Inter-terminal transport on Maasvlakte 1 and 2 in 2030

Towards a multidisciplinary and innovative approach on future inter-terminal transport options

Deliverable 2.2

Optimizing Inter-Terminal Transportation at the Port of Rotterdam: An Asset-light Solution

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Optimizing Inter-Terminal Transportation at the Port of Rotterdam: An Asset-light Solution

Master Thesis

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Abstract

This thesis mainly explores the asset-light solution for the Inter-Terminal Transportation system at the Port of Rotterdam. Further building on the innovative optimization model of Tierney et al. (2013), this thesis investigates the possibility of utilizing residual capacity of visiting vehicles from external parties. Variation in demand size and demand patterns mean that the ITT system require different number of vehicles on different days. This thesis thus tries to study how much effect extra capacity will have on the ITT system, i.e., reducing the number of vehicles needed. In addition, this thesis also looks at different ways to utilize extra capacity and compare their performance. The results of this study shows a significant effect present and encourages further study and adoption of the asset-light solution.

This research is carried out within the framework of the TUDelft, Erasmus University, and Port of Rotterdam Authority joint project "Inter-terminal transport on Maasvlakte 1 and 2 in 2030 - Towards a multidisciplinary and innovative approach on future inter-terminal transport options".

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1. Introduction

The rapid growth in international trade has prompted ports around the world to continue expanding the capacity to deal with the increasing amount of containers. Multiple terminals often serve to transfer containers between different modes of transportation including barges, railways and other forms of hinterland transportation. The movement of containers between terminals is called inter-terminal transportation (ITT). The ITT system functions as a backbone for the whole port and it has to be carefully planned to satisfy the demand of the port. Important decisions that have to be made in the strategic planning of the ITT system include the layout of terminals, transportation connections between terminals, the number and type of vehicles.

The plan to construct Maasvlakte 2 involves designing a new ITT system and offers the opportunity to save costs using innovative solutions. An efficient ITT system yields a minimal amount of delay in moving containers between terminals and requires substantial investment in infrastructure, equipment, technology and labor. How to make the right choice about infrastructure and vehicle configuration therefore has significant implications on both cost and performance of the ITT system.

Research in the area of ITT system is mainly focused on analyzing the performance using simulation techniques, while Tierney et al. (2013) developed a novel mathematical model to optimize the flow of containers. Dekker et al.

(2012) proposed an asset-light solution which seeks to utilize the residual capacity of visiting vehicles and reduce the initial investment in purchasing vehicles. Examples of unused transport capacity include: a barge which first visits ECT – DDE, next Euromax and finally RWG can be used to transport extra containers from ECT to RWG; a truck that needs to drop a container off at ECT and has to collect another one at Euromax can move one extra container from ECT to Euromax; Truckers who have some time left over in their duties are available to do some ITT trips. If all these unused capacity can be identified, purchased and utilized alongside vehicles owned by the port, the number of vehicles needed is expected to drop and the associated operation and maintenance costs would also become less. On the other hand, by 2030, multiple terminals at the sea-side will compete in a market situation, most probably with a surplus of capacity. This competitive environment will be part of the basic context of the asset-light solution.

In this thesis, I therefore would like to focus explicitly on this "asset-light" solution, which takes advantage of unused transport capacity, and discuss the feasibility of adopting this unique solution as well as the implications for planning and operating the ITT. Building upon the mathematical model developed by Tierney et al. (2013) and using input from results of other ITT sub-projects, I will systematically study the effect of extra transport capacity on the number of minimum required number of vehicles and try to find the best way to utilize this capacity if the effect is found to be significant. The research will offer useful guidance for both Port of Rotterdam and other ports with similar expansion plans. The research questions of this thesis can be formulated as follows:

1. How to optimize the effect extra vehicles have on the ITT system by adding extra vehicles in the right way?
2. Is the optimal effect found significant enough to justify further investigation on the asset-light solution?

This paper is organized as follows. First past research findings on ITT are summarized. Then the problem and demand data are described, followed by an explanation of the mathematical model used in this thesis. Finally, the results of this study are presented and analyzed.

2. Literature Review

Most studies that simulate and optimize container movements have focused on intra-terminal transportation (e.g. Briskorn and Hartmann (2006); Grunow et al. (2007); Nguyen and Kim (2009)). However, most of these models are not ideal for the case of inter-terminal transportation because vehicles typically have to travel much longer distances over publicly accessible roads with a lot of external traffic interactions in an ITT system, which is in strong contrast to intra-terminal transportation.

Ottjes et al. (1996) presented a generic object oriented simulation model for inter-terminal transportation with the nonperformance percentage (late arrival percentage) being the main performance indicator. Another simulation study in ITT done by Duinkerken et al. (2006) compared three different transportation systems and analyzed the different characteristics of the transport systems. These models mainly used simulation approaches to model the ITT at the port of Rotterdam but a simulation model is not able to optimize container movements in the ITT system.

Choobineh et al. (2011) used multi-class closed queuing networks to model operations of automated guided vehicles in a manufacturing or distribution environment. They modeled the steady-state behaviour of the closed queueing network by a linear program whose optimal value is the estimate of the required fleet-size. They also compared the analytical model with simulation studies for a set of numerical examples and concluded that the analytical model provides a good estimate for the required number of vehicles.

Tierney et al. (2013) developed a novel integer programming model for analyzing ITT and applied the model to optimize the container movements for the port of Hamburg and the port of Rotterdam. In their study, MTS is shown to perform better than both AGVs and ALVs. Their research was the first to incorporate optimization of vehicle routes and container flows in order to provide ports and terminals with the best performance a particular configuration of vehicles and infrastructure is capable of delivering. One main difference between the Tierney et al. (2013) study and this thesis is that in this study, different demand instances are solved by different solution methods. In this study, demand instances are closer to reality and the methodology allows adding extra vehicles.

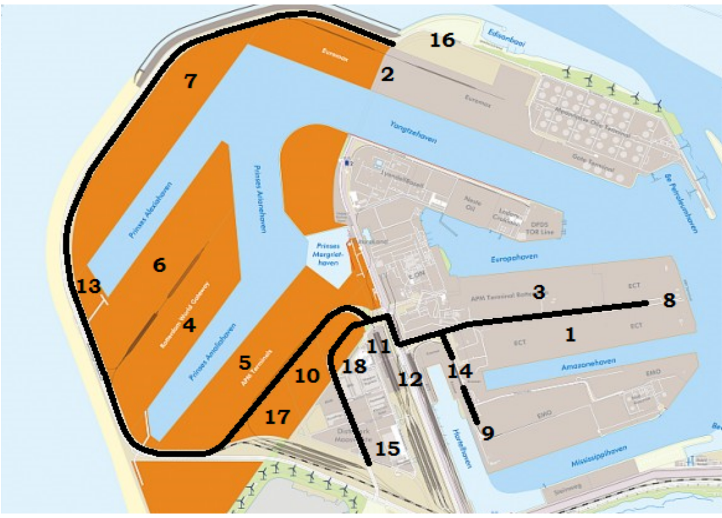
Nieuwkoop et al. (2013) extended the original model by Tierney et al. (2013) and presented a new model which can quickly calculate the optimal vehicle configuration. They applied the model on three different demand scenarios at the Maasvlakte area and concluded that less number of ALVs are required than AGVs to achieve the same performance. Their study also recommended vehicles with higher speed in order to reduce the number of vehicles required and the associated investment costs.

As a basis for this research, Van den Berg (2013) studied the asset-light solution using a simulation approach and concluded that extra capacity in the asset-light solution has a negligible influence on the ITT system and therefore the asset-light solution is not recommended for the ITT system at Maasvlakte. In his study, even after adding a large number of extra vehicles (400 extra vehicles), the number of basic vehicles required only drop slightly (from 89 to 88).

3. Problem Description

3.1 Maasvlakte terminals

This research studied the asset-light solution for the Maasvlakte expansion project. The Maasvlakte area consists of different terminals including deep sea terminals, rail terminals and hinterland terminals. The layout of the Maasvlakte area is shown in figure 1.



number	Terminals and service providers
1	ECT Delta Terminal
2	ECT Euromax
3	APMT Maasvlakte 1
4	Rotterdam World Gateway (RWG)
5	APMT Maasvlakte 2
6	Terminal 3
7	Terminal 4
8	ECT Delta Barge Feeder Terminal
9	Delta Container Services
10	Common Rail Terminal
11	Rail Terminal West
12	Barge Service Centre Hartelhaven
13	Common Barge Service Centre
14	Kramer Delta depot
15	Van Doorn Container Depot
16	Empty depot Maasvlakte 1
17	Empty depot Maasvlakte 2
18	Customs

Figure 1: Layout of the Maasvlakte area

3.2 ITT Vehicles

There are a range of different vehicle types available for ITT, each vehicle type with its own characteristics. Those vehicles mainly include regular road trucks, Automated Guided Vehicle (AGV), Automated Lifting Vehicle (ALV), Multi Trailer System (MTS), and Barge. Tierney et al. (2013) studied these different vehicle types and concluded that MTS has the best performance in terms of punctuality. Since this study does not intend to compare vehicle types, only ALV is chosen to be used in the model, which means any vehicle capacity including extra unused capacity are provided by ALVs. ALV instead of MTS is chosen because the objective of this study is not to recommend the best vehicle configuration and a vehicle type with average performance would be more representative of the general case and avoid over optimism. ALVs are automated vehicles that can carry one forty-foot container or two twenty-foot containers. They are also equipped with lifting capabilities and thus do not require cranes for loading and unloading operations.

3.3 ITT Demands

ITT demands are modeled using a multi-commodity flow in the same way as in Tierney et al. (2013). Each demand models the flow of containers between terminals at various times and includes origin node, destination node, amount of containers, release time, due time and a penalty function which is a piecewise linear function of the lateness of the arrival of the containers. However, the original demand instances in Tierney et al. (2013) are not used in this research because most data used in the demand instances are assumed rather than taken from real data. Instead, I took the results of Jansen (2013) and extracted 11 different demand instances for my research. Jansen (2013) not only predicted the annual throughput under four different scenarios based on different economic factors, but also studied the hourly and daily variation in demand by investigating the arrival pattern of containers.

However, it remains unclear whether the assumptions made in the Jansen (2013) study are realistic and there is an ongoing research project on improving the demand generator. Therefore, this research can be repeated using results from future research on ITT demand.

3.4 Asset-light solution

In this asset-light solution, vehicles are added to the demand instances for a limited time period. In this research, a two-hour time window is assumed for the extra capacity. During the two-hour time window, the extra vehicles can do ITT trips between any two terminals in the same way as normal vehicles, meaning that they can do as many ITT trips as possible within the two-hour time limit. Any extra vehicle starts at a certain terminal, but does not need to return to the original terminal or any other specific terminal. In other words, extra vehicles can end up at any terminal. It is worth mentioning that in practice, some extra vehicles can only start at certain terminal and finish at another fixed terminal. Therefore, the setting used in this research is an optimistic one. However, it is possible to account for fixed ending terminal by reducing the available time period for extra vehicles. In this way, extra vehicles are allowed enough time to travel to the terminal by certain time.

4.Methodology

In this paper, we used a revised version of the integer programming model and the C++ program developed by Tierney et al. (2013) to run demand instances generated from Jansen (2013)'s study in order to test the asset-light solution. In the revised model, one constraint is modified and one more constraint is added in order to allow extra vehicles. The objective of the IP model is to minimize penalty caused by late delivery of containers and the IP model is solved to optimality by CPLEX with the time limit set at 1800 seconds. The program returns "timeout" when time limit is exceeded. In my research, "timeout" has not occurred for a single time.

4.1 Model Assumptions

The model, which was created by Tierney et al. (2013), is based on a time-space graph. Loading and unloading of containers, transporting containers between terminals and traffic congestion are all incorporated in this model. It should be noted that several assumptions are made in this model. First of all, early arrival is not penalized and only lateness will result in penalties; In addition, short vehicle activities, such as connecting a tractor to a trailer loaded with containers in an MTS, are not modeled due to its requirement of fine discretization; Finally, it is assumed that all containers are 40 foot containers.

4.2 Time-space Graph

The time-space graph is constructed from a base graph, a non-temporal graph that describes the terminals and the connections between the terminals at the

Maasvlakte area. The “terminal” here means “either end of a carrier line having facilities for the handling of freight and passengers” instead of other meanings of the word “terminal” might have. All the terminals and intersection points, which means physical intersections between roads at the Maasvlakte area, constitute the set of all nodes of the base graph and the traffic connections between the terminals are represented by the set of arcs. Each terminal has a unique terminal node in the base graph. Let n be the number of terminal nodes and m be the number of intersection nodes, the base graph can then be defined as G=(V,A) where V={1,…,n+m} is the set of all nodes and A is the set of arcs (i, j) where $i, j \in V$. The base graph is then expanded into a time-space graph over time where τ is the total number of time periods. The time-space graph is defined as $G^T = (V^T, A^T)$ where V^T is the set of nodes and A^T is set of arcs. For every node in V, τ copies of the node are made in V^T. The arcs in the time-space graph incorporate the minimum time for a vehicle to move from one terminal node to another terminal node. There are in total τ time steps in the time-space graph and each time step represents a moment in time.

The time-space graph consists of three types of nodes: terminal nodes, intersection nodes and long-term nodes (LT nodes), which are copies of terminal nodes used to model long term loading/unloading of containers. LT nodes are required for some vehicles, which take more than a single time discretization to load or unload. In the case of this where only ALVs are used, LT nodes do not function in the model. When LT nodes are not needed, a single node in each time period is created for both terminals and intersection nodes. For each node in the time-space graph two properties are associated: the number of vehicles at the node, which includes both the vehicles made available at the start of optimization and the extra flexible vehicles made available at any time, and the maximum loading/unloading moves per time period. Contrary to Tierney (2013)'s research, in which only those nodes at time zero have vehicles available, this study has allowed nodes at time periods other than zero also to have vehicles to model adding extra vehicles at any time point.

There are also three types of arcs that connect the nodes. First of all, stationary arcs connect nodes for the same terminal at different time periods and allow vehicles and containers to stay in the same terminal over time. Secondly, long-term arcs connect terminal nodes with its long-term nodes. Finally, the normal arcs connect nodes representing different terminals over different time periods in order to model the movement of vehicles and containers from one terminal to another terminal. For each arc we associate a capacity indicated by the maximum number of vehicles that can travel on it in a single time period.

4.3 IP Model

The revised IP model, which allows adding vehicles at any time, is presented as follows.

Parameters used in the IP model are as follows:

n	Number of nodes in the base graph
τ	Number of time periods
V	Set of nodes in the base graph
V^{T}	Set of nodes in the time-space graph

A^{T}	Set of arcs in the time-space graph
Θ	Number of demands
In(i)	Set of nodes with an arc to node $i \in V^{\mathrm{T}}$
Out(i)	Set of nodes with an arc from node $i \in V^{\mathrm{T}}$
V_θ^D	Set of nodes excluding any time-space node that matches the origin or destination of θ
$V_i^{\vec{\mathrm{T}}}$	Outgoing, non-stationary, non-LT arcs from node $i \in V^{\mathrm{T}}$
$V_i^{\overleftarrow{\mathrm{T}}}$	Origin node in V of demand θ
d_θ	Destination node in V of demands θ
a_θ	Amount of containers in demand θ
r_θ	Release time step of demand θ
u_θ	Due time step of demand θ
$c_{i\theta}$	The unit penalty of containers arriving at node i for demand θ
$p_\theta(\cdot)$	Late delivery penalty function
$\delta_{ij\theta}$	Equal to 0 iff arc $(i,j) \in A^{\mathrm{T}}$ is a stationary arc from the demand origin of θ or is an LT arc
c_{ij}	Maximum number of vehicles on arc $(i,j) \in A^{\mathrm{T}}$
m_i	Maximum number of container load/unload moves during a time period at node i
m_i^{LT}	Maximum number of LT vehicle load/unload moves during a time period at node i
s_i	Amount of vehicles present at node $i \in V^{\mathrm{T}}$ at the start of optimization
γ_i	Maximum vehicle throughput of node $i \in V^{\mathrm{T}}$
μ_{ij}	Maximum container capacity of a vehicle on arc $(i,j) \in A^{\mathrm{T}}$

H Set of extra vehicle time periods, indexed by h

s_{ih} Number of extra vehicles to become available at time space node $i \in V^T, h \in H$

t_h^{End} the end time of extra vehicle period h ∈ H

V_h^T Set of time-space nodes with the end time of extra vehicle period $h \in H; V_h^T = \{i \in V^T | t_i \leq t_h^{End} \leq t_{i+1}\}$, where $\mathrm{t_i}$ is the time that time − space node i ∈ $\mathrm{V^T}$ occurs and t_{i+1} is next time step for the same terminal

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There are two sets of decision variables: $x_{ij} \in \{0, \dots, c_{ij}\}$: is the amount of vehicles on arc $(i, j) \in \mathrm{A^T} \backslash \mathrm{A^{LT}}$. It does not include LT arcs because LT nodes are only duplicates of normal terminal nodes. $y_{ij\theta} \in \{0, \dots, a_\theta\}$ is the amount of containers flowing on arc $(i, j) \in \mathrm{A^T}$ for demand θ

The objective function and constraints are as follows:

$$\min \sum_{1 \leq \theta \leq \Theta} \sum_{u_\theta < t < \tau} \sum_{i \in \mathrm{In}(d')} c_{d'\theta} y_{id'\theta}\, , d' = \tau d_\theta + t \qquad (1)$$

$$\sum_{1 \leq \theta \leq \Theta} \delta_{ij\theta} y_{ij\theta} \leq \mu_{ij} x_{ij} \qquad \forall (i, j) \in \mathrm{A^T} \qquad (2)$$

$$\sum_{j \in Out(i)} x_{ij} - \sum_{k \in In(i)} x_{ki} \leq s_i + \sum_{h \in H} s_{ih} \qquad \forall i \in \mathrm{V^T} \quad (3a) *$$

$$\sum_{i\in V_h^T}\left(\sum_{j\in Out(i)} x_{ij} - \sum_{k\in In(i)} x_{ki}\right)$$

$$\leq \sum_{i\in V_h^T}\sum_{h'\in H} s_{ih'} - \sum_{j\in V^T} s_{jh} - \sum_{l\in V^T}\sum_{h''\in H, t_{h''}^{End}=t_h^{End}} s_{lh''} \quad \forall h \in H \quad (3b) *$$

$$\sum_{j\in Out(i)} x_{ij} + \sum_{j\in In(i)} x_{ji} \leq \gamma_i \qquad \forall i \in \mathrm{V^T} \quad (4)$$

$$\sum_{j\in Out(o')} y_{o'j\theta} = a_\theta \;\; \forall 1 \leq \theta \leq \Theta, o' = \tau o_\theta + r_\theta \quad (5)$$

$$\sum_{j\in Out(i)} y_{ij\theta} - \sum_{k\in In(i)} y_{ki\theta} = 0 \qquad \forall 1 \leq \theta \leq \Theta, i \in V_\theta^D \quad (6)$$

$$\sum_{\tau d_\theta \leq j < \tau(d_\theta+1)} \sum_{i\in In(j)} y_{ij\theta} = a_\theta \quad \forall 1 \leq \theta \leq \Theta \qquad (7)$$

$$\sum_{1\leq\theta\leq\Theta}\left(\sum_{j\in \vec{V}_i^T} y_{ij\theta} + \sum_{j\in \overleftarrow{V}_i^T} y_{ji\theta}\right) \leq m_i \;\; \forall 0 \leq i \leq n\tau \quad (8)$$

$$\sum_{1\leq\theta\leq\Theta} \left(y_{ij\theta} + y_{ji\theta}\right) \leq m_i^{LT} \quad \forall 0 \leq i \leq n\tau, j = n\tau + i \qquad (9)$$

The objective function (1) minimizes the penalty caused by lateness of container arrivals. d' is the time-space node at time t for node d_θ in the base graph and $c_{d'\theta}$ is the unit penalty coefficient which is determined by time and the demand. Constraint 2 limits the number of containers on an arc to be less than the total capacity of all vehicles travelling on this arc. However, stationary arcs are not bounded by this constraint.

In constraint 3a, the total number of vehicles leaving a certain time-space node i, $\sum_{j\in Out(i)} x_{ij}$, should be bounded by the sum of the number of vehicles which start at that node, including both basic vehicles, s_i , and extra vehicles, $\sum_{h\in H} s_{ih}$, and the number of vehicles entering that node, $\sum_{k\in In(i)} x_{ki}$. In other words, the net outflow at certain time-space i should be bounded by the total number of vehicles that become available at that time-space node. The vehicles that become available at certain time-space node include two parts, s_i and $\sum_{h\in H} s_{ih}$, but note that s_i has a positive value only when i is a time-space node at time zero, this is because all basic vehicles become available at time zero. On the other hand, there is no such limit to $\sum_{h\in H} s_{ih}$ because extra vehicles can be added at any time at any terminal.

When a certain extra vehicle period h (e.g., h can be "from 12:00 to 2:00") comes to an end, those extra vehicles whose availability ends at this time can no longer come out of any time-space node i at the end time (all such time-space nodes constitute the set V_h^T) to do more ITT trips. This termination of availability is captured in constraint 3b.

On the left side of the constraint is the net flow for all nodes in V_h^T. On the right side of the constraint, $\sum_{i\in V_h^T} \sum_{h'\in H} s_{ih'}$ represents the total number of extra vehicles that are added at all nodes in V_h^T, $\sum_{j\in V^T} s_{jh}$ is the total amount of extra vehicles with extra time period h, and $\sum_{l\in V^T} \sum_{h''\in H, t_{h''}^{End}=t_h^{End}} s_{lh''}$ indicates the total number of extra vehicles whose availability happens to end at t_h^{End}. The first item $\sum_{i\in V_h^T} \sum_{h'\in H} s_{ih'}$ and the third item $\sum_{l\in V^T} \sum_{h''\in H, t_{h''}^{End}=t_h^{End}} s_{lh''}$ are added to account for the possibility that there might be other extra vehicles starting or ending at the same time as the end time of h. However, in this research, this scenario does not happen and therefore both items will always be equal to zero.

Constraint 4 constraints the number of vehicles entering and leaving a node in a particular time step. The flow of containers through the network is modelled in constraints 5, 6, and 7: the origin nodes of a demand must have a total outflow equaling the total number of containers in that demand, the destination nodes of a demand must have a total inflow equaling the total number of containers in that demand, and any other nodes have equal inflow and outflow for that demand. Constraint 8 bounds the loading/unloading capacity at a node in a single time period and constraint 9 bounds the loading/unloading rate at long-term nodes.

5.Heuristics

The mathematical model presented in chapter 4 is first used to solve the demand instances without extra vehicles as the basis for further results. In this process, I try to search for the minimum number of vehicles to achieve zero penalties for each instance. In order to do so, I used a binary search approach to find the optimal number of vehicles. The binary search works as follows: starting from 100 vehicles, if the penalty is zero, then 100 is the upper bound of the optimal number and 0 being lower bound. Then we try the half value which is 50 (on the other hand, if the penalty is larger than zero, we double the value and try 200 vehicles), if the penalty is larger than zero, then 50 becomes the new lower bound and we will try the half value of 100 and 50, which is 75. This process is repeated several times until we find the minimum number of vehicles for the instance to have zero penalties. The basic results will give information about the lower bounds for the experiments with extra vehicles.

Then in the asset-light solution, five different heuristics are investigated using the same mathematical model to find the best way to add extra vehicles. The five heuristics are explained as follows:

5.1 Heuristic 1

In heuristic 1, we add extra vehicles to transport penalty generating demands, i.e. demands with containers arriving late. We first run the instances with a certain small number of vehicles that are all available for the whole time period. Then the penalty result is collected and analyzed. All the containers arriving late will together contribute to the total penalty. Heuristic 1 will then add extra vehicles at the starting nodes or origins of the late containers and the number of extra vehicles is equal to the number of containers that arrive late. It can be expected that adding vehicles in this way will almost certainly result in zero penalty and we need to search for the smallest number that generates zero penalty. Therefore, we need to reduce the number of extra vehicles and try different values until we find the minimum number to achieve zero penalties. Again binary search is used in this process. In the process, half value is taken for the extra vehicles for each node.

5.2 Heuristic 2 and 3

In heuristic 2 and heuristic 3, extra vehicles are added at peak hours (i.e., peak hours of container demands) and pre-peak hours (the hours immediately preceding peak hours) respectively.

The second heuristic tested in this study is adding extra vehicles at peak hours. A peak in demand is very likely to cause a peak in container traffic as well. Therefore, we expect to find an effect by adding vehicles at those peak hours. The following two graphs show the demand in the number of containers over time for instance 1, with the first graph sorted in minutes and second in hours. The number of containers in a single demand are proportionately divided over the time period between its release time and due time, e.g. 120 containers released at time 0 and due at time 80 will add 1.5 containers (120/80=1.5) per minute from time 0 to time 80 in the first graph and add 90 containers (120*60/80=90) in hour 1 and 30 containers in hour 2 in the second graph.

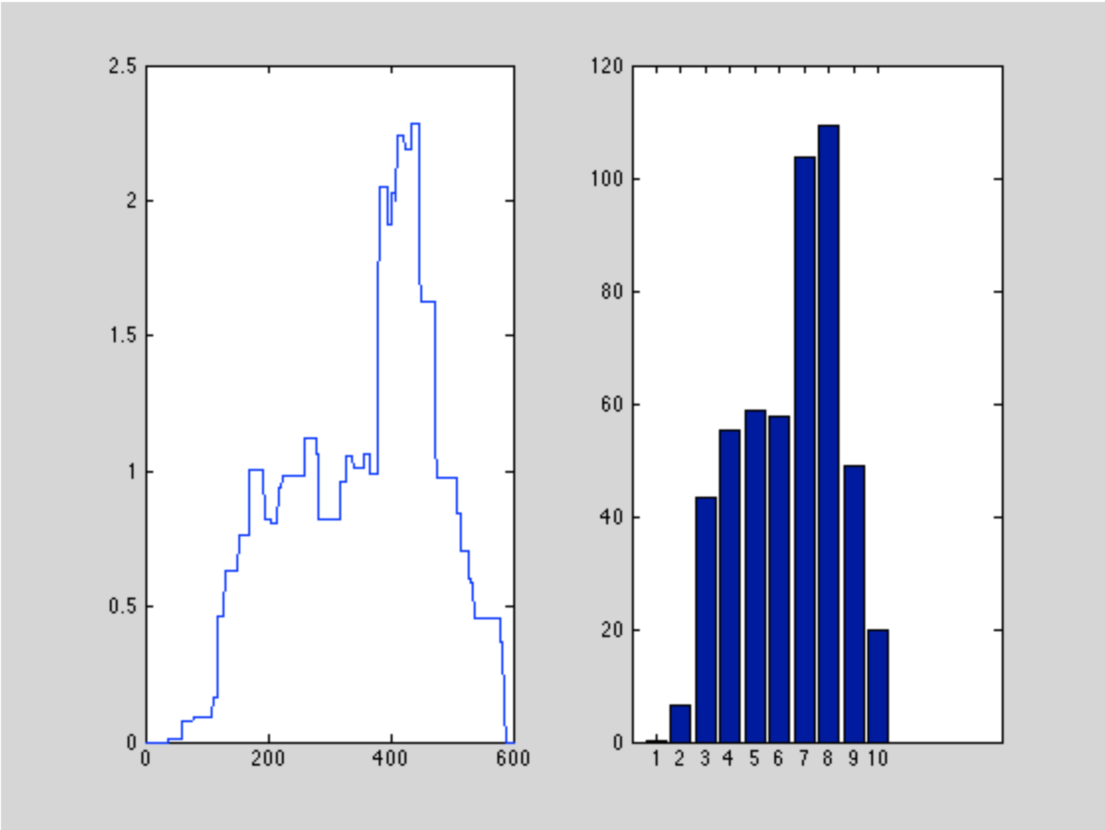

Figure 2: Number of containers over time

In the above figures, hour 7 and hour 8 would be counted as peak hours and all extra vehicles will be available from time 360 to time 480 and evenly distributed over the terminals. In searching for the minimum number of vehicles required, the lower bound is chosen as the starting value and the same binary search approach is used.

For comparison reasons, heuristic 3, adding vehicles at pre-peak hours, is also tried with the 11 instances. Pre-peak hours are the two hours immediately preceding the peak hours. In the case of instance 1, hour 5 and hour 6 is chosen as the non-peak hour and all extra vehicles are added from time 240 to time 360.

The following table lists the peak hours and pre-peak hours for all 11 instances.

Instance	1	2	3	4	5	6	7	8	9	10	11
Peak hours	360-480	240-360	360-480	360-480	240-360	300-420	360-480	300-420	360-480	300-420	360-480
Pre-peak hours	240-360	120-240	240-360	240-360	120-240	180-300	240-360	180-300	240-360	180-300	240-360

Table 1: Peak hours and pre-peak hours for all 11 instances in this study

5.3 Heuristic 4

In heuristic 4, extra vehicles are added to deal with those demands with smallest slack, i.e. the most urgent demands with the tightest deadlines and the least flexibility. Slack is defined as follows:

$$slack = due\ time - release\ time - MinTimeBetweenOriginDestination$$

Apparently, those demands with small slack must be transported as soon as possible after they are released; otherwise penalty is very likely to occur. Therefore, by adding extra vehicles to deal with those demands, one might expect other vehicles can be freed up and have more flexibility in transporting containers.

In the binary search process, the lower bound calculated earlier will be the starting value of the number of extra vehicles. The extra vehicles will be added to the origins of those demands in order of increasing slack.

5.5 Heuristic 5

In heuristic 5, we add all extra vehicles at the same time period and search for the best time period to add extra vehicles. Heuristic 5 is developed based on the results of heuristic 2 and heuristic 3. Since the combination of those two heuristics would have excellent performance with number of extra vehicles needed close to lower bound in most of the 11 instances, searching for the best fixed time period to add extra vehicles before running binary search would guarantee a performance at least as good as the combination of heuristic 2 and heuristic 3. The process works as follows: extra vehicles are added to the 11 instances at 8 different fixed time periods: 0-120, 60-180, 120-240, 180-300, 240-360, 300-420, 360-480, 420-540 and 480-600 with the number of extra vehicles equal to lower bound; the time period with the lowest penalty will be chosen to proceed with the binary search process to find the minimum number of extra vehicles required to get zero penalty.

5.6 Summary

In heuristic 2, heuristic 3 and heuristic 5, extra vehicles are evenly distributed over the different terminals. In contrast, in heuristic 1 and heuristic 4, extra vehicles are added at the origin terminals of penalty generating demands and urgent demands respectively.

In heuristic 1 and heuristic 4, extra vehicles may not necessarily become available at the same time, e.g. some vehicle might become available at time 120 and others become available at time 180. On the other hand, for heuristic 2, heuristic 3 and heuristic 5, all extra vehicles are available for the same time period, e.g., from time 120 to time 240.

In each heuristic, we search for the minimum number of vehicles required to achieve zero penalty for all 11 instances. Binary search is used in this process and, except for the case of heuristic 1, the starting number of extra vehicles is the lower bound of the extra vehicles needed. The lower bound is obtained by calculating the number of extra vehicles required in the scenario which assumes that all extra vehicles are available for the whole time period of 11 hours. In heuristic 1, the starting number of extra vehicles is equal to the total number of containers arriving late.

6.Data Description

As mentioned earlier, the data used in this study includes the demand instances and the basic parameters of the ITT system. The demand instances all have a 10-hour time period with an 8 minute discretization. For the demand instances taken from Jansen (2013), each demand has an origin terminal, a destination terminal, a release time, a due time and a penalty function. By taking into consideration of the minimum time required for a vehicle to travel from the origin terminal and destination terminal, the release time and due time of each demand have been manipulated to prevent infeasible instances, i.e. instances that have demands that are impossible to deliver on time.

6.1 ITT parameters

In this joint ITT project, common parameters are used in different sub projects. The Maasvlakte area consists of 18 different terminals and 10 intersections. The OD matrix is shown in appendix. The parameters for the vehicle (ALV) used in this study are listed in the following table:

Name	**ALV**
Capacity (TEU)	2
Manned	No
Avg. speed (km/hr)	40
Length (m)	13,7
Purchase costs (euro)	500000
Fixed costs (euro)	N/A*

Wage costs (euro/hr)	N/A
Fuel costs (euro/km)	N/A
Penalty costs (euro/hr)	N/A
Mooring time (min)	0

Table 2: ALV parameters used in the joint ITT project

*N/A means not available

Since the real penalty costs are not available, the penalty parameters $c_{i\theta}$ are assumed in this study. They are calculated in the C++ program by the penalty function p_θ. p_θ is a piecewise linear function that penalizes late arrival of containers and p_θ is equal to zero when the container arrives early or on time. The mathematical definition of p_θ is as follows: $p_\theta: \{0, \dots, \tau - 1\} \to \mathbb{R}$ where lateness in minutes is mapped to penalty and $p_\theta(t) = 0$ for all $t \leq u_\theta$. In this research, each demand has its own penalty function, but all penalty functions share the same format:

$$p_\theta(t) = 0 \; for \; all \; t \leq u_\theta$$

$$p_\theta(t) = c_1 \; for \; all \; u_\theta \leq t \leq t_1;$$

$$p_\theta(t) = c_2 \; for \; all \; t1 \leq t \leq t2;$$

$$\dots$$

$$with \;\; c_1, c_2, \dots being \; constants.$$

Most penalty functions used in this research has three or four pieces and the constants in the function can take different values based on needs. In this study, the constants are taken the values such that $c_{n+1} = 2c_n$. Due to the discretization of time in the model, more complicated penalty function can be used in future research without increasing the complexity of the model.

6.2 Demand data

The following two figures by Jansen (2013) show the demand patterns on both weekdays and weekend.

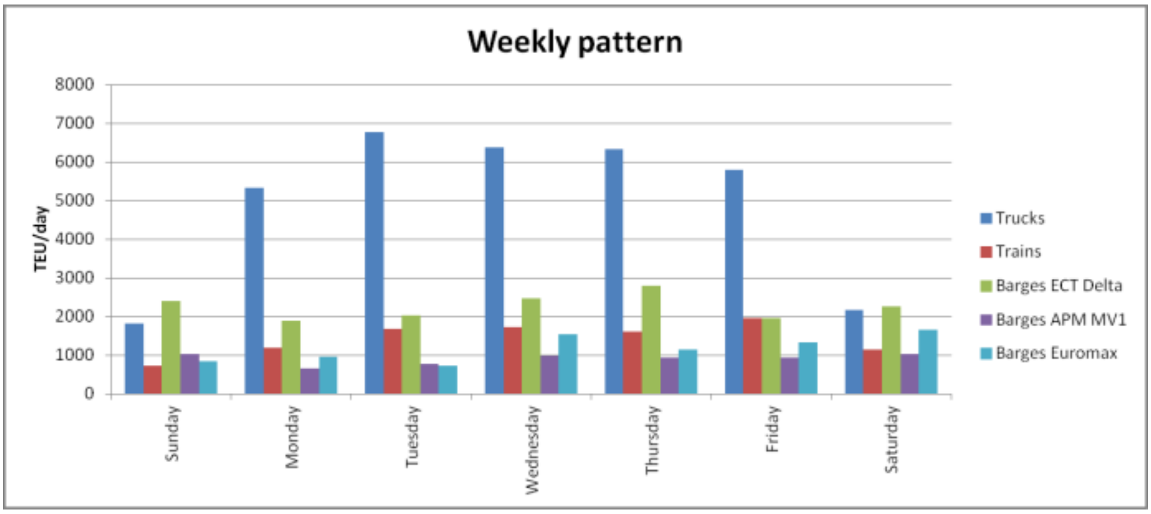

Figure 3: Arrival pattern of containers on various terminals

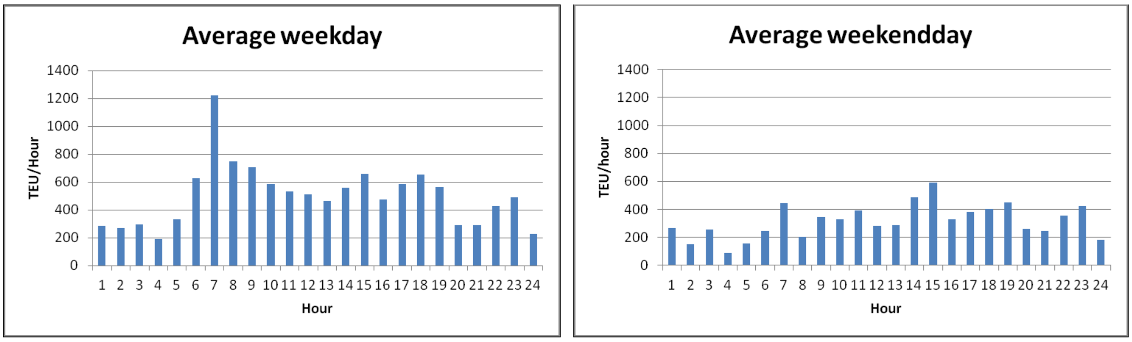

Figure 4: Average daily arrival pattern of containers on both weekdays and weekends

The 11 demand instances used in this study are derived from the demand data by Jansen (2013) by breaking the large instances into smaller instances over an 11-hour time period and 8-minute discretization and adjusting the format so that they can be read by the program used in this study. The 11 demand instances represent 11 different average weekdays. The due time of any demand is within the first 10 hours in order to prevent infeasible instances.

We also calculated the minimum time to transport each container in each demand for all 11 instances using the speed and distance data. By adding them up for all the containers in one instance and then dividing it by the total amount of time available, which is 680 minutes in this study, we arrive at the theoretical minimum number of vehicles required for each instance. In this ideal situation, each vehicle will be fully loaded for the whole 680 minutes and will be always transporting containers, meaning 100% utilization rate for all vehicles. While this is impossible in practice, this data gives an overview of the workload for all 11 instances. The following table summarizes the theoretical minimum for all 11 instances.

Instance	Theoretical Minimum
1	19,13
2	21,24
3	22,09
4	16,21
5	17.87
6	13,81
7	16.82
8	17,78
9	19,75
10	18,79
11	17,99

Table 3: The theoretical minimum number of vehicles required for all eleven instances

6.3 Extra vehicles data

In all five heuristics, extra vehicles are all available for two hours and two hours only. After being available for two hours, these extra vehicles can no longer do further ITT trips. Any ITT trip carried out by extra vehicles also needs to be finished before the end time of their availability. All extra vehicles do not need to return to any specific terminal by the end of the extra time period.

7. Results

7.1 Basic Results

We first present the basic results, in which no extra vehicles are added to the instances. The following table gives an overview of the binary search process and the final result for the first 4 instances. The “time” in the table means computation time, which is the time it takes for the program to return a solution.

	Instances	**1**	**2**	**3**	**4**
Nr. Vehicles					
100	Penalty	0	0	0	0
	Time	89.12	58.47	72.67	69.97
	Search order	1	1	1	1
75	Penalty	0	0	0	0
	Time	99.59	69.12	81.64	74.04
	Search order	3	3	3	3
70	Penalty	0		0	0
	Time	101.89		110.92	58.75
	Search order	5		5	5
68	Penalty			**0**	
	Time			**93.74**	
	Search order			7	
67	Penalty	0		270	0
	Time	108.76		540.56	69.92
	Search order	6		6	6
66	Penalty	**0**			0
	Time	**89.56**			93.16

	Search order	7			**7**
65	Penalty	270			**0**
	Time	125.07			**90.33**
	Search order	4			8
64	Penalty		0	17280	750
	Time		59.92	181.49	95.02
	Search order		4	4	4
62	Penalty		0		
	Time		90.65		
	Search order		**7**		
61	Penalty		**0**		
	Time		**96.42**		
	Search order		8		
60	Penalty		500		
	Time		99.35		
	Search order		6		
57	Penalty		34050		
	Time		207.64		
	Search order		5		
50	Penalty	172000	250430	519150	11250
	Time	237.48	164.60	193.46	127.07
	Search order	**2**	**2**	**2**	**2**
Min Nr. Vehicles		**66**	**61**	**68**	**65**

Table 4: Binary search process for the first four demand instances

Take the first instance as an example: we first start with 100 vehicles and get zero penalty; then we try the half value 50 but we get a positive penalty value; we add the vehicle number to 75 and the penalty value drops to zero; we then decrease the vehicle number to 65 and the penalty value increases to 270; so we increase the vehicle number to 70 and we again get zero penalty; the last two numbers tried for this instance are 67 and 66 respectively, both with zero penalty. Therefore, the minimum number of vehicles required is 66 because the penalty is zero at 66 and larger than zero at 65.

In this way, we find the minimum number of vehicles required for all 11 demand instances, which are listed in the following table and figure. The "theoretical minimum" is taken from the "data description" section for comparison.

Instances	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Theoretical Minimum	19.1	21.2	22.1	16.2	17.9	13.8	16.8	17.8	19.8	18.8	18.0
Min Nr. Vehicles	66	61	68	65	47	52	45	88	61	52	64

Table 5: Minimum number of vehicles required for 11 instances

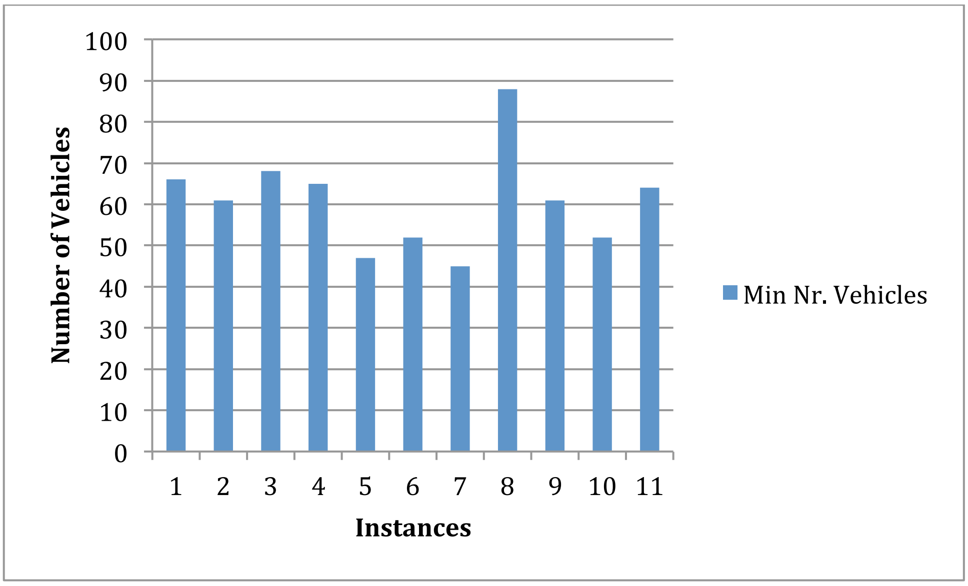

Figure 5: Minimum number of vehicles required for 11 instances

The above result shows that different instances require largely different number of vehicles. Suppose the 11 instances represent demands on 11 different days, then we need at least 88 vehicles to make sure that there is no delay in container transportation on any day. However, on most days, we do not need 88 vehicles and the vehicle utilization rate is low.

7.2 Results for asset-light solution

In the asset-light solution, there will be extra unused capacity available for ITT trips for a limited amount of time. We are interested in how much influence extra capacity will have on reducing penalty.

Given the results from 5.1, if we have only 50 vehicles available, then only 2 out of 11 instances will have zero penalties. Now suppose we have unlimited extra capacity available for unlimited amount of time, then the number of extra vehicles required is simply the difference between the result in 5.1 and 50. The number of extra vehicles required in this ideal scenario is listed in the following table and figure. In the table, the first row is taken directly from the result of 7.1. The second row indicates the number of basic vehicles that are available for the whole time period and the third row gives the number of extra vehicles required in the case when extra vehicles are also available for the whole time period.

Instances	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Min Nr. Vehicles Needed	66	61	68	65	47	52	45	88	61	52	64
Number of basic vehicles	50	50	50	50	50	50	50	50	50	50	50

Nr. extra vehicles needed	16	11	18	15	0	2	0	38	11	12	14

Table 6: Number of extra vehicles needed when extra vehicles are available for unlimited amount of time

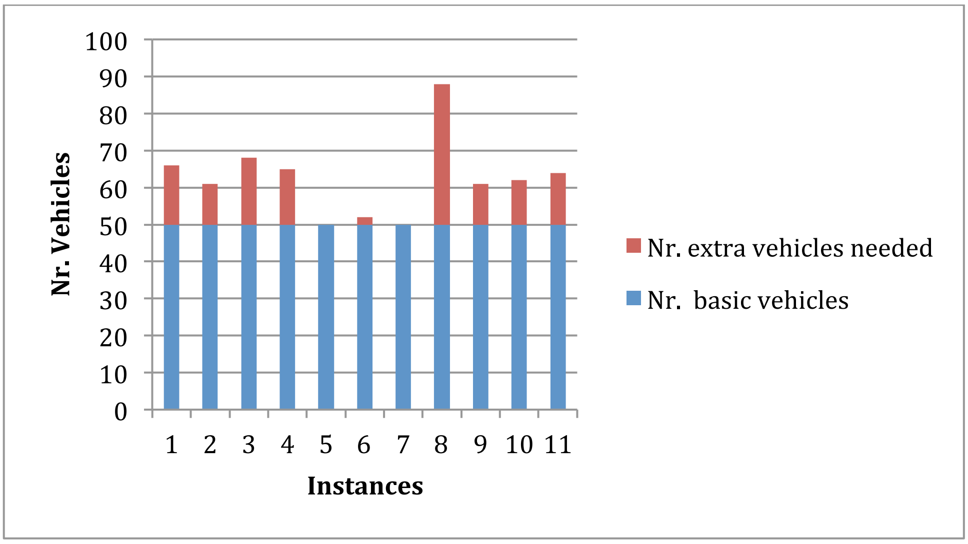

Figure 6: Number of extra vehicles needed when extra vehicles are available for unlimited amount of time

In this study, we assume that extra vehicles are only available for two hours in the whole time period of 11 hours. Logically, we expect to need more than the number in table 6. Therefore, when we search for the number of extra vehicles needed in the case when extra vehicles are only available for two hours, the numbers in table 6 will be the lower bounds of the final solutions.

However, when and where to add those extra vehicles need to be predetermined before we search for the number of extra vehicles needed. There are infinitely many ways to add extra vehicles and trying to find the optimal way to add extra vehicles is unrealistic. Therefore, in this study we try to find a heuristic which is easy, fast and effective. Next, we present the results of five different heuristics of adding extra vehicles.

7.2.1 Results of heuristic 1

If there are only 50 vehicles, penalties will be generated for most instances. The first heuristic is to add vehicles where penalties are generated. Take instance 1 as an example, when there are only 50 vehicles, the final penalty is 172000. The breakdown of the total penalty is listed in the following table.

	Demand Number	Total Nr. Containers Arriving Late	Total Penalty	Start Node	Release Time
Instance1	0	3	810	7	27
	3	2	540	5	3
	7	22	65940	7	35
	10	10	24780	3	13
	12	31	30520	4	48
	14	23	24450	5	41
	17	19	21630	7	50
	18	7	3330	1	47

Table 7: Breakdown of penalty for instance 1 with 50 vehicles

Based on the above table, vehicles will be added at the starting nodes of the penalty generating demands and the number of vehicles equals the number of containers that arrive late (e.g. 3 vehicles will be added at node 7 at time 27 for two hours and 2 vehicles will be added at node 5 at time 3 also for two hours). The following table lists the final results for all 11 instances. The first row lists the basic result without extra vehicles from section 7.1 and the second row presents the lower bound of extra vehicles needed when 50 basic vehicles are present. The last row gives the minimum number of extra vehicles needed for heuristic 1 when 50 basic vehicles are available for the whole time period. Furthermore, we also show the relationship between penalty and number of extra vehicles for instance 1 in the graph below.

Instances		1	2	3	4	5	6	7	8	9	10	11
Basic (No Extra Vehicles)	Nr. Vehicles Needed (Vehicles available for the whole time period)	66	61	68	65	47	52	45	88	61	52	64
Lower Bound	Nr. Extra Vehicles	16	11	18	15	0	2	0	38	11	2	14
Nr. Extra Vehicles Needed		22	52	36	15	0	4	0	55	19	3	20

Table 8: Minimum number of extra vehicles needed for heuristic 1

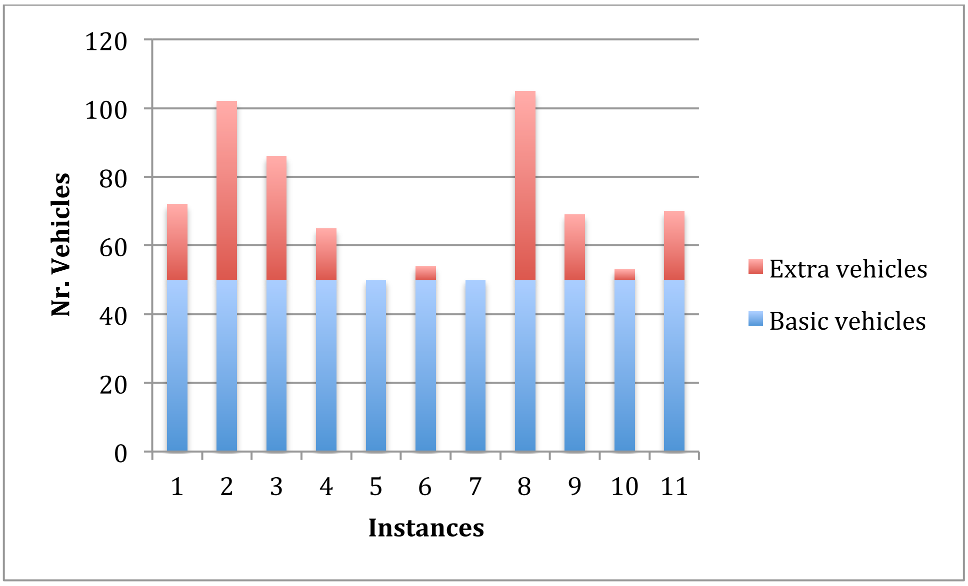

Figure 7: Minimum number of extra vehicles needed for heuristic 1

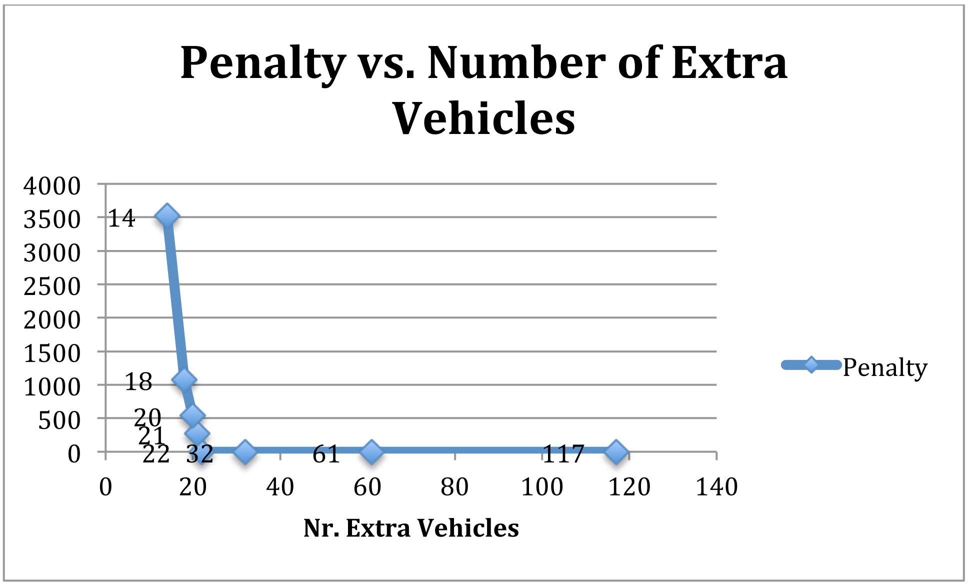

Figure 8: The relationship between lateness penalty and number of extra vehicles for instance 1

The above table shows that adding extra vehicles using heuristic 1 does have a significant effect in reducing penalties. In instances 4, we even only need to add 15 vehicles for two hours, which is the lower bound of the extra vehicles needed. The maximum number of extra vehicles needed is 55, which is in instance 8.

Overall, this heuristic has a reasonable performance in the 11 instances tested with the model. Without further experimenting with other heuristics, it can already be safely concluded that using extra vehicles with two-hour availability is cheaper than having vehicles available for the whole 11 hours since the number of extra vehicles needed is relatively low.

We also produced two graphs of vehicle utilization rate for instance 3 under both basic solution and asset-light solution. Vehicle utilization rate at any given time point is the percentage of vehicles that are transporting containers. Instance 3 is chosen because the above result shows that instance 3 require the most number of extra vehicles on top of the lower bound, which in general means the worst case scenario. Below we show two separate graphs for basic solution and asset-light solution respectively and another graph for a comparison of the utilization rate.

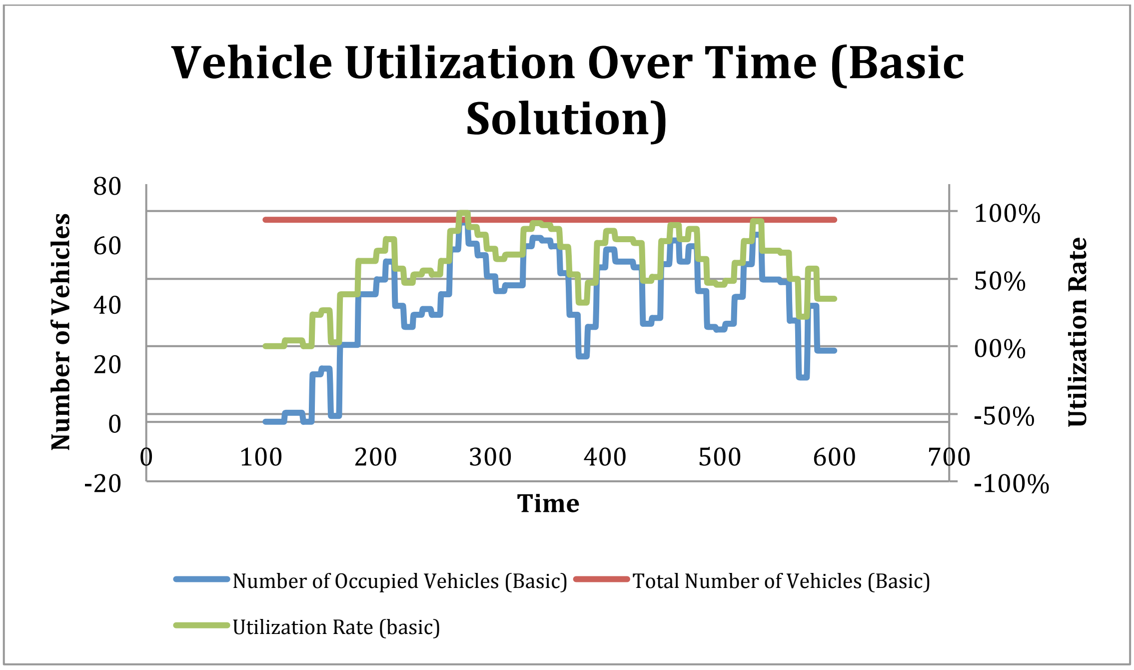

Figure 9: Vehicle utilization over time for instance 3 under the basic solution with 68 vehicles

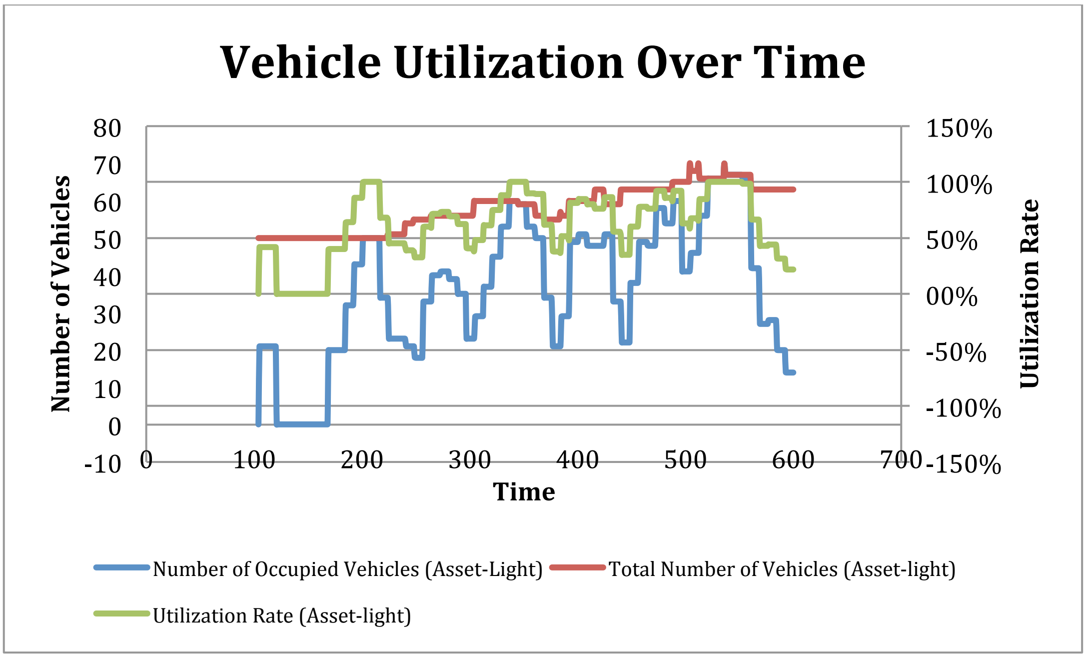

Figure 10: Vehicle utilization over time for instance 3 under the asset-light solution with 50 basic vehicles and 36 extra vehicles

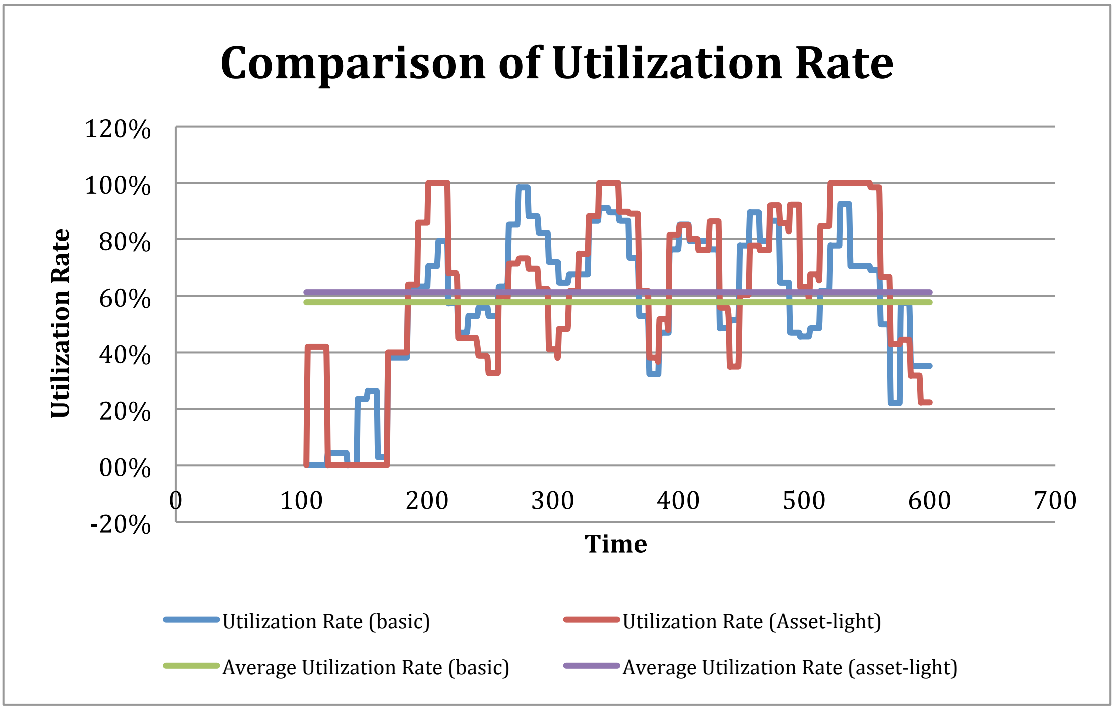

Figure 11: Comparison of vehicle utilization rate for instance 3 under basic solution and asset-light solution

Overall, for instance 3, the average vehicle utilization rate under the basic solution is 57.76% and the average vehicle utilization rate under the asset-light solution (using heuristic 1) is 61.26%. Is should be noted that the asset-light solution (using heuristic 1) so far has the worst performance for instance 3. Nevertheless, the vehicle utilization rate increased from 57.76% to 61.26%. Therefore, we can confidently conclude that the asset-light solution has a significant effect in increasing the vehicle utilization rate.

7.2.2 Results of heuristic 2 and heuristic 3

Below is a summary of the results for both heuristic 2 and heuristic 3. Again the first two rows list the number of vehicles needed in the basic scenario and the lower bound for the number of extra vehicles needed when there are 50 basic vehicles available for the whole time period. The last two rows give the results for heuristic 2 and heuristic 3, indicating the minimum number of extra vehicles needed to achieve zero penalty when 50 basic vehicles are available for the whole time period.

Instances		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Basic (No extra vehicles)	Nr. Vehicles Needed	66	61	68	65	47	52	45	88	61	52	64
Lower Bound	Nr. Extra Vehicles Needed	16	11	18	15	0	2	0	38	11	2	14
Heuristic 2	Nr. Extra Vehicles Needed	29	42	34	15	0	3	0	infeasible	21	3	31
Heuristic 3	Nr. Extra Vehicles Needed	20	31	19	15	0	4	0	44	19	3	17

Table 9: Minimum number of extra vehicles needed for heuristic 2 and heuristic 3

From the above table, heuristic 3 surprisingly performs better than heuristic 2 in most of the instances except in instance 6. This contradicts the common expectation that adding vehicles at the peak hours would be more efficient in reducing penalties. It is possible that adding vehicles at peak hours will add to the burden at busy terminals and the throughput of those terminal nodes becomes the bottleneck. In other words, constraint 4 becomes binding and limits the effect of extra vehicles. This can be well illustrated by instance 8, in which adding extra vehicles at peak hours is not able to reduce the penalty to zero. On the other hand, adding vehicles at pre-peak hours is less likely to cause such a congestion effect and it can also eliminate more jobs right before peak hours and therefore reduce the workload during the peak hours. Nevertheless, combing the results of both heuristic 2 and heuristic 3, it can be seen that adding all the extra vehicles at the same fixed time period, which means all extra vehicles are made available at the same time, can perform very well as long as they are added at the right time.

7.2.3 Results of heuristic 4

The distribution of demand urgency as defined by slack is shown in the following table, with the average slack meaning the average slack across all demands in a particular instance.

Slack (hours)	0-1	1-2	2-3	3-4	4-5	>5	Average Slack (minutes)
Instance 1	20.8%	14.4%	13.0%	21.6%	9.6%	20.6%	182.306
Instance 2	25.2%	31.0%	1.4%	3.2%	23.2%	16.0%	159.628
Instance 3	33.0%	26.6%	3.8%	19.8%	8.4%	8.4%	132.356
Instance 4	28.2%	9.0%	8.4%	12.6%	10.0%	31.8%	201.566
Instance 5	36.80%	22.40%	11.00%	9.80%	9.20%	10.8%	125.08
Instance 6	12.6%	8.4%	48.6%	10.0%	12.6%	9.6%	170.934
Instance 7	19.20%	36.20%	8.20%	12.20%	1.00%	23.2%	155.996
Instance 8	31.8%	14.4%	23.2%	2.6%	8.6%	19.4%	161.476
Instance 9	13.6%	20.8%	12.0%	19.4%	30.4%	3.8%	168.332
Instance 10	11.4%	19.8%	11.0%	5.6%	26.2%	26.0%	221.46
Instance 11	16.4%	25.6%	16.4%	38.8%	2.8%	0.0%	149.566

Table 10: The distribution of slack and average slack for 11 instances

For heuristic 4, I start with the lower bound and the results are shown as follows:

Instances	1	2	3	4	5	6	7	8	9	10	11
Nr. Extra vehicles	16	11	18	15		2		38	11	2	14
Penalty	740	29240	145140	0		870		1350	21960	1890	32400
Computation Time	228.07	333.58	174.44	97.94		112.47		187.29	254.17	498.05	225.55

Table 11: Penalty results for heuristic 4 with number of extra vehicles equal to lower bound

The "computation time" row lists the time for the program to return a solution in a single run and does not include manual operation time. It can be seen that the penalty is quite large for most of the instances. After comparing this result with the first three heuristics, I have concluded that this heuristic has the worst performance and therefore does not worth further searching.

7.2.4 Results of heuristic 5

In heuristic 5, we first look for the best time period to add extra vehicles and then search for the minimum number of extra vehicles needed. Theoretically, it might take up to about 15 different trials with the program until we can find the optimum since we need 8 different trials to find the best time periods and another 7 different trials in the binary search process if the difference between upper bound and lower bound is less than 128, which would be very likely to hold true based on the search process recorded in heuristic 2 and heuristic 3. However, the above process is possible to stop early. For example, when zero penalties is found for a certain time period with the lower bound, then further search will no longer need to be carried out. In addition, since it is expected that the final result will be rather close to the lower bound, it is unlikely to take up to seven different trials in the binary search process to find the optimum. The final results are shown in the following table:

Instances	1	2	3	4	5	6	7	8	9	10	11
Lower Bound	16	11	18	15	0	2	0	38	11	2	14
Nr. Extra Vehicles Needed	20	31	19	15	0	2	0	44	17	3	17
Best Time Period	240-360	120-240	240-360	240-360	N/A	240-360	N/A	180-300	300-420	180-300	240-360
Pre-peak Hours	240-360	120-240	240-360	240-360	N/A	180-300	N/A	180-300	240-360	180-300	240-360
Total Computation Time	1942.24	2471.30	1674.34	1234.19	N/A	2324.15	N/A	1553.10	1528.79	1035.21	1489.27

Table 12: Minimum number of extra vehicles needed for heuristic 5

As can be seen from the table, the best time period to add extra vehicles turns out to be the same as the pre-peak hours in 9 out of 11 instances except instance 6 and instance 9. Even in instance 6 and instance 9, the performance of heuristic 5 is only slightly better than heuristic 3. In heuristic 3, the number of extra vehicles needed for instance 6 and instance 9 are 4 and 19 respectively. In addition, the total computation time, which is the total amount of time for running the model excluding any manual operation time, is quite large for all 11 instances.

7.2.5 Summary of five heuristics

The following table lists the results of the above-mentioned heuristics without the result of heuristic 4 since it has been dropped as a bad solution. It can bee clearly seen from the table that heuristic 5 has the best performance. However, it can also be observed that heuristic 5 only performs slightly better than heuristic 3 but heuristic 5 takes much more time than heuristic 3 since heuristic 5 on average takes 15 runs (8 trials to find the best time period and 7 additional trials to find the minimum number of extra vehicles) and heuristic 3 takes on average only 7 runs.

Instances		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Basic (No Extra Vehicles)	Nr. Vehicles	66	61	68	65	47	52	45	88	61	52	64
Lower Bound	Nr. Extra Vehicles	16	11	18	15	0	2	0	38	11	2	14
Heuristic 1	Nr. Extra Vehicles	22	52	36	15	0	4	0	55	19	3	20
Heuristic 2	Nr. Extra Vehicles	29	42	34	15	0	3	0	Infeas.*	21	3	31
Heuristic 3	Nr. Extra Vehicles	20	31	19	15	0	4	0	44	19	3	17
Heuristic 5	Nr. Extra Vehicles	20	31	19	15	0	2	0	44	17	3	17

Table 13: Comparison of results for heuristic 1, 2, 3 and 5
* “Infeas.” means infeasible.

8. Conclusions

The main objective of this thesis is to study the effect of extra connections or extra vehicles on ITT optimization and the feasibility of the asset-light solution. The methodology of this study is mainly based on the mathematical model developed by Tierney et al. (2013), which is also the main difference between this study and van den Berg (2013)'s simulation study. In strong contrast to the results of van den Berg (2013), this thesis shows that adding extra connections does have a significant effect on reducing the number of basic vehicles needed. and increasing the average vehicle utilization rate. As a result, based on this observation, it is recommended that this asset-light solution be further studied, especially the economic feasibility of this solution.

In addition, this study also investigated five different heuristics of adding extra connections so as to maximize the effect. After comparing the results of five heuristics, it is concluded that heuristic 5 has the best performance of all and that heuristic 3 closely follows. This is contrary to the expectation that adding extra vehicles at peak hours would have the most effect. This might be because adding vehicles at non-peak hours avoids queues at terminals and congestion on roads. In addition, adding vehicles at pre-peak hours would allow jobs to be done early before peak hours and reduce the burden during peak hours. Accounting for both the difference in computation time and difference in performance between heuristic 3 and heuristic 5, I conclude that heuristic 3 is the best heuristic found to guarantee good performance with reasonable amount of computation time (approximately 900 seconds or 15 minutes).

This study is also subject to some limitations. First of all, the binary search is done manually. In the future, either binary search can be written into the computer program or even more efficient way to find the optimal number of vehicles can be found. For example, a new mathematical model with the objective function being minimizing the number of extra vehicles and an added constraint limits the total penalty to be zero. Secondly, the instances used in this study were simplified based on another study due to the limitations of the computer program I use. Therefore, the program can be further improved to accommodate demand instances which reflect the reality more accurately. Thirdly, it is assumed in this paper that extra vehicles can be added at any time at any terminal, which might be difficult to achieve in practice. This assumption therefore makes the conclusion of this research an optimistic one. Finally, the mathematical model used in this paper is a deterministic one and therefore cannot deal with uncertain capacity. This makes studying the uncertain supply of extra vehicles difficult. However, given that any lateness in container arrival is highly undesirable, the uncertainty in the supply of extra vehicles represent a major challenge to this asset-light solution.

Future study on the asset-light solution should not only deal with the limitations in this study, but the findings in this study should also be validated with improved methodology. More heuristics to add extra vehicles should also be explored, e.g., adding extra vehicles based on the vehicle utilization information, adding extra vehicles at the busiest terminals, etc. Furthermore, more practical aspects such as economic feasibility, ways to secure extra capacity, risks and risk management for this asset-light solution, etc. are among the most important subjects to be investigated before this solution can be put into practice.

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*Private communication with Dr. Kevin Tierney and Dr. Remy Spliet in formulating constraint 3a and 3b.

Appendix A OD-Matrix of Maasvlakte Terminals

Origin-Destination matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	0	13.7	0.7	6.4	3.2	6.7	9.8	0.7	2.3	2.6	2.9	1.4	7.3	2.3	3.2	14.1	3.6	2.3
2	13.7	0	13.2	7.3	10.5	7	3.9	14.5	14.5	11.1	13.4	13.2	6.4	13.7	13.3	0.4	10.1	12.4
3	0.7	13.2	0	5.9	2.7	6.2	9.3	1.3	1.7	2.1	2.4	1.7	6.8	1.8	2.4	13.6	3.1	1.4
4	6.4	7.3	5.9	0	3.2	0.3	3.4	7.2	7.2	3.8	6.1	5.9	8.5	6.4	6	7.7	2.8	5.1
5	3.2	10.5	2.7	3.2	0	3.5	6.6	4	4	0.6	2.9	2.7	5.3	3.2	2.8	10.9	0.5	1.9
6	6.7	7	6.2	0.3	3.5	0	3.1	9.6	4.7	4.1	6.4	6.2	8.8	6.7	6.3	7.4	3.1	5.4
7	9.8	3.9	9.3	3.4	6.6	3.1	0	12.9	7.8	7.2	9.5	9.3	2.5	9.8	9.4	4.3	6.2	8.5
8	0.7	14.5	1.3	7.2	4	9.6	12.9	0	3	3.4	3.6	2.1	8.1	2.8	5.5	14.9	4.4	2.7
9	2.3	14.5	1.7	7.2	4	4.7	7.8	3	0	3.4	3.3	1	8.1	0.3	3.9	14.9	4.4	2.5
10	2.6	11.1	2.1	3.8	0.6	4.1	7.2	3.4	3.4	0	2.3	2.1	4.7	2.6	2.2	11.5	1	1.3
11	2.9	13.4	2.4	6.1	2.9	6.4	9.5	3.6	3.3	2.3	0	2.6	7	3.2	0.9	13.8	3.3	0.8
12	1.4	13.2	1.7	5.9	2.7	6.2	9.3	2.1	1	2.1	2.6	0	6.8	0.4	3.1	13.6	3.1	1.8
13	7.3	6.4	6.8	8.5	5.3	8.8	2.5	8.1	8.1	4.7	7	6.8	0	7.3	6.9	6.8	3.7	6
14	2.3	13.7	1.8	6.4	3.2	6.7	9.8	2.8	0.3	2.6	3.2	0.4	7.3	0	3.6	14.1	3.6	2.3
15	3.2	13.3	2.4	6	2.8	6.3	9.4	5.5	3.9	2.2	0.9	3.1	6.9	3.6	0	13.7	3.2	1.8
16	14.1	0.4	13.6	7.7	10.9	7.4	4.3	14.9	14.9	11.5	13.8	13.6	6.8	14.1	13.7	0	10.5	12.8
17	3.6	10.1	3.1	2.8	0.5	3.1	6.2	4.4	4.4	1	3.3	3.1	3.7	3.6	3.2	10.5	0	2.3
18	2.3	12.4	1.4	5.1	1.9	5.4	8.5	2.7	2.5	1.3	0.8	1.8	6	2.3	1.8	12.8	2.3	0

number	Terminals and service providers
1	ECT Delta Terminal
2	ECT Euromax
3	APMT Maasvlakte 1
4	Rotterdam World Gateway (RWG)
5	APMT Maasvlakte 2
6	Terminal 3
7	Terminal 4
8	ECT Delta Barge Feeder Terminal
9	Delta Container Services
10	Common Rail Terminal
11	Rail Terminal West
12	Barge Service Centre Hartelhaven
13	Common Barge Service Centre
14	Kramer Delta depot
15	Van Doorn Container Depot
16	Empty depot Maasvlakte 1
17	Empty depot Maasvlakte 2
18	Douane