperature settings in Fahrenheit are transformed to Celsius. The categories for temperature are below 0 degrees, between 0 and 3 degrees, between 3 and 8 degrees, and above 8 degrees. Not every container has a temperature setting, these containers are categorised in the category 'no temperature settings'.

Each container has a certain weight. In general, the weight of a container is between 2000 kg (empty) and 35.000 kg (full). In the logistic data set, some container weight values are much higher. By plotting the containers in an histogram (Figure C.3), with the weights ranging from 0 kg to 100.000, it can be observed that the vast majority of containers ranges between 0 kg and 35.000 kg. This is in line with the expectation. Consequently, containers with a weight over 35.000 kg are excluded from the data set. This corresponds to 0.25% of the containers in the data.

Thereafter, the containers are categorised in five categories. The categories are formulated based on four quantiles, $q = 20\%$, $q = 40\%$, $q = 60\%$, $q = 80\%$. The resulting categories for container weight are below 5528 kg, between 5528 kg and 10.521 kg, between 10.521 kg and 17.912 kg, between 17.912 kg and 22.2264 kg, and above 22.2264 kg.

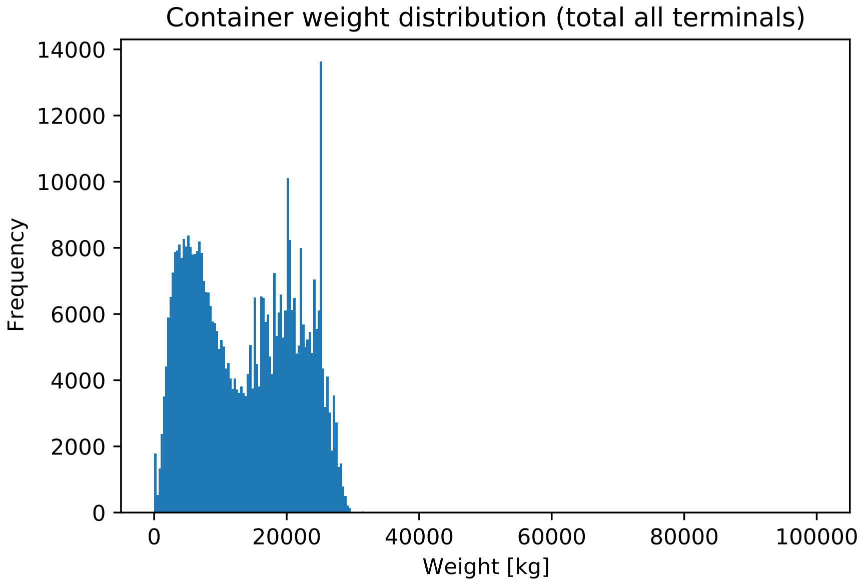


Figure C.3: Weight distribution for the total of import containers in 2017

Other interesting logistic data is the call size the specific containers are part of. The call size is not in the data set. However, the call size can be calculated based on the deep sea reference number and deep sea arrival time attributes in the data. The number of containers with the same deep sea reference number and deep sea arrival time are counted, resulting in the call sizes. To categorise the containers in call sizes, the containers are distributed based on their call size (Figure C.4).

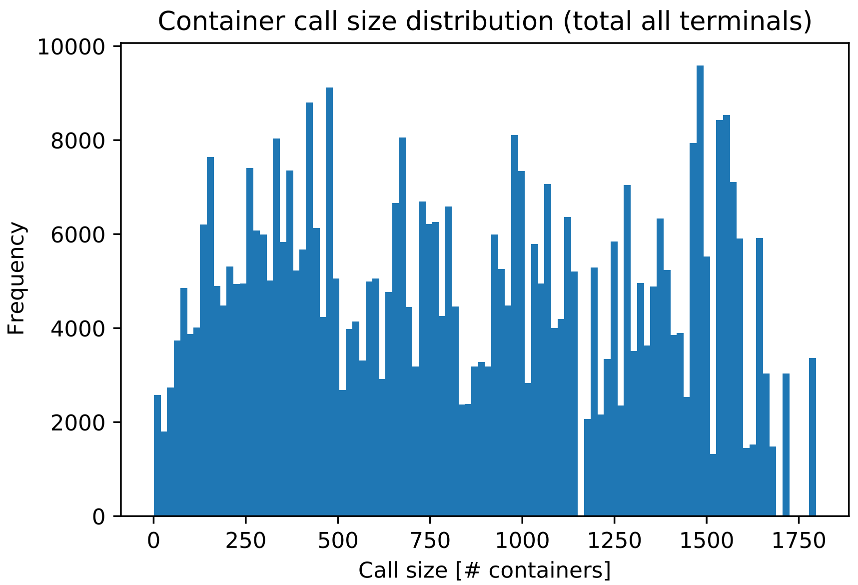


Figure C.4: Call size distribution for the total of import containers in 2017

The call size categories are formulated the same way as the weight categories, using four quantiles ($q = 20\%$, $q = 40\%$, $q = 60\%$, $q = 80\%$). This results in 5 categories, namely smaller than 322, between 322 and 567, between 567 and 900, between 900 and 1250 and larger than 1250. The unit of call size is number of containers.

Furthermore, the time slots for pick up ETA are categorised in four time periods. This ensures more accurate results (see next section Section C.2) and saves a lot of computational time for the choice model. The use of time periods instead of time slots will not deteriorate the value of the choice model. The time periods are formulated as night (from 21:00 until 3:00), morning (from 4:00 until 9:00), midday (from 10:00 until 14:00), and afternoon (from 15:00 until 20:00). These periods are based on observed arrival patterns and categories used in practice at the terminals.

From the terminal model (Appendix B), waiting time profiles for each terminal for the year 2017 are obtained. The traffic and logistic data is combined by incorporating the waiting time profiles for each terminal in the logistic data. There are two ways to link the waiting time and containers.

The first approach is to match the container ETA with the average waiting time in the hour corresponding to the ETA of the container. Note that each terminal has a specific waiting time profile. Hence, for matching waiting time and container, the corresponding terminal should be taken into account. This provides insight in the waiting time that is encountered on average at the terminal and ETA of pick up for the container.

The second approach is to link a random waiting time from each time period (night, morning, midday, and afternoon) to the container. This can provide insight in the impact of waiting time in other time periods on the preferred pick up time of a container by the TOC (the ETA). Note that in this approach, the corresponding terminal should also be accounted for.

The first approach provides insight solely in the waiting time in the specific ETA and the effect on TOC. The second approach provides insight in the effect of waiting time along the entire day on the TOC preference for pick up time. Therefore, the second approach is applied to gain more insight in the effect of waiting time along the day for pick up time preference.

All in all, after pre-processing the data, 8.3% of the containers in the original data set is excluded from the logistic data due to faulty data. Other initially faulty data is processed in such a way the data becomes useful. For example, distributing the default logged containers along the day with Monte Carlo simulation. Some additional data, call sizes and waiting time, is computed or added to the logistic data to gain more insight in the data. Lastly, most attributes in the logistic data are transformed to categorical values, except for the waiting time.

C.2 DATA ANALYSIS

To gain insight in the situation at each of the terminals, the pre-processed logistic data is analysed. Analysing the data increases the value of the data for the research. Additionally, analysing the data before developing the choice model allows to estimate the choice model on very specific data. This leads to more reliable results as the logistic data might be correlated.

Several graphs are created from the logistic data. This helps to get a feeling for what kind of containers are preferred for pick up at a certain time slot at the four terminals. The graphs contain information about the distribution of containers and pick up preferences along the day based on the day of the week (Section C.4.1), container type category (Section C.4.2), length category (Section C.4.3), commodity type category (Section C.4.4), temperature category (Section C.4.5), weight category (Section C.4.6), call size category (Section C.4.7).

To keep a clear structure in this appendix, the graphs can be found in Section C.4. The sequence the graphs are shown in Section C.4 is the day of the week, container type category, length category, commodity type category, temperature category, weight category, call size category. For each data attribute, the order of the terminals is from A through D. Each figure in Section C.4 consists of two sub figures. The first sub figure is the distribution of the containers in absolute numbers. The second sub figure provides insight in the proportional share of the specific data attribute in the figure per time slot. Findings from analysis of the logistic data are discussed in this section. If necessary, a references is made to the specific graph.

C.2.1 Analysis

A finding from the logistic data is that, similar to the traffic data, peaks can be observed in the early morning and late afternoon at the terminals. Additionally, it can be observed that for the terminals with a time slot management policy, the containers are spread over more time slots than the containers at the terminals with an open door policy.

This can be explained by the fact that at the time slot policy terminals, the pick up ETA is directly the reservation for a time slot. Since each time slot has a certain quota for the number of reservations of a time slot, the TOC are limited in reporting the ETA at the time slot policy terminals. This leads to a wider spread of preferred container pick ups compared to the terminals with an open door policy. For the terminals with an open door policy, the preferred pick up times are more concentrated between 8:00 and 17:00. This preference for ETA between 8:00 and 17:00 can be explained as these time slots are in line with the operating hours of the hinterland warehouses. This indicates that during these hours, there is more demand (arriving trucks for container pick up) than supply (terminal capacity) in these hours. This can result in waiting time at the terminals.

From the statistical analysis in Appendix A, it was concluded that the arrival profile of trucks is not significantly different between days of the work week. The graphs in Section C.4.1, sustain this finding. It can be observed that the proportional share of preferred container pick up of each time slot is rather equal for each working day.

An important finding from the logistical data analysis is that the terminals differ much from each other considering container types (Section C.4.2). For example, terminal A handles much higher shares of reefer containers compared to the other terminals (Figure C.9). Moreover, the shares of specific containers types differ along the day. This indicates that there might be a relation between the pick up time preference and the type of container that requires pick up.

From the graphs in Section C.4.3, it can be concluded that each of the terminals handles more $40/45ft$ containers compared to $20ft$ containers. However, the exact ratio between $40/45ft$ and $20ft$ containers differs among the terminals. This ratio is valuable insight since the $40/45ft$ containers result in more truck arrivals at the terminals compared to the $20ft$ containers. Furthermore, it is notable that the proportional shares of container length categories are rather equal for each time slot and for each terminal. This could indicate that the container length does not influence the pick up time preference.

As mentioned in the data pre-processing section (Section C.1), many of the containers are reported without a commodity type. These are categorised into an unknown commodity category. The share of unknown commodities differs among the terminals. Some terminals handle much more unknown commodities than others. For these terminals the unknown commodity is excluded from the proportional graph to provide insight in the other commodity types, since these are much lower and become invisible if the unknown category is included (Figure C.17 and Figure C.18).

The commodity type categories spread along the day in Section C.4.4 shows that the ratios of commodity type handled differ per time slot and per terminal. This shows that the terminals are a bit different from each other considering the commodity types that are handled per terminal. Even though the difference in ratio of commodity types along the day is not extreme, it could indicate that TOC have a pick up time preference for certain commodity types.

It might be expected that the temperature setting of a container could influence the pick up time preference. For example, perishable products are often transported in a container with temperature settings above 0 degrees to keep the products fresh. As most containers have no temperature settings, this category is excluded from the proportional graph to provide insight in the other temperature categories, since these are much lower and become invisible if the no temperature setting category is included (Section C.4.5). It can be concluded that the share of containers with temperature settings are much higher in some of the time slots compared to the other time slots. For example, terminal B has a much higher share of containers with temperature settings around $4:00$ and $5:00$ (Figure C.22). These kind of peaks are also visible for the other terminals, nevertheless it differs per terminal at which time slot the peak arises. This could indicate that the TOC are influenced by the temperature of the container for pick up time preference.

Naturally, it is expected that the proportional shares of container weight categories and call size categories are rather equal since these categories are formulated based on quantiles. Nevertheless, these categories are made based on the handled containers in the entire port area. Therefore, there are some striking results observed from the graphs in Section C.4.6 and Section C.4.7 when these data attributes are analysed per terminal. For example, some of the terminals do not handle certain weights or call sizes.

Moreover, in the analysis of the logistical data, the attributes in the data set are checked for correlations to ensure that there is no multicollinearity in the data. The container type and temperature settings category are found to be correlated with a factor 0.64. This is expected because general purpose containers do not have temperature settings, and reefer, chemical and tank containers do have temperature settings. For other attributes in the data set, the correlation check is not as insightful as for the temperature settings category attribute.

Nearly all attributes are categorical and the relations between the attributes and the time slot are non linear. Therefore, a correlation matrix and collinearity analysis are not best suited to analyse the relation, dependence and influence of the attributes on the pick up time preference of a TOC. Therefore, a machine learning technique named random forest is used [Koehrsen, 2017]. This method aims to predict the preferred time slot for container pick up, based on the attributes in the data set. As a result the importance of certain attributes for the prediction is indicated. The output of the method is a list of important attributes to predict the dependent attribute, in this case the time slot ETA. Based on this list some attributes that are not important for predicting the time slot can be excluded because these will not explain trucking behaviour.

Two striking insights are obtained from the machine learning technique. First of all, it was found that container type and commodity category are important features in the data set to predict the preferred pick up time. The container weight and call size do not influence the pick up preference much. An explanation for this could be the approach taken in formulating the categories. Additionally, it was found that the model is not very accurate in predicting the correct preferred pick up time in hours. The accuracy of the model is only 11.4% if the pick up time is in hours. This accuracy increases to 38.8% when the pick up time is categorised in four periods instead of hourly slots. Even though, 38.8% accuracy is not very high, it is still better than 11.4% accuracy that corresponds with the hourly time slots. Moreover, the aim of the logistic data and choice model is not to perfectly predict pick up times. The aim is to obtain an understanding of which factors influence the preference for a container pick up time. Consequently, to obtain better results from the choice model, the pick up time preference is divided in four time periods. These time periods are night, morning, midday, and afternoon, as mentioned in Section C.1.

C.2.2 Conclusion

The mathematical model that is specified for the choice model based on the logistic data, contains several attributes. In discrete choice modelling there are two types of attributes, namely dependent and independent attributes. A dependent, or endogenous, attribute is the choice attribute, in this research that is the preferred time period for container pick up. An independent, or exogenous, attribute is the explanatory attribute.

Generally, a choice model contains multiple independent attributes. To allow for the choice model specification and parameter estimation, the data was analysed to understand patterns and prevent the inclusion of attributes that are not valuable. attributes that do not impact the preference for a certain time slot are excluded from the model. Additionally, if attributes are mutually correlated, one is excluded as this could manipulate the model results.

All in all, from the data analysis it was found that two data attributes from the logistic data set have the highest impact on the preferred ETA of the TOC. These two are the container type and commodity type category. The other attributes regarding container length, weight and call size, are excluded from further research. Another data attribute that could potentially influence the pick up preference of the TOC, is found to be correlated with one of the prior data attributes. Therefore, the temperature settings attribute is also excluded from further analysis.

Moreover, it can be concluded from the data analysis that a separate choice model must be specified for each terminal as the terminals differ from each other considering container types and commodity types handled. This could result in different preferences of the TOC for pick up time (ETA) based on the terminal the container must be picked up.

Even though not all attributes are eventually included in the choice model, the analysis of the logistic data is very useful to gain insight in the situation at the different terminals and the spread of containers along the day. This benefits the design of the TAS.

C.3 DATA SUMMARY

In this section a summary of the remaining data attributes and their levels for the choice model specification and shifting model is presented. The data presented in this section is used to sustain judgements made in the choice model formulation. For example, which attribute levels to incorporate in the choice model. Too many or invaluable attributes in the choice model could deteriorate the model accuracy. Moreover, the data provides insight in potential ways to formulate the utility functions in the choice model for valuable results. Furthermore, the data presented here is used to combine the traffic data and terminal model with the logistic data and choice model. In the shift model the traffic and logistic data is combined by translating container types and commodity types to trucks.

The data is structured per terminal, A through D. Per terminal an overview is provided for the data arranged per container type and time period, commodity type and time period, and container type and commodity type. The latter set of tables is very useful to find overlap between the attributes in the logistic data.

As the choice model is probabilistic, each attribute and attribute level can be associated with a certain probability. The data is summarised based on absolute value occurrence, the joint probabilities, the marginal probabilities, and the conditional probabilities. Especially, the percentage values are meaningful as these allow to combine the logistic data with the traffic data (Appendix E). The mathematical notation for the probabilities are denoted in Equation C.1 through Equation C.3, in which i is the dependent attribute (time period) and k is the independent attribute (container type or commodity type).

The joint probability is the probability that i is equal to l, and k is equal to j:

$$Pr(i = l, k = j) \tag{C.1}$$

The marginal probability is the probability for a single attribute (i or k) is equal to a given value (l or j). By enumerating all possible values of the other attribute, the marginal probability can be derived from the joint probability:

$$Pr(i = l) = \sum_j Pr(i = l, k = j) \tag{C.2}$$

The conditional probability is the probability that i is equal to l, conditional to the fact that k is equal to j. When the value of one attribute is known, the probability for the other attribute is the conditional probability:

$$Pr(i = l | k = j) \tag{C.3}$$

C.3.1 Terminal A

Container type and time period data

Table C.1: Contingency table occurrence of container type in time period for terminal A in absolute values (all 2017)

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Totals
Afternoon	1393	8272	8034	1845	**19544**
Midday	1933	11732	8802	2164	**24631**
Morning	950	6208	6305	1382	**14845**
Night	507	2844	2542	373	**6266**
Totals	**4783**	**29056**	**25683**	**5764**	**65286**

Table C.2: Contingency table joint probabilities and marginal probabilities for container type and time period for terminal A in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Marginal probability for i
Afternoon	2.13%	12.67%	12.31%	2.83%	**29.94%**
Midday	2.96%	17.97%	13.48%	3.31%	**37.73%**
Morning	1.46%	9.51%	9.66%	2.12%	**22.74%**
Night	0.78%	4.36%	3.89%	0.57%	**9.60%**
Marginal probability for k	**7.33%**	**44.51%**	**39.34%**	**8.83%**	**100.00%**

Table C.3: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for container type and time period for terminal A in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank
Afternoon	29.12%	28.47%	31.28%	32.01%
Midday	40.41%	40.38%	34.27%	37.54%
Morning	19.86%	21.37%	24.55%	23.98%
Night	10.60%	9.79%	9.90%	6.47%

Table C.4: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal A in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Chemical	7.13%	7.85%	6.40%	8.09%
General purpose	42.33%	47.63%	41.82%	45.39%
Reefer	41.11%	35.74%	42.47%	40.57%
Tank	9.44%	8.79%	9.31%	5.95%

Commodity type and time period data

Table C.5: Contingency table occurrence of commodity type in time period for terminal A in absolute values (all 2017)

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Afternoon	2259	728	312	100	354	280	467	396	274	716	13658	**19544**
Midday	2509	963	423	62	396	345	664	569	321	1096	17283	**24631**
Morning	1661	633	262	45	228	234	285	268	245	618	10366	**14845**
Night	527	212	116	17	94	90	103	121	169	715	4102	**6266**
Totals	**6956**	**2536**	**1113**	**224**	**1072**	**949**	**1519**	**1354**	**1009**	**3145**	**45409**	**65286**

Table C.6: Contingency table joint probabilities and marginal probabilities for commodity type and time period for terminal A in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Afternoon	3.46%	1.12%	0.48%	0.15%	0.54%	0.43%	0.72%	0.61%	0.42%	1.10%	20.92%	**29.94%**
Midday	3.84%	1.48%	0.65%	0.09%	0.61%	0.53%	1.02%	0.87%	0.49%	1.68%	26.47%	**37.73%**
Morning	2.54%	0.97%	0.40%	0.07%	0.35%	0.36%	0.44%	0.41%	0.38%	0.95%	15.88%	**22.74%**
Night	0.81%	0.32%	0.18%	0.03%	0.14%	0.14%	0.16%	0.19%	0.26%	1.10%	6.28%	**9.60%**
Marginal probability for k	**10.65%**	**3.88%**	**1.70%**	**0.34%**	**1.64%**	**1.45%**	**2.33%**	**2.07%**	**1.55%**	**4.82%**	**69.55%**	**100.00%**

Table C.7: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and time period for terminal A in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Afternoon	32.48%	28.71%	28.03%	44.64%	33.02%	29.50%	30.74%	29.25%	27.16%	22.77%	30.08%
Midday	36.07%	37.97%	38.01%	27.68%	36.94%	36.35%	43.71%	42.02%	31.81%	34.85%	38.06%
Morning	23.88%	24.96%	23.54%	20.09%	21.27%	24.66%	18.76%	19.79%	24.28%	19.65%	22.83%
Night	7.58%	8.36%	10.42%	7.59%	8.77%	9.48%	6.78%	8.94%	16.75%	22.73%	9.03%

Table C.8: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal A in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Agricultural	11.56%	10.19%	11.19%	8.41%
Chemical products	3.72%	3.91%	4.26%	3.38%
Fertilizers	1.60%	1.72%	1.76%	1.85%
Iron	0.51%	0.25%	0.30%	0.27%
Miscellaneous	1.81%	1.61%	1.54%	1.50%
Ores	1.43%	1.40%	1.58%	1.44%
Other food	2.39%	2.70%	1.92%	1.64%
Petroleum	2.03%	2.31%	1.81%	1.93%
Raw minerals	1.40%	1.30%	1.65%	2.70%
Solid mineral fuels	3.66%	4.45%	4.16%	11.41%
Unknown	69.88%	70.17%	69.83%	65.46%

Container type and commodity type data

Table C.9: Contingency table occurrence of commodity type in container type for terminal A in absolute values (all 2017)

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Chemical	135	1177	338	45	415	351	669	460	539	636	18	**4783**
General purpose	189	1289	759	170	637	595	608	741	463	1854	21751	**29056**
Reefer	1900	0	0	0	1	0	136	27	0	33	23586	**25683**
Tank	4732	70	16	9	19	3	106	126	7	622	54	**5764**
Totals	**6956**	**2536**	**1113**	**224**	**1072**	**949**	**1519**	**1354**	**1009**	**3145**	**45409**	**65286**

Table C.10: Contingency table joint probabilities and marginal probabilities for commodity type and container type for terminal A in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Chemical	0.21%	1.80%	0.52%	0.07%	0.64%	0.54%	1.02%	0.70%	0.83%	0.97%	0.03%	**7.33%**
General purpose	0.29%	1.97%	1.16%	0.26%	0.98%	0.91%	0.93%	1.14%	0.71%	2.84%	33.32%	**44.51%**
Reefer	2.91%	0.00%	0.00%	0.00%	0.00%	0.00%	0.21%	0.04%	0.00%	0.05%	36.13%	**39.34%**
Tank	7.25%	0.11%	0.02%	0.01%	0.03%	0.00%	0.16%	0.19%	0.01%	0.95%	0.08%	**8.83%**
Marginal probability for k	**10.65%**	**3.88%**	**1.70%**	**0.34%**	**1.64%**	**1.45%**	**2.33%**	**2.07%**	**1.55%**	**4.82%**	**69.55%**	**100.00%**

Table C.11: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and container type for terminal A in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Chemical	1.94%	46.41%	30.37%	20.09%	38.71%	36.99%	44.04%	33.97%	53.42%	20.22%	0.04%
General purpose	2.72%	50.83%	68.19%	75.89%	59.42%	62.70%	40.03%	54.73%	45.89%	58.95%	47.90%
Reefer	27.31%	0.00%	0.00%	0.00%	0.09%	0.00%	8.95%	1.99%	0.00%	1.05%	51.94%
Tank	68.03%	2.76%	1.44%	4.02%	1.77%	0.32%	6.98%	9.31%	0.69%	19.78%	0.12%

Table C.12: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and container type for terminal A in percentage values

Container type (k)	Container type (i) Chemical	General purpose	Reefer	Tank
Agricultural	2.82%	0.65%	7.40%	82.10%
Chemical products	24.61%	4.44%	0.00%	1.21%
Fertilizers	7.07%	2.61%	0.00%	0.28%
Iron	0.94%	0.59%	0.00%	0.16%
Miscellaneous	8.68%	2.19%	0.00%	0.33%
Ores	7.34%	2.05%	0.00%	0.05%
Other food	13.99%	2.09%	0.53%	1.84%
Petroleum	9.62%	2.55%	0.11%	2.19%
Raw minerals	11.27%	1.59%	0.00%	0.12%
Solid mineral fuels	13.30%	6.38%	0.13%	10.79%
Unknown	0.38%	74.86%	91.84%	0.94%

C.3.2 Terminal B

Container type and time period data

Table C.13: Contingency table occurrence of container type in time period for terminal B in absolute values (all 2017)

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Totals
Afternoon	6682	24165	2331	552	**33730**
Midday	5096	17842	3959	696	**27593**
Morning	4122	14445	5041	729	**24337**
Night	1063	3779	499	92	**5433**
Totals	**16963**	**60231**	**11830**	**2069**	**91093**

Table C.14: Contingency table joint probabilities and marginal probabilities for container type and time period for terminal B in percentage values

Time period (i)	Container type (k)				Marginal probability for i
	Chemical	General purpose	Reefer	Tank	
Afternoon	7.34%	26.53%	2.56%	0.61%	**37.03%**
Midday	5.59%	19.59%	4.35%	0.76%	**30.29%**
Morning	4.53%	15.86%	5.53%	0.80%	**26.72%**
Night	1.17%	4.15%	0.55%	0.10%	**5.96%**
Marginal probability for k	**18.62%**	**66.12%**	**12.99%**	**2.27%**	**100.00%**

Table C.15: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for container type and time period for terminal B in percentage values

Time period (i)	Container type (k)			
	Chemical	General purpose	Reefer	Tank
Afternoon	39.39%	40.12%	19.70%	26.68%
Midday	30.04%	29.62%	33.47%	33.64%
Morning	24.30%	23.98%	42.61%	35.23%
Night	6.27%	6.27%	4.22%	4.45%

Table C.16: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal B in percentage values

Container type (k)	Time period (i)			
	Afternoon	Midday	Morning	Night
Chemical	19.81%	18.47%	16.94%	19.57%
General purpose	71.64%	64.66%	59.35%	69.56%
Reefer	6.91%	14.35%	20.71%	9.18%
Tank	1.64%	2.52%	3.00%	1.69%

Commodity type and time period data

Table C.17: Contingency table occurrence of commodity type in time period for terminal B in absolute values (all 2017)

Time period (i)	Commodity type (k)											Totals
	Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	
Afternoon	682	2912	787	181	1826	992	406	1038	1300	1048	22558	**33730**
Midday	1003	2201	515	112	1121	699	414	712	850	1131	18835	**27593**
Morning	1276	1543	485	63	841	537	374	537	643	841	17197	**24337**
Night	148	479	108	27	278	130	118	146	210	136	3653	**5433**
Totals	**3109**	**7135**	**1895**	**383**	**4066**	**2358**	**1312**	**2433**	**3003**	**3156**	**62243**	**91093**

Table C.18: Contingency table joint probabilities and marginal probabilities for commodity type and time period for terminal B in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Afternoon	0.75%	3.20%	0.86%	0.20%	2.00%	1.09%	0.45%	1.14%	1.43%	1.15%	24.76%	**37.03%**
Midday	1.10%	2.42%	0.57%	0.12%	1.23%	0.77%	0.45%	0.78%	0.93%	1.24%	20.68%	**30.29%**
Morning	1.40%	1.69%	0.53%	0.07%	0.92%	0.59%	0.41%	0.59%	0.71%	0.92%	18.88%	**26.72%**
Night	0.16%	0.53%	0.12%	0.03%	0.31%	0.14%	0.13%	0.16%	0.23%	0.15%	4.01%	**5.96%**
Marginal probability for k	**3.41%**	**7.83%**	**2.08%**	**0.42%**	**4.46%**	**2.59%**	**1.44%**	**2.67%**	**3.30%**	**3.46%**	**68.33%**	**100.00%**

Table C.19: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and time period for terminal B in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Afternoon	21.94%	40.81%	41.53%	47.26%	44.91%	42.07%	30.95%	42.66%	43.29%	33.21%	36.24%
Midday	32.26%	30.85%	27.18%	29.24%	27.57%	29.64%	31.55%	29.26%	28.31%	35.84%	30.26%
Morning	41.04%	21.63%	25.59%	16.45%	20.68%	22.77%	28.51%	22.07%	21.41%	26.65%	27.63%
Night	4.76%	6.71%	5.70%	7.05%	6.84%	5.51%	8.99%	6.00%	6.99%	4.31%	5.87%

Table C.20: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal B in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Agricultural	2.02%	3.63%	5.24%	2.72%
Chemical products	8.63%	7.98%	6.34%	8.82%
Fertilizers	2.33%	1.87%	1.99%	1.99%
Iron	0.54%	0.41%	0.26%	0.50%
Miscellaneous	5.41%	4.06%	3.46%	5.12%
Ores	2.94%	2.53%	2.21%	2.39%
Other food	1.20%	1.50%	1.54%	2.17%
Petroleum	3.08%	2.58%	2.21%	2.69%
Raw minerals	3.85%	3.08%	2.64%	3.87%
Solid mineral fuels	3.11%	4.10%	3.46%	2.50%
Unknown	66.88%	68.26%	70.66%	67.24%

Table C.21: Contingency table occurrence of commodity type in container type for terminal B in absolute values (all 2017)

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Chemical	307	4815	1123	150	2790	1613	598	1349	2094	2110	14	**16963**
General purpose	83	2202	757	227	1233	711	591	943	900	800	51784	**60231**
Reefer	1219	2	0	0	0	0	73	22	0	70	10444	**11830**
Tank	1500	116	15	6	43	34	50	119	9	176	1	**2069**
Totals	**3109**	**7135**	**1895**	**383**	**4066**	**2358**	**1312**	**2433**	**3003**	**3156**	**62243**	**91093**

Table C.22: Contingency table joint probabilities and marginal probabilities for commodity type and container type for terminal B in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Chemical	0.34%	5.29%	1.23%	0.16%	3.06%	1.77%	0.66%	1.48%	2.30%	2.32%	0.02%	**18.62%**
General purpose	0.09%	2.42%	0.83%	0.25%	1.35%	0.78%	0.65%	1.04%	0.99%	0.88%	56.85%	**66.12%**
Reefer	1.34%	0.00%	0.00%	0.00%	0.00%	0.00%	0.08%	0.02%	0.00%	0.08%	11.47%	**12.99%**
Tank	1.65%	0.13%	0.02%	0.01%	0.05%	0.04%	0.05%	0.13%	0.01%	0.19%	0.00%	**2.27%**
Marginal probability for k	**3.41%**	**7.83%**	**2.08%**	**0.42%**	**4.46%**	**2.59%**	**1.44%**	**2.67%**	**3.30%**	**3.46%**	**68.33%**	**100.00%**

Table C.23: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and container type for terminal B in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Chemical	9.87%	67.48%	59.26%	39.16%	68.62%	68.41%	45.58%	55.45%	69.73%	66.86%	0.02%
General purpose	2.67%	30.86%	39.95%	59.27%	30.32%	30.15%	45.05%	38.76%	29.97%	25.35%	83.20%
Reefer	39.21%	0.03%	0.00%	0.00%	0.00%	0.00%	5.56%	0.90%	0.00%	2.22%	16.78%
Tank	48.25%	1.63%	0.79%	1.57%	1.06%	1.44%	3.81%	4.89%	0.30%	5.58%	0.00%

Table C.24: Contingency table conditional probabilities in the form of $P(k=j|i=l)$ for container type and container type for terminal B in percentage values

Container type (k)	Container type (i) Chemical	General purpose	Reefer	Tank
Agricultural	1.81%	0.14%	10.30%	72.50%
Chemical products	28.39%	3.66%	0.02%	5.61%
Fertilizers	6.62%	1.26%	0.00%	0.72%
Iron	0.88%	0.38%	0.00%	0.29%
Miscellaneous	16.45%	2.05%	0.00%	2.08%
Ores	9.51%	1.18%	0.00%	1.64%
Other food	3.53%	0.98%	0.62%	2.42%
Petroleum	7.95%	1.57%	0.19%	5.75%
Raw minerals	12.34%	1.49%	0.00%	0.43%
Solid mineral fuels	12.44%	1.33%	0.59%	8.51%
Unknown	0.08%	85.98%	88.28%	0.05%

C.3.3 Terminal C

Container type and time period data

Table C.25: Contingency table occurrence of container type in time period for terminal C in absolute values (all 2017)

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Totals
Afternoon	3744	50812	2242	2544	**59342**
Midday	3103	37254	3097	2473	**45927**
Morning	2697	31023	3532	2295	**39547**
Night	549	7239	271	428	**8487**
Totals	**10093**	**126328**	**9142**	**7740**	**153303**

Table C.26: Contingency table joint probabilities and marginal probabilities for container type and time period for terminal C in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Marginal probability for i
Afternoon	2.44%	33.14%	1.46%	1.66%	**38.71%**
Midday	2.02%	24.30%	2.02%	1.61%	**29.96%**
Morning	1.76%	20.24%	2.30%	1.50%	**25.80%**
Night	0.36%	4.72%	0.18%	0.28%	**5.54%**
Marginal probability for k	**6.58%**	**82.40%**	**5.96%**	**5.05%**	**100.00%**

Table C.27: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for container type and time period for terminal C in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank
Afternoon	37.10%	40.22%	24.52%	32.87%
Midday	30.74%	29.49%	33.88%	31.95%
Morning	26.72%	24.56%	38.63%	29.65%
Night	5.44%	5.73%	2.96%	5.53%

Table C.28: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal C in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Chemical	6.31%	6.76%	6.82%	6.47%
General purpose	85.63%	81.12%	78.45%	85.30%
Reefer	3.78%	6.74%	8.93%	3.19%
Tank	4.29%	5.38%	5.80%	5.04%

Commodity type and time period data

Table C.29: Contingency table occurrence of commodity type in time period for terminal C in absolute values (all 2017)

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Afternoon	2255	11508	3924	1105	5695	3625	1321	5385	4722	5633	14169	**59342**
Midday	2920	8425	3097	680	3439	2634	1171	3970	2988	6043	10560	**45927**
Morning	3275	6889	2326	463	2515	2337	1277	3379	2253	5541	9292	**39547**
Night	311	1892	583	129	870	528	147	678	707	768	1874	**8487**
Totals	**8761**	**28714**	**9930**	**2377**	**12519**	**9124**	**3916**	**13412**	**10670**	**17985**	**35895**	**153303**

Table C.30: Contingency table joint probabilities and marginal probabilities for commodity type and time period for terminal C in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Afternoon	1.47%	7.51%	2.56%	0.72%	3.71%	2.36%	0.86%	3.51%	3.08%	3.67%	9.24%	**38.71%**
Midday	1.90%	5.50%	2.02%	0.44%	2.24%	1.72%	0.76%	2.59%	1.95%	3.94%	6.89%	**29.96%**
Morning	2.14%	4.49%	1.52%	0.30%	1.64%	1.52%	0.83%	2.20%	1.47%	3.61%	6.06%	**25.80%**
Night	0.20%	1.23%	0.38%	0.08%	0.57%	0.34%	0.10%	0.44%	0.46%	0.50%	1.22%	**5.54%**
Marginal probability for k	**5.71%**	**18.73%**	**6.48%**	**1.55%**	**8.17%**	**5.95%**	**2.55%**	**8.75%**	**6.96%**	**11.73%**	**23.41%**	**100.00%**

Table C.31: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and time period for terminal C in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Afternoon	25.74%	40.08%	39.52%	46.49%	45.49%	39.73%	33.73%	40.15%	44.25%	31.32%	39.47%
Midday	33.33%	29.34%	31.19%	28.61%	27.47%	28.87%	29.90%	29.60%	28.00%	33.60%	29.42%
Morning	37.38%	23.99%	23.42%	19.48%	20.09%	25.61%	32.61%	25.19%	21.12%	30.81%	25.89%
Night	3.55%	6.59%	5.87%	5.43%	6.95%	5.79%	3.75%	5.06%	6.63%	4.27%	5.22%

Table C.32: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal C in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Agricultural	3.80%	6.36%	8.28%	3.66%
Chemical products	19.39%	18.34%	17.42%	22.29%
Fertilizers	6.61%	6.74%	5.88%	6.87%
Iron	1.86%	1.48%	1.17%	1.52%
Miscellaneous	9.60%	7.49%	6.36%	10.25%
Ores	6.11%	5.74%	5.91%	6.22%
Other food	2.23%	2.55%	3.23%	1.73%
Petroleum	9.07%	8.64%	8.54%	7.99%
Raw minerals	7.96%	6.51%	5.70%	8.33%
Solid mineral fuels	9.49%	13.16%	14.01%	9.05%
Unknown	23.88%	22.99%	23.50%	22.08%

Container type and commodity type data

Table C.33: Contingency table occurrence of commodity type in container type for terminal C in absolute values (all 2017)

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Chemical	338	2635	953	151	1023	860	779	913	1019	1355	67	**10093**
General purpose	1484	25191	8911	2107	11235	8108	2363	10986	9579	13194	33170	**126328**
Reefer	5437	349	22	10	74	48	381	635	11	1081	1094	**9142**
Tank	1502	539	44	109	187	108	393	878	61	2355	1564	**7740**
Totals	**8761**	**28714**	**9930**	**2377**	**12519**	**9124**	**3916**	**13412**	**10670**	**17985**	**35895**	**153303**

Table C.34: Contingency table joint probabilities and marginal probabilities for commodity type and container type for terminal C in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Chemical	0.22%	1.72%	0.62%	0.10%	0.67%	0.56%	0.51%	0.60%	0.66%	0.88%	0.04%	**6.58%**
General purpose	0.97%	16.43%	5.81%	1.37%	7.33%	5.29%	1.54%	7.17%	6.25%	8.61%	21.64%	**82.40%**
Reefer	3.55%	0.23%	0.01%	0.01%	0.05%	0.03%	0.25%	0.41%	0.01%	0.71%	0.71%	**5.96%**
Tank	0.98%	0.35%	0.03%	0.07%	0.12%	0.07%	0.26%	0.57%	0.04%	1.54%	1.02%	**5.05%**
Marginal probability for k	**5.71%**	**18.73%**	**6.48%**	**1.55%**	**8.17%**	**5.95%**	**2.55%**	**8.75%**	**6.96%**	**11.73%**	**23.41%**	**100.00%**

Table C.35: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and container type for terminal C in percentage values

Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Chemical	3.86%	9.18%	9.60%	6.35%	8.17%	9.43%	19.89%	6.81%	9.55%	7.53%	0.19%
General purpose	16.94%	87.73%	89.74%	88.64%	89.74%	88.86%	60.34%	81.91%	89.78%	73.36%	92.41%
Reefer	62.06%	1.22%	0.22%	0.42%	0.59%	0.53%	9.73%	4.73%	0.10%	6.01%	3.05%
Tank	17.14%	1.88%	0.44%	4.59%	1.49%	1.18%	10.04%	6.55%	0.57%	13.09%	4.36%

Table C.36: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and container type for terminal C in percentage values

Container type (k)	Container type (i) Chemical	General purpose	Reefer	Tank
Agricultural	3.35%	1.17%	59.47%	19.41%
Chemical products	26.11%	19.94%	3.82%	6.96%
Fertilizers	9.44%	7.05%	0.24%	0.57%
Iron	1.50%	1.67%	0.11%	1.41%
Miscellaneous	10.14%	8.89%	0.81%	2.42%
Ores	8.52%	6.42%	0.53%	1.40%
Other food	7.72%	1.87%	4.17%	5.08%
Petroleum	9.05%	8.70%	6.95%	11.34%
Raw minerals	10.10%	7.58%	0.12%	0.79%
Solid mineral fuels	13.43%	10.44%	11.82%	30.43%
Unknown	0.66%	26.26%	11.97%	20.21%

C.3.4 Terminal D

Container type and time period data

Table C.37: Contingency table occurrence of container type in time period for terminal D in absolute values (all 2017)

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Totals
Afternoon	10907	29758	1935	2492	**45092**
Midday	16549	45147	2468	3368	**67532**
Morning	8056	22020	1536	1638	**33250**
Night	2919	8317	460	332	**12028**
Totals	**38431**	**105242**	**6399**	**7830**	**157902**

Table C.38: Contingency table joint probabilities and marginal probabilities for container type and time period for terminal D in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank	Marginal probability for i
Afternoon	6.91%	18.85%	1.23%	1.58%	**28.56%**
Midday	10.48%	28.59%	1.56%	2.13%	**42.77%**
Morning	5.10%	13.95%	0.97%	1.04%	**21.06%**
Night	1.85%	5.27%	0.29%	0.21%	**7.62%**
Marginal probability for k	**24.34%**	**66.65%**	**4.05%**	**4.96%**	**100.00%**

Table C.39: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for container type and time period for terminal D in percentage values

Time period (i)	Container type (k) Chemical	General purpose	Reefer	Tank
Afternoon	28.38%	28.28%	30.24%	31.83%
Midday	43.06%	42.90%	38.57%	43.01%
Morning	20.96%	20.92%	24.00%	20.92%
Night	7.60%	7.90%	7.19%	4.24%

Table C.40: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal D in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Chemical	24.19%	24.51%	24.23%	24.27%
General purpose	65.99%	66.85%	66.23%	69.15%
Reefer	4.29%	3.65%	4.62%	3.82%
Tank	5.53%	4.99%	4.93%	2.76%

Table C.41: Contingency table occurrence of commodity type in time period for terminal D in absolute values (all 2017)

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Totals
Afternoon	1735	10034	2776	645	4597	3679	1888	4099	3843	4157	7639	**45092**
Midday	2410	14287	3935	1047	6897	5830	2527	6092	5946	6378	12183	**67532**
Morning	1584	7504	2188	452	3284	2868	1128	2723	3440	2874	5205	**33250**
Night	444	3630	714	88	1068	887	376	792	1191	986	1852	**12028**
Totals	**6173**	**35455**	**9613**	**2232**	**15846**	**13264**	**5919**	**13706**	**14420**	**14395**	**26879**	**157902**

Table C.42: Contingency table joint probabilities and marginal probabilities for commodity type and time period for terminal D in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Afternoon	1.10%	6.35%	1.76%	0.41%	2.91%	2.33%	1.20%	2.60%	2.43%	2.63%	4.84%	**28.56%**
Midday	1.53%	9.05%	2.49%	0.66%	4.37%	3.69%	1.60%	3.86%	3.77%	4.04%	7.72%	**42.77%**
Morning	1.00%	4.75%	1.39%	0.29%	2.08%	1.82%	0.71%	1.72%	2.18%	1.82%	3.30%	**21.06%**
Night	0.28%	2.30%	0.45%	0.06%	0.68%	0.56%	0.24%	0.50%	0.75%	0.62%	1.17%	**7.62%**
Marginal probability for k	**3.91%**	**22.45%**	**6.09%**	**1.41%**	**10.04%**	**8.40%**	**3.75%**	**8.68%**	**9.13%**	**9.12%**	**17.02%**	**100.00%**

Table C.43: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and time period for terminal D in percentage values

Time period (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Afternoon	28.11%	28.30%	28.88%	28.90%	29.01%	27.74%	31.90%	29.91%	26.65%	28.88%	28.42%
Midday	39.04%	40.30%	40.93%	46.91%	43.53%	43.95%	42.69%	44.45%	41.23%	44.31%	45.33%
Morning	25.66%	21.16%	22.76%	20.25%	20.72%	21.62%	19.06%	19.87%	23.86%	19.97%	19.36%
Night	7.19%	10.24%	7.43%	3.94%	6.74%	6.69%	6.35%	5.78%	8.26%	6.85%	6.89%

Table C.44: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and time period for terminal D in percentage values

Container type (k)	Time period (i) Afternoon	Midday	Morning	Night
Agricultural	3.85%	3.57%	4.76%	3.69%
Chemical products	22.25%	21.16%	22.57%	30.18%
Fertilizers	6.16%	5.83%	6.58%	5.94%
Iron	1.43%	1.55%	1.36%	0.73%
Miscellaneous	10.19%	10.21%	9.88%	8.88%
Ores	8.16%	8.63%	8.63%	7.37%
Other food	4.19%	3.74%	3.39%	3.13%
Petroleum	9.09%	9.02%	8.19%	6.58%
Raw minerals	8.52%	8.80%	10.35%	9.90%
Solid mineral fuels	9.22%	9.44%	8.64%	8.20%
Unknown	16.94%	18.04%	15.65%	15.40%

Container type and commodity type data

Table C.45: Contingency table occurrence of commodity type in container type for terminal D in absolute values (all 2017)

Container type (i)	Commodity type (k) Agricultural	Chemical products	Fertilizers	Iron	Miscellaneous	Ores	Other food	Petroleum	Raw minerals	Solid mineral fuels	Unknown	Totals
Chemical	666	9359	3087	613	5420	4580	2265	3960	4455	3904	122	**38431**
General purpose	884	24983	6343	1584	10290	8580	2562	8239	9787	7716	24274	**105242**
Reefer	3245	515	120	30	95	54	633	354	114	319	920	**6399**
Tank	1378	598	63	5	41	50	459	1153	64	2456	1563	**7830**
Totals	**6173**	**35455**	**9613**	**2232**	**15846**	**13264**	**5919**	**13706**	**14420**	**14395**	**26879**	**157902**

Table C.46: Contingency table joint probabilities and marginal probabilities for commodity type and container type for terminal D in percentage values

Container type (i)	Commodity type (k) Agricultural	Chemical products	Fertilizers	Iron	Miscellaneous	Ores	Other food	Petroleum	Raw minerals	Solid mineral fuels	Unknown	Marginal probability for i
Chemical	0.42%	5.93%	1.96%	0.39%	3.43%	2.90%	1.43%	2.51%	2.82%	2.47%	0.08%	**24.34%**
General purpose	0.56%	15.82%	4.02%	1.00%	6.52%	5.43%	1.62%	5.22%	6.20%	4.89%	15.37%	**66.65%**
Reefer	2.06%	0.33%	0.08%	0.02%	0.06%	0.03%	0.40%	0.22%	0.07%	0.20%	0.58%	**4.05%**
Tank	0.87%	0.38%	0.04%	0.00%	0.03%	0.03%	0.29%	0.73%	0.04%	1.56%	0.99%	**4.96%**
Marginal probability for k	**3.91%**	**22.45%**	**6.09%**	**1.41%**	**10.04%**	**8.40%**	**3.75%**	**8.68%**	**9.13%**	**9.12%**	**17.02%**	**100.00%**

Table C.47: Contingency table conditional probabilities in the form of $P(i = l|k = j)$ for commodity type and container type for terminal D in percentage values

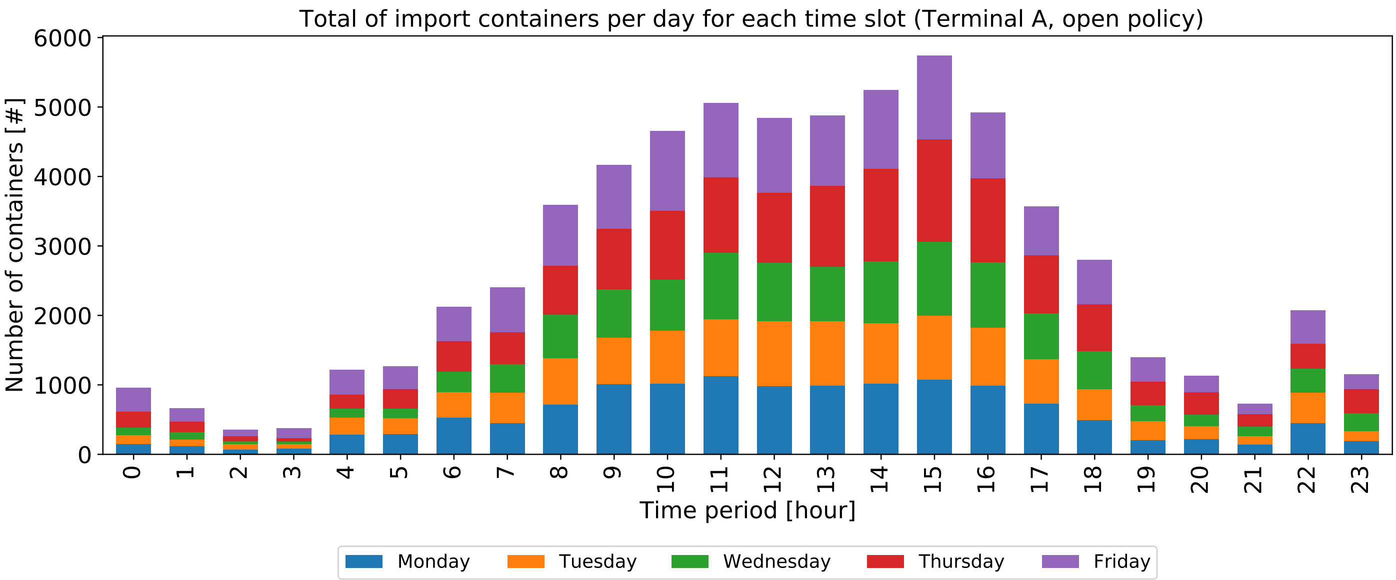
Container type (i)	Commodity type (k) Agri-cultural	Chemical products	Ferti-lizers	Iron	Miscel-laneous	Ores	Other food	Petro-leum	Raw minerals	Solid mineral fuels	Unknown
Chemical	10.79%	26.40%	32.11%	27.46%	34.20%	34.53%	38.27%	28.89%	30.89%	27.12%	0.45%
General purpose	14.32%	70.46%	65.98%	70.97%	64.94%	64.69%	43.28%	60.11%	67.87%	53.60%	90.31%
Reefer	52.57%	1.45%	1.25%	1.34%	0.60%	0.41%	10.69%	2.58%	0.79%	2.22%	3.42%
Tank	22.32%	1.69%	0.66%	0.22%	0.26%	0.38%	7.75%	8.41%	0.44%	17.06%	5.81%

Table C.48: Contingency table conditional probabilities in the form of $P(k = j|i = l)$ for container type and container type for terminal D in percentage values

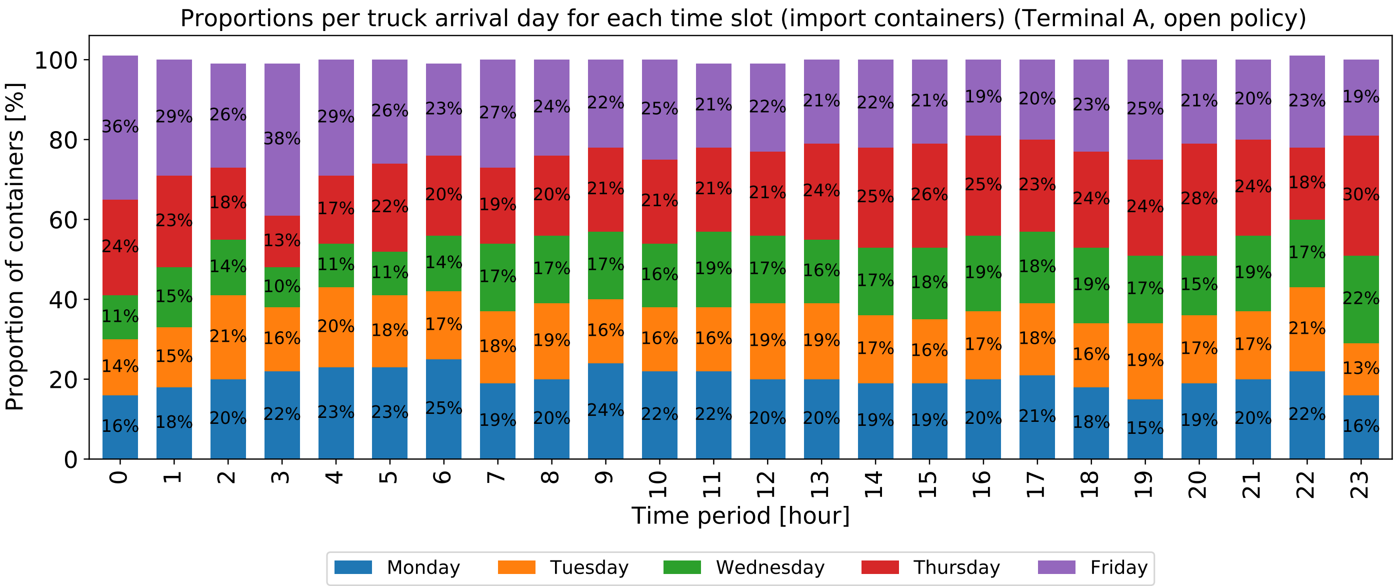
Container type (k)	Container type (i) Chemical	General purpose	Reefer	Tank
Agricultural	1.73%	0.84%	50.71%	17.60%
Chemical products	24.35%	23.74%	8.05%	7.64%
Fertilizers	8.03%	6.03%	1.88%	0.80%
Iron	1.60%	1.51%	0.47%	0.06%
Miscellaneous	14.10%	9.78%	1.48%	0.52%
Ores	11.92%	8.15%	0.84%	0.64%
Other food	5.89%	2.43%	9.89%	5.86%
Petroleum	10.30%	7.83%	5.53%	14.73%
Raw minerals	11.59%	9.30%	1.78%	0.82%
Solid mineral fuels	10.16%	7.33%	4.99%	31.37%
Unknown	0.32%	23.06%	14.38%	19.96%

C.4 GRAPHS OF LOGISTIC DATA

C.4.1 Day of the week

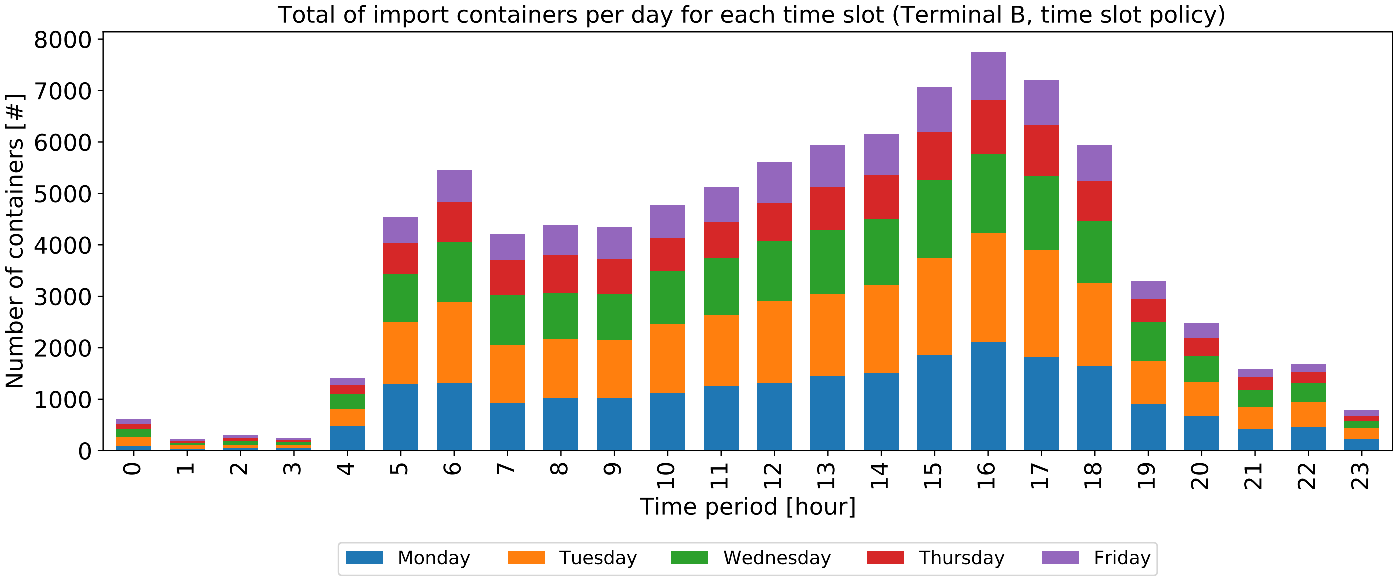


(a) Totals, absolute numbers

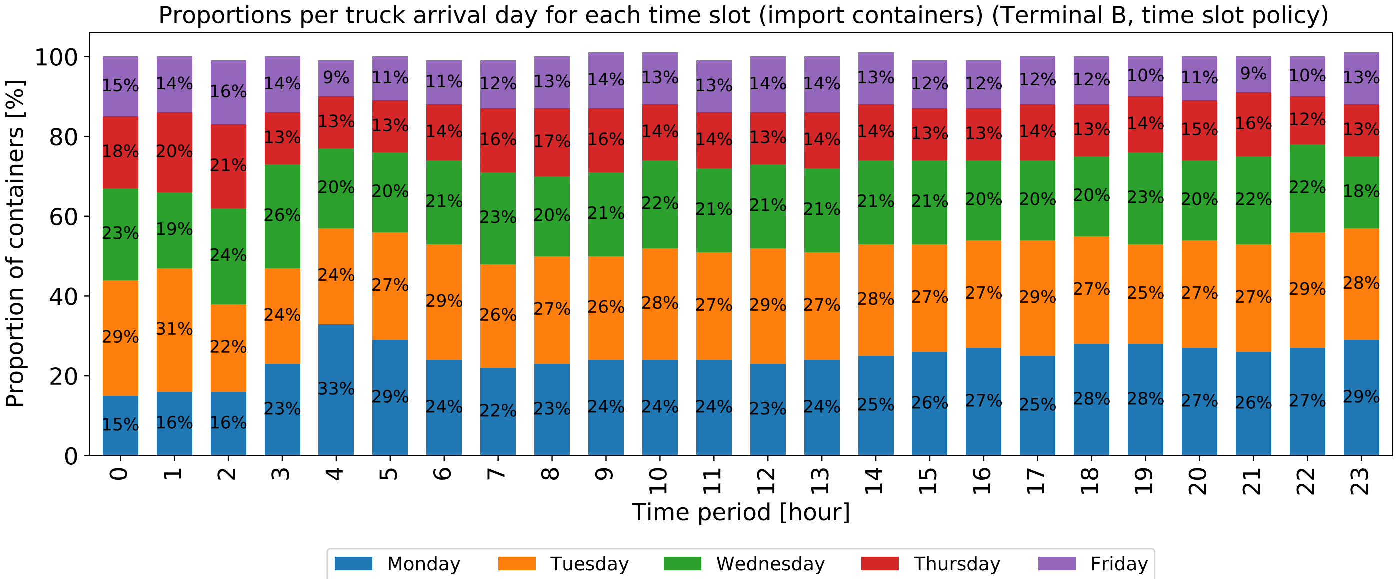


(b) Proportions, percentages

Figure C.5: Import container pick up preference distributed per hour based on day of the week (terminal A)

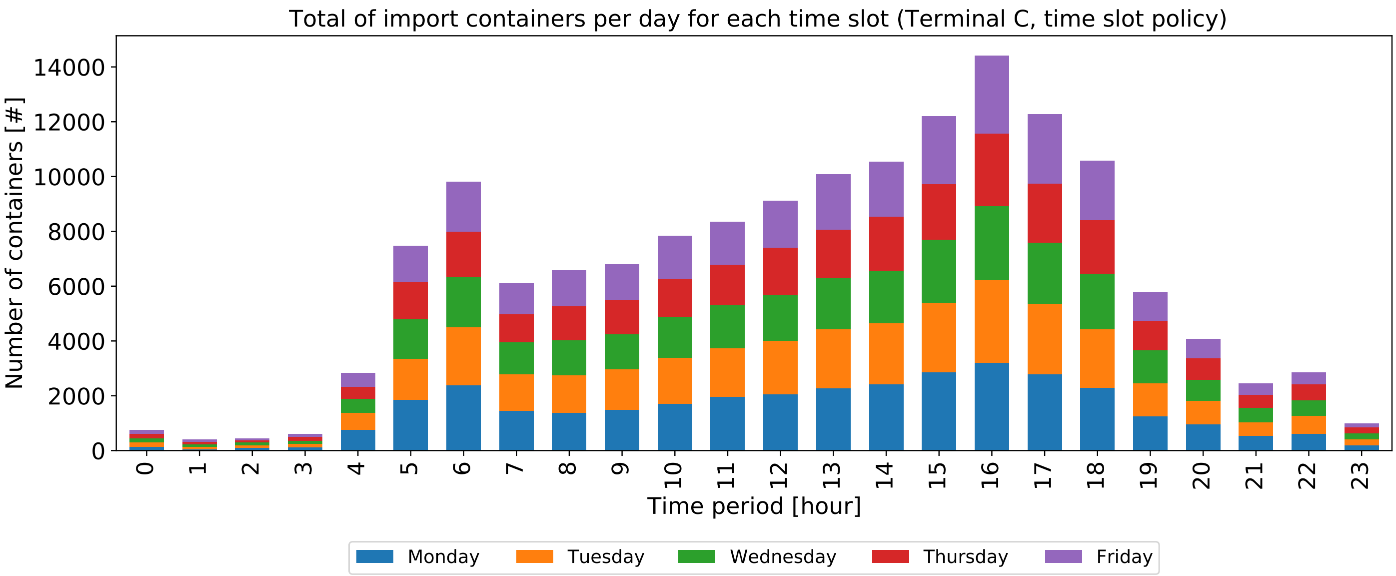


(a) Totals, absolute numbers

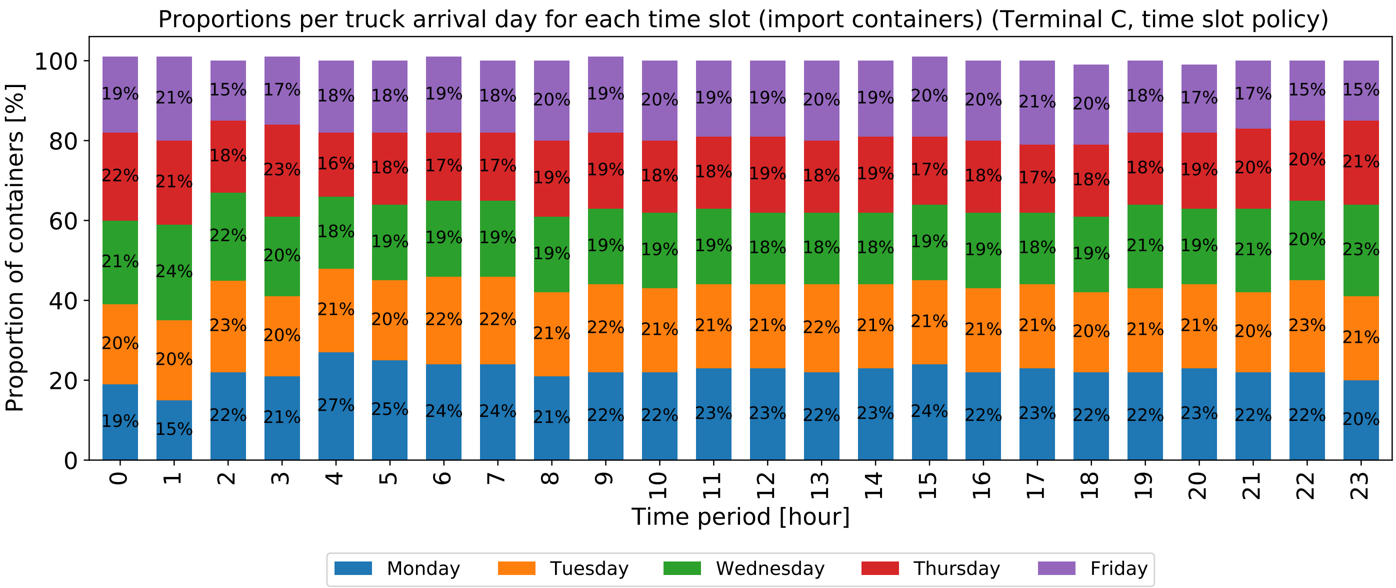


(b) Proportions, percentages

Figure C.6: Import container pick up preference distributed per hour based on day of the week (terminal B)

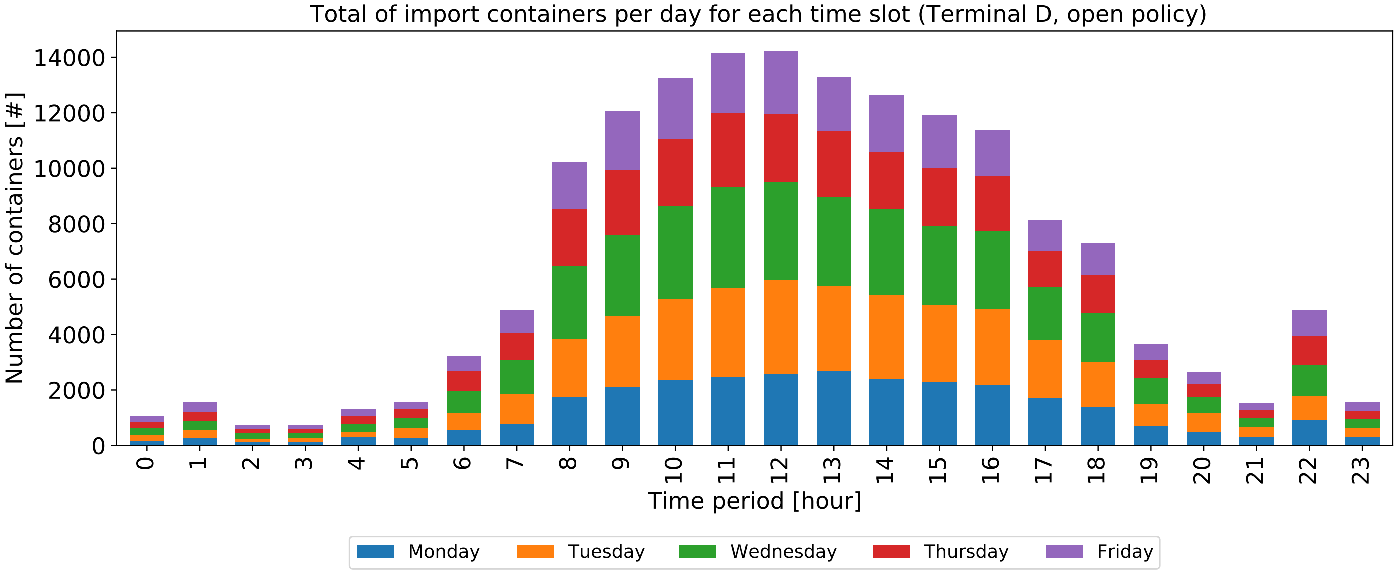


(a) Totals, absolute numbers

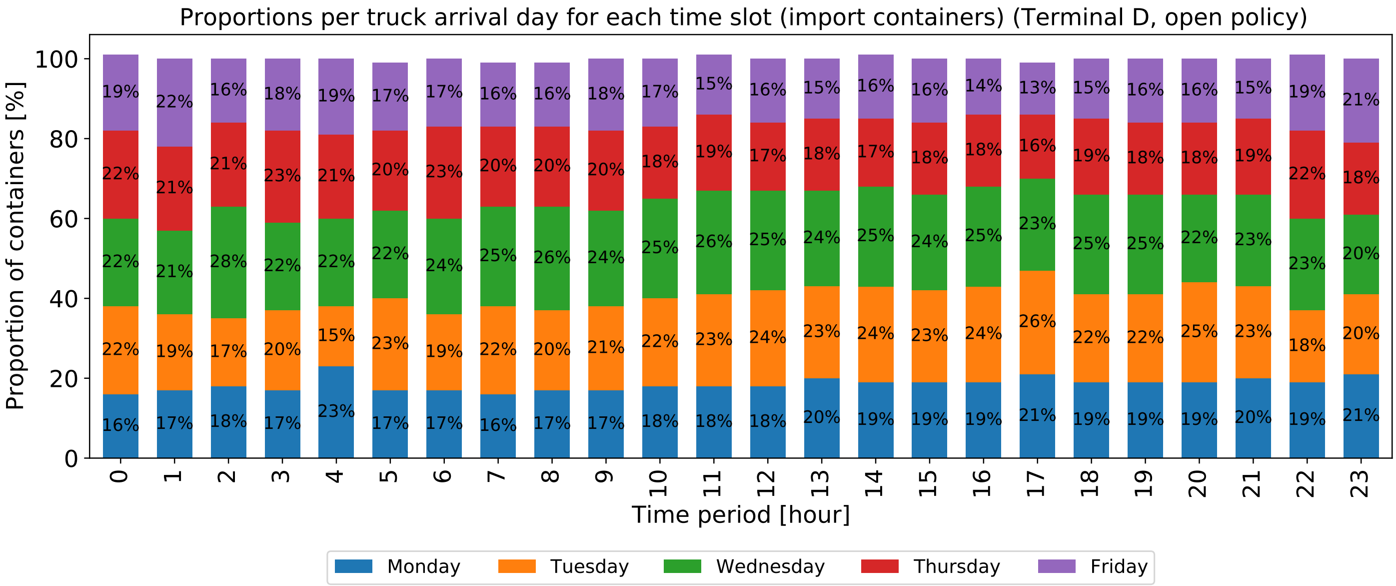


(b) Proportions, percentages

Figure C.7: Import container pick up preference distributed per hour based on day of the week (terminal C)



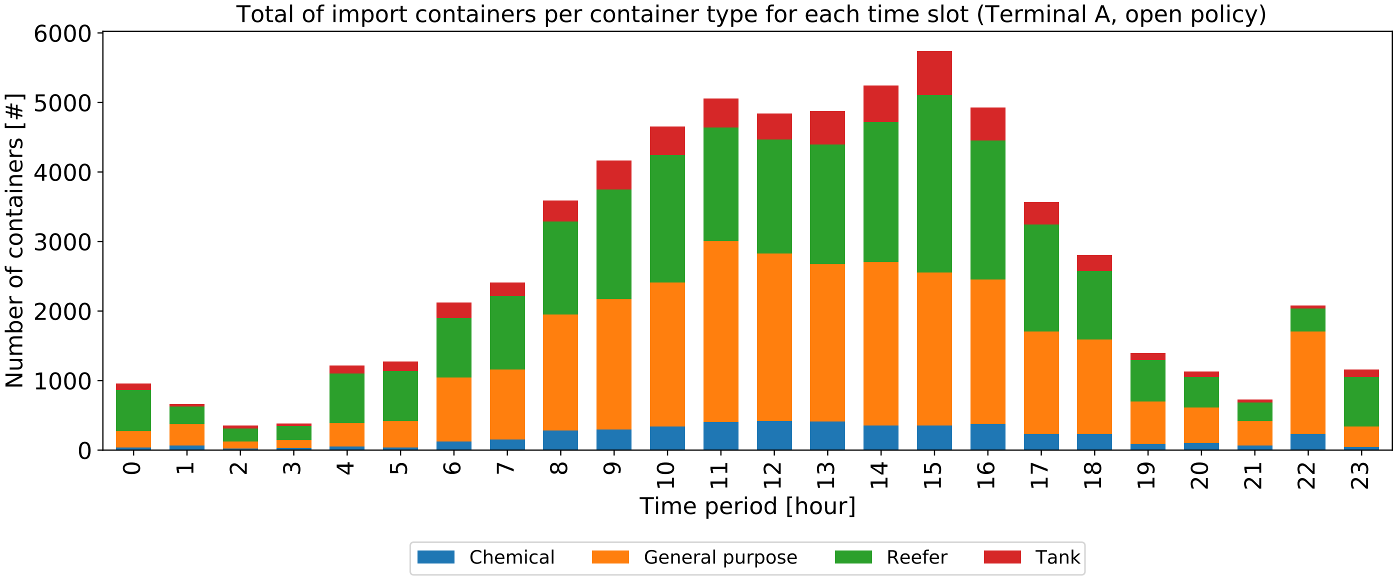
(a) Totals, absolute numbers



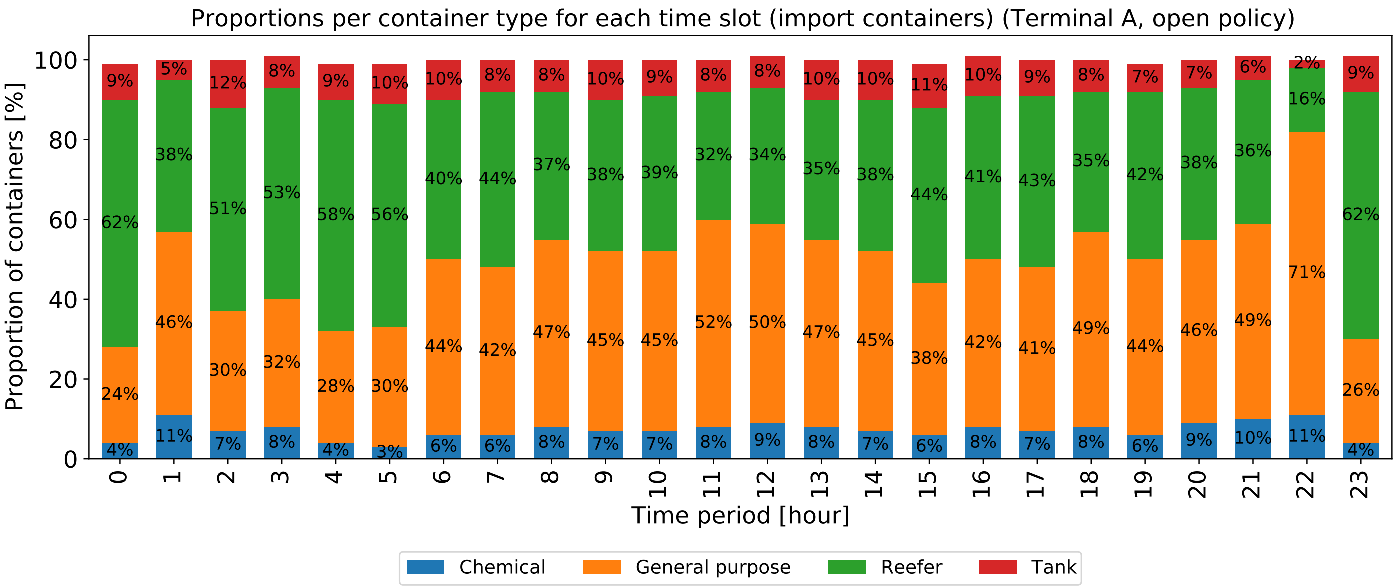
(b) Proportions, percentages

Figure C.8: Import container pick up preference distributed per hour based on day of the week (terminal D)

C.4.2 Container type category

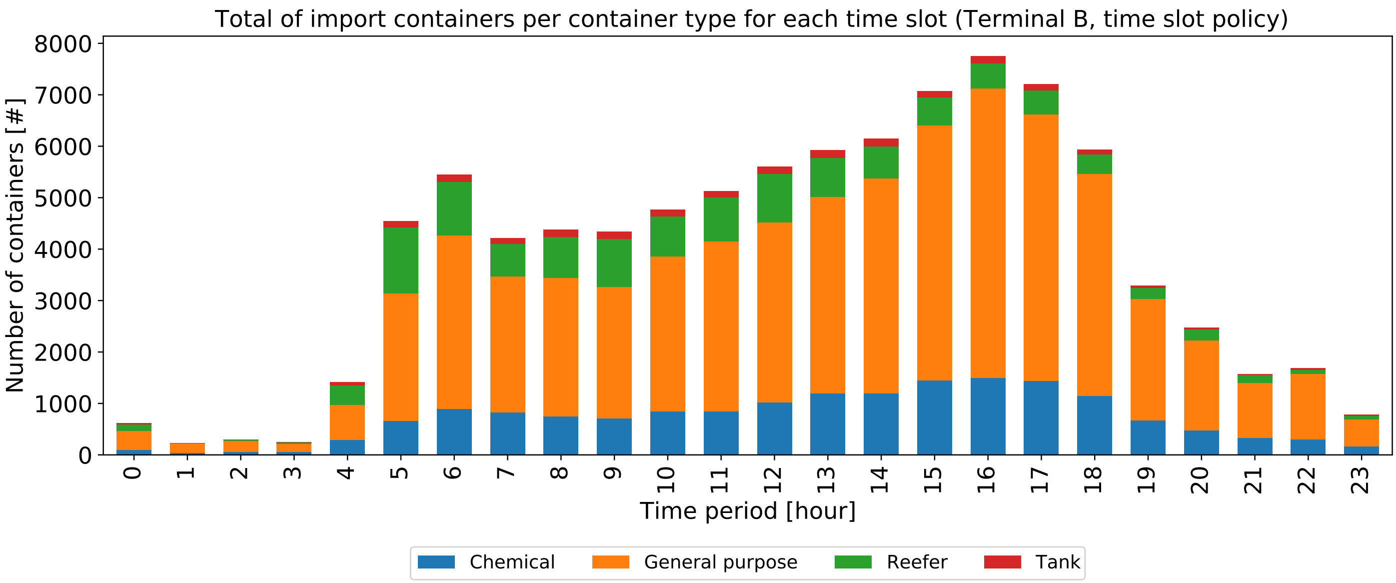


(a) Totals, absolute numbers

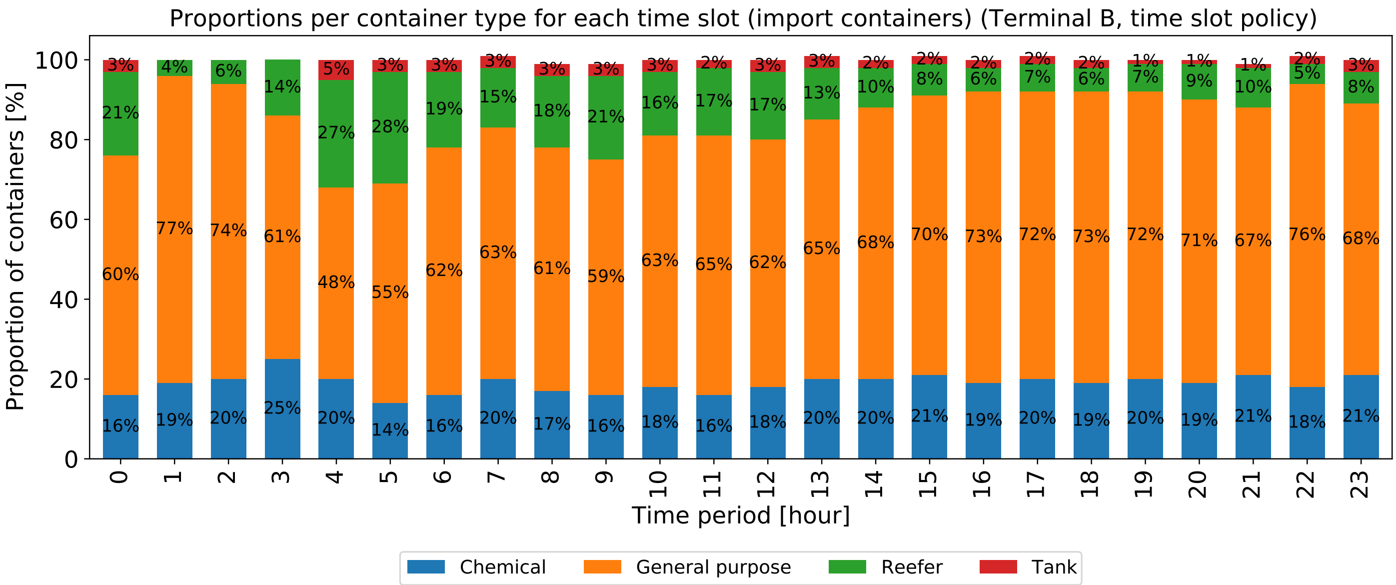


(b) Proportions, percentages

Figure C.9: Import container pick up preference distributed per hour based on container type category (terminal A)

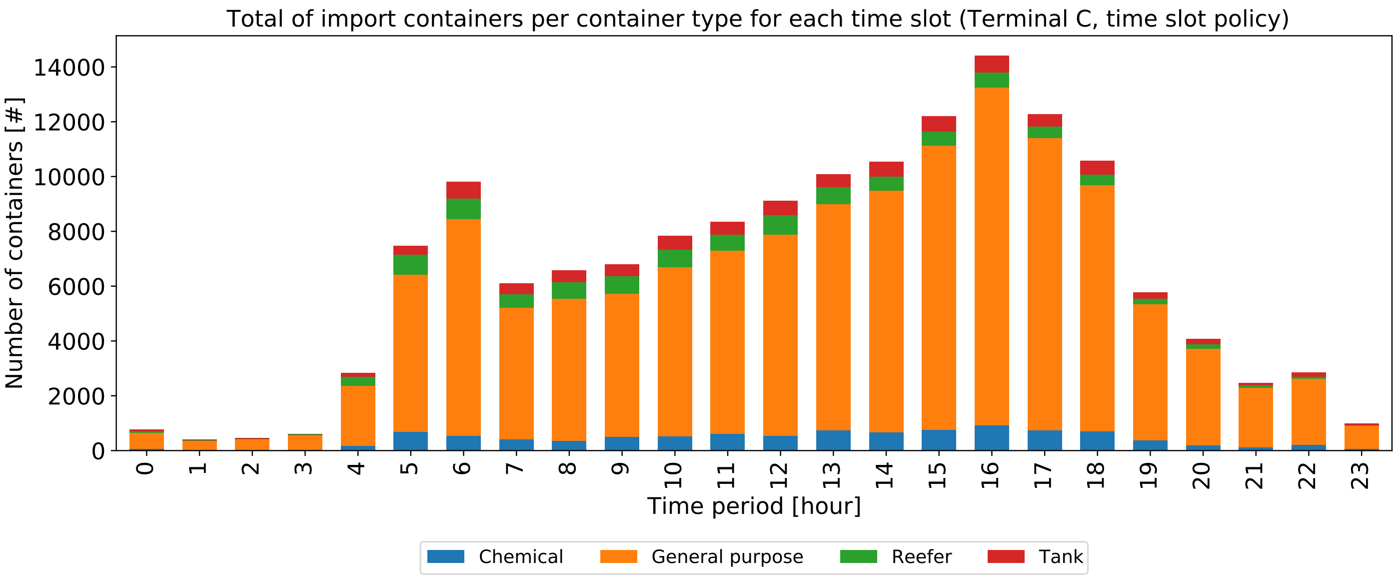


(a) Totals, absolute numbers

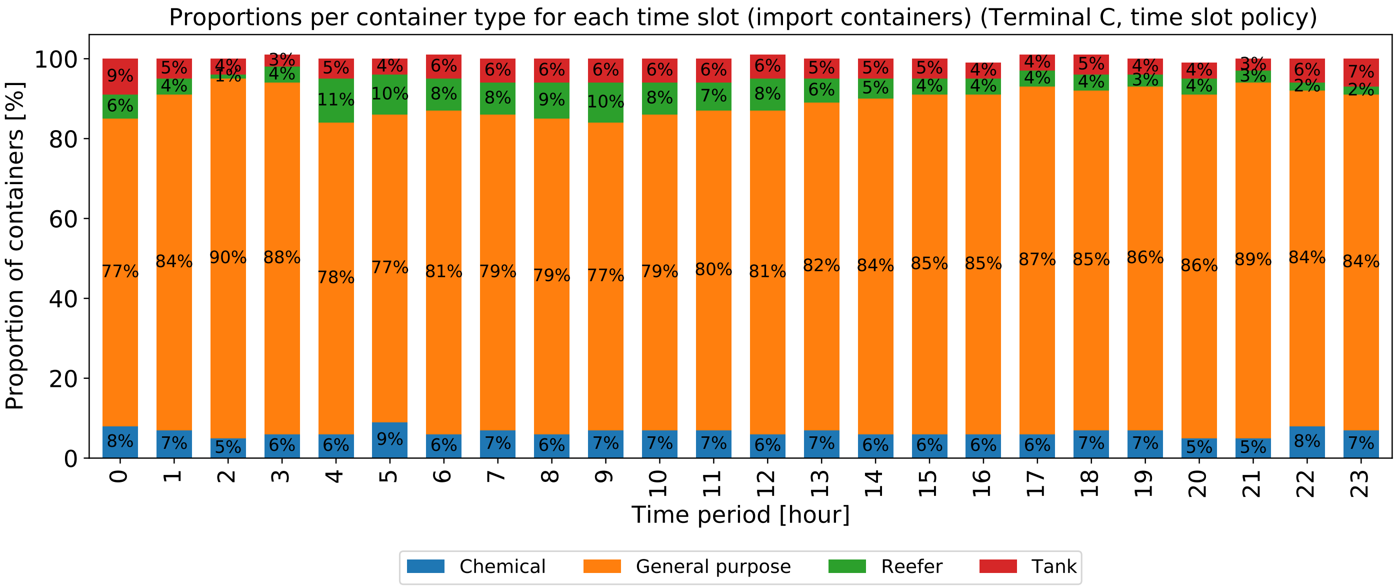


(b) Proportions, percentages

Figure C.10: Import container pick up preference distributed per hour based on container type category (terminal B)

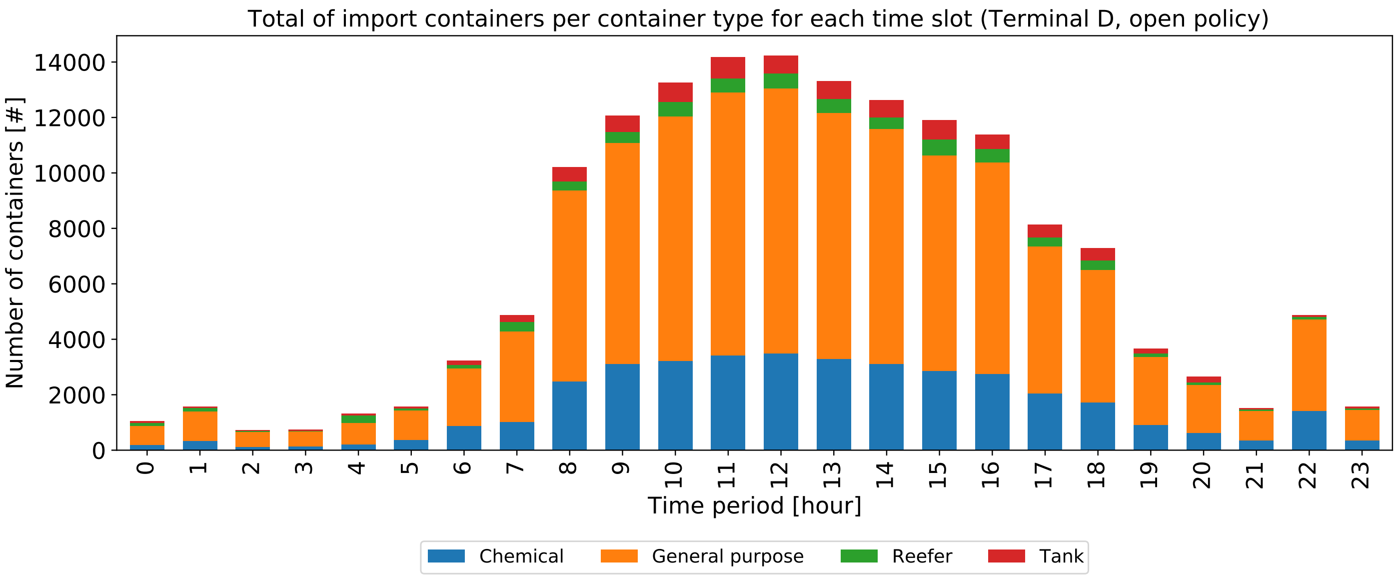


(a) Totals, absolute numbers

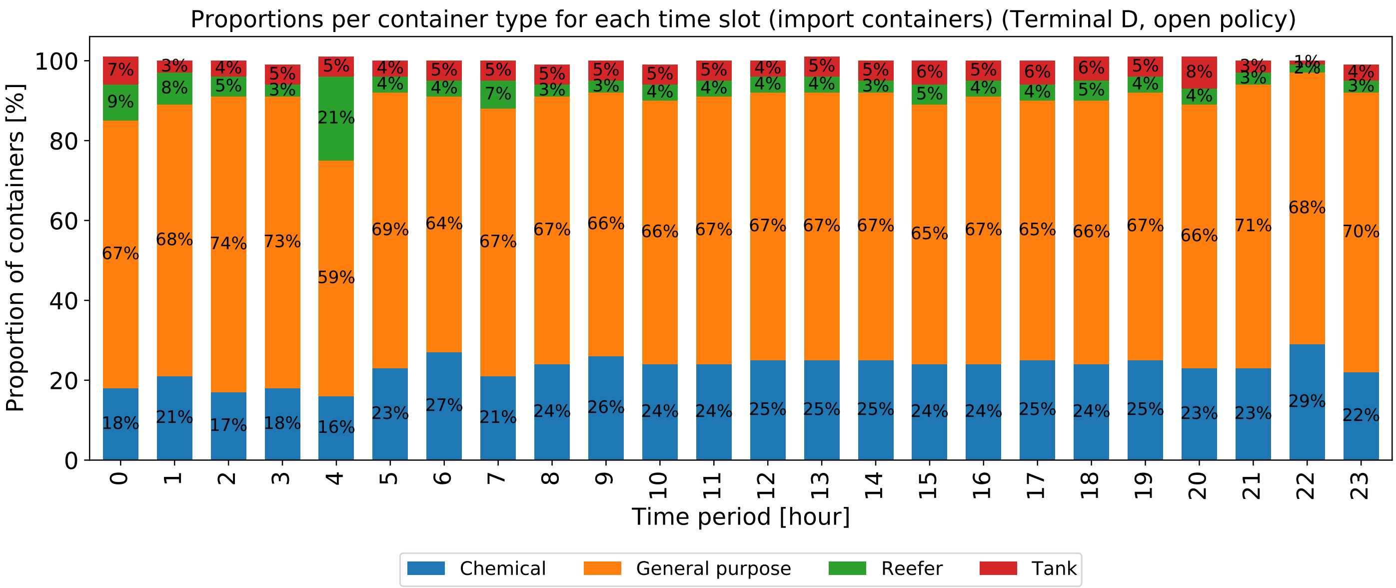


(b) Proportions, percentages

Figure C.11: Import container pick up preference distributed per hour based on container type category (terminal C)



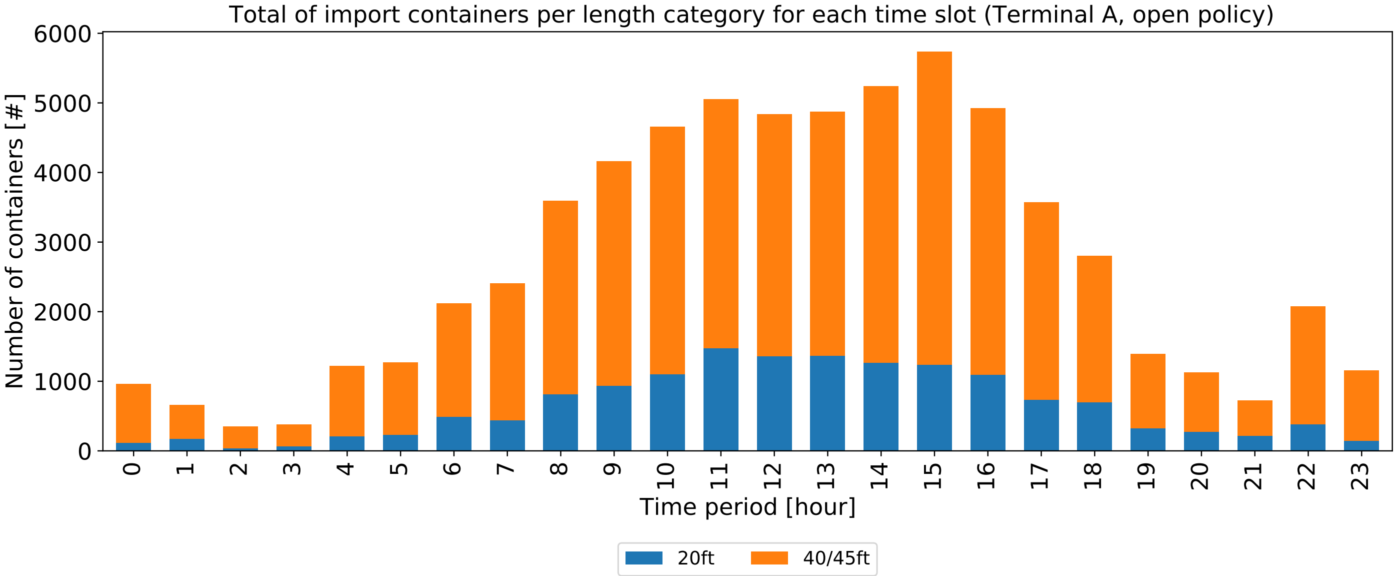
(a) Totals, absolute numbers



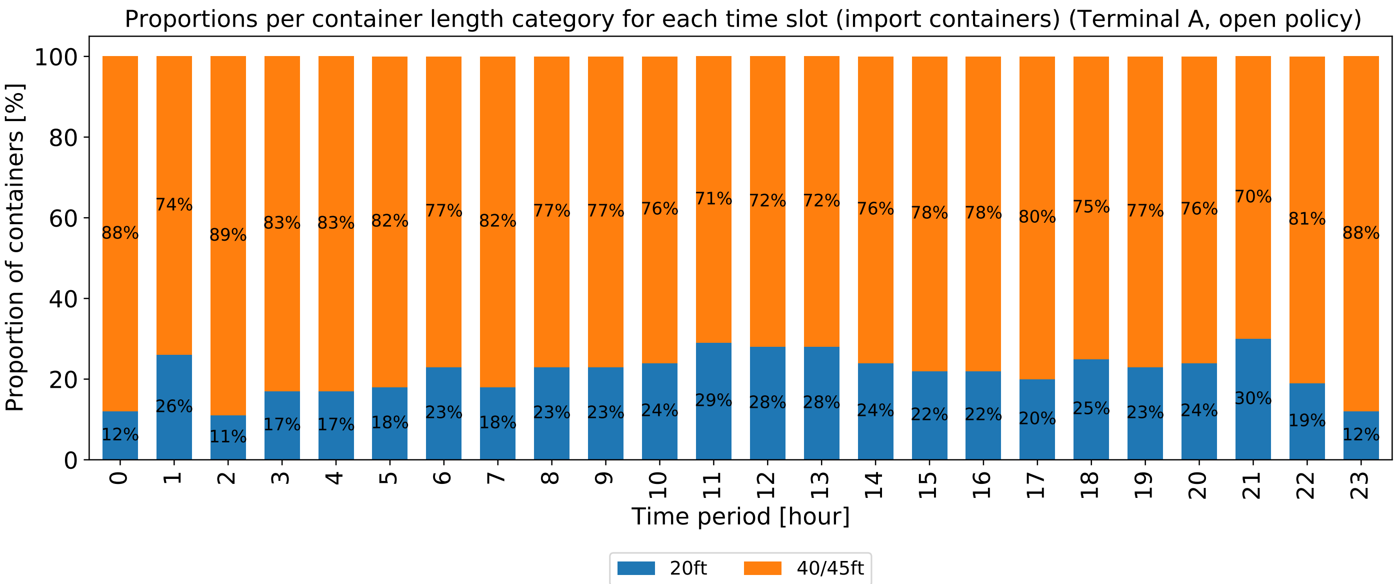
(b) Proportions, percentages

Figure C.12: Import container pick up preference distributed per hour based on container type category (terminal D)

C.4.3 Length category

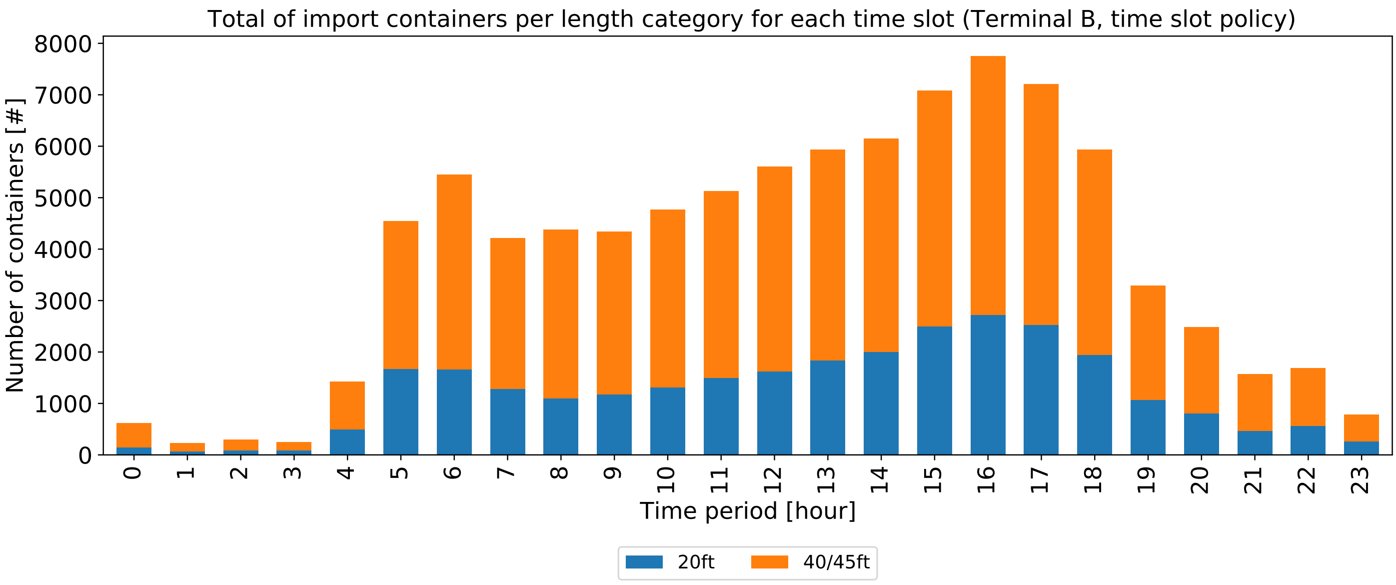


(a) Totals, absolute numbers

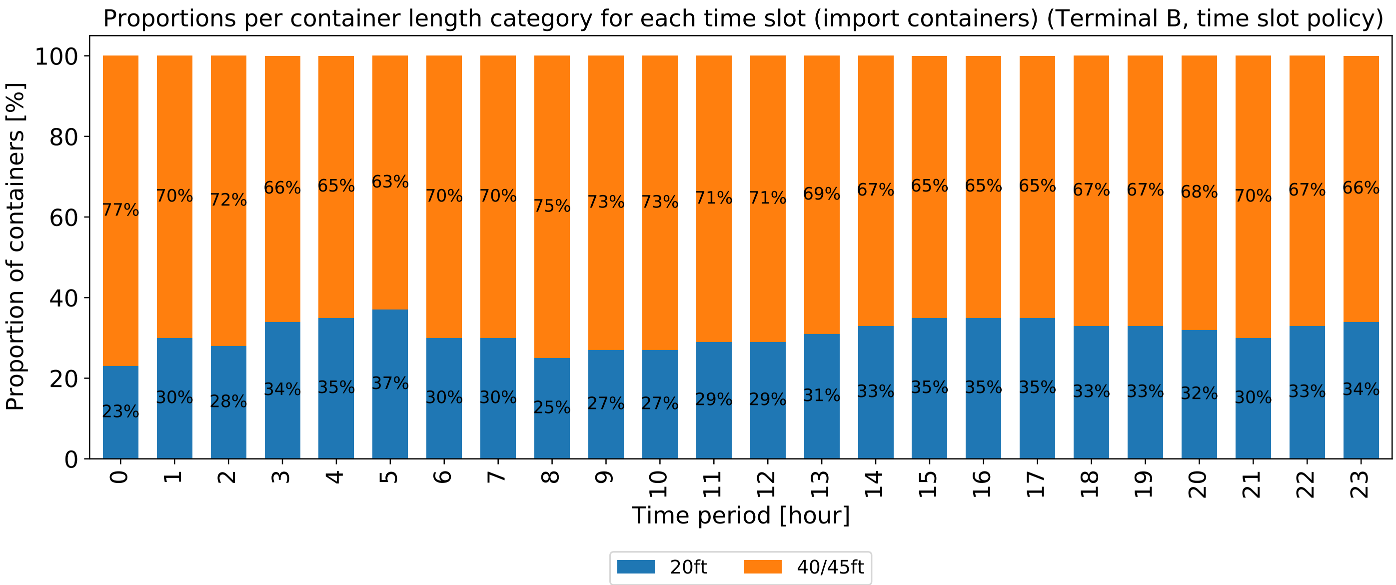


(b) Proportions, percentages

Figure C.13: Import container pick up preference distributed per hour based on length category (terminal A)

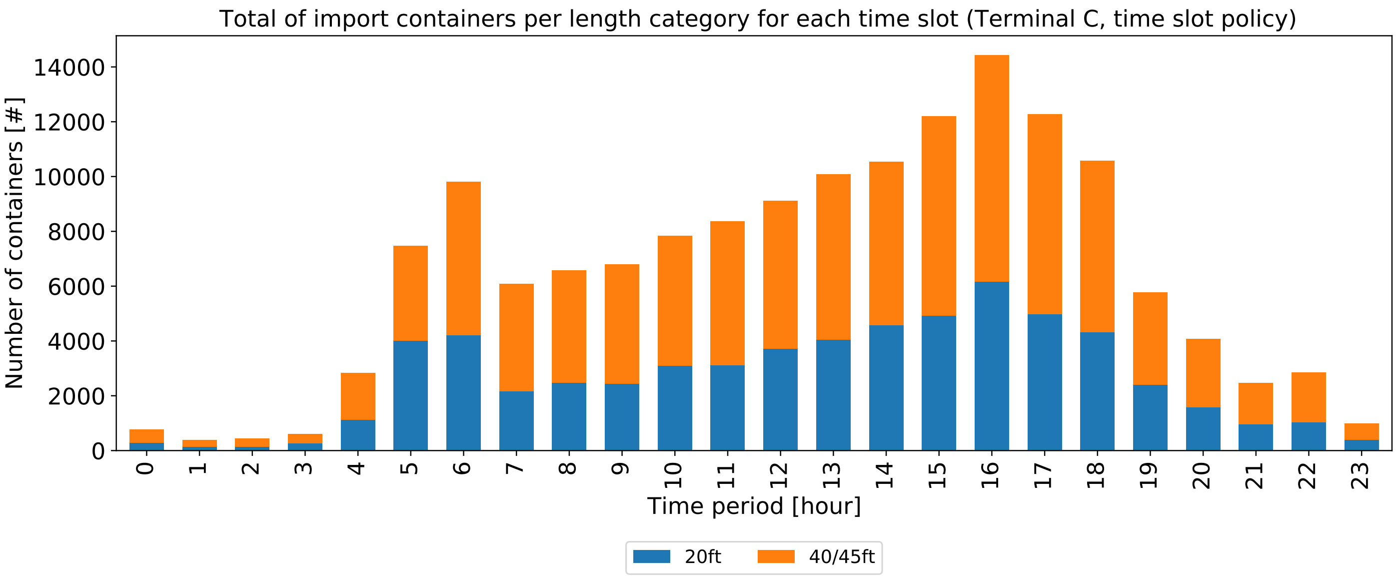


(a) Totals, absolute numbers

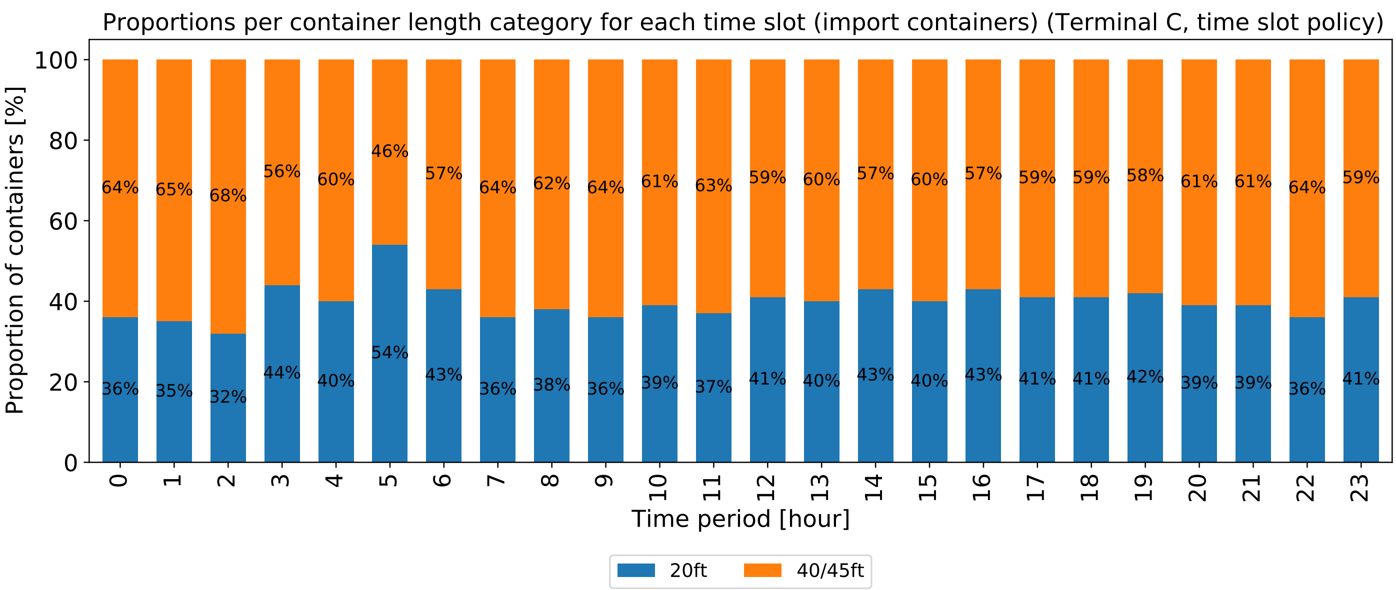


(b) Proportions, percentages

Figure C.14: Import container pick up preference distributed per hour based on length category (terminal B)

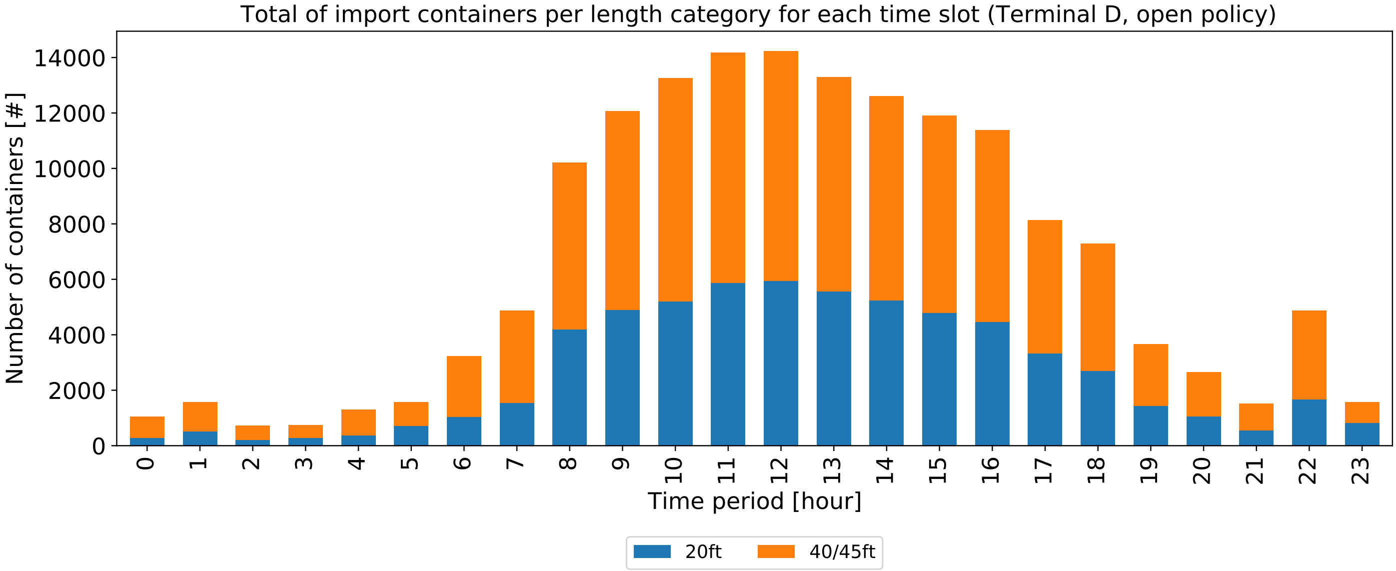


(a) Totals, absolute numbers

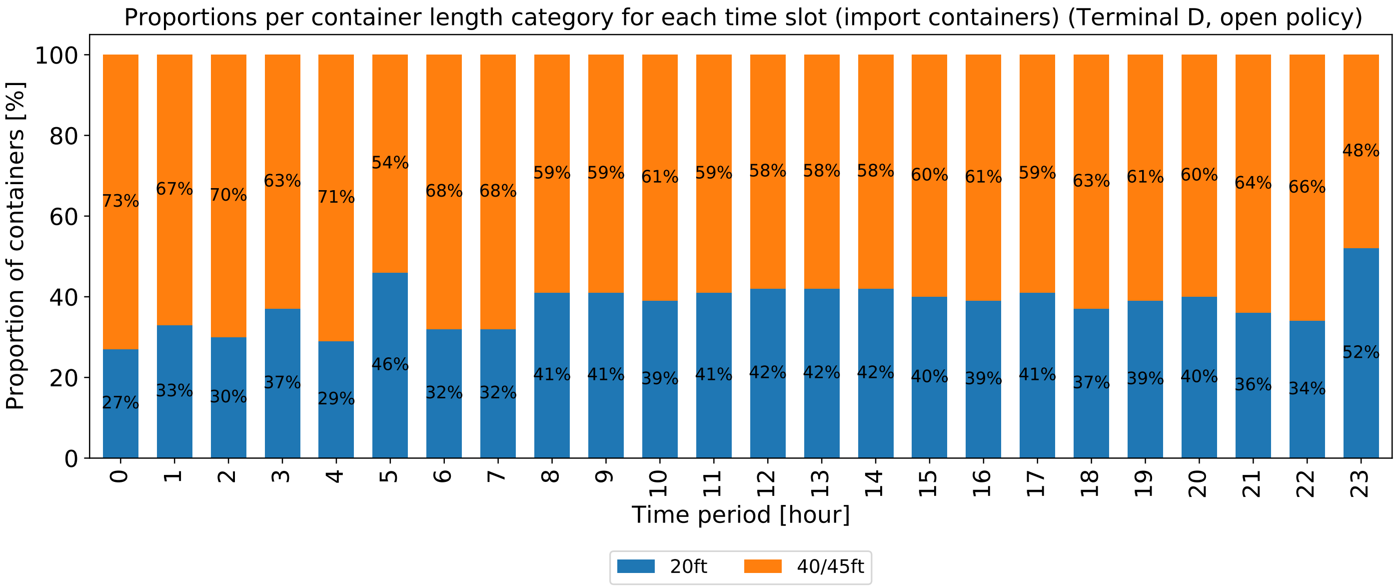


(b) Proportions, percentages

Figure C.15: Import container pick up preference distributed per hour based on length category (terminal C)



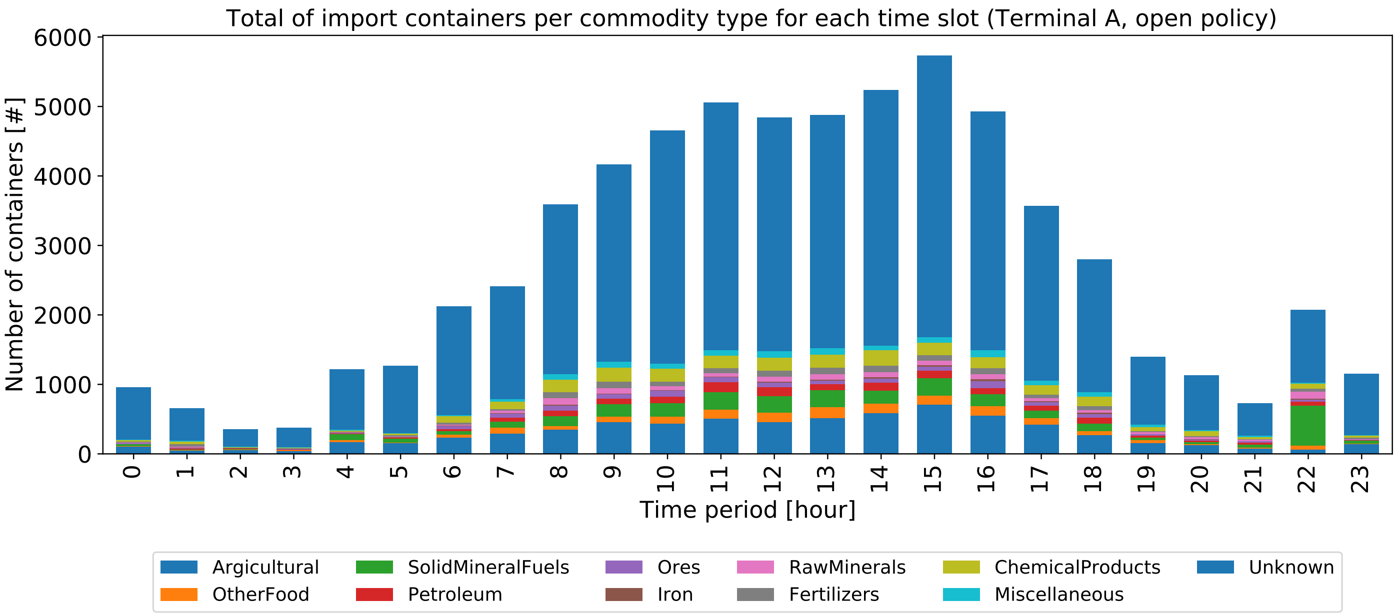
(a) Totals, absolute numbers



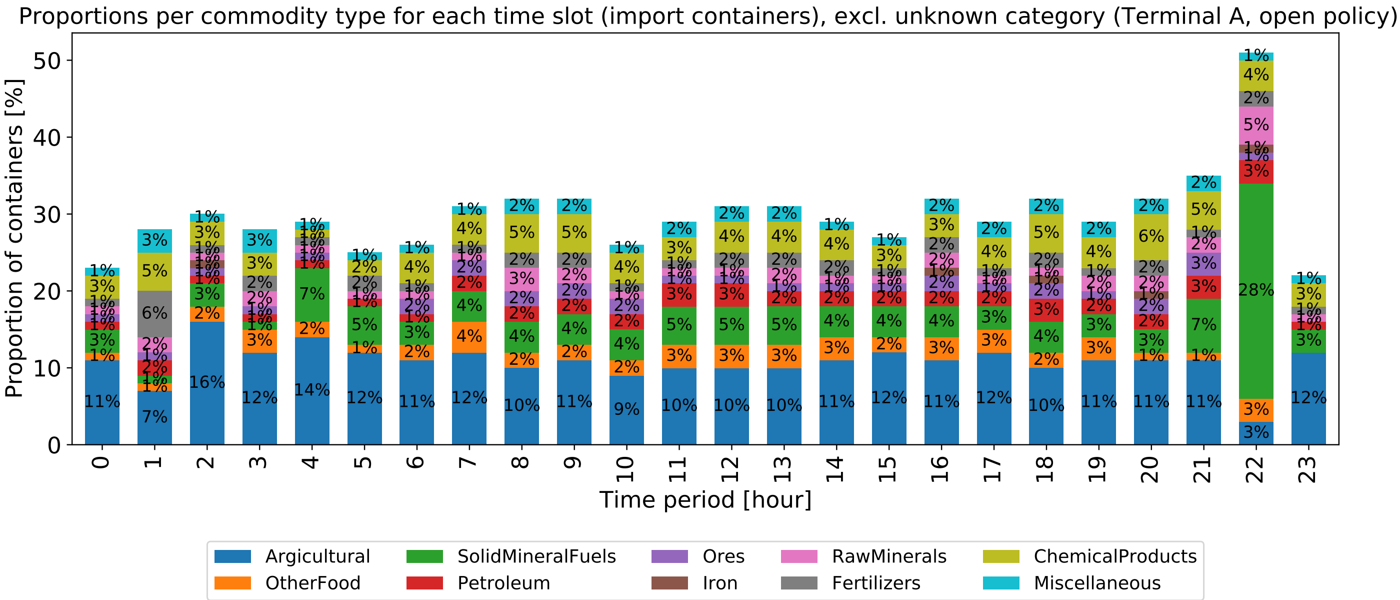
(b) Proportions, percentages

Figure C.16: Import container pick up preference distributed per hour based on length category (terminal D)

c.4.4 Commodity type category

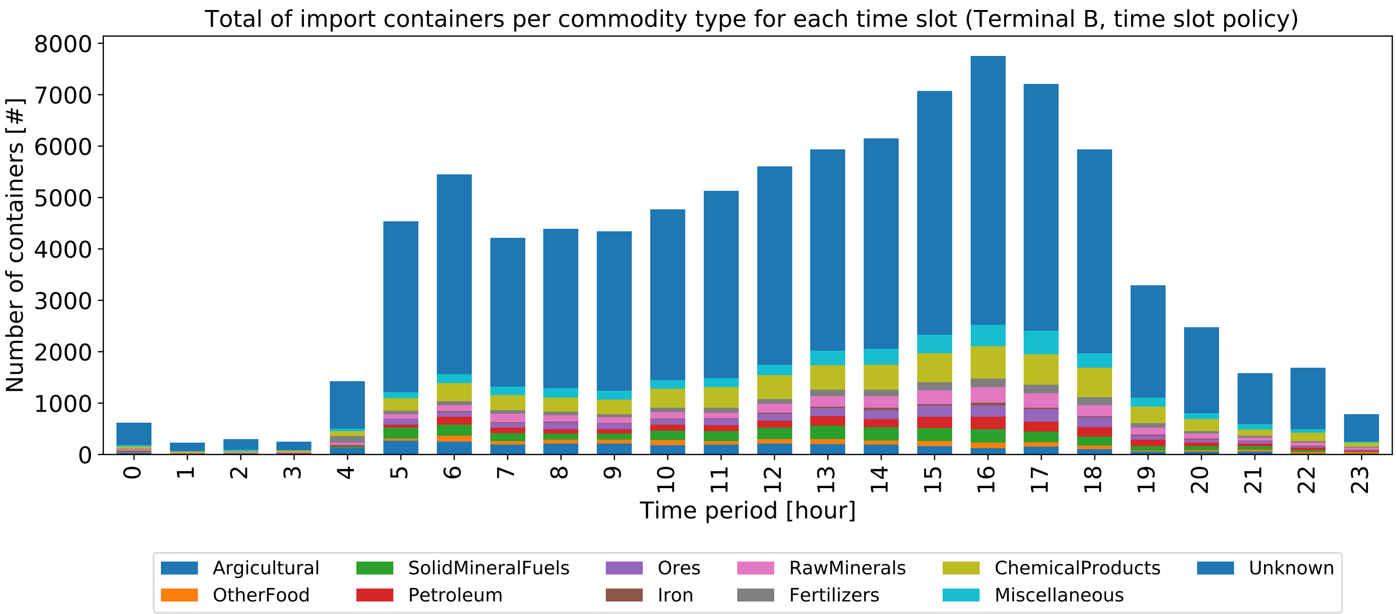


(a) Totals, absolute numbers

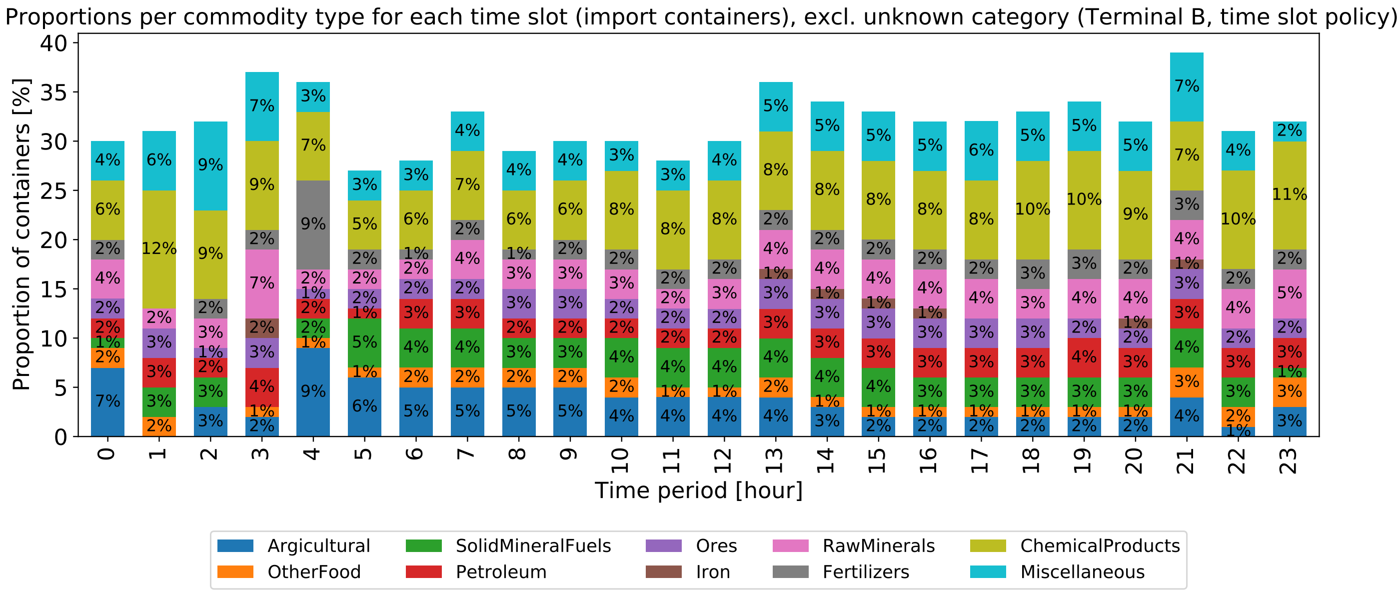


(b) Proportions, percentages

Figure C.17: Import container pick up preference distributed per hour based on commodity category (terminal A)

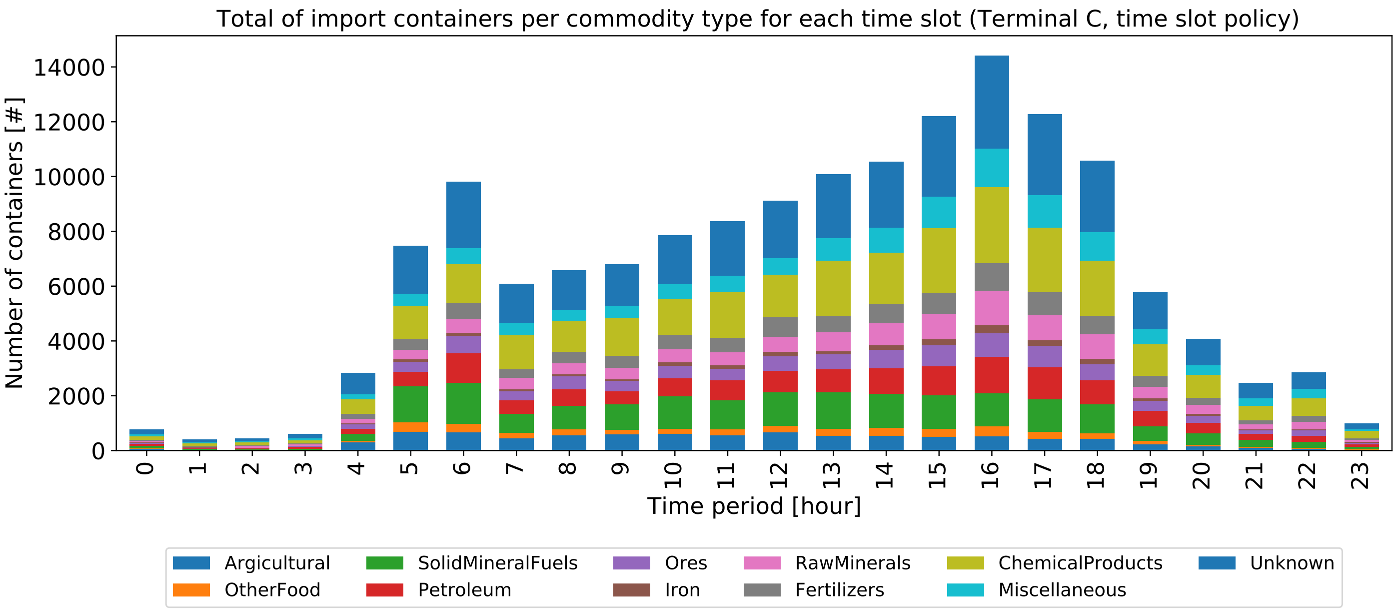


(a) Totals, absolute numbers

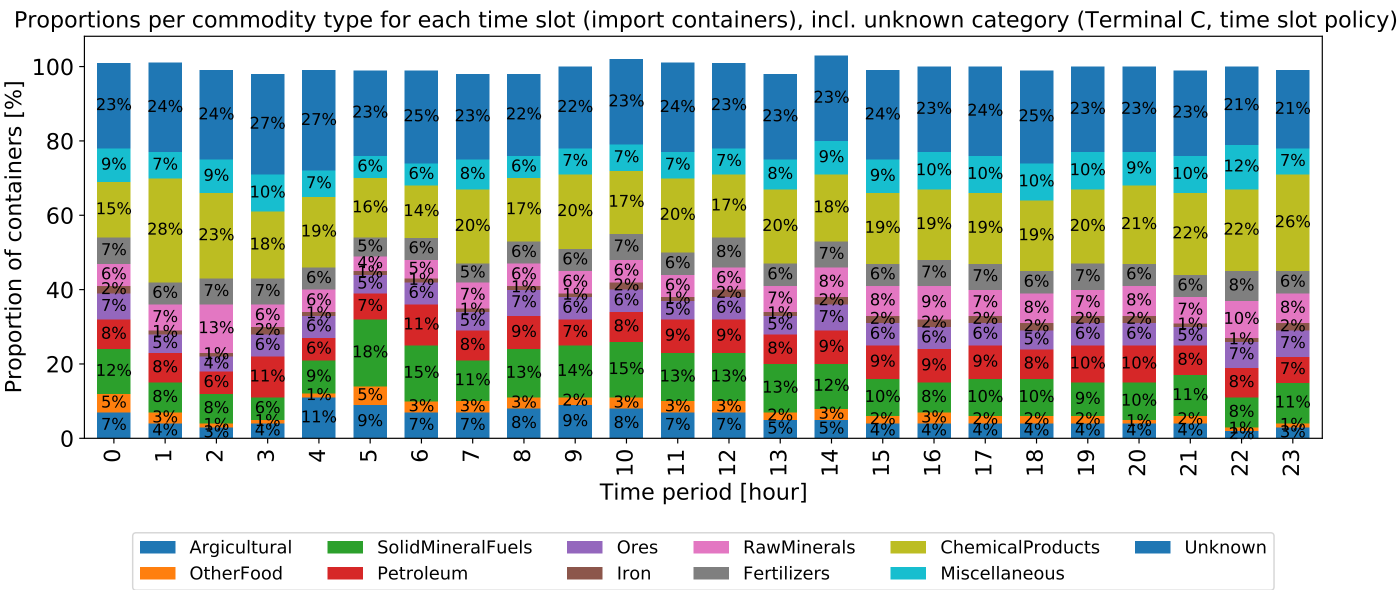


(b) Proportions, percentages

Figure C.18: Import container pick up preference distributed per hour based on commodity category (terminal B)

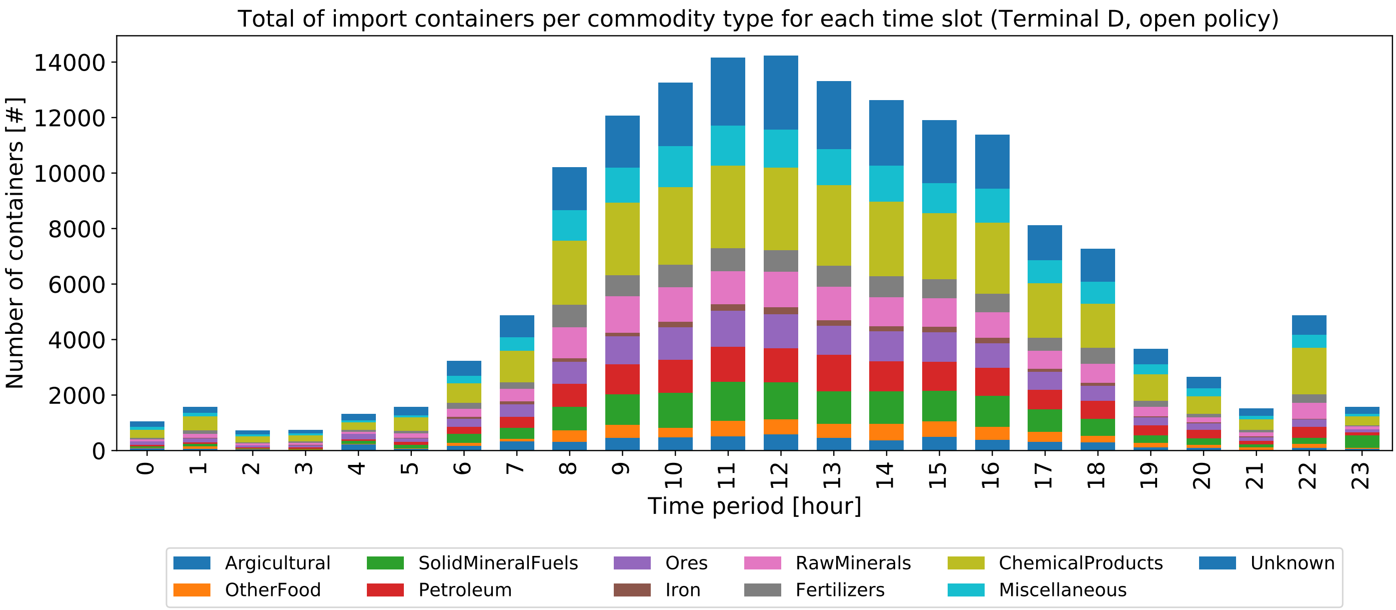


(a) Totals, absolute numbers

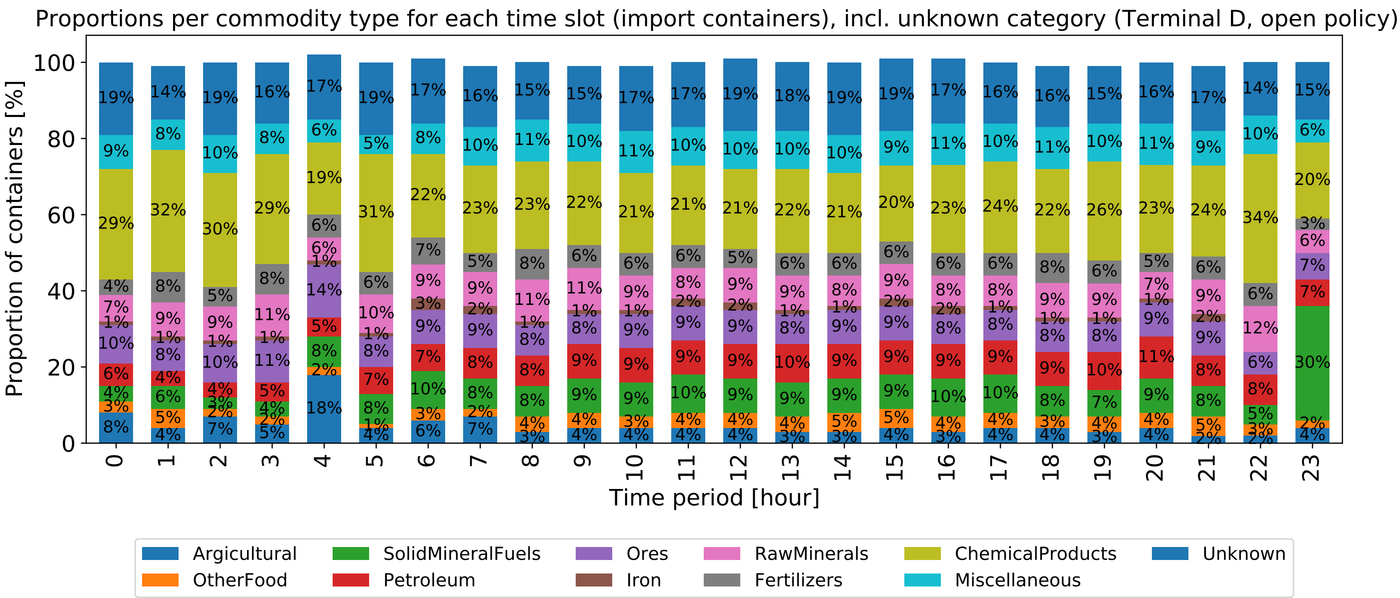


(b) Proportions, percentages

Figure C.19: Import container pick up preference distributed per hour based on commodity category (terminal C)



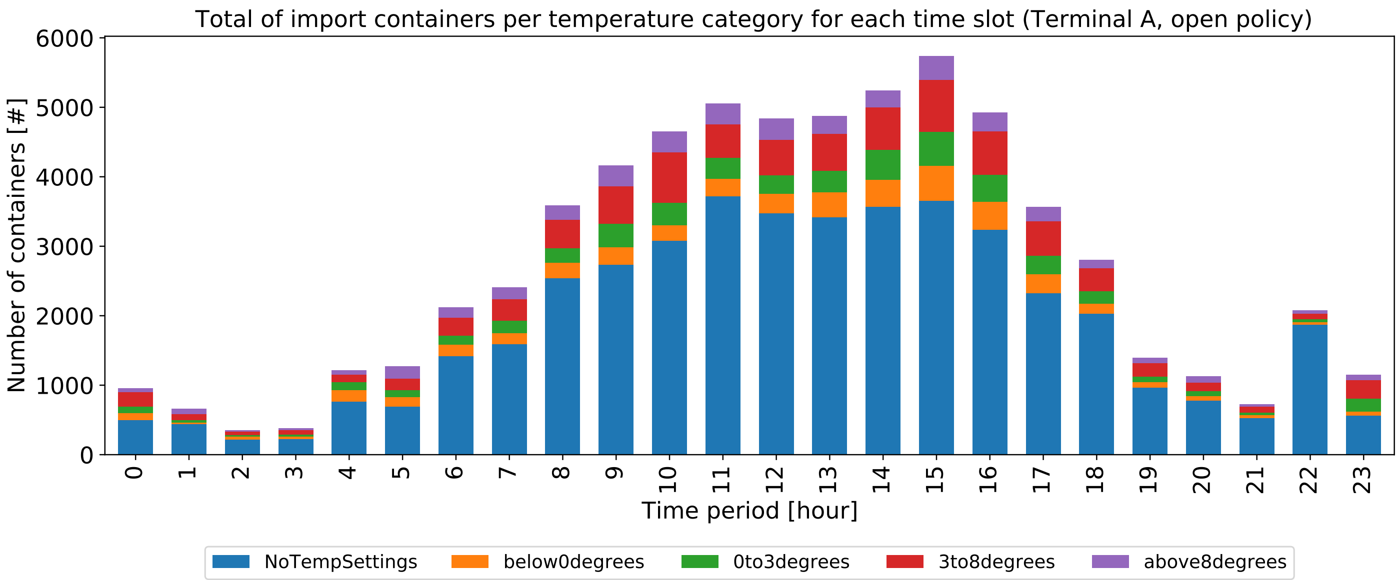
(a) Totals, absolute numbers



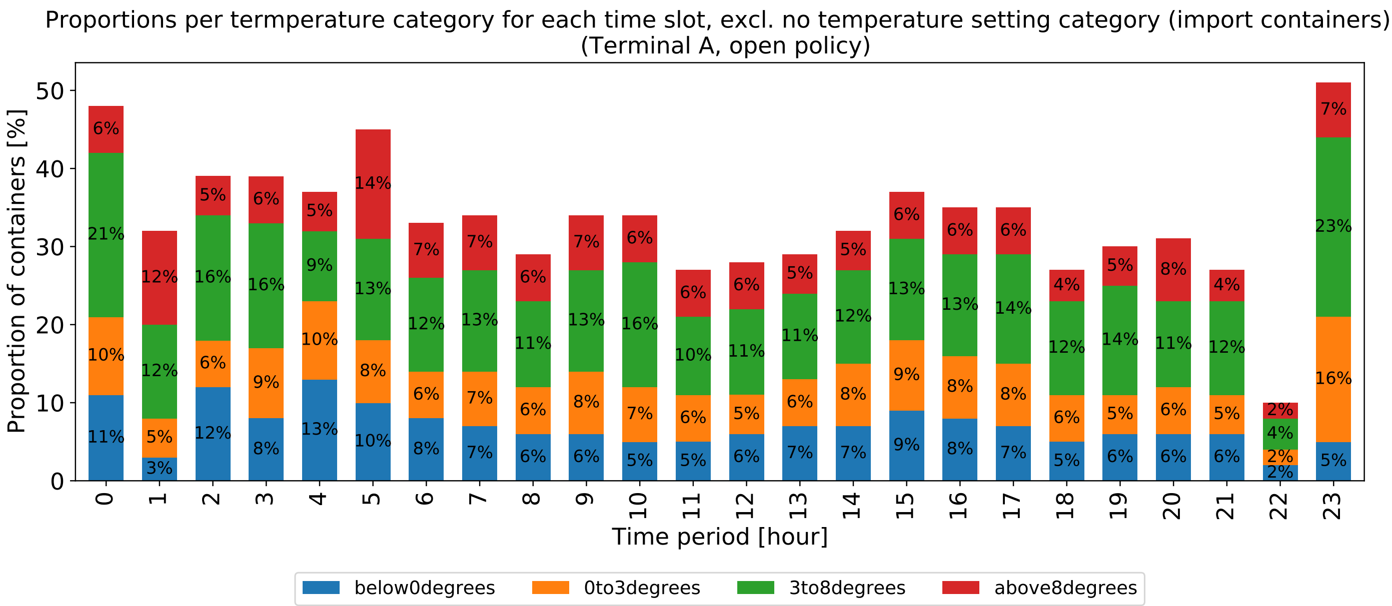
(b) Proportions, percentages

Figure C.20: Import container pick up preference distributed per hour based on commodity category (terminal D)

C.4.5 Temperature category

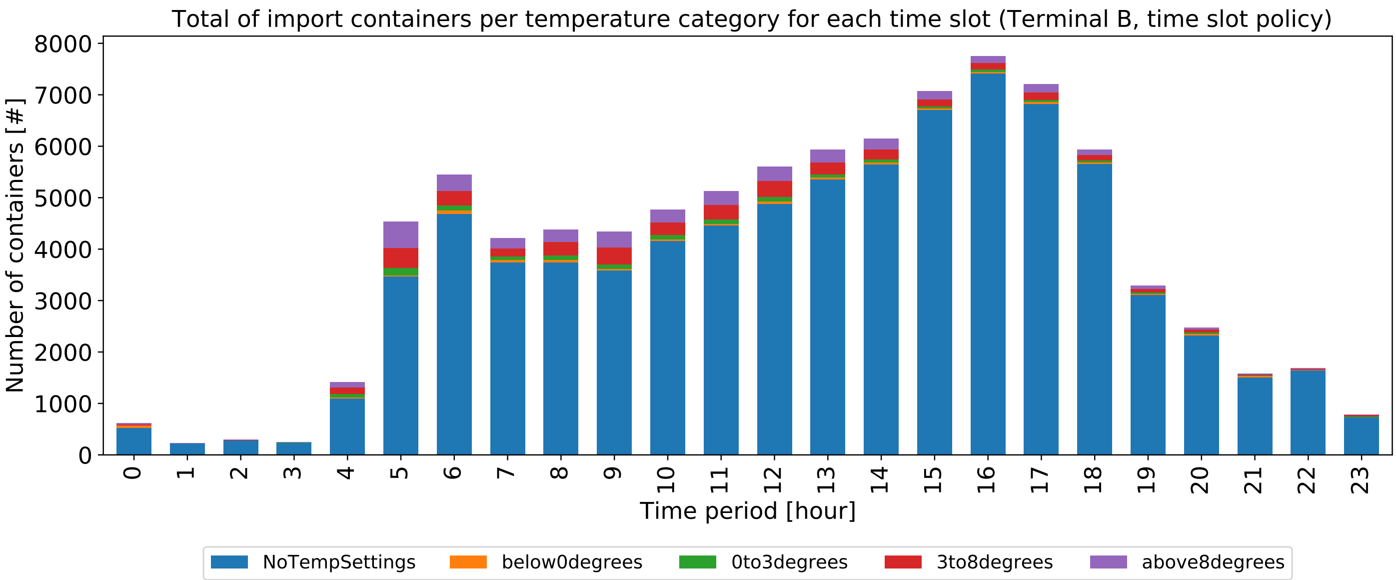


(a) Totals, absolute numbers

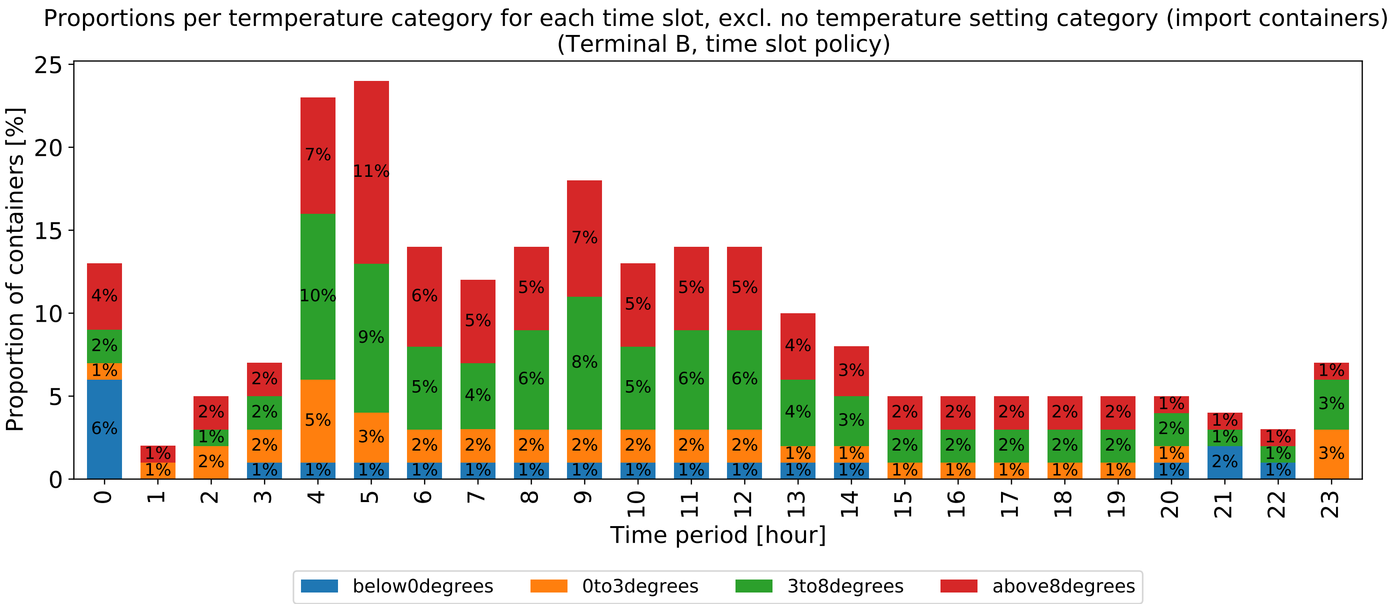


(b) Proportions, percentages

Figure C.21: Import container pick up preference distributed per hour based on temperature category (terminal A)

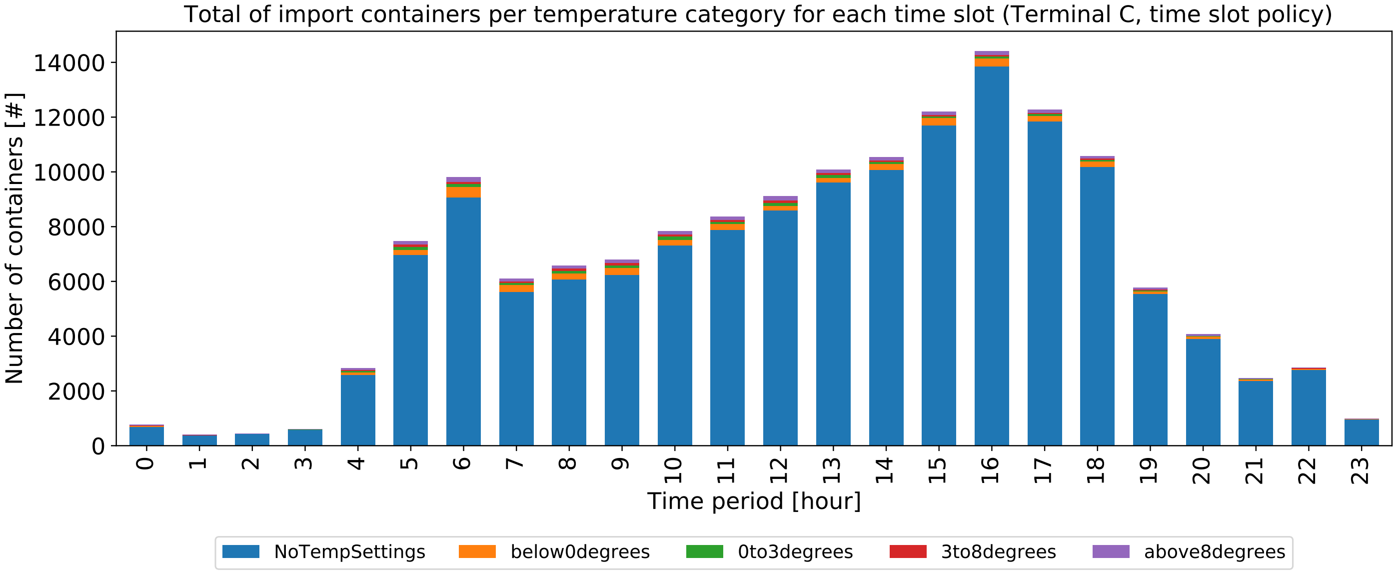


(a) Totals, absolute numbers

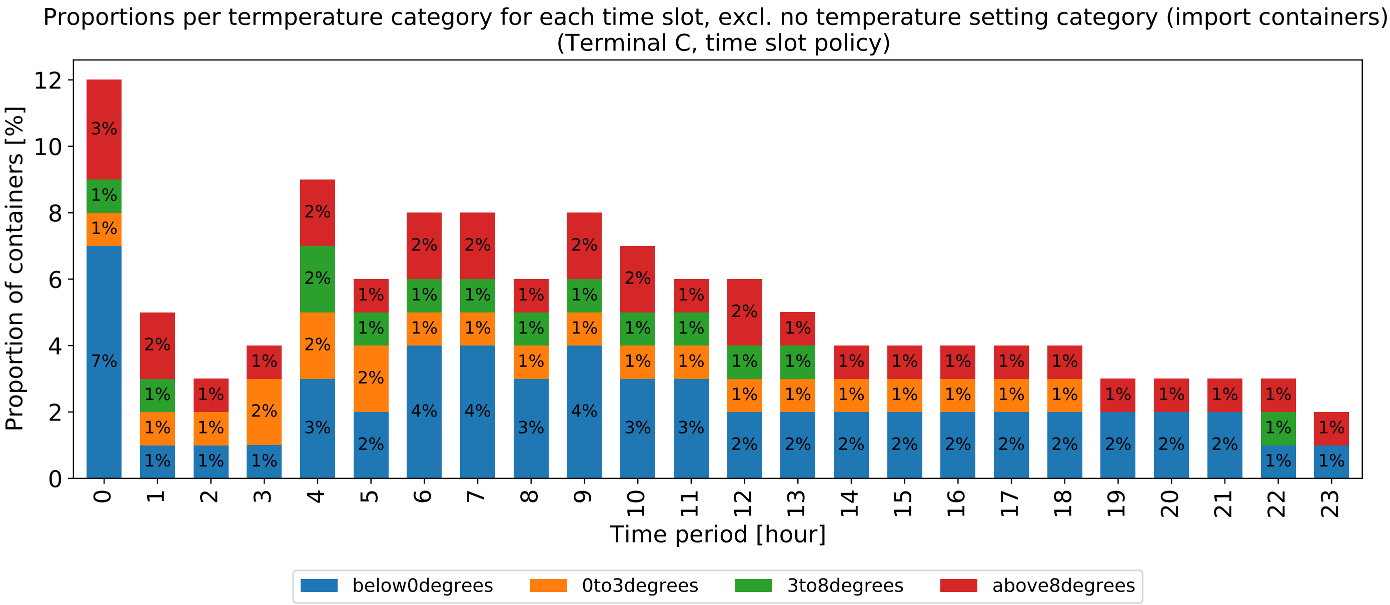


(b) Proportions, percentages

Figure C.22: Import container pick up preference distributed per hour based on temperature category (terminal B)

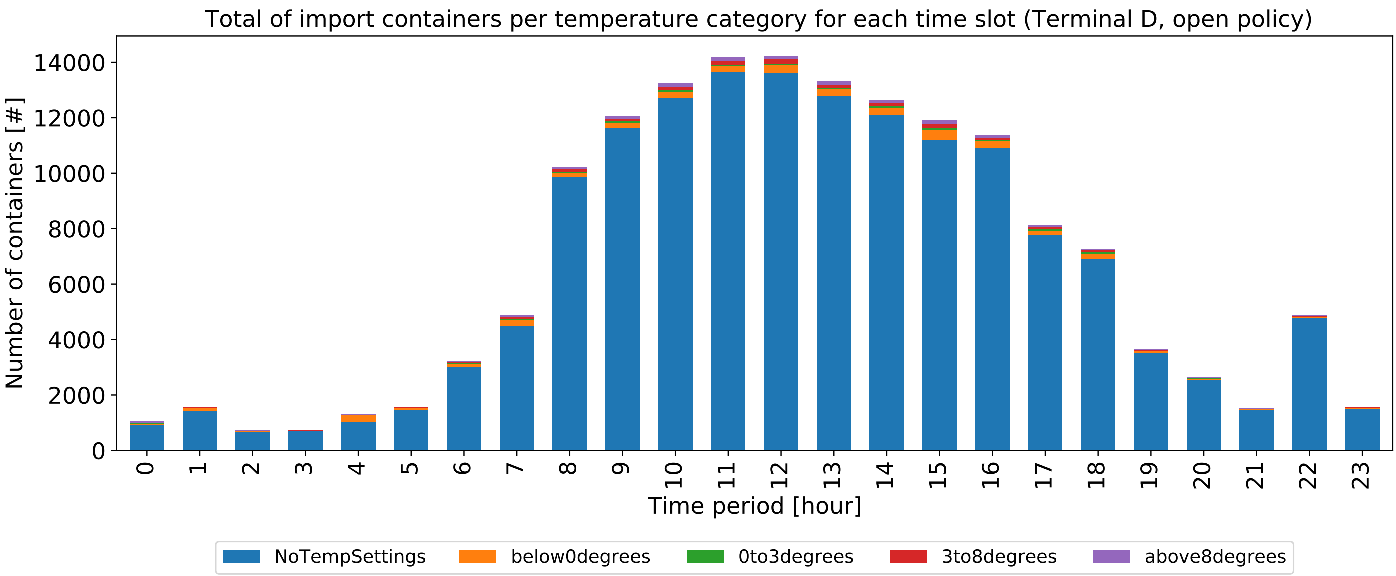


(a) Totals, absolute numbers

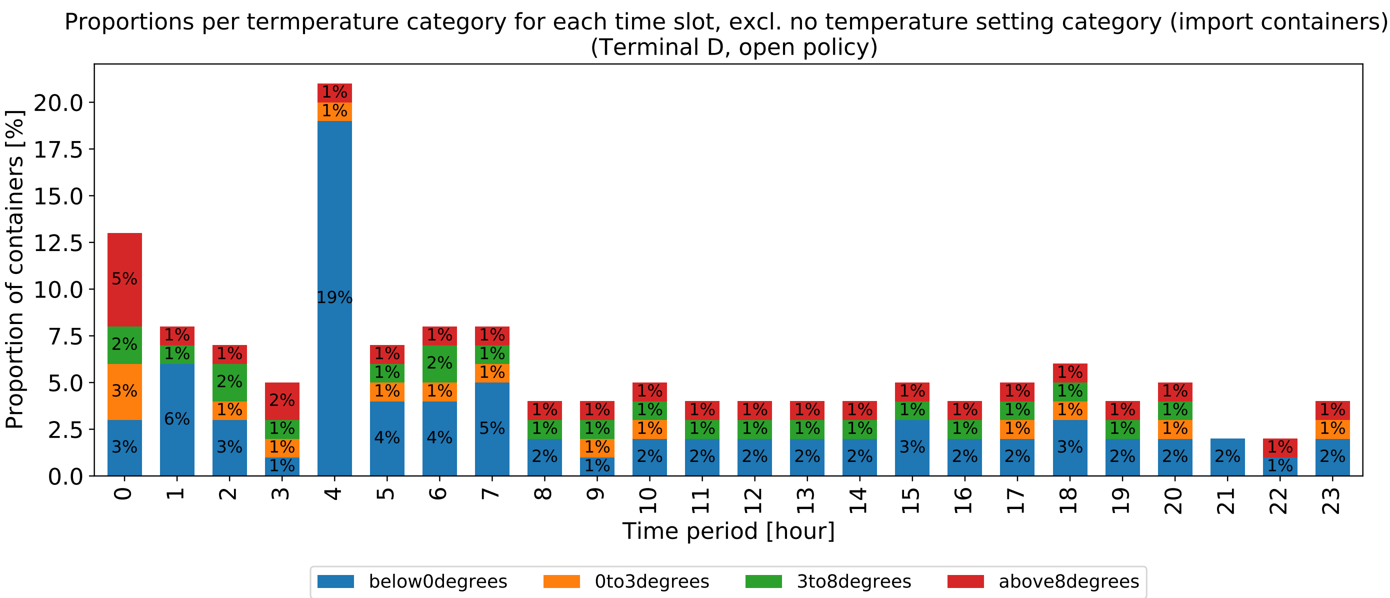


(b) Proportions, percentages

Figure C.23: Import container pick up preference distributed per hour based on temperature category (terminal C)



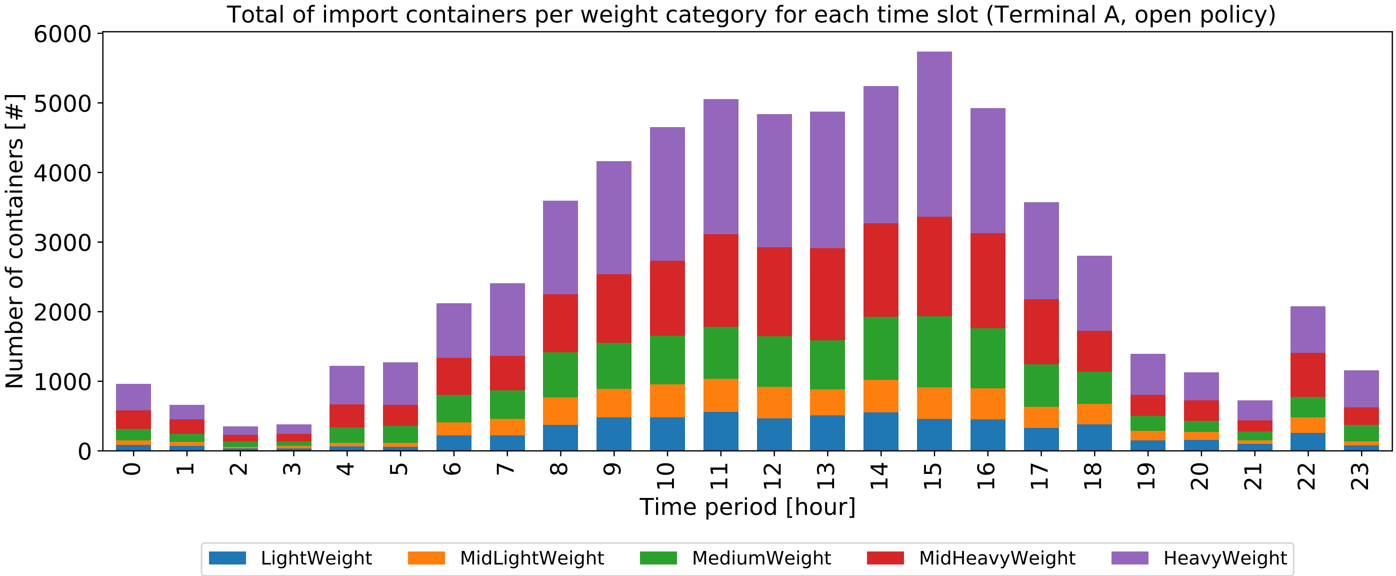
(a) Totals, absolute numbers



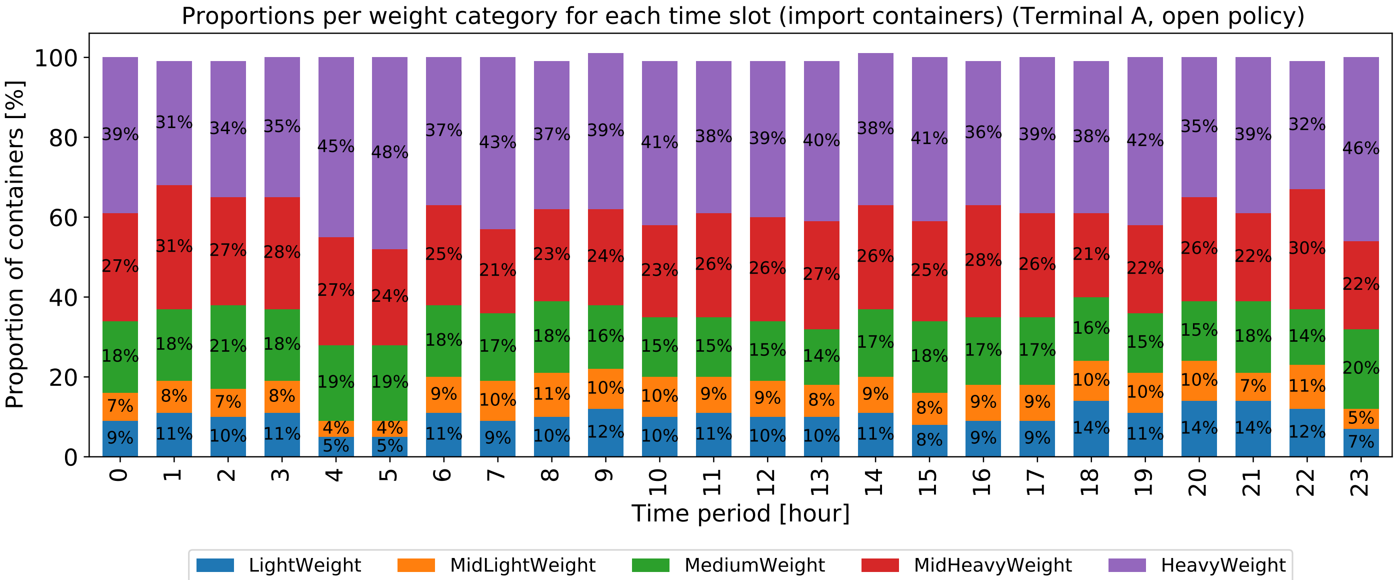
(b) Proportions, percentages

Figure C.24: Import container pick up preference distributed per hour based on temperature category (terminal D)

C.4.6 Weight category

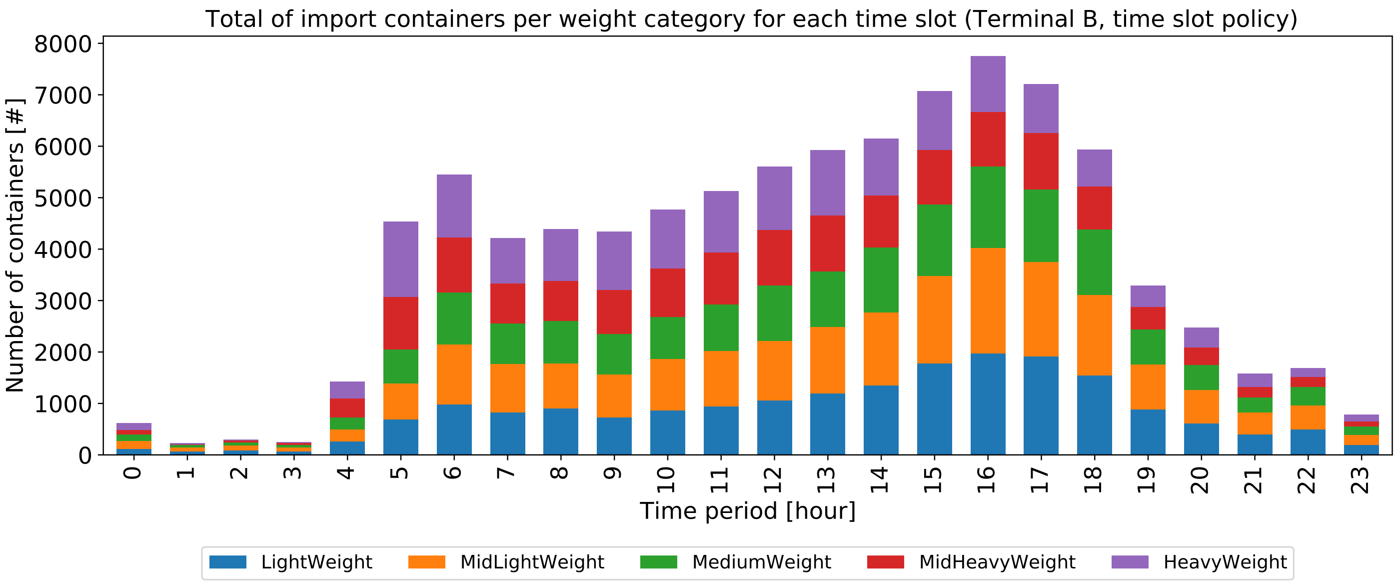


(a) Totals, absolute numbers

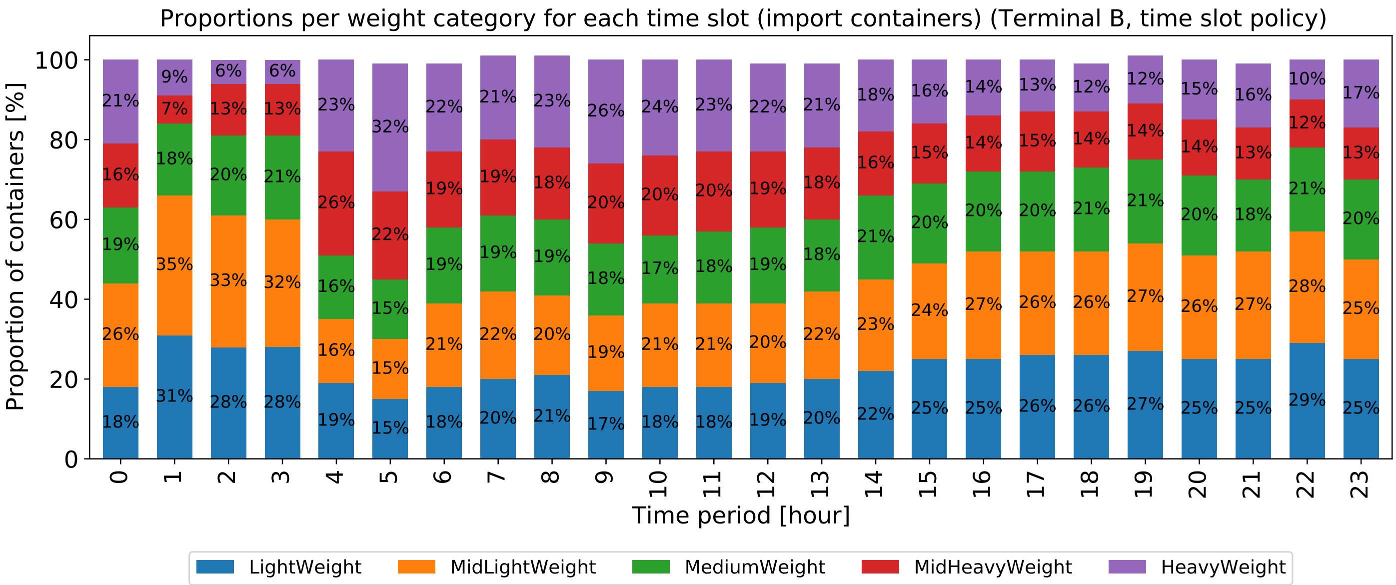


(b) Proportions, percentages

Figure C.25: Import container pick up preference distributed per hour based on weight category (terminal A)

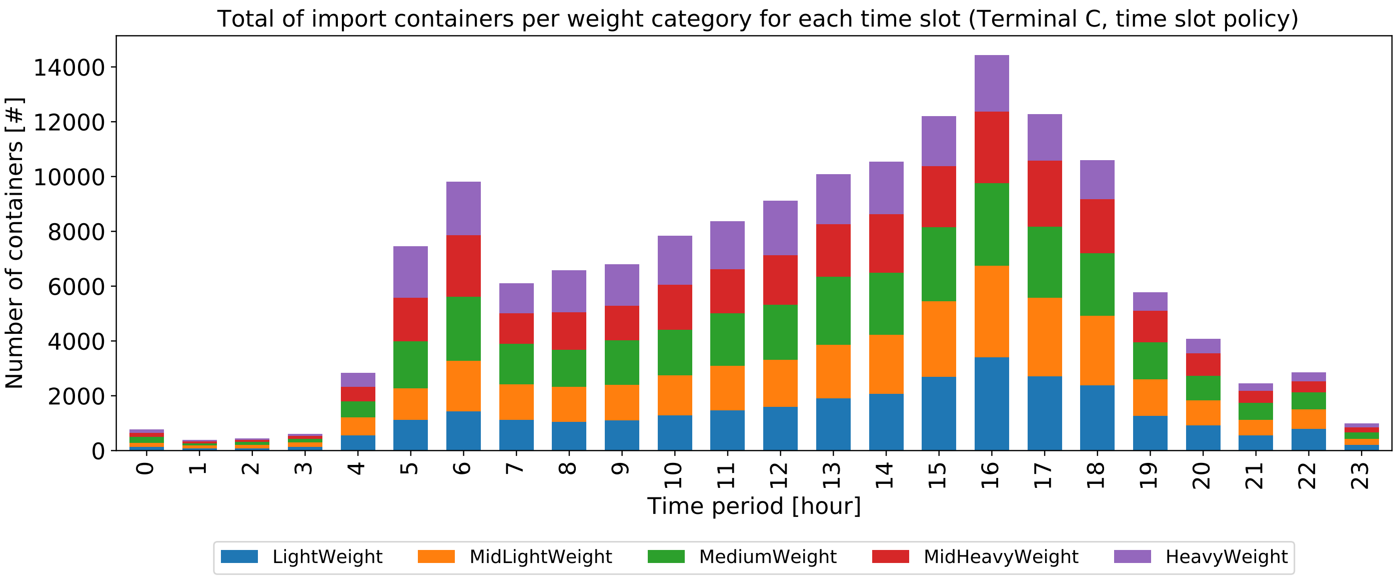


(a) Totals, absolute numbers

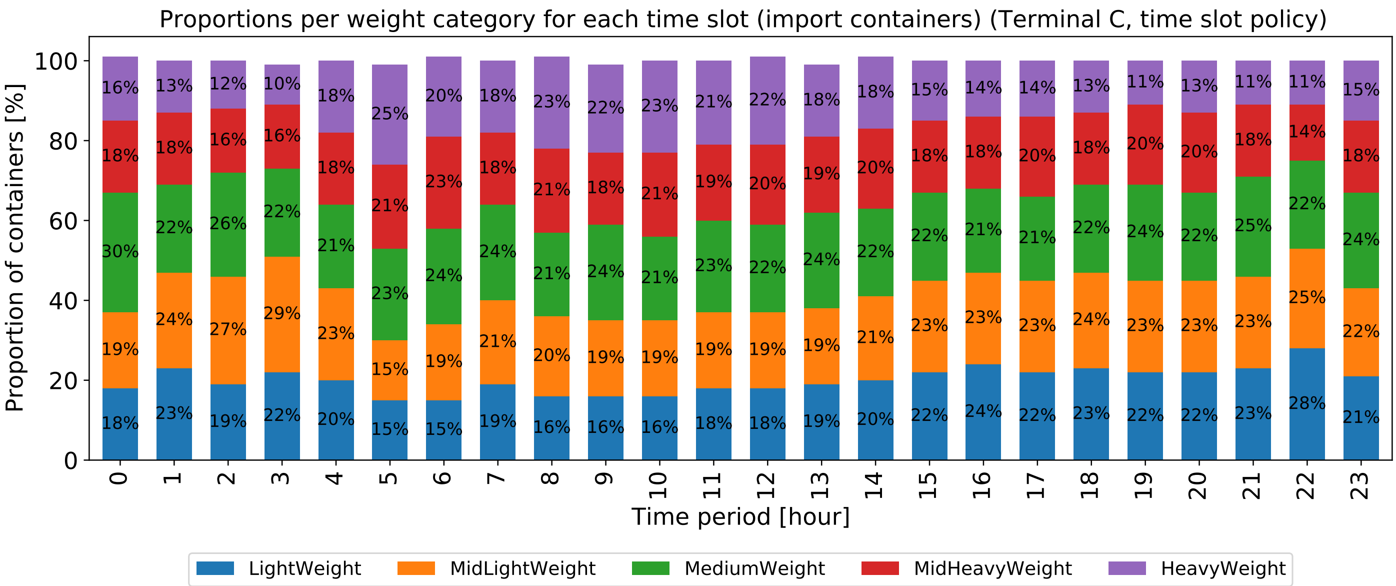


(b) Proportions, percentages

Figure C.26: Import container pick up preference distributed per hour based on weight category (terminal B)

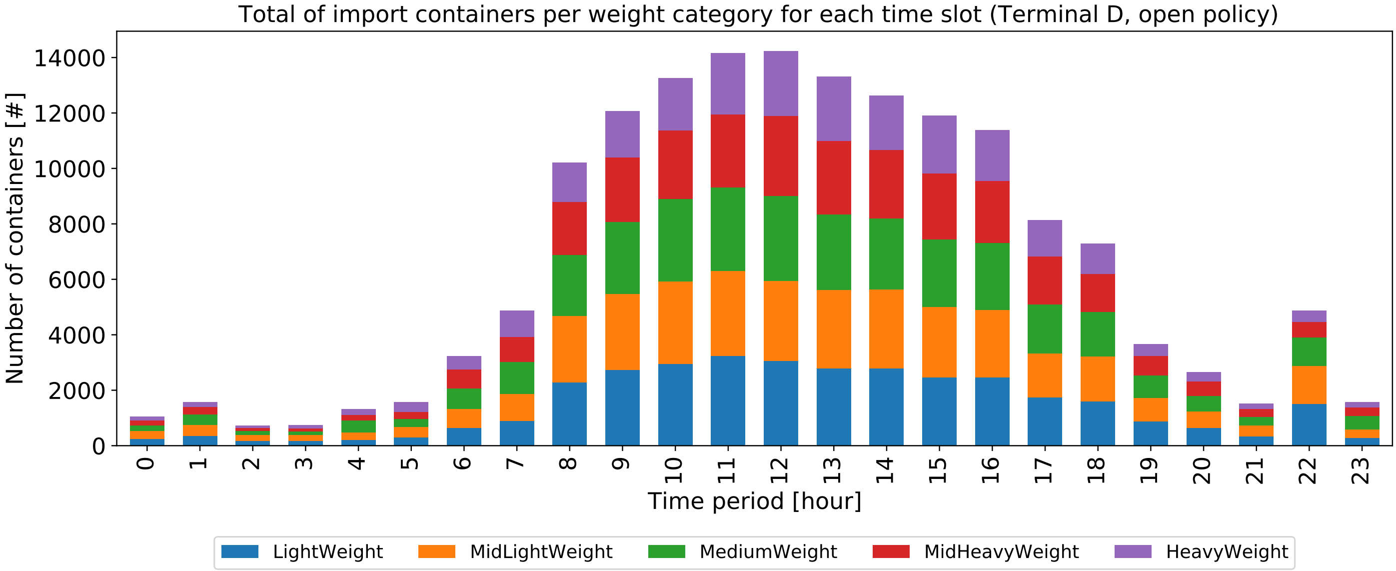


(a) Totals, absolute numbers

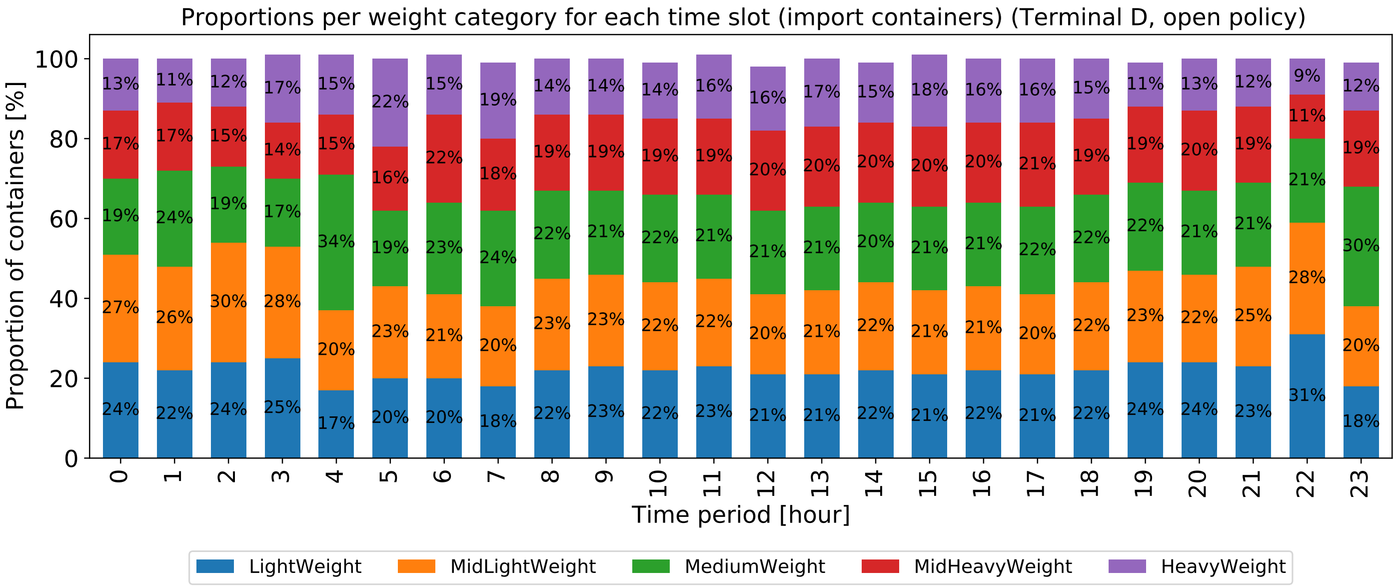


(b) Proportions, percentages

Figure C.27: Import container pick up preference distributed per hour based on weight category (terminal C)



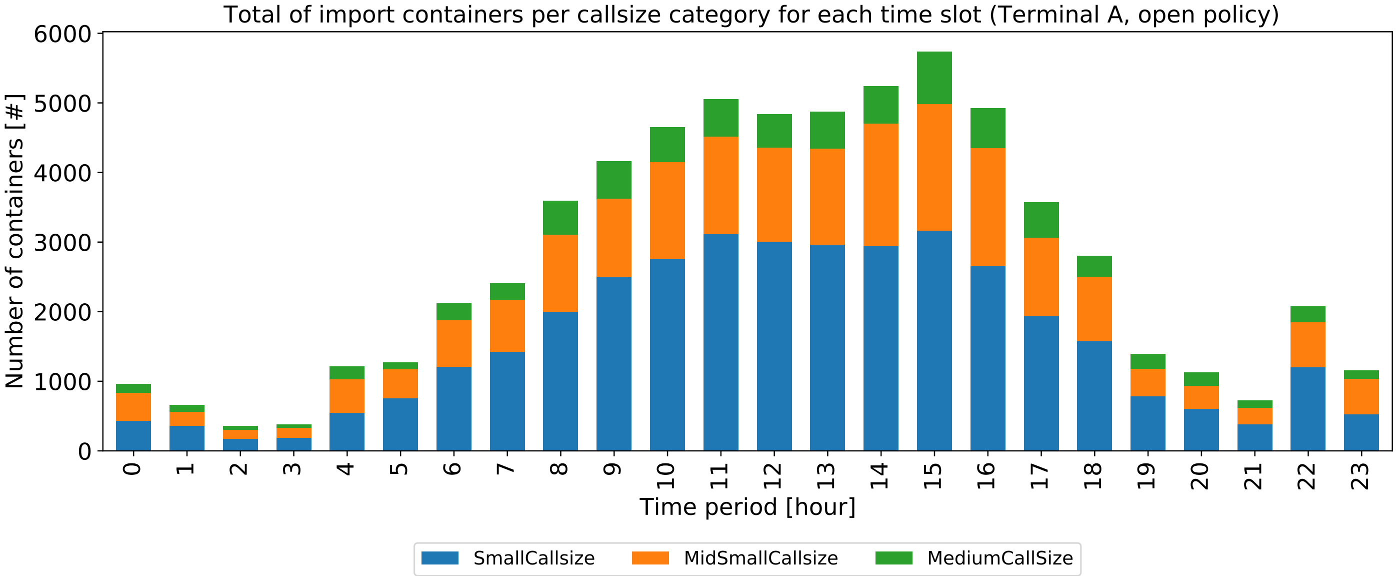
(a) Totals, absolute numbers



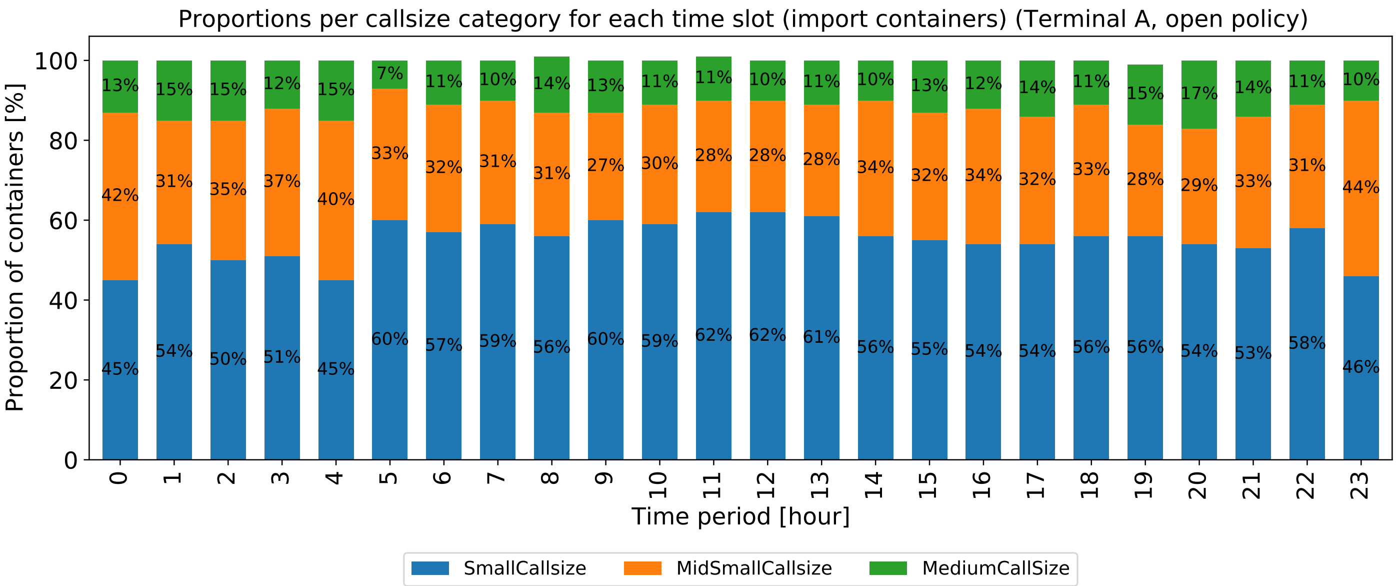
(b) Proportions, percentages

Figure C.28: Import container pick up preference distributed per hour based on weight category (terminal D)

C.4.7 Call size category

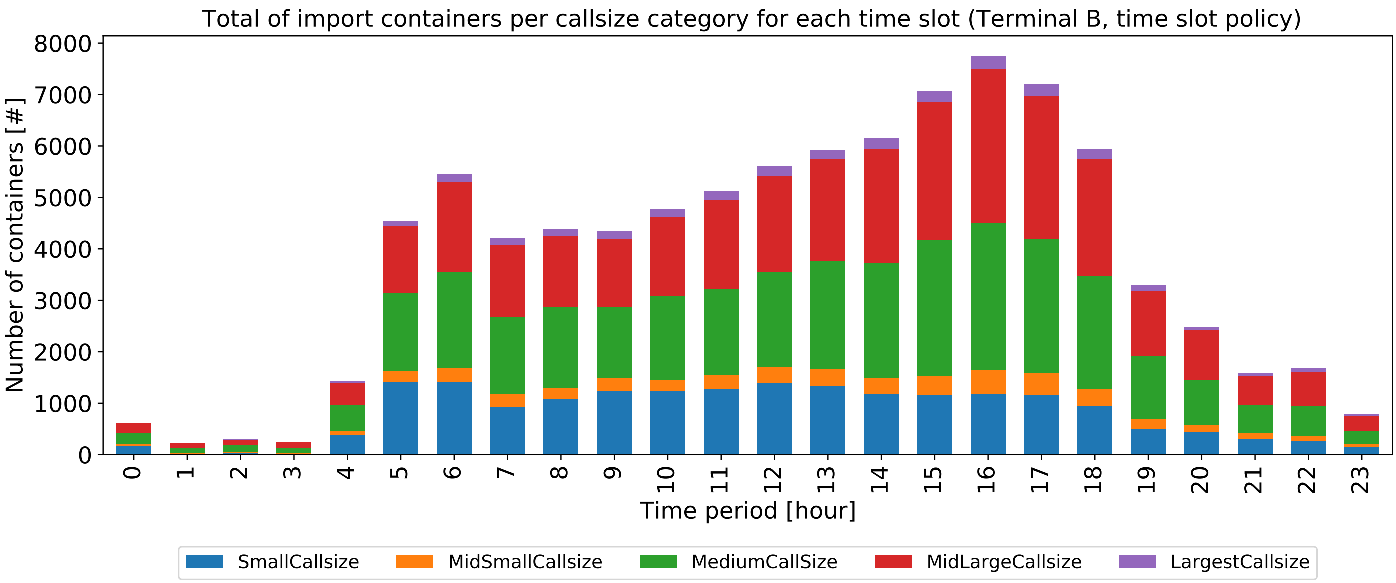


(a) Totals, absolute numbers

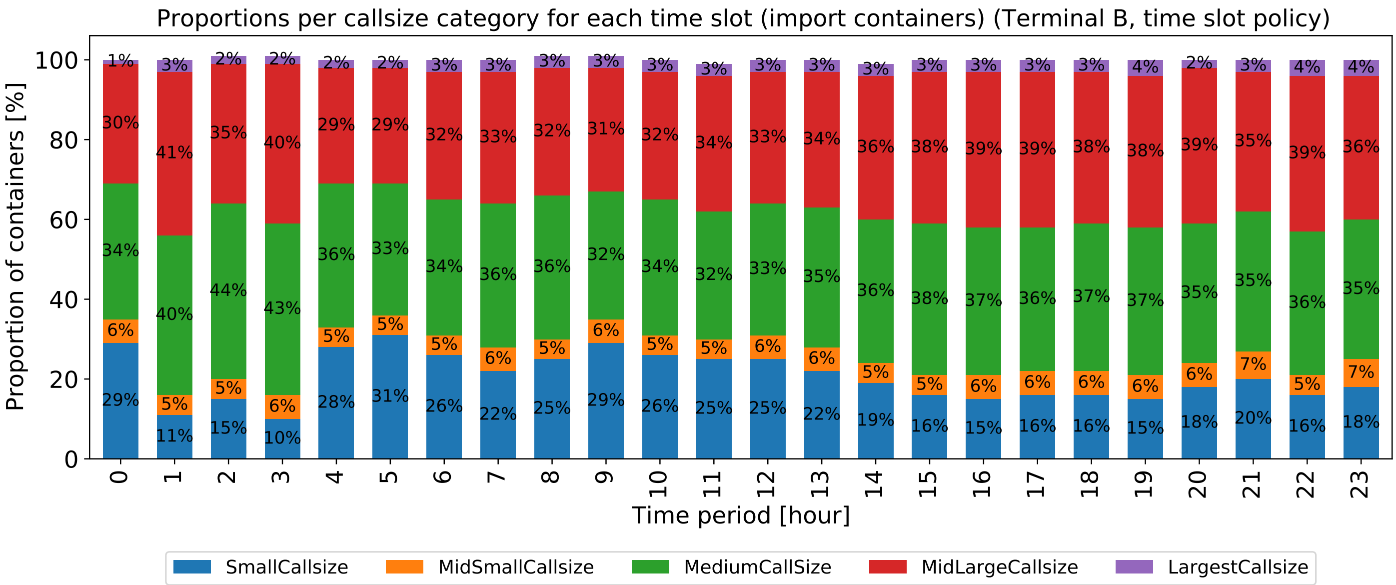


(b) Proportions, percentages

Figure C.29: Import container pick up preference distributed per hour based on call size category (terminal A)

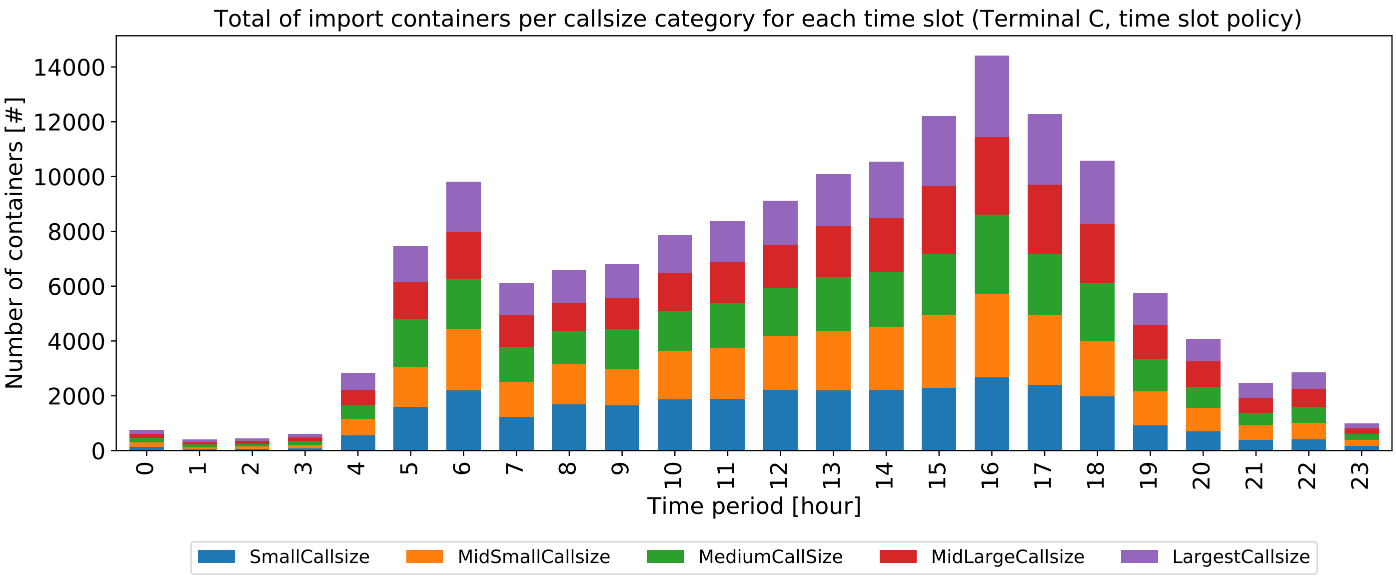


(a) Totals, absolute numbers

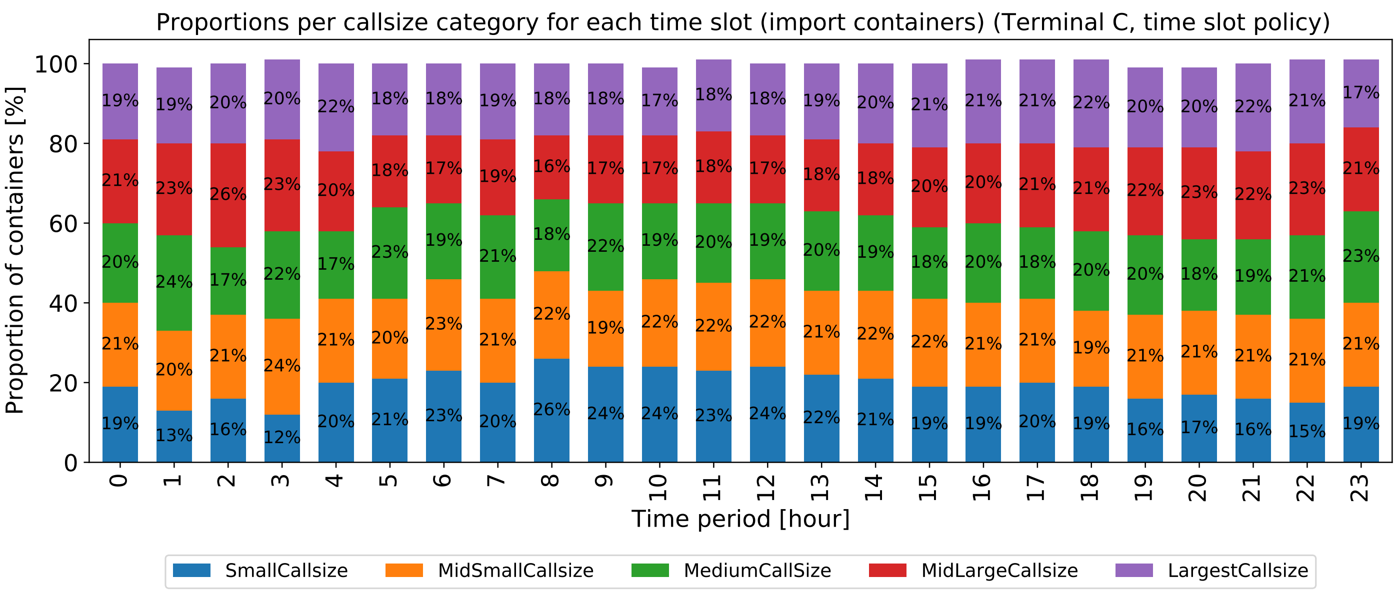


(b) Proportions, percentages

Figure C.30: Import container pick up preference distributed per hour based on call size category (terminal B)

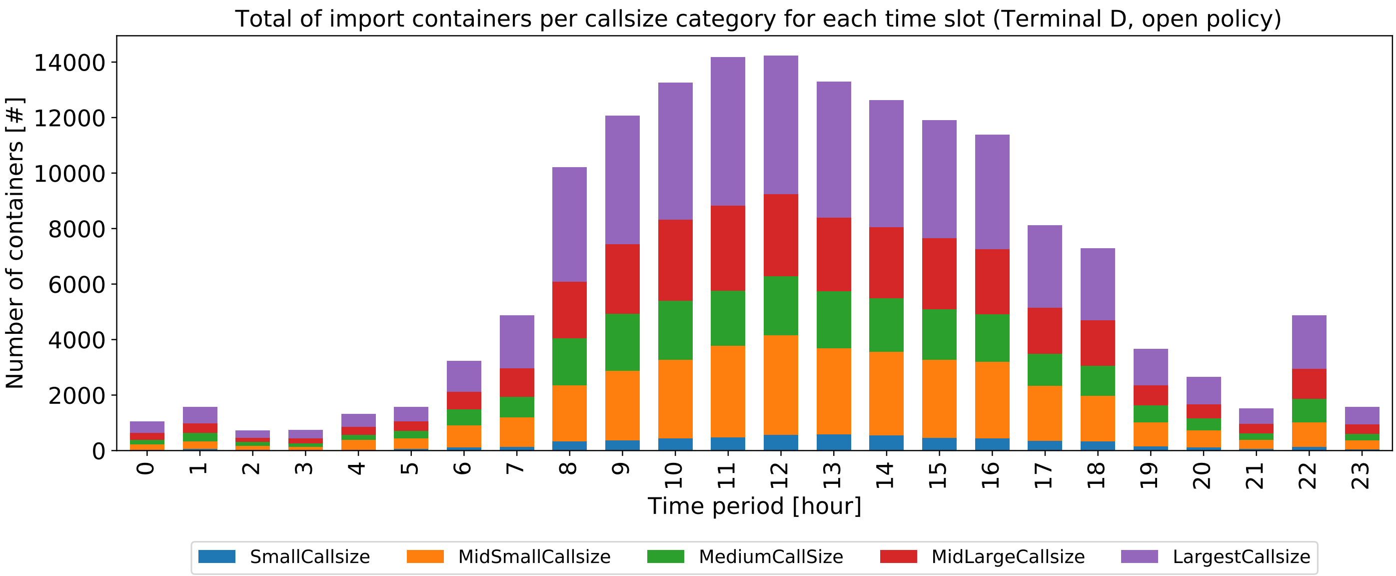


(a) Totals, absolute numbers

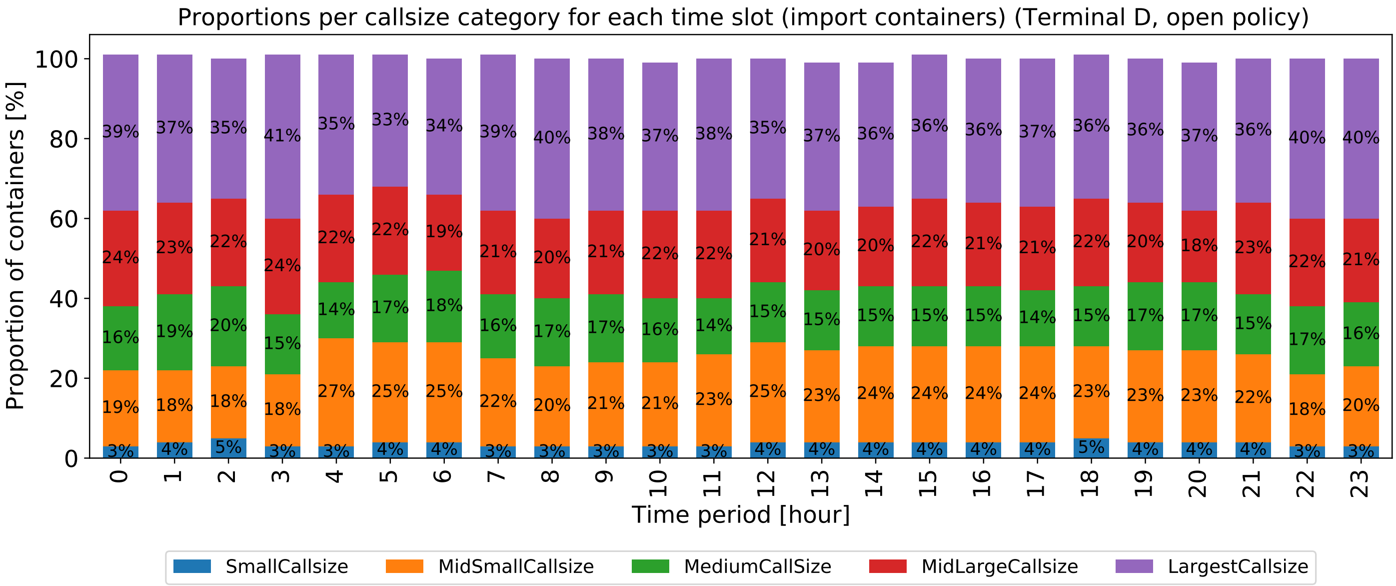


(b) Proportions, percentages

Figure C.31: Import container pick up preference distributed per hour based on call size category (terminal C)



(a) Totals, absolute numbers



(b) Proportions, percentages

Figure C.32: Import container pick up preference distributed per hour based on call size category (terminal D)

D TIME PERIOD CHOICE MODEL

For this research, a choice model is developed to gain insight in the behaviour of the TOC regarding time period choice for container pick up. In this appendix the set up of the time period choice model is elaborated. The choice model is based on the logistic data described in Appendix C. Moreover, discrete choice theory is used to define the model.

The set up of the model consists of several steps. These steps are the definition of the problem, the data, the model specification, the parameter estimation, and the model application.

From the data analysis in Appendix C it was found that each of the four terminals located at the MVII in the port of Rotterdam area, are different. Therefore, a separate choice model must be specified for each terminal. Despite that each terminal requires a separate choice model, there are general aspects in the choice models. To avoid too much repetition, the appendix structure is to describe the choice model setup mostly generally for all terminals. Where it is necessary, specifics per terminal model are elaborated.

D.1 PROBLEM DEFINITION

The goal of the choice model is to gain insight into the preference of the TOC to pick up a container at a certain time. The choice model is based on discrete choice theory. In a discrete choice model, for each alternative a utility function is formulated. This utility function captures the influence of an attribute on the probability of choosing an alternative.

The definition of the choice problem in this research, can be formulated as the choice of a TOC to pick up a container in a certain time period. To allow for more accurate results (Section C.2), the choice variable in the model is aggregated from 24 specific time slots to four time periods. The time periods are formulated as night (from 21:00 until 3:00), morning (from 4:00 until 9:00), midday (from 10:00 until 14:00), and afternoon (from 15:00 until 20:00). These periods are based on observed arrival patterns and categories used in practice at the terminals.

D.2 DATA

The discrete choice model is based on revealed preference data of TOC for container pick up. This data, elaborated in Appendix C, is collected from Portbase, the port community system at the port of Rotterdam.

A mathematical model is specified for the choice model and contains several attributes. In discrete choice modelling there are two types of attributes, namely dependent and independent attributes. A dependent, or endogenous, attribute is the choice variable, in this research that is time period. An independent, or exogenous, attribute is the explanatory variable. Generally, a choice model contains multiple independent variables. Based on the logistic data, it is attempted to identify the independent attributes.

To allow for the choice model specification and parameter estimation, the data is pre-processed (Section C.1) and analysed (Section C.2) to understand patterns and prevent the inclusion of attributes that are not valuable. Attributes that do not impact the preference for a certain time slot are excluded from the model. Additionally, if attributes are mutually correlated, one is excluded as this could manipulate the model results.

The data pre-processing and analysis elaborated in Appendix C, led to identified independent attributes. These attributes are container type and commodity type. Additionally, waiting time is included in the choice model in an effort to grasp the effect of waiting on TOC preferences for time period choice. For the extensive data pre-processing, analysis and result overview, one is referred to Appendix C.

D.2.1 Container type

Container type is an attribute with four levels. Therefore, the container type variable in the choice model is a discrete and categorical variable. The levels are general purpose container, reefer container, chemical container, and tank container. It depends on the terminal which levels of the attribute are included in the choice model. Levels are included or excluded based on the share of containers the level captures. Moreover, the spread of the levels along the day is considered, as this could indicate that for certain attribute levels, TOC prefer a specific time period.

D.2.2 Commodity type

Commodity type is also a discrete and categorical variable. Commodity type is an attribute with eleven levels. However, in the choice model not all levels are included in the commodity type attribute. The same criteria as for including or excluding container type attribute levels, apply for commodity type attribute levels.

D.2.3 Waiting time

Opposed to the container type and commodity type, the waiting time is a continuous variable. The waiting time is simulated with the terminal model (Appendix B). For each container in the logistic data set, an averaged waiting time for one hour in each time period is randomly assigned. Hence, the waiting time that could potentially be encountered by the TOC in each of the time periods, is included in the choice model. This allows to capture the effect of waiting time along the entire day, on the pick up period preference of the TOC. Perhaps the preference of the TOC for the morning alternative increases if the TOC is aware that the encountered waiting time in the midday or afternoon is potentially higher.

D.2.4 Data summary

As the choice model is probabilistic, each attribute and attribute level can be associated with a certain probability. The data is summarised based on absolute value occurrence, the joint probabilities, the marginal probabilities, and the conditional probabilities. An extensive overview of the data is provided per terminal in Section C.3. This data is the foundation for the model specification and parameter estimation.

D.3 MODEL SPECIFICATION

The choice model is specified based on the findings in the data and the goal of the choice model. The choice variable is the time period. There are four alternatives for this choice, namely night, morning, midday and afternoon. These alternatives make up the discrete choice set. The choice set is the same for each individual decision maker (the TOC). The attractiveness of an alternative can be captured by the utility function. Consequently, the probability that a TOC chooses time period t can be computed if the underlying distributions of utility are known. The utility can be calculated using the independent variables.

The utility function for each alternative is unique in the specified choice model. The reason for this is that the model is predominantly based on discrete and categorical attributes. If all attributes were to be included in all utility functions, the model becomes unidentified. Choice modelling is build on the concept of the alternatives being attractive relative to each other. Therefore, the effect of one alternative being more attractive than another would be cancelled out if all attributes would be included in all utility functions.

Several behavioural assumptions are made in the specification of the model. First of all, with the inclusion of an attribute in the utility function, it is assumed that the attribute actually impacts the choice for a certain alternative.

Another behavioural assumption made in choice modelling is that the decision maker, in this choice model the TOC, is rational and a perfect optimiser. Therefore, in theory the alternative with the highest utility is always chosen (Equation D.1).

$$P(t|T) = Pr(U_t \geq U_j, \forall j \in T) \tag{D.1}$$

Nonetheless, humans tend to behave random and may choose an alternative that does not seem to provide the highest utility. This is due to the fact that it is impossible to capture all factors in the choice model that influence the choice. The utility function (U_t), therefore, consists of two parts (Equation D.2).

$$U_t = V_t + \varepsilon_t \tag{D.2}$$

The first part is the deterministic part (V_t), which includes the attributes that are found to influence the choice of a certain alternative. The second part of the utility function contains an error term (ε_t). This error term represents the unobserved behaviour that influence the choice. The error term is assumed to be i.i.d and follow an Extreme Value distribution ($EV(0, \mu)$) in which μ is the scale parameter. In general, the scale parameter is normalised to 1.

Another method to capture the unobserved behaviour in choice modelling, is by the formulation of an ASC. By the formulation of an ASC, the mean of the error term is moved to the deterministic part of the utility function. The ASC is a parameter in deterministic part that can be estimated from data.

D.3.1 Model variables and parameters

To capture the unobserved utility for a certain alternative, an ASC is formulated for two of the alternatives (ASC_{alt}). From the revealed preference data it can be observed that the midday and afternoon alternatives for pick up are most preferred (see marginal probabilities for i in Section C.3). Based on this observation, the ASCs are formulated for the night and morning alternative to capture the unobserved factors that decrease the preference for these two alternatives.

The observed behaviour in the utility for a certain alternative is captured by the independent variables in the deterministic part of the utility (V_t). The independent variables in the model are container type (x_{type}), commodity type (y_{type}), and waiting time per alternative (w_{alt}).

Since the container type and commodity type attributes are categorical, these are formulated as dummy variables in the model. If the container is a general purpose container, the model holds an 1 for the general purpose variable (x_{GP}) and 0 for the rest of the container types. The same principle applies to the commodity type. If the container contains agricultural commodities, the model holds an 1 for the agricultural variable (y_{Agr}) and 0 for the rest. If the container contains a commodity that is not specified in the attribute levels of commodity type, all commodity type variables become 0. This is explained by the assumption that that commodity type does not influence the preference of a TOC for pick up time period.

To capture the influence of the independent variables on the choice, several parameters are formulated (β). The value of these parameters can be estimated from data by the choice model. The parameters represent the preference for a certain alternative based on the container type, commodity type and waiting time as the β interact with the independent variables.

The parameter sign provides insight in the taste of the decision maker for an alternative. A negative sign ($-$) generally indicates a decrease in utility for an alternative, a positive sign ($+$) generally indicates an increase in utility. This information helps to interpret the choice model.

Moreover, the magnitude of the parameter value indicates the impact of the parameter on the utility, thus on the attractiveness of an alternative. It is crucial to keep in mind that the parameter interacts with the independent variable. Therefore, the magnitude of the independent variable additionally impacts the attractiveness of an alternative. Nevertheless, in the specified model two independent variables are formulated as dummy variable, hence obtain a value of 0 or 1. For these two variables the magnitude of the parameter is dominant. The impact on the attractiveness of the alternative is either 0 or the estimated value of the parameter. The independent variable for waiting time is continuous. Hence, for this variable the interaction between parameter and variable is crucial for the impact on the alternative attractiveness.

D.3.2 Utility functions

For each terminal a separate choice model must be defined. Therefore, for each terminal a separate set of utility functions is formulated. V_1 represents the utility function for the night alternative (Equation D.3, D.7, D.11, and D.15). V_2 represents the utility function for the morning alternative (Equation D.4, D.8, D.12, and D.16). V_3 represents the midday alternative (Equation D.5, D.9, D.13, and D.17). Lastly, V_4 represents the utility function for the afternoon alternative (Equation D.6, D.10, D.14, and D.18). The utility function captures the attractiveness of an alternative. It is assumed that all utility functions are linear.

Below, the set of utility functions for the choice model of each terminal is displayed. With the inclusion of an attribute in the utility function, it is assumed that the attribute actually impacts the choice for a certain alternative. The utility function for each alternative is unique in the specified choice model. As the model is entirely based on discrete and categorical variables, including the variables in all utility functions ensures that the model becomes unidentified.

As previously mentioned, the ASCs are formulated for the night and morning alternative. The reason for including an ASC in these utility functions is that an increase of utility for these alternatives could help to spread the truck arrivals more evenly throughout the day.

The utility functions are formulated such that the influence of a specific container or commodity type on a specific alternative could provide insight in TOC behaviour. Container or commodity types might have a higher or lower probability of being picked up in a certain time period (Section C.3). Moreover, some container of commodity type might occur very often at a specific terminal. This would increase the impact of the shifting strategy for that container. On the other hand, if a container or commodity type does not occur often at the terminal, the impact of a strategy for shifting that container is less. An understanding of choice behaviour of a TOC based on the preference for the pick up of a container type or commodity in a certain time period, allows to develop potential strategies. Such a strategy aims to spread truck arrivals more evenly along the day, consequently decreasing the waiting time.

To gain insight in the effect of waiting time on the choice of a TOC, waiting time is included in some of the utility functions. For some terminals the included waiting time correspond to the time period the utility function represents, so midday waiting time in V_3. However, for some terminals the waiting time included in a utility function do not correspond to the time period the utility function represents. For example, in V_3 for terminal A, the morning waiting time is included in the utility function for the midday. This allows to capture the effect of waiting time in other time periods on the choice of a TOC. Note that there is no parameter for the night waiting time as TOC never encounter waiting time during the night (Section B.5).
To summarise the model specifications, Table D.1 provides an overview.

Terminal A

$$V_1 = ASC_{Night} + \beta_{RE} \cdot x_{RE} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{D.3}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{Chem} \cdot y_{Chem} \tag{D.4}$$

$$V_3 = \beta_{WT,Morning} \cdot w_{Morning} + \beta_{TC} \cdot x_{TC} + \beta_{CC} \cdot x_{CC} \tag{D.5}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{GP} \cdot x_{GP} \tag{D.6}$$

Terminal B

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{Chem} \cdot y_{Chem} + \beta_{RawMin} \cdot y_{RawMin} \tag{D.7}$$

$$\begin{aligned} V_2 = & ASC_{Morning} + \beta_{WT,Morning} \cdot w_{Morning} + \beta_{CC} \cdot x_{CC} + \beta_{Agr} \cdot y_{Agr} \\ & + \beta_{SolMinFu} \cdot y_{SolMinFu} \end{aligned} \tag{D.8}$$

$$V_3 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{WT,Afternoon} \cdot w_{Afternoon} \tag{D.9}$$

$$V_4 = \beta_{RE} \cdot x_{RE} + \beta_{Petro} \cdot y_{Petro} \tag{D.10}$$

Terminal C

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{CC} \cdot x_{CC} + \beta_{TC} \cdot x_{TC} \tag{D.11}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{D.12}$$

$$\begin{aligned} V_3 = & \beta_{WT,Morning} \cdot w_{Morning} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{TC} \cdot x_{TC} \\ & + \beta_{Fert} \cdot y_{Fert} + \beta_{RawMin} \cdot y_{RawMin} \end{aligned} \tag{D.13}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + +\beta_{Chem} \cdot y_{Chem} + \beta_{Ores} \cdot y_{Ores} + \beta_{Petro} \cdot y_{Petro} \tag{D.14}$$

Terminal D

$$V_1 = ASC_{Night} + \beta_{CC} \cdot x_{CC} + \beta_{Chem} \cdot y_{Chem} \tag{D.15}$$

$$V_2 = ASC_{Morning} + \beta_{GP} \cdot x_{GP} + \beta_{RawMin} \cdot y_{RawMin} + \beta_{Agr} \cdot y_{Agr} \tag{D.16}$$

$$V_3 = \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Petro} \cdot y_{Petro} \tag{D.17}$$

$$V_4 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{CC} \cdot x_{CC} + \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Ores} \cdot y_{Ores} \tag{D.18}$$

Table D.1: Overview of the symbols and description for the choice models specification

Symbol	Description
T	Choice set ($T = \{Night, Morning, Midday, Afternoon\}$)
V_1	Deterministic part of the utility function for the night alternative
V_2	Deterministic part of the utility function for the morning alternative
V_3	Deterministic part of the utility function for the midday alternative
V_4	Deterministic part of the utility function for the afternoon alternative
ASC_{Night}	Alternative specific constant for the night alternative
$ASC_{Morning}$	Alternative specific constant for the morning alternative
x_{GP}	Container type: general purpose container
x_{RE}	Container type: reefer container
x_{CC}	Container type: chemical container
x_{TC}	Container type: tank container
β_{GP}	Parameter for general purpose container
β_{RE}	Parameter for reefer container
β_{CC}	Parameter for chemical container
β_{TC}	Parameter for tank container
y_{Agr}	Commodity type: agricultural
y_{Chem}	Commodity type: chemical products
$y_{SolMinFu}$	Commodity type: solid mineral fuels
y_{RawMin}	Commodity type: raw minerals and products
y_{Petro}	Commodity type: petroleum
y_{Ores}	Commodity type: ores
y_{Fert}	Commodity type: fertilisers
β_{Agr}	Parameter for agricultural commodity
β_{Chem}	Parameter for chemical products commodity
$\beta_{SolMinFu}$	Parameter for solid mineral fuels commodity
β_{RawMin}	Parameter for raw minerals and products commodity
β_{Petro}	Parameter for petroleum commodity
β_{Ores}	Parameter for ores commodity
β_{Fert}	Parameter for fertilisers commodity
$w_{Morning}$	Waiting time in the morning time period
w_{Midday}	Waiting time in the midday time period
$w_{Afternoon}$	Waiting time in the afternoon time period
$\beta_{WT,Morning}$	Parameter for waiting time in the morning time period
$\beta_{WT,Midday}$	Parameter for waiting time in the midday time period
$\beta_{WT,Afternoon}$	Parameter for waiting time in the afternoon time period

D.4 PARAMETER ESTIMATION

Based on the logistic data, the value of the parameters can be estimated by means of an optimisation algorithm. With the estimated parameters, the choice model serves to interpret TOC preferences. The potential choices of TOC and the impact of variables on alternative attractiveness is captured.

D.4.1 Optimisation algorithm

The parameters (ASC and β) can be estimated using the maximum log-likelihood estimation. Maximum likelihood is the probability that the model correctly fits the observations from data. In the maximum log-likelihood estimation, the model aims to estimate the parameters such that the model has the highest probability of fitting the observed data. Hence, the parameter values are estimated as such that these maximise the log-likelihood. Equation D.19 presents the maximum log-likelihood function. In which $\mathcal{L}$ indicates the log-likelihood. If an individual chooses alternative t, $y_{tn} = 1$, otherwise $y_{tn} = 0$. $P_n(t|T_n)$ represent the logit model (Equation D.20).

$$\max \mathcal{L}(\hat{\beta}_1, ..., \hat{\beta}_K) = \sum_{n=1}^{N} \left(\sum_{t \in T_n} y_{tn} \ln P_n(t|T_n) \right) \tag{D.19}$$

The specified model is estimated using Biogeme software [Bierlaire, nd]. In the model set-up the model specifications (Section D.3.2) are defined. Consequently, the model is estimated using the MNL model depicted in Equation D.20. V_{tn}, the deterministic part of the utility function (Equation D.2), indicates the utility of individual n for alternative t. $P_n(t|T_n)$ indicates the probability that individual n chooses alternative t from choice set T_n.

$$P_n(t|T_n) = \frac{e^{V_{tn}}}{\sum_{j \in T_n} e^{V_{jn}}} \tag{D.20}$$

The MNL model is used because the choice set is not binary but multinomial, there are multiple alternatives to choose from. Since the decision makers are assumed to be homogeneous the MNL model is very suited for the parameter estimation. Moreover, thanks to the closed form of the MNL model, there is less complexity involved.

The model estimation provides several useful outputs. The main outputs of the model are the parameter estimates ($\hat{\beta}$) and the value of the log-likelihood function of the model with the estimated parameters ($\mathcal{L}(\hat{\beta}_1, ..., \hat{\beta}_K)$).

Other output values are t-values and p-values. These outputs assist in statistical analysis of the estimated parameters in the model. A null hypothesis ($H0$) and alternative hypothesis ($H1$) are formulated. $H0$ states that the true value of β equals 0. The alternative hypothesis states that the true value of β is not 0. The null hypothesis is rejected when the t-value is equal to or smaller than -1.96, or equal or larger than 1.96. The t-value is calculated by

$$t_k = \frac{\hat{\beta}_k}{\sigma_k}, \tag{D.21}$$

where $\hat{\beta}$ is the estimate of parameter β and σ_k is the standard error of the parameter. Consequently, $H0$ is rejected and $H1$ accepted with an 95% confidence interval if $|t_k| \geq 1.96$.

From the t-value the p-value can be computed. This is done with Equation D.22. $\Phi(\cdot)$ indicates the cumulative density function of the univariate standard normal distribution.

$$p_k = 2(1 - \Phi(t_k)) \tag{D.22}$$

Similar to the t-value, $H0$ and $H1$ are considered. $H0$ can be rejected with a confidence interval of $1 - p_k$. Consequently, a p-value smaller than 0.05 indicates that the parameter value is estimated correctly at a 95% confidence level.

Lastly, an interesting output of the model estimation is the goodness of fit. This goodness of fit can be observed from the likelihood ratio statistic (Equation D.23).

$$-2(\mathcal{L}(0) - \mathcal{L}(\hat{\beta})) \tag{D.23}$$

The likelihood ratio statistic compares a model where all parameters are set to zero ($\mathcal{L}(0)$), which leads to a model with equal probabilities, to the model with the estimated parameter ($\mathcal{L}(\hat{\beta})$. The likelihood ratio statistic indicates whether the estimated model is significant, thus whether the estimated model fits the data better than the model with equal probabilities. For the statistical analysis of the model, a null hypothesis ($H0$) and an alternative hypothesis ($H1$) are formulated. $H0$ states that the estimated model ($\mathcal{L}(\hat{\beta})$ is equivalent to the model with equal probabilities ($\mathcal{L}(0)$). $H1$ states that this is not true.

The likelihood ratio statistic is asymptotically distributed as χ^2 with K degrees of freedom under $H0$. The exact critical value for χ^2 at a 95% confidence interval depends on the K degrees of freedom. As rule of thumb a critical value of 79.08 is applied, this corresponds with 60 degrees of freedom. Using 60 degrees of freedom ensures that if the test statistic is well above the critical value ($\chi^2 > 79.08$), $H0$ can safely be rejected. It can be concluded with a 95% confidence interval, that imposing restrictions to the choice model does not lead to a better model. Hence, the estimated model provides a better fit with the observed data than a model with equal choice probabilities. Generally, the higher the likelihood ratio, the higher the confidence level that the estimated model fits the observed data.

D.4.2 Model results

The likelihood ratio statistics for the choice model for each terminal is depicted in Table D.2. These values indicate the goodness of fit of the estimated model on the data. If the model with equal probabilities causes a statistically significant loss of fit, it can be concluded that the estimated model fits the observed data better than a model with equal probabilities. A loss of fit can be measured by a decrease in log likelihood. The likelihood ratio reported by the estimated models (Table D.2), indicate a statistically significant loss of fit of the models with equal probabilities. The likelihood statistic values are larger than the critical value, mentioned in the previous section. It can be concluded that estimating the parameters in the specified model (Section D.3), results in a model that fits the observed data better than a model with equal probabilities.

Table D.2: Overview of the likelihood ratio statistic value of the specified choice model for each terminal

	Terminal A	Terminal B	Terminal C	Terminal D
Likelihood ratio statistic	13326.87	26640.73	46274.5	118682.2

Moreover, Table D.3, D.5, D.7, and D.9 on the following pages display the parameter estimation results from the specified choice models for each terminal. It can be observed that each estimated parameter has an absolute t-value larger than 1.96 and a p-value smaller than 0.05. These t-values and p-values indicate that the parameters are estimated correctly at a 95% confidence level. Furthermore, each parameter is proven to influence the alternative attractiveness based on the formulated utility functions. Hence, the estimated parameter provides insight in the behaviour of the TOC. Furthermore, no significant correlation between estimated parameters in the specified models are observed in the model results.

Subsequently, it can be concluded that the specified choice models are statistically proven to provide accurate results. Thereupon, the estimated parameter values for each terminal should be interpreted. First some general notes are provided. Next, the parameters for each separate model will be discussed. The parameter interpretation is structured per terminal. Lastly, the preferences of the TOC for specific terminals are compared to place the results of the choice models for each terminal in perspective.

As the variables for container type and commodity type in the specified model are non monetary, it is difficult to interpret the results by illustrating trade-offs. Nevertheless, the parameters have meaning and the potential to explain behaviour of TOC. Therefore, the results of the estimated model are elaborated in terms of the direction of the impact ($+$ or $-$) and the magnitude of the estimated parameters.

To structure the interpretation of the parameters some extra columns are added in the results tables (Table D.3, D.5, D.7, and D.9). For each estimated parameter, the effect on the utility is noted. Moreover, the magnitude of the effect is provided.

Considering the effect of the utility, there are two options. These are that the parameter indicates an increasing effect on the utility or a decreasing effect. An increasing effect can be interpreted as such there is a preference for picking up a certain container of commodity in the corresponding time period. A decreasing effect can be interpreted as a dislike for picking up a certain container of commodity in the corresponding time period. However, it should be kept in mind that choice modelling is build upon the concept of relative attractiveness of alternatives. Hence, a decreasing effect of a certain container type for time period t, is indirectly a increase of attractiveness for the other alternatives. Consequently, a dislike for a certain time period indicates a preference for another time period. The attribute levels are divided over the utility functions in the choice models to avoid an undefined model. Therefore, the estimated parameters might also be interpreted for the utility functions they are not part of.

The magnitude of the effect is categorised in four categories. An absolute value of the parameter between 0.0 and 0.2 is categorised as a small effect. An absolute parameter value of 0.2 through 0.6 is a medium effect on the utility. An absolute parameter value between 0.6 and 1 is categorised as a large magnitude of effect. Lastly, absolute parameter values larger than 1 are indicated as huge effects on the utility. The categories are determined based on the distribution of the coefficient values and relative effect compared to the other coefficients in the specified model.

In the interpretation of the parameters, in general and for terminals individually, several explanations for the parameters are provided. These explanations relate for example to the traffic states on access roads, the type of goods in the containers, the clients of the goods, the industry where the goods are used, and assumptions for combining trips. However, two factors that might explain the parameter value, hence the preference of the TOC, are not included in the interpretation of the parameter. These factors are the arrival time of the vessel that transported the container, and the exact origin and destination of the containers.

The prior might explain the pick up preference for certain containers or commodity types because perhaps vessels with high shares of a certain container or commodity type always arrive in the evening. Subsequently, the TOC might prefer to pick up the specific containers the next morning. However, there is no data explored in this research that would provide insight in this factor and how it could explain specific TOC preference.

Additionally, regarding the specific origin and destination of containers, there no information about this factor. For some commodity types there are some insights that these have destinations near the port. For example, it is known that the 'Westland', near the port, is a popular destination for agricultural products. It is expected that the destination of the goods will to some extend impact the preference of a TOC. However, there is no data explored in this research that would provide insight in the exact origin and destination for specific containers. Even though this factor might explain the parameter value, it is excluded for the interpretation of the parameter.

Parameter interpretation in general

Even though, separate choice models are estimated for the four terminals as these are found to be different from each other, some similar results are observed for all terminals. These general findings are discussed in this subsection.

To begin with, it can be observed from the estimated coefficients for the ASC of the night alternative (ASC_{Night}) that at each of the terminals there is much unobserved behaviour that influences the choice for the night alternative. Moreover, the sign of the estimated coefficient indicates that the unobserved behaviour decreases the utility for the night alternative, making it less attractive compared to the other alternatives.

This is in line with the expectations for the night alternative. The observed pick up pattern from the data (Section C.4) reveals that the night alternative is used less for container pick up at each of the terminals. Moreover, there are some factors that are known to influence the attractiveness of the night alternative, however these factors are not captured in the estimated model. An obvious example of this is that the night alternative requires working outside operational hours of hinterland warehouses (Section 2.4). Therefore, it makes sense that there is much unobserved behaviour that decreases the attractiveness of the night alternative.

The interpretation of the ASC for the morning alternative ($ASC_{Morning}$) is similar to the analysis of the ASC parameter for night. The sign ($-$) is expected as the observed data (Section C.3) already showed that the morning alternative is less attractive for container pick up compared to the midday and afternoon alternatives.

Like the night alternative, some factors that decrease the utility for morning pick up are not captured in the estimated model. This explains the direction ($-$) of the ASC for morning. A reason for this could be that the morning alternative is less attractive because the port is less accessible in the morning. This is because of the morning peak on the road. However, compared to the night alternative, there is less unobserved behaviour. The magnitude of the effect on the morning alternative is much smaller compared to the magnitude of ASC_{Night}. This indicates that the attributes included in the utility for the morning alternative, capture the decision makers' preference to a larger extent than in the night alternative.

The TOC show similar preference at each terminal regarding the pick up period of general purpose containers. For the pick up of general purpose containers the sign (+) of the coefficient for the estimated parameter ($\hat{\beta}_{GP}$) indicates an increase of utility for night pick up at two of the four terminals. For the other two terminals, a negative sign ($-$) indicates a decrease of utility for morning and afternoon pick up. This indirectly indicates that at the other two terminals, the TOC would rather pick up a general purpose container in another time period, for example at night. The magnitude of the parameter for general purpose containers ($\hat{\beta}_{GP}$), is categorised as medium for all terminals. The direction and magnitude of the effect on the utility illustrate that there is a preference for night pick up time period regarding general purpose containers.

A reason for this could be that general purpose containers are predominantly not very special or urgent. Therefore, these might be preferred to be picked up at night since they can more easily be parked near a hinterland warehouse location. Hence, the operating hours in the hinterland have less impact on the transport of general purpose containers. Another explanation could be that products transported by general purpose containers more often have a destination that is a few hours driving. If the container is picked up at night, it arrives during the opening hours of the receiver.

The estimated parameter to reflect the preference for reefer container pick up ($\hat{\beta}_{RE}$) indicates a medium preference for the night and morning alternative compared to the other two alternatives. Additionally, a decreasing effect, hence a dislike, for afternoon pick up is observed from the results. This indirectly indicates a preference for reefer pick up in another time period, for example the morning. The magnitude of the estimated parameter for reefer containers is similar among the choice model results, namely medium.

This preference for reefer containers in the night and morning alternative is not a surprise. Experts at PoR speak of a reefer peak in the early morning at the terminals. The reason for this is that reefer containers often contain products that have to be delivered to distribution centers early in the day so the retail stores can restock products during the day. Note that these products in reefer containers are not only agricultural commodities (Section C.3). Furthermore, transport with reefer containers is more expensive compared to other container types. Therefore, it might be that there is a strong desire from the forwarder to have the reefer container be picked up first thing in the morning.

The choice models indicate that the TOC do not have much preferences regarding tank containers. The tank container variable is solely estimated for two of the four terminals. For the other terminals, tank containers do not influence the attractiveness of the alternatives. At the terminals where tank containers do influence the pick up time period attractiveness, the results are very similar. It is observed from the results of both terminals, that the magnitude of the estimated tank container parameter ($\hat{\beta}_{TC}$) is rather small. Moreover, the estimated parameter appears to have an increasing effect on the midday alternative. Consequently, the results indicated that there is a slight preference for the midday alternative.

Even though the impact on the alternative attractiveness is rather small, there might be some explanation for the preference. For example, because the operating hours at the destinations are very strict. Tank containers, opposed to general purpose containers, cannot be parked near the warehouse location outside of operating hours as they might contain more dangerous goods. Therefore, it might be desired to pick up the tank container in a time period that matches the hinterland operating hours. Furthermore, since pick up in the midday alternative avoids the morning and afternoon peak on the road network, this could explain a specific preference for the midday alternative. However, the magnitude of the preference is not very large because the tank container could also be picked up in the morning or afternoon alternative and still match hinterland operating hours. Lastly, a reason could be that the TOC do not have much preference for a pick up time of tank containers because the preference for delivery of these containers is more dominant. Tank containers require transport with a special truck that can only transport tank containers, hence it is crucial to combine export and import container trips. The preference for delivery time of export tank containers might be determined by the closing time at the terminal for export containers. The TOC might choose a time of arrival based on the preference for the export container and consequently pick up the import tank container.

Complementary to preference for reefer container pick up, the estimated parameter for the agricultural commodity ($\hat{\beta}_{Agr}$) indicates an increasing effect (+) of container pick up across all terminals. The agricultural products impact the morning alternative with a small to medium magnitude.

The parameters for agricultural commodity pick up preferences are estimated as expected. Agricultural products are often directed to retail stores. Therefore, there is a certain rush to pick up the containers in the morning so the products can be distributed to the stores. Subsequently, the retail stores can restock fresh products during the day. Moreover, agricultural products often have a destination near the port of Rotterdam area. Near the port the agricultural products are processed and distributed to other locations. As agricultural products are often perishable, the time to do this is limited. This might explain the preference to pick up agricultural commodities in the morning alternative.

The containers containing solid mineral fuels ($\hat{\beta}_{SolMinFu}$) positively influence (+ sign) the attractiveness of the night alternative with an huge magnitude for pick up at terminal A. For terminal B and C a preference (+ sign) is found for the morning alternative. This the increasing effect of solid mineral fuels on the utility is less than for the night alternative at terminal A. For terminal D a small decreasing effect (− sign) is observed for pick up during the midday and afternoon. Therefore, it can be concluded that the TOC prefer to pick up solid mineral fuels in the night or morning, rather than in the midday or afternoon.

This could be explained by the fact that solid mineral fuels are products often utilised by factories. Factories could want the materials before the morning shift starts to operate.

Similar to the preferences for picking up solid mineral fuels, the TOC are found to have a preference (increasing effect) for the pick up of raw minerals ($\hat{\beta}_{RawMin}$) at night. The magnitude of the effect on utility is smaller than for solid mineral fuels. Yet, it is not small, the magnitude of the effect falls in the medium category. Additionally, for another terminal the TOC show a decreasing effect with medium magnitude for morning and midday pick up of raw minerals. Consequently, this indicates a preference for another time period for pick up such as the night.

These results for pick up preference and dislike for raw minerals could be explained with the same reasoning as solid mineral fuels. The raw minerals are often used in industry. There might be a desire to receive the material at night or very early morning to match the operational planning of factories and construction sites.

TOC seem to have a terminal wide preference for the pick up of petroleum in the midday or afternoon. The effect on utility of the midday or afternoon alternative is increasing (+ sign). The magnitude, however, is rather small. Still, the estimated parameter ($\hat{\beta}_{Petro}$) indicates a small preference for midday or afternoon pick up of petroleum.

The preference for midday or afternoon pick up of petroleum could be explained by the general preference for midday or afternoon pick up for all containers. The logistic data (Section C.3) shows that the midday and afternoon are more popular for container pick up. This is explained by the operating hours in the hinterland. Perhaps, the processors of petroleum have very strict opening hours. As petroleum is used in very traditional industries, the 9 to 5 culture might be very strong. Consequently, there might be little flexibility for the TOC to pick up goods during other time periods.

The interpretation of the remaining estimated parameters, $\hat{\beta}_{CC}$, $\hat{\beta}_{Chem}$, $\hat{\beta}_{Ores}$, $\hat{\beta}_{Fert}$, and $\hat{\beta}_{WT,alt}$, is discussed per terminal. For these variables different preferences or dislikes are found across the terminals. Moreover, some variables only influence the attractiveness of an alternative of a specific terminal.

Parameter interpretation terminal A

In addition to the general findings from the choice model results, some specific findings for terminal A are discussed.

From the estimated model it can be observed that chemical containers impact utility for the midday container pick up alternative ($\hat{\beta}_{CC}$). The sign of the parameter (+), suggests that there is higher preference for the midday alternative when a chemical container is considered compared to the other alternatives. However, the magnitude of the estimated parameter is categorised as small. Nevertheless, comparing the magnitude of the parameter for chemical containers to the other parameters estimated for the midday alternative attractiveness, provides valuable insight. It can be concluded that the attractiveness of the midday alternative is at its highest for the chemical container type.

A reason for the preference for pick up of chemical containers in the midday at terminal A, might be to avoid rush hours on the traffic network on access and exit roads. Another reason could be that the chemical containers are picked up in the midday to combine a round trip with an export container. Often the pick up of chemical containers are combined with the delivery of an export chemical container. This is done because a more heavy truck is required for transportation of chemical products and it is very expensive to have an empty trip with such trucks. Moreover, the trucks for chemical container transport can only transport chemical containers. The time period preference for the delivery of the export container might be the dominant preference. For export containers a closing time must be met. This closing time is often at the end of the day. Therefore, the preference to deliver the export chemical container before closing time could lead to the preference for chemical container pick up as observed from the choice model.

The preference for pick up period for chemical products is different from the preference for chemical containers. It should be noted that this is not as striking as it may seem. The chemical products and chemical containers might have a similar name, yet they do not necessarily comprehend the same goods (see Section C.3). Based on the estimated choice model for terminal A, the attractiveness for morning pick up is found to increase (+ sign) with a medium magnitude for containers transporting chemical products ($\hat{\beta}_{Chem}$).

This preference for the morning period to pick up chemical products at terminal A could be explained by the need for chemical products during the day. Chemical products are used in industry. Similarly to agricultural products for retail stores, there might be a desire to restock the chemicals through out the day. Therefore, the TOC might show a increasing effect on the attractiveness of morning pick up.

The interpretation of the waiting time parameters is a bit different from the other variable parameters. Opposed to the container and commodity type variable, the waiting time is a continuous variable. Hence, the interaction of the estimated parameter with the waiting time determines the precise impact on the attractiveness of the alternatives. In Table D.4 the average, minimum and maximum impact of the waiting time multiplied with the estimated parameter values are presented. These values are based on the average, minimum and maximum in the waiting time profile from the terminal model (Section B.5).

For terminal A, the waiting time in the morning is included in the midday alternative. The waiting time in the midday and afternoon are included in the afternoon alternative. Based on the absolute value of impact, thus the estimated parameter multiplied with the waiting time in minutes, the waiting time categorises as small impact. This absolute magnitude of impact is the same for midday waiting time and afternoon.

The reason for this is that the waiting time is higher in the midday and afternoon. Nevertheless, it is interesting that one minute of waiting time in the morning is perceived as more valuable than waiting time in the midday or afternoon. Perhaps this is because TOC in general tend to pick up containers in the midday or afternoon. Therefore, they might take waiting time in the midday and afternoon for granted. Whilst, additional waiting time in the morning might feel more costly for the TOC to pick up containers.

Table D.3: Estimated parameter results from the specified choice model for terminal A
*This is based on the value magnitude after parameter is multiplied with the waiting time variable w_{alt}

	Estimated parameter value	In utility function	Effect on utility	Magnitude of effect	Standard error	t-value	p-value
ASC_{Night}	-1.52	V1	Decrease	Huge	0.0192	-78.9	0
$ASC_{Morning}$	-0.601	V2	Decrease	Large	0.0166	-36.2	0
β_{GP}	-0.265	V4	Decrease	Medium	0.0176	-15.1	0
β_{RE}	0.288	V1, V2	Increase	Medium	0.0185	15.6	0
β_{CC}	0.187	V3	Increase	Small	0.0311	6.01	0
β_{TC}	0.0855	V3	Increase	Small	0.0302	2.83	0.00462
β_{Agr}	0.177	V2	Increase	Small	0.0318	5.57	0
β_{Chem}	0.27	V2	Increase	Medium	0.0479	5.64	0
$\beta_{SolMinFu}$	1.18	V1	Increase	Huge	0.0452	26.1	0
$\beta_{WT,Morning}$	0.079	V3	Increase	Small*	0.0335	2.36	0.0185
$\beta_{WT,Midday}$	-0.00386	V4	Decrease	Small*	0.00128	-3.01	0.00264
$\beta_{WT,Afternoon}$	-0.00193	V4	Decrease	Small*	0.000864	-2.24	0.0253

Table D.4: Overview of absolute impact of waiting time on alternative attractiveness at terminal A

	$w_{Morning} \cdot \hat{\beta}_{Morning}$	$w_{Midday} \cdot \hat{\beta}_{Midday}$	$w_{Afternoon} \cdot \hat{\beta}_{Afternoon}$
Average	0.0174	-0.039	-0.0239
Minimum	0	-0.00386	-0.00058
Maximum	0.043	-0.073	-0.041

Another striking result, the estimated parameter for morning waiting time indicates that the waiting time in the morning increases the attractiveness for the midday pick up. On the other hand, waiting time in the midday and afternoon seem to decrease the attractiveness of the afternoon pick up. Consequently, it can be concluded that a TOC has more tendency to pick up the container in the midday when there is waiting time in the morning. Whilst the waiting time in the midday and afternoon ensure that there is less tendency for afternoon pick up.

This could be explained by the previous observation that morning waiting time is perceived as more valuable for the TOC. They rather pick up the container in the midday. However, if there is waiting time in the midday, the TOC dislike container pick up in the afternoon. This could be because midday waiting time is very likely to progress to afternoon waiting time. Consequently, picking up a container in the afternoon could be risky for the TOC as the waiting time could result in delay. This might cause the TOC to arrive outside of the operating hours of the hinterland warehouses.

Parameter interpretation terminal B

A few specific findings for terminal B are discussed in this section.

From the estimated model for terminal B, it can be observed that chemical containers impact utility for the morning pick up alternative ($\hat{\beta}_{CC}$). The sign of the parameter ($-$), suggests that there is higher preference for the other time periods (not morning) when a chemical container is considered for pick up. Even though, the magnitude of the estimated parameter indicates that the utility for morning pick up is only impacted slightly. Nevertheless, the estimated parameter indicates that TOC have less preference for the morning time period compared to the other time periods for the pick up of chemical containers.

This slight dislike for morning pick up of chemical containers at terminal B could come from the experience of TOC. As terminal B handles similar shares of chemical and reefer containers these might compete for pick up period (Section C.4). For reefers it is found, terminal wide, that there is preference to pick them up in the morning period. Therefore, it might be that the morning period is busy with the pick up of reefer containers. This could lead to a dislike for picking up chemical containers in the morning. Another reason could be that there are less export chemical containers that must be delivered around the morning time period. The trucks for chemical container transport can only transport chemical containers. Therefore, the TOC does not desire to pick up chemical containers in the morning as they cannot combine the trips. Combining trips for chemical containers is crucial for TOC as the transport is more expensive and requires a more heavy truck.

The preference for night pick up at terminal B, is found to increase (+ sign) for chemical products ($\hat{\beta}_{Chem}$). The magnitude of the effect is medium.

A reason for this found preference could be that the chemical products are used in agricultural and industrial activities. The receivers of the chemical products might desire a delivery of the products before the working day starts. For example, agricultural activity starts very early in the morning. Hence, this would match the night period pick up.

Table D.5: Estimated parameter results from the specified choice model for terminal B
**This is based on the value magnitude after parameter is multiplied with the waiting time variable w_{alt}*

	Estimated parameter value	**In utility function**	**Effect on utility**	**Magnitude of effect**	**Standard error**	**t-value**	**p-value**
ASC_{Night}	-2.13	V1	Decrease	Huge	0.0284	-75	0
$ASC_{Morning}$	-0.407	V2	Decrease	Medium	0.012	-33.9	0
β_{GP}	0.325	V1	Increase	Medium	0.0318	10.2	0
β_{RE}	-0.906	V4	Decrease	Large	0.0242	-37.4	0
β_{CC}	-0.096	V2	Decrease	Small	0.0206	-4.67	0
β_{Agr}	0.548	V2	Increase	Medium	0.0376	14.6	0
β_{Chem}	0.287	V1	Increase	Medium	0.0511	5.61	0
$\beta_{SolMinFu}$	0.0967	V2	Increase	Small	0.0423	2.29	0.0223
β_{RawMin}	0.333	V1	Increase	Medium	0.0742	4.48	0
β_{Petro}	0.175	V4	Increase	Small	0.0417	4.2	0
$\beta_{WT,Morning}$	0.0688	V2	Increase	Small*	0.0306	2.25	0.0248
$\beta_{WT,Midday}$	-0.0222	V3	Decrease	Small*	0.00162	-13.7	0
$\beta_{WT,Afternoon}$	-0.0177	V3	Decrease	Medium*	0.00114	-15.5	0

In Table D.6 the average, minimum and maximum impact of the waiting time multiplied with the estimated parameter values are presented for terminal B. These values are based on the average, minimum and maximum in the waiting time profile (Section B.5).

Table D.6: Overview of absolute impact of waiting time on alternative attractiveness at terminal B

	$w_{Morning} \cdot \hat{\beta}_{Morning}$	$w_{Midday} \cdot \hat{\beta}_{Midday}$	$w_{Afternoon} \cdot \hat{\beta}_{Afternoon}$
Average	0.0165	-0.1265	-0.177
Minimum	0	-0.0155	0
Maximum	0.055	-0.262	-0.366

For terminal B, the waiting time in the morning is included in the morning alternative. The waiting time in the midday and afternoon are included in the midday alternative. Based on the absolute values of the impact, depicted in Table D.6, the waiting time for morning and midday categorise as small. Afternoon waiting time is categorised as medium as most waiting time in that time period result in an absolute impact larger than 0.2. Since the magnitude of the estimated parameters for the three time periods are quite close to one another, the differences between absolute impact of waiting time between the three periods is considerable.

This is explained by the simulated waiting profile. The waiting time in the morning are much smaller than in the midday and especially the afternoon. Therefore, similar magnitudes of waiting time parameters result in larger differences in absolute values.

Moreover, morning waiting time is found to increase preference for the morning alternative, whilst the midday and afternoon waiting time decrease preference for midday pick up. Striking is that waiting time do not necessarily decrease the attractiveness of an alternative.

This could be because morning waiting time is less risky for TOC as they can still meet the operating hour deadlines in the hinterland. The negative impact of afternoon waiting time on the midday pick up alternative might be explained by the approach applied to include the waiting time in the choice model. The approach ensures that the TOC is aware of the waiting time in the morning, midday and afternoon. Therefore, a TOC might not prefer midday pick up due to afternoon waiting time. As earlier mentioned, midday waiting time often propagate to afternoon waiting time. Hence, if the TOC is aware of afternoon waiting time, they might not desire a midday pick up because they know it will be very busy in the midday as well. Then they might divert to night or morning pick up.

Even though, the magnitudes of the estimated parameter values are quite close together, it can be observed that the morning waiting time is perceived as more impactful compared to the waiting time in the midday and afternoon. The same interpretation for terminal A, regarding perceiving waiting time, applies here.

Parameter interpretation terminal C

In addition to the general findings from the choice model results, some specific findings for terminal C are discussed.

From the estimated model it can be observed that at terminal C, chemical containers ($\hat{\beta}_{CC}$) impact utility for the night pick up alternative. Even though, the impact is of a small magnitude, the sign of the parameter (+), suggests that there is higher preference for the night alternative for chemical container pick up.

A reason for the preference for pick up of chemical containers in the night at terminal B, might be to avoid rush hours on the traffic network on access and exit roads. Another reason could be that there are many export chemical containers that must be delivered at night. Therefore, the TOC desires to pick up chemical containers as they can combine the trips. Combining trips for chemical containers is crucial for TOC as the transport is more expensive and requires a more heavy truck. Moreover, the trucks for chemical container transport can only transport chemical containers.

Based on the estimated model, the preference for afternoon pick up is found to increase (+ sign) for containers picking up chemical products ($\hat{\beta}_{Chem}$) at terminal C. The magnitude of the effect is categorised as small. However, as there is no unobserved behaviour in the afternoon alternative, the small magnitude has a relatively high impact compared to the other alternatives.

The preference for afternoon pick up of chemical products at terminal C might be explained by the desire of the receiver. The receiver of the chemical products transported via terminal C might need the chemical products for industrial activities. This could cause a desire to receive the goods before the evening starts so the goods are on time for the morning shift. An other reason could be that the chemical products transported via terminal C have a destination that requires a few hours driving time. Picking up the products in the afternoon ensures that the products are delivered at the far hinterland location on time for the start of the operating hours.

A very similar, compared to chemical products, effect and magnitude of effect can be observed for the pick up period of ores ($\hat{\beta}_{Ores}$). The same reasoning for this preference as for chemical products applies to ores.

From the estimated choice model, fertilisers ($\hat{\beta}_{Fert}$) are found to be slightly impact the attractiveness for midday pick up at terminal C. A decreasing effect with small magnitude can be observed. This indicates that other time periods are slightly more attractive relatively to the midday period.

This could be explained by the utilisation of fertilisers. Fertilisers are mainly used in agricultural activities. As previously mentioned, these activities start very early in the morning. Therefore, there is little use to pick up the fertiliser products in the middle of the day. The other alternatives make more sense to pick up the products.

Table D.7: Estimated parameter results from the specified choice model for terminal C
**This is based on the value magnitude after parameter is multiplied with the waiting time variable w_{alt}*

	Estimated parameter value	**In utility function**	**Effect on utility**	**Magnitude of effect**	**Standard error**	**t-value**	**p-value**
ASC_{Night}	-2.01	V1	Decrease	Huge	0.04	-50.4	0
$ASC_{Morning}$	-0.338	V2	Decrease	Medium	0.00837	-40.4	0
β_{GP}	0.245	V1	Increase	Medium	0.0416	5.89	0
β_{RE}	0.418	V2	Increase	Medium	0.0283	14.7	0
β_{CC}	0.196	V1	Increase	Small	0.0593	3.31	0.000932
β_{TC}	0.0801	V1, V3	Increase	Small	0.0247	3.24	0.0012
β_{Agr}	0.344	V2	Increase	Medium	0.0293	11.7	0
β_{Chem}	0.124	V4	Increase	Small	0.0133	9.31	0
$\beta_{SolMinFu}$	0.297	V2	Increase	Medium	0.0177	16.8	0
β_{RawMin}	-0.217	V3	Decrease	Medium	0.0222	-9.77	0
β_{Petro}	0.134	V4	Increase	Small	0.0185	7.26	0
β_{Ores}	0.108	V4	Increase	Small	0.0221	4.87	0
β_{Fert}	-0.0656	V3	Decrease	Small	0.0223	-2.94	0.00331
$\beta_{WT,Morning}$	-0.173	V3	Decrease	Small*	0.059	-2.93	0.00338
$\beta_{WT,Midday}$	-0.0173	V3	Decrease	Small*	0.00194	-8.94	0
$\beta_{WT,Afternoon}$	0.00806	V4	Increase	Small*	0.000543	14.8	0

In Table D.8 the average, minimum and maximum impact of the waiting time multiplied with the estimated parameter values are presented. These values are based on the average, minimum and maximum in the waiting time profile (Section B.5).

Table D.8: Overview of absolute impact of waiting time on alternative attractiveness at terminal C

	$w_{Morning} \cdot \hat{\beta}_{Morning}$	$w_{Midday} \cdot \hat{\beta}_{Midday}$	$w_{Afternoon} \cdot \hat{\beta}_{Afternoon}$
Average	-0.00692	-0.0571	0.1145
Minimum	0	-0.00294	0.00484
Maximum	-0.0433	-0.1678	0.1959

For terminal C, the waiting time in the morning and midday is included in the midday alternative. The waiting time in the afternoon is included in the afternoon alternative. Compelling is that waiting time in both morning and midday decreases the attractiveness of the midday alternative. Moreover, the afternoon waiting time increases the attractiveness for the afternoon pick up period.

Propagating waiting time from the morning to the midday alternative could be an explanation for the decreasing effect of morning waiting time on midday pick up attractiveness. Regarding the increased attractiveness for the afternoon by waiting time in the afternoon, this indicates an opposite relation between the preference of TOC and the waiting time in the afternoon. The preference of the TOC for the afternoon leads to higher waiting time in the afternoon period. Consequently, the TOC have no choice but to accept the large waiting time. The dynamics of this preferences is assumed to come from unobserved attitudes from TOC. The actual reason for this behaviour would require more research.

From the magnitude of the estimated parameters it can be concluded that TOC perceive morning waiting time a factor 10 more impactful. Nevertheless, as the waiting time in the morning are much lower, the absolute impact on the alternative attractiveness is smaller for the morning. Yet, the fact that TOC rate one minute of waiting time in the morning more heavily than for a minute waiting in the midday or afternoon is a valuable observation. The explanation for this is the same as mentioned previously for terminal A.

Parameter interpretation terminal D

In addition to the general findings from the choice model results, some specific findings for terminal D are discussed.

From the estimated model, it can be observed that chemical containers ($\hat{\beta}_{CC}$) impact the attractiveness of the afternoon and night pick up alternative at terminal D. The sign of the parameter ($-$), suggests that there is higher preference for the morning and midday alternative when a chemical container is considered. Moreover, the magnitude of the estimated parameter indicates that the utility for is only very slightly affected by the preference of the TOC.

A reason for this might be that the chemical containers cannot be delivered at hinterland locations during the night and late afternoon. The receivers might want the chemical containers in the middle of the day as this is the period they operate. An other reason might be that the closing time for export containers is around the afternoon. Hence, the TOC want to deliver the export container before the afternoon. Since the transport of chemical containers requires a more heavy truck and is more expensive, the TOC desire to combine the trip for export and import containers. Moreover, the trucks for chemical container transport can only transport chemical containers. Consequently, the TOC pick up a chemical container in the morning.

Based on the estimated model, the preference for night pick up at terminal D, is found to increase ($+$ sign) for containers transporting chemical products ($\hat{\beta}_{Chem}$). The magnitude of the effect is medium.

A reason for this found preference could be that the chemical products are used in agricultural and industrial activities. The receivers of the chemical products might desire a delivery of the products before the working day starts. For example, agricultural activity starts around 3 in the night. Hence, this would match the night period pick up.

The estimated model indicates a slight dislike for pick up of ores ($\hat{\beta}_{Ores}$) in the afternoon alternative. The effect is decreasing with a very small magnitude. Hence, the estimated parameter indicates that the TOC might prefer pick up of ores in the night, morning or midday.

Ores might be needed for industry activities during the day. Picking up ores in the afternoon might cause a delay for the industry. Therefore, the TOC might have a dislike for afternoon pick up of ores. Another reason to dislike afternoon pick up could be to avoid the afternoon peak hour in the traffic network.

In Table D.10 the average, minimum and maximum impact of the waiting time multiplied with the estimated parameter values are presented. These values are based on the average, minimum and maximum in the waiting time profile (Section B.5).

For terminal D, the waiting time in the midday is included in the afternoon alternative. The estimated parameter for midday waiting time indicates that the midday waiting time decreases the attractiveness of the afternoon pick up alternative. This could be explained by the propagation of waiting time in the midday to the afternoon.

Solely the midday waiting time was found to impact the attractiveness of the alternatives. However, this magnitude is rather small for both the estimated parameter value as for the absolute value. Nevertheless, it is valuable to be aware that the morning and afternoon waiting time do not impact the preference of TOC for pick up period at terminal D. A reasons could be that the TOC take the waiting time at a terminal for granted.

Table D.9: Estimated parameter results from the specified choice model for terminal D

**This is based on the value magnitude after parameter is multiplied with the waiting time variable w_{alt}*

	Estimated parameter value	In utility function	Effect on utility	Magnitude of effect	Standard error	t-value	p-value
ASC_{Night}	-1.68	V1	Decrease	Huge	0.00687	-244	0
$ASC_{Morning}$	-0.333	V2	Decrease	Medium	0.00722	-46.2	0
β_{GP}	-0.107	V2	Decrease	Small	0.00808	-13.2	0
β_{CC}	-0.0374	V1, V4	Decrease	Small	0.00874	-4.28	0
β_{Agr}	0.322	V2	Increase	Medium	0.0151	21.3	0
β_{Chem}	0.265	V1	Increase	Medium	0.0148	17.9	0
$\beta_{SolMinFu}$	-0.088	V3, V4	Decrease	Small	0.0115	-7.66	0
β_{RawMin}	-0.0569	V2	Decrease	Small	0.0146	-3.91	0
β_{Petro}	0.0532	V3	Increase	Small	0.0122	4.37	0
β_{Ores}	-0.0378	V4	Decrease	Small	0.0136	-2.78	0.00548
$\beta_{WT,Midday}$	-0.0139	V4	Decrease	Small*	0.0017	-8.17	0

Table D.10: Overview of absolute impact of waiting time on alternative attractiveness at terminal D

	$w_{Midday} \cdot \hat{\beta}_{Midday}$
Average	-0.03197
Minimum	-0.0042
Maximum	-0.0723

Parameter interpretation terminal comparison

Above, each estimated parameter in the choice model is elaborated. There are some valuable findings that require some extra discussion. In this section some results are compared.

As previously mentioned, there is overlap in preferences of TOC for container pick up across the several terminals. However, differences between the terminals become very clear if the estimated parameters for a number of specific container types or commodity types are compared.

For example, the impact of chemical containers and chemical products on the attractiveness of the alternatives is entirely different. For terminal A, a preference for midday pick up of chemical containers is observed. Contrarily, the TOC show a preference for night time pick up of chemical containers at terminal C. Regarding chemical products, the TOC show a preference for the pick up of chemical products in the morning at terminal A. At terminal C this preference is for the afternoon time period. For terminal B and D this preference is found for the night time pick up of chemical products. Note that the point is not to compare chemical containers and chemical products but to illustrate that more than once the pick up preferences are very different across the terminals. Despite having a similar name, the chemical containers and chemical products to not necessarily comprehend the same goods.

Consequently, it can be concluded that there can be large difference in preference for the same container or commodity type at terminals. For some terminals, the preferences of a specific container or commodity type is pick up in the middle of the day, whilst for another terminal this preference is for the night for the same container or commodity type. In the interpretation of the estimated parameters, some potential explanation or reasoning is discussed for the preferences. However, these might be contradictory if terminals are compared.

Subsequently, the reasoning for the preferences could be faulty. However, this is not necessarily the case. Even though it is difficult to interpret the difference in pick up preference for the same container, it is interesting to explore.

There are a few reasons that might explain the contradictory preferences for the same container type. The question is why the TOC have a preference to pick up a chemical container in the midday at terminal A, and in the night at terminal C.

To begin with, the difference in preference could originate from the way the terminals are organised. Perhaps at one of the terminals, the container is often located in a very busy stack in the morning, hence there is a preference to pick up the container at night when the stack is less busy. Whilst at the other terminal the stack where chemical containers are often located, is very busy in the afternoon, hence the TOC prefer pick up in the midday.

Another reason could be the role of the hinterland destination. Often forwarders have agreements with a certain terminal to transit the goods. Perhaps the forwarder that arranges transport via terminal A, has customers that want to receive their container in the middle of the day. The forwarder that transits the goods at terminal C might have clients that desire the containers during the night or in the early morning. Moreover, the customers of the containers might be located more often far away. This could also explain why there are different time period preferences for the same goods. The hinterland locations might want to receive the goods around the same time. However, the TOC might requires a longer drive for the containers transported via terminal A, hence the TOC has a preference for another time period.

The magnitude of impact regarding agricultural products on the morning alternative attractiveness is another eye-catching difference between terminals. For each terminal a similar preference is found for pick up of agricultural products in the morning. However, the magnitude of the preference deviates among the terminals. At terminal B the estimate parameter has the highest value, followed by D and C. The terminal with the smallest value is A.

By analysing the data (Section C.3 and Section C.4) it can be observed that terminal B does not necessarily handle large shares of agricultural products. However, in the morning a higher share can be observed. Terminal A, on the other hand, handles higher shares of agricultural products. Yet, for terminal A the shares are more spread along the day. For terminal C and D, the shares of agricultural products are comparable to the shares at terminal B. Nevertheless, a slightly higher share in the morning is observed in the morning for terminal C. Additionally, for terminal D the share of agricultural products in the morning is not higher than in the midday or afternoon. However, an outlier peak in shares can be observed (Figure C.20) in the morning. Consequently, the differences in magnitudes are explainable from the logistic data.

Similarly to the magnitude of the estimate parameter for agricultural products, the solid mineral fuels parameters have different magnitudes. In general the TOC show a preference for the night and morning alternative directly, or indirectly via a dislike for midday and afternoon pick up. However, the magnitude of the preference deviates between terminals.

This is an interesting observation that might be explained by the characteristics of the terminal. Additionally, it could be explained be the approach in model set up. As for each terminal a different choice model is specified, it is difficult to compare the estimated parameters one on one. Especially when the estimated parameters are all in other utilities for different time period, as is the case with the solid mineral fuels. The final choice probabilities (discussed in the next subsection) show that the market shares for the solid mineral fuels are quite similar for the alternative in which the solid mineral fuels parameter is formulated. Therefore, it can be concluded that the difference in magnitude of the parameters for solid mineral fuels is due to the formulation of the specific choice models for the different terminals.

Lastly, the estimated parameters for waiting time are valuable to compare across the different terminals. The impact of waiting time is found to be different depending on the terminal. It is already discussed per terminal that TOC seem to perceive morning waiting time as more impactful compared to midday and afternoon. Additionally, it is found that the TOC value one minute of the waiting time more heavily of one terminal compared to another. Especially for terminals B and C the waiting time impacts in the midday and afternoon are noticeable. One minute of waiting time in the midday and afternoon is rated more valuable for these two terminals compared to the terminals A and D.

This is a striking result as the terminals B and C operate with a time slot management strategy, whilst terminal A and D operate based on a open door policy. From these results, it can be concluded that TOC rate waiting time at time slot terminals in the midday and afternoon with an higher value compared to waiting time at an open door terminal. The reason for this is that the TOC are aware that with an open door policy a queue at the terminal may arise. However, with a time slot management system at the terminal, in theory, there should be no queue at the terminal. This is because the terminal should not allow more trucks to arrive than the terminal capacity. Therefore, in the event a queue does occur at the time slot management terminals, the TOC perceive the waiting time as more costly.

Choice probabilities

The specific value of estimated parameters provides important insight in TOC behaviour, potential preferences or dislikes. However, the eventual probability that a TOC chooses a certain time period for container pick up is determined by more than the value of the estimated parameter alone. Choice modelling is based on attractiveness of alternatives relative to each other. Hence, the interaction of the parameters and the ratio of utility functions for the alternatives determine the choice probability for an alternative. By integrating the estimated parameter values in the formulated utility functions (Section D.3.2), the probability of choosing an alternative can be computed as formulated in Equation D.20.

In Table D.11 through Table D.14, the choice probabilities are provided for each terminal, each alternative and based on each container type and commodity type. In other words these provide insight in the choice probability distribution along the alternatives for each attribute. This indicates the probability that a TOC picks up a certain container or commodity in a specific time period. In the probability calculation the waiting time parameters are excluded as the waiting time effects are not used for the scenario formulation. Furthermore, the probabilities excluding waiting time provide a clear overview of the tendency to choose a time period based specifically on the container or commodity type. For each container and commodity type, the choice probabilities for the alternatives sum up to 100%.

From the choice probability distributions for each attribute and at each terminal, it becomes clear that the midday and afternoon alternatives will still predominantly be chosen by the TOC. This is explained by the unobserved behaviour for the night and morning alternative captured in the model. However, for some container or commodity types it can be observed that the night or morning alternative also have considerable probabilities to be chosen.

All in all, this concludes the extensive analysis of the results from the choice models, the interpretation of the estimated parameters, and the insights from the choice probability distributions. Consequently, the findings from the choice models will be applied to formulate strategies for truck shifting to reduce waiting time at the terminals. Thereafter, the strategies will be evaluated based on an experimental plan.

Table D.11: Overview of the choice probabilities based on the attributes container type and commodity type for terminal A

	Night ($V1$)	**Morning ($V2$)**	**Midday ($V3$)**	**Afternoon ($V4$)**
General purpose container	8.6%	21.6%	39.5%	30.3%
Reefer container	9.6%	24.2%	33.1%	33.1%
Chemical container	7.4%	18.4%	40.6%	33.6%
Tank container	7.7%	19.2%	38.1%	35.0%
Agricultural products	7.6%	22.8%	34.8%	34.8%
Chemical products	7.4%	24.5%	34.0%	34.0%
Solid mineral fuels	21.8%	16.8%	30.7%	30.7%

Table D.12: Overview of the choice probabilities based on the attributes container type and commodity type for terminal B

	Night ($V1$)	Morning ($V2$)	Midday ($V3$)	Afternoon ($V4$)
General purpose container	5.8%	23.5%	35.3%	35.3%
Reefer container	5.4%	30.4%	45.7%	18.5%
Chemical container	4.4%	22.2%	36.7%	36.7%
Agricultural products	3.6%	35.2%	30.6%	30.6%
Chemical products	5.6%	23.6%	35.4%	35.4%
Solid mineral fuels	4.2%	25.7%	35.1%	35.1%
Raw minerals	5.9%	23.5%	35.3%	35.3%
Petroleum	4.0%	22.4%	33.6%	40.0%

Table D.13: Overview of the choice probabilities based on the attributes container type and commodity type for terminal C

	Night ($V1$)	Morning ($V2$)	Midday ($V3$)	Afternoon ($V4$)
General purpose container	5.9%	24.7%	34.7%	34.7%
Reefer container	4.2%	33.7%	31.1%	31.1%
Chemical container	5.7%	24.8%	34.8%	34.8%
Tank container	4.9%	24.2%	36.8%	34.0%
Agricultural products	4.3%	32.0%	31.8%	31.8%
Chemical products	4.5%	23.9%	33.6%	38.0%
Solid mineral fuels	4.3%	31.0%	32.3%	32.3%
Raw minerals	5.1%	26.9%	30.4%	37.7%
Petroleum	4.5%	23.8%	33.4%	38.2%
Ores	4.5%	24.1%	33.8%	37.6%
Fertiliser	4.8%	25.6%	33.6%	35.9%

Table D.14: Overview of the choice probabilities based on the attributes container type and commodity type for terminal D

	Night ($V1$)	Morning ($V2$)	Midday ($V3$)	Afternoon ($V4$)
General purpose container	6.6%	22.8%	35.3%	35.3%
Chemical container	6.2%	24.7%	34.5%	34.5%
Agricultural products	5.9%	31.1%	31.5%	31.5%
Chemical products	8.2%	24.2%	33.8%	33.8%
Solid mineral fuels	6.8%	26.2%	33.5%	33.5%
Raw minerals	6.5%	23.6%	34.9%	34.9%
Petroleum	6.3%	24.2%	35.7%	33.8%
Ores	6.5%	25.0%	34.9%	33.6%

D.5 MODEL APPLICATION

From the choice model results various opportunities can be identified to spread the arrival of trucks more evenly along the day. These opportunities stem from the observed preferences and dislikes of TOC and the choice probability distribution for container and commodity types. The tendency of a TOC to pick up a container in another time period than currently chosen, allows to shift truck arrivals from one time period to another.

D.5.1 Truck shifting strategies

For several container and commodity types, a preference or dislike for picking up the container in a certain time period is observed from the choice model. Based on this information a truck shifting strategy can be formulated per terminal.

In general, the goal of the truck shifting strategy is to spread the container pick up, hence the truck arrivals, more equally along the day. In other words, a flatten the curve or peak shaving strategy is the foundation for the TAS. For each of the terminals, a peak in truck arrivals is observed in the midday and afternoon time period (Section A.2). Consequently, with the peak shaving strategy, it is aimed to shift truck arrival from the midday and afternoon towards the morning and night alternative.

Shifting the trucks away from the peak is done based on the observed preferences and dislikes of the TOC. Using this information, the trucks that pick up a certain container or commodity type can be shifted from one time period to another. To illustrate this, if a preference for the night is observed for a general purpose container, but the general purpose containers are currently often picked up in the afternoon, a truck can be shifted from the afternoon to the night. This shift can be sustained by the observed willingness of the TOC to pick up the general purpose container in the morning.

Terminal A

Based on the findings from the choice model for terminal A, a specific strategy is defined to reduce the peak in truck arrival.

To begin with, in the truck shifting strategy for terminal A, two container types are ignored in the shifting strategy. For the pick up of tank and chemical container the TOC show a preference for midday pick up. Therefore, the TOC indirectly dislike pick up of tank and chemical containers in the night or morning alternative. Consequently, it is not realistic to shift these trucks to the night or morning alternative.

For the pick up of general purpose containers, the TOC are found to dislike the afternoon pick up. Therefore, in the truck shifting strategy for terminal A, the general purpose containers are shifted away from afternoon. Additionally, the trucks for reefer container pick up are shifted towards the night and morning alternative.

Regarding commodity types, the TOC shows a preference for the pick up of agricultural and chemical products in the morning time period. The trucks for pick up of these commodities are therefore shifted from the midday and afternoon alternatives to the morning time period. Moreover, for the pick up of solid mineral fuels a preference for the night is observed. Consequently, the trucks for solid mineral fuels pick up are shifted towards the night period.

Terminal B

In the truck shifting strategy for terminal B, the trucks for general purpose container pick up are shifted to the night time period. Trucks for reefer container pick up are shifted away from the afternoon. Chemical container pick ups are shifted from the morning towards the night.

Regarding commodity types, the pick up of agricultural products can be shifted to the morning. Moreover, chemical products, solid mineral fuels and raw mineral pick ups are shifted to the night.

Terminal C

The preferences of TOC at terminal C show that trucks for general purpose container and chemical container pick up can be shifted to the night. Reefer container pick ups can be shifted to the morning.

Additionally, trucks for agricultural product and solid mineral fuel pick ups can be shifted to the morning time period. Raw minerals can be shifted away from the midday alternative.

In the truck shifting strategy for terminal C, various container and commodity types are ignored. Some of these, chemical products and petroleum, are preferred for pick up in the midday or afternoon. Consequently, it would not be realistic to shift these truck arrivals to the morning or night. Moreover, fertilisers and ores are ignored in the shifting strategy since these commodity types have much overlap with general purpose and chemical containers (Section C.3). This means that fertilisers and ores are very often transported in general purpose and chemical containers. Consequently, shifting trucks based on these container types will capture the commodity as well. Lastly, tank containers are not shifted as the magnitude of the preference is very small, and the tank container pick ups overlap with agricultural products and solid mineral fuels container pick up.

Terminal D

Dislike for the pick up of general purpose containers is found for the morning alternative at terminal D. Therefore, trucks for general purpose container pick ups are shifted away from the morning. On the other hand, chemical containers are shifted towards the morning alternative.

Regarding commodity types, the agricultural products can be shifted to the morning. Truck arrivals for chemical products can be shifted to the night. Solid mineral fuel pick ups can be shifted to night and morning. Trucks for ores pick up can be shifted away from the afternoon. Container pick ups containing raw mineral can be shifted from the morning towards the night.

Lastly, trucks for petroleum pick ups are ignored in the shifting strategy for terminal D as a preference for the midday alternative is observed.

D.5.2 Experimental plan

As found from the choice probability distributions, the preferences observed from the estimated parameters cannot be translated one on one to be the ultimate choice of the TOC. The preferences and dislikes identified based on the estimated parameter values are merely to indicate that the TOC might have some tendency to pick up a specific container or commodity type in another time period. This insight led to the formulation of truck shifting strategies.

By shifting the truck arrivals, new arrival profile is obtained. How this is done is elaborated in Appendix E. Consequently, this is input for the terminal model (Appendix B) to generate a new simulated arrival and departure profile. This provides a waiting time profile based on shifted trucks. Together the new arrival and waiting time profile ensure insight in the potential gain from the truck shifting strategies (Appendix F).

Obviously, it is not realistic to expect that all TOC will apply to the truck shifting strategy. Therefore, various what-if scenarios are developed to evaluate the effect of application rates of TOC on the spread of truck arrival along the day. Consequently, using the terminal model, the effect on the waiting time at the terminals can be assessed. Additionally, the formulation of what-if scenarios allows to gain insight in the percentage of TOC that should apply to the truck shifting strategy to achieve a waiting time gain.

Furthermore, the scenarios provide insight in the drawback of shifting truck arrival. When too many trucks are shifted away from the peak, a new peak might occur during other time periods. This will cause waiting time in other time periods. This is basically moving the current waiting time issue in the midday and afternoon to another time. Hence, simply shifting as many trucks as possible is not the right approach to the problem. The what-if scenarios provide insight in the turning point of truck shifting, from which application rate a waiting time loss instead of gain is encountered.

E TRUCK SHIFTING HEURISTIC

For this research, a heuristic approach is designed for the evaluation of truck shift policy. The purpose of the truck shifting heuristic is to compute new arrival profiles based on the truck shifting strategies that resulted from the choice models (Appendix D). New arrival profiles are computed for various what-if scenarios. The what-if scenarios indicate the TOC application rates to the truck shifting strategy.

E.1 HEURISTIC DESIGN

To shift the trucks and compute new arrival profiles, various steps are required. A detailed visual overview of the heuristic is represented in Figure E.1.

1. **Convert containers to trucks**: First of all, the logistic data (Appendix C) and traffic data (Appendix A) are combined to convert containers to trucks.
2. **Calculate total potential shifts**: Secondly, the truck distribution for computed arrivals is made similar to the observed arrival distribution.
3. **Compute shift matrices**: Thereafter, a shift matrix for each scenario is computed.
4. **Shift trucks in arrival profiles**: Lastly, the shift matrices are transformed to an arrival profile that matches each scenario.

Similar to the terminal and choice model development, for each terminal the truck shifting heuristic is applied separately since the input, truck shifting strategy and output is different for each terminal. Nonetheless, the set up for each of the trucks' shift is entirely the same.

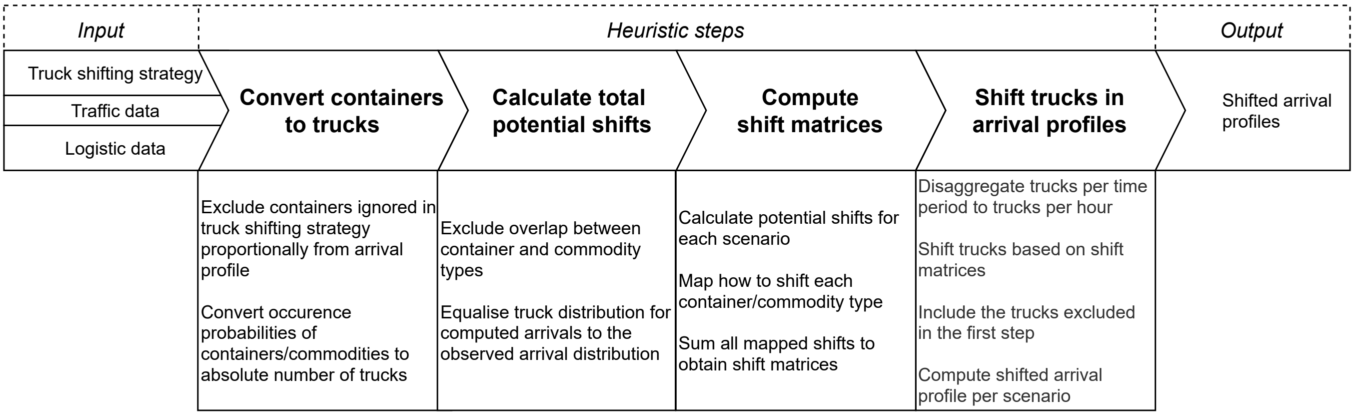


Figure E.1: Overview of the truck shifting heuristic

E.1.1 Containers to trucks

This step comprehends the coupling of traffic and logistic data. The logistic data is summarised in probability percentages (Section C.3). Hence, these can be converted to absolute numbers of trucks transporting the specific container type or commodity type.

Logistic data

Table E.1 through Table E.4 contain the probability (in percentage) for a container or commodity type for occurring in each alternative. Note that these can also be found in Section C.3. However, for readability and structure, the probabilities are additionally presented here. Moreover, only the container types and commodity types used in the truck shifting strategy per terminal are displayed.

Traffic data

The total truck arrivals on an average working day are 797 at terminal A, 725 at terminal B, 1324 at terminal C, and 1130 at terminal D. Before computing the absolute number of trucks that might be shifted in each time period, the containers, that are ignored in the truck shifting strategy (Section D.5.1), are excluded. From the logistic data, the percentage of trucks that cannot be shifted are known. These percentages are 4.863%, 0.294%, 2.493%, and 3.443% for terminal A, B, C, and D, respectively. This is the percentage of trucks that is not captured in the truck shifting strategy. Hence, these trucks cannot be shifted and remain stationary in the new arrival profiles. Consequently, this percentage of trucks is excluded from the total of truck arrivals at each terminal. Excluding the commodities that are not captured in the truck shifting strategy results in a total of 758 (terminal A), 723 (terminal B), 1291 (terminal C), and 1091 (terminal D) arriving trucks on an average working day. These are the truck arrivals that might be shifted, hence the potential shifts.

Table E.1: Occurrence [%] of container and commodity type per time period at terminal A, from logistic data (Section C.3)

	Agricultural products	**Chemical products**	**Solid mineral fuels**	**General purpose container**	**Reefer container**
Night	0.81%	0.32%	1.10%	4.36%	3.89%
Morning	2.54%	0.97%	0.95%	9.51%	9.66%
Midday	3.84%	1.48%	1.68%	17.97%	13.48%
Afternoon	3.46%	1.12%	1.10%	12.67%	12.31%

Table E.2: Occurrence [%] of container and commodity type per time period at terminal B, from logistic data (Section C.3)

	Agricultural products	**Chemical products**	**Solid mineral fuels**	**Raw minerals**	**General purpose container**	**Reefer container**	**Chemical container**
Night	0.16%	0.53%	0.15%	0.23%	4.15%	0.55%	1.17%
Morning	1.40%	1.69%	0.92%	0.71%	15.86%	5.53%	4.53%
Midday	1.10%	2.42%	1.24%	0.93%	19.59%	4.35%	5.59%
Afternoon	0.75%	3.20%	1.15%	1.43%	26.53%	2.56%	7.34%

Table E.3: Occurrence [%] of container and commodity type per time period at terminal C, from logistic data (Section C.3)

	Agricultural products	**Solid mineral fuels**	**Raw minerals**	**General purpose container**	**Reefer container**	**Chemical container**
Night	0.20%	0.50%	0.46%	4.72%	0.18%	0.36%
Morning	2.14%	3.61%	1.47%	20.24%	2.30%	1.76%
Midday	1.90%	3.94%	1.95%	24.30%	2.02%	2.02%
Afternoon	1.47%	3.67%	3.08%	33.14%	1.46%	2.44%

Table E.4: Occurrence [%] of container and commodity type per time period at terminal D, from logistic data (Section C.3)

	Agricultural products	Chemical products	Solid mineral fuels	Raw minerals	Ores	General purpose container	Chemical container
Night	0.28%	2.30%	0.62%	0.75%	0.56%	5.27%	1.85%
Morning	1.00%	4.75%	1.82%	2.18%	1.82%	13.95%	5.10%
Midday	1.53%	9.05%	4.04%	3.77%	3.69%	28.59%	10.48%
Afternoon	1.10%	6.35%	2.63%	2.43%	2.33%	18.85%	6.91%

Coupling

To convert the container data to trucks, the occurrence probability (Table E.1 through Table E.4) is multiplied by the absolute number of trucks arriving at the terminal on an average working day. Thence, there is insight in the number of trucks that arrive in each time period to pick up a certain container type or commodity type. The spread of truck arrival for an average working day based on specific container and commodity types are provided in Table E.5 through Table E.8. This spread of trucks arrivals represents the total potential shifts for each container and commodity type in each time period.

Note that in this approach the container dimensions are ignored. As the translation from container to truck is done based on percentages, the fact that a truck might arrive to pick two containers at once, is captured. Nevertheless, the assumption is made that a truck will only transport one container type or one commodity type.

Table E.5: Overview of the spread of truck arrival [#] for an average working day based on specific container and commodity types based on probability of occurrence at terminal A (Table E.1)

	Agricultural products	Chemical products	Solid mineral fuels	General purpose container	Reefer container	Total
Night	6	2	8	33	30	79
Morning	19	7	7	72	73	179
Midday	29	11	13	136	102	292
Afternoon	26	8	8	96	93	232
Total	81	29	37	337	298	783

Table E.6: Overview of the spread of truck arrival [#] for an average working day based on specific container and commodity types based on probability of occurrence at terminal B (Table E.2)

	Agricultural products	Chemical products	Solid mineral fuels	Raw minerals	General purpose container	Reefer container	Chemical container	Total
Night	1	4	1	2	30	4	8	50
Morning	10	12	7	5	115	40	33	221
Midday	8	17	9	7	142	31	40	255
Afternoon	5	23	8	10	192	18	53	310
Total	25	57	25	24	478	94	135	837

Table E.7: Overview of the spread of truck arrival [#] for an average working day based on specific container and commodity types based on probability of occurrence at terminal C (Table E.3)

	Agricultural products	Solid mineral fuels	Raw minerals	General purpose container	Reefer container	Chemical container	Total
Night	3	6	6	61	2	5	83
Morning	28	47	19	261	30	23	407
Midday	25	51	25	314	26	26	467
Afternoon	19	47	40	428	19	32	584
Total	74	151	90	1064	77	85	1541

Table E.8: Overview of the spread of truck arrival [#] for an average working day based on specific container and commodity types based on probability of occurrence at terminal D (Table E.4)

	Agricultural products	Chemical products	Solid mineral fuels	Raw minerals	Ores	General purpose container	Chemical container	Total
Night	3	25	7	8	6	57	20	127
Morning	11	52	20	24	20	152	56	334
Midday	17	99	44	41	40	312	114	667
Afternoon	12	69	29	27	25	206	75	443
Total	43	245	99	100	92	727	266	1571

E.1.2 Potential shifts

The computed spread of truck arrivals in the previous step should be compared with the historic traffic data (Section A.2). This is to ensure that the computed spread of truck arrivals, based on container and commodity type, and on time period, reflects the reality.

The first thing that should be noted in Table E.5 through Table E.8, is that the total of trucks sum up to a value that is higher than the number of trucks arriving on an average working day. The total arrivals on an average working day that have the potential to be shifted, are 758, 723, 1291, and 1091 for terminal A, B, C and D, respectively. Therefore, it can be concluded that there is overlap in container type and commodity type, as some containers may transport a certain commodity.

A typical example is a reefer container transporting agricultural products. However, it is not necessarily true that the reefer containers always transports agricultural products, nor that agricultural products are always transported in reefer containers.

Summing up the probabilities in each table (Table E.1 through Table E.4) indicates a value higher than 100%. Hence, an overrepresentation of containers. The overlap in container and commodity type are 3.2% (terminal A), 15.74% (terminal B), 19.36% (terminal C), and 44% (terminal D). Converting these percentages to trucks would lead to more trucks (in absolute value) than observed in the historical traffic data (Section A.2). The latter is why the totals in Table E.5 through Table E.8 sum up to a value higher than expected.

Consequently, the overlap should be accounted for. In Section C.3 the container type and commodity type are examined in contrast. For each terminal, this probability matches the percentage of overlap found by summing the cells in table Table E.1 through Table E.4. This indicates the probability that a specific container type contains a specific commodity. Moreover, it can be observed from which container and commodity type the overlap originates. This provides that the overlap can be excluded correctly. To ensure consistency between terminals for the truck shifting, the overlap is always excluded from container type. Furthermore, the overlap is excluded proportionally as it is unknown in which time period the overlap of container type and commodity type exactly occurs.

The method for excluding proportionally is based on the share of container in a time period. To illustrate this, imagine that a general purpose container has 5% overlap with all commodities captured by the shifting strategy. The trucks for general purpose containers are found to have a 10% share in the morning period. This means that 10% of the trucks that arrive for a general purpose container, arrive in the morning. Subsequently, the overlap accounted for in the morning period for general purpose containers is 0.5%.

To ensure that the truck spread along the day in Table E.5 through Table E.8, matches the observed spread all overlap is excluded. For each container type, the total percentages of trucks transporting a certain container is subtracted from the probability of occurrence (Table E.1 through Table E.4). Subsequently, the new probabilities of occurrence are multiplied with the total of truck arrivals. This results in an updated spread of trucks along the day. The totals of truck arrivals match the observed traffic data. Yet, it should be studied whether the number of trucks in each time period deviates from the observed data. To do so, the updated spread of trucks is again compared with the arrival profile from historic traffic data (Section A.2).

The arrival profile from historic data is aggregated to trucks per hour. However, the container data is aggregated to trucks per time period. Therefore, the arrival profile from the traffic data is likewise aggregated to time periods. Later in the last step of the truck shift procedure, the traffic data will disaggregated back to trucks per hour.

From aggregating the arrival profile, the number of truck arrivals per time period are obtained. The distribution of number of trucks per time period is depicted in Table E.9.

Table E.9: Distribution of truck arrivals along the day for each terminal [%] obtained from historic traffic data (Section A.2)

	Terminal A	**Terminal B**	**Terminal C**	**Terminal D**
Night	4.02%	4.83%	6.72%	3.98%
Morning	29.23%	27.59%	25.60%	27.79%
Midday	38.02%	36.14%	35.42%	35.31%
Afternoon	28.73%	31.45%	32.25%	32.92%

With the distribution of truck arrivals along the day from historic data, the truck arrivals in absolute number of trucks can be calculated. Logically, the trucks transporting commodities that are not captured in the truck shifting strategy, are excluded. Table E.10 shows the observed number of trucks in each time period for all terminals.

Table E.10: Distribution of truck arrivals in number of trucks [#] along the day for each terminal obtained from historic traffic data (Section A.2)

	Terminal A	**Terminal B**	**Terminal C**	**Terminal D**
Night	30	35	87	43
Morning	222	199	331	303
Midday	288	261	457	385
Afternoon	218	227	416	359

The observed arrival in Table E.10 is compared with the computed arrival per terminal in Table E.5 through Table E.8 (most right column). From the comparison, it should be noticed that the spread along the day is different. The reason for this is that the computed arrivals are calculated based on the logistic data. The logistic data, however, comprehends the ETA of the TOC (Appendix C). Consequently, the computed arrivals are the number of trucks per time period in which the TOC expected to arrive. The observed arrivals are the number of trucks per time period in which the TOC actually arrived.

Therefore, the computed arrivals are processed to match the observed arrivals per time period. The computed arrivals show that for some time periods there is a surplus of trucks, compared to the observed arrivals. In the consecutive time period less truck arrivals are computed compared to the observed data. Therefore, it is assumed that a share of the TOC arrives earlier or later than expected. However, they arrive at least around the arrival time they indicated in the logistic data (the ETA). The aim for computing the spread of trucks is to match it with the observed arrivals per time period. Consequently, the surplus of trucks are distributed in the time periods where a shortage is observed.

Finally, the potential shifts for trucks at each terminal is represented in Table E.11 through Table E.14. These indicate the final and total potential shifts of trucks on an average working day per time period, and per container and commodity type.

Table E.11: Total potential shifts in absolute number of trucks [#] per time period, and per container and commodity type for an average working day at terminal A

	Agricultural products	Chemical products	Solid mineral fuels	General purpose container	Reefer container	Total
Night	3	1	4	10	10	28
Morning	23	9	12	91	90	224
Midday	29	11	13	136	102	292
Afternoon	26	8	8	85	86	214
Total	81	29	37	323	289	758

Table E.12: Total potential shifts in absolute number of trucks [#] per time period, and per container and commodity type for an average working day at terminal B

	Agricultural products	Chemical products	Solid mineral fuels	Raw minerals	General purpose container	Reefer container	Chemical container	Total
Night	1	3	1	1	23	3	3	35
Morning	10	13	7	5	112	36	16	200
Midday	9	20	10	8	156	30	25	259
Afternoon	5	20	7	9	155	14	17	227
Total	25	57	25	24	446	84	61	721

Table E.13: Total potential shifts in absolute number of trucks [#] per time period, and per container and commodity type for an average working day at terminal C

	Agricultural products	Solid mineral fuels	Raw minerals	General purpose container	Reefer container	Chemical container	Total
Night	3	7	6	55	1	4	77
Morning	27	46	19	213	10	16	331
Midday	27	57	30	313	12	23	462
Afternoon	17	42	35	304	4	19	420
Total	74	151	90	885	27	62	1290

Table E.14: Total potential shifts in absolute number of trucks [#] per time period, and per container and commodity type for an average working day at terminal D

	Agricultural products	Chemical products	Solid mineral fuels	Raw minerals	Ores	General purpose container	Chemical container	Total
Night	2	16	4	5	4	11	1	43
Morning	13	63	25	28	24	119	36	309
Midday	15	87	39	36	36	136	35	385
Afternoon	13	78	31	30	28	134	39	353
Total	43	245	99	100	92	401	111	1091

As an extra check for the final potential shifts, the choice probabilities (Table D.11 through Table D.14 in Section D.4.2), can be used. By multiplying the choice probabilities with the totals for each container type and commodity type, a spread of truck arrivals (in absolute number of trucks) can be calculated. This spread of trucks per time period, and per container and commodity type is found to be similar to the final potential shifts. Hence, the truck shifting heuristic has the ability to compute the potential shifts close to the potential shifts in reality.

E.1.3 Shift matrices

Table E.11 through Table E.14 represent the spread of trucks along the day per container and commodity type, and time period. It provides insight in how many trucks arrive during the time periods to pick up a certain container type or commodity type. From this it can be derived how many truck arrivals can potentially be shifted from one time period to another. Hence, the total potential shifts that is found at each of the terminals. The approach for truck shifting is based on the experimental plan discussed in Section D.5.2.

Since it is unrealistic and undesirable to shift the truck arrivals with the full potential, various what-if scenarios are formulated. With the what-if scenarios several TOC application rates are evaluated. The application rates vary from 5% to 100%. For the scenarios from 5% to 50%, the application rate is increased with 5% each scenario. From 50% to 100%, the application rate is subsequently increased with 10% for each scenario.

This method is chosen because the steps of 5% allow to assess the effect of small changes in arrivals more closely. Hence, to approximate the minimal application rate of TOC, that is required to shift for a waiting time gain, more precisely. Additionally, larger application rates are evaluated. These larger application rates are increased with steps of 10% instead of 5%. It is expected that an application rate of more than 50% is not realistic. However, it is important to understand what would happen with the waiting time profile if these high application rates where to be experienced. The higher application rate scenarios allow to study the potential turning point of truck shifting and the consequences.

In total, 16 what-if scenarios are formulated. As mentioned the first scenarios vary from application rates between 5% and 50%, each scenario is increased with steps of 5%. Scenario 1 indicates a 5% shift of truck arrivals, scenario 2 a 10% shift, and so forth until scenario 10 in which an application rate of 50% is evaluated.

Scenario 11 until 15 correspond to an application rate of 60% until 100%, respectively. For these scenarios, the application rates are subsequently increased in steps of 10%.

Lastly, a 16th scenario is formulated in which the truck arrivals are spread perfectly equal along the day. In this scenario trucks not shifted based on application rates. The total number of trucks arriving in a day is divided by 24, this results in the number truck arrivals in each time slots for one day. This 16th scenario is used as a reference scenario as the perfect arrival profile would be an equal spread of trucks along the day. The waiting time gain for each scenario is compared with this reference scenario, to review the effectiveness of shifting of trucks under various application rates.

Consequently, the PoR and terminals gain insight in the effect of truck shifting and the designed TAS. The advantages encountered with small application rates, as well as the risks of too high application rates are evaluated with the scenarios.

The general strategy for truck shifting is an approach in which the truck arrivals during peak periods are shifted towards quieter moments. This approach is referred to as peak shaving. The results of the choice model are applied to define a more specific shift strategy for each of the terminals. The shift strategy for each terminal indicates precisely which trucks can be shifted from the peak periods to the quieter time periods. The elaboration of the shift strategies can be found in Section D.5. Here, a recapitulation of the truck shifting strategy per terminal is provided.

- Terminal A: agricultural products to the morning, chemical products to the morning, solid mineral fuels to the night, general purpose containers away from the afternoon, reefer containers to the night and the morning.
- Terminal B: agricultural products to the morning, chemical products to the night, raw minerals to the night, solid mineral fuels to the night, chemical containers not to the morning, general purpose containers to the night, reefer containers away from the afternoon.

- Terminal C: agricultural products to the morning, raw minerals away from the midday, solid mineral fuels to the morning, chemical containers to the night, reefer containers to the morning, general purpose containers to the night.

- Terminal D: chemical products to the night, agricultural products to the morning, ores away from the afternoon, raw minerals away from the morning, solid mineral fuels to the morning and the night, chemical containers to the morning, general purpose containers away from the morning.

Based on the application rates from the what-if scenarios and the truck shifting strategies, shift matrices can be computed. These shift matrices indicate how many trucks are shifted from a certain time period to another certain time period for each what-if scenario.

There are three steps in the approach to obtain the shift matrices. First, the number of trucks per container and commodity type, and time period are calculated for each scenario. This is done by multiplying the total potential shifts (Table E.11 through Table E.14) with the application rate of each scenario. This results in the potential shifts per scenario. To illustrate this, an example is provided. If the total potential shifts of general purpose containers in the afternoon is 85 trucks, and the scenario evaluates an application rate of 10%. The potential shifts of general purpose containers in the afternoon under a 10% application rate is 8.5 trucks. As trucks require an integer value, the potential shifts in this example is rounded to 9 trucks.

The next step is to combine the shift strategy with the potential shifts under the specified application rate. To do this, for each container or commodity in the strategy it is mapped from and to where the container or commodity should be shifted.

Lastly, all trucks that are shifted from one time period to another are summed. This results in the shift matrix. The shift matrices are similar to origin destination matrices. In the rows, the time period from where the truck should be shifted, hence the origin, is represented. In the columns, the time period towards which the truck is shifted, is indicated, hence the destination. For each application rate scenario, a separate shift matrix is computed. These are displayed in for each terminal in Table E.15 through Table E.21.

Table E.15: Shift matrices for terminal A corresponding to the what-if scenarios

(a) Scenario 1: 5% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	1	0	0	0
Midday	1	7	0	0
Afternoon	7	4	0	0

(b) Scenario 2: 10% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	1	0	0	0
Midday	1	14	0	0
Afternoon	14	7	0	0

(c) Scenario 3: 15% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	2	21	0	0
Afternoon	22	10	0	0

(d) Scenario 4: 20% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	3	29	0	0
Afternoon	29	14	0	0

(e) Scenario 5: 25% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	3	0	0	0
Midday	3	36	0	0
Afternoon	36	18	0	0

(f) Scenario 6: 30% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	4	0	0	0
Midday	4	43	0	0
Afternoon	43	21	0	0

(g) Scenario 7: 35% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	4	0	0	0
Midday	4	50	0	0
Afternoon	51	24	0	0

(h) Scenario 8: 40% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	5	0	0	0
Midday	5	57	0	0
Afternoon	58	28	0	0

(i) Scenario 9: 45% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	5	0	0	0
Midday	6	64	0	0
Afternoon	66	31	0	0

(j) Scenario 10: 50% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	6	0	0	0
Midday	6	71	0	0
Afternoon	73	34	0	0

(k) Scenario 11: 60% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	7	0	0	0
Midday	8	86	0	0
Afternoon	88	41	0	0

(l) Scenario 12: 70% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	8	0	0	0
Midday	9	100	0	0
Afternoon	102	48	0	0

(m) Scenario 13: 80% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	10	0	0	0
Midday	10	114	0	0
Afternoon	117	55	0	0

(n) Scenario 14: 90% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	11	0	0	0
Midday	11	128	0	0
Afternoon	131	62	0	0

(o) Scenario 15: 100% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	12	0	0	0
Midday	13	143	0	0
Afternoon	146	69	0	0

Table E.17: Shift matrices for terminal B corresponding to the what-if scenarios

(a) Scenario 1: 5% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	1	0	0	0
Midday	11	0	0	0
Afternoon	10	0	0	0

(b) Scenario 2: 10% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	22	1	0	0
Afternoon	22	1	0	0

(c) Scenario 3: 15% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	33	1	0	0
Afternoon	32	3	0	0

(d) Scenario 4: 20% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	3	0	0	0
Midday	44	2	0	0
Afternoon	44	3	0	0

(e) Scenario 5: 25% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	4	0	0	0
Midday	55	2	0	0
Afternoon	54	5	0	0

(f) Scenario 6: 30% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	5	0	0	0
Midday	66	3	0	0
Afternoon	65	5	0	0

(g) Scenario 7: 35% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	6	0	0	0
Midday	77	3	0	0
Afternoon	76	6	0	0

(h) Scenario 8: 40% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	6	0	0	0
Midday	88	3	0	0
Afternoon	86	8	0	0

(i) Scenario 9: 45% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	7	0	0	0
Midday	99	4	0	0
Afternoon	97	8	0	0

(j) Scenario 10: 50% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	8	0	0	0
Midday	110	4	0	0
Afternoon	108	8	0	0

(k) Scenario 11: 60% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	10	0	0	0
Midday	132	5	0	0
Afternoon	130	11	0	0

(l) Scenario 12: 70% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	11	0	0	0
Midday	154	6	0	0
Afternoon	152	12	0	0

(m) Scenario 13: 80% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	13	0	0	0
Midday	176	7	0	0
Afternoon	174	14	0	0

(n) Scenario 14: 90% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	14	0	0	0
Midday	198	8	0	0
Afternoon	196	15	0	0

(o) Scenario 15: 100% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	16	0	0	0
Midday	220	9	0	0
Afternoon	216	18	0	0

Table E.19: Shift matrices for terminal C corresponding to the what-if scenarios

(a) Scenario 1: 5% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	1	0	0	0
Midday	18	6	0	0
Afternoon	16	3	0	0

(b) Scenario 2: 10% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	37	13	0	0
Afternoon	32	6	0	0

(c) Scenario 3: 15% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	2	0	0	0
Midday	55	19	0	0
Afternoon	48	9	0	0

(d) Scenario 4: 20% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	3	0	0	0
Midday	73	25	0	0
Afternoon	65	13	0	0

(e) Scenario 5: 25% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	4	0	0	0
Midday	92	31	0	0
Afternoon	81	16	0	0

(f) Scenario 6: 30% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	5	0	0	0
Midday	110	38	0	0
Afternoon	97	19	0	0

(g) Scenario 7: 35% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	6	0	0	0
Midday	128	44	0	0
Afternoon	113	22	0	0

(h) Scenario 8: 40% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	6	0	0	0
Midday	147	50	0	0
Afternoon	129	25	0	0

(i) Scenario 9: 45% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	7	0	0	0
Midday	165	56	0	0
Afternoon	145	28	0	0

(j) Scenario 10: 50% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	8	0	0	0
Midday	183	63	0	0
Afternoon	161	31	0	0

(k) Scenario 11: 60% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	10	0	0	0
Midday	220	75	0	0
Afternoon	194	38	0	0

(l) Scenario 12: 70% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	11	0	0	0
Midday	257	88	0	0
Afternoon	226	44	0	0

(m) Scenario 13: 80% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	13	0	0	0
Midday	293	100	0	0
Afternoon	258	50	0	0

(n) Scenario 14: 90% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	15	0	0	0
Midday	330	113	0	0
Afternoon	291	56	0	0

(o) Scenario 15: 100% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	16	0	0	0
Midday	366	125	0	0
Afternoon	323	63	0	0

Table E.21: Shift matrices for terminal D corresponding to the what-if scenarios

(a) Scenario 1: 5% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	9	0	0	0
Midday	6	2	0	0
Afternoon	6	3	0	0

(b) Scenario 2: 10% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	17	0	0	0
Midday	13	5	0	0
Afternoon	13	6	0	0

(c) Scenario 3: 15% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	26	0	0	0
Midday	19	7	0	0
Afternoon	18	10	0	0

(d) Scenario 4: 20% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	35	0	0	0
Midday	25	10	0	0
Afternoon	25	13	0	0

(e) Scenario 5: 25% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	43	0	0	0
Midday	32	12	0	0
Afternoon	31	16	0	0

(f) Scenario 6: 30% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	52	0	0	0
Midday	38	15	0	0
Afternoon	37	20	0	0

(g) Scenario 7: 35% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	60	0	0	0
Midday	44	17	0	0
Afternoon	43	23	0	0

(h) Scenario 8: 40% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	69	0	0	0
Midday	51	20	0	0
Afternoon	50	26	0	0

(i) Scenario 9: 45% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	78	0	0	0
Midday	57	22	0	0
Afternoon	55	29	0	0

(j) Scenario 10: 50% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	86	0	0	0
Midday	63	25	0	0
Afternoon	62	33	0	0

(k) Scenario 11: 60% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	104	0	0	0
Midday	76	30	0	0
Afternoon	74	38	0	0

(l) Scenario 12: 70% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	121	0	0	0
Midday	89	35	0	0
Afternoon	87	45	0	0

(m) Scenario 13: 80% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	138	0	0	0
Midday	101	40	0	0
Afternoon	99	53	0	0

(n) Scenario 14: 90% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	155	0	0	0
Midday	114	45	0	0
Afternoon	112	59	0	0

(o) Scenario 15: 100% application rate

O/D	Night	Morning	Midday	Afternoon
Night	0	0	0	0
Morning	173	0	0	0
Midday	127	50	0	0
Afternoon	124	66	0	0

E.1.4 Shift transformation

The last step in the truck shifting heuristic is to convert the shift matrices to new arrival profiles.

The arrival profile obtained from historic traffic data (Section A.2) serves as the base case. Consequently, for each scenario the trucks in this base case are shifted as indicated by the shift matrices. This results in new arrival profiles for each scenario.

As mentioned in Section E.1.1, there is a share of trucks that can simply not be shifted because the trucks transport containers or commodities that are ignored in the truck shifting strategy. Therefore, some trucks in the arrival profile are set to arrive in the same hour they originally did. However, it is unknown in which hour that was. Hence, the trucks, that cannot be shifted, are distributed along the day proportionally and excluded for the next steps. What remains is an arrival profile with trucks that can be shifted. Eventually, the arrival profile will be complemented with the trucks that cannot be shifted.

At this stage, there is a base case arrival profile with trucks that can be shifted. Additionally, there is a shift matrix that indicates how many trucks and from to where these trucks should be shifted. The arrival profiles indicate the number of trucks arriving per hour of the day. However, the data in the shift matrices is aggregated to trucks per time period. Therefore, the data requires to be disaggregated. Disaggregating the data is done by distributing the shifts, indicated by the shift matrices, proportionally along the base case arrival profile. This is elaborated step by step in the next paragraphs.

For each time period the share of trucks in a specific hour is calculated by dividing the trucks in the specific hour by the total of trucks in that time period. For each hour the share of trucks is obtained.

Subsequently, the number of trucks in the shift matrix is proportionally taken out of the time period origin. This means that the number of truck taken out of a specific hour is the share of that hour multiplied with the total of trucks that should be shifted from the time period the hour is part of. This total of trucks is indicated by the shift matrix.

To illustrate this, imagine that 20 trucks should be shifted from the midday to the morning according to the shift matrix. If 20% of the trucks in the midday arrive between 2 p.m. and 3 p.m. (14:00 - 15:00), a total of 4 trucks is taken out the 14:00 - 15:00 time slot.

Consequently, the trucks that are taken out of the origin time period should be added in the destination time period. This is also done proportionally. Hence, if 20 trucks should be shifted from the midday to the night, and 10% of the trucks arrive between 0:00 and 1:00, 2 trucks are added to this hour.

As the data is disaggregated, it is established how many trucks should be taken out of each hour and how many trucks should be added to each hour, a new arrival profile can be computed. Computing the new arrival profile starts from the base case arrival profile. The trucks taken out of the origin hours are subtracted from the base case arrival profile and the trucks added to the destination hours are summed to the base case arrival profile. Lastly, the trucks that cannot be shifted are included in the arrival profile. Finally, for each scenario a corresponding arrival profile is computed.

Note that the arrival profile for the 16th scenario, the reference scenario, is computed differently. As the 16th scenario represents an equal spread of trucks along the day, the arrival profile is computed by dividing the total number of truck in one day by 24.

E.2 RESULTS

The results of the truck shifting heuristic are new arrival profiles. In the following graphs (Figure E.3 through Figure E.6) the arrival profiles from the truck shifting heuristic for various scenarios are presented per terminal. These arrival profiles will be used as input for the terminal model (Appendix B). As a reference, the historic arrival profile for each terminal, depicted in Section A.2, is additionally presented in Figure E.2.

What stands out from the computed arrival profiles in (Figure E.3 through Figure E.6), are the dips around time slots 4, 10, 14, and 20, and the peaks between 2-3, 5-9, and 21-23 (depending on the exact terminal), that arise as the application rate increases. This is due to the formulation of the time periods and the approach for computing the new arrival profiles in the trucks shifting heuristic (Section E.1.4).

The shifting strategy aims to shift trucks from the afternoon and midday to the night and morning, and in some strategies from morning to night as well. For the cause of the dips at the begin and end of the morning, midday and afternoon time periods, an example is provided. The afternoon period is defined from 15:00 until 20:00. Therefore, there are no trucks shifted to 20:00 as this time slot is part of the afternoon time period. This explains the dip at 20. The same reasoning applies when a dip occurs at 4, 10 and 14, depending on the specific terminal.

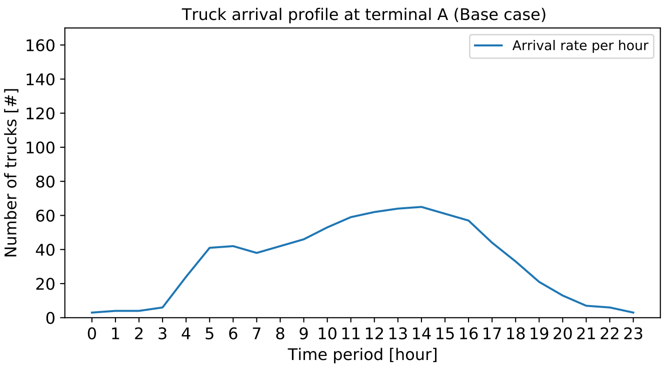
Moreover, the trucks are shifted proportionally from one time period to another. This explains the peaks. For example, the share of trucks in the night time period is largest for the 21-23 time slots. Subsequently, many trucks that are shifted towards the night time period, end up in the 21-23 time slots. This causes the peak at the end of the day. The same reasoning applies to the peaks at 2-3 and 5-9, depending on the exact terminal.

That these peaks and dips arise at the end of the day instead of a rather equal spread around the transition of the different time periods is a limitation of the truck shifting heuristic caused by aggregating and subsequently disaggregating the traffic data.

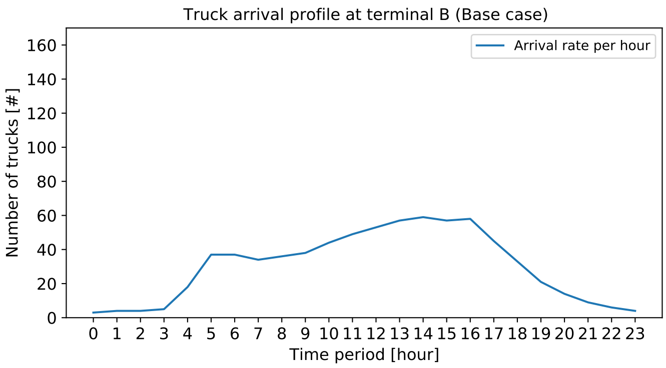
Nevertheless, the large dips and peaks that arise at more extreme application rates, are not inaccurate. The dips and peaks logically increase when the application rates are higher, since more trucks are shifted. In reality, it is expected that the number of truck arrivals at the transition time slots is more comparable to the surrounding hours. Therefore, computed arrival profiles in the scenarios with smaller application rates are more realistic. Yet, the extreme application rates are evaluated to provide insight in the risks of truck shifting.

Note that the y-axis is the same for all graphs. This is to allow for easy comparison between the graphs. The y-axis value of 160 is chosen based on the most extreme arrival profile from the scenarios. However, it might give a distorted image for some graphs as some terminals have a much lower number of truck arrivals on an average working day. Therefore, for terminal A and B, the spread seems more equal along the day in the base case compared to terminals C and D. It can be observed from the graphs for terminal A and B (Figure E.2), that the peak is less extreme. Yet, the spread in the base case is certainly not equal. The relative difference in percentage of truck arrivals between the morning and midday hours is approximately 75% and 50% increase of trucks for terminal A and B, respectively. For terminal C and D the difference between morning and midday is 100% and 80% increase, respectively.

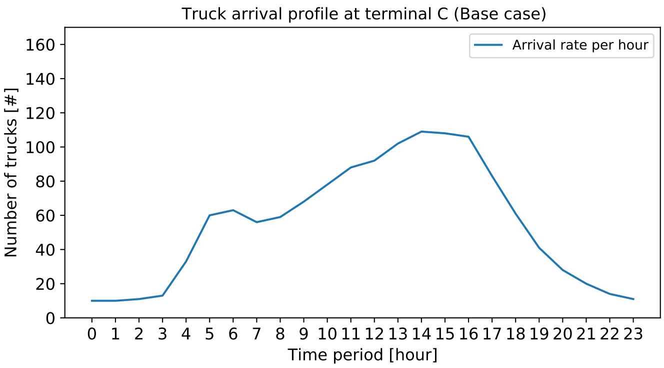
With the terminal model, the waiting time profiles, corresponding to the scenario arrival profiles, can be simulated. Comparing the simulated waiting time profiles from the scenarios with the base case a waiting time gain can be calculated. This process is elaborated in Appendix F.



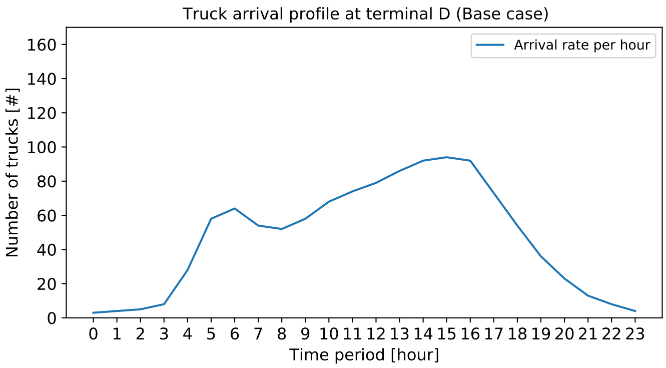
(a) Terminal A



(b) Terminal B



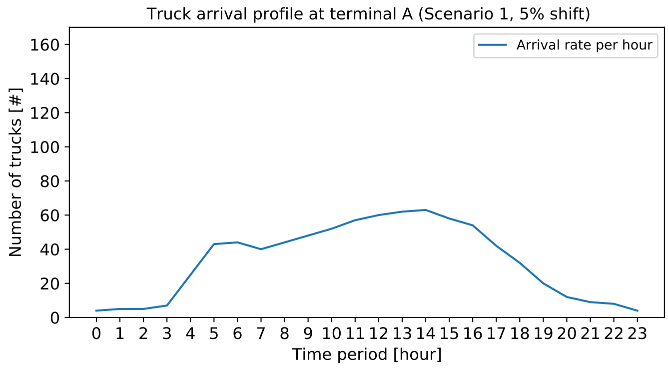
(c) Terminal C



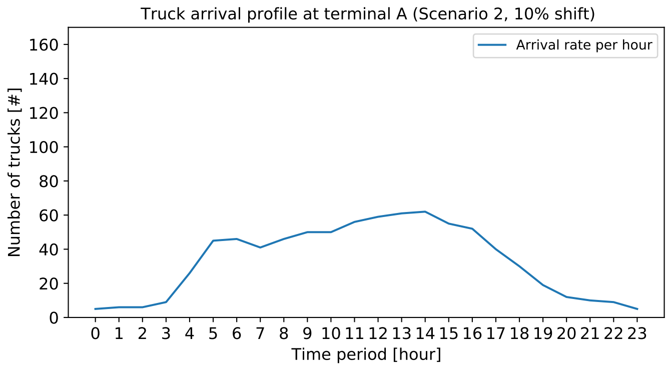
(d) Terminal D

Figure E.2: Base case arrival profiles for each terminal, from historic traffic data (Appendix A)

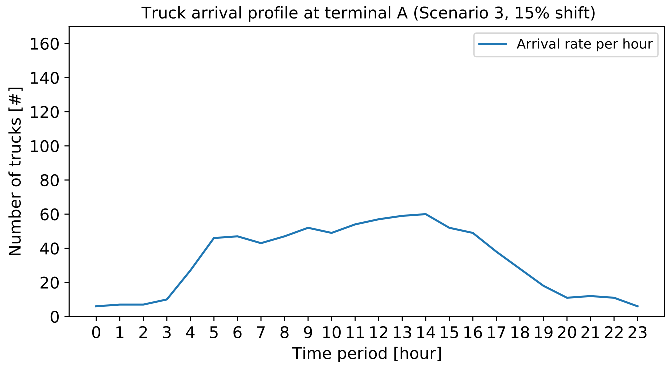
Terminal A



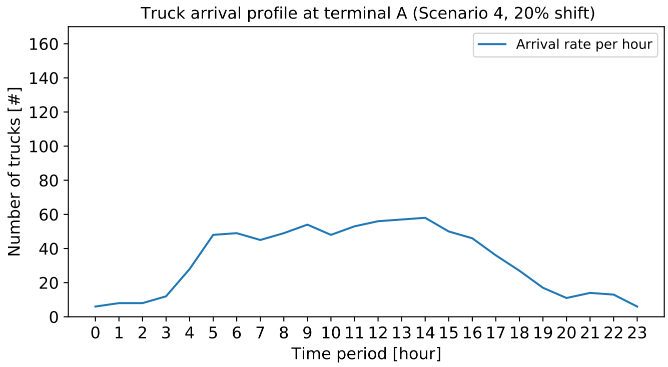
(a) Scenario 1, 5% application rate



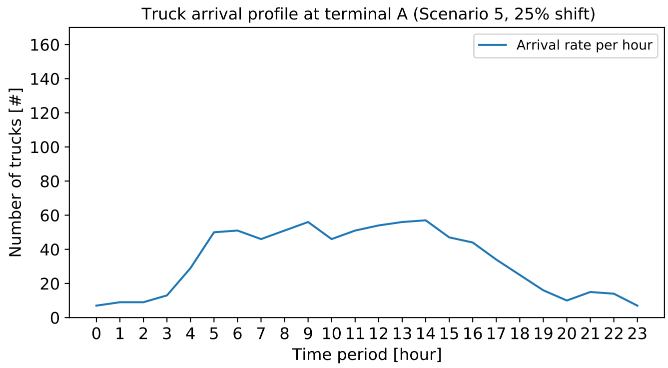
(b) Scenario 2, 10% application rate



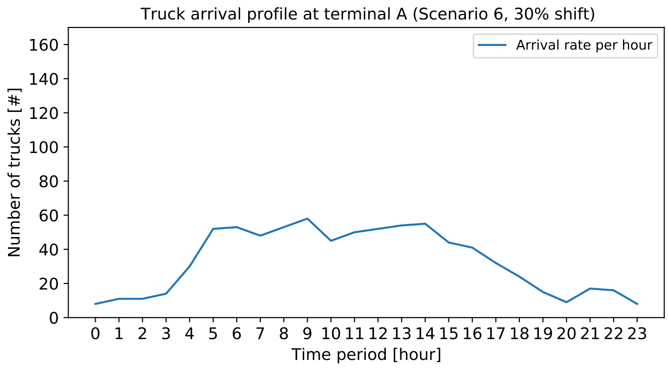
(c) Scenario 3, 15% application rate



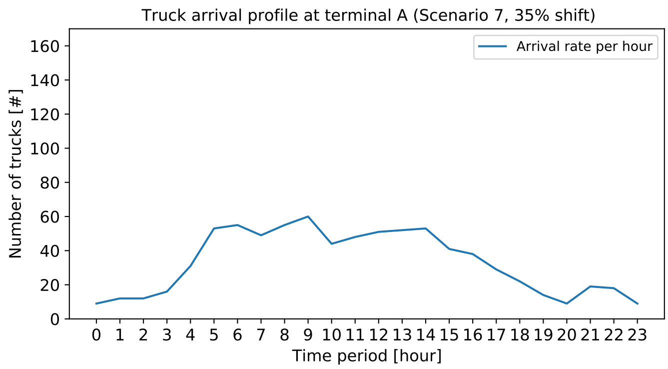
(d) Scenario 4, 20% application rate



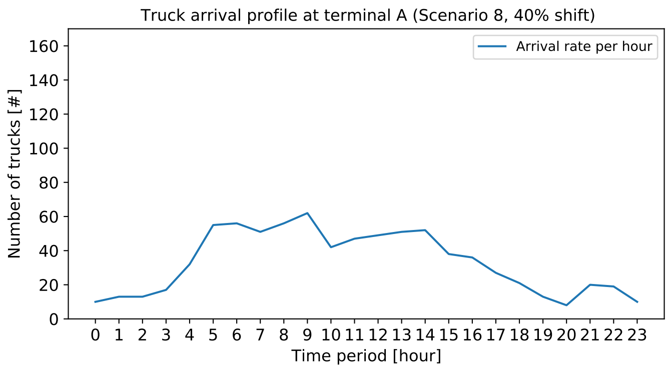
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

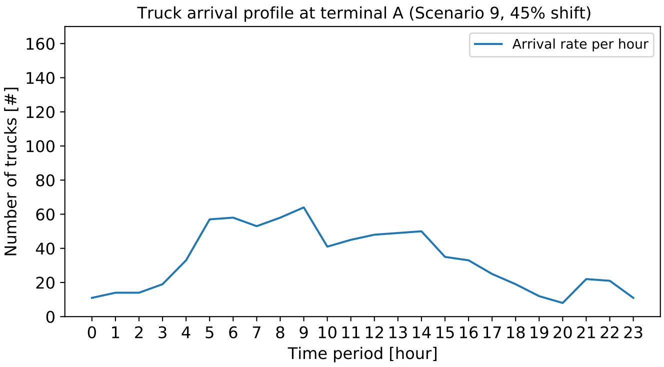


(g) Scenario 7, 35% application rate

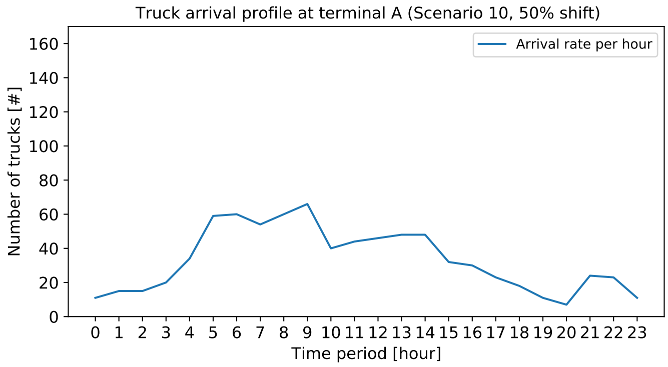


(h) Scenario 8, 40% application rate

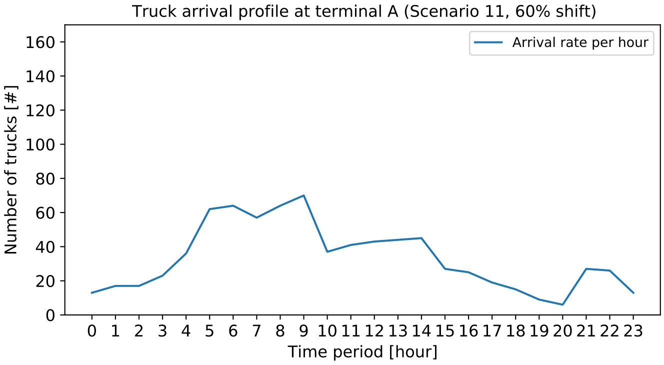
Figure E.3: Arrival profiles at terminal A for each scenario, computed with truck shifting heuristic



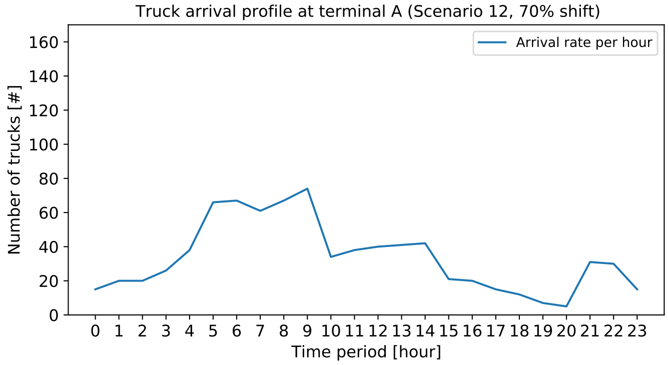
(i) Scenario 9, 45% application rate



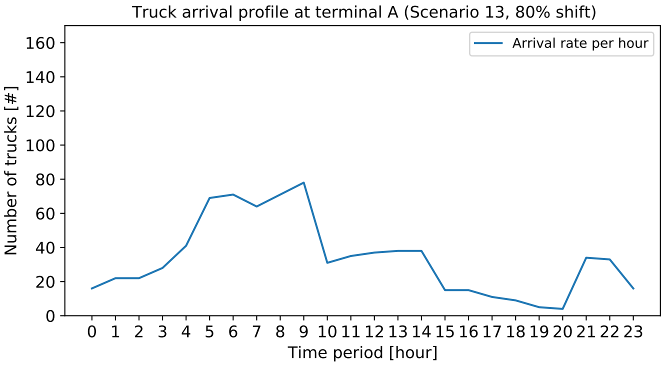
(j) Scenario 10, 50% application rate



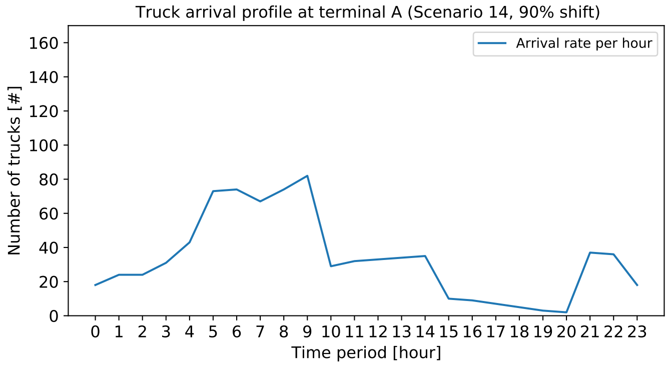
(k) Scenario 11, 60% application rate



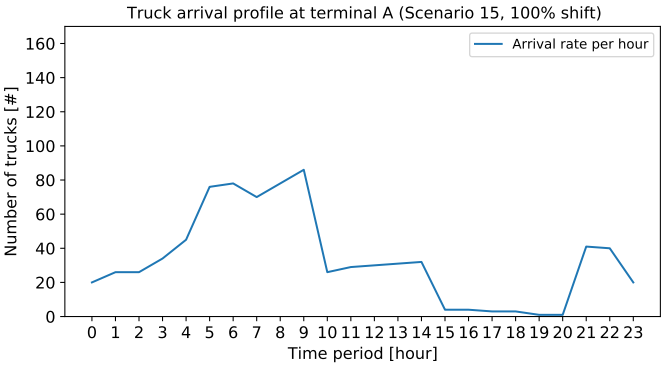
(l) Scenario 12, 70% application rate



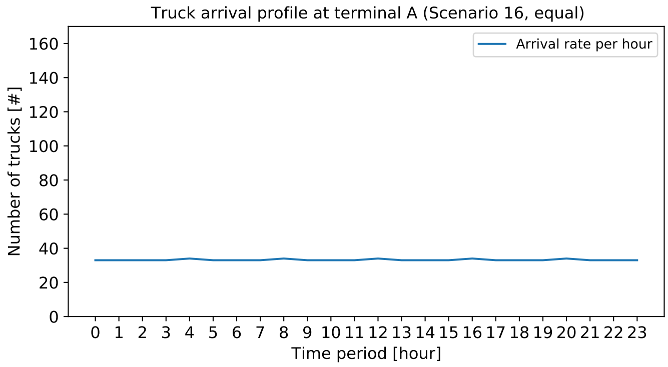
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



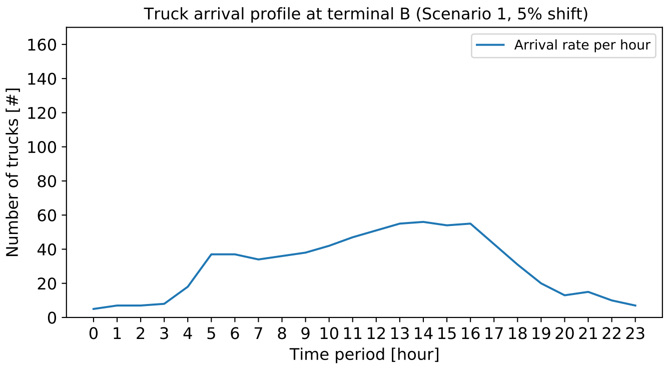
(o) Scenario 15, 100% application rate



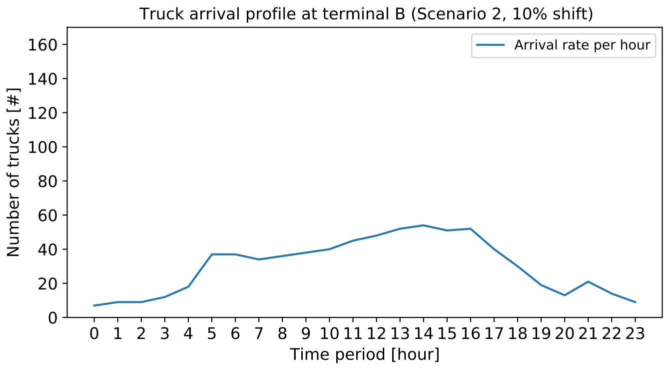
(p) Scenario 16, equal spread

Figure E.3: Arrival profiles at terminal A for each scenario, computed with truck shifting heuristic

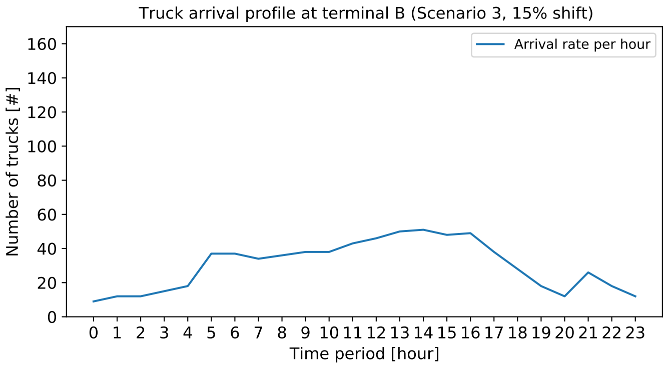
Terminal B



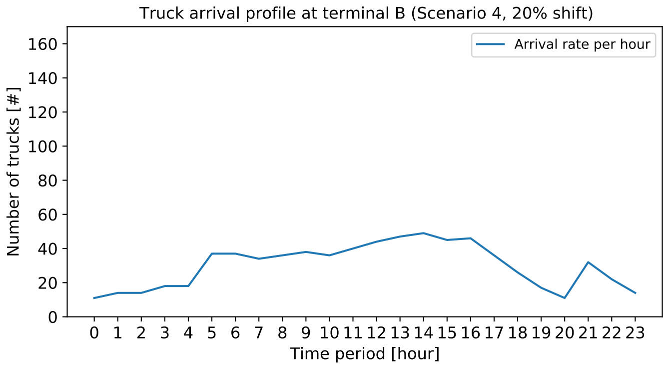
(a) Scenario 1, 5% application rate



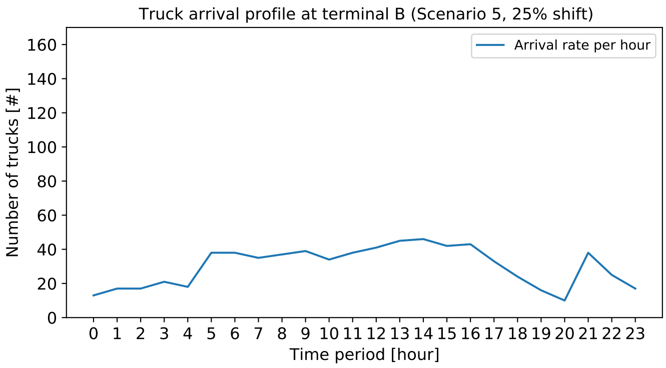
(b) Scenario 2, 10% application rate



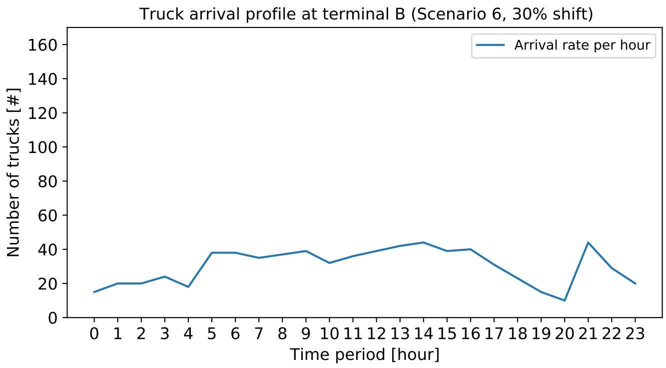
(c) Scenario 3, 15% application rate



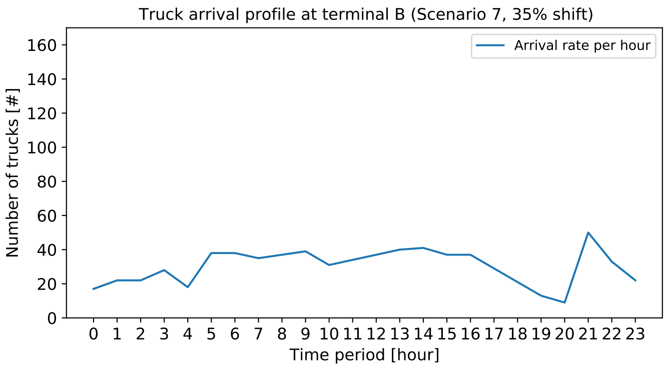
(d) Scenario 4, 20% application rate



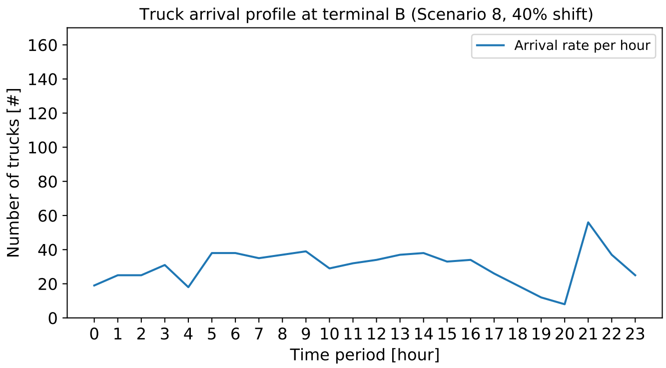
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

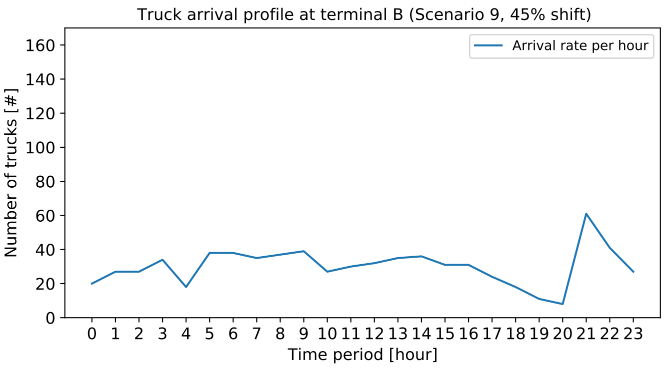


(g) Scenario 7, 35% application rate

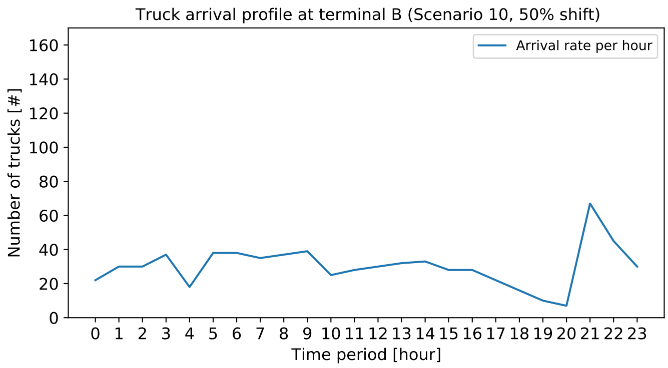


(h) Scenario 8, 40% application rate

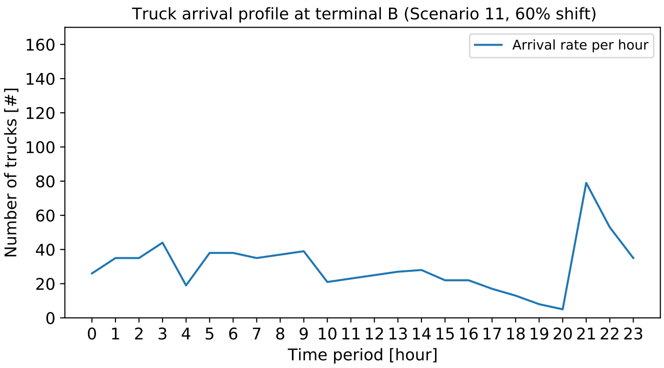
Figure E.4: Arrival profiles at terminal B for each scenario, computed with truck shifting heuristic



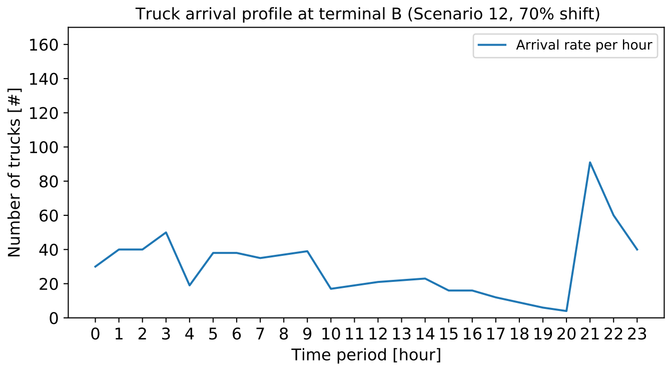
(i) Scenario 9, 45% application rate



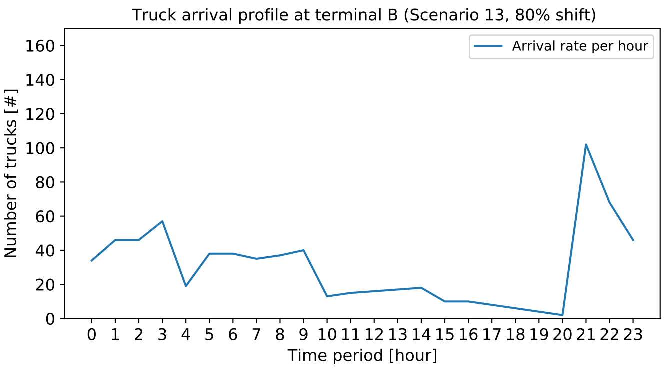
(j) Scenario 10, 50% application rate



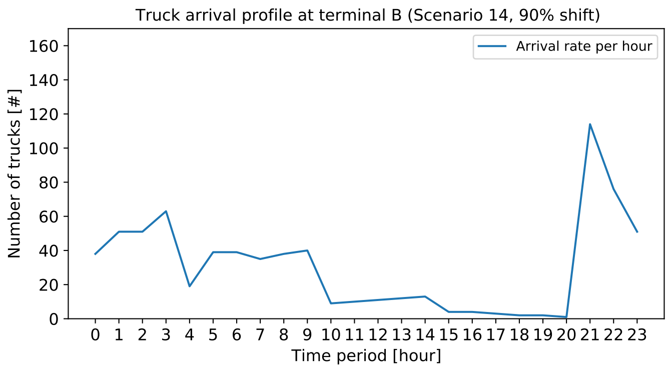
(k) Scenario 11, 60% application rate



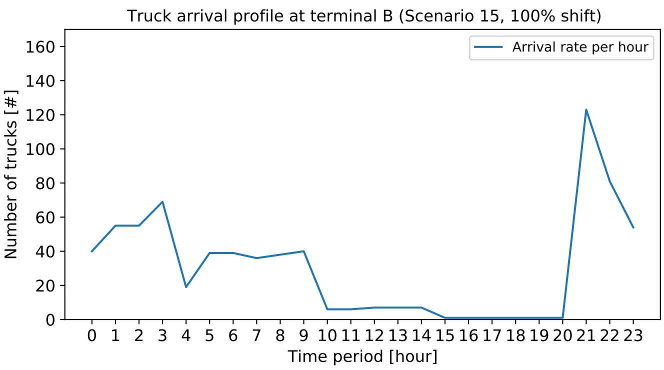
(l) Scenario 12, 70% application rate



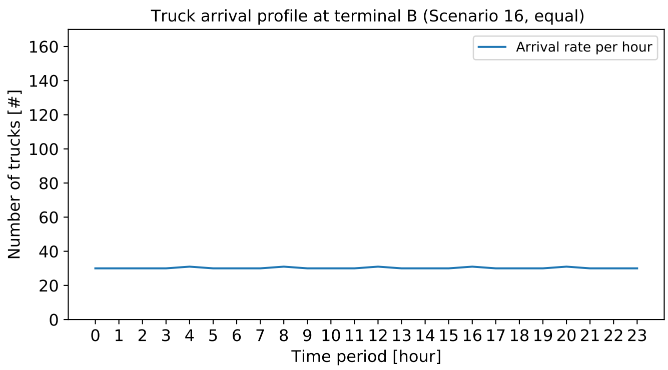
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



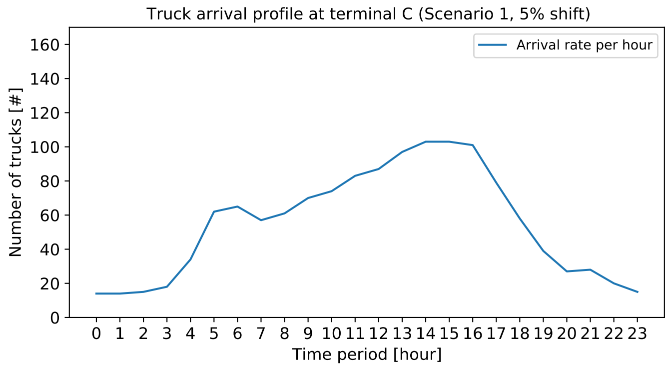
(o) Scenario 15, 100% application rate



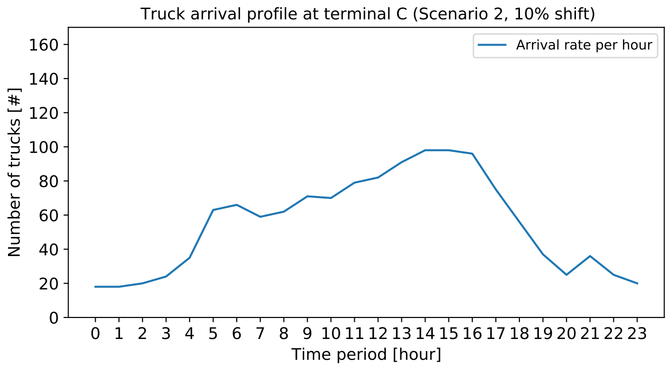
(p) Scenario 16, equal spread

Figure E.4: Arrival profiles at terminal B for each scenario, computed with truck shifting heuristic

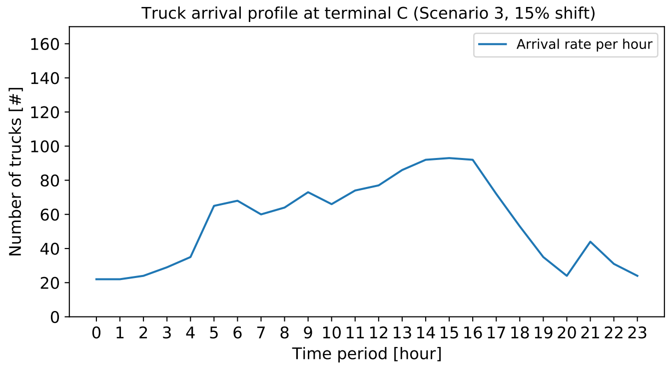
Terminal C



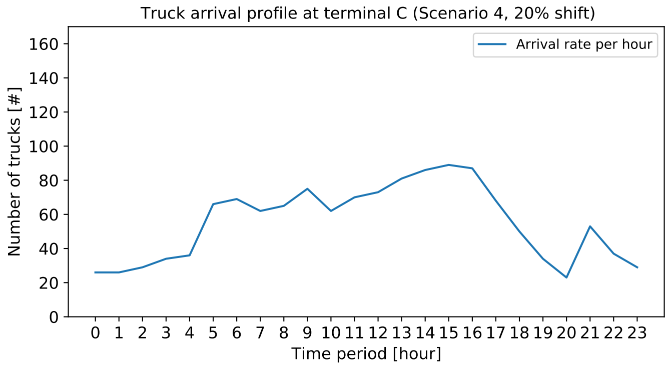
(a) Scenario 1, 5% application rate



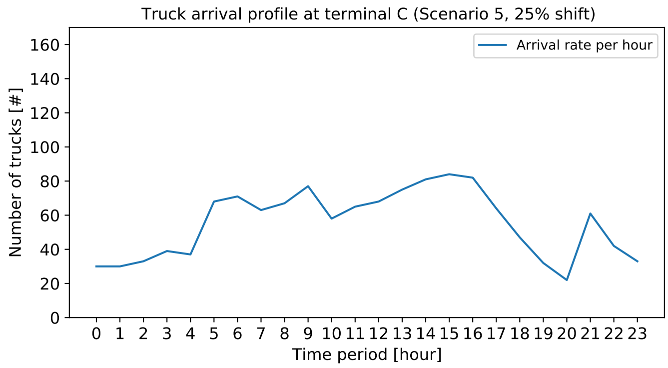
(b) Scenario 2, 10% application rate



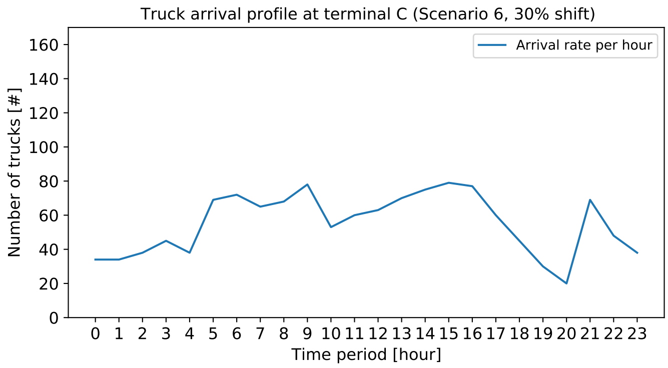
(c) Scenario 3, 15% application rate



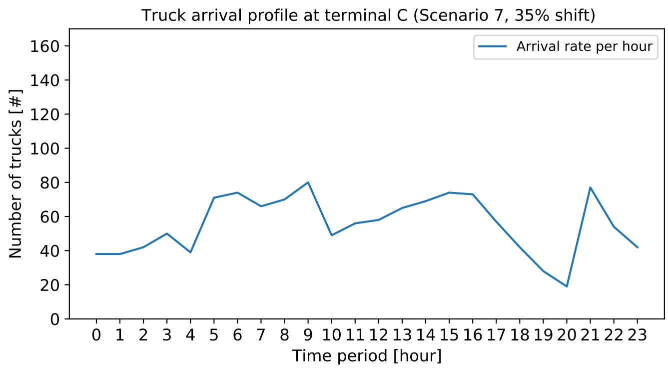
(d) Scenario 4, 20% application rate



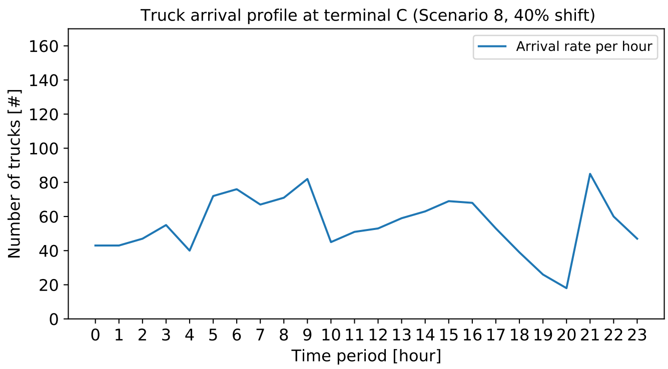
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

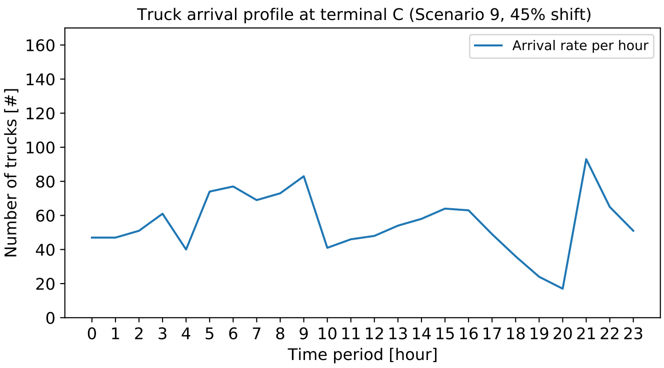


(g) Scenario 7, 35% application rate

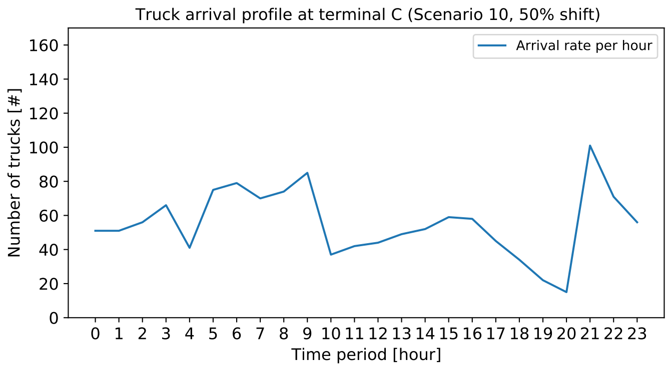


(h) Scenario 8, 40% application rate

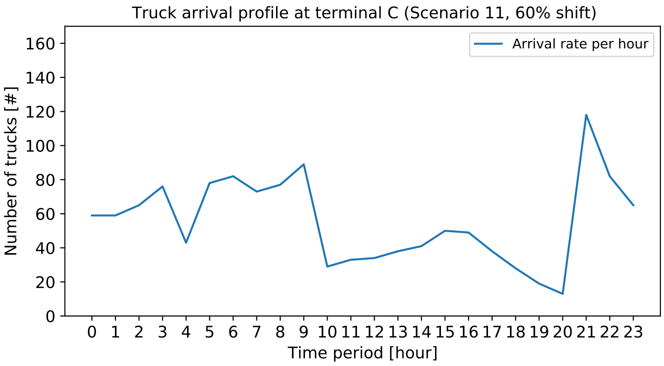
Figure E.5: Arrival profiles at terminal C for each scenario, computed with truck shifting heuristic



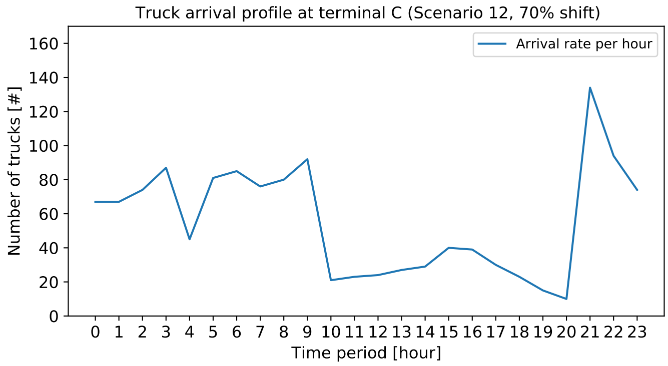
(i) Scenario 9, 45% application rate



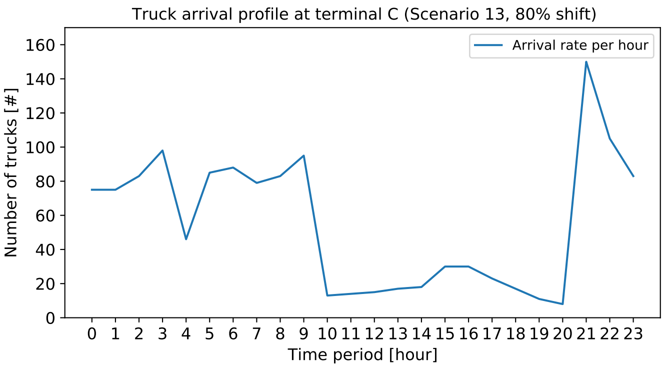
(j) Scenario 10, 50% application rate



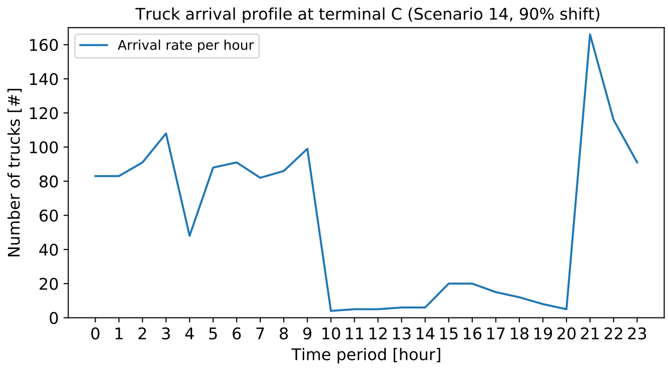
(k) Scenario 11, 60% application rate



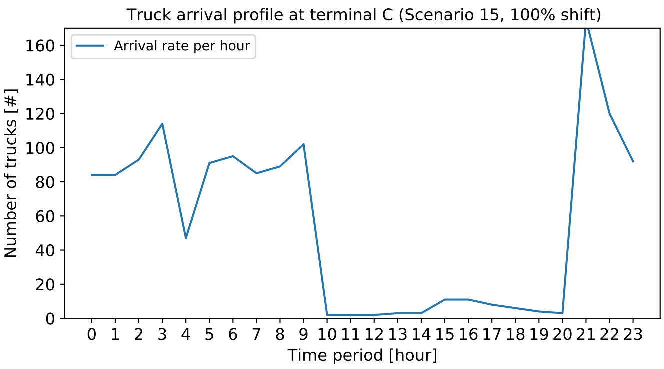
(l) Scenario 12, 70% application rate



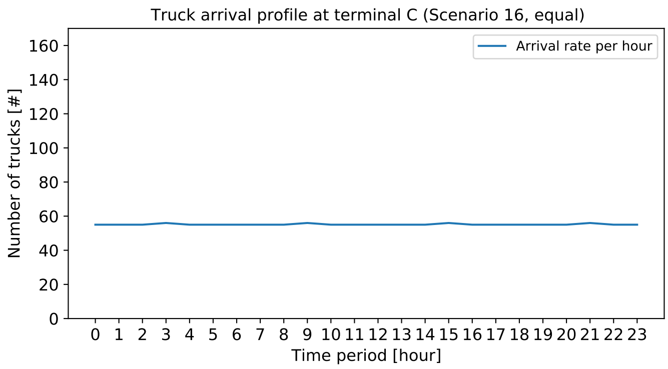
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



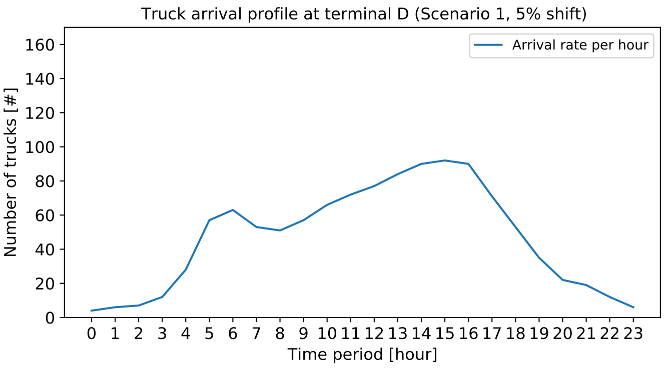
(o) Scenario 15, 100% application rate



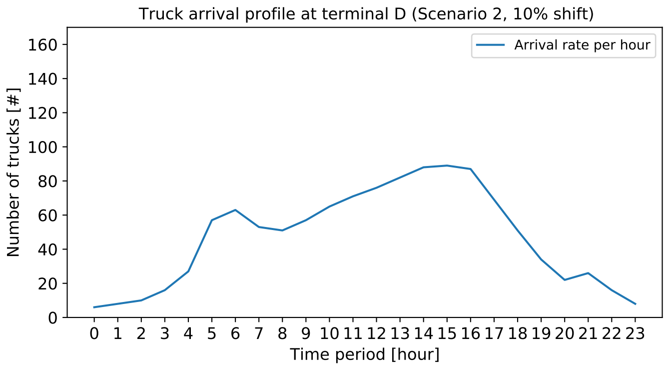
(p) Scenario 16, equal spread

Figure E.5: Arrival profiles at terminal C for each scenario, computed with truck shifting heuristic

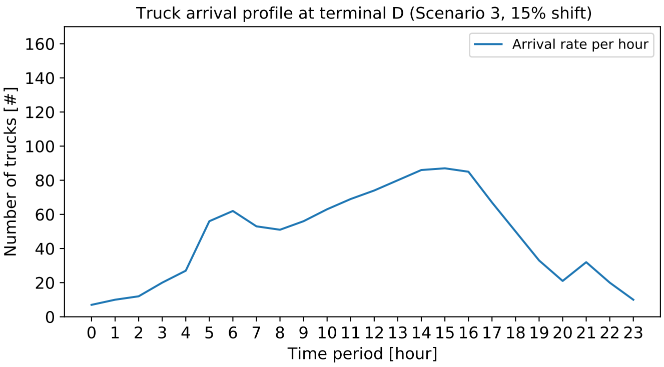
Terminal D



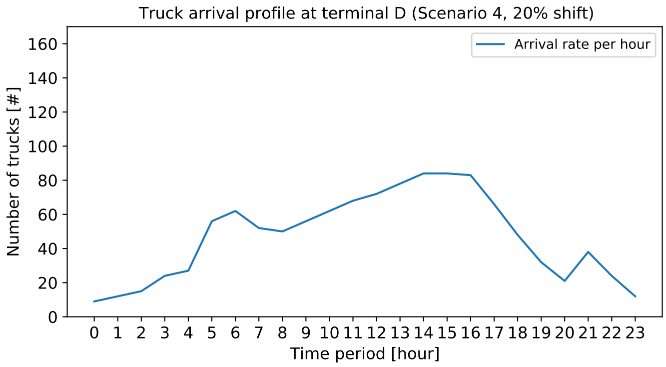
(a) Scenario 1, 5% application rate



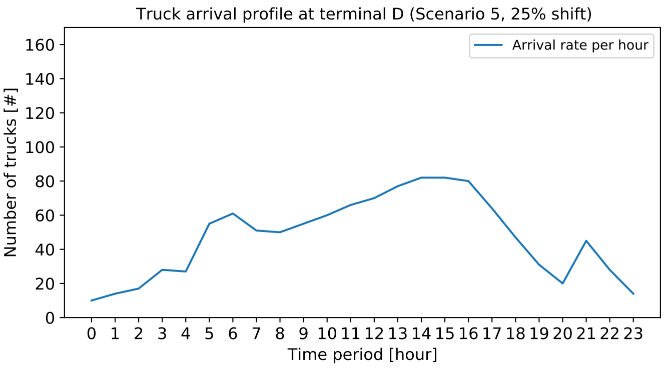
(b) Scenario 2, 10% application rate



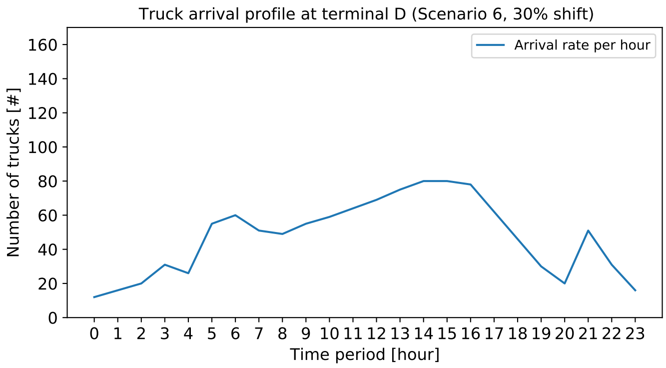
(c) Scenario 3, 15% application rate



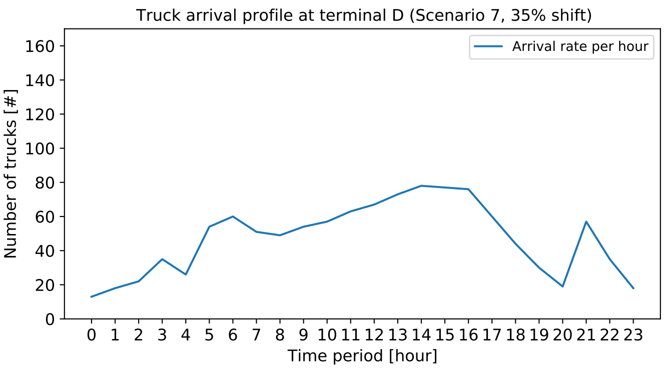
(d) Scenario 4, 20% application rate



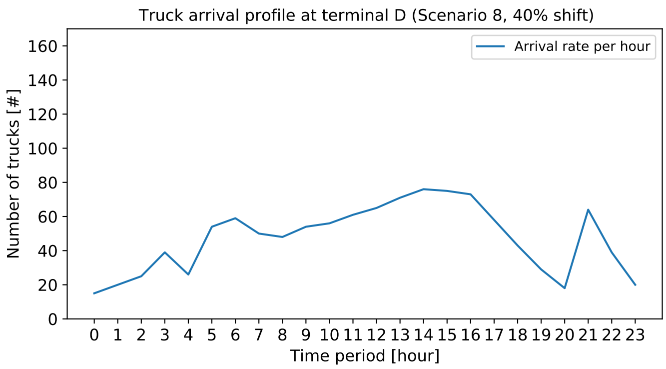
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

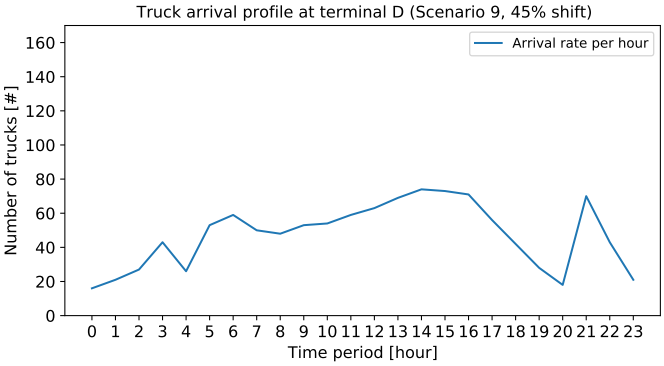


(g) Scenario 7, 35% application rate

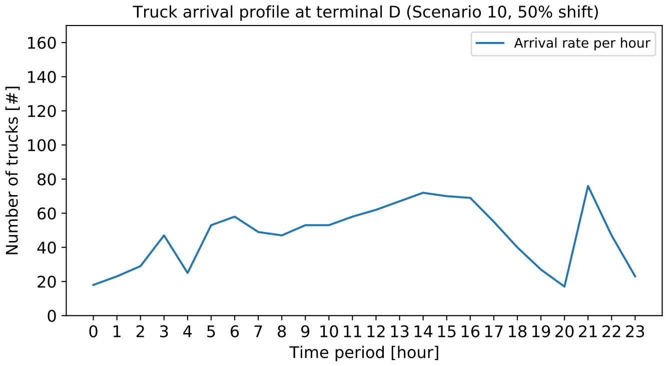


(h) Scenario 8, 40% application rate

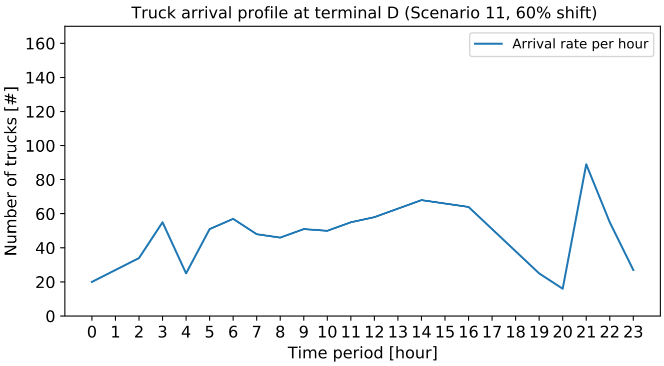
Figure E.6: Arrival profiles at terminal D for each scenario, computed with truck shifting heuristic



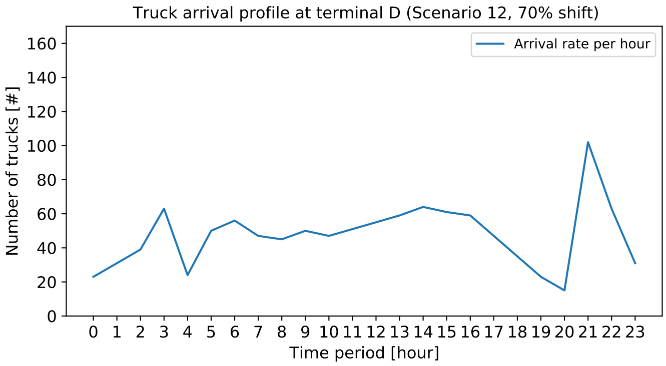
(i) Scenario 9, 45% application rate



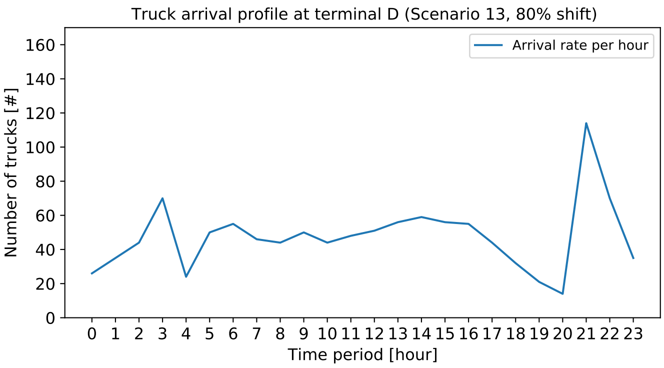
(j) Scenario 10, 50% application rate



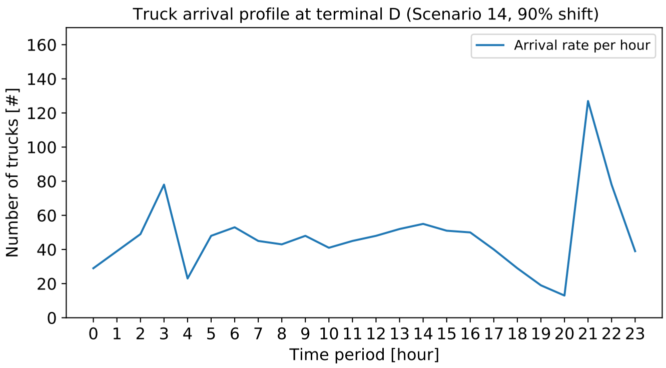
(k) Scenario 11, 60% application rate



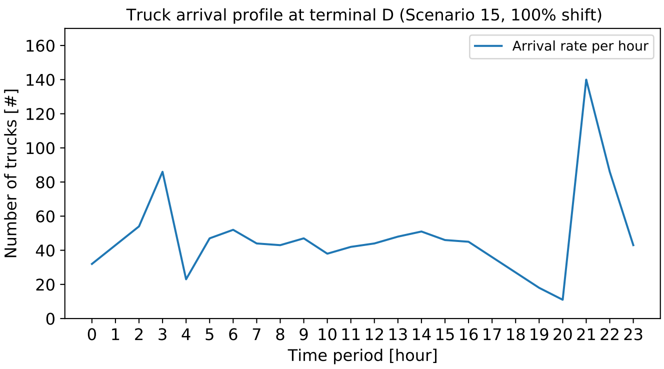
(l) Scenario 12, 70% application rate



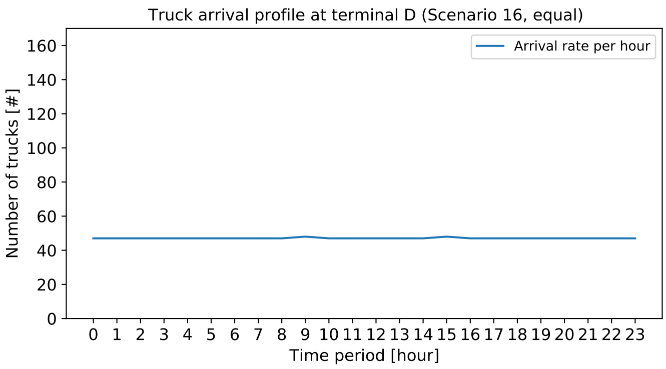
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



(o) Scenario 15, 100% application rate



(p) Scenario 16, equal spread

Figure E.6: Arrival profiles at terminal D for each scenario, computed with truck shifting heuristic

F WAITING TIME GAIN CALCULATION

To achieve the research objective, it is necessary to obtain insight in the waiting time gain that could be achieved by truck shifting. The waiting time gain results from the combining the developed models (Appendix B, D, and E). In this appendix it is described how the waiting time gain is obtained exactly. Additionally, the results are elaborated and reflected up on.

F.1 SIMULATED PROFILES

From the developed choice model (Appendix D), a truck shifting strategy is formulated for each terminal. In general, the strategy comprehends the shifting of trucks from the peak periods, midday and afternoon, to the quieter time periods, night and morning. As each terminal is unique in terminal characteristics, truck arrival profiles and preferences of TOC, the details of the trucks shifting strategy are terminal specific. These details include which trucks can and should be shifted from peak periods to more quiet periods.

Subsequently, the developed truck shifting heuristic (Appendix E), computes new arrival profiles based on the formulated truck shifting strategy. The arrival profiles are computed for various scenarios to evaluate several TOC application rates to the shift strategy.

These computed arrival profiles are the input for the developed terminal model (Appendix B). The terminal model simulates the average arrival profiles and corresponding departure profiles. Consequently, an average waiting time profile is simulated for each scenario.

F.1.1 Arrival and departure

In Figure F.2 through Figure F.5, the simulated arrival and departure profile is presented for each scenario, structured per terminal. The simulated arrival profile is similar to the computed arrival profiles in Section E.2. However, in the simulated arrival profiles, stochasticity in truck arrival is accounted for.

The simulated base case arrival and departure profile for each terminal is discussed in Section B.5. For convenience, the simulated profiles in the base case are additionally presented in Figure F.1.

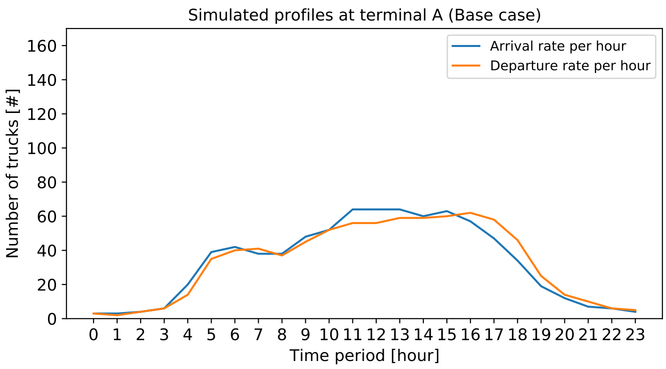
The dips and peaks in the simulated profiles are a catch in the eye, as the application rate increases. The cause of the dips and peaks that appear in large application rate scenario profiles, is elaborated in Section E.2.

From the graphs, it can be observed that the terminal model is able to simulate corresponding departure profiles. By comparing the arrival profile with the departure profile, some initial conclusions can be drawn for the waiting time profiles that result from the different application rate scenarios. These conclusions are based on the difference between the departure profile and the arrival profile. If the arrival and departure profile overlap more closely, thus a smaller offset for the departure profile, less waiting time is expected (Section B.5).

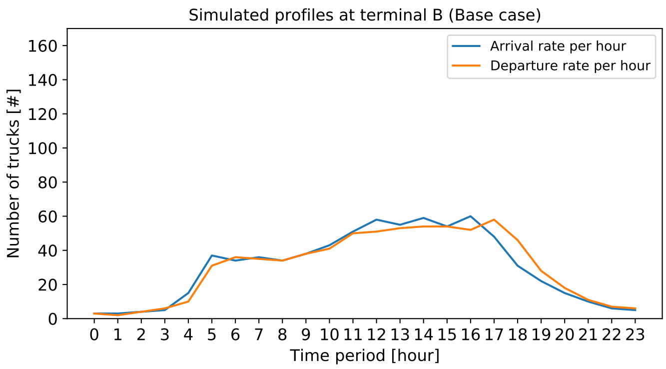
Consequently, it can be observed that with only small application rates, already a large reduction of waiting time is obtained. As the application rates increase, larger differences between arrival and departure profiles are observed. Therefore, it is expected that with higher application rates, waiting time increases again.

From an initial grasp of the simulated profiles, it is expected that, in general, the waiting time decreases until an application rate of about 40%-50%. From an application rate of about 50%-60% the waiting time is expected to increase. However, this differs per terminal. In Section F.1.2, the waiting time profiles are presented. These provide insight in the exact waiting time per terminal and the development of these waiting time under the different application rates.

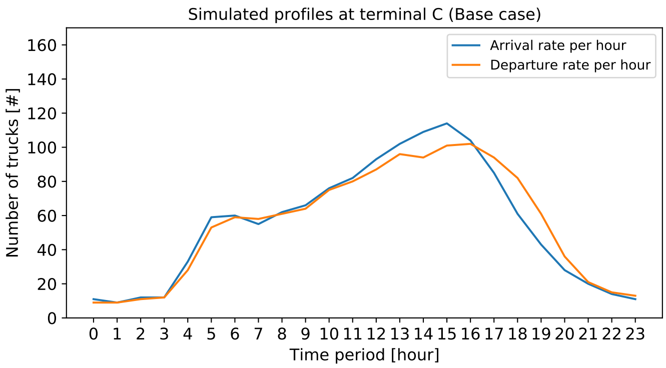
Note that the y-axis is the same for all graphs. This is to allow for easy comparison between the graphs. The y-axis value of 160 is chosen based on the most extreme arrival profile from the scenarios. However, it might give a distorted image for some graphs as some terminals have a much lower number of truck arrivals on an average working day. Therefore, for terminal A and B, the spread seems more equal along the day in the base case compared to terminals C and D. It can be observed from the graphs for terminal A and B (Figure F.1), that the peak is less extreme. Yet, the spread in the base case is certainly not equal. The relative difference in percentage of truck arrivals between the morning and midday hours is approximately 75% and 50% increase of trucks for terminal A and B, respectively. For terminal C and D the difference between morning and midday is 100% and 80% increase, respectively.



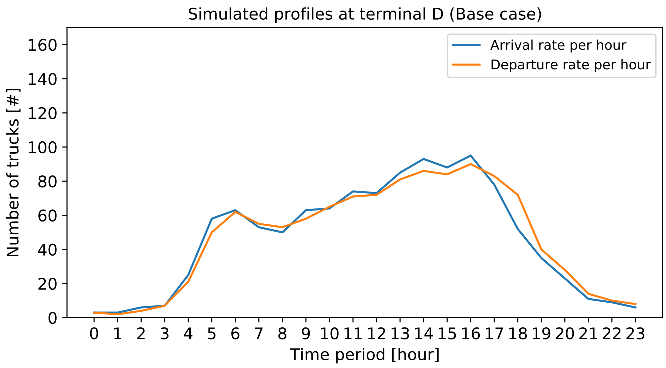
(a) Terminal A



(b) Terminal B



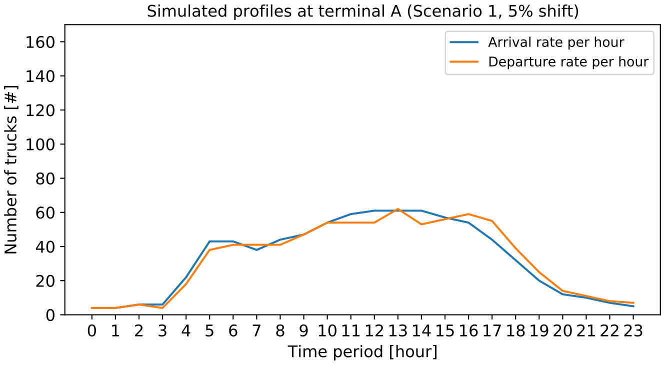
(c) Terminal C



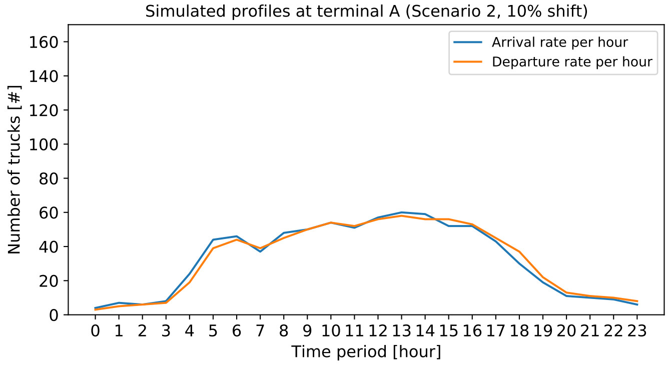
(d) Terminal D

Figure F.1: Base case arrival profiles for each terminal, from historic traffic data (Appendix A)

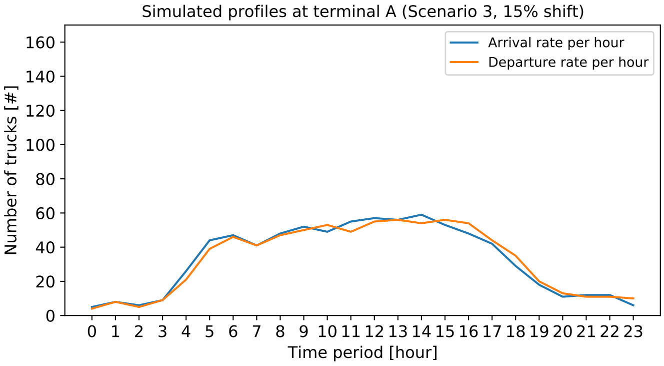
Terminal A: simulated arrival and departure profile



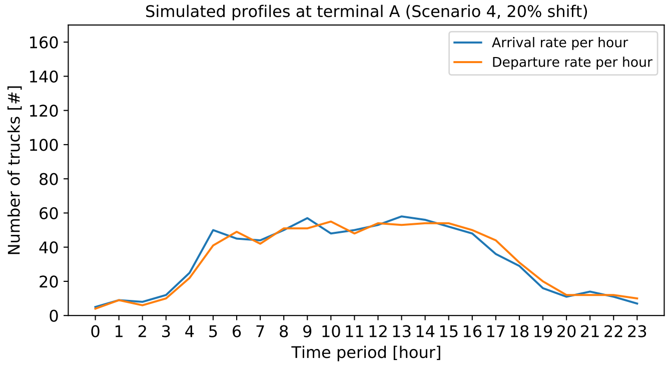
(a) Scenario 1, 5% application rate



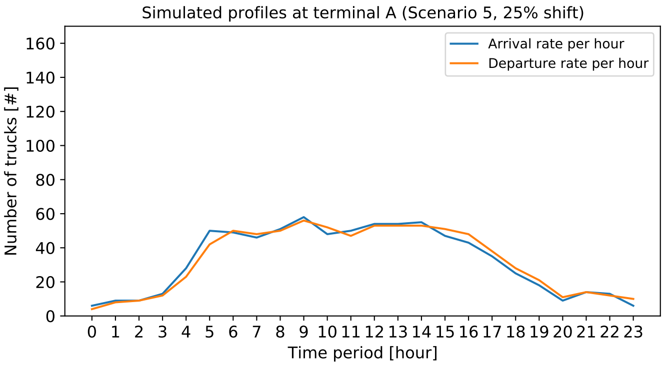
(b) Scenario 2, 10% application rate



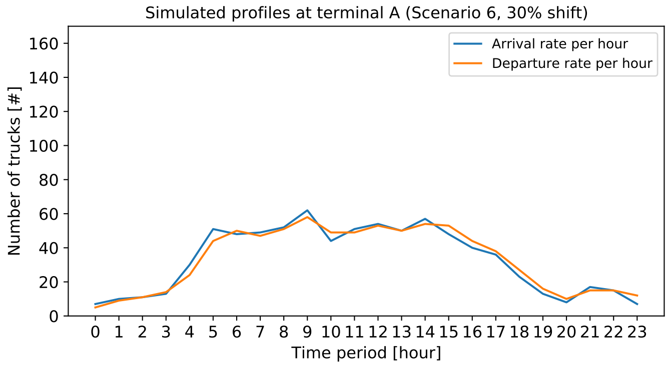
(c) Scenario 3, 15% application rate



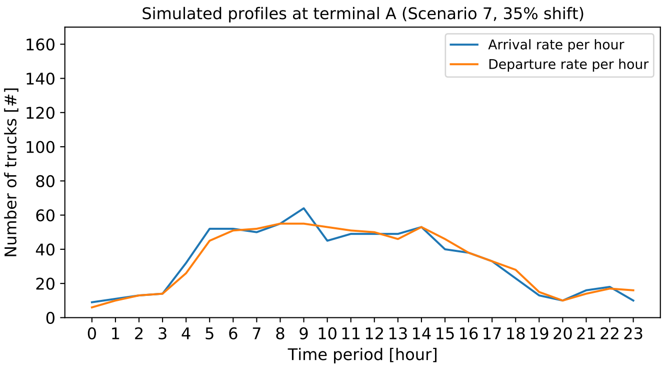
(d) Scenario 4, 20% application rate



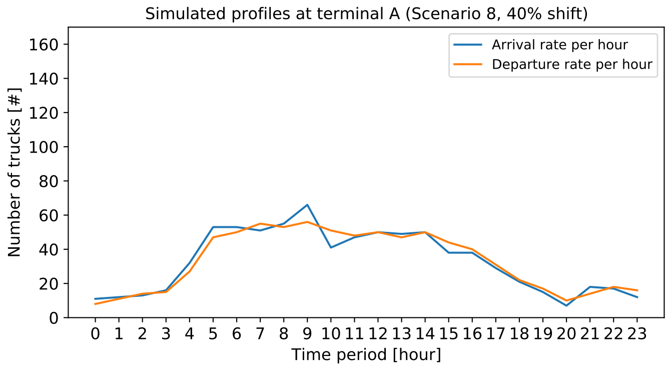
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

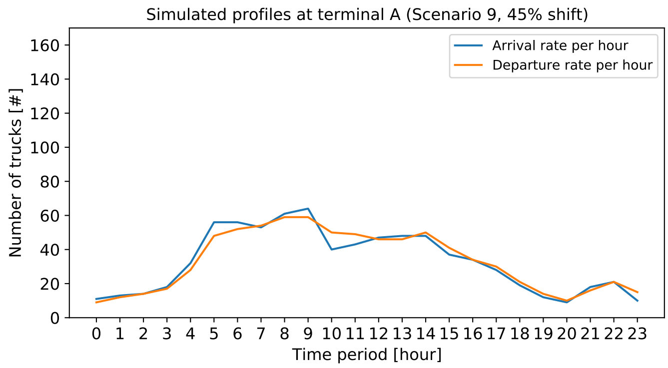


(g) Scenario 7, 35% application rate

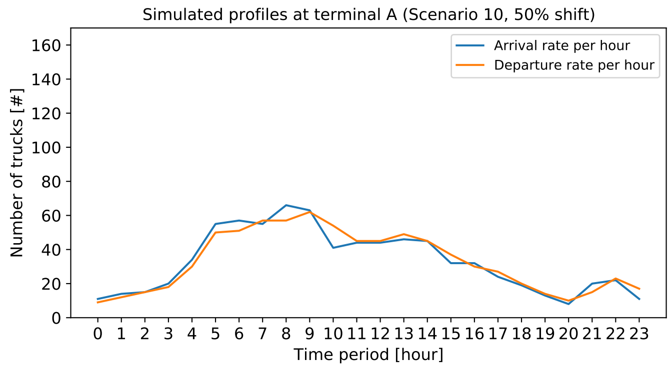


(h) Scenario 8, 40% application rate

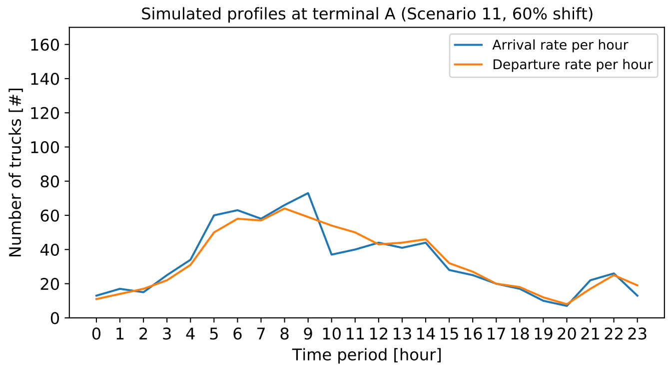
Figure F.2: Simulated arrival and departure profiles at terminal A for each scenario, from terminal model (Appendix B)



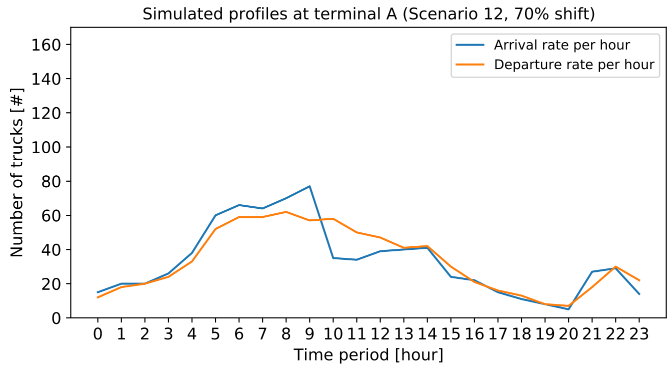
(i) Scenario 9, 45% application rate



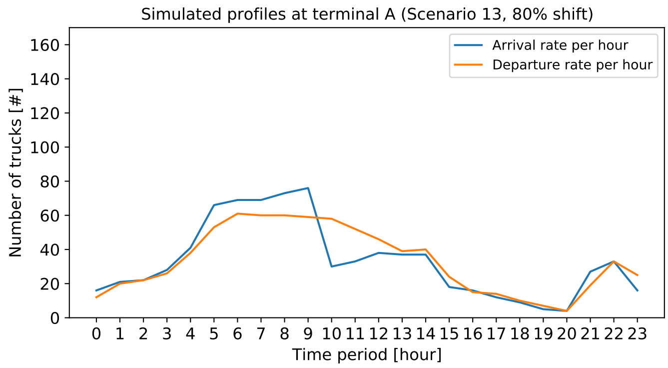
(j) Scenario 10, 50% application rate



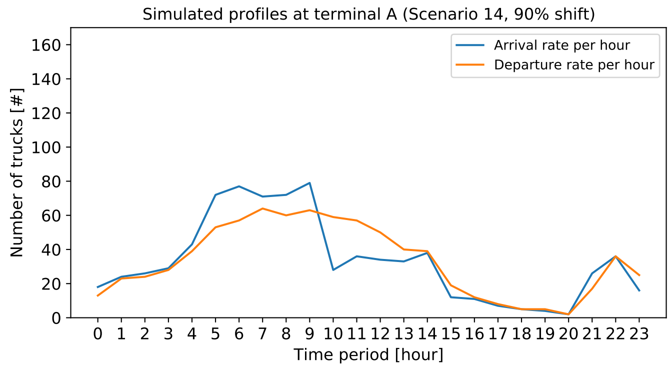
(k) Scenario 11, 60% application rate



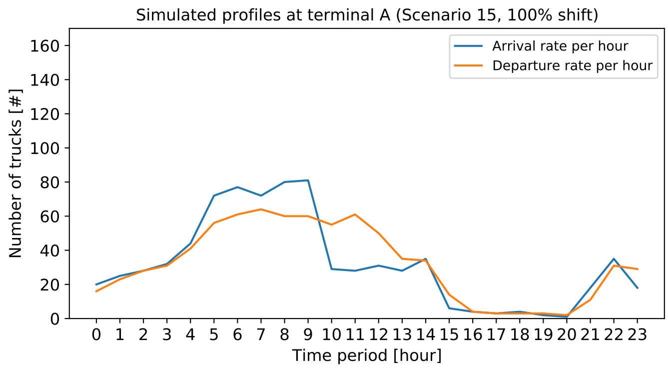
(l) Scenario 12, 70% application rate



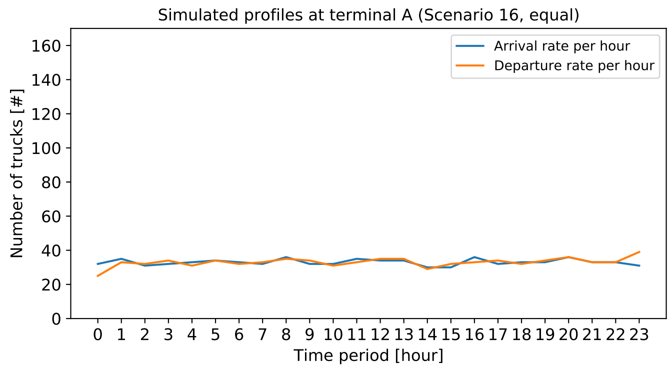
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



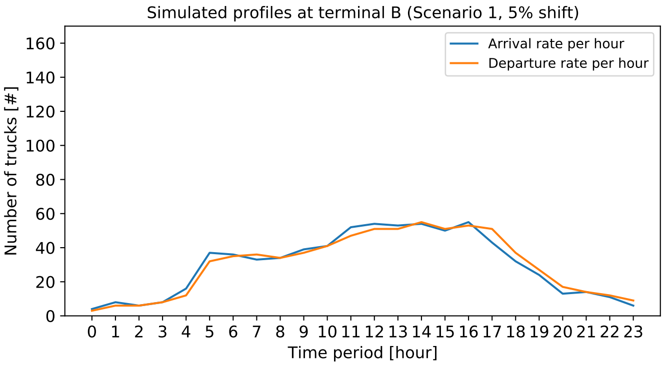
(o) Scenario 15, 100% application rate



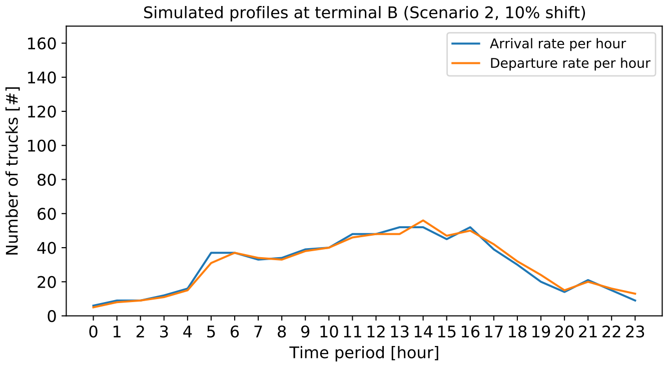
(p) Scenario 16, equal spread

Figure F.2: Simulated arrival and departure profiles at terminal A for each scenario, from terminal model (Appendix B)

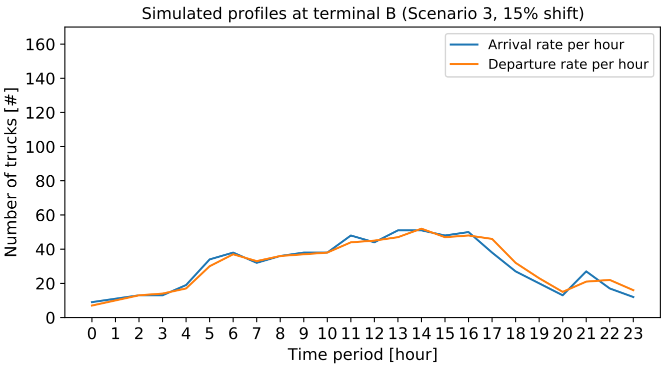
Terminal B: simulated arrival and departure profile



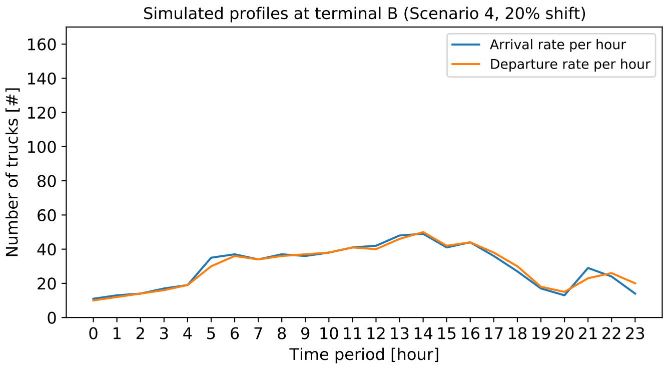
(a) Scenario 1, 5% application rate



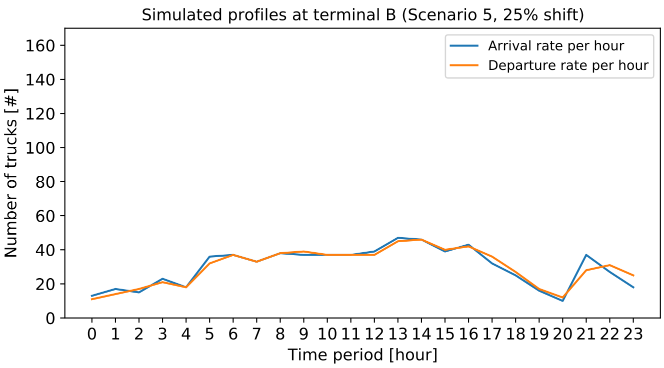
(b) Scenario 2, 10% application rate



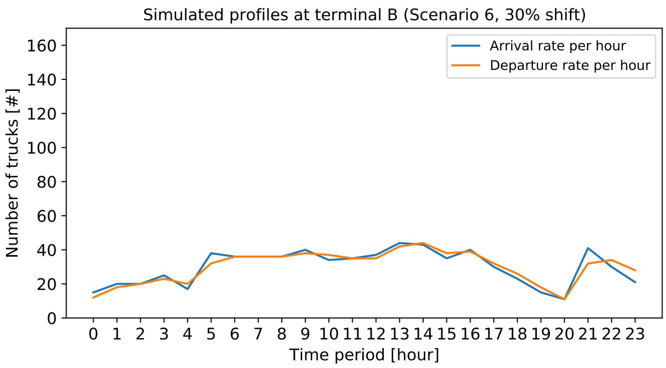
(c) Scenario 3, 15% application rate



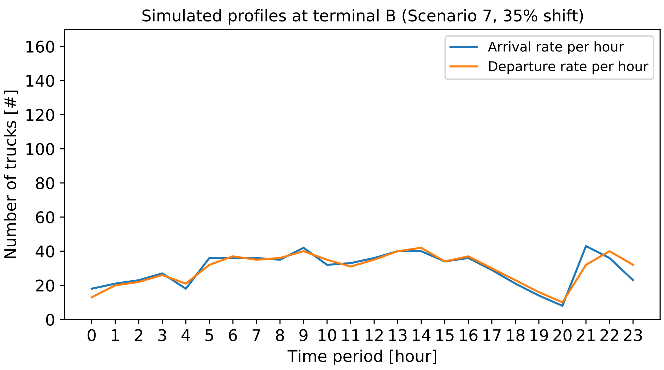
(d) Scenario 4, 20% application rate



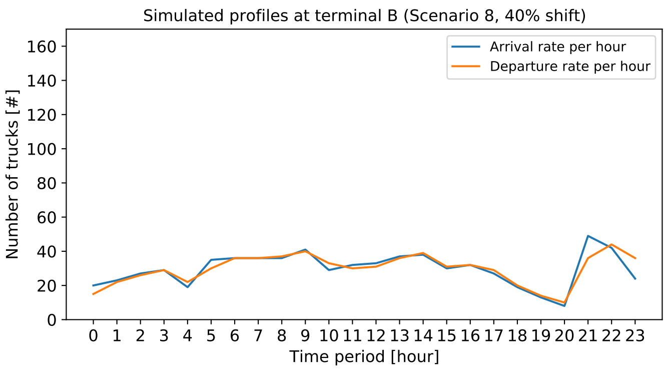
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

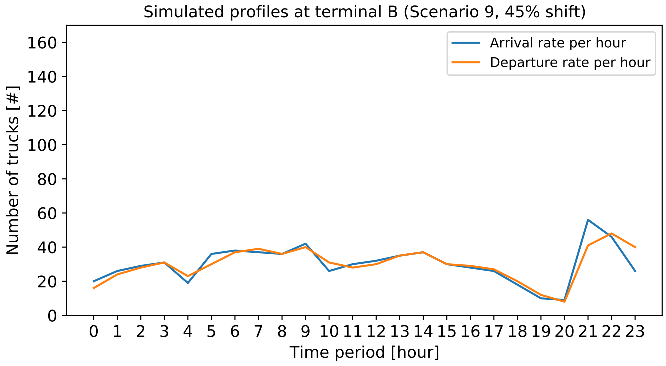


(g) Scenario 7, 35% application rate

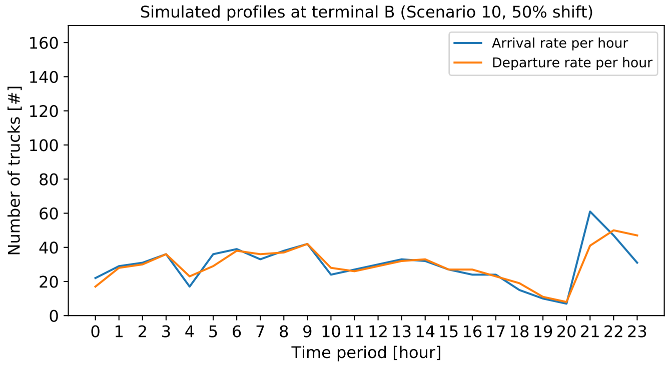


(h) Scenario 8, 40% application rate

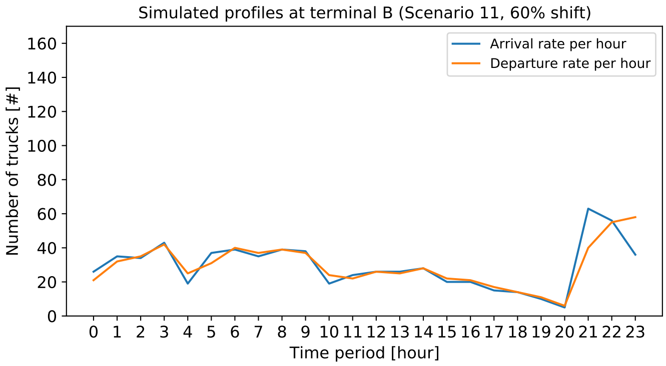
Figure F.3: Simulated arrival and departure profiles at terminal B for each scenario, from terminal model (Appendix B)



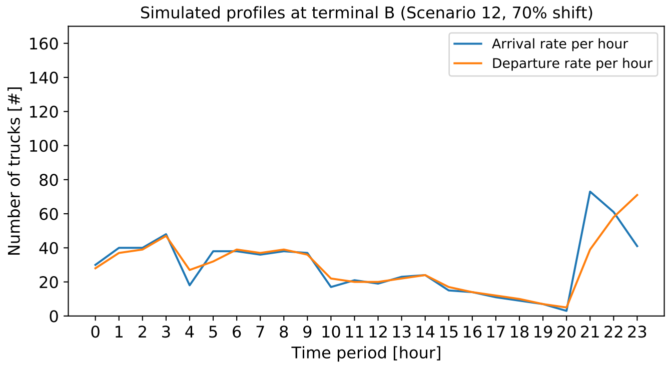
(i) Scenario 9, 45% application rate



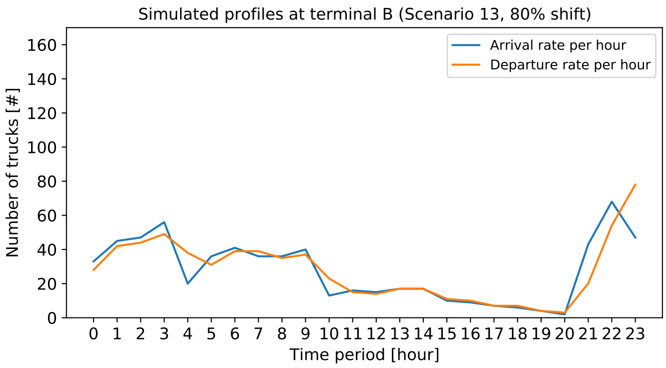
(j) Scenario 10, 50% application rate



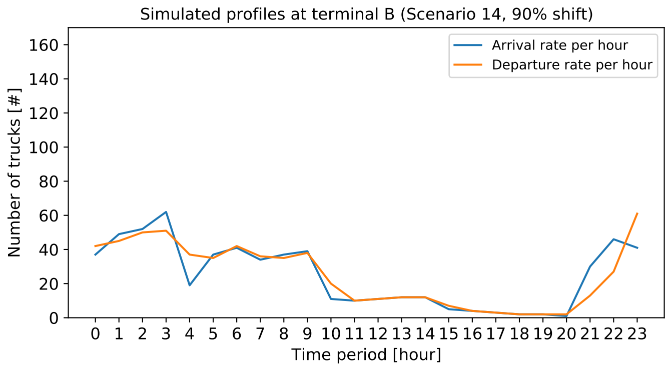
(k) Scenario 11, 60% application rate



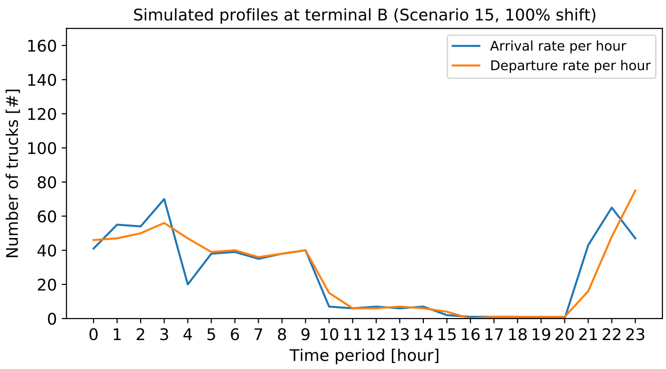
(l) Scenario 12, 70% application rate



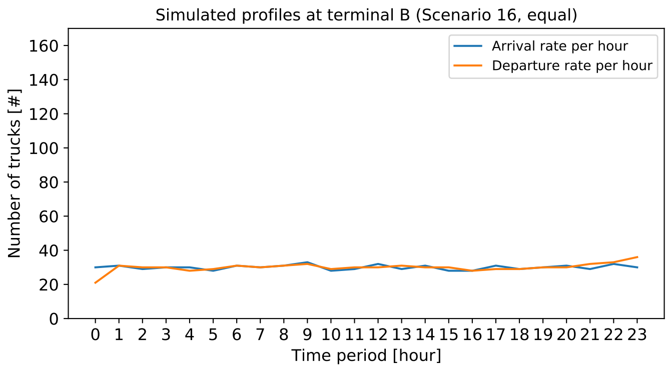
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



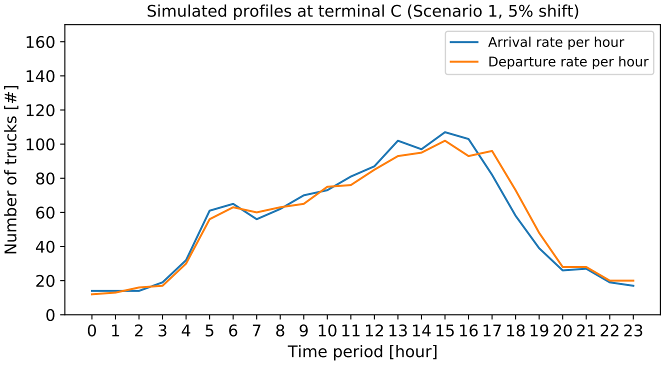
(o) Scenario 15, 100% application rate



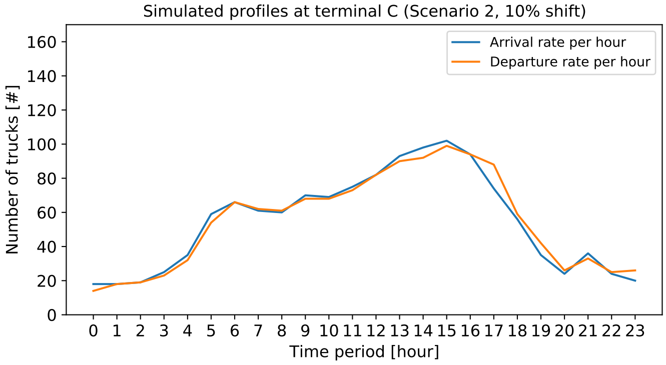
(p) Scenario 16, equal spread

Figure F.3: Simulated arrival and departure profiles at terminal B for each scenario, from terminal model (Appendix B)

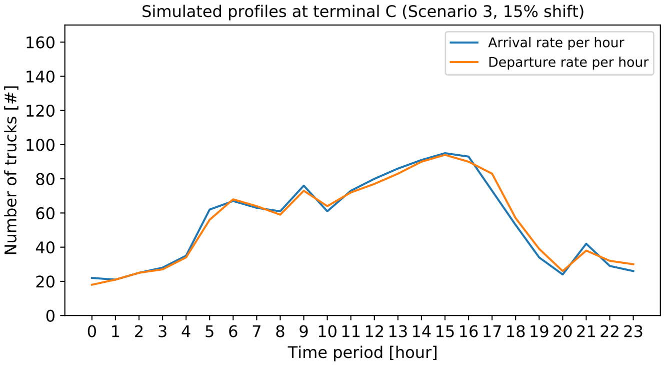
Terminal C: simulated arrival and departure profile



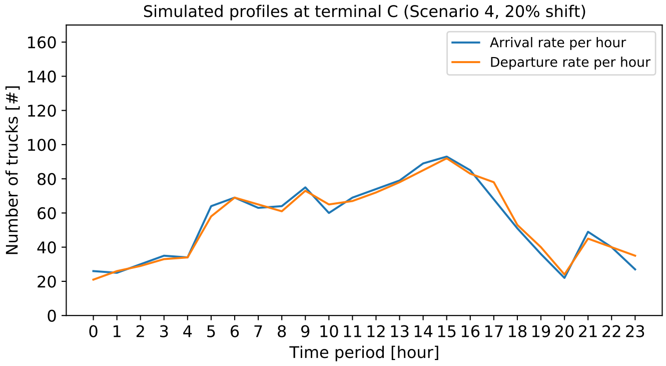
(a) Scenario 1, 5% application rate



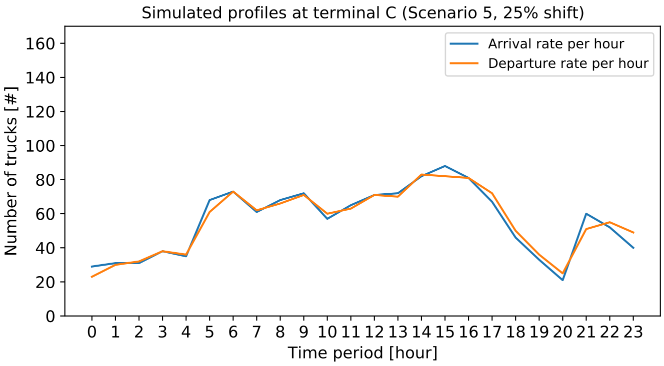
(b) Scenario 2, 10% application rate



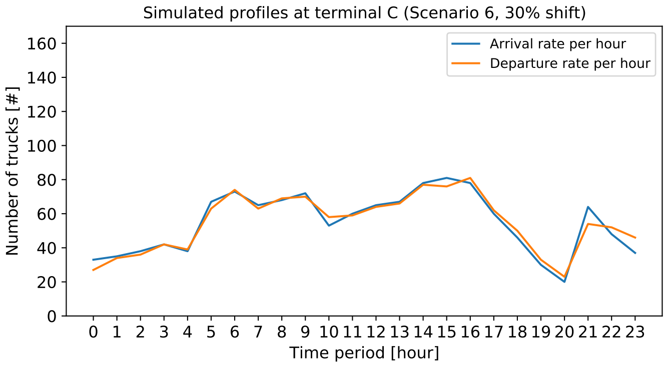
(c) Scenario 3, 15% application rate



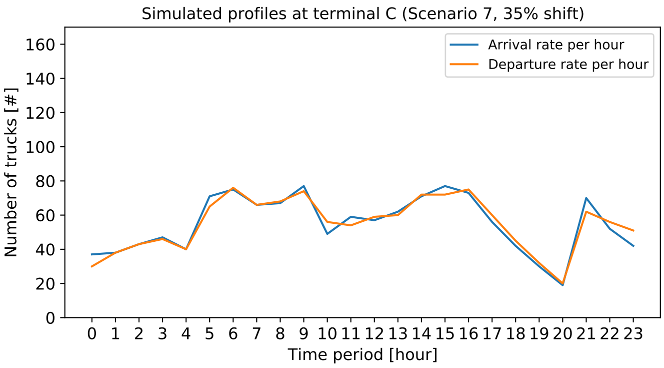
(d) Scenario 4, 20% application rate



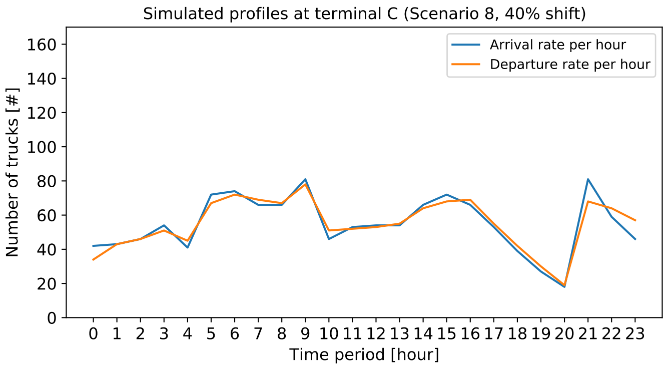
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

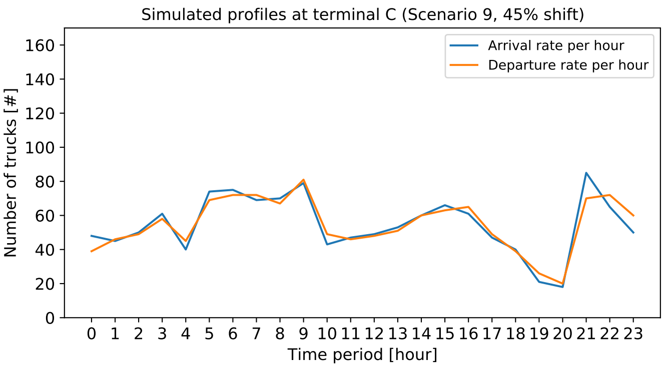


(g) Scenario 7, 35% application rate

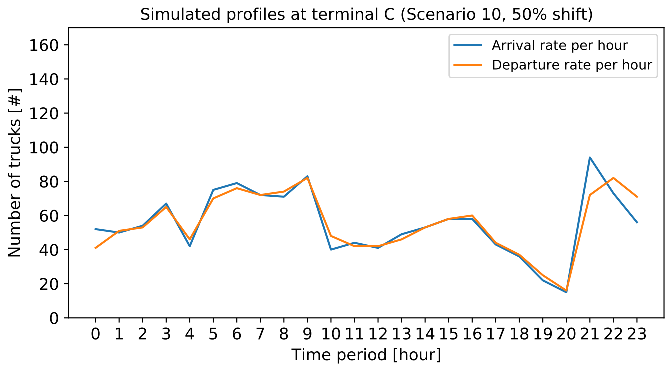


(h) Scenario 8, 40% application rate

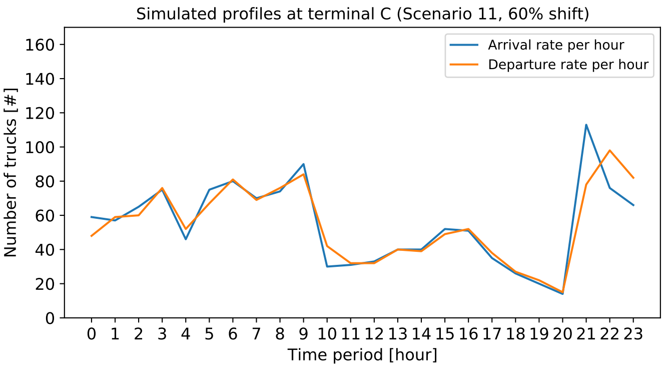
Figure F.4: Simulated arrival and departure profiles at terminal C for each scenario, from terminal model (Appendix B)



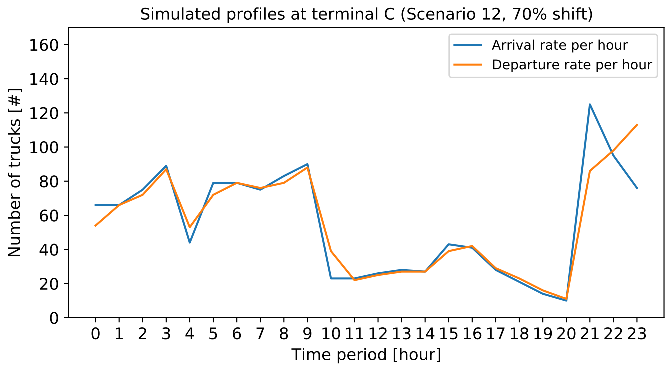
(i) Scenario 9, 45% application rate



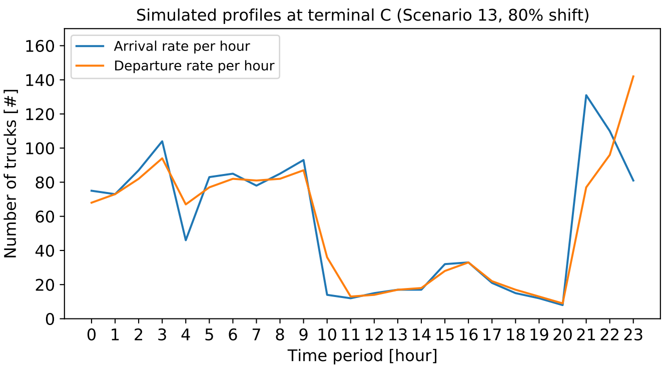
(j) Scenario 10, 50% application rate



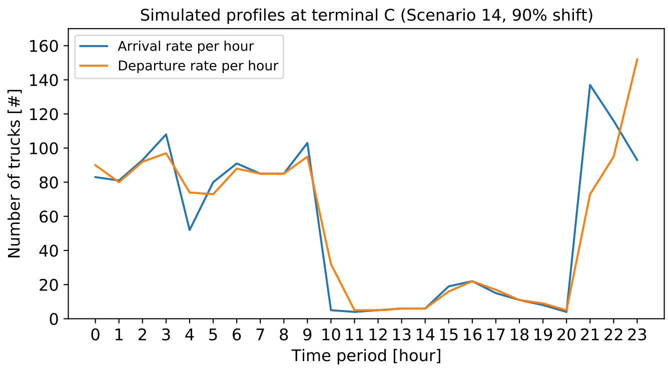
(k) Scenario 11, 60% application rate



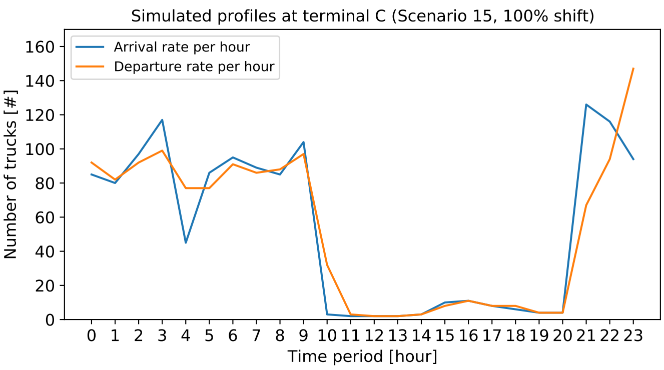
(l) Scenario 12, 70% application rate



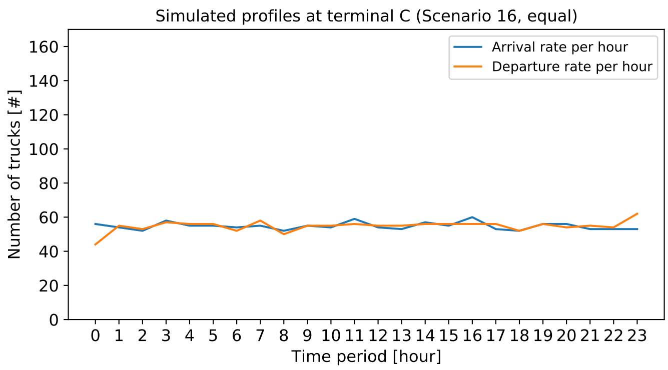
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



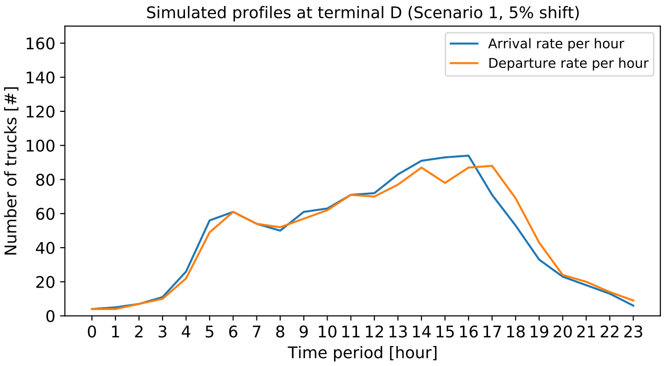
(o) Scenario 15, 100% application rate



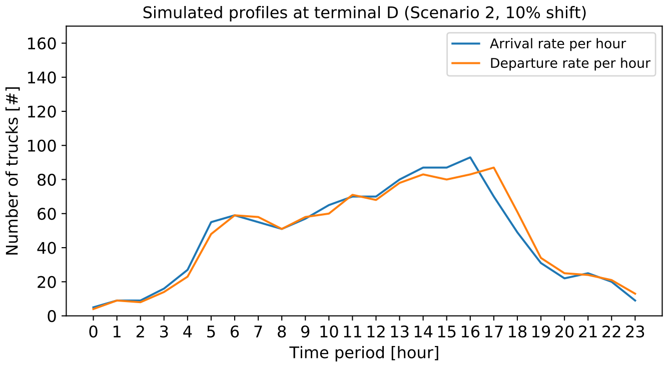
(p) Scenario 16, equal spread

Figure F.4: Simulated arrival and departure profiles at terminal C for each scenario, from terminal model (Appendix B)

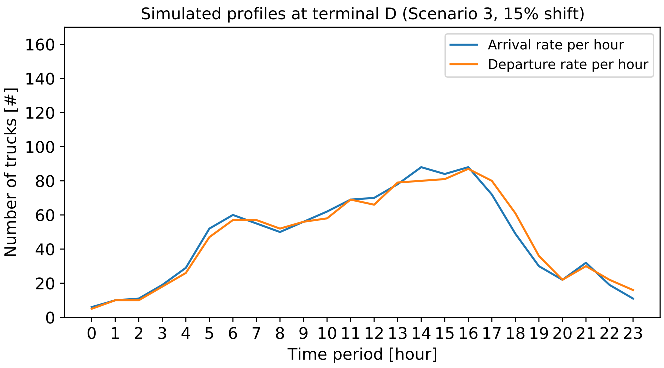
Terminal D: simulated arrival and departure profile



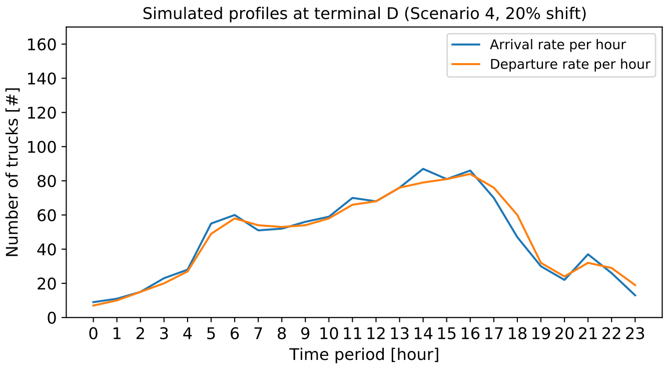
(a) Scenario 1, 5% application rate



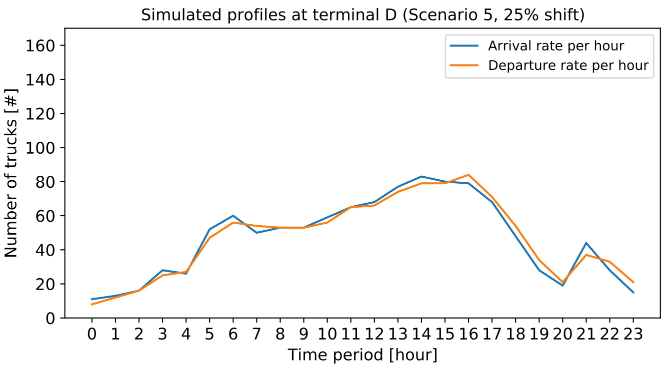
(b) Scenario 2, 10% application rate



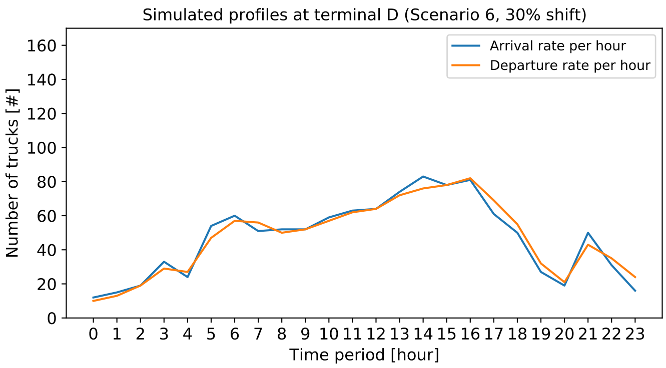
(c) Scenario 3, 15% application rate



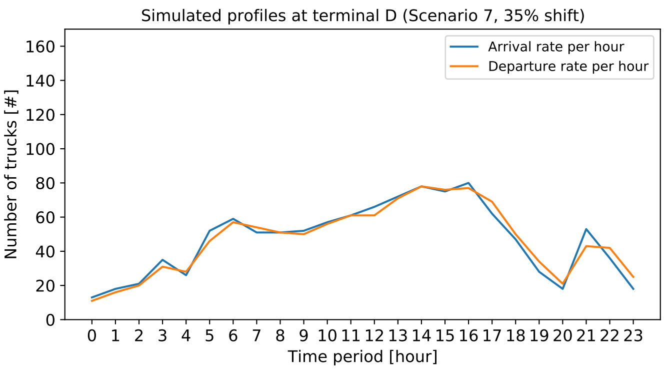
(d) Scenario 4, 20% application rate



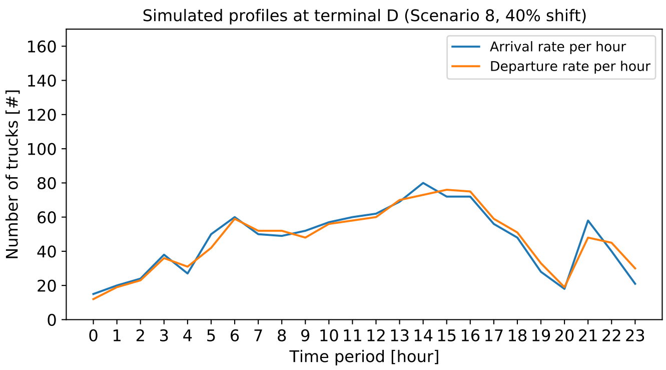
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

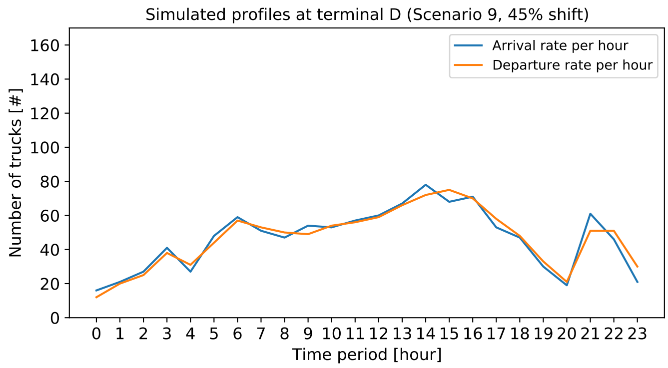


(g) Scenario 7, 35% application rate

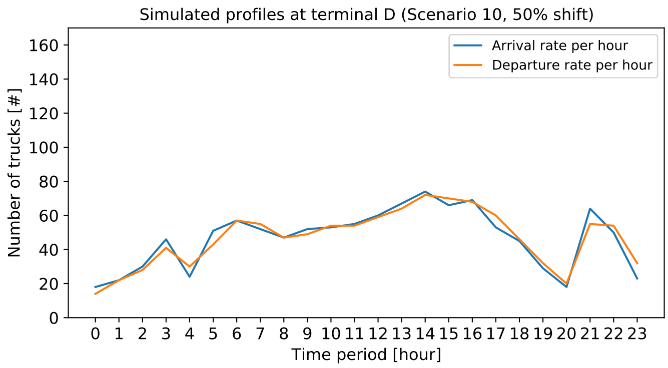


(h) Scenario 8, 40% application rate

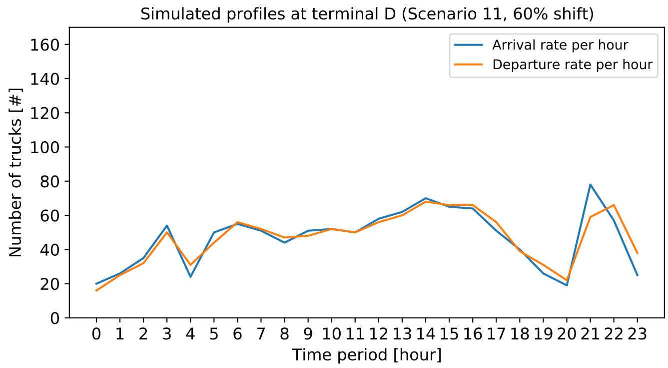
Figure F.5: Simulated arrival and departure profiles at terminal D for each scenario, from terminal model (Appendix B)



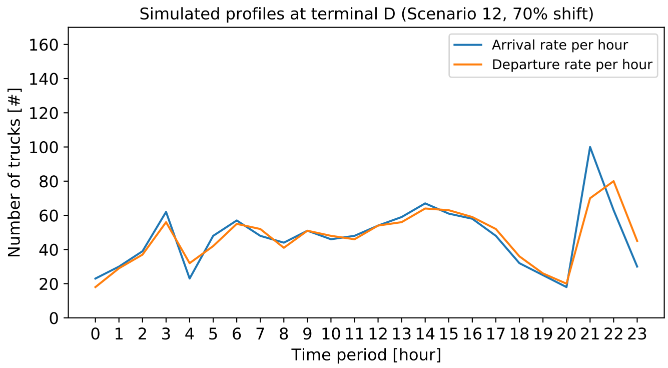
(i) Scenario 9, 45% application rate



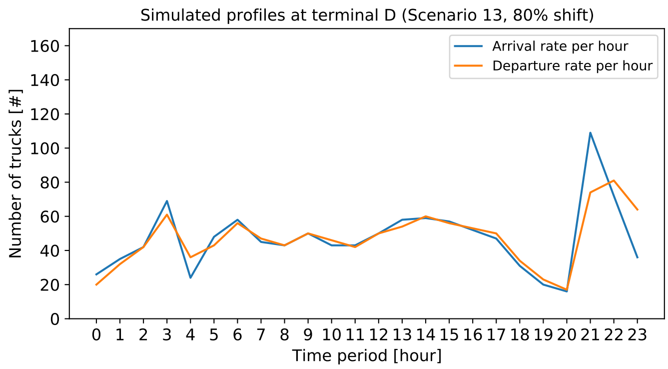
(j) Scenario 10, 50% application rate



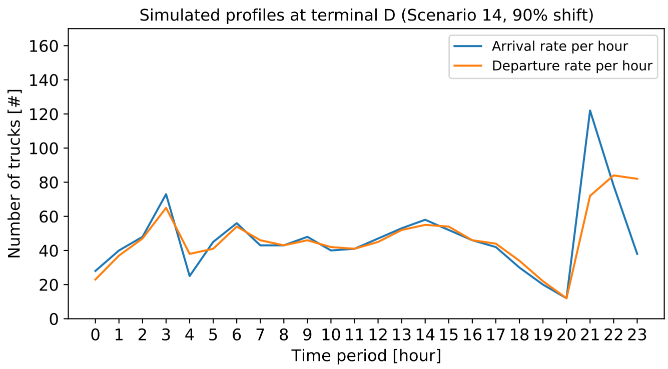
(k) Scenario 11, 60% application rate



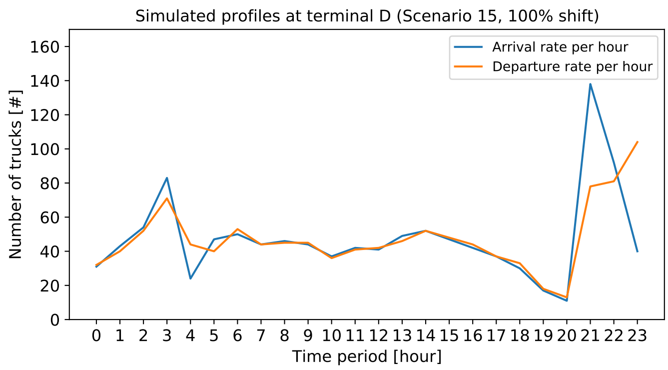
(l) Scenario 12, 70% application rate



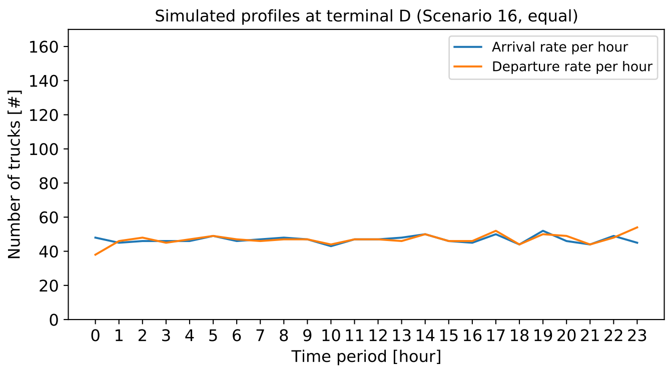
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



(o) Scenario 15, 100% application rate



(p) Scenario 16, equal spread

Figure F.5: Simulated arrival and departure profiles at terminal D for each scenario, from terminal model (Appendix B)

F.1.2 Waiting time

In Figure F.6 through Figure F.9, the waiting time profile for each scenario is presented, structured per terminal. The waiting profile represents the average waiting time for one truck in each hour. Hence, this is the waiting time that is encountered by one truck if it arrives in a certain time slot. The waiting time profiles are simulated with the terminal model (Appendix B).

In each graph, in Figure F.6 through Figure F.9, a red solid line and a gray dashed line is plotted. The red solid line represents the waiting time profile corresponding to the scenario. The gray dashed line indicates the waiting time profile in the base case. Consequently, the waiting time in the base case and the scenario can be easily compared.

From the graphs, the initial conclusion in Section F.1.1 can be substantiated. It can be observed that with only very small application rates the waiting time decreases considerably. Whereas with higher application rates, the waiting time increases. Hence, it can be concluded that the truck shifting strategy is able to reduce waiting time.

However, there is a turning point. In Appendix E it was mentioned that truck shifting also carries a risk. This risk is the increase of waiting time in hours that are quiet in the base case. The appearance of waiting time in initially quieter hours is not necessarily a bad thing. As long as the waiting time remain smaller than in the base case. In Figure F.6 through Figure F.9, it can be observed that the waiting time for most scenarios does not exceed the waiting time in the base case. However, this should be analysed more closely.

To check whether the waiting time profiles from the scenarios are significantly different from the base case waiting profile, a statistical analysis is done. Using the two sided t-test, the following formulated hypotheses are tested:

$H0$: The waiting time is the same
$H1$: The waiting time is different

The null hypothesis ($H0$), indicates that the waiting time is not significantly reduced compared to the base case. The alternative hypothesis ($H1$), means that the waiting time in the scenario are reduced significantly. The prior, $H0$, implies that waiting time may have appeared some where else during the day, or that the application rate is not high enough to reduce waiting time. A judgement in the statistical analysis is passed based on the following rule:

Accept $H0$: t-value $\geq -1.96 \wedge$ t-value ≤ 1.96, p-value > 0.05
Reject $H0$ and accept $H1$: t-value $\leq -1.96 \vee$ t-value ≥ 1.96, p-value < 0.05

The results of the statistical analysis are depicted in Table F.1. From the results it can be concluded that the application rates between 10% and 40% reduce the waiting time at terminal A significantly. For terminal B, the application rates between 10% and 60% result in a significantly reduced waiting time. Terminal C and terminal D experience significant reduced waiting time with application rates between 10% and 60%, and between 35% and 70%, respectively. Note that for some application rates the p-value is a bit larger than 0.05, however the t-value is larger than 1.96, hence $H0$ is rejected and $H1$ accepted anyway.

For the scenarios in which the waiting time is not reduced significantly, this does not necessarily suggest that the waiting time is not reduced at all. Therefore, another measure is valuable to explore regarding the reduction of waiting time. This measure is the waiting time gain and is discussed in Section F.2.

Additionally, the waiting time profile indicates the waiting time on average per hour that is encountered by one truck. The waiting time is at maximum 10 to 25 minutes in the base case. This might not seem much, however, it should be noted that this waiting time is encountered by every truck that arrives in the specific hour. Therefore, it is valuable to analyse the waiting time in relation with the arrival profile.

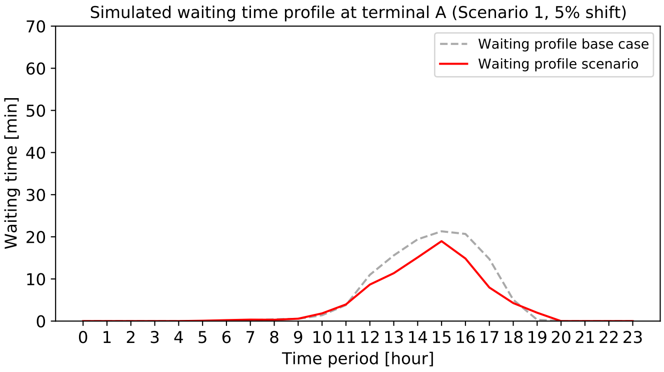
Hence, insight in the waiting time gain can be obtained by analysing the waiting time compared to the base case and in relation with the arrival profile. This is elaborated in Section F.2.

Lastly, to understand what waiting time means, what the consequences of waiting time are and who carries these consequences further analysis is required. Moreover, waiting time in minutes is rather difficult to grasp. Therefore, more understanding might be obtained by placing the waiting time in perspective. This is elaborated in Section F.3.

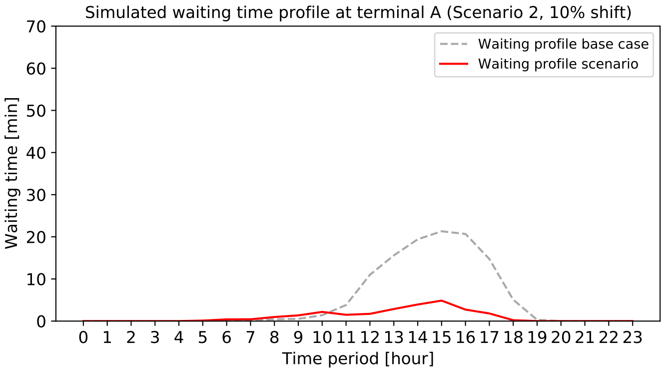
Table F.1: Overview of results from statistical analysis for waiting time

	Terminal A		Terminal B		Terminal C		Terminal D	
	t-value	**p-value**	**t-value**	**p-value**	**t-value**	**p-value**	**t-value**	**p-value**
Scenario 1 (5% shift)	0.513	0.611	1.341	0.189	1.287	0.207	-0.345	0.732
Scenario 2 (10% shift)	2.358	0.027	2.511	0.019	2.094	0.046	0.913	0.367
Scenario 3 (15% shift)	2.037	0.051	2.022	0.053	2.416	0.024	0.962	0.342
Scenario 4 (20% shift)	2.075	0.048	2.767	0.011	2.411	0.024	1.35	0.186
Scenario 5 (25% shift)	2.067	0.049	2.78	0.011	2.549	0.018	1.559	0.129
Scenario 6 (30% shift)	2.105	0.045	2.823	0.01	2.61	0.016	1.879	0.071
Scenario 7 (35% shift)	2.17	0.039	2.867	0.009	2.622	0.015	2.25	0.034
Scenario 8 (40% shift)	2.105	0.045	2.804	0.01	2.618	0.015	2.36	0.027
Scenario 9 (45% shift)	1.818	0.079	2.644	0.014	2.602	0.016	2.518	0.019
Scenario 10 (50% shift)	1.535	0.135	2.501	0.019	2.533	0.019	2.534	0.018
Scenario 11 (60% shift)	0.76	0.452	2.117	0.043	2.299	0.03	2.512	0.019
Scenario 12 (70% shift)	-0.315	0.755	1.063	0.293	1.838	0.076	2.053	0.05
Scenario 13 (80% shift)	-0.945	0.351	1.222	0.229	0.605	0.548	1.506	0.14
Scenario 14 (90% shift)	-1.616	0.117	0.261	0.796	-0.041	0.967	0.417	0.679
Scenario 15 (100% shift)	-1.503	0.144	-0.333	0.741	-0.184	0.855	-0.474	0.639
Scenario 16 (equal)	3.049	0.006	2.911	0.008	2.672	0.014	2.718	0.012

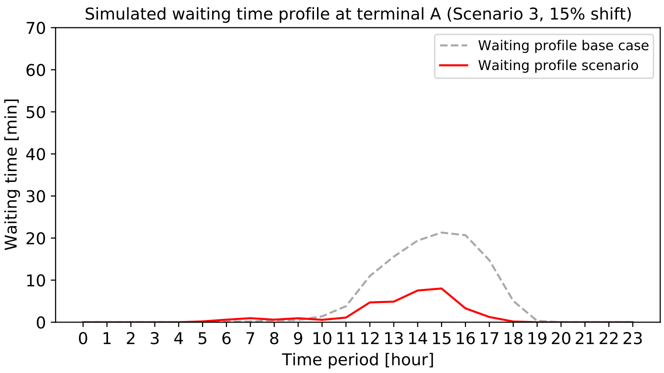
Terminal A: average waiting time profile



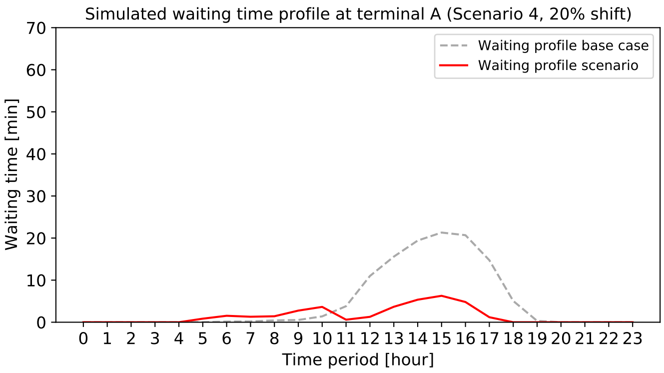
(a) Scenario 1, 5% application rate



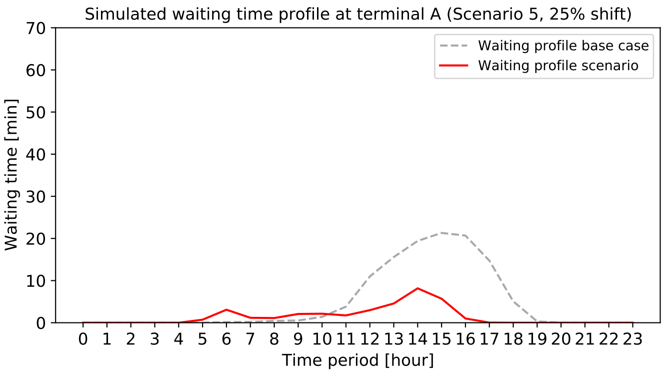
(b) Scenario 2, 10% application rate



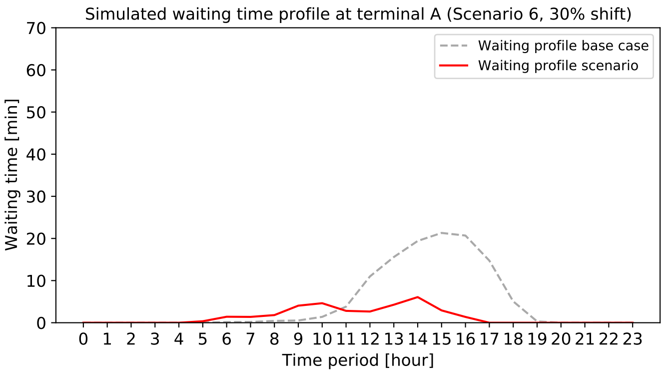
(c) Scenario 3, 15% application rate



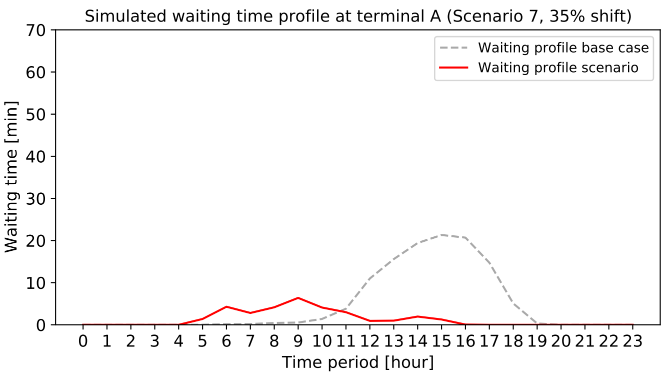
(d) Scenario 4, 20% application rate



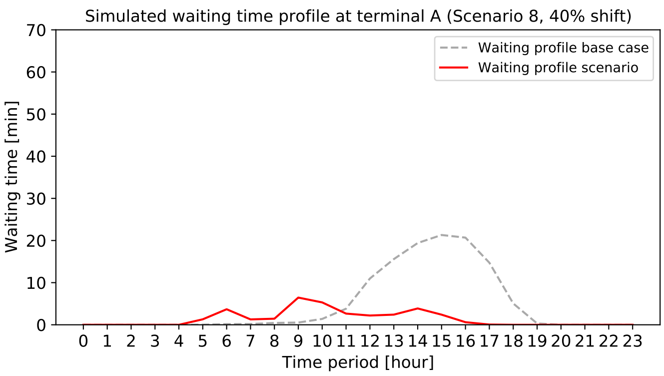
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

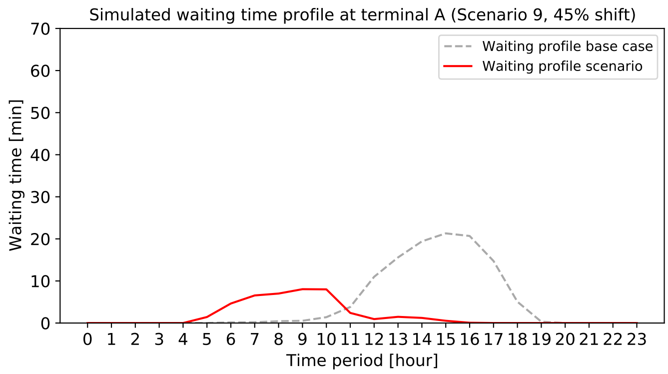


(g) Scenario 7, 35% application rate

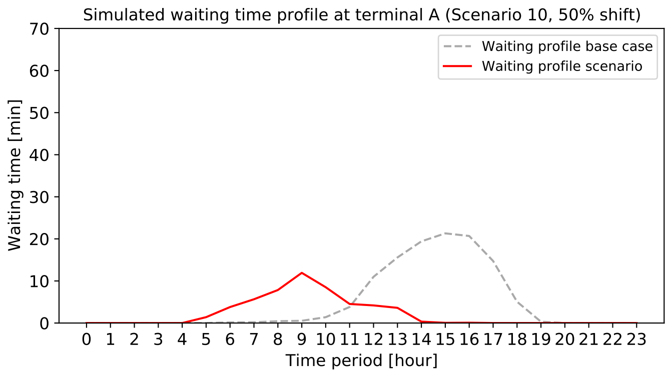


(h) Scenario 8, 40% application rate

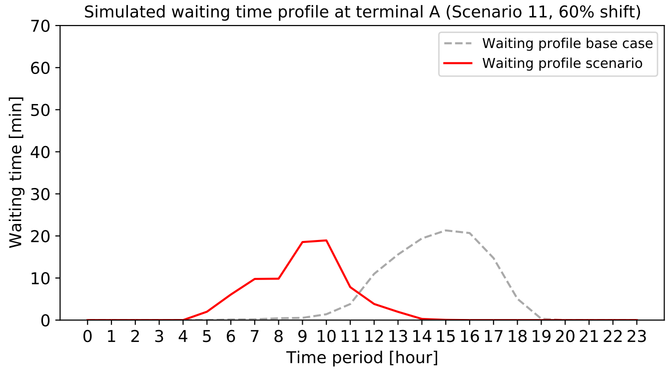
Figure F.6: Simulated average waiting time profiles at terminal A for each scenario, from terminal model (Appendix B)



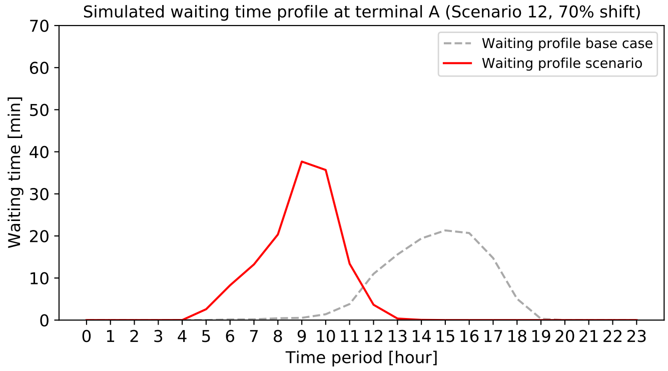
(i) Scenario 9, 45% application rate



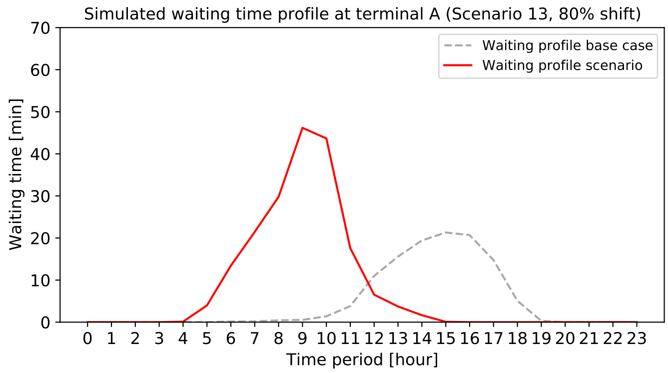
(j) Scenario 10, 50% application rate



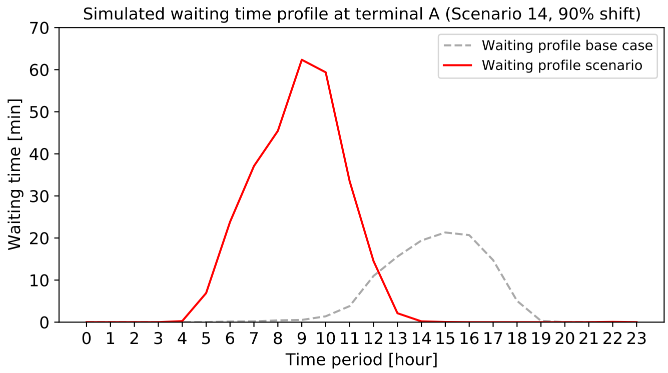
(k) Scenario 11, 60% application rate



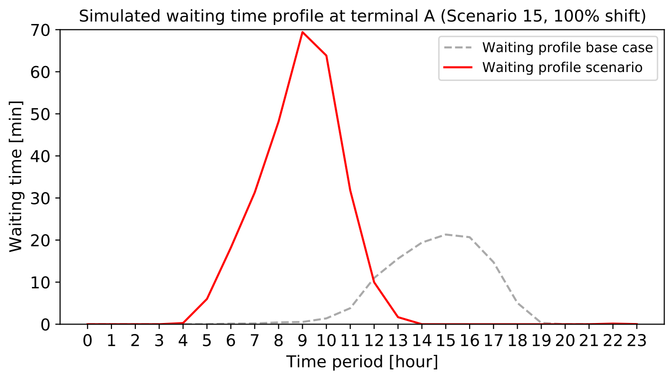
(l) Scenario 12, 70% application rate



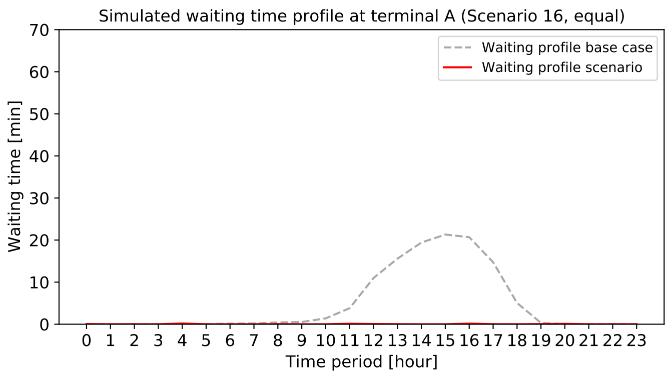
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



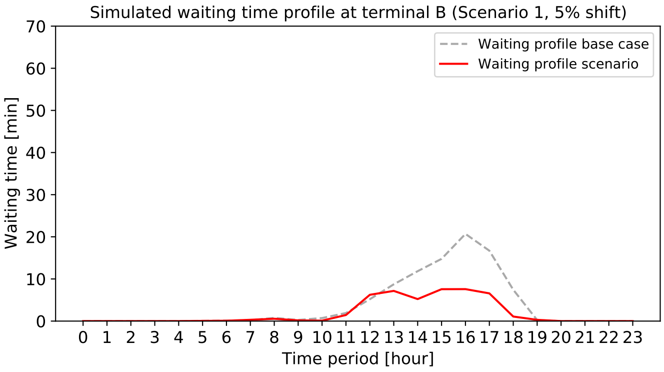
(o) Scenario 15, 100% application rate



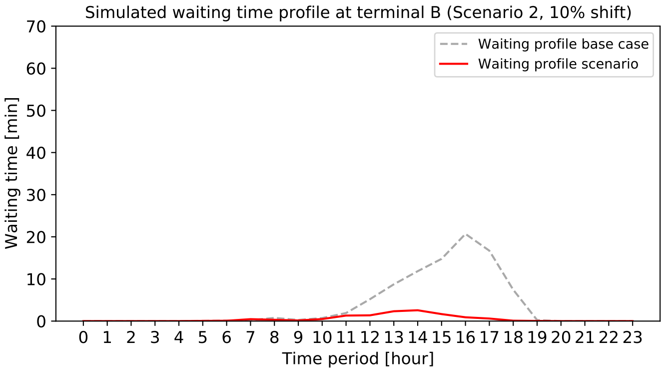
(p) Scenario 16, equal spread

Figure F.6: Simulated average waiting time profiles at terminal A for each scenario, from terminal model (Appendix B)

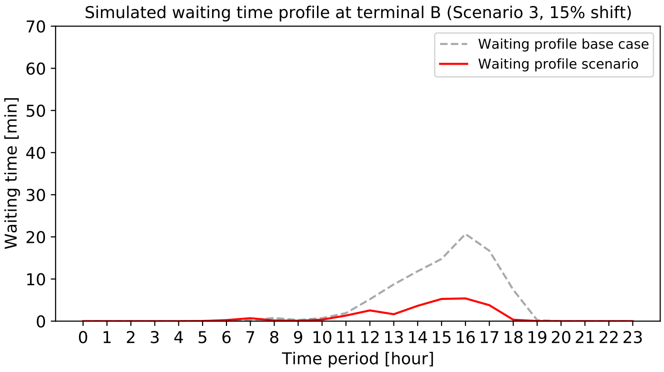
Terminal B: average waiting time profile



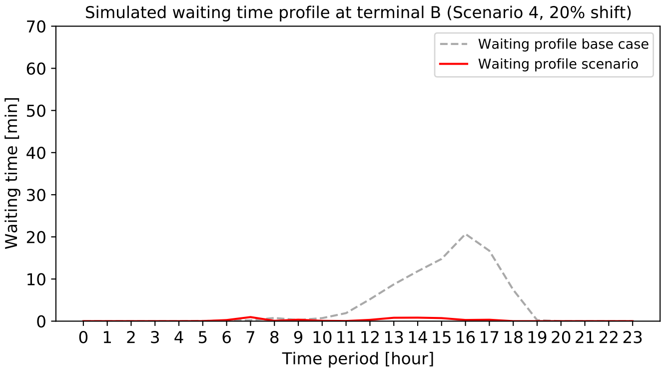
(a) Scenario 1, 5% application rate



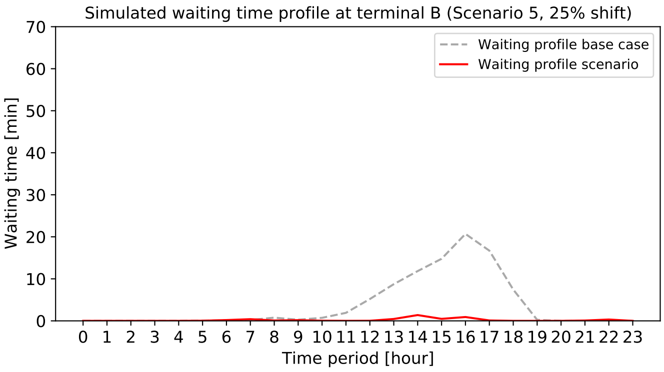
(b) Scenario 2, 10% application rate



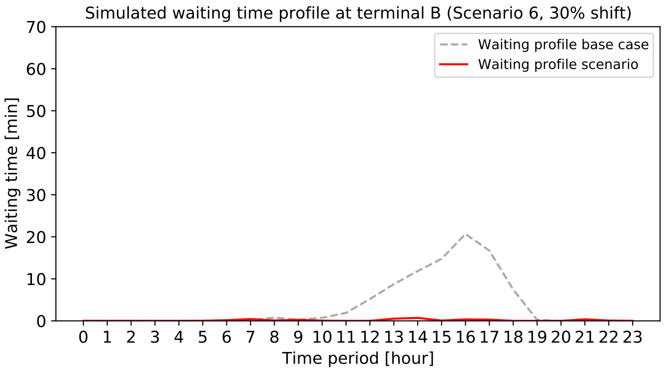
(c) Scenario 3, 15% application rate



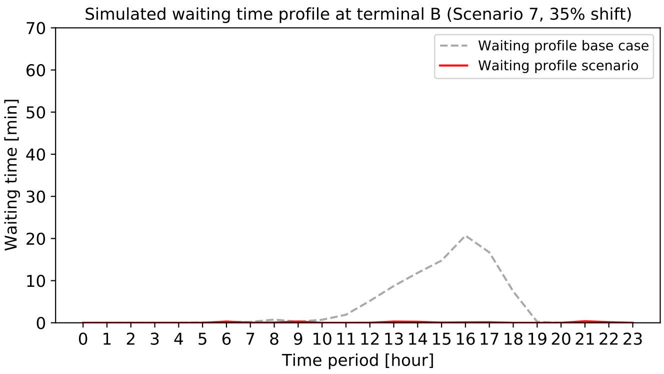
(d) Scenario 4, 20% application rate



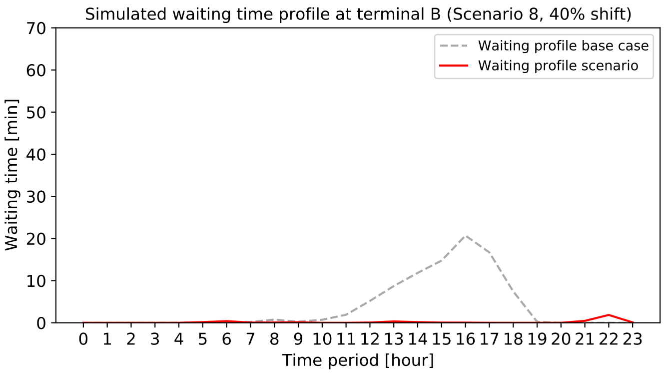
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

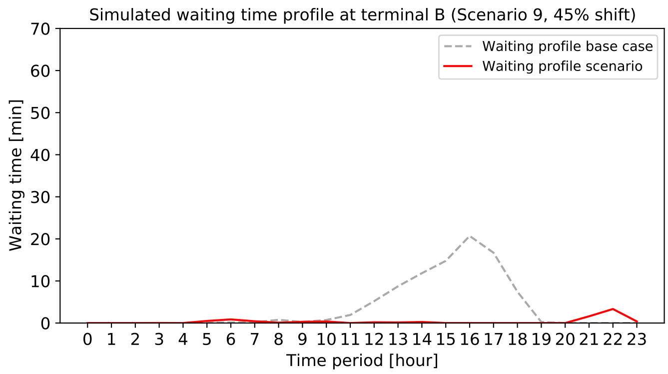


(g) Scenario 7, 35% application rate

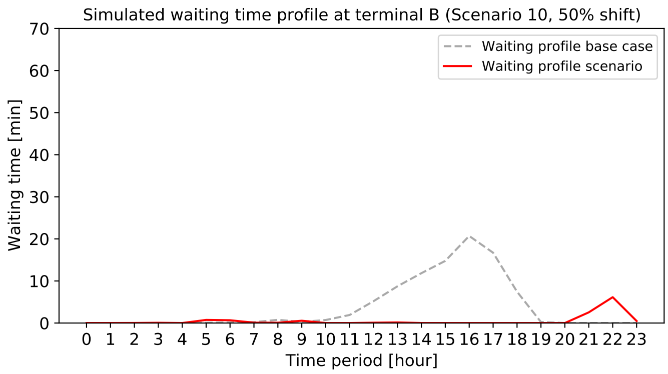


(h) Scenario 8, 40% application rate

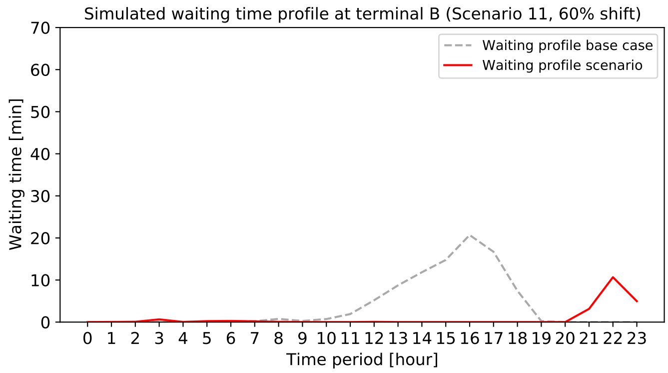
Figure F.7: Simulated average waiting time profiles at terminal B for each scenario, from terminal model (Appendix B)



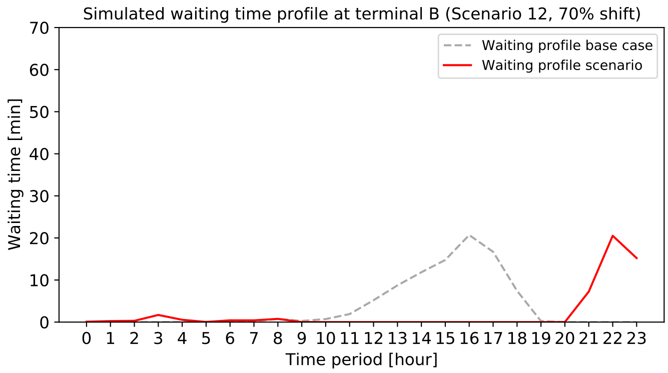
(i) Scenario 9, 45% application rate



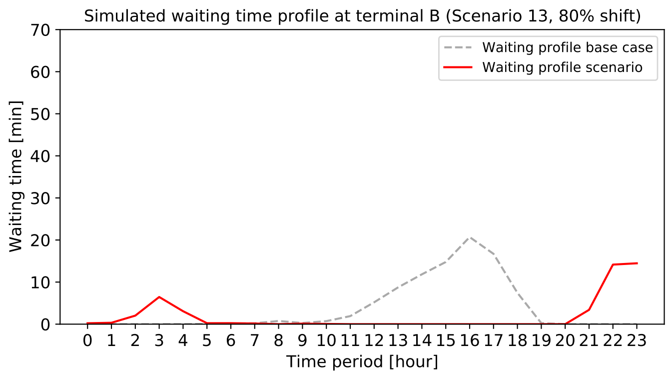
(j) Scenario 10, 50% application rate



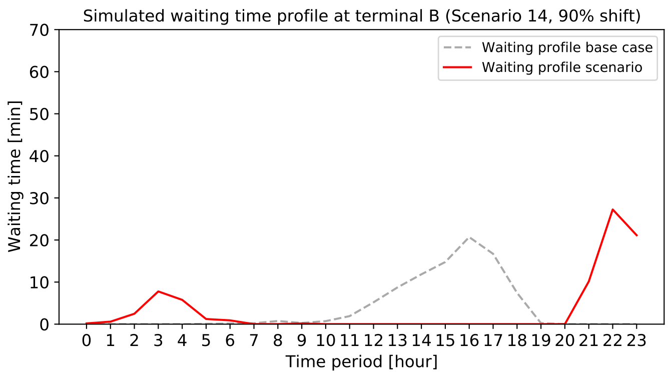
(k) Scenario 11, 60% application rate



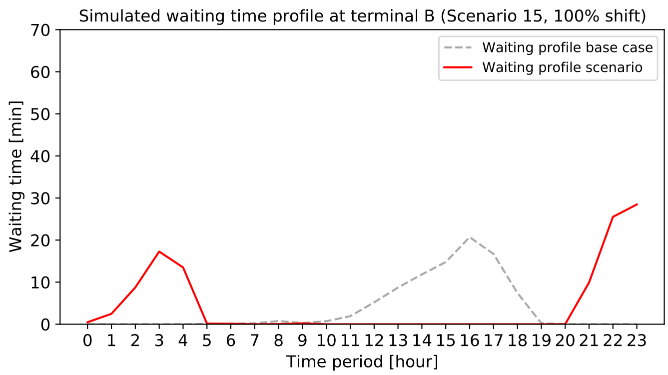
(l) Scenario 12, 70% application rate



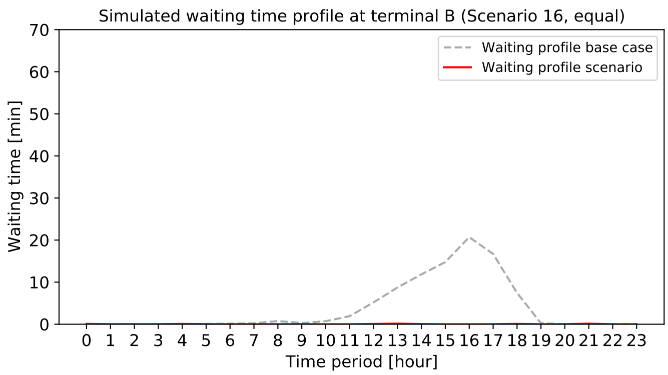
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



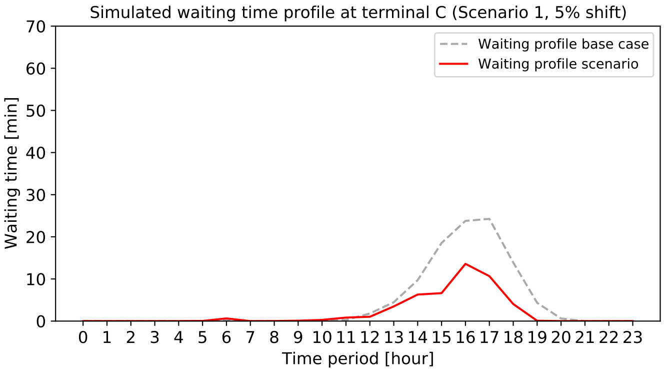
(o) Scenario 15, 100% application rate



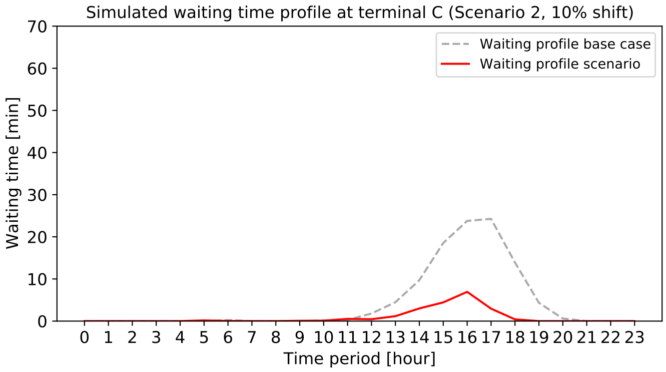
(p) Scenario 16, equal spread

Figure F.7: Simulated average waiting time profiles at terminal B for each scenario, from terminal model (Appendix B)

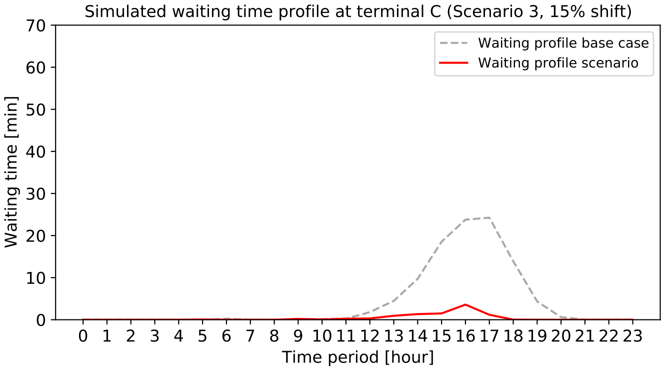
Terminal C: average waiting time profile



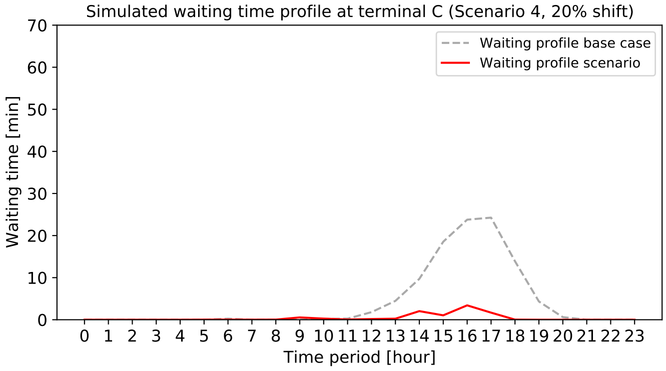
(a) Scenario 1, 5% application rate



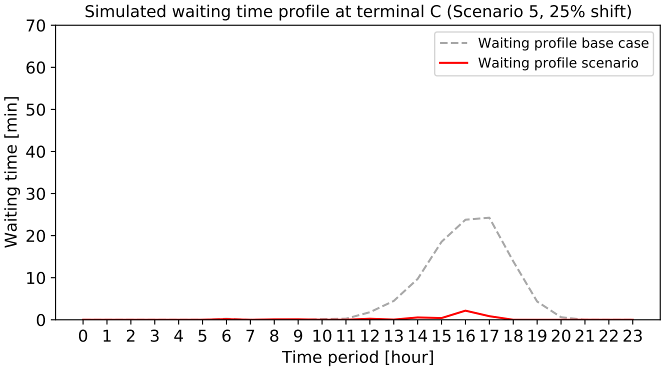
(b) Scenario 2, 10% application rate



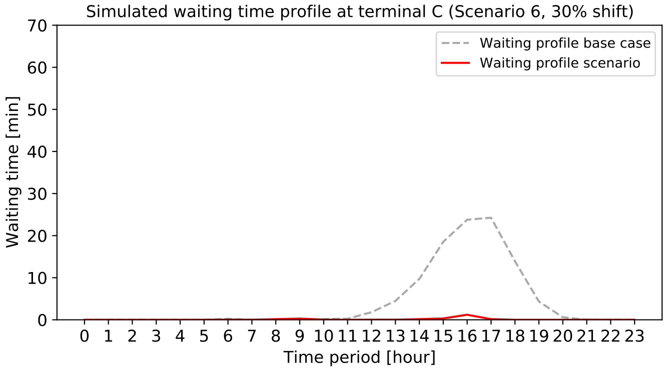
(c) Scenario 3, 15% application rate



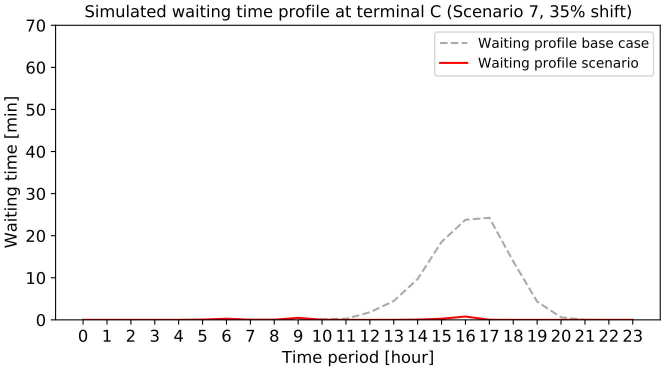
(d) Scenario 4, 20% application rate



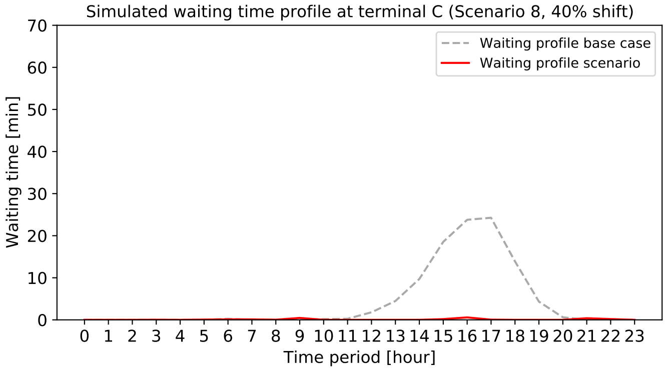
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

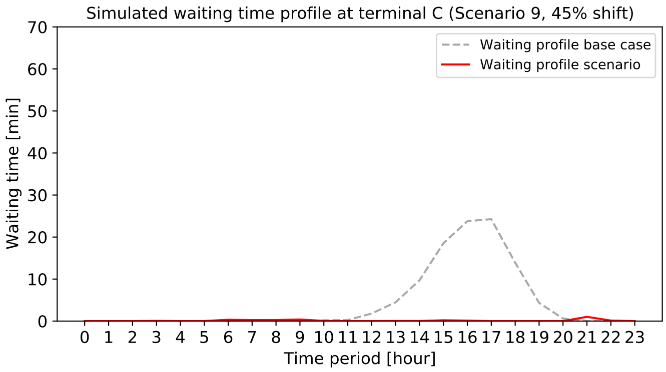


(g) Scenario 7, 35% application rate

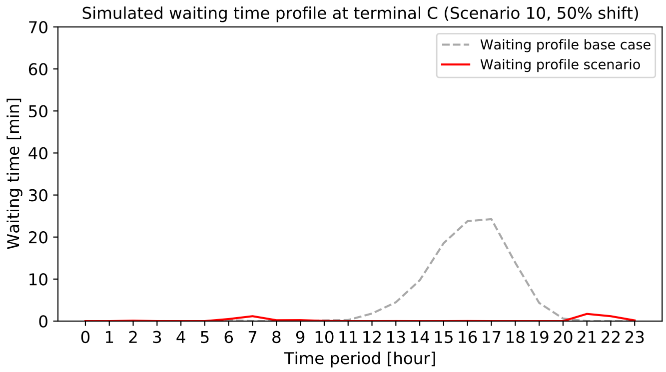


(h) Scenario 8, 40% application rate

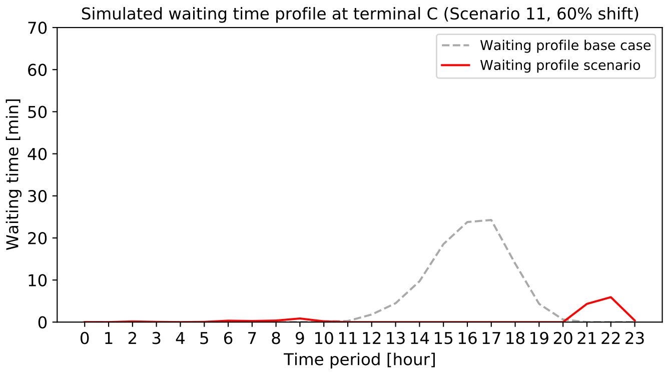
Figure F.8: Simulated average waiting time profiles at terminal C for each scenario, from terminal model (Appendix B)



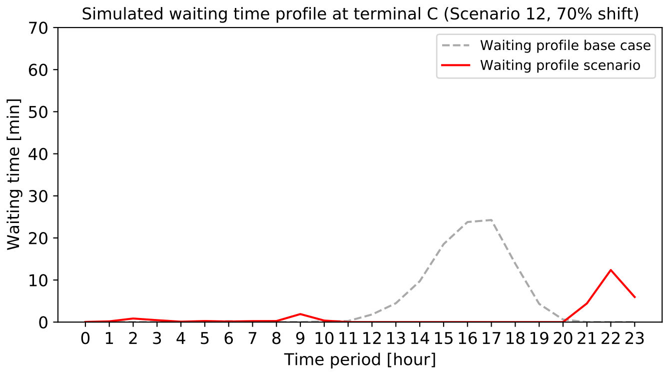
(i) Scenario 9, 45% application rate



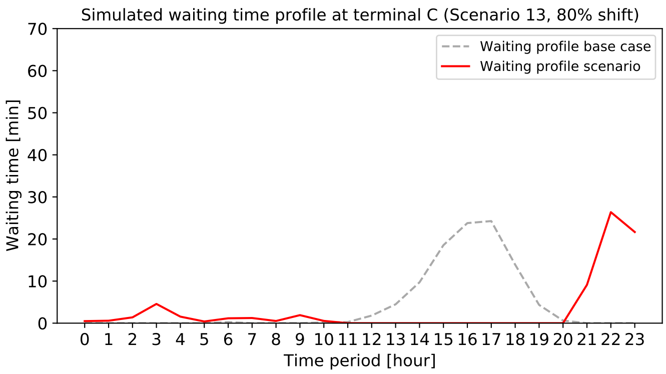
(j) Scenario 10, 50% application rate



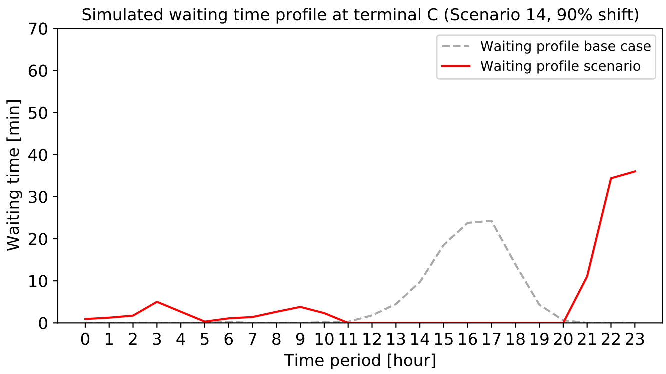
(k) Scenario 11, 60% application rate



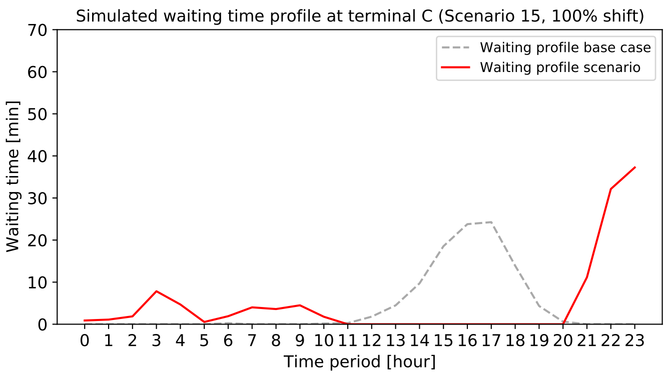
(l) Scenario 12, 70% application rate



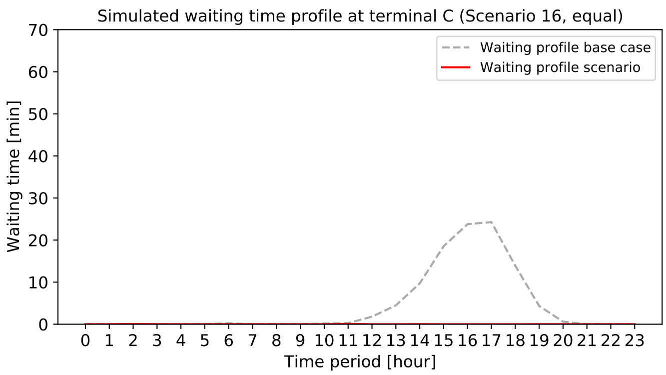
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



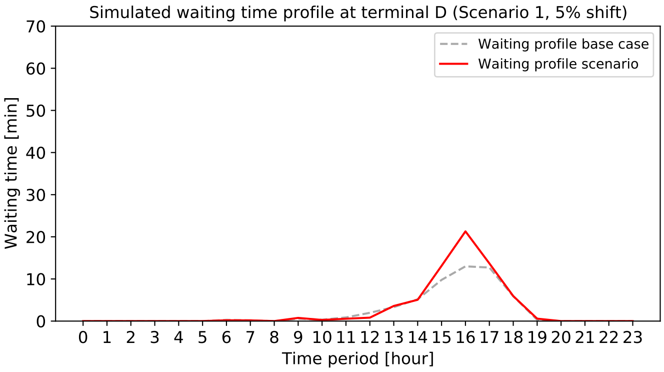
(o) Scenario 15, 100% application rate



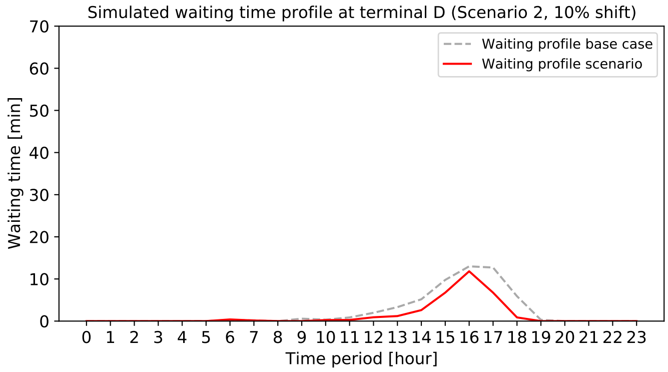
(p) Scenario 16, equal spread

Figure F.8: Simulated average waiting time profiles at terminal C for each scenario, from terminal model (Appendix B)

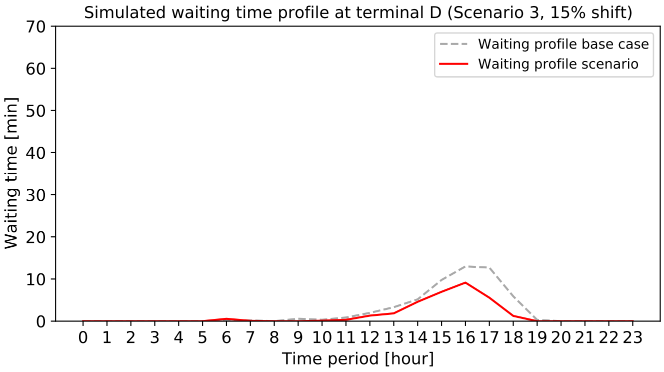
Terminal D: average waiting time profile



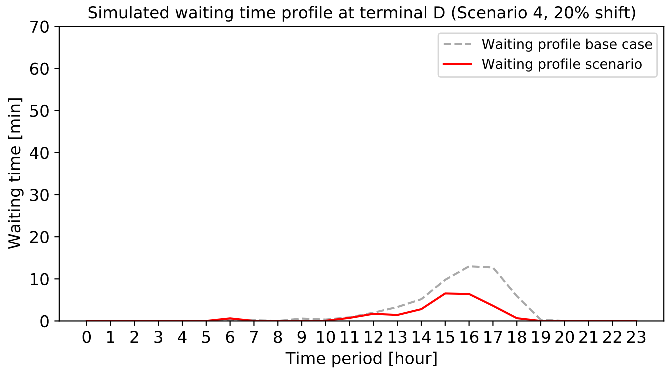
(a) Scenario 1, 5% application rate



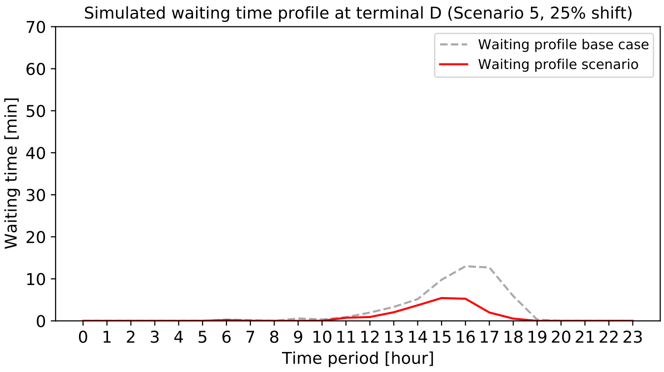
(b) Scenario 2, 10% application rate



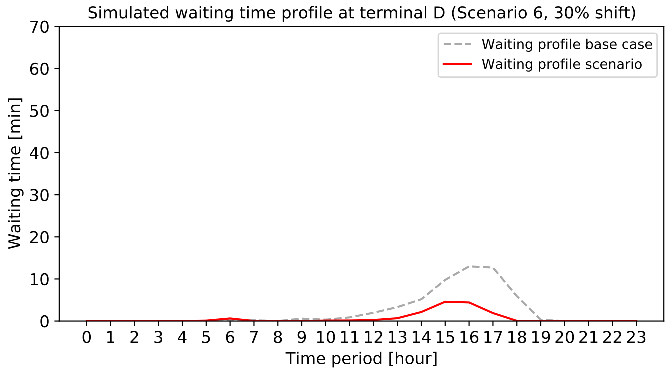
(c) Scenario 3, 15% application rate



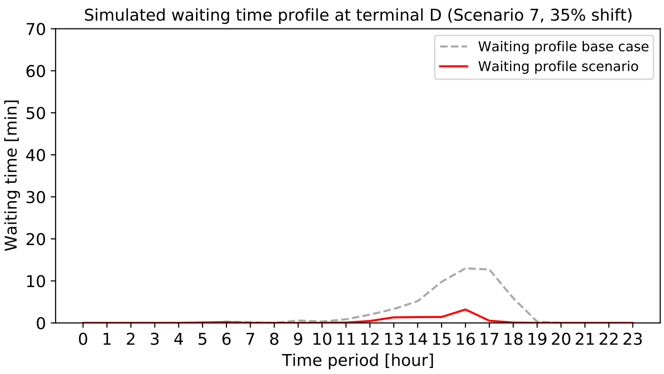
(d) Scenario 4, 20% application rate



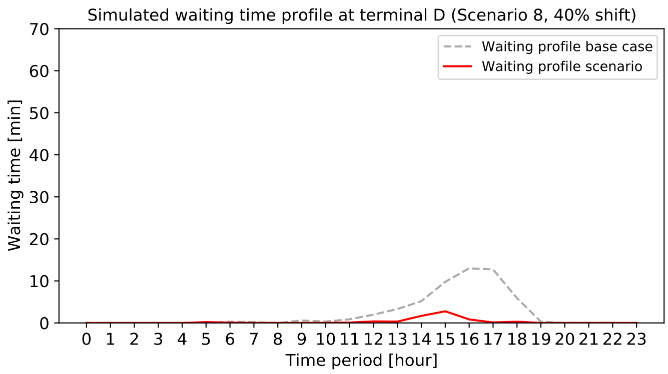
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

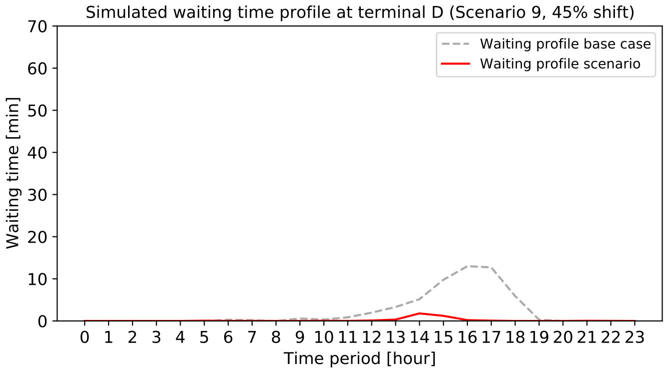


(g) Scenario 7, 35% application rate

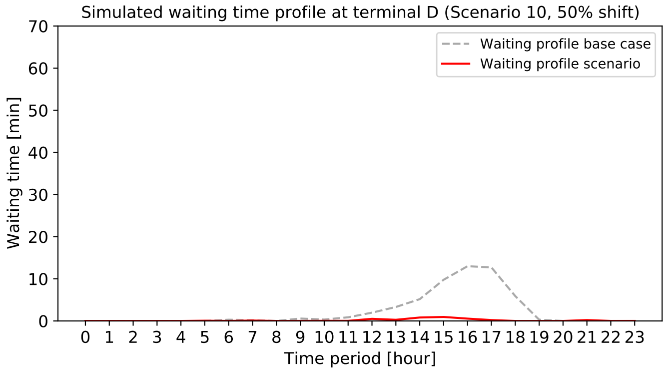


(h) Scenario 8, 40% application rate

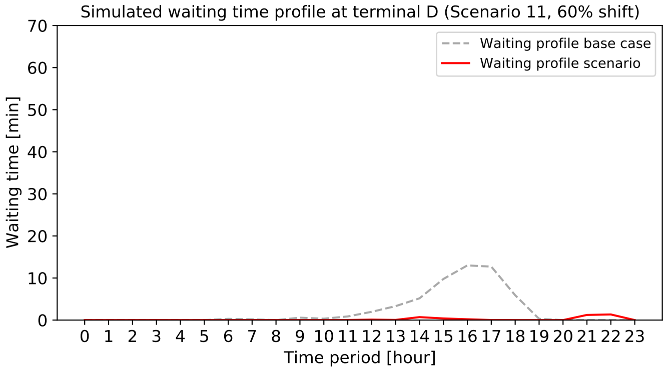
Figure F.9: Simulated average waiting time profiles at terminal D for each scenario, from terminal model (Appendix B)



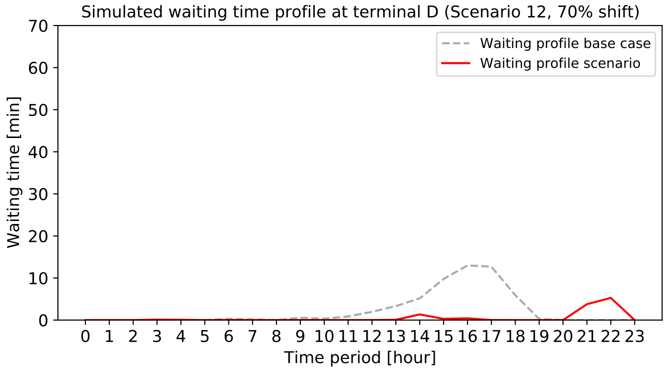
(i) Scenario 9, 45% application rate



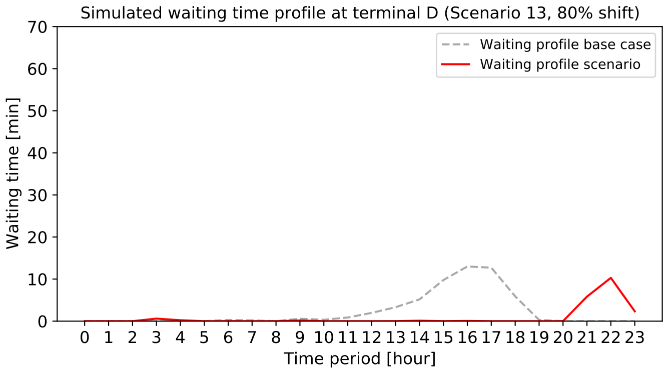
(j) Scenario 10, 50% application rate



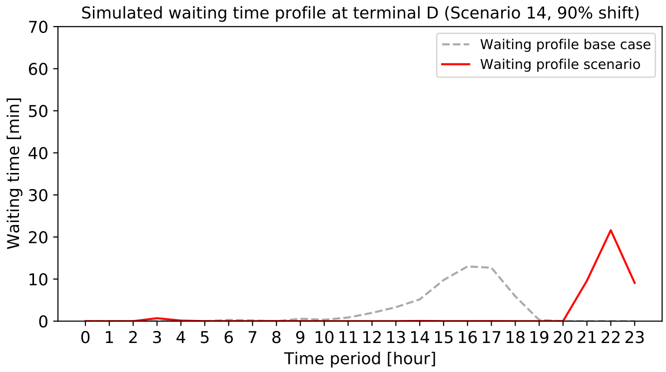
(k) Scenario 11, 60% application rate



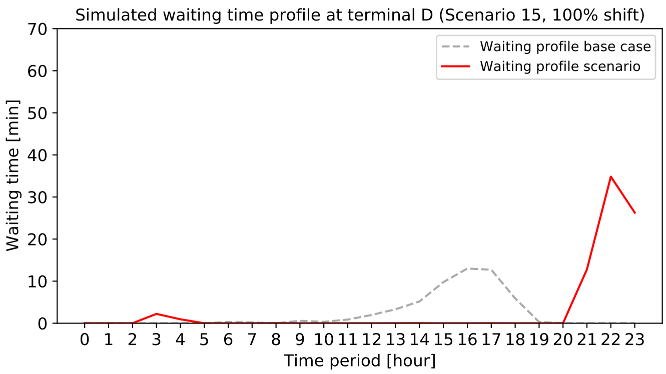
(l) Scenario 12, 70% application rate



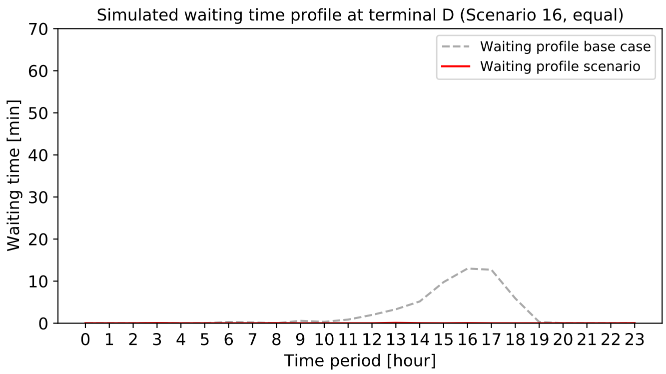
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



(o) Scenario 15, 100% application rate



(p) Scenario 16, equal spread

Figure F.9: Simulated average waiting time profiles at terminal D for each scenario, from terminal model (Appendix B)

F.2 WAITING TIME GAIN

In Figure F.12 through Figure F.15, the development of the total waiting time along the day is displayed, structured per terminal. The patterns for each scenario are similar to the waiting profiles shown in Section F.1.2. However, the patterns are not exactly the same because the graphs in this section account for the number of truck arrivals per hour. Accordingly, the total waiting time for each hour along the day is captured.

From the total waiting time, more insight is obtained regarding the impact of the waiting time. Furthermore, the total waiting time for each scenario can be compared with total waiting time in the base case. With the average waiting time profiles this is also possible, however, the total impact of waiting time might not be entirely captured. The total waiting time comprehends the impact on the entire system instead of for only one truck. Consequently, the total waiting time is the most suitable measure to compare the waiting time in each scenario with the base case.

Moreover, from the statistical analysis in Section F.1.2, it was found that the truck shifting strategies are capable to reduce waiting time significantly under certain application rates. However, for some application rates the waiting time seem to have reduced from the graphs (Figure F.6 through Figure F.9) but are found to not be significantly different. To provide insight in the eventual gain for all scenarios, even though not significantly different, an analysis of the total waiting is valuable.

By subtracting the total waiting time for each scenario from the base case for each hour, and consequently summing the difference per hour, the waiting time gain can be calculated.

Subtracting the waiting time in the scenario from the base case results in the graphs presented in Figure F.16 through Figure F.19. It should be noted that, opposed to the other graphs for waiting time, the y-axis ranges between negative and positive values. When the plotted line is on the positive side of the y-axis, this implies a positive waiting time gain. When the plotted line obtains negative values, this implies a negative gain, hence a waiting time loss.

A negative gain or waiting time loss indicates that the total waiting time in the scenario is higher in the corresponding hour than the total waiting time in the base case. This does not necessarily mean that the application rate in the scenario does not lead to a reduced waiting time. As mentioned, it might happen that waiting time appear in other time periods due to shifting trucks. Ultimately, the aim is to reduce the waiting time for the entire system and for the entire day.

Consequently, to get insight in whether the waiting time in the scenarios are no larger than in the base case, the gain per hour is summed. This results in the total waiting time gain or loss for the entire day. The total waiting time gain for the entire day indicates the impact of truck shifting under a certain application rate of TOC. If a positive value is obtained, the truck shifting strategy leads to a waiting time gain under the application rate scenario. If negative value is obtained, this implies that the truck shifting strategy is not successful to reduce waiting time under a certain application rate.

The total waiting time gain per scenario is depicted in Table F.2. This table provides an overview of the total waiting time gain for each scenario compared to the base case on an average working day. The waiting time gain is provided in minutes and in hours to easily grasp the value without converting it. Some striking results are obtained from this table (Table F.2).

In general, for all terminals an increase of the waiting time gain can be observed from the first scenario (5% shift) until the seventh scenario (35% shift). Thereafter, for each terminal, the waiting time gain decreases and eventually becomes negative for some terminals. This insight indicates that there is an optimum for shifting trucks to reduce waiting time. Additionally, it can be observed that the gain with small application rates (5% - 10%) is already very close to the optimum.

There are two exceptions. First of all, at terminal A the highest waiting time gain is achieved at a 10% application rate. Additionally, terminal D is an exception, here the increase of the waiting time gain occurs from scenario 2 (10%) until scenario 9 (45%).

Figure F.10 displays the trend in waiting time gain along scenarios, an optimum can be observed from this graph for each terminal. Note that scenario 16 is not included in trend line plot in Figure F.10 as is used as reference scenario for the ideal situation at the terminals. Including scenario 16 in the graph would not provide insight in the trend line, thus would not be of added value in the graph.

Scenario 16 represents the scenario in which an entirely equal spread of trucks along the day is simulated. The scenario is used as reference scenario as an entirely equal spread of trucks is the perfect situation at the terminal for truck arrival. The number of trucks arriving will always stay below the terminal capacity and there will not be any waiting time. Consequently, the waiting time gain is the largest possible compared to the base case.

The waiting time gain for each scenario can be compared with the ideal situation, scenario 16. This provides insight in how good the waiting time gain in each scenario is. For example, a waiting time gain of 28 hours might seem very good, however, if the best possible waiting time is 110, this the 28 hour gain is placed in perspective.

From the waiting time gains in Table F.2, it can be concluded that ideal situation at the terminal can almost be achieve with the shift strategies for terminals. For some terminals, the optimum gain obtained from truck shifting under an application ratio of 35%, 35% and 45%, for terminal B, C and D, respectively, is very close to the gain in the reference scenario. At terminal B, C and D the optimum gain deviates only 1, 2 and 4 hours respectively. For terminal A, the difference between the optimum for shift strategy and the ideal scenario, is larger, 22 hours. In Figure F.11, the gain in the reference scenario is plotted against the shift trend along scenarios. This shows how close the truck shifting strategy waiting time gains are to the ideal scenarios.

The results are very promising as it can be concluded that the truck shifting strategies are capable to reduce waiting time. In Section F.3, it is elaborated how the results should be interpreted and what this means for practice.

Table F.2: Total waiting time gain on an average working day for each scenario

	Terminal A		**Terminal B**		**Terminal C**		**Terminal D**	
	Minutes	**Hours**	**Minutes**	**Hours**	**Minutes**	**Hours**	**Minutes**	**Hours**
Scenario 1 (5% shift)	1676	28	2497	42	5015	84	-1007	-17
Scenario 2 (10% shift)	5299	88	4148	69	7582	126	1806	30
Scenario 3 (15% shift)	4758	79	3558	59	8600	143	1899	32
Scenario 4 (20% shift)	4846	81	4527	75	8647	144	2533	42
Scenario 5 (25% shift)	4853	81	4546	76	9066	151	2859	48
Scenario 6 (30% shift)	4883	81	4602	77	9244	154	3323	55
Scenario 7 (35% shift)	4977	83	4655	78	9277	155	3806	63
Scenario 8 (40% shift)	4913	82	4580	76	9272	155	3980	66
Scenario 9 (45% shift)	4381	73	4373	73	9218	154	4179	70
Scenario 10 (50% shift)	3839	64	4186	70	9010	150	4212	70
Scenario 11 (60% shift)	2280	38	3698	62	8294	138	4186	70
Scenario 12 (70% shift)	-1107	-18	2154	36	6875	115	3601	60
Scenario 13 (80% shift)	-4068	-68	2378	40	2383	40	2934	49
Scenario 14 (90% shift)	-9988	-166	1465	24	-1311	-22	1198	20
Scenario 15 (100% shift)	-10156	-169	216	4	-2884	-48	-1725	-29
Scenario 16 (equal)	6602	110	4713	79	9419	157	4449	74

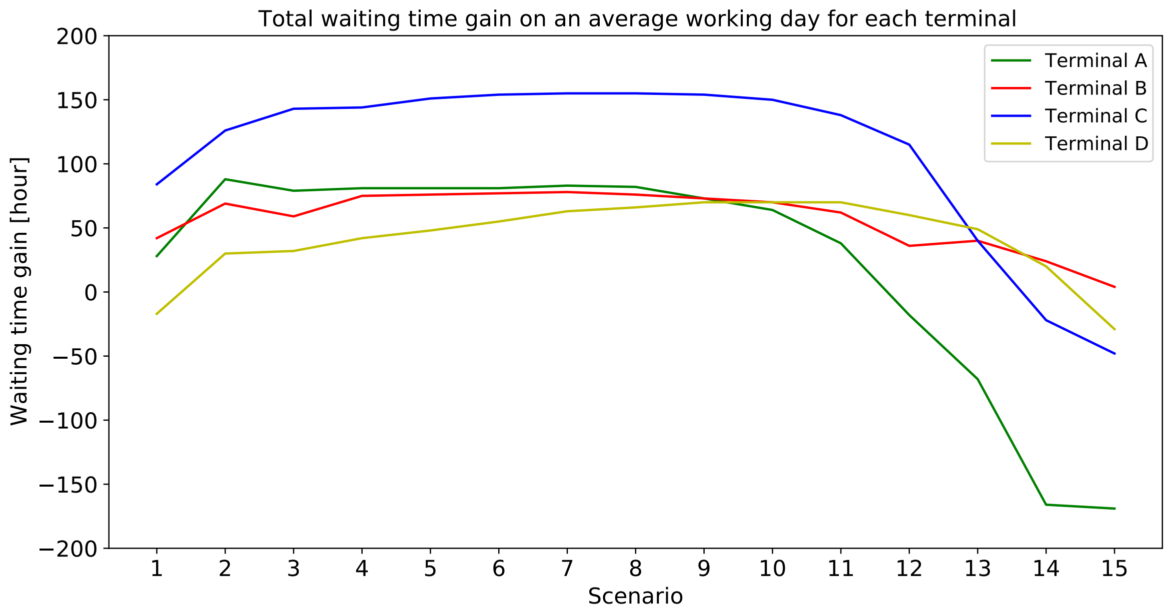
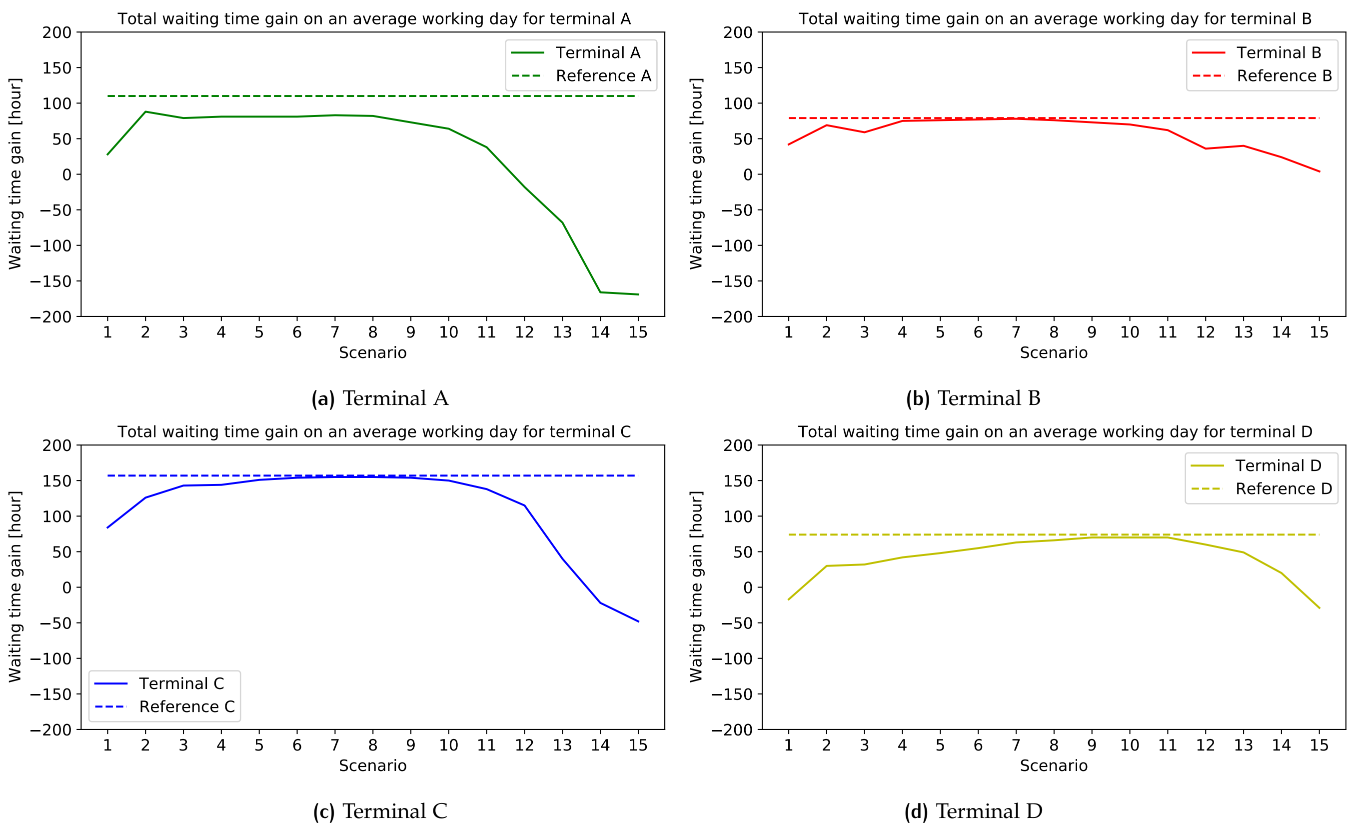


Figure F.10: Total waiting time gain for each terminal, trend along the scenarios



(a) Terminal A

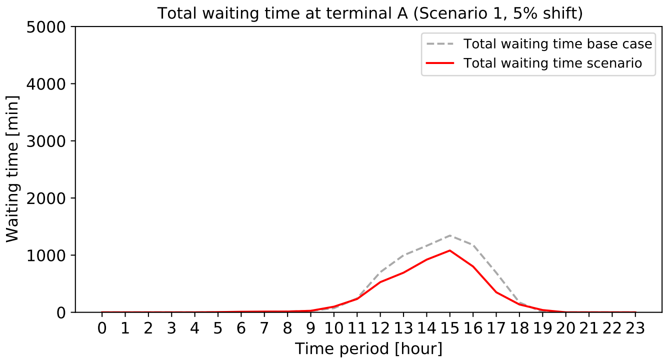
(b) Terminal B

(c) Terminal C

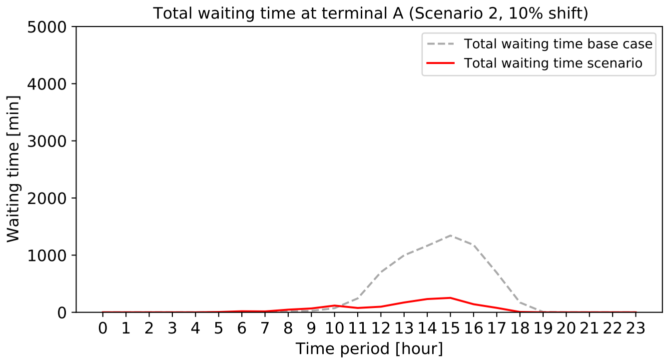
(d) Terminal D

Figure F.11: Trend of waiting time gains along the scenarios, in comparison with the reference scenario

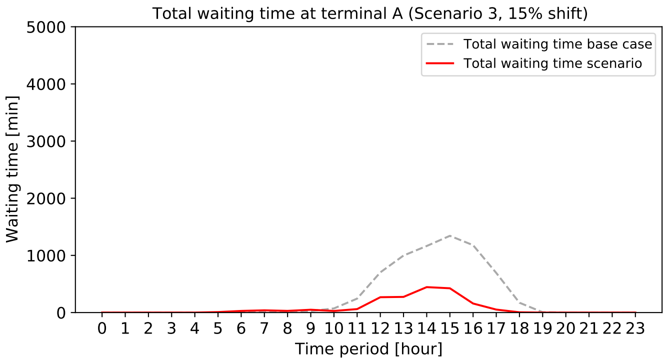
Terminal A: total waiting time



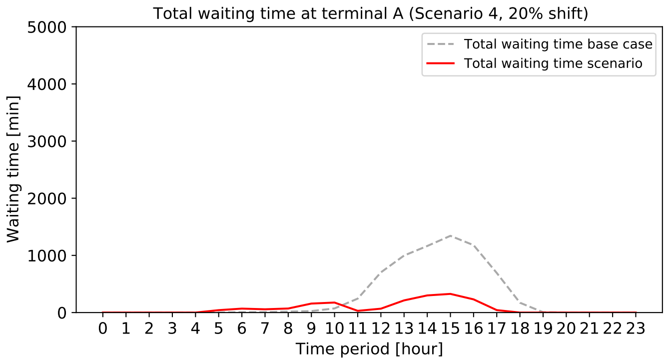
(a) Scenario 1, 5% application rate



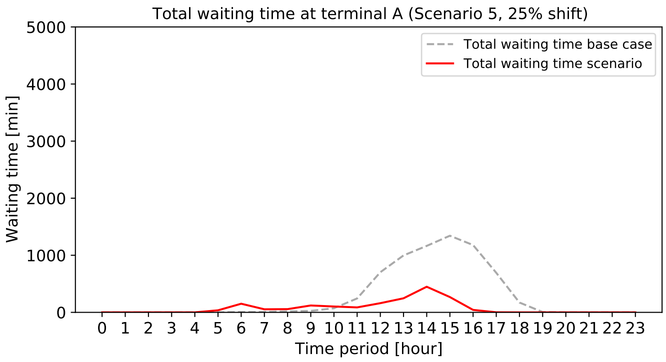
(b) Scenario 2, 10% application rate



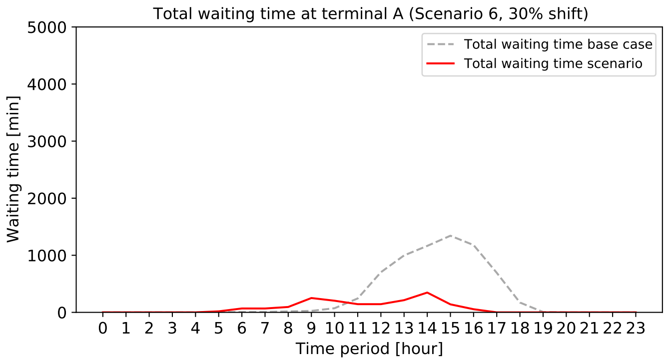
(c) Scenario 3, 15% application rate



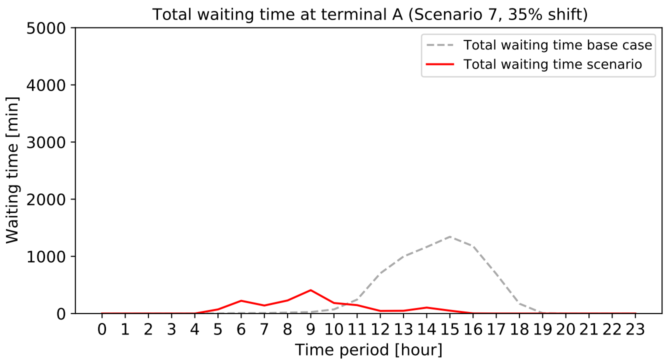
(d) Scenario 4, 20% application rate



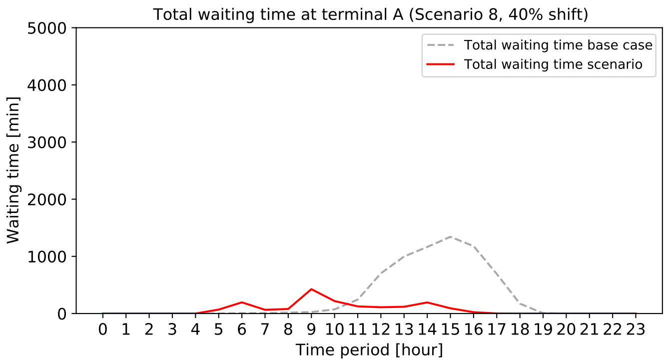
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

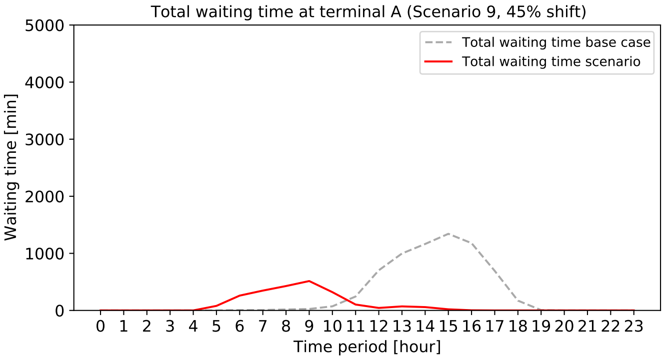


(g) Scenario 7, 35% application rate

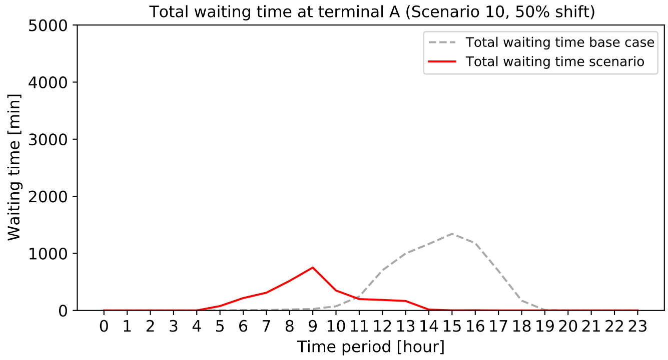


(h) Scenario 8, 40% application rate

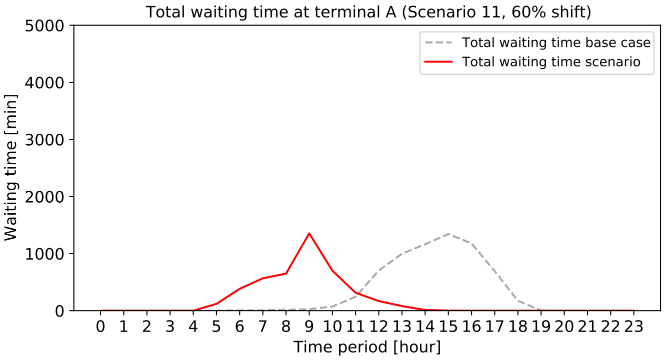
Figure F.12: Total waiting time at terminal A for each scenario, calculated with waiting time profile (Figure F.6) · arrival profile (Figure F.2)



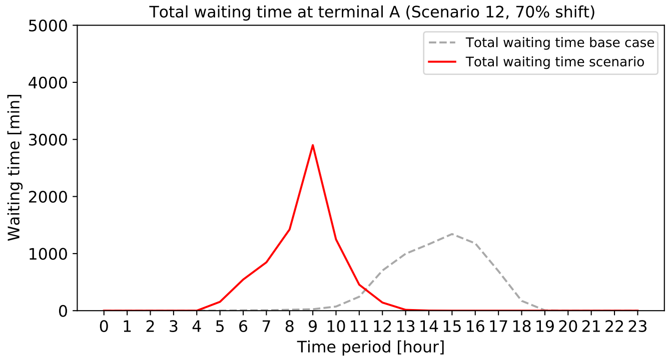
(i) Scenario 9, 45% application rate



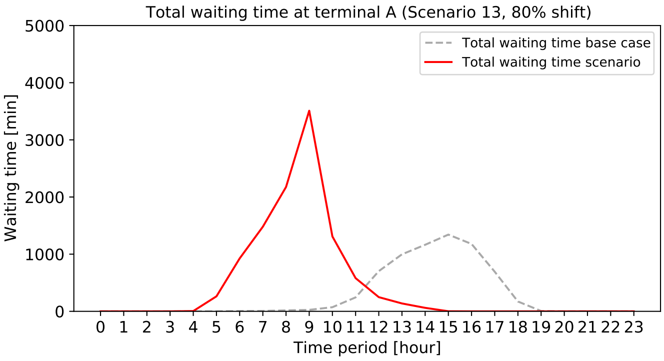
(j) Scenario 10, 50% application rate



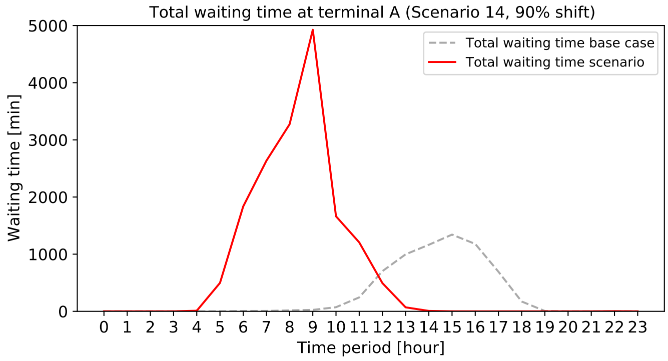
(k) Scenario 11, 60% application rate



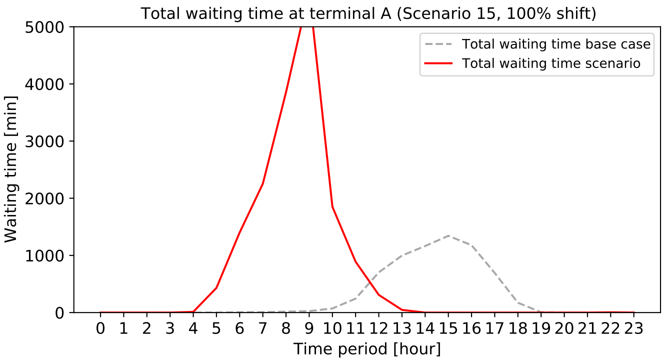
(l) Scenario 12, 70% application rate



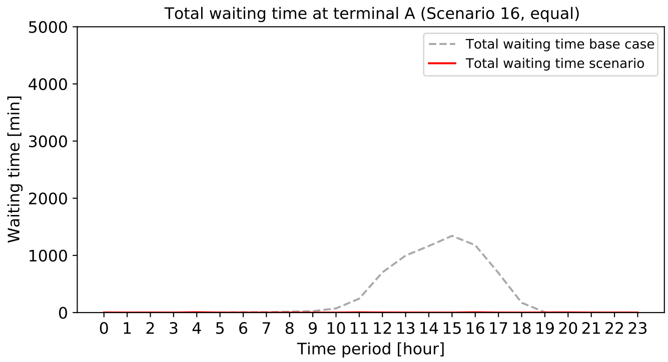
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



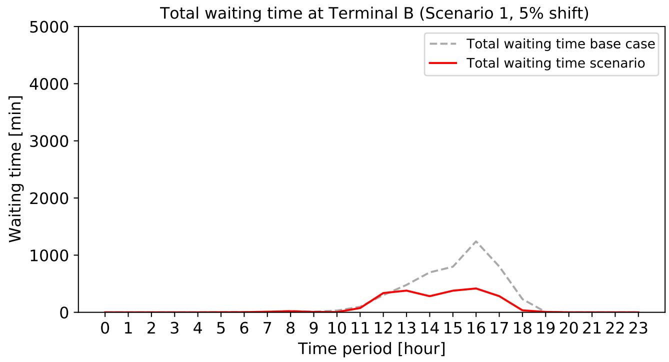
(o) Scenario 15, 100% application rate



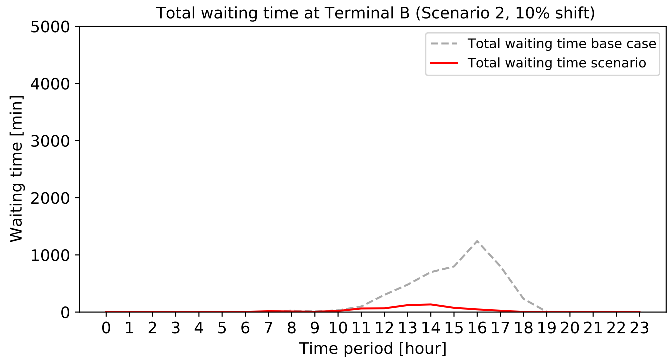
(p) Scenario 16, equal spread

Figure F.12: Total waiting time at terminal A for each scenario, calculated with waiting time profile (Figure F.6) · arrival profile (Figure F.2)

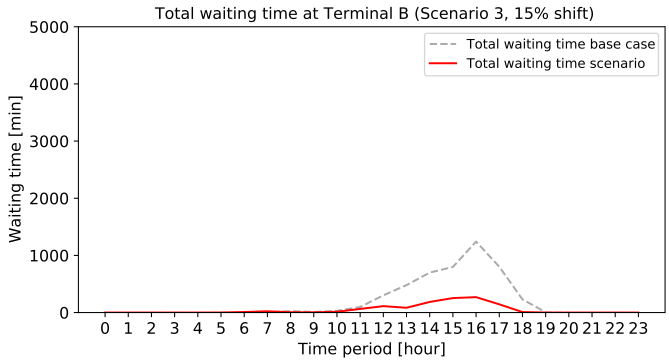
Terminal B: total waiting time



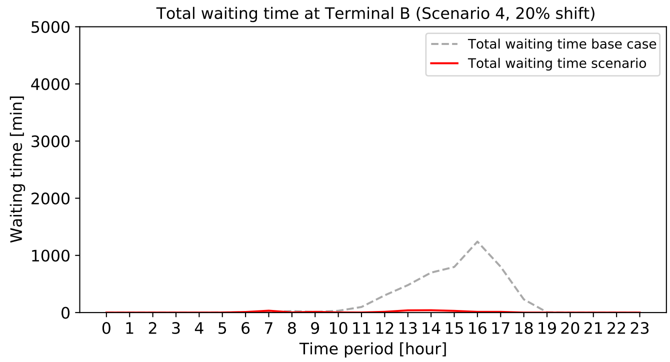
(a) Scenario 1, 5% application rate



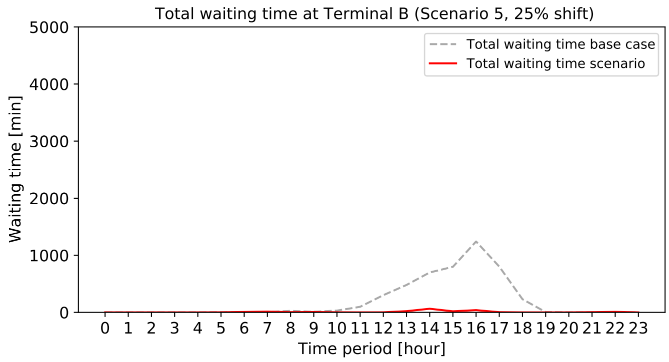
(b) Scenario 2, 10% application rate



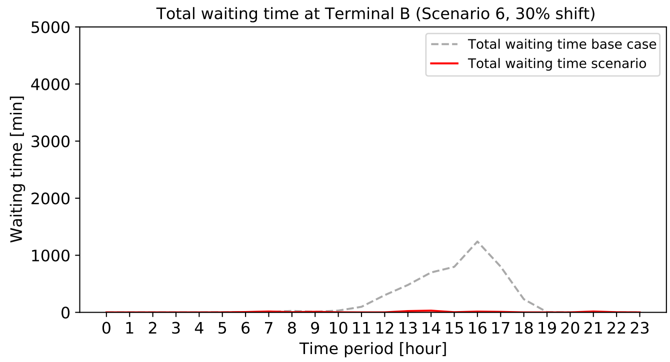
(c) Scenario 3, 15% application rate



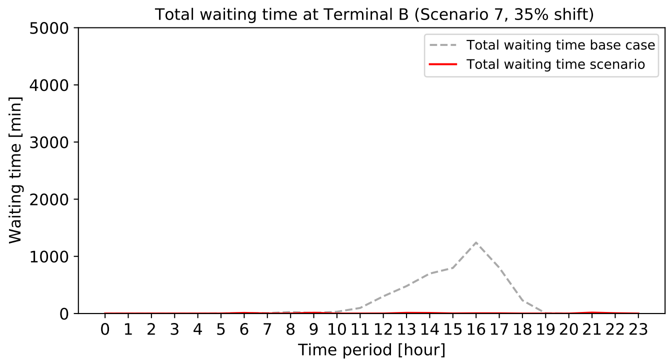
(d) Scenario 4, 20% application rate



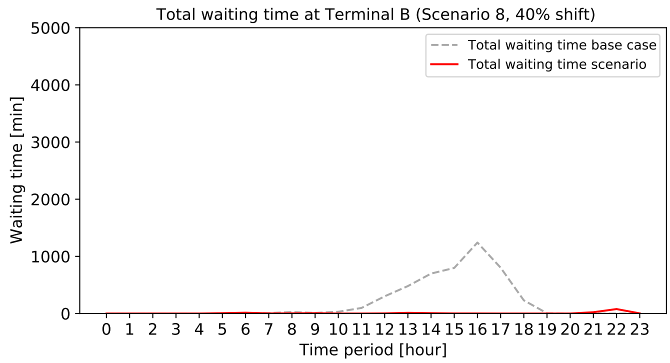
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

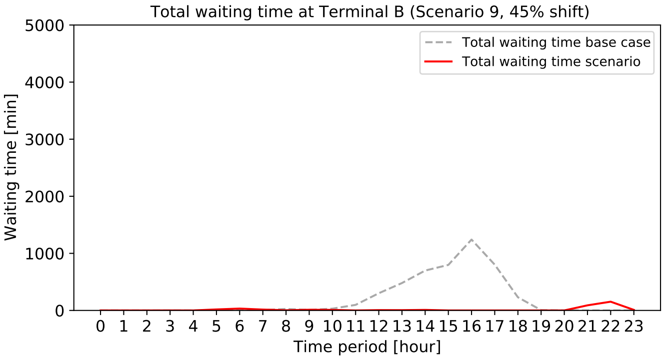


(g) Scenario 7, 35% application rate

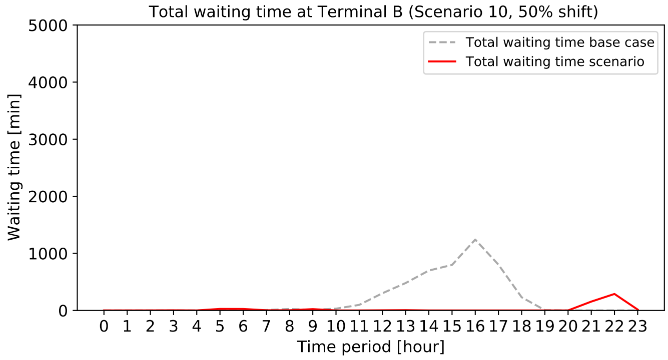


(h) Scenario 8, 40% application rate

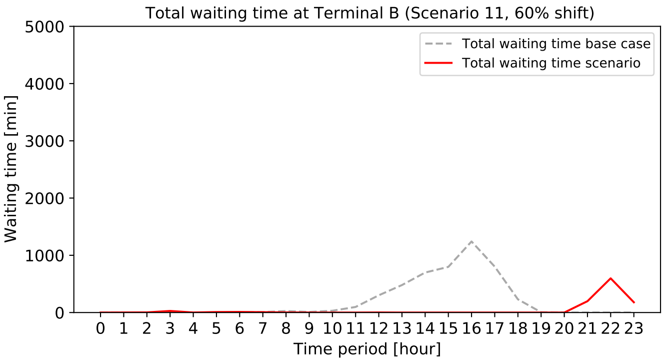
Figure F.13: Total waiting time at terminal B for each scenario, calculated with waiting time profile (Figure F.7) · arrival profile (Figure F.3)



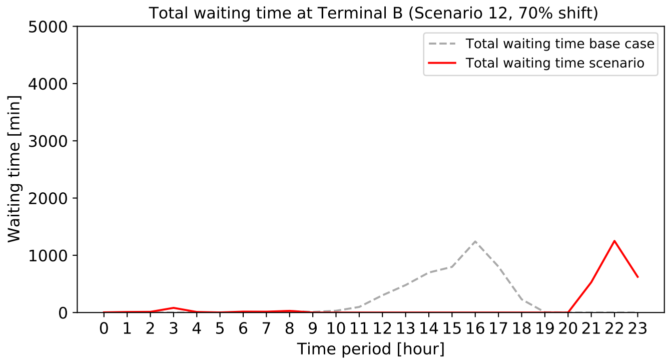
(i) Scenario 9, 45% application rate



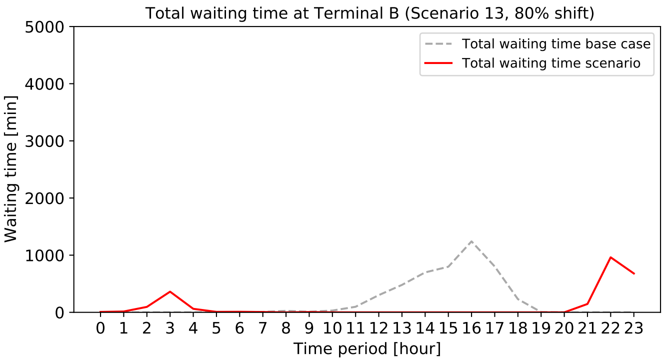
(j) Scenario 10, 50% application rate



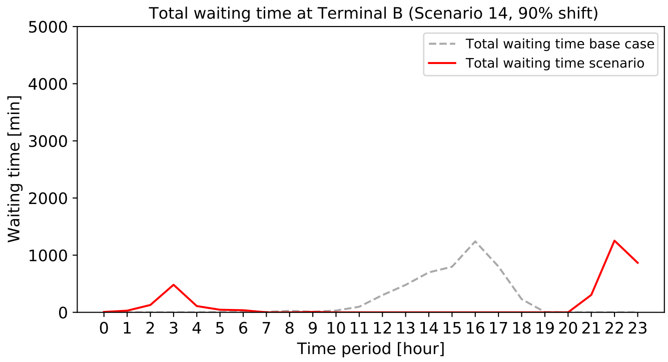
(k) Scenario 11, 60% application rate



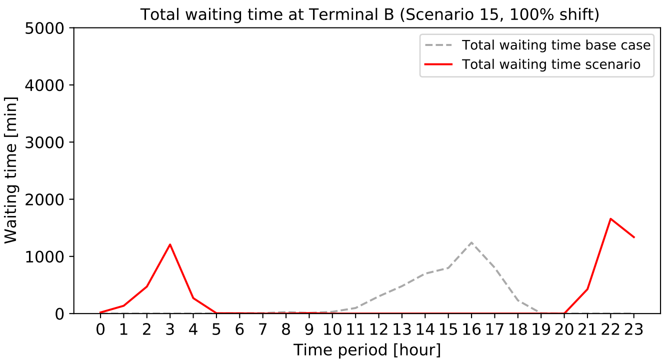
(l) Scenario 12, 70% application rate



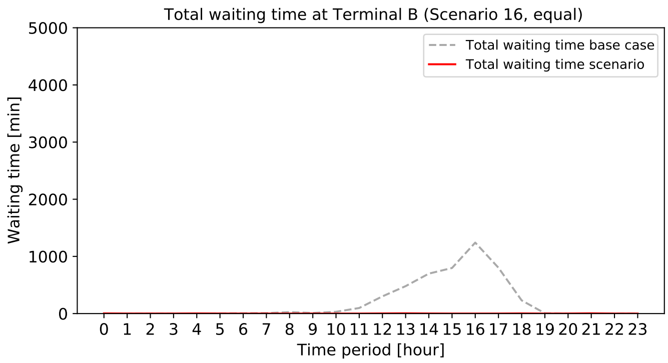
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



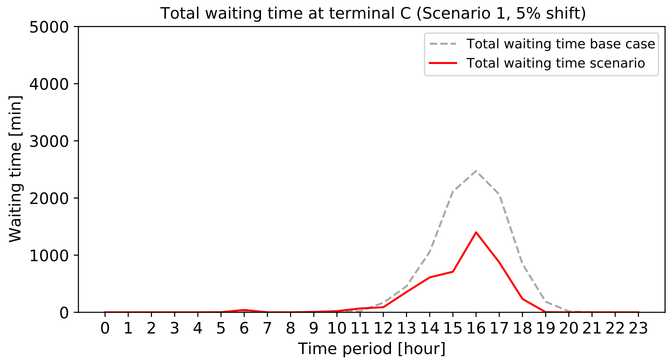
(o) Scenario 15, 100% application rate



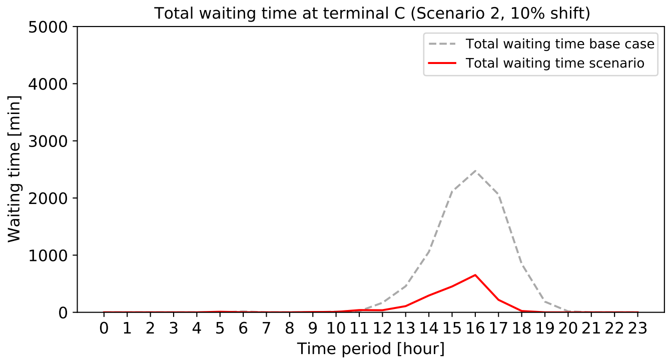
(p) Scenario 16, equal spread

Figure F.13: Total waiting time at terminal B for each scenario, calculated with waiting time profile (Figure F.7) · arrival profile (Figure F.3)

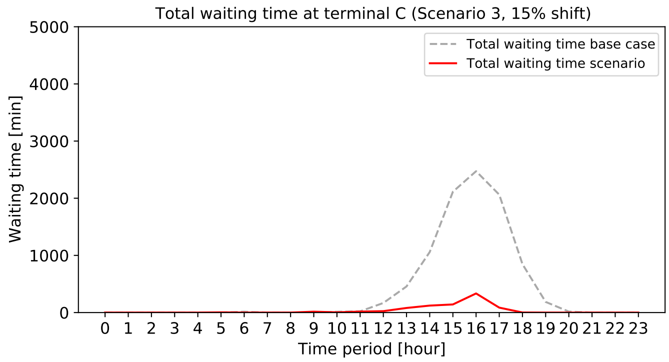
Terminal C: total waiting time



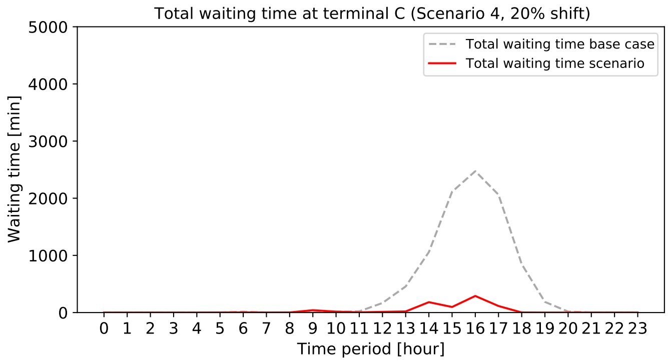
(a) Scenario 1, 5% application rate



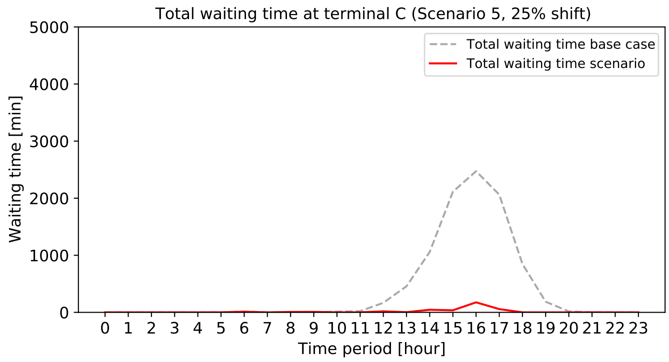
(b) Scenario 2, 10% application rate



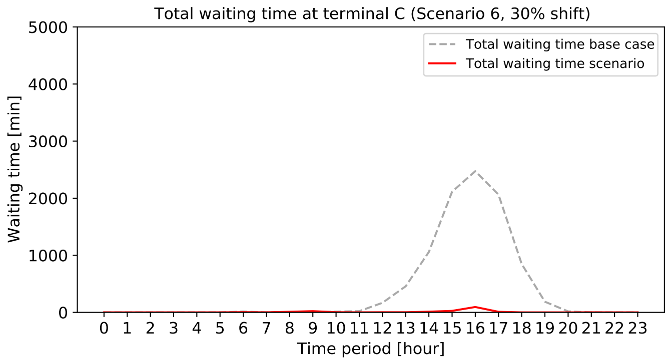
(c) Scenario 3, 15% application rate



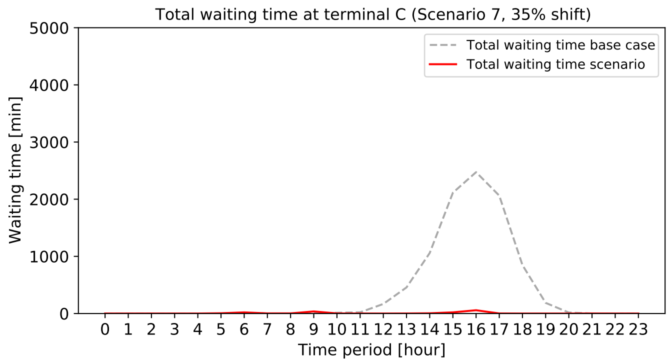
(d) Scenario 4, 20% application rate



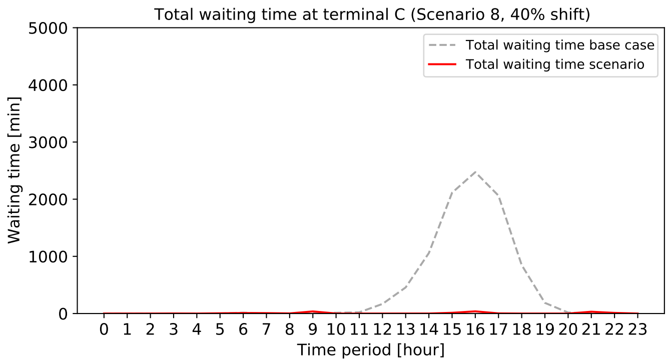
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

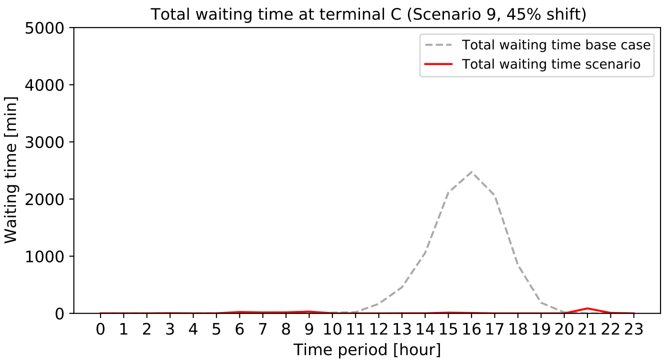


(g) Scenario 7, 35% application rate

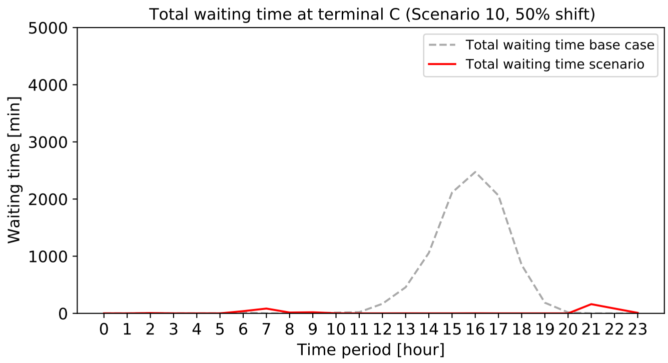


(h) Scenario 8, 40% application rate

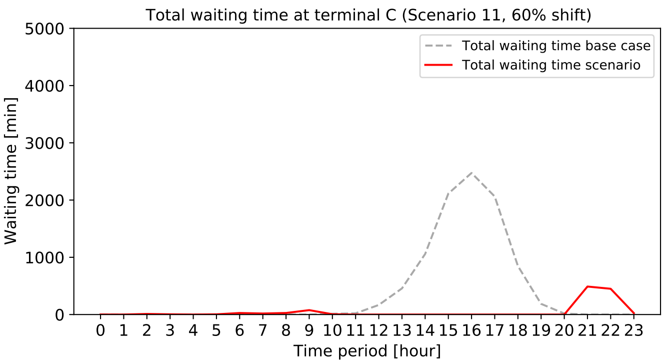
Figure F.14: Total waiting time at terminal C for each scenario, calculated with waiting time profile (Figure F.8) · arrival profile (Figure F.4)



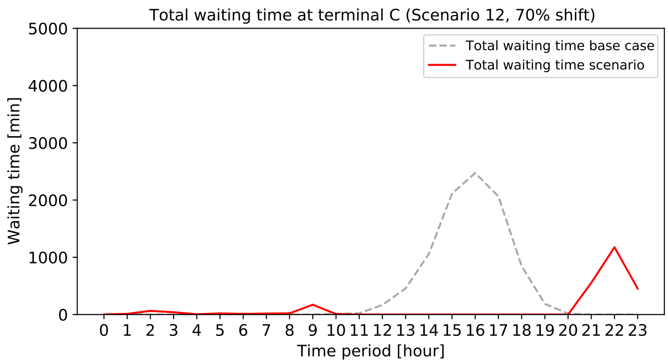
(i) Scenario 9, 45% application rate



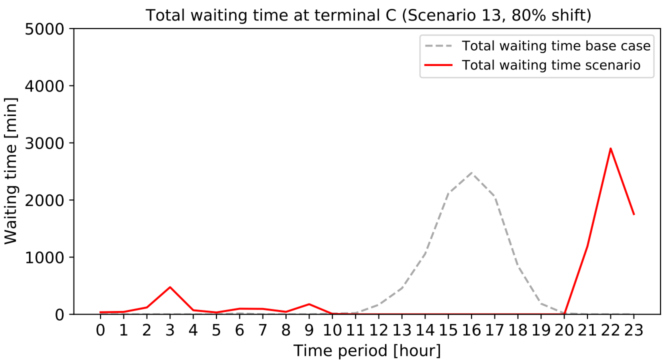
(j) Scenario 10, 50% application rate



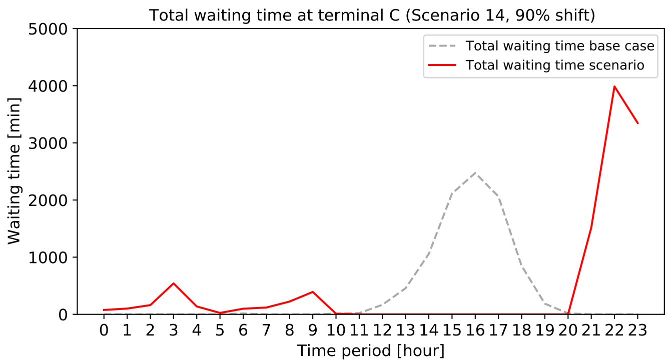
(k) Scenario 11, 60% application rate



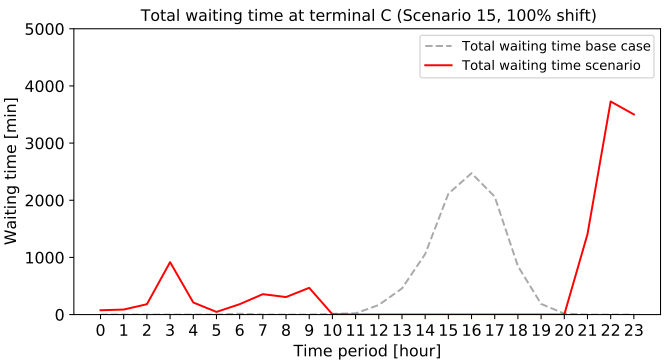
(l) Scenario 12, 70% application rate



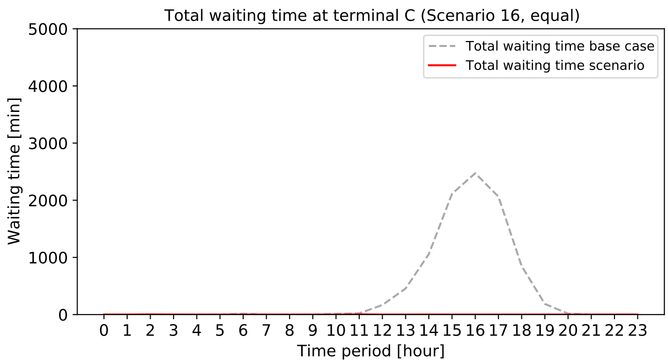
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



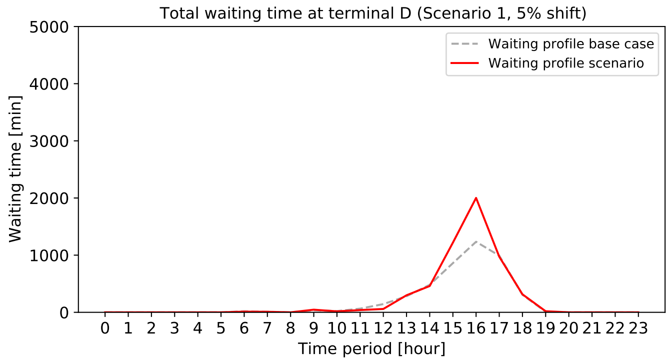
(o) Scenario 15, 100% application rate



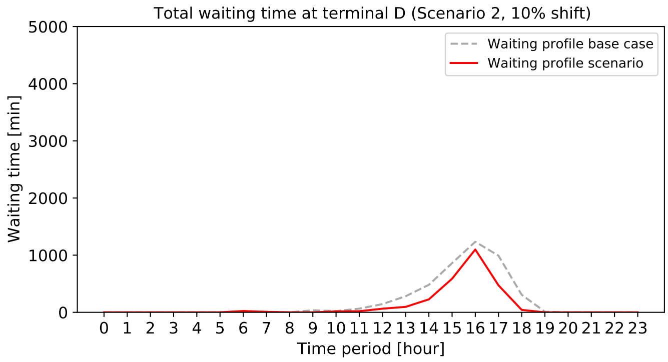
(p) Scenario 16, equal spread

Figure F.14: Total waiting time at terminal C for each scenario, calculated with waiting time profile (Figure F.8) · arrival profile (Figure F.4)

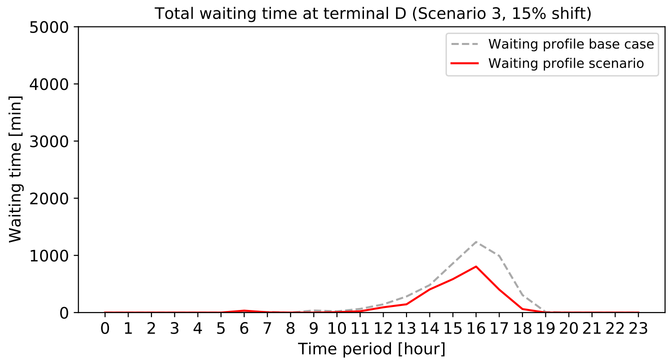
Terminal D: total waiting time



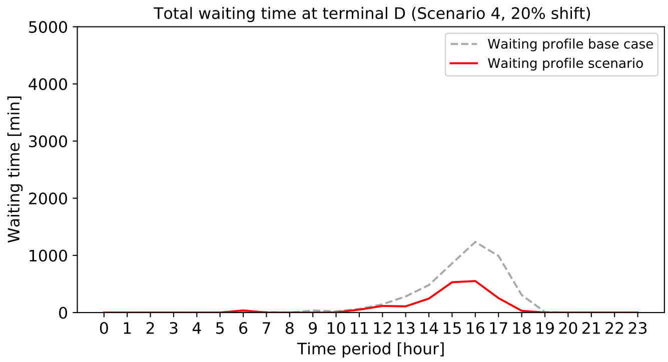
(a) Scenario 1, 5% application rate



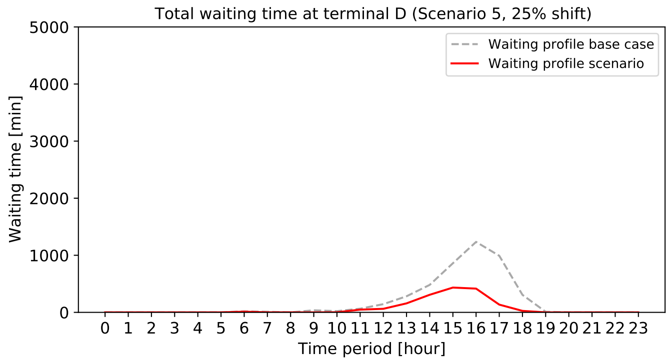
(b) Scenario 2, 10% application rate



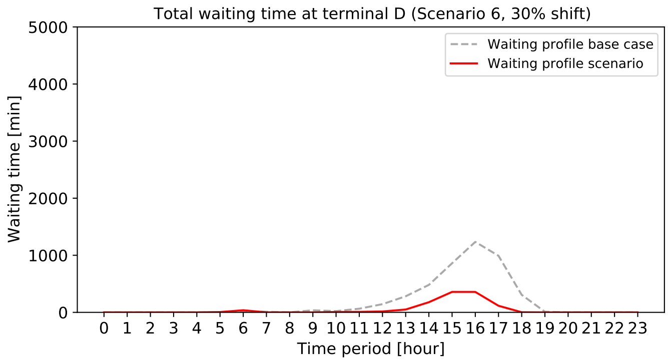
(c) Scenario 3, 15% application rate



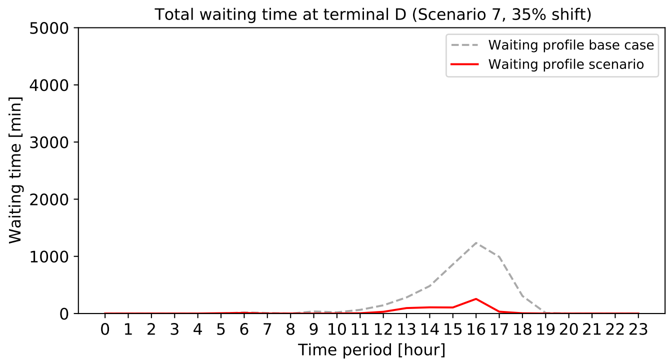
(d) Scenario 4, 20% application rate



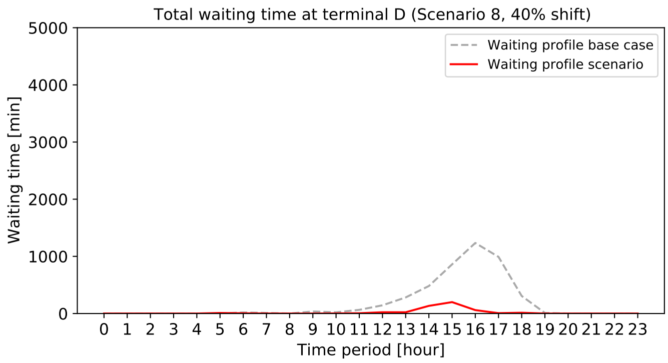
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

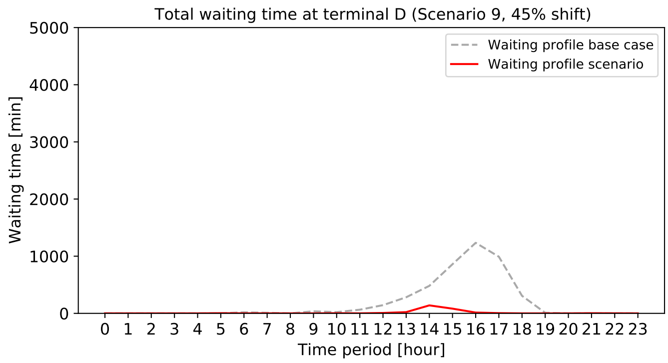


(g) Scenario 7, 35% application rate

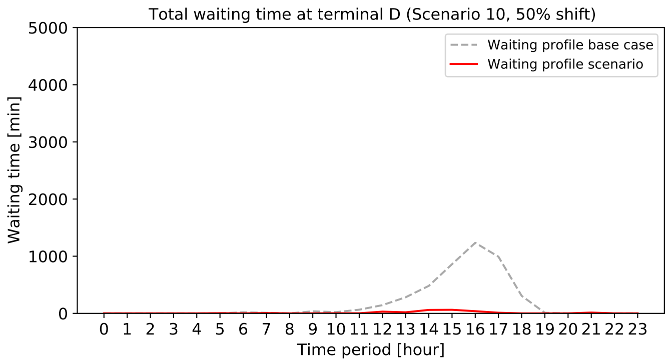


(h) Scenario 8, 40% application rate

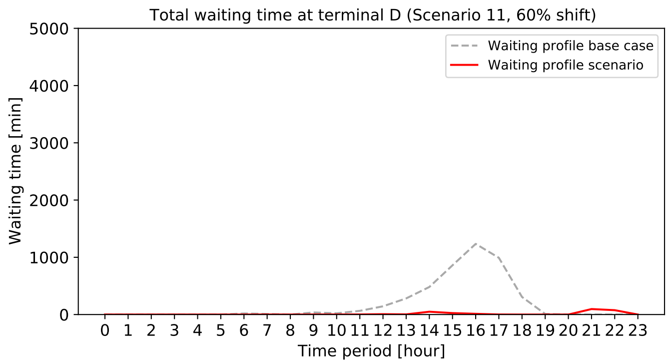
Figure F.15: Total waiting time at terminal D for each scenario, calculated with waiting time profile (Figure F.9) · arrival profile (Figure F.5)



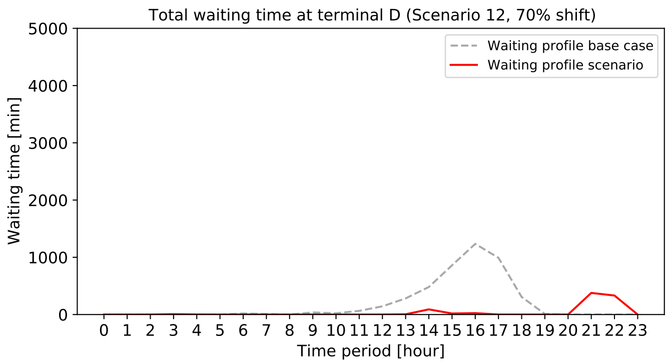
(i) Scenario 9, 45% application rate



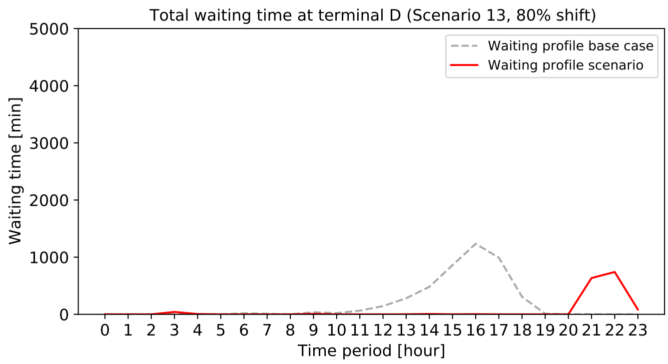
(j) Scenario 10, 50% application rate



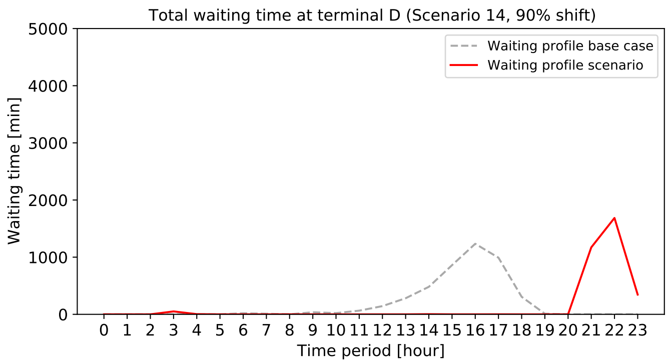
(k) Scenario 11, 60% application rate



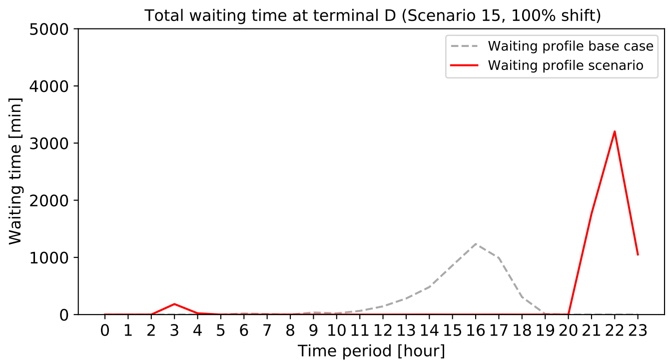
(l) Scenario 12, 70% application rate



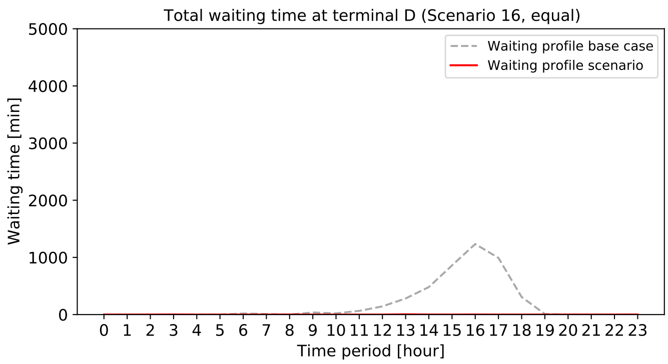
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



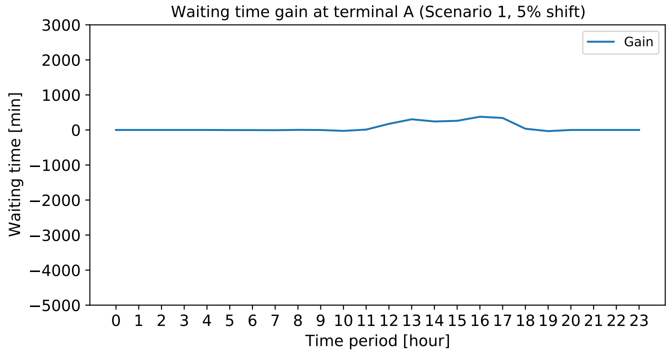
(o) Scenario 15, 100% application rate



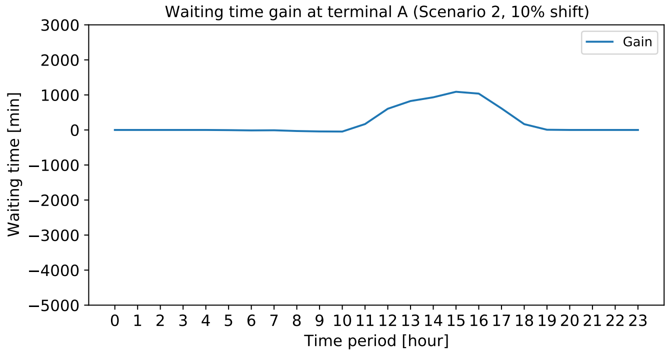
(p) Scenario 16, equal spread

Figure F.15: Total waiting time at terminal D for each scenario, calculated with waiting time profile (Figure F.9) · arrival profile (Figure F.5)

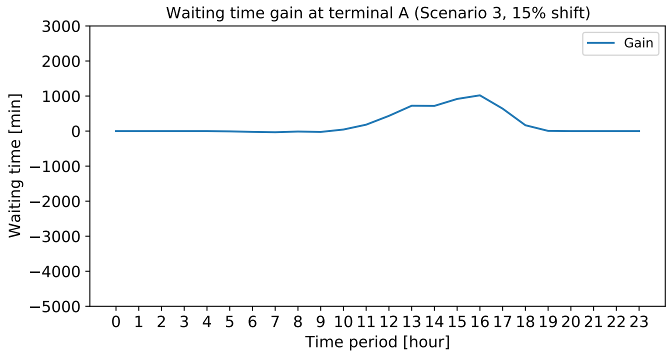
Terminal A: waiting time gain



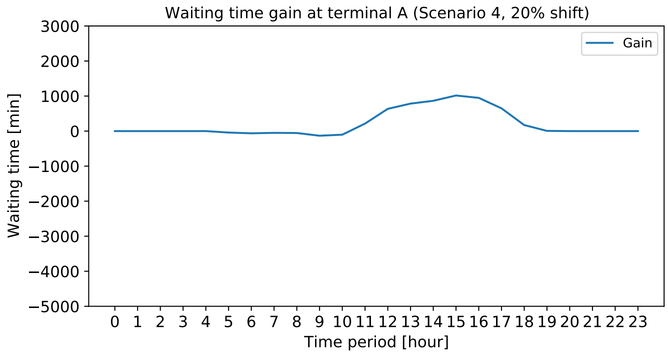
(a) Scenario 1, 5% application rate



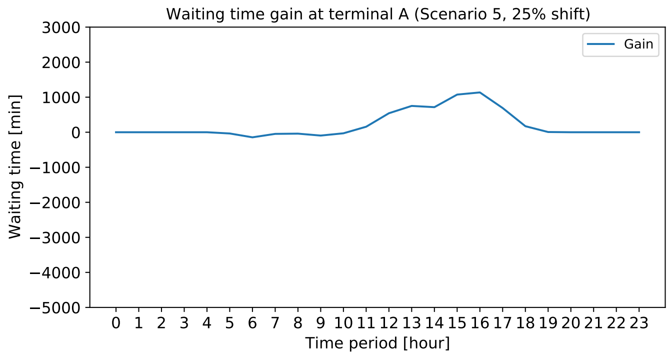
(b) Scenario 2, 10% application rate



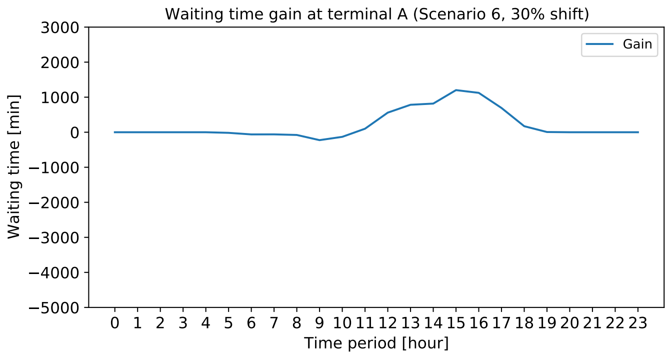
(c) Scenario 3, 15% application rate



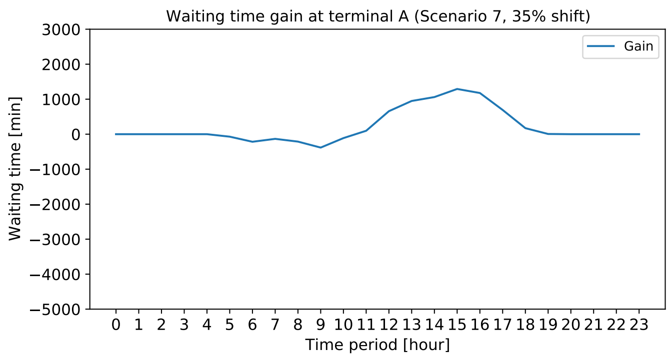
(d) Scenario 4, 20% application rate



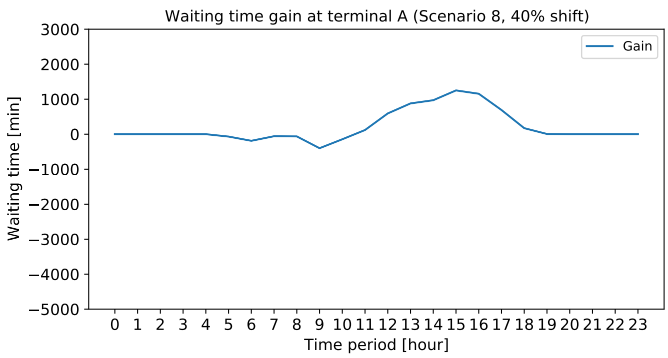
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

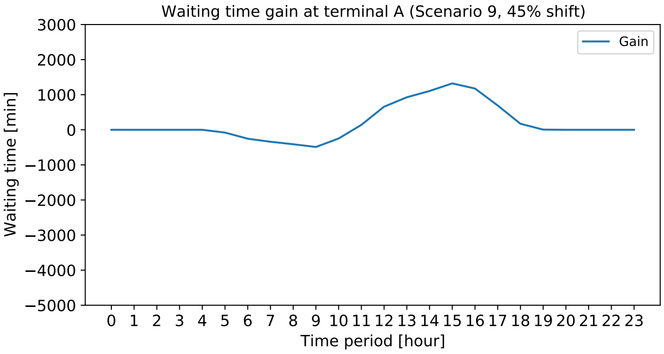


(g) Scenario 7, 35% application rate

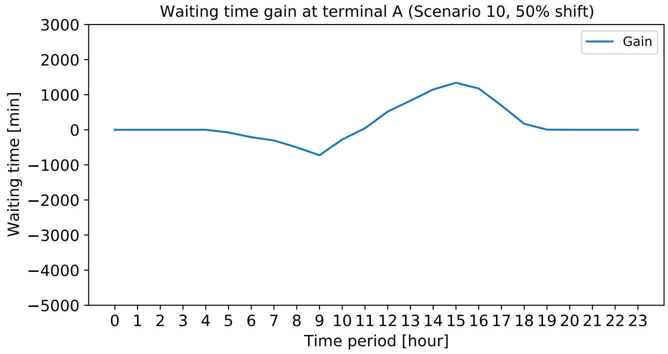


(h) Scenario 8, 40% application rate

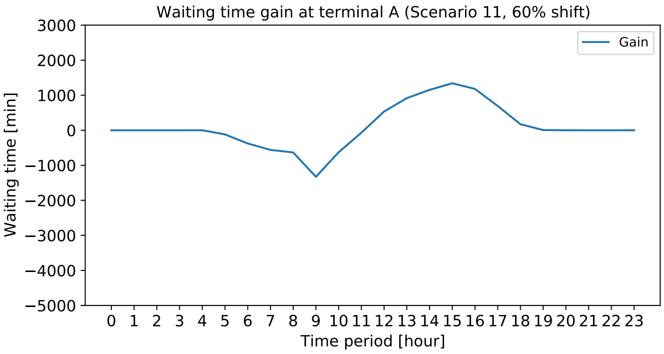
Figure F.16: Waiting time gain along the day at terminal A for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case



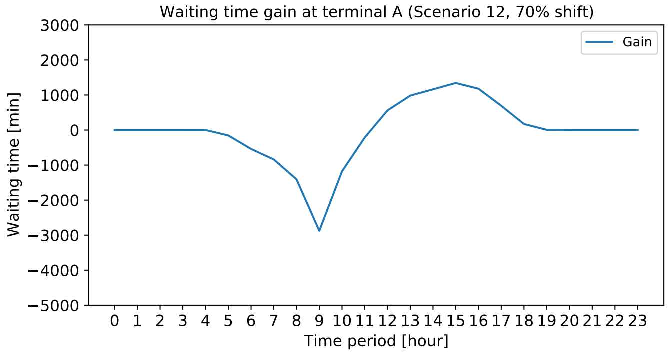
(i) Scenario 9, 45% application rate



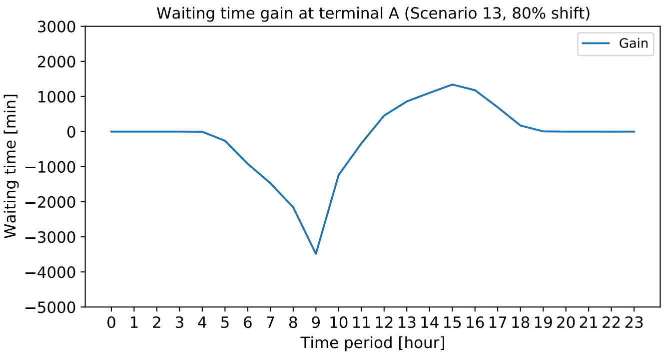
(j) Scenario 10, 50% application rate



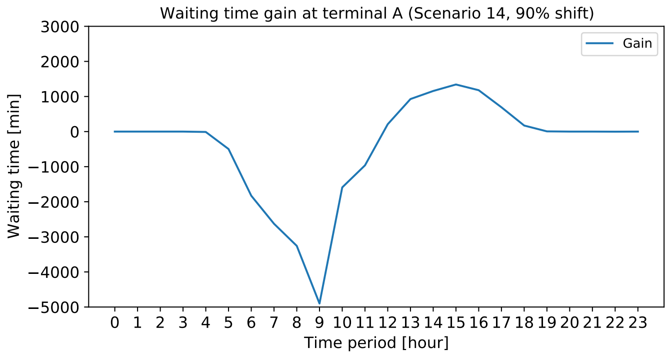
(k) Scenario 11, 60% application rate



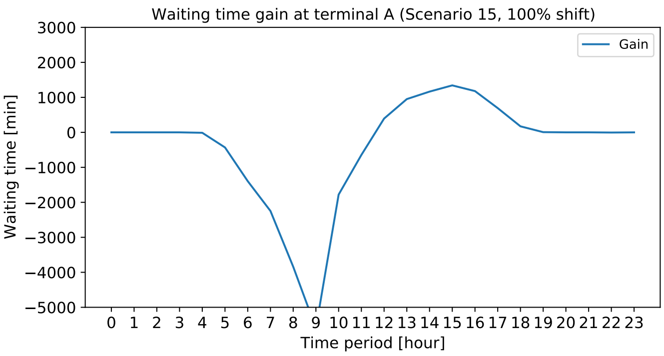
(l) Scenario 12, 70% application rate



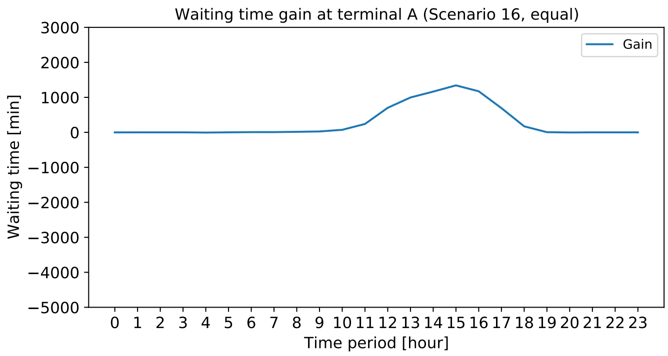
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



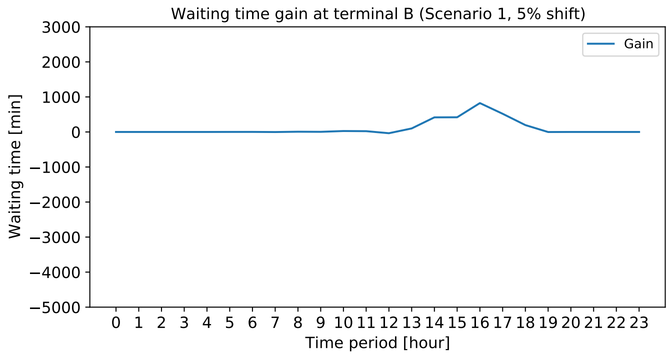
(o) Scenario 15, 100% application rate



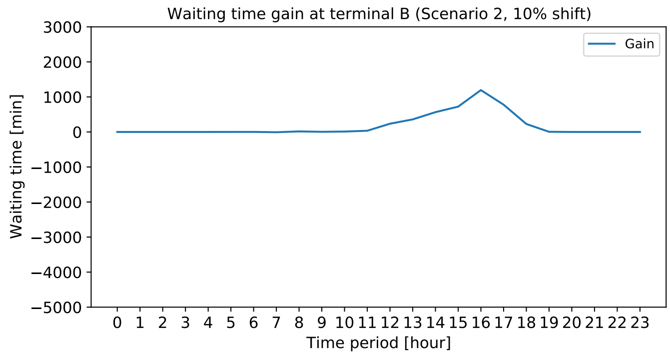
(p) Scenario 16, equal spread

Figure F.16: Waiting time gain along the day at terminal A for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case

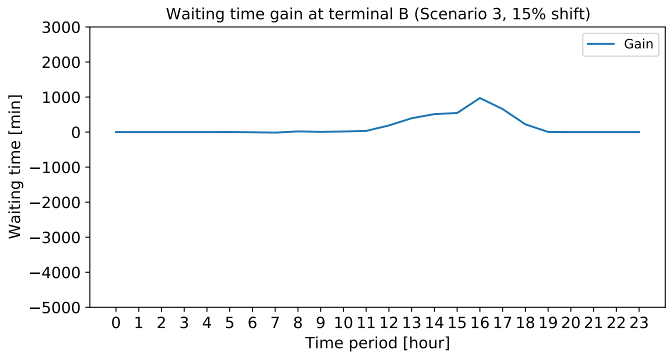
Terminal B: waiting time gain



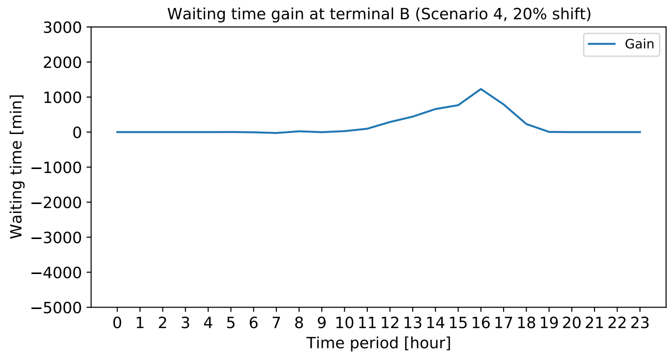
(a) Scenario 1, 5% application rate



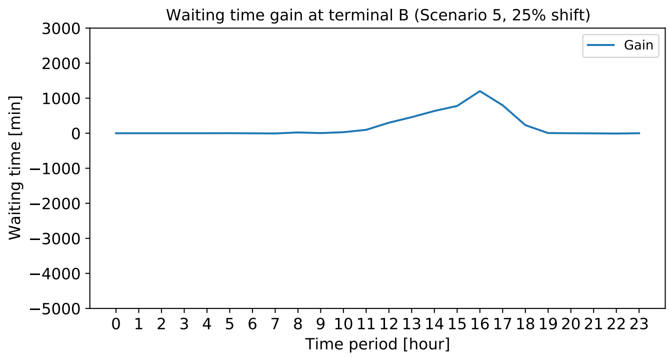
(b) Scenario 2, 10% application rate



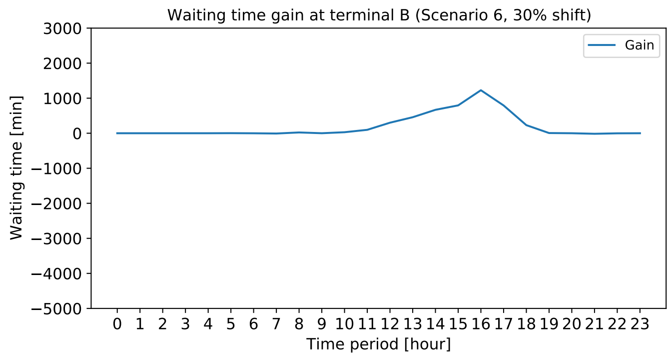
(c) Scenario 3, 15% application rate



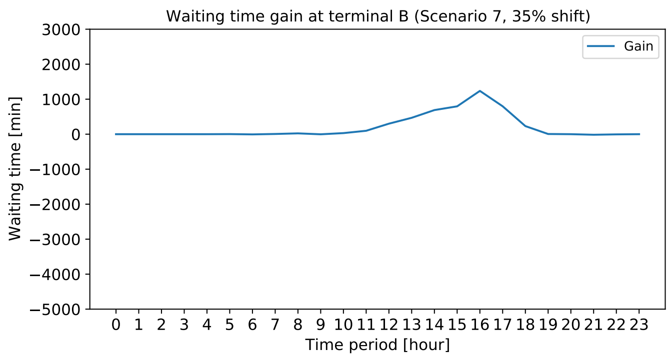
(d) Scenario 4, 20% application rate



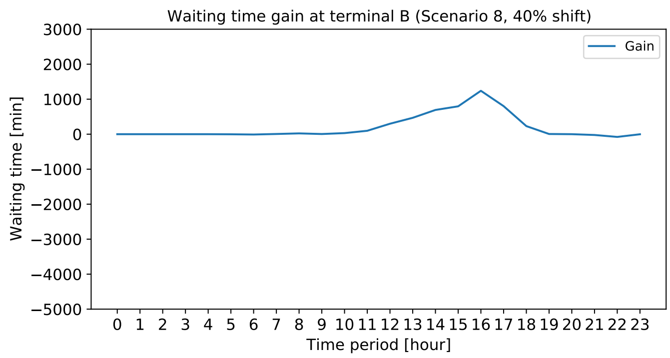
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

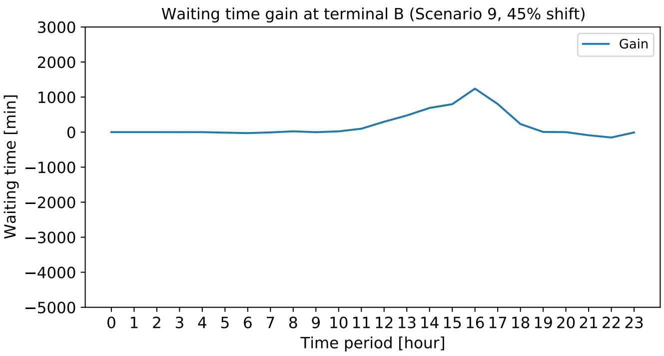


(g) Scenario 7, 35% application rate

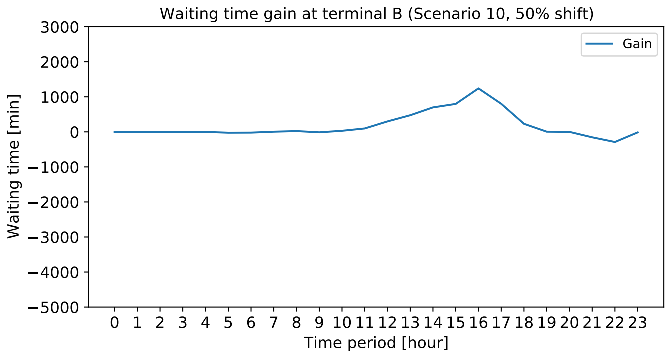


(h) Scenario 8, 40% application rate

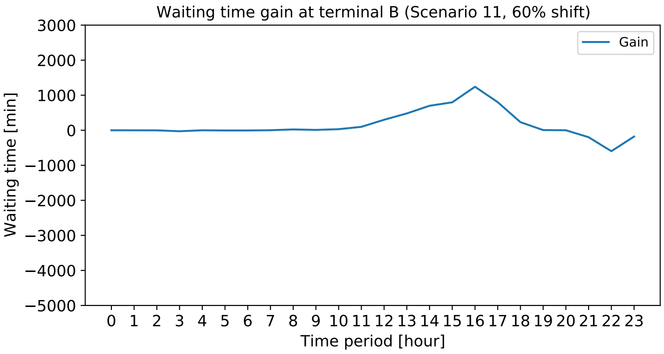
Figure F.17: Waiting time gain along the day at terminal B for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case



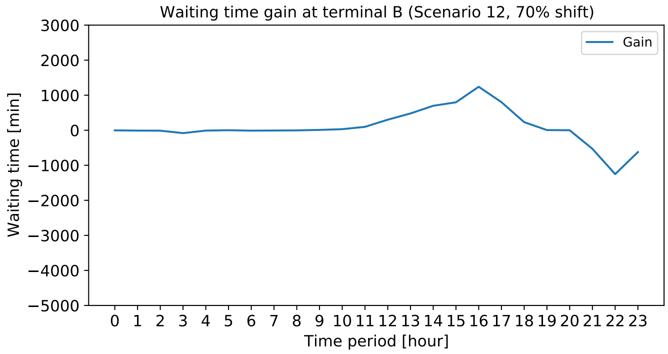
(i) Scenario 9, 45% application rate



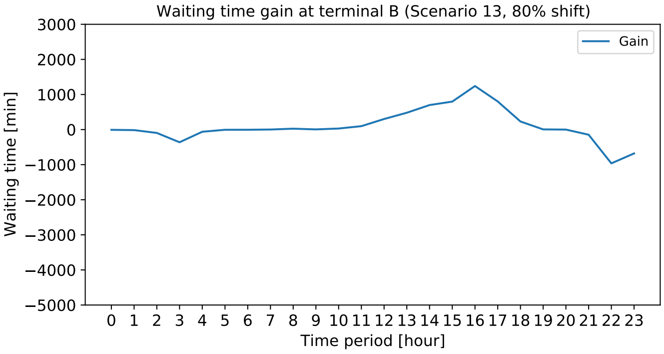
(j) Scenario 10, 50% application rate



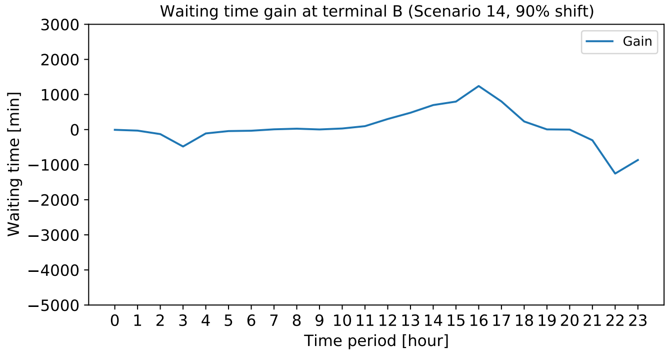
(k) Scenario 11, 60% application rate



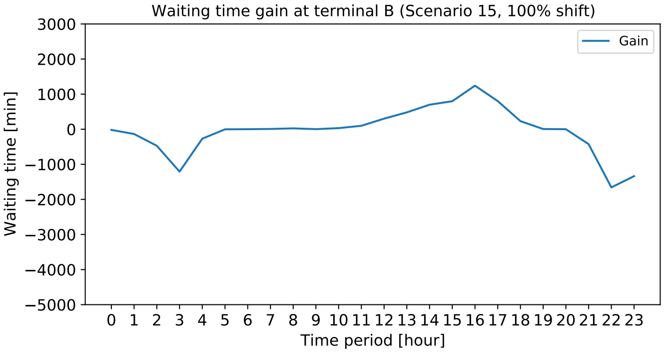
(l) Scenario 12, 70% application rate



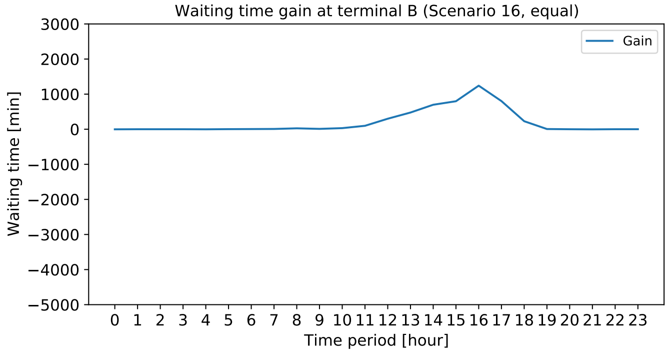
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



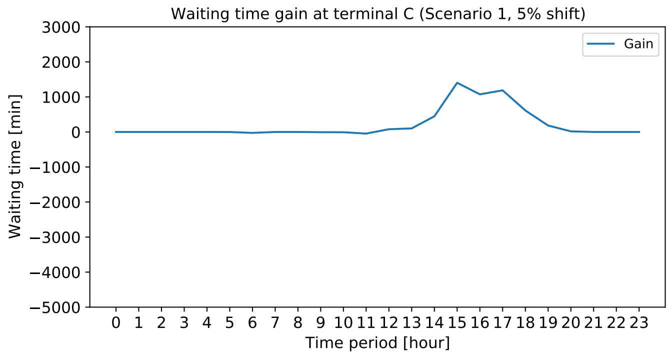
(o) Scenario 15, 100% application rate



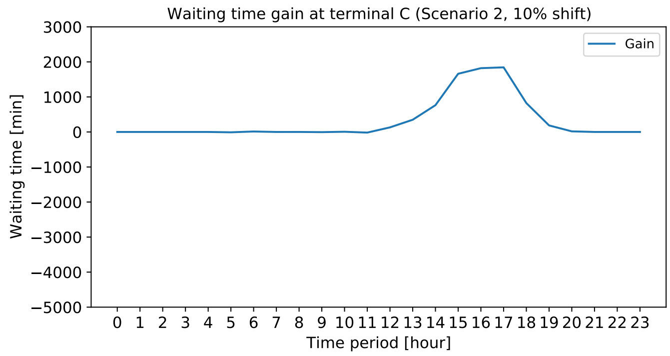
(p) Scenario 16, equal spread

Figure F.17: Waiting time gain along the day at terminal B for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case

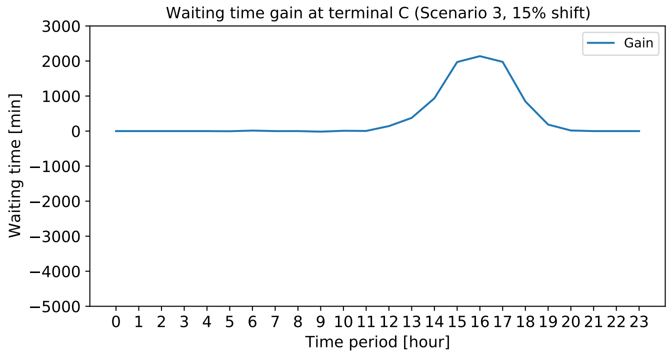
Terminal C: waiting time gain



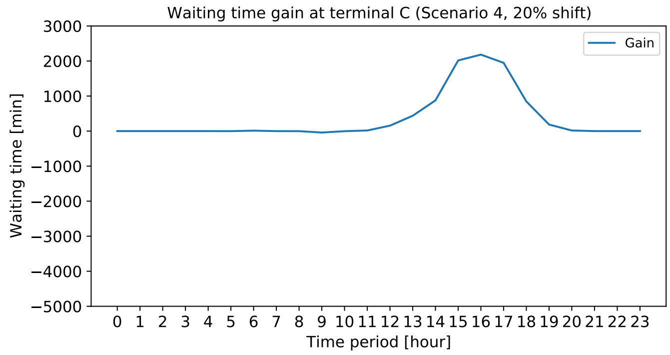
(a) Scenario 1, 5% application rate



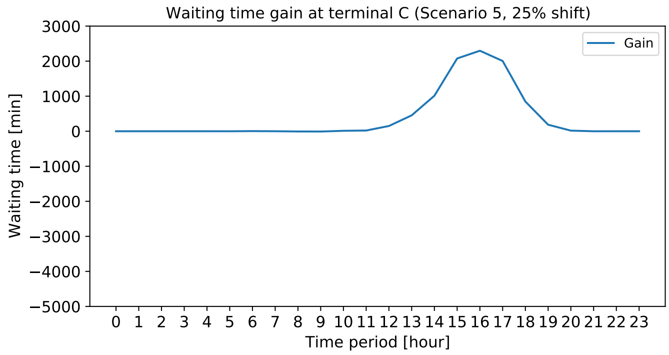
(b) Scenario 2, 10% application rate



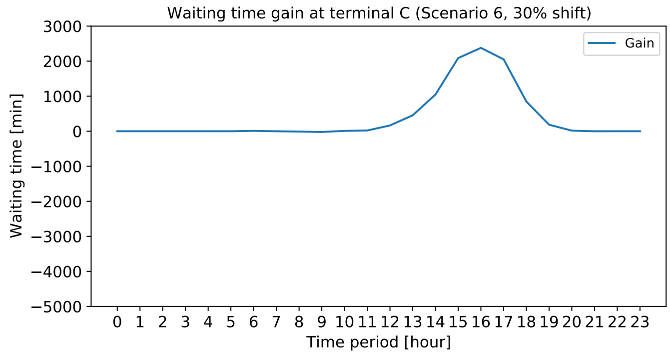
(c) Scenario 3, 15% application rate



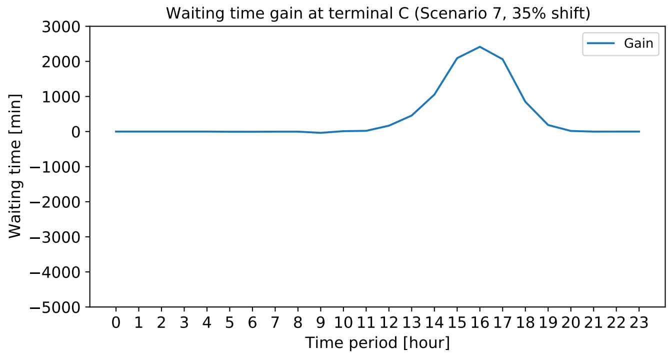
(d) Scenario 4, 20% application rate



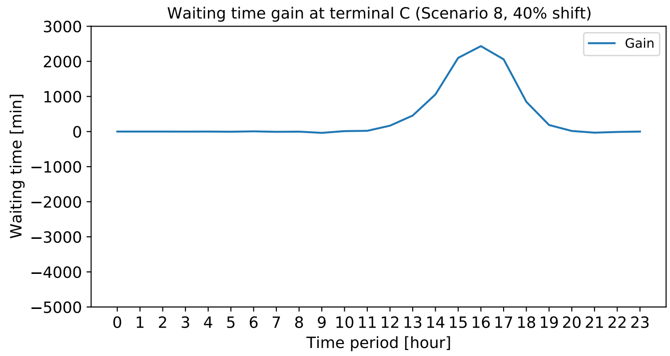
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

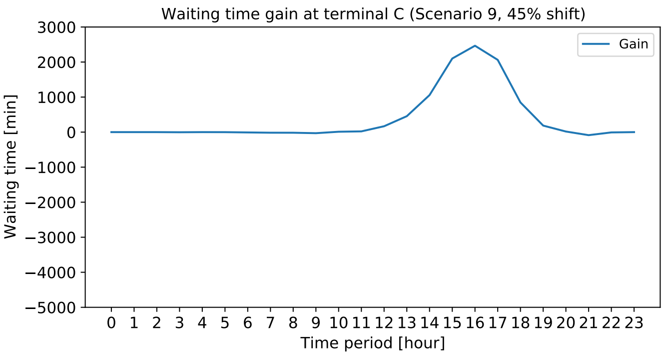


(g) Scenario 7, 35% application rate

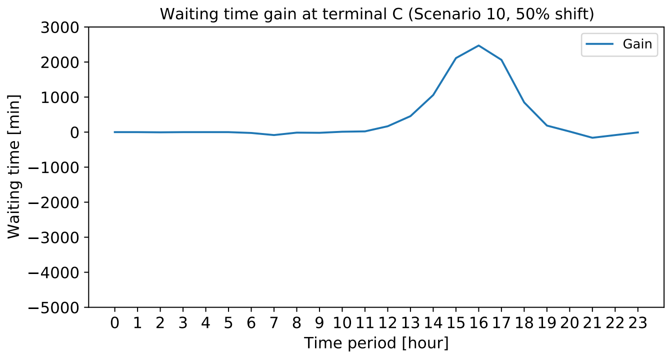


(h) Scenario 8, 40% application rate

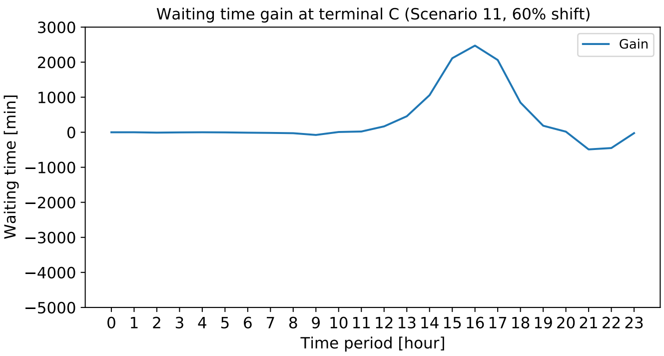
Figure F.18: Waiting time gain along the day at terminal C for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case



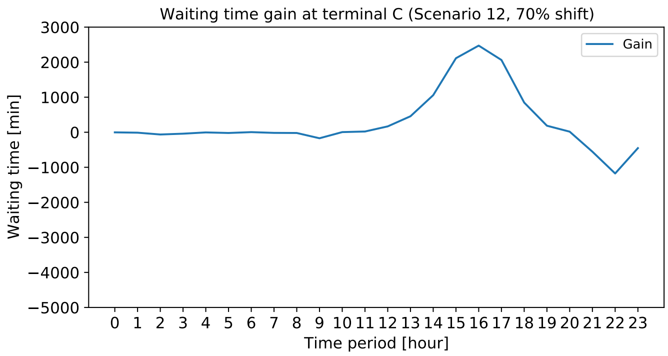
(i) Scenario 9, 45% application rate



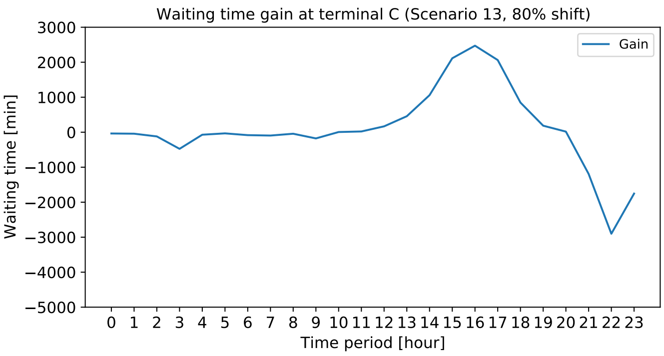
(j) Scenario 10, 50% application rate



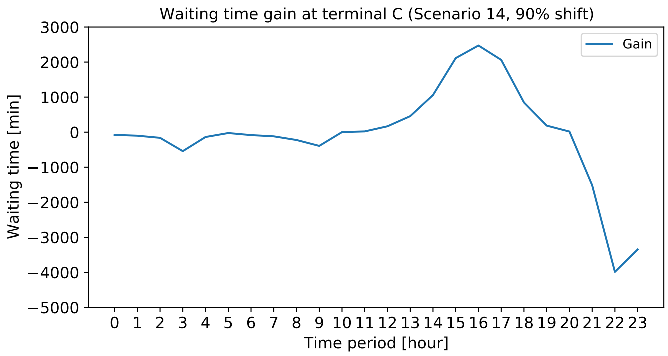
(k) Scenario 11, 60% application rate



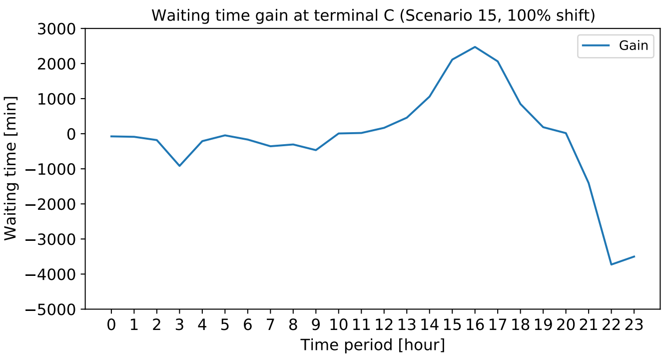
(l) Scenario 12, 70% application rate



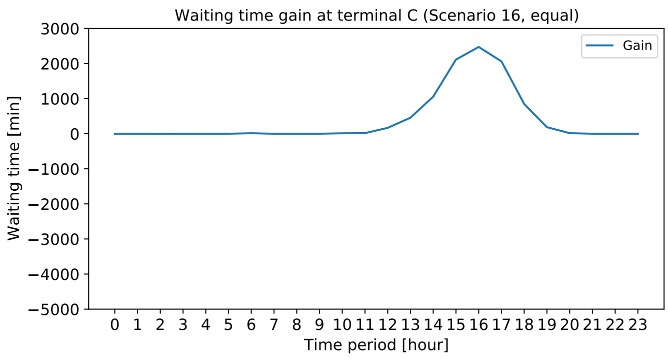
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



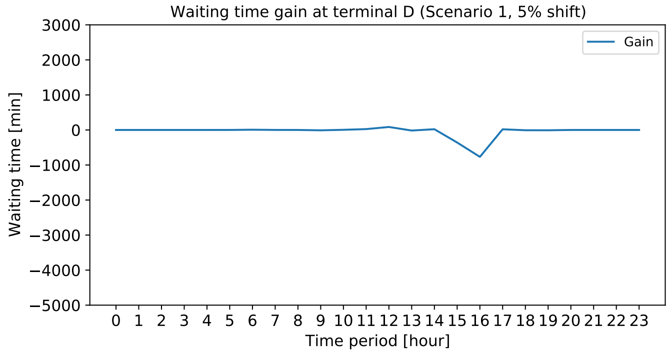
(o) Scenario 15, 100% application rate



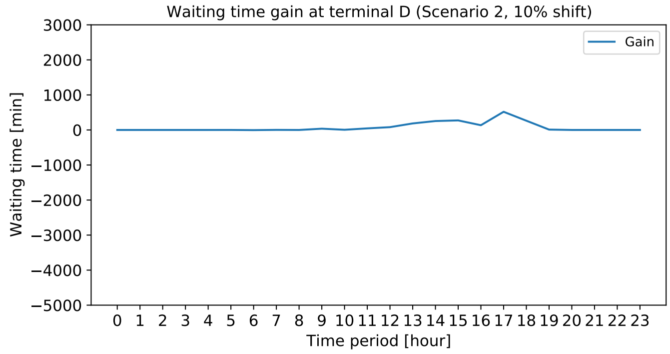
(p) Scenario 16, equal spread

Figure F.18: Waiting time gain along the day at terminal C for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case

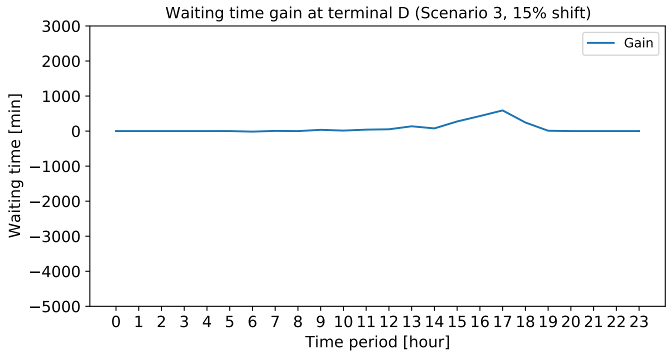
Terminal D: waiting time gain



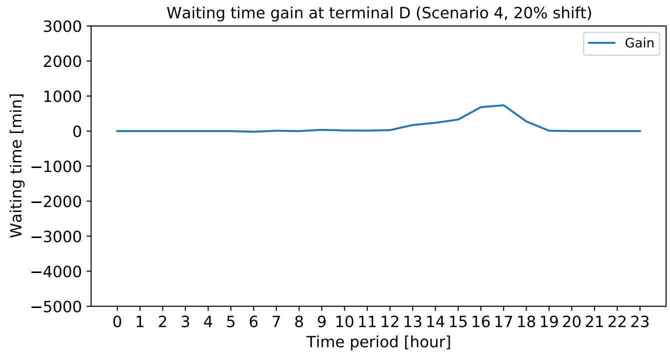
(a) Scenario 1, 5% application rate



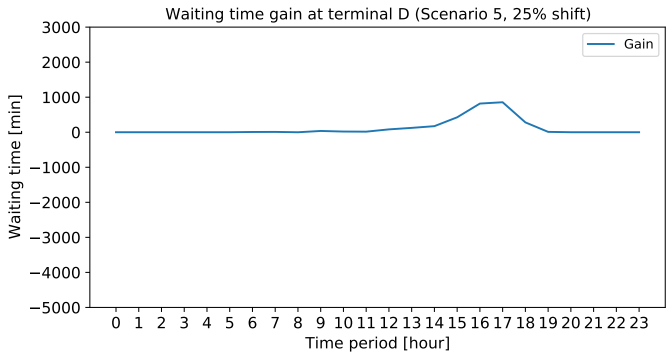
(b) Scenario 2, 10% application rate



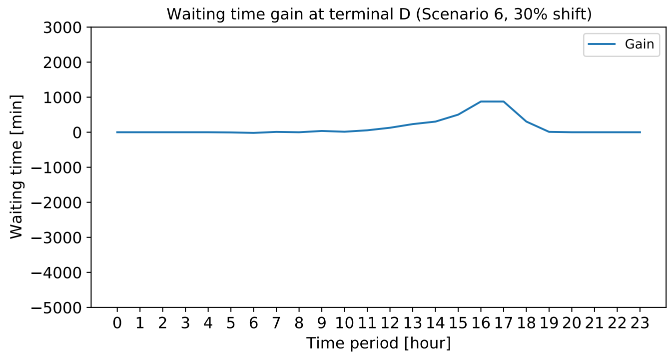
(c) Scenario 3, 15% application rate



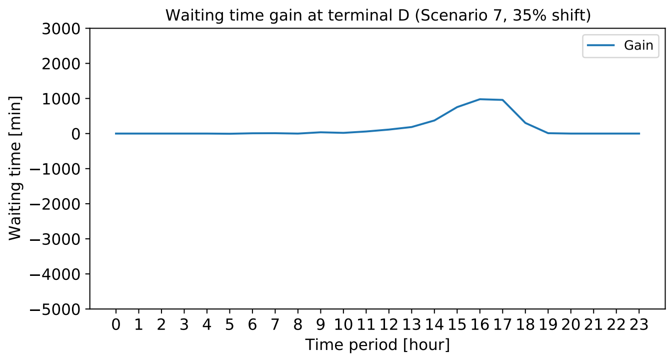
(d) Scenario 4, 20% application rate



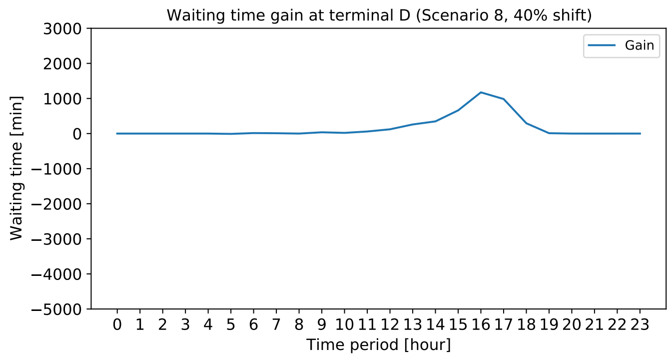
(e) Scenario 5, 25% application rate



(f) Scenario 6, 30% application rate

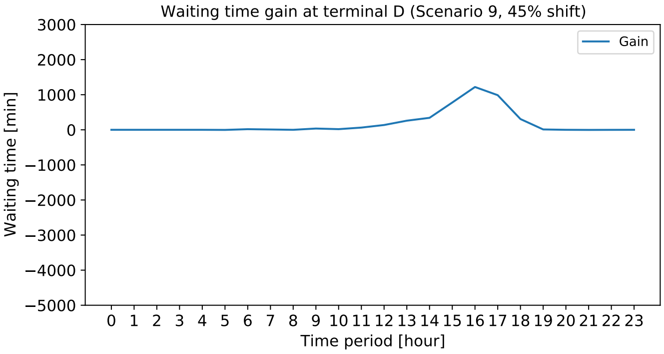


(g) Scenario 7, 35% application rate

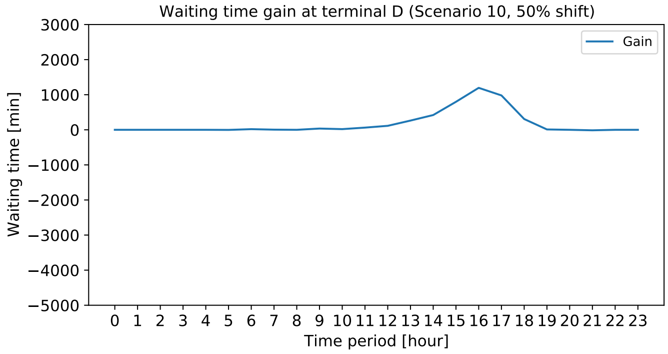


(h) Scenario 8, 40% application rate

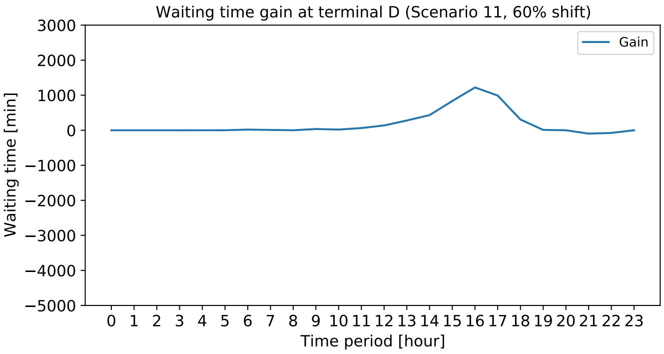
Figure F.19: Waiting time gain along the day at terminal D for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case



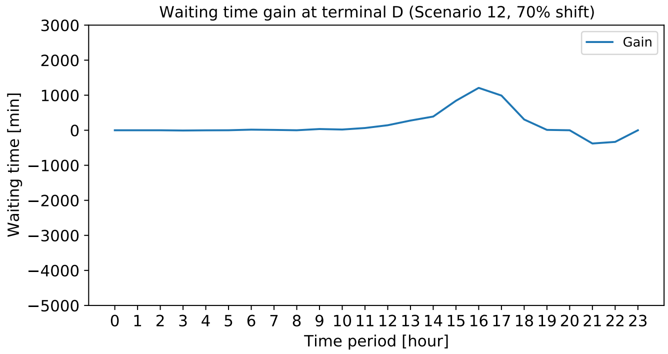
(i) Scenario 9, 45% application rate



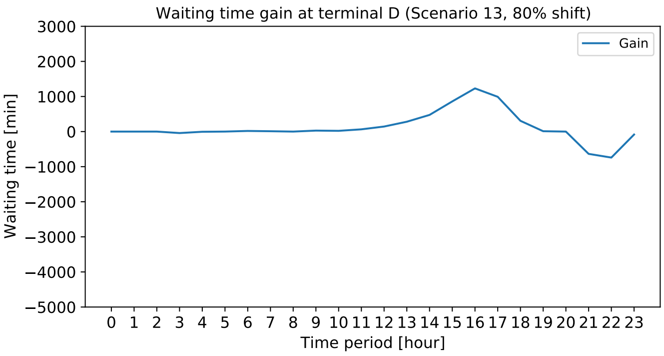
(j) Scenario 10, 50% application rate



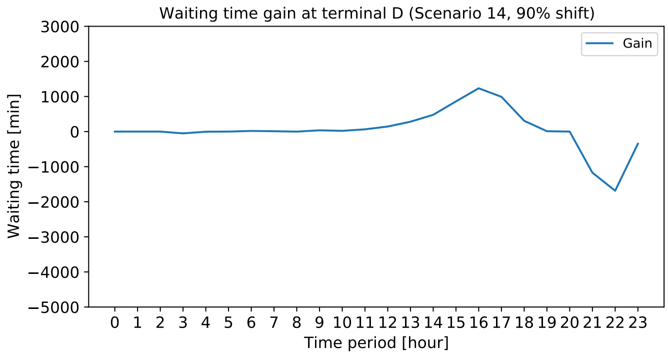
(k) Scenario 11, 60% application rate



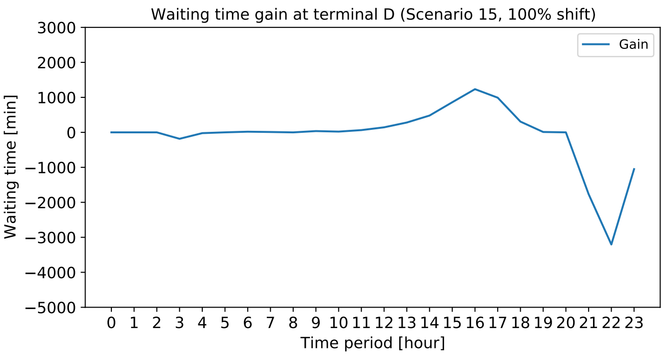
(l) Scenario 12, 70% application rate



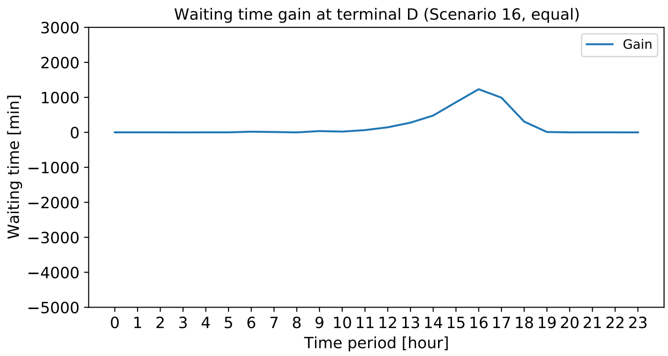
(m) Scenario 13, 80% application rate



(n) Scenario 14, 90% application rate



(o) Scenario 15, 100% application rate



(p) Scenario 16, equal spread

Figure F.19: Waiting time gain along the day at terminal D for each scenario, calculated by subtracting the total waiting time for the scenario from the total waiting time in the base case

F.3 INTERPRETATION OF WAITING TIME RESULTS

The results elaborated in Section F.2 are very promising. The truck shifting strategies for peak shaving based on what container type or commodity type the trucks transport, show to be capable of reducing waiting time at the terminals. However, the effect of reduced waiting time in the entire system must be explored to draw final conclusions for practice.

Hourly waiting time gains are difficult to interpret for the entire system as it is not immediately clear what one hour of waiting time gain means and for who this gain is beneficial. For the interpretation of the results, the waiting time gains in hours are converted to monetary values. By doing so, the gain can be interpreted more easily.

Converting the hourly waiting time gain to monetary values is possible using cost figures. The KiM publishes these for freight transport. The cost figures are based on research towards the economic costs of freight transporters. In the year 2017, the costs for waiting in container transport are approximated on 38 euro per hour [KiM, 2020].

Consequently, the waiting time gain in euro can be calculated. The results are presented in Table F.3. These values represent the waiting time gain in euro on an average working day. To provide an understanding of what this means on a yearly base Table F.4 represents the waiting time gain in euro for a year. Note that only working days are included in this calculation as on weekend days the waiting time is negligible.

Additionally, the costs for idling of a truck while waiting are explored. These costs are not included in the waiting time cost figures of the KiM [2020]. Nevertheless, the TOC leave their truck idling while waiting at the terminal gates. This consumes fuel and induces more cost for the TOC. A rough estimate for idling costs for the TOC is provided in Table F.5 on daily base and Table F.6 for a year. For this estimate, the fuel consumption for idling is obtained from U.S. Department of Energy [2015]. The cost of fuel are obtained from CBS [2017].

The total estimated costs of TOC are presented in Table F.7 and Table F.8. These total costs capture the costs for waiting and the cost for idling during the waiting time.

So far cost figures represent the cost for TOC. How these costs are distributed in the system should be explored. For example, what the waiting time gain implies for hinterland warehouses, terminals, shipper, and forwarders.

A rough estimate is made for terminals and the PoR by exploring costs for CO_2 emissions in Table F.9. The emissions are caused by the idling trucks. The amount of CO_2 in kg is calculated based on fuel consumption and emissions due to idling [U.S. Department of Energy, 2015; ANWB, nd]. Note that for this estimate the emissions are based on consumption of gas. However, trucks used for container transport often drive on diesel. As diesel is more polluting than gas, the CO_2 emissions are expected to be even higher than currently estimated in Table F.9.

Table F.3: Total waiting time gain in monetary value [€] on an average working day for each scenario, based on TOC waiting costs (38€/h)

	Terminal A		**Terminal B**		**Terminal C**		**Terminal D**	
	Hours	**Euro**	**Hours**	**Euro**	**Hours**	**Euro**	**Hours**	**Euro**
Scenario 1 (5% shift)	28	€ 1.061,24	42	€ 1.581,54	84	€ 3.176,36	-17	€ -638,06
Scenario 2 (10% shift)	88	€ 3.356,13	69	€ 2.626,81	126	€ 4.801,88	30	€ 1.144,02
Scenario 3 (15% shift)	79	€ 3.013,51	59	€ 2.253,13	143	€ 5.446,75	32	€ 1.202,91
Scenario 4 (20% shift)	81	€ 3.069,39	75	€ 2.866,85	144	€ 5.476,50	42	€ 1.604,27
Scenario 5 (25% shift)	81	€ 3.073,45	76	€ 2.878,95	151	€ 5.741,86	48	€ 1.810,66
Scenario 6 (30% shift)	81	€ 3.092,87	77	€ 2.914,40	154	€ 5.854,83	55	€ 2.104,76
Scenario 7 (35% shift)	83	€ 3.151,97	78	€ 2.948,01	155	€ 5.875,69	63	€ 2.410,23
Scenario 8 (40% shift)	82	€ 3.111,57	76	€ 2.900,39	155	€ 5.872,44	66	€ 2.520,77
Scenario 9 (45% shift)	73	€ 2.774,59	73	€ 2.769,83	154	€ 5.838,09	70	€ 2.646,60
Scenario 10 (50% shift)	64	€ 2.431,45	70	€ 2.650,88	150	€ 5.706,17	70	€ 2.667,36
Scenario 11 (60% shift)	38	€ 1.443,88	62	€ 2.342,18	138	€ 5.252,81	70	€ 2.651,18
Scenario 12 (70% shift)	-18	€ -700,82	36	€ 1.364,48	115	€ 4.354,22	60	€ 2.280,48
Scenario 13 (80% shift)	-68	€ -2.576,47	40	€ 1.505,94	40	€ 1.509,16	49	€ 1.858,21
Scenario 14 (90% shift)	-166	€ -6.325,79	24	€ 927,74	-22	€ -830,28	20	€ 758,70
Scenario 15 (100% shift)	-169	€ -6.432,39	4	€ 136,67	-48	€ -1.826,26	-29	€ -1.092,39
Scenario 16 (equal)	110	€ 4.181,41	79	€ 2.985,13	157	€ 5.965,62	74	€ 2.817,73

Table F.4: Total waiting time gain in monetary value [€] on a yearly base (260 working days) for each scenario, based on TOC waiting costs (38€/h)

	Terminal A	Terminal B	Terminal C	Terminal D
Scenario 1 (5% shift)	€ 275.921,76	€ 411.200,52	€ 825.852,38	€ -165.896,49
Scenario 2 (10% shift)	€ 872.593,14	€ 682.971,78	€ 1.248.489,59	€ 297.444,42
Scenario 3 (15% shift)	€ 783.513,57	€ 585.813,70	€ 1.416.155,69	€ 312.755,81
Scenario 4 (20% shift)	€ 798.040,58	€ 745.382,29	€ 1.423.890,58	€ 417.111,07
Scenario 5 (25% shift)	€ 799.097,03	€ 748.528,27	€ 1.492.884,15	€ 470.770,71
Scenario 6 (30% shift)	€ 804.147,37	€ 757.744,34	€ 1.522.254,85	€ 547.238,65
Scenario 7 (35% shift)	€ 819.512,67	€ 766.482,32	€ 1.527.679,51	€ 626.659,54
Scenario 8 (40% shift)	€ 809.008,71	€ 754.100,43	€ 1.526.834,18	€ 655.399,95
Scenario 9 (45% shift)	€ 721.392,73	€ 720.155,00	€ 1.517.903,37	€ 688.115,29
Scenario 10 (50% shift)	€ 632.175,99	€ 689.228,74	€ 1.483.604,95	€ 693.513,52
Scenario 11 (60% shift)	€ 375.407,56	€ 608.965,51	€ 1.365.731,00	€ 689.305,56
Scenario 12 (70% shift)	€ -182.213,04	€ 354.765,33	€ 1.132.098,19	€ 592.924,92
Scenario 13 (80% shift)	€ -669.883,42	€ 391.545,65	€ 392.381,44	€ 483.135,07
Scenario 14 (90% shift)	€ -1.644.705,16	€ 241.211,42	€ -215.873,94	€ 197.262,78
Scenario 15 (100% shift)	€ -1.672.420,85	€ 35.535,09	€ -474.827,54	€ -284.021,34
Scenario 16 (equal)	€ 1.087.167,51	€ 776.133,21	€ 1.551.061,24	€ 732.610,24

Table F.5: Total waiting time gain in monetary value [€] on an average working day for each scenario, based on TOC idling costs (5.312€/h)

	Terminal A		Terminal B		Terminal C		Terminal D	
	Hours	**Euro**	**Hours**	**Euro**	**Hours**	**Euro**	**Hours**	**Euro**
Scenario 1 (5% shift)	28	€ 148,35	42	€ 221,08	84	€ 444,02	-17	€ -89,19
Scenario 2 (10% shift)	88	€ 469,15	69	€ 367,20	126	€ 671,25	30	€ 159,92
Scenario 3 (15% shift)	79	€ 421,26	59	€ 314,96	143	€ 761,40	32	€ 168,15
Scenario 4 (20% shift)	81	€ 429,07	75	€ 400,76	144	€ 765,56	42	€ 224,26
Scenario 5 (25% shift)	81	€ 429,64	76	€ 402,45	151	€ 802,65	48	€ 253,11
Scenario 6 (30% shift)	81	€ 432,35	77	€ 407,40	154	€ 818,44	55	€ 294,22
Scenario 7 (35% shift)	83	€ 440,61	78	€ 412,10	155	€ 821,36	63	€ 336,92
Scenario 8 (40% shift)	82	€ 434,97	76	€ 405,44	155	€ 820,91	66	€ 352,38
Scenario 9 (45% shift)	73	€ 387,86	73	€ 387,19	154	€ 816,10	70	€ 369,97
Scenario 10 (50% shift)	64	€ 339,89	70	€ 370,57	150	€ 797,66	70	€ 372,87
Scenario 11 (60% shift)	38	€ 201,84	62	€ 327,41	138	€ 734,29	70	€ 370,61
Scenario 12 (70% shift)	-18	€ -97,97	36	€ 190,74	115	€ 608,67	60	€ 318,79
Scenario 13 (80% shift)	-68	€ -360,16	40	€ 210,52	40	€ 210,96	49	€ 259,76
Scenario 14 (90% shift)	-166	€ -884,28	24	€ 129,69	-22	€ -116,07	20	€ 106,06
Scenario 15 (100% shift)	-169	€ -899,18	4	€ 19,11	-48	€ -255,29	-29	€ -152,70
Scenario 16 (equal)	110	€ 584,52	79	€ 417,29	157	€ 833,93	74	€ 393,89

Table F.6: Total waiting time gain in monetary value [€] on a yearly base (260 working days) for each scenario, based on TOC idling costs (5.312€/h)

	Terminal A	Terminal B	Terminal C	Terminal D
Scenario 1 (5% shift)	€ 38.570,96	€ 57.481,50	€ 115.445,47	€ -23.190,58
Scenario 2 (10% shift)	€ 121.979,34	€ 95.472,27	€ 174.525,70	€ 41.579,60
Scenario 3 (15% shift)	€ 109.526,95	€ 81.890,59	€ 197.963,66	€ 43.719,97
Scenario 4 (20% shift)	€ 111.557,67	€ 104.196,60	€ 199.044,92	€ 58.307,74
Scenario 5 (25% shift)	€ 111.705,35	€ 104.636,37	€ 208.689,49	€ 65.808,79
Scenario 6 (30% shift)	€ 112.411,34	€ 105.924,68	€ 212.795,20	€ 76.498,20
Scenario 7 (35% shift)	€ 114.559,25	€ 107.146,16	€ 213.553,51	€ 87.600,41
Scenario 8 (40% shift)	€ 113.090,90	€ 105.415,30	€ 213.435,35	€ 91.618,01
Scenario 9 (45% shift)	€ 100.843,11	€ 100.670,09	€ 212.186,91	€ 96.191,27
Scenario 10 (50% shift)	€ 88.371,55	€ 96.346,92	€ 207.392,36	€ 96.945,89
Scenario 11 (60% shift)	€ 52.478,03	€ 85.126,97	€ 190.914,82	€ 96.357,66
Scenario 12 (70% shift)	€ -25.471,46	€ 49.592,46	€ 158.255,41	€ 82.884,66
Scenario 13 (80% shift)	€ -93.642,65	€ 54.733,96	€ 54.850,80	€ 67.537,20
Scenario 14 (90% shift)	€ -229.912,47	€ 33.718,82	€ -30.176,90	€ 27.575,26
Scenario 15 (100% shift)	€ -233.786,83	€ 4.967,43	€ -66.375,89	€ -39.703,19
Scenario 16 (equal)	€ 151.974,57	€ 108.495,25	€ 216.822,03	€ 102.411,20

Table F.7: Total waiting time gain in monetary value [€] on an average working day for each scenario, based on TOC waiting and idling costs (43.312€/h)

	Terminal A		Terminal B		Terminal C		Terminal D	
	Hours	Euro	Hours	Euro	Hours	Euro	Hours	Euro
Scenario 1 (5% shift)	28	€ 1.209,59	42	€ 1.802,62	84	€ 3.620,38	-17	€ -727,26
Scenario 2 (10% shift)	88	€ 3.825,28	69	€ 2.994,02	126	€ 5.473,14	30	€ 1.303,94
Scenario 3 (15% shift)	79	€ 3.434,77	59	€ 2.568,09	143	€ 6.208,15	32	€ 1.371,06
Scenario 4 (20% shift)	81	€ 3.498,45	75	€ 3.267,61	144	€ 6.242,06	42	€ 1.828,53
Scenario 5 (25% shift)	81	€ 3.503,09	76	€ 3.281,40	151	€ 6.544,51	48	€ 2.063,77
Scenario 6 (30% shift)	81	€ 3.525,23	77	€ 3.321,80	154	€ 6.673,27	55	€ 2.398,99
Scenario 7 (35% shift)	83	€ 3.592,58	78	€ 3.360,11	155	€ 6.697,05	63	€ 2.747,15
Scenario 8 (40% shift)	82	€ 3.546,54	76	€ 3.305,83	155	€ 6.693,34	66	€ 2.873,15
Scenario 9 (45% shift)	73	€ 3.162,45	73	€ 3.157,02	154	€ 6.654,19	70	€ 3.016,56
Scenario 10 (50% shift)	64	€ 2.771,34	70	€ 3.021,44	150	€ 6.503,84	70	€ 3.040,23
Scenario 11 (60% shift)	38	€ 1.645,71	62	€ 2.669,59	138	€ 5.987,10	70	€ 3.021,78
Scenario 12 (70% shift)	-18	€ -798,79	36	€ 1.555,22	115	€ 4.962,90	60	€ 2.599,27
Scenario 13 (80% shift)	-68	€ -2.936,64	40	€ 1.716,46	40	€ 1.720,12	49	€ 2.117,97
Scenario 14 (90% shift)	-166	€ -7.210,07	24	€ 1.057,42	-22	€ -946,35	20	€ 864,76
Scenario 15 (100% shift)	-169	€ -7.331,57	4	€ 155,78	-48	€ -2.081,55	-29	€ -1.245,09
Scenario 16 (equal)	110	€ 4.765,93	79	€ 3.402,42	157	€ 6.799,55	74	€ 3.211,62

Table F.8: Total waiting time gain in monetary value [€] on a yearly base (260 working days) for each scenario, based on TOC waiting and idling costs (43.312€/h)

	Terminal A	Terminal B	Terminal C	Terminal D
Scenario 1 (5% shift)	€ 314.492,71	€ 468.682,02	€ 941.297,86	€ -189.087,08
Scenario 2 (10% shift)	€ 994.572,48	€ 778.444,05	€ 1.423.015,30	€ 339.024,02
Scenario 3 (15% shift)	€ 893.040,52	€ 667.704,29	€ 1.614.119,34	€ 356.475,78
Scenario 4 (20% shift)	€ 909.598,25	€ 849.578,89	€ 1.622.935,50	€ 475.418,81
Scenario 5 (25% shift)	€ 910.802,38	€ 853.164,64	€ 1.701.573,64	€ 536.579,50
Scenario 6 (30% shift)	€ 916.558,70	€ 863.669,02	€ 1.735.050,06	€ 623.736,85
Scenario 7 (35% shift)	€ 934.071,92	€ 873.628,48	€ 1.741.233,02	€ 714.259,94
Scenario 8 (40% shift)	€ 922.099,62	€ 859.515,73	€ 1.740.269,53	€ 747.017,97
Scenario 9 (45% shift)	€ 822.235,84	€ 820.825,09	€ 1.730.090,28	€ 784.306,56
Scenario 10 (50% shift)	€ 720.547,53	€ 785.575,67	€ 1.690.997,31	€ 790.459,41
Scenario 11 (60% shift)	€ 427.885,59	€ 694.092,48	€ 1.556.645,81	€ 785.663,22
Scenario 12 (70% shift)	€ -207.684,50	€ 404.357,79	€ 1.290.353,60	€ 675.809,58
Scenario 13 (80% shift)	€ -763.526,07	€ 446.279,61	€ 447.232,24	€ 550.672,26
Scenario 14 (90% shift)	€ -1.874.617,63	€ 274.930,24	€ -246.050,84	€ 224.838,05
Scenario 15 (100% shift)	€ -1.906.207,68	€ 40.502,52	€ -541.203,43	€ -323.724,53
Scenario 16 (equal)	€ 1.239.142,09	€ 884.628,46	€ 1.767.883,28	€ 835.021,44

Table F.9: Total waiting time gain in CO_2 emissions [kg] on an average working day and yearly base (260 working days) for each scenario, based on emissions per hour of idling (7.26 kg CO_2/h)

	Terminal A		Terminal B		Terminal C		Terminal D	
	Daily	**Yearly**	**Daily**	**Yearly**	**Daily**	**Yearly**	**Daily**	**Yearly**
Scenario 1 (5% shift)	203	52721	302	78570	607	157799	-122	-31698
Scenario 2 (10% shift)	641	166730	502	130498	918	238554	219	56834
Scenario 3 (15% shift)	576	149709	431	111934	1041	270590	230	59759
Scenario 4 (20% shift)	586	152485	548	142423	1046	272068	307	79699
Scenario 5 (25% shift)	587	152686	550	143024	1097	285251	346	89952
Scenario 6 (30% shift)	591	153651	557	144785	1119	290863	402	104563
Scenario 7 (35% shift)	602	156587	563	146455	1123	291899	461	119738
Scenario 8 (40% shift)	595	154580	554	144089	1122	291738	482	125230
Scenario 9 (45% shift)	530	137839	529	137603	1116	290031	506	131481
Scenario 10 (50% shift)	465	120792	507	131693	1090	283478	510	132512
Scenario 11 (60% shift)	276	71731	448	116357	1004	260955	507	131708
Scenario 12 (70% shift)	-134	-34816	261	67786	832	216314	436	113292
Scenario 13 (80% shift)	-492	-127997	288	74814	288	74974	355	92314
Scenario 14 (90% shift)	-1209	-314260	177	46089	-159	-41248	145	37692
Scenario 15 (100% shift)	-1229	-319556	26	6790	-349	-90727	-209	-54269
Scenario 16 (equal)	799	207729	570	148299	1140	296367	538	139983

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