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

Design, Modelling, and Simulation Approach

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Abstract

This paper proposes a truck arrival shift (TAS) policy to control truck arrivals at seaport terminals. The aim is to reduce congestion at terminal gates which is caused by a lack of port-hinterland alignment. We proposed, developed, and applied a modeling framework to assesses the impact of the TAS policy for the use case of the Port of Rotterdam. This policy is designed for the implementation of a Time Slot Management System (TSMS) and takes the behavioural aspect of Truck Operating Companies (TOC) into account. The time of day preferences of TOC for container pick-ups are inferred from the exchange of information between port and hinterland stakeholders using discrete choice modelling (DCM). These preferences are used to shift truck arrivals and consequently reduce the high waiting time of trucks at terminals gates. To evaluate the effectiveness of the designed TAS policy, we developed a simulation platform that resembles terminal operations using discrete-event simulation (DES). For the allocation of trucks to a certain time period, a choice-based heuristic is designed to approximate the optimum configuration of the TAS policy. The optimum TAS policy design shows that significant gain can be obtained at a low shift rate. Moreover, a measurable amount of waiting time gain can be achieved by the application of the designed TAS policy.

Keywords port-hinterland alignment · traffic control strategy · Truck Arrival Shift policy · Time Slot Management System · discrete-event simulation · discrete choice modelling · allocation heuristic

1 Introduction

High waiting time for trucks at the terminal gates of seaports is an issue that is increasingly receiving more attention. Long queues of idling trucks at terminal gates 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 area, the largest European port (World Shipping Council, 2020), are no exception to these issues as the waiting time for trucks at the terminal gates have been rapidly increasing the past 6 years (Drewes and Gorter, 2017).

The problem of congestion, high waiting time and therefore non-optimal turnaround time for trucks at the terminal, is due to 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 the connectivity between port and hinterland (Martinho, 2008; Notteboom, 2009; Franc and Van der Horst, 2010; Wan et al., 2018). 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).

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 as well as medium-term strategies. 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. Nevertheless, various studies (Sharif et al., 2011; Chen et al., 2011, 2013a; Wibowo and Fransoo, 2020) find that there is potential for digital solutions for connectivity by controlling traffic demand patterns

In this research, we contribute to the literature enhancing digital connectivity by exploring short-term solutions to solve day-to-day truck traffic issues at the terminals. 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).

Previous research towards TAS design lacks inclusion of all relevant intricacies associated with the system in the design (Huynh et al., 2016). For example, there are two sides of the system that have to be considered while designing a TAS policy. 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, truck operating companies (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), Chen et al. (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. To fill the identified knowledge gaps with this research, we aim to design a new TAS policy for TSMS to reduce truck waiting time at terminals. We strongly believe that it is essential to consider both the port and hinterland side, seeing the role of key stakeholders in this policy.

In this research, we propose a modelling and simulation approach to design and evaluate TAS policy around the case of the Rotterdam port area.To evaluate the performance of this intervention, we introduce a novel modeling framework. The framework includes parametric modeling of truck handling process at terminals' gates, behavioural modeling of TOC preferences of container pick up times, and a heuristic to assess different configurations of the TAS policy towards an optimum setup. This modelling framework assures an accurate communication between two sides of the system, e.g. port and hinterland, and gives a comprehensive assessment of the potential gains for the application of the TAS policy .

In section 2 we provide an overview of previous literature to gain insight in application and design of different TAS policies to reduce waiting time at the terminals. Consequently, in section 3 we elaborate on the design, modelling and simulation methodology for the TAS policy. Thereafter, we present and discuss the results of the research in section 4. Lastly, in section 5, we provide a discussion and conclusion for the research. Additionally, we propose implications for future research.

2 Literature

As the root of misalignment at the port of Rotterdam lies within inadequate control of truck arrival (Zomer et al., 2019), 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, by implementing a TAS control strategy. With a TAS, 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 truck arrival shift is the implementation of a truck appointment system. A truck appointment system is optimised through a TSMS. The effectiveness of a TSMS to reduce congestion at seaport terminals is extensively proven with previous research (e.g. Morais and Lord (2006); Huynh and Walton (2008); Guan and Liu (2009); Zhao and Goodchild (2010); Lange et al. (2017)). In this section, we study the methodology for the design of TSMS to consequently be able to design and evaluate the TAS policy.

The focus of this research is on the arrival of trucks and serving the trucks at the terminal, consequently the trucks depart from the terminal. Conceptually this process looks like

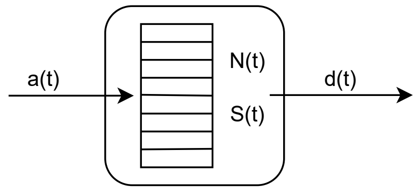


Figure 1: High level conceptualisation of the port processes

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

$$\frac{\partial N(t)}{\partial t} = a(t) - S(t) - d(t) \tag{1}$$

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 second component is an allocation framework (the controller) which is required to guarantee the best match between truck arrival and service, and hence an optimal arrival of trucks at the terminal.

2.1 Simulation platform

For the simulation platform, a discrete-event simulation (DES) model is predominantly used for the design of a TSMS (Huynh and Walton, 2008). 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. A DES queueing model includes the stochastic arrival process and queue process. Despite the effort of many scholars to develop an accurate simulation platform for TSMS design, a gap remains regarding the inclusion of all relevant intricacies associated with the system in the design (Huynh et al., 2016). Inaccurate assumptions or unjustified simplifications have been made for the design components of a TSMS. Especially in the arrival and queueing process there is a gap regarding the reality.

An accurate arrival process is essential as the distributions for inter arrival rate influence the queueing model (Chen et al., 2013a; Hillier and Lieberman, 2015). In most studies fitting to a probability distribution is the method used for the arrival process. 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 independently and identically distributed (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 2 provides an example of fitting historical data of mean arrival rate to an exponential distribution to obtain inter arrival time between trucks in minutes.

$$IAT = exp\left(\frac{60}{\lambda}\right) \tag{2}$$

where IAT denotes the inter arrival time between trucks (in minutes) and λ represents the mean arrival rate (trucks/hour). Consequently, in Equation 3, $f(IAT)$ 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.

$$f(IAT, \lambda) = \lambda e^{-\lambda IAT} \tag{3}$$

The queueing process is extensively discussed in TSMS research (e.g. 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. In the design of the queueing process the inclusion of certain terminal operations, service policies and activity sequences are critical. 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 (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. Stationary queueing models assume constant rates for arrival and service at the terminal (Green and Kolesar, 1991). A stationary queueing model allows for a more simple estimation of waiting time (Hillier and Lieberman, 2015). Non-stationary queueing models overcome the limitations of a stationary queueing model by assuming a time-varying arrival and service process. Most researchers (e.g. Chen et al. (2011, 2013a,c,b); Zhang et al. (2019); Wibowo and Fransoo (2020)) adopt non-stationary queueing models to estimate queue lengths and waiting time in TSMS design. 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.

2.2 Allocation framework

The allocation framework is the second component required to develop a TSMS. The allocation framework is used to ensure the match between truck arrival from the hinterland and terminal service. There are two approaches to ensure this match. The match can come from the terminal side, by using a decision variable to determine the optimal appointment quota (Chen et al., 2013a; Zehendner and Feillet, 2014) or time slot duration (Wibowo and Fransoo, 2020) at the terminal. The match can also come from the hinterland 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.

In the design of TSMS, Chen et al. (2013a,b,c); Zhang et al. (2013) apply the Genetic Algorithm (GA) to heuristically find an optimum for allocating trucks at the terminal. Heuristics can also be used as strategies for decision making and finding a solution to complex problems. In another research field, 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, this creates insight in the effects of non optimal solutions.

In the field of TSMS design, most researchers aim to optimise the TSMS from a terminal's perspective (Zehendner and Feillet, 2014; Schulte et al., 2017). By doing so, many studies fail to recognise the impact of a TSMS on TOC, for example on their scheduling operations (Huynh et al., 2016). Therefore, Chen et al. (2011, 2013a); Wibowo and Fransoo (2020) recommend the optimisation of TSMS including several stakeholders by applying a multi-objective or joint optimisation. 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 discrete choice modelling (DCM) allows to explore trucker behaviour. DCM is a method that is, to our knowledge, never used in TSMS research. However, we believe 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.

In DCM, data is analysed and relations between independent variables and dependent variables are used to explain or predict a choice (Bierlaire, 1998). Hence, DCM using revealed preference data (historical data from past choices), might be a suitable method to obtain insight in TOC preferences for arrival. Several behavioural assumptions are made in the specification of a 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. 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 the deterministic part that can be estimated from data.

Table 1 provides an overview of the most related literature towards TSMS and the placement of this research.

Table 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 Method

With the insight from previous research to design a TSMS, we propose a methodology for the design of the TAS policy. The approach for controlling truck arrivals and evaluating the effects on waiting time is presented in the modelling framework depicted in Figure 2.

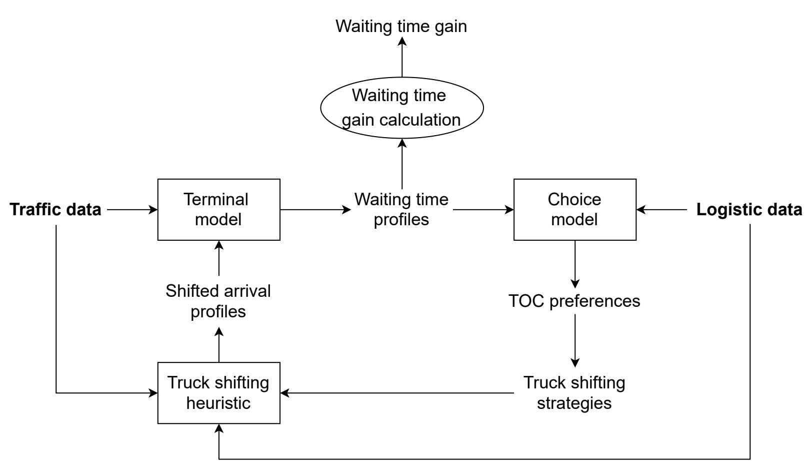


Figure 2: Framework research methodology

We develop a terminal model to simulate the processes at the terminal. The terminal model represents the simulation platform. With the terminal model, we can simulate a waiting time profile from an arrival profile. We use discrete-event simulation and historic traffic data to set up the terminal model. Moreover, we develop a choice model to gain insight in the behaviour of the TOC regarding time period preference for container pick up. Based on this insight, we can formulate a truck shifting strategy to control truck arrivals at the terminals. We apply discrete choice modelling and historic logistic data to set up the choice model. Subsequently, the truck shifting strategy is input for the truck shifting heuristic. The truck shifting heuristic represents the allocation framework. With this heuristic, we compute new truck arrival profiles from the historic traffic data, based on the truck shifting strategy and what-if scenarios regarding application rates to the TAS policy. The output of the truck shifting heuristic (the shifted arrival profiles) is the new input for the terminal model. We can simulate the shifted arrival profiles in the terminal model, this allows us to obtain the waiting time profiles for the shifted arrivals. Lastly, we compare the waiting time profiles simulated from the shifted arrival profiles with the waiting time profiles in the base case year. Consequently, we can calculate the waiting time gain for the truck shifting strategy and scenarios. 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 at the terminals.

3.1 Data collection

The data we collect for the methodology is twofold. First is historic traffic data (2017), collected from loop detectors located at the terminal gates. This data captures the number of trucks that arrive at the terminal per time period. For our research data for truck arrivals is aggregated to trucks per hour. This represents the arrival profile. The second data source is historic logistic data (2017), collected from the port community system. The logistic data captures details of import containers. This is revealed preference data of TOC for container pick up. The data set contains information of transaction data for the 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. Additionally, the waiting time at the terminals obtained from the terminal model is included in the logistic data set.

3.2 Terminal model

We formulate the terminal model as a queueing model and discrete-event simulation is used to represent the port system. For the simulation model we use the discrete event simulation package salabim (van der Ham, 2018). The terminal model includes three components, these are 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. Figure 3 provides a graphical overview of the terminal model.

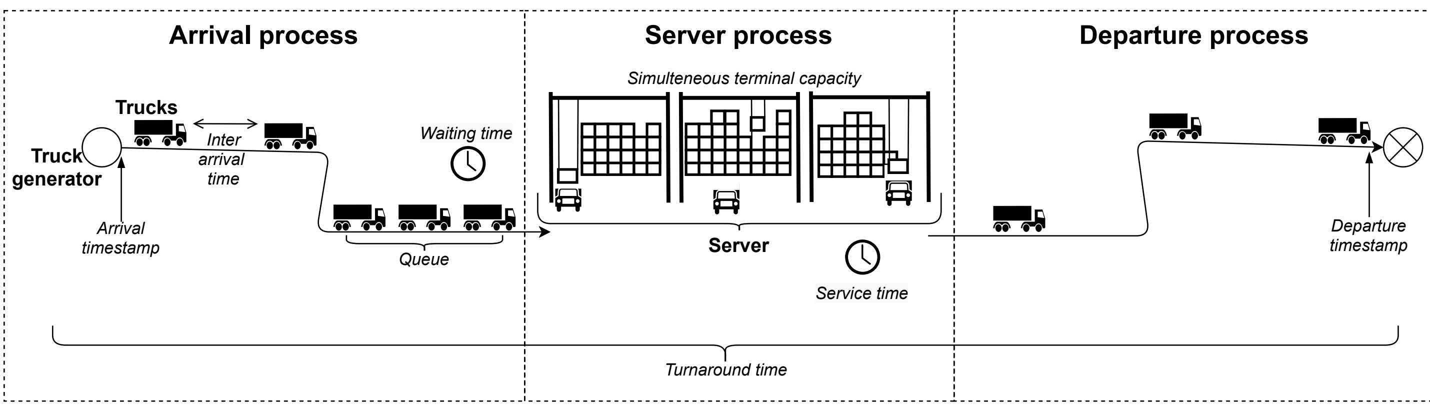


Figure 3: Graphical representation of the terminal model, the components and the simulated processes

We formulate the terminal model as a $M/M/s$ queueing model as we assume 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. For the arrival process we use a non-stationary arrival profile as the inter arrival time between trucks is different for each hour of the day (IAT_h in min). The historic traffic data from loop detectors at terminal gates contains the average number of trucks arriving for each hour of the day (λ_h). Equation 4 presents the inter arrival time calculation:

$$IAT_h = exp\left(\frac{60}{\lambda_h}\right) \tag{4}$$

The terminals in the port of Rotterdam area operate each hour of the day, utilising all servers. Therefore, we formulate a stationary service process. The mathematical foundation for calculating waiting time is provided by Equation 5a through Equation 5d (Hillier and Lieberman, 2015),

$$L = \lambda_h W \tag{5a}$$

$$L_q = \lambda_h W_q \tag{5b}$$

$$W = W_q + \frac{1}{\mu} \tag{5c}$$

$$W_q = \frac{L_q}{\lambda_h} \tag{5d}$$

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).

There are two unknown parameter values in our system, these are the mean service time and the number of servers (simultaneous terminal capacity). We estimate the number of servers and mean service time in the service process by means of Bayesian optimisation (Bergstra et al., 2013). In this estimation method for the unknown parameter values the objective function is to minimise the difference between simulated departure profile and the observed departure profile from historic data. For the formulation of the objective function, the Mean Square Error (MSE) method is used, denoted in Equation 6,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{6}$$

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 hyper-parameter values are tuned such that the deviation from the historic departure profile is minimised.

3.3 Discrete choice model

The choice model is based on discrete choice theory. 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.

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 ($P(t|T)$) is computed from the attractiveness of the alternatives. The attractiveness is measured from the utility function for each alternative (U). The utility function captures the influence of an attribute from the data. In theory the alternative with the highest utility is always chosen (Equation 7),

$$P(t|T) = Pr(U_t \geq U_j, \forall j \in T). \tag{7}$$

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 8),

$$U_t = V_t + \varepsilon_t \tag{8}$$

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. We formulate an alternative specific constant (ASC), to capture the unobserved behaviour in the deterministic part of the utility function.

To obtain insight in which attributes from the logistic data impact the choice of the TOC, we apply the random forest machine learning technique (Koehrsen, 2017). With this method we aim 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 TOC' behaviour. These excluded attributes might be correlated with the other attributes, we desire to prevent this as collinearity might deteriorate the value of the data. Furthermore, 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. Consequently, to obtain better results from the choice model, we aggregate the hourly pick up time preference 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 time slot categories used in practice at the terminals.

For each terminal a separate choice model must be defined. Therefore, for each terminal a separate set of utility functions is formulated. The utility function captures the attractiveness of an alternative. We assume that all utility functions are linear. 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), where V_1 represents the night, V_2 the morning, V_3 the midday, and V_4 the afternoon alternative. The independent variables in the model are container type (x_{type}), commodity type (y_{type}), and waiting time per alternative (w_{alt}). With the inclusion of an attribute in the utility function, it is assumed that the attribute actually impacts the choice for a certain alternative. Container type and commodity type are both an attribute with several levels. Therefore, the container type variable and commodity type variable in the choice model are discrete and categorical variables. In the choice model not all levels are included in the commodity type attribute. The utility function for each alternative is unique in the specified choice model. As the model is based on discrete and categorical variables, including the variables in all utility functions would ensure that the model becomes unidentified. 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. 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. 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.

From the revealed preference logistic data we observed that the midday and afternoon alternatives for pick up are most preferred. Based on this observation, we formulate the ASCs for the night and morning alternative to capture the unobserved factors that decrease the preference for these two alternatives (ASC_{alt}). 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. Below, the set of utility functions for the choice model of each terminal is displayed.

Utility functions for terminal A:

$$V_1 = ASC_{Night} + \beta_{RE} \cdot x_{RE} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{9a}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{Chem} \cdot y_{Chem} \tag{9b}$$

$$V_3 = \beta_{WT,Morning} \cdot w_{Morning} + \beta_{TC} \cdot x_{TC} + \beta_{CC} \cdot x_{CC} \tag{9c}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{GP} \cdot x_{GP} \tag{9d}$$

Utility functions for terminal B:

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{Chem} \cdot y_{Chem} + \beta_{RawMin} \cdot y_{RawMin} \tag{10a}$$

$$V_2 = ASC_{Morning} + \beta_{WT,Morning} \cdot w_{Morning} + \beta_{CC} \cdot x_{CC} + \beta_{Agr} \cdot y_{Agr} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{10b}$$

$$V_3 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{WT,Afternoon} \cdot w_{Afternoon} \tag{10c}$$

$$V_4 = \beta_{RE} \cdot x_{RE} + \beta_{Petro} \cdot y_{Petro} \tag{10d}$$

Utility functions for terminal C:

$$V_1 = ASC_{Night} + \beta_{GP} \cdot x_{GP} + \beta_{CC} \cdot x_{CC} + \beta_{TC} \cdot x_{TC} \tag{11a}$$

$$V_2 = ASC_{Morning} + \beta_{RE} \cdot x_{RE} + \beta_{Agr} \cdot y_{Agr} + \beta_{SolMinFu} \cdot y_{SolMinFu} \tag{11b}$$

$$V_3 = \beta_{WT,Morning} \cdot w_{Morning} + \beta_{WT,Midday} \cdot w_{Midday} + \beta_{TC} \cdot x_{TC} + \beta_{Fert} \cdot y_{Fert} + \beta_{RawMin} \cdot y_{RawMin} \tag{11c}$$

$$V_4 = \beta_{WT,Afternoon} \cdot w_{Afternoon} + +\beta_{Chem} \cdot y_{Chem} + \beta_{Ores} \cdot y_{Ores} + \beta_{Petro} \cdot y_{Petro} \tag{11d}$$

Utility functions for terminal D:

$$V_1 = ASC_{Night} + \beta_{CC} \cdot x_{CC} + \beta_{Chem} \cdot y_{Chem} \tag{12a}$$

$$V_2 = ASC_{Morning} + \beta_{GP} \cdot x_{GP} + \beta_{RawMin} \cdot y_{RawMin} + \beta_{Agr} \cdot y_{Agr} \tag{12b}$$

$$V_3 = \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Petro} \cdot y_{Petro} \tag{12c}$$

$$V_4 = \beta_{WT,Midday} \cdot w_{Midday} + \beta_{CC} \cdot x_{CC} + \beta_{SolMinFu} \cdot y_{SolMinFu} + \beta_{Ores} \cdot y_{Ores} \tag{12d}$$

We can estimate parameters (ASC and β) 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. Equation 13 presents the maximum log-likelihood function

$$\max\mathcal{L}(\hat{\beta}_1, ..., \hat{\beta}_K) = \sum_{n=1}^{N} \left(\sum_{t \in T_n} y_{tn} \ln P_n(t|T_n) \right), \tag{13}$$

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 14). The specified model is estimated using Biogeme software (Bierlaire, nd). In the model set-up we define the model specifications for the utility functions. Consequently, we estimate the model using the multinomial logit (MNL) model

$$P_n(t|T_n) = \frac{e^{V_{tn}}}{\sum_{j \in T_n} e^{V_{jn}}}, \tag{14}$$

where V_{tn}, the deterministic part of the utility function, 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. We apply the MNL model 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.

To judge the performance and accuracy of the choice model we use the goodness of fit, t-values, and p-values. The goodness of fit can be observed from the likelihood ratio statistic

$$-2(\mathcal{L}(0) - \mathcal{L}(\hat{\beta})). \tag{15}$$

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. The t-value is calculated by

$$t_k = \frac{\hat{\beta}_k}{\sigma_k}, \tag{16}$$

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

$$p_k = 2(1 - \Phi(t_k)), \tag{17}$$

where $\Phi(\cdot)$ indicates the cumulative density function of the univariate standard normal distribution.

From the choice model results various opportunities can be identified to spread the arrival of trucks more evenly along the day. 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, peak shaving strategy is the foundation for the TAS policy. For each of the terminals, a peak in truck arrivals is observed in the midday and afternoon time period. 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. We formulate various what-if scenarios 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 us 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 scenarios provide insight in the turning point of truck shifting, from which application rate a waiting time loss instead of gain is encountered.

3.4 Truck shifting heuristic

Based on the truck shifting strategies that result from the choice model, we develop the truck shifting heuristic. 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 and the what-if scenarios. There are various steps involved to shift trucks and compute new arrival profiles. A detailed visual overview of the heuristic is represented in Figure 4.

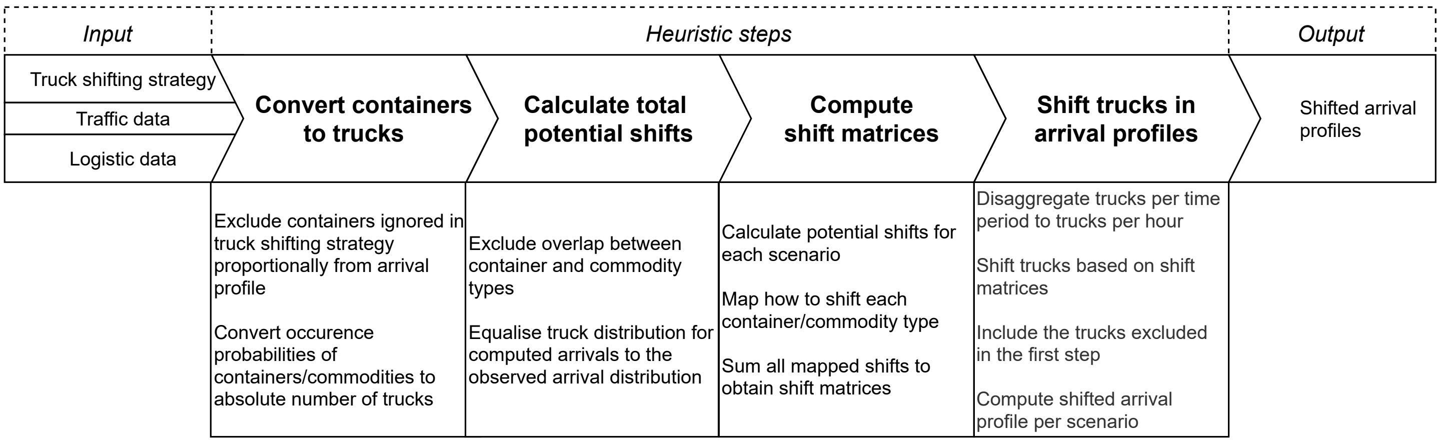


Figure 4: Overview of the truck shifting heuristic

1. **Convert containers to trucks**: First of all, the logistic data and traffic data are combined to convert containers to trucks. From the logistic data of import containers we obtain occurrence probability percentages for container types and commodity types for each time period. This allows us to calculate an absolute number of trucks transporting the specific container type or commodity. 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. Consequently, a parameter r is formulated that represents the rate of trucks that can be shifted in the strategy.

2. **Calculate total potential shifts**: Secondly, we ensure that the truck distribution for computed arrivals is similar to the observed arrival distribution using some data manipulation steps to exclude containers that can not be shifted (r) and match the observed profile with the TOC behaviour. Consequently, we obtain the total potential shifts of trucks on an average working day per time period, and per container and commodity type. 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 $C = \{1, 2, 3, ..., c\}$.

$$N_{TxC} = \begin{bmatrix} N_{11} & \dots & N_{1c} \\ \vdots & \ddots & \vdots \\ N_{t1} & \dots & N_{tc} \end{bmatrix}_{TxC} \qquad \forall t \in T, c \in C \tag{18}$$

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

$$N_{pq} = P(t, c) \cdot r \cdot \sum_{t}^{T} a(t), \quad \forall p \in T, q \in C, \tag{19}$$

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.

3. **Compute shift matrices**: Thereafter, a shift matrix for each scenario is computed. Based on the application rates from the what-if scenarios and the truck shifting strategies, shift matrices (X_{TxT}) can be computed.

$$X_{TxT} = \begin{bmatrix} X_{11} & \dots & X_{1t} \\ \vdots & \ddots & \vdots \\ X_{t1} & \dots & X_{tt} \end{bmatrix}_{TxT} \quad \forall t \in T \tag{20}$$

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

$$x_{ij} = N_{TxC} \cdot \gamma, \quad i, j \in T, \tag{21}$$

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

$$J = arg \max_t (P(t|c)) \tag{22}$$

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 14).

4. **Shift trucks in arrival profiles**: Lastly, the shift matrices are transformed to an arrival profile that matches each scenario. The arrival profile obtained from historic traffic data 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 and we get $t' \in T' = \{1, 2, 3, ..., 24\}$. Consequently, we computed a new arrival profile with

$$a'(t') = a(t') + \sum_t^T s(t') \cdot x_{tj} - s(t') \cdot x_{pj} \quad \forall j \in T, t' \in T', p \in T, \tag{23}$$

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.

An exception in the approach for computing the shifted arrival profiles 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.

3.5 Waiting time gain calculation

The waiting time gain calculation provides us with 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 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. 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 to 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.

4 Results

As a result of the truck shifting heuristic, 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 rate scenarios. These are input for the terminal model. The terminal model simulates arrival and departure profiles based on these shifted arrival profiles. 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.

4.1 Terminal model calibration

We ensure that the terminal model is close to reality and can simulate the arrival, service and departure of trucks accurately, by calibrating the terminal model. 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. In each specific model, we tune the parameters in the arrival and service process to a specific terminal. We tune these parameters based on the historic traffic data arrival profile and departure profile obtained from the loop detectors located at the specific terminal. An average working day average is sufficient for the calibration of the model as we found from statistical analysis using an ANOVA statistic and a two sided t-test, that there are no significant monthly or daily trends that we must account for in arrival or departure profile ($p > 0.05$).

4.1.1 Arrival process

We calibrate the parameters (IAT_h) for the arrival process based on the arrival profile from historic traffic data. The tuned parameters are input for the terminal model and consequently we simulate the arrival process as discussed in section 3. To ensure that the simulated arrival profile is similar to the observed profile, we apply a statistical analysis in the form of a two sided t-test to compare the observed and simulated arrival profile. The results of this statistical analysis are depicted in Table 2. We seek an absolute t-value smaller than 1.96 and a p-value larger than 0.05 for statistical accuracy of the simulated arrival profile. In addition to the t-test in the statistical analysis, we use a polynomial regression 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, with 1 indicating a perfect match.

Table 2: 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

4.2 Service process

For the service process we calibrate two parameters, simultaneous terminal capacity (number of servers) and the mean service time. The historic departure profile is used to tune the parameters. As mentioned in section 3, we apply Bayesian optimisation to tune the values of these parameters to 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 3, the loss is calculated with the MSE method (Equation 6). The estimated parameter values are depicted in Table 3. These estimated parameters are used as the final settings for the simulation model of each terminal.

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. Therefore, we additionally calculate the Mean Absolute Percentage Error (MAPE) score using Equation 24. The calculation of the MAPE score is similar to the MSE, 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.

Table 3: 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%

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \tag{24}$$

Similar to the calibration of the arrival process, we apply a statistical analysis in the form of a two sided t-test to compare the observed and simulated departure profile. Moreover, we use a polynomial regression to analyse the correlation between the observed and simulated arrival profile. The results of these analysis are depicted in Table 4.

Table 4: 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

4.3 Terminal model validation

We validate the terminal model using a train and test set of data. By splitting the historic traffic data set into two parts, the train and test set are created. The train set comprehends traffic data of 11 months of the year. The test set includes the data of the remaining month. We calibrate the terminal model and tune the parameters 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, therefore it allows us 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. We apply statistical testing and polynomial regression using the two sided t-test and R-square. In these analysis we compare the results of the observed and simulated profiles of the test set. The results are shown in Table 5.

Table 5: 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

4.4 Truck Operating Companies' preferences

The results from the choice model for time period choice are depicted in Table 6. 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 based on trade-offs or value-of-time. However, we can interpret the parameters 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. 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. 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 we do not explore the impact of waiting time on the TOC any further 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, whereas 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.

Table 6: 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			

Based on the results of the choice models, we infer the time period preferences of TOC for container pick up (Table 7). 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 we did not explore data in this research that could provide insight in these factors, these are not considered in the result interpretation.

We use the insight in TOC' behaviour from the choice models 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 truck shifting strategy formulated from the choice model are listed below.

- 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.

4.5 Truck Arrival Shift

With the truck shifting heuristic we compute shifted arrival profiles under various what-if scenarios. These what-if scenarios represent application rates of TOC to the formulated truck shifting strategy. 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 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 we consider an entirely equal spread of trucks

Table 7: Overview of preferences of TOC to pick up certain container or commodity type in a time period. The preference is indicated by x. In bolt are the containers and commodities considered in the truck shifting strategies

		Time period preference (indicated by x)			
	Type	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	

the perfect situation at the terminal for truck arrival. The scenarios allow us to evaluate the effect of the truck shifting strategies under various TOC application rates. By shifting the truck arrivals, we obtain new arrival profiles. The shifted arrival profiles are input for the terminal model to generate new simulated arrival and departure profiles and the corresponding waiting time profiles. The simulated waiting time profiles provide insight in the effect of the TAS policy on the waiting time. Together the new arrival and waiting time profiles ensure insight in the potential gain from the truck shifting strategies. Furthermore, the new arrival and waiting time profiles 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. 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.

4.5.1 Statistical analysis waiting time reduction

A statistical analysis provides insight in the effect of shifting trucks on waiting time. With the statistical analysis we analyse whether the observed waiting time reduction is significant ($|t| > 1.96$, $p \leq 0.05$). The statistical measure we apply 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 8 the exact t-values and p-values are depicted. 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, we observed preference for pick up during quiet periods more often. An other 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.

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. We expect that for higher application rates, more effort is required. From Table 8, we conclude 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.

Table 8: Overview of results from statistical analysis for waiting time reduction

	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

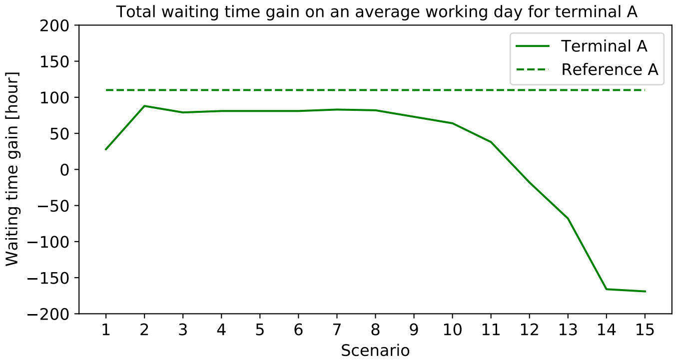
4.5.2 Total waiting time gain

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 total waiting time gain. The development of waiting time gain under various application rates (scenarios) is displayed in Figure 5. 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 we consider an entirely equal spread of trucks to be 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.

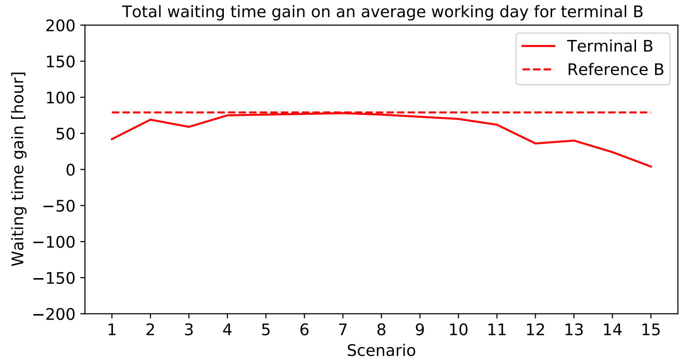
From Figure 5 we conclude that the ideal situation at the terminal can nearly be achieved with the shift strategies. Moreover, we observe that there is no linear relation between application rates and waiting time gain. An increase of 5% for shifting trucks does not cause a 5% increase in waiting time gain. A general observation from Figure 5 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, we observe that the gain with small application rates (5% - 10%) is already very close to this optimum. The optimum 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 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. There is also a turning point or risk of shifting truck arrivals. Figure 5 provides insight in this turning point. Under high application rates of truckers to the control of truck arrivals, there is no waiting time gain, but a loss. Consequently, the high application rates will no further be discussed since these high application rates are not realistic yet.

4.5.3 Monetary gain

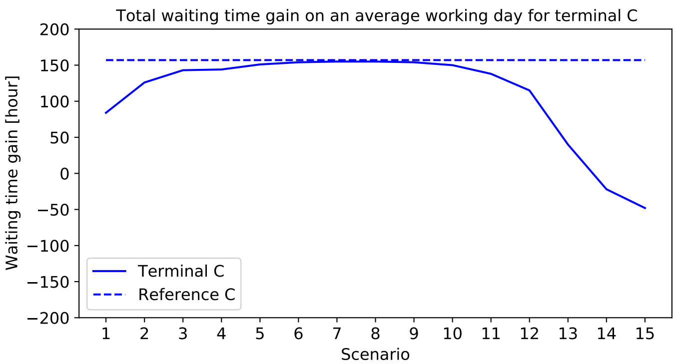
We find that the truck shifting strategies for peak shaving based on what container type or commodity type the trucks transport, are capable of reducing waiting time at the terminals. However, the effect of reduced waiting time in the entire system must be explored to draw final conclusions for practice. 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, we convert the waiting time gains in hours to monetary values (euro). 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



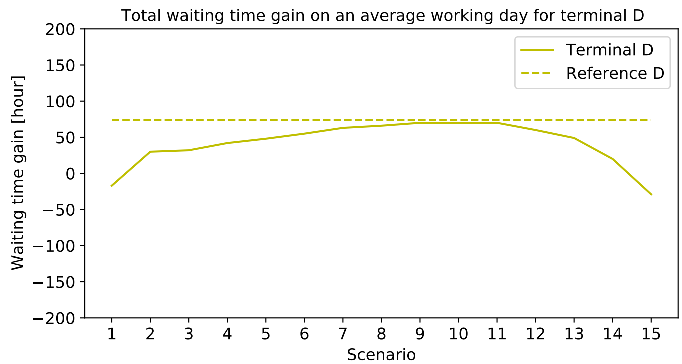
(a) Terminal A



(b) Terminal B



(c) Terminal C



(d) Terminal D

Figure 5: Development of the waiting time gain along the scenarios, in comparison with the reference scenario

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.

In Table 9 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 9 (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. We calculate this by dividing the total waiting time gain (terminal wide) by the cost of transporting a container on the road (62€/h). The TAS 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. This is 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 9: 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

5 Discussion, conclusion, recommendations

We find the results to be very promising as the implementation of a TAS policy can successfully flatten peaks in demand. We see a significant reduction of waiting time under various shift percentage, 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.

5.1 Discussion

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.

We conducted this research mainly from a TOC and port authority perspective. From this perspective, we find benefit is 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 applying a multi-stakeholder analysis.

Furthermore, we focused predominantly on the potential gains from the TAS policy in this research. 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 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. Consequently, to implement an effective TAS 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.

Lastly, we want to note 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.

5.1.1 Limitation

We organise the limitations in three categories. The categories are limitations from data, limitations in the methodology, and limitations regarding the changing environment in the port area.

Limitations from data
We explored and applied two sets of data 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. Since only import container data was available for this research, we worked with the assumption 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. Therefore, solely handling import container data might have impacted the outcome of the choice model, and consequently 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. Nevertheless, we expect that the effect from only including import data on the results is merely that the exact reduction of waiting time under a certain TOC application rate might be different. This difference can 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.

Limitations in methodology
There are some limitations regarding the method proposed in this research. We made some fair assumptions 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. We attempted to overcome this problem 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 provided us with a calibrated and validated terminal model. However, there is still some deviation from the observed departure profiles. Therefore, the simulated waiting time profile might be slightly impacted due to sensitivity of the terminal model. Nevertheless, since the terminal model is validated the impact on the results is expected to be minimal.

Additionally, we made some simplifications in the choice model. As the model was not able to predict preferred pick up time of a container to the exact hour, we aggregated the hourly pick up time 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, we found that this only affects the results slightly under very high application rates. Application rates to the TAS policy higher than 50% are unrealistic, consequently 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.

Despite the limitations in the methodology, we do not believe that these limitations have led to significant different results of the research. The simplifications are all considered to be legitimate as they are sustained by valid argumentation or statistical analysis.

Changing environment in the port area
The port area where the terminals are located is only operative since 2013, and most container terminals were not yet operating at full capacity in 2017. However, the data and, therefore, the methodology is entirely based on the year 2017. Since 2017, several developments followed, which we did not include 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, we believe that the waiting time profiles obtained for the year 2017 are representative, and not in any way 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.

5.2 Conclusion

We aimed to design a new TAS policy for TSMS to reduce truck waiting time at terminals. We strongly believed that it is essential to consider both the port and hinterland side, seeing the role of key stakeholders in this policy.

We developed a terminal model to simulate the processes at the terminal using DES. The terminal model represents the simulation platform. With the terminal model, we can simulate a waiting time profile from an arrival profile. Moreover, based on shortcomings from previous research we developed a choice model, using DCM to include the behaviour and preferences of TOC in the TAS development. Based on this insight, a truck shifting strategy can be formulated to control truck arrivals at the terminals. The truck shifting strategy is input for the truck shifting heuristic. The truck shifting heuristic represents the allocation framework. With this heuristic, we compute new truck arrival profiles. The output of the truck shifting heuristic, 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. We compare the waiting time profiles simulated from the shifted arrival profiles with the waiting time profiles in the base case year. Consequently, we can calculate a waiting time gain for the truck shifting strategy and scenarios. 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.

We found the potential waiting time gain, productivity gain and social gain by controlling small rates of truck arrivals by means of a TAS policy to be 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 in the port of Rotterdam, that results in waiting times, lies within inadequate control of truck arrival. We find truck shifting 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.

5.3 Recommendations

Various implication for future research arise. 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. 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.

Regarding the choice model 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 interesting 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 valuable topic for future research. It is expected that this would provide a more complete grasp of TOC preferences for arrival time.

Furthermore, 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. Moreover, 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.

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, port authority and terminals. Therefore a multi-stakeholder analysis is recommended for future research. 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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