Fair assignment of shared autonomous vehicles at North Sea Port Vlissingen

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Management summary

This research has been conducted at Distribute, an Enschede-based company focused on smart logistics and autonomous systems. More specifically, we participated in a project with North Sea Port Vlissingen, a cross-border port located in Zeeland, which is interested in using autonomous vehicles to transport containers. It focused on whether implementing a fair shared shuttle service for first- and last-mile logistics using autonomous vehicles is possible.

North Sea Port plans to centralize container pick-up and drop-off by building the so-called Central Gate. The Central Gate will offer resting facilities for truck drivers and have around 450 parking places for trucks and containers. Transportation from the Central Gate to the terminals, and vice versa, will happen with autonomous vehicles. These vehicles will be shared among fifteen terminals located within the port. The research aimed to see whether sharing can take place fairly while maintaining sufficient logistical performance. Therefore, the main research question is:

How can a fair shuttle service be designed for a first- and last-mile shared shuttle service using autonomous vehicles at North Sea Port Vlissingen?

By decoupling first- and last-mile transportation from long-haul trips, specialized vehicles can be used for all transportation legs. Highly automated vehicles are already used in enclosed areas such as container terminals and are being tested on open roads. Fairness becomes crucial when resources are limited. Various allocation methods aim to protect the rights of smaller parties. Fairness can also be ensured using game-theoretic concepts, such as the core and Shapley-value, though these methods are computationally demanding.

The shuttle service at North Sea Port should balance logistical performance, fairness and adaptability. As the level of dynamism encountered at NSP is low, a schedule insertion algorithm was used to assign jobs to vehicles. When a job becomes available for planning, all possible vehicles and positions in the schedule are evaluated. A job is assigned to the place in the schedule that yields the shortest schedule completion time among all vehicles.

A two-way approach was chosen for designing the first- and last-mile shuttle service at North Sea Port. First, a simulation model was used to test various configurations. Experiments were run to gain insights into the number of autonomous vehicles required, container dwell time, vehicle utilization and the number of kilometres travelled. Moreover, a comparison was made between the shared situation and the situation in which each terminal has its own dedicated vehicle. Second, a weekly cost allocation was calculated using the standalone cost and proportional allocation methods. Weigh factors for the proportional method were based on the standalone costs and number of autonomous vehicles required by a terminal when acting individually.

When 16 autonomous vehicles are used, the average container dwell time is just over half an hour, with over ninety per cent of the jobs being delivered on time. Both performance indicators are consistent among terminals. Without sharing, 24 vehicles are needed to obtain the same performance. As such, sharing can reduce the number of required vehicles from 24 to 16, saving a third of the fixed vehicle costs. Moreover, sharing allows for the pooling of inbound jobs at one terminal with outbound jobs at another terminal.

When it comes to the allocation of weekly costs, the standalone cost of a terminal acts as an upper bound and the outcome of the proportional allocation as a lower bound. A terminal shall not be assigned more than it is upper bound and not less than its lower bound to keep the system stable. The proportional cost allocation method with standalone cost or the number of non-shared AVs as

weigh factors favours smaller terminals as they are assigned more savings than the larger ones. This allocation ensures they are protected against the larger ones who can bear the financial investments of buying autonomous vehicles alone. Table M-1 shows that using a proportional allocating method based on the standalone costs or the number of AVs in the non-shared scenario reduces costs for all terminals compared to working alone. By sharing, each terminal saves around twenty per cent of the total weekly costs.

Terminal	Upper bound	Lower bound
KB123	€ 20.286	€ 16.336
KB4	€ 9.673	€ 7.257
KB5	€ 9.874	€ 7.578
AMC	€ 4.329	€ 2.997
ZZC	€ 4.367	€ 2.943
VB2	€ 21.803	€ 16.341
VB3	€ 17.191	€ 12.845
VB1	€ 13.238	€ 9.628
SUP	€ 3.950	€ 2.575
VOP	€ 4.346	€ 3.084
ZER	€ 3.648	€ 2.088
AWT	€ 4.227	€ 2.923

Table M-1: Weekly cost bounds per terminal

In conclusion, a shuttle service with autonomous vehicles can be designed fairly at North Sea Port Vlissingen. Using a schedule insertion algorithm for job-to-vehicle assignment and having a total of sixteen autonomous vehicles, the average container dwell time is around half an hour and consistent among the terminals. Utilization levels show no extremes, and due times are generally met. By allocating costs according to the proportional method, each terminal has financial benefits from sharing vehicles as they all pay less than the situation in which they would have their dedicated vehicles. When using AV fractions as the weight value of the proportional methods, the savings per terminal are comparable at twenty per cent. In contrast, when using the standalone costs as the weight factor, the smaller terminals achieve even higher savings.

Further research on North Sea Port can extent the model by implementing vehicle battery constraints, different travel speeds, and penalty costs for Vehicle

missing deadlines, all of which were excluded or simplified in this research. When different demand patterns are used as input, the cost allocation should be updated to reflect these changes. Updating can be done by recalculating the standalone costs of the terminals and once again using these values as weigh factors for the proportional allocation method.

Preface

Though through personal circumstances, it took a while to finish this thesis, the fact you can read this thesis marks the end of my study period at the University of Twente. I really enjoyed studying Industrial Engineering and Management and the atmosphere at the UT and in Enschede.

First of all, I would like to thank Berry Gerrits for being supportive throughout the whole process and providing a good working atmosphere at Distribute. Always dropping ideas related and unrelated to research, a great conservation was never far away. I would also like to thank the other graduate students at Distribute for their support and the nice discussions ranging from world politics to sports.

Second, I would like to thank Martijn Mes for being the lead supervisor of this thesis and providing valuable insights and directions for research. Furthermore, I would like to thank Eduardo Lalla as second supervisor. Though he was only involved for a short period, his constructive feedback during that time improved this thesis. From the UT, I must also thank Cornelis ten Napel for being a listening ear at the many meetings we have had over the years to discuss my personal situation.

At last, I must thank the people who made my time studying great. With V.A. Coq, I have played countless “klaverjassen” and board games, and I have done many bike rides and (successful) pub quizzes. Skeuvel was not only a place to train and achieve speedskating results, but the club also provided me with great association life over the past ten years.

Yoran Nijenhuis

Enschede, January 2025

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List of abbreviations

AV Autonomous Vehicle
ADR European Agreement concerning the International Carriage of Dangerous goods by road
CATALYST Connected Automated Transport And Logistics Yielding SustainabiliTy
CG Central Gate
KPI Key Performance Indicator
LHV Longer Heavier Vehicle
NSP North Sea Port
UT University of Twente
VRP Vehicle routing problem

Terminal abbreviations:

AWT Access World Terminals
KB Kloosterboer
SUP Supermaritime
VB Verbrugge
VOP Vopak
ZER Zeeland Refinery
ZZC Zoomweg Zeeland Coldstores

1. Introduction

This chapter introduces the research on developing a fair shared shuttle service for first- and last-mile transportation. Section 1.1 introduces the North Sea Port Vlissingen use case. Section 1.2 outlines the problem statement and the Central Gate concept. Section 1.3 introduces the CATALYST consortium, of which this research is part. Section 1.4 briefly introduces Distribute, the company where this research was conducted. Section 1.5 covers the research motivation, and Section 1.6 defines the scope of research. Lastly, Section 1.7 introduces the formulated research questions.

1.1 North Sea Port

North Sea Port (NSP) is a cross-border port established in 2018 following a merger of the Dutch ports of Vlissingen and Terneuzen and the Belgium port of Ghent. Spanning 60 kilometres and 9100 acres, North Sea Port is ranked eighth in Europe, handling 71.5 million tons of cargo and generation added value of 14 billion euros in 2019. Over 90% of all transhipped cargo is wet, dry or breakbulk. The port is home to 550 companies employing 100,000 people (North Sea Port, 2020).

Outbound transportation to the hinterland utilizes all standard modes of transportation like trucks, barges, trains and pipelines. Due to its strategic location at the crossroads of waterways connecting the Netherlands, Belgium, France, and Germany, barges and other ships conduct half of the hinterland transport. In contrast, only a third of hinterland transport occurs by road compared to 75% of the whole sector.

This report includes a case study focused on the port division located in Oost Vlissingen. This division of North Sea Part covers 300 acres of businesses, with 150 acres still available for expansion. The companies located in Oost Vlissingen primarily focus on creating added value through container transhipment.

1.2 Central Gate

Truck drivers visiting North Sea Port in Vlissingen currently face safety and security challenges when parking and taking rest periods. Due to limited parking within the port, trucks are often forced to park in nearby towns. This parking in towns leads to safety concerns, such as containers carrying flammable and dangerous goods parked in residential areas. Additionally, parking on open roads exposes containers to the risk of break-ins.

Finding suitable parking places is problematic for several reasons. First, there are few support facilities for trucks and truck drivers to rest and refresh themselves. These truck rest places typically have adequate parking places, which are lacking around the port of Vlissingen. Second, inefficient utilization of terminal capacity results in uneven distribution of (un)loading requests throughout the day. At peak hours in the early morning and after lunch, the demand for parking places is currently too high to be satisfied. This inefficient usage of terminal capacity arises through the absence of central and uniform registration processes, leading to delays and uncertainty in truck arrival times and the luck of buffer zones where trucks can wait before proceeding to the terminals at a predefined time.

To overcome these practical problems and challenges, North Sea Port plans to build the so-called Central Gate, a centralized facility for trucks and drives serving multiple functions. It will provide 450 parking places for trucks and include facilities where drivers can take their mandatory rest periods. For the latter, the gate will have cleaning and maintenance facilities for the trucks, showers, a restaurant and toilets for the truck drivers.

Moreover, the Central Gate will be a decoupling point for dropping off and picking up containers. Autonomous vehicles will handle the first- and last-mile delivery and retrieval of containers. Centralizing drop-off and pick-up points will prevent terminal overflow, and using autonomous vehicles will be a step towards 24/7 operations with reduced staff requirements. North Sea Port's ambitions for the Central Gate are that it will (North Sea Port, 2019):

- Provide a sustainable, innovative, secure arrival, collection and service location for trucks and truck drivers.
- Stimulate developments in logistics by offering an experimental environment for future test projects.
- Foster the energy transition by using non-fossil-fuelled modes of transportation.
- Increase safety in and around the port area.

The problems currently encountered drive this list's first and last points and are practical problems. The other two are future-based by actively trying to make the port a frontrunner in environmental developments in logistics. However, the Central Gate and its related ambitions involve knowledge and research gaps. The use of autonomous vehicles is a rapidly evolving field with many areas for improvement and unresolved questions. Moreover, vehicle sharing is a new concept for North Sea Port, leading to research problems that must be addressed before system implementation.
In light of these research challenges, North Sea Port seeks to understand how to assign vehicles to jobs, manage different demand patterns over the day and week and determine whether it is possible to achieve a stable situation where terminals are better off cooperating than alone. Figure 1-1 shows these questions and their relationship to the usage of the CG in a problem cluster.

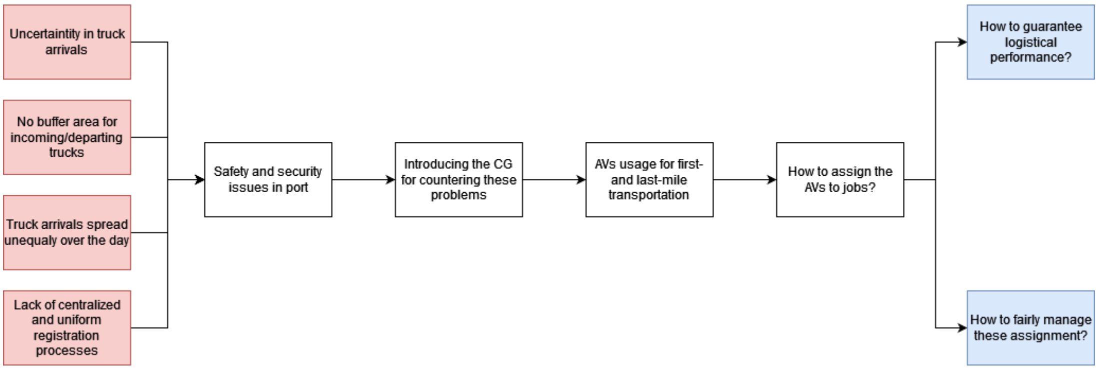

Figure 1-1: Problem relations related to the usage of autonomous vehicles for the first- and last-mile at NSP

The Central Gate and related processes at North Sea Port will be further detailed in Chapter 2, including information on Gate accessibility, registration and transportation processes, travel distances and times, and the impact and use of early information.

1.3 CATALYST

North Sea Port is committed to developing the port area sustainably and innovatively. To achieve this, North Sea Port is a partner in the CATALYST project. CATALYST stands for *Connected Automated Transport And Logistics Yielding SustainabiliTy*. It is a consortium of logistics companies that aims to exploit the automation of end-to-end transport and logistics on enclosed buffer areas and corridors through living labs. A living lab is a methodology that helps to address complex multi-stakeholder challenges in which innovations are developed and deployed in practice.

The goal of the CATALYST living labs is to identify and define the requirements of connected automated transport (CAT) to facilitate practical implementation. This goal contributes to a durable ecosystem by implementing sustainable practices that improve efficiency, traffic throughput, and costs.

The CATALYST living lab is divided into multiple integrated subprojects focusing on CAT innovations. The project leader of CATALYST is TNO, and the University of Twente is a partner in this project. North Sea Port is one of the logistic service providers hosting a living lab. Other locations for the living labs within CATALYST are the Port of Moerdijk, Schiphol and the distribution centre of DPD in Oirschot.

1.4 Distribute

This master thesis was executed at Distribute. Distribute is a research company located in Enschede that develops simulation models to study the impacts of distributed planning approaches. Focus areas are smart mobility, autonomous systems, industry 4.0, Internet of Things, artificial intelligence and smart logistics (Distribute, 2021a). As such, Distribute is a partner in the CATALYST project and has conducted a simulation study for the Central Gate at North Sea Port, focussing on the utilization of the Central Gate.

1.5 Research motivation

Recently, there has been an increased focus on connectivity, automation and autonomy in logistics and transport. Connected automated transport is expected to continue developing in the upcoming years. This report focussed on shared shuttle services for logistic hubs and how such a service could be implemented, using the Central Gate at North Sea Port as a case study.

North Sea Port plans to use autonomous vehicles for its inter-terminal shuttle service. Given the considerable financial investments and commitments required from terminals in the port, North Sea Port wants to know the added value of deploying autonomous vehicles at the Central Gate. Additionally, the best approach to vehicle ownership—whether each terminal should have its vehicles or whether sharing vehicles is more effective in performance and financial investment—is still unclear.

The port comprises fifteen terminals from nine companies that will share the autonomous vehicles. A fair distribution of vehicle usage across these terminals is essential to maintain stakeholder satisfaction. This concern is a significant motivation for the research.

1.6 Scope

This research focuses on deploying shared autonomous vehicles for the first- and last-mile logistics and how to assign vehicles to available jobs fairly. If fairness is not achieved or perceived, companies may be less willing to participate in a shared shuttle service. While North Sea Port has addressed practical problems, as outlined in the problem cluster, it lacks solutions for the knowledge gaps related to using shared autonomous vehicles.

For this research, the travel from and to the Central Gate is considered as first- and last-mile transport in this research as the mode of transportation changes. However, this leg may still be part of the long haul when a container is transported by barge or delivered to the end customer by smaller vehicles.

This research focuses on shared shuttle services, which are expected to play an important role in future transportation by increasing vehicle utilization and reducing overall emissions.

1.7 Research questions

This research aims to design a shared shuttle service at North Sea Port Vlissingen using autonomous vehicles that is fair for terminals. As such, the main research question is:

How can a fair shuttle service be designed for a first- and last-mile shared shuttle service using autonomous vehicles at North Sea Port Vlissingen?

To help answer the main question, the following sub-questions are formulated:

1. What are the current processes in place at North Sea Port, and which changes will occur when the Central Gate is implemented?
    a. What will the Central Gate look like?
    b. What is the terminal structure within the port?
    c. What are the job patterns at NSP during the day and week?

This sub-question aims to give a basic introduction to the processes at North Sea Port, both current and when the Central Gate is complemented. Moreover, it aims to give an overview of the terminal structure and insights into historic job patterns.

2. How can first- and last-mile transport be implemented and managed fairly?
    a. What is known about connected automated transport and first- and last-mile logistics?
    b. Why does decoupling occur between the long haul and the first- and last-mile?
    c. What different applications of first- and last-mile logistics do exist?
    d. How define fairness?
    e. What concepts can be used to evaluate fairness?
    f. What are the possible methods for collaboration in allocation methods?

This sub-question aims, through a literature study, to understand better connected automated transport (CAT), including its current status and anticipated future developments. Moreover, it aims to give an insight into first- and last-mile logistics, highlighting how these differ from long-haul transportation. Different types of logistics hubs will be analysed since first- and last-mile logistics applications are tailored to specific situations. As equal treatment of terminals is crucial for first- and last-mile transport at NSP, factors influencing fairness and collaborative planning methods will also be included in the literature review.

3. What is a suitable method for implementing a fair-use shared shuttle service at NSP?
    a. What principles should be fulfilled?
    b. Under what conditions should the assignment take place?
    c. How can a cost division per terminal be obtained?

This question involves formulating the solution design for the problem at North Sea Port. It will involve the design for the planning jobs, cost sharing and the simulation approach.

4. How can a simulation model of North Sea Port be designed and evaluated?
    a. What does the conceptual model of simulation look like?
    b. Which processes are excluded or simplified?
    c. What type of simulation reflects the processes at NSP?
    d. What are the most important processes of the model?
    e. Can the model be verified and validated?

A simulation study will evaluate a fair shared shuttle service for the NSP Vlissingen use case. The study will implement the solution design formulated in the previous sub-question, with deliverables including a conceptual and simulation model.

5. What performance can be expected of the fleet management algorithm at North Sea Port Vlissingen?
    a. How does the shared system compare to the non-shared one?
    b. What level of logistics performance can be expected in real life?
    c. What is a stable configuration in terms of costs?

This sub-question discusses the simulation study results, providing insights into the logistics performance of the shared shuttle service at North Sea Port. The results will be benchmarked against a scenario where vehicles are not shared, and each terminal has its dedicated vehicles. At last, costs are allocated using the method proposed in the solution design. These results are presented in Chapter 6.

Thesis outline

In summary, Chapter 2 of the report describes the current processes at North Sea Port and the proposed processes implemented at the Central Gate, answering the first research question. Chapter 3 presents a literature review to help answer the second research question. Chapter 4 discusses the solution design for the North Sea Port use case, which corresponds with the third research question. Chapter 5 comprises the conceptual model related to the fourth research question, while Chapter 6 includes the main simulation results answering research question five. Finally, Chapter 7 summarizes the main findings and provides a discussion on the limitations of this research and the possibilities for further research.

2. North Sea Port

This chapter introduces the proposed design processes at the Central Gate at North Sea Port Vlissingen. First, in Section 2.1, the current and proposed situation will be discussed, followed in Section 2.2 by a definition of the problem concerning the assignment of autonomous vehicles. In Section 2.3, an analysis of job distributions and travel distances within the port is given. The chapter concludes with earlier conducted research on the Central Gate in Section 2.4

2.1 Current and proposed situation

This section outlines the proposed layout of the Central Gate, the terminals involved and the processes related to container registration and pick up or drop off.

As discussed in Section 1.2, North Sea Port faces several challenges regarding container arrivals and departures. Truck arrivals are spread unequally over the day, and there is uncertainty in the arrivals themselves. Moreover, the port lacks truck buffer zones and a standardized terminal registration process. To address these issues and accommodate the anticipated growth of the North Sea Port, a Central Gate will be constructed at North Sea Port Vlissingen.

Opening the Central Gate will also mark a transition to autonomous vehicles for transport from and to the terminals and the Central Gate. Consequently, the transportation process will shift from the situation depicted at the top in Figure 2-1, where trucks drive to the main terminal to pick up or drop off containers, to the situation with first- and last-mile transport. In the latter scenario, autonomous vehicles transport containers from the terminal gate to another place, a so-called extended gate, from which truck drivers pick them up.

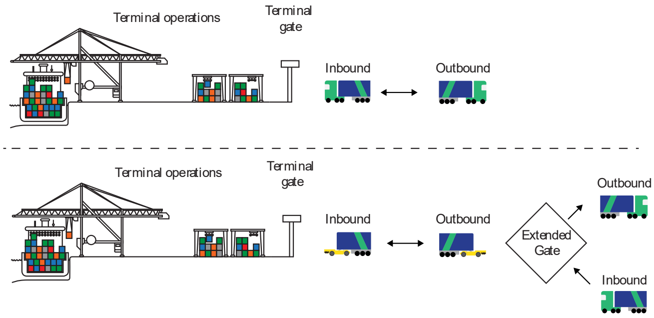

Figure 2-1: Illustration of the current process (top) and the proposed situation (bottom) (Gerrits, 2023).

2.1.1 Gate Layout

The Central Gate will be adjacent to the N62 trunk road, near the intersection between the N62 and N254 roads. The N62 directly connects with the A58 highway, the primary road into Zeeland. Hence, the Gate will be easily accessible for trucks arriving at North Sea Port Vlissingen. Independent research commissioned by NSP found this the best location as it offers the required space and is located outside a residential area (North Sea Port, 2019).

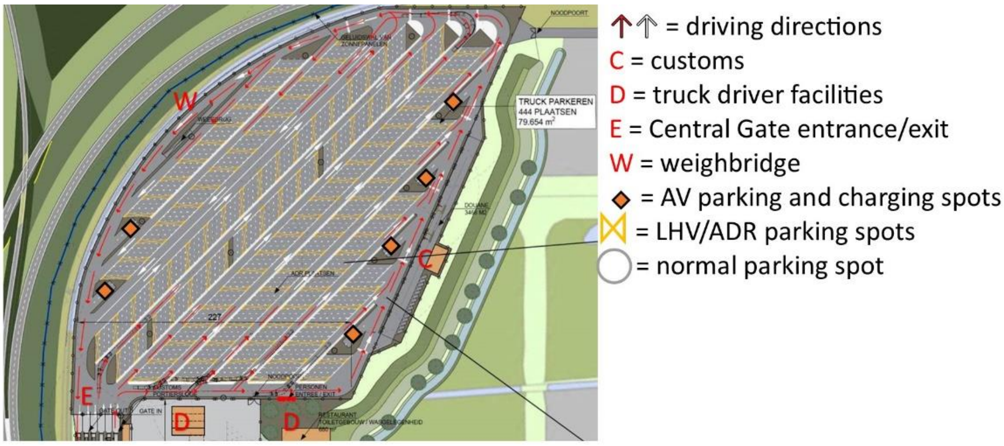

Figure 2-2: Proposed layout of the Central Gate (Distribute, 2021b)

Figure 2-2 shows the proposed layout of the Central Gate, with interesting locations highlighted. The gate will operate with one-way traffic, with trucks entering and exiting at the lower-left corner and following an anti-clockwise route, as indicated by the arrows. In this research, autonomous and human-driven vehicles are treated equally, meaning that conventional traffic rules apply, and both sets of vehicles have to give way to others coming from the right.

In addition to serving as a buffer zone for incoming trucks, the Central Gate will offer value-added services for truck drivers visiting North Sea Port Vlissingen. It will provide a safe location for drivers to take their mandatory 45-hour rest periods, including restrooms, dining areas, and cleaning services.

Facilities for truck drivers, such as a restaurant and showers, will be located in the southeast section of the gate. Dedicated parking places are assigned to Longer Heavier Vehicles (LHVs) and trucks carrying dangerous goods as defined by the European ADR treaty. Idle autonomous vehicles will be located near the charging stations on the ring. An illustration of a utilized Central Gate can be found in Figure 2-3.

Figure 2-3: Illustration of a utilized Central Gate (Distribute, 2021b)

2.1.2 Registration process

The introduction of the Central Gate will centralize and standardize the registration process for arriving trucks. North Sea Port expects this will reduce registration time by 60%. Instead of each terminal having its entry gate, there will be a single-entry point. Additionally, using a digital check-in, registration will take only one minute. The digital registration system could be expanded to include customs documents, driver identification, and detailed cargo information.

2.1.3 Involved terminals

The Central Gate will serve nine companies. Two companies have multiple terminals: Kloosterboer has five, and Verbruggen has three, bringing the total number of terminals in the port to 15. The terminals and their respective routes to and from the Central Gate are shown in Figure 2-4, with each terminal's route indicated by a different colour.

The port area is roughly divided into three sections: a northern section where most terminals are located, a middle section and a southern section consisting of just two terminals. The northern section is expected to benefit the most from shared services, as the travel distances between terminals in this area are relatively short.

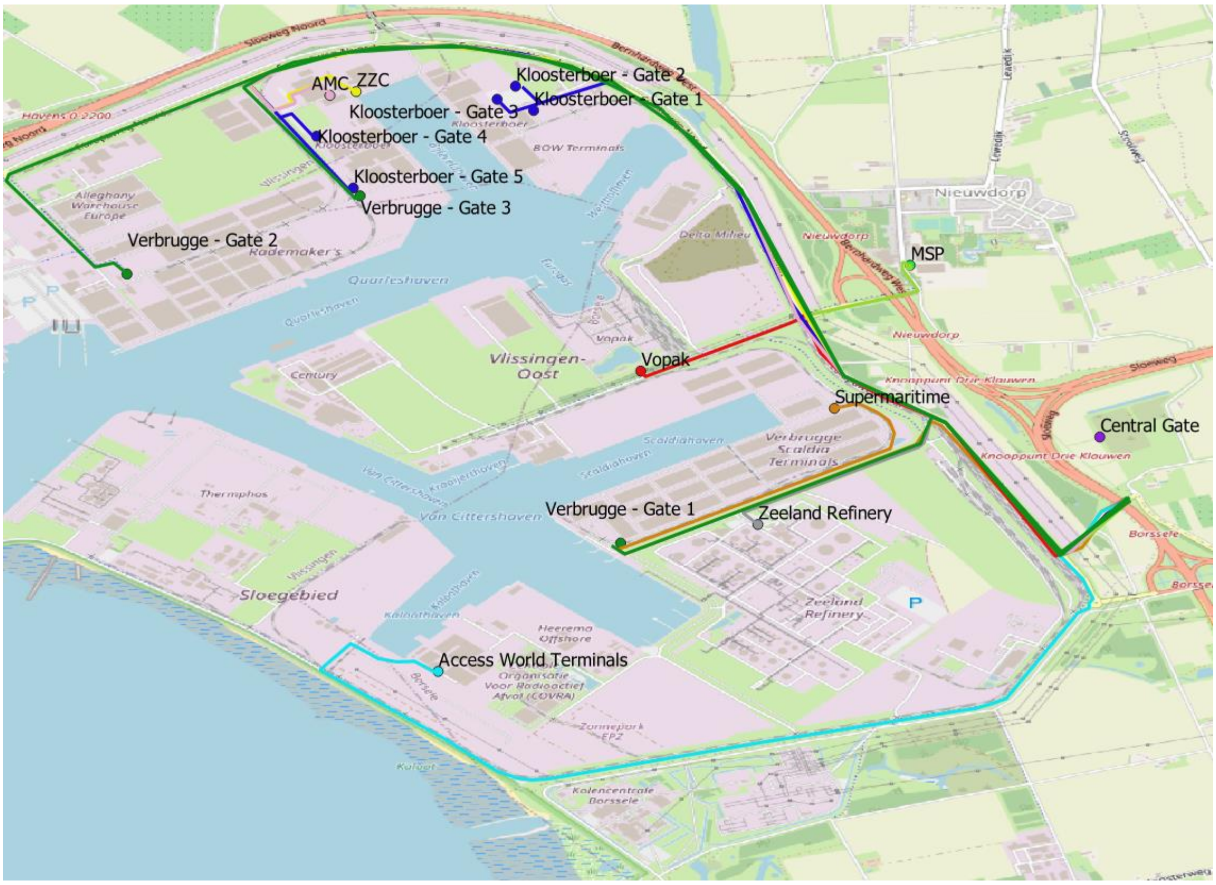

Figure 2-4: Map of North Sea Port Vlissingen

As can be seen in Figure 2-4, the port spans a large area. From the Central Gate, the distance to the closest terminal is three kilometres and eight kilometres to the furthest terminal. The longest possible trip in the port is from Verbrugge Gate 2 to Access World Terminals. This trip takes thirteen kilometres. Travel times and distances will be discussed in further detail in Section 2.3.

The terminals operate 24/7, but only a few truck arrivals occur at night. Most arrivals and departures occur between 6 a.m. and 7 p.m. While the terminals continue operations over the weekend, the number of arrivals is significantly lower than on weekdays, with Sunday being quieter than Saturday. More details on the travel distances and job distributions are given in Section 2.3.

2.1.4 Container drop-off and pick-up processes

Not all containers are suitable for autonomous vehicles' drop off and pick up. Containers carrying ADR payloads (dangerous goods) can not be left behind without a truck. Similarly, containers with unbalanced weight distributions must stay on a truck to prevent tipping. In such cases, the truck drivers only use the Central Gate as a rest and waiting place until they can drop off their loads at the terminal.

Trucks can arrive with or without an attached container. Both processes are shown in Figure 2-5 and Figure 2-6 flowcharts. These are current practices in the non-automatic scenario.

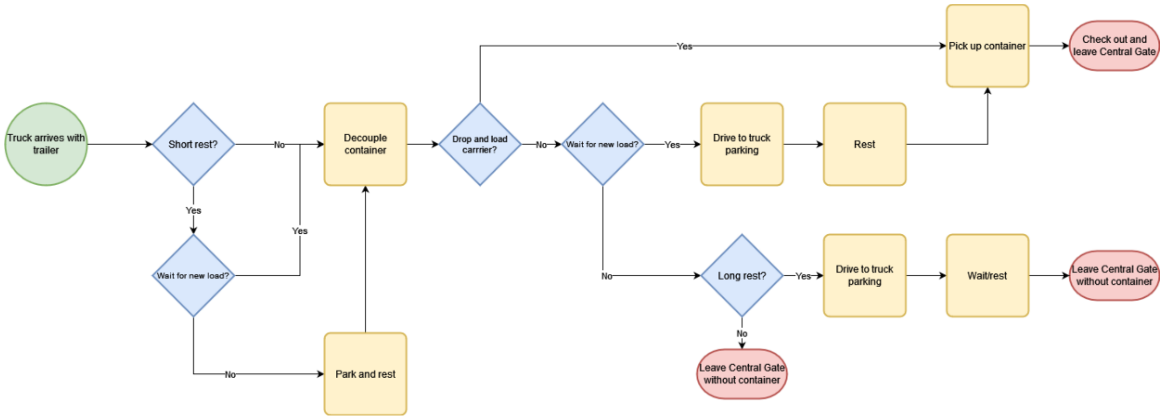

Figure 2-5: Process flow of a truck arriving at the gate with a trailer attached.

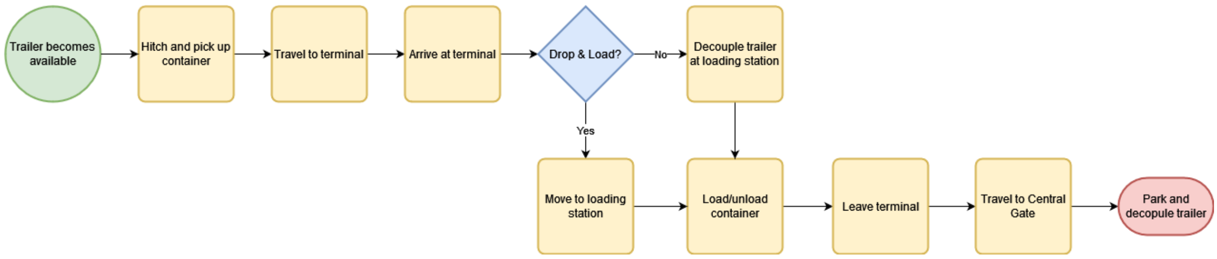

Figure 2-6: Process flow of a truck arriving at the gate without a trailer attached.

2.2 Problem introduction

This section describes the problem faced at North Sea Port, followed by a small introduction example in Section 2.2.1.

Using the framework on multi-robot systems of Gerkey & Matarić (2004), the problem at North Sea Port can be classified as a single task, single robot and time-extended assignment problem. Each autonomous vehicle can transport only one container at a time, requiring one robot. The arrival times of incoming trucks are uncertain and may differ significantly from their expected times; an indication of future task arrivals is known in advance. Problems in the ST-SR-TA class are NP-hard. The multi-robot system classification framework will be discussed in more detail in Section 3.1.3.

The difficulty of this problem varies depending on the time of day. When demand is lower than capacity, for example, during the night and weekends, allocating autonomous vehicles will be more straightforward. However, during peak hours, the number of incoming and outbound containers will exceed the number of available vehicles.

Time window constraints can be imposed on the assignment of AVs. Containers may need to arrive at a terminal by a specific time to avoid delays in further processing. Moreover, a time window constraint may be enforced when a truck is at the Gate for a short rest and is slated to leave with a new container. In such cases, the container should be made available early to improve truck turnaround times and free up space at the Central Gate.

Decisions concerning the assignment, routing, and possibly charging will be made at an operational level. The number of vehicles is not yet set in stone. Initially, North Sea Port planned to use six autonomous vehicles for budgetary reasons. However, earlier preliminary research indicated that this number may not be sufficient to ensure a well-functioning system.

2.2.1 Introducing example

Figure 2-7 shows an example problem with two terminals and a central location is shown. On the left side of the figure, two delivery jobs from the terminals to the central location are processed. In this case, no jobs can be combined as both jobs are outbound from the terminal. As such, the travel costs can directly be attributed to a terminal, though it depends on the AV's previous location.

When the goal is minimizing the total travel kilometres, the job sequence on the right is optimal. In this case, a vehicle starts at the central location from which it delivers a container to location A. After delivering a container at A, the vehicle travels empty to B before returning to the central location with a container from B. As both terminals have their jobs completed, they can be satisfied. However, the question of who will pay for the empty travel kilometres from A to B arises as both terminals get a positive reward for this combination.

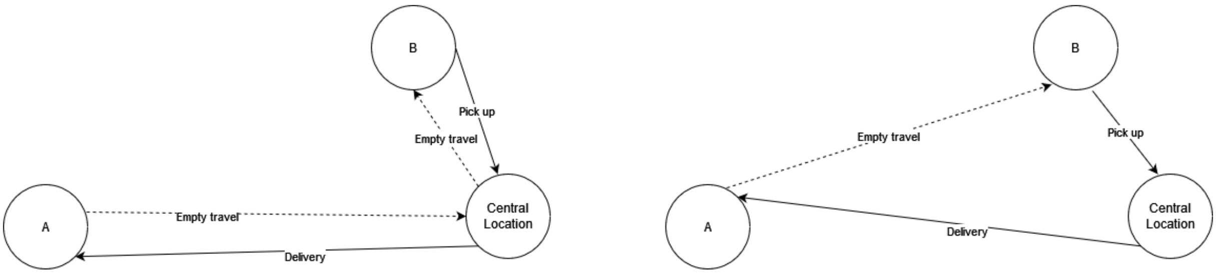

Figure 2-7: Problem example with two terminals and a central buffer location

Since the autonomous vehicles to be used by North Sea Port can transport only one container at a time, the possibilities for pooling jobs for the first- and last-mile are limited. Intuitively, companies close to each other are expected to obtain the highest value in sharing vehicles and combining jobs.

2.3 Job patterns

This section provides insights into the data-related aspects of the North Sea Port use case. Section 2.3.1 focuses on the distribution of jobs throughout the day and week, and Section 2.3.2 focuses on travel distances and times.

2.3.1 Distribution of jobs

In the case of North Sea Port Vlissingen, job arrivals and departures follow a distinct pattern. Most jobs arrive in the morning and gradually decrease throughout the afternoon. As Table 2-1 shows, almost no jobs occur during the evening and night, so these hours are omitted from the graphical representation in Figure 2-8. Additionally, there is a slight difference between the patterns for inbound and outbound jobs.

Hour	In/hour	Out/hour	Hour	In/hour	Out/hour
0	0.0%	0.0%	**12**	7.4%	9.3%
1	0.0%	0.0%	**13**	11.0%	10.2%
2	0.0%	0.0%	**14**	8.3%	9.3%
3	0.0%	0.0%	**15**	5.0%	7.5%
4	0.0%	0.0%	**16**	3.4%	5.0%
5	0.0%	0.0%	**17**	1.7%	3.3%

6	0.6%	1.3%	**18**	1.2%	2.0%
7	15.8%	13.2%	**19**	1.1%	0.6%
8	12.8%	9.7%	**20**	0.4%	0.3%
9	9.9%	9.5%	**21**	0.1%	0.1%
10	11.7%	9.2%	**22**	0.1%	0.0%
11	9.6%	9.4%	**23**	0.0%	0.0%

Table 2-1: Daily job distribution

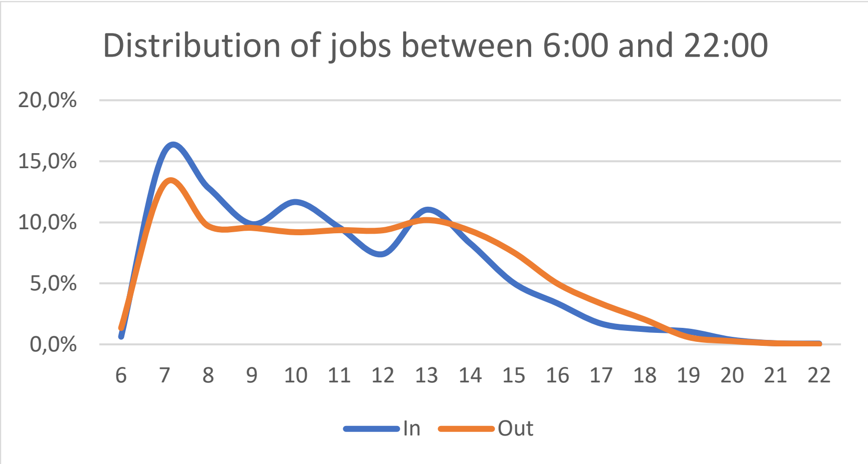

Figure 2-8: Graphical representation of the jobs between 6 a.m. and 10 p.m.

Second, almost all handling takes place on the weekdays, with Wednesdays and Fridays being the busiest. Saturday handles are ten times lower than weekdays, and no work occurs on Sundays. Holiday-related terminal closures, if applicable, are not considered in this report.

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
In	18.6%	18.9%	21.2%	19.1%	20.4%	1.8%	0.0%
Out	17.7%	21.1%	20.4%	18.6%	20.6%	1.4%	0.0%
Total	17.9%	20.6%	20.6%	18.7%	20.6%	1.5%	0.0%

Table 2-2: Percentage of jobs taking place per category per weekday

Lastly, on average, the number of outbound jobs is 3.44 times as high as that of inbound jobs. This value indicates that when implementing a shuttle service for first- and last-mile transport, more containers must be picked up than delivered. Therefore, there are plenty of opportunities to combine deliveries to a terminal with pick-ups at the same or another terminal before returning to the Central Gate.

2.3.2 Travel distances and times

Table 2-3 shows the length of the shortest trip, longest trip and average trip length per terminal. In this case, the travel times are calculated assuming an autonomous vehicle travels forty-five km/h between terminals. As travel conditions are ignored and the speed is assumed to be fixed, a linear relationship exists between distance and time. The distances between the terminals can be found in Figure 2-9.

From/to	CG	KB1	KB2	KB3	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	MSP	ZER	AWT
CG		4,84	4,97	5,06	6,68	7,02	6,69	6,86	8,20	7,09	3,37	5,17	3,47	3,33	2,82	5,68
KB1	4,84		0,21	0,23	2,72	2,98	2,58	1,04	4,23	3,06	5,46	6,85	3,16	3,11	4,47	8,59
KB2	5,14	0,31		0,12	2,82	3,32	2,82	2,80	4,51	3,38	5,77	7,15	3,46	3,40	4,77	9,49
KB3	5,04	0,20	0,39		2,97	3,17	2,69	1,06	4,42	3,13	6,38	6,96	3,36	3,30	4,67	9,39
KB4	6,68	2,88	2,59	2,68		1,04	0,56	1,31	2,13	0,99	6,78	8,29	3,31	4,90	6,25	10,37
KB5	7,02	3,32	3,02	3,14	1,05		1,05	1,03	1,32	0,10	7,52	9,08	5,39	5,36	6,71	11,76
AMC	6,69	2,89	2,59	2,71	0,57	1,05		1,45	2,22	1,02	6,78	8,63	4,94	4,90	6,25	10,86
ZZC	6,86	1,04	1,22	1,34	1,31	1,03	1,45		2,20	0,98	5,99	7,84	4,15	4,12	5,47	10,52
VB2	8,20	4,53	4,23	4,35	2,13	1,30	2,21	2,24		1,21	8,45	11,48	6,59	6,56	7,91	12,97
VB3	7,09	3,30	3,00	3,12	0,99	0,10	1,02	1,04	1,21		7,88	9,91	5,34	5,31	6,66	11,36
VB1	3,37	5,49	5,19	5,31	8,66	7,52	6,78	5,99	8,45	7,88		1,94	3,63	3,47	0,71	2,36
SUP	5,17	7,30	7,00	7,12	8,29	9,08	8,63	7,84	11,48	9,91	1,94		5,38	5,26	2,60	4,15
VOP	3,47	3,63	3,33	3,45	3,31	5,39	4,94	4,15	6,59	5,34	3,63	5,38		1,62	2,97	8,02
MSP	3,33	3,47	3,17	3,29	4,90	5,36	4,90	4,12	6,56	5,31	3,47	5,26	1,62		2,90	7,99
ZER	2,82	4,91	4,61	4,73	4,67	6,25	6,71	6,25	7,91	6,66	0,71	2,60	2,97	2,90		2,66
AWT	5,68	10,00	9,70	9,82	10,37	11,76	10,86	10,52	12,97	11,36	2,36	4,15	8,02	7,99	2,66	

Figure 2-9: Distances in kilometres between terminals and the Central Gate.

Terminal	Shortest trip	Longest trip	Average trip
Central Gate	3.76	10.93	7.22
Access World Terminals	5.53	17.29	11.59
AMC	1.13	14.47	5.36
Kloosterboer 1	0.28	11.45	4.59
Kloosterboer 2	0.16	12.65	4.94
Kloosterboer 3	0.27	12.52	4.90
Kloosterboer 4	1.32	13.82	5.17
Kloosterboer 5	0.13	15.68	5.57
MSP	2.16	10.65	5.47
Supermaritime	2.59	15.31	8.43
Verbrugge 1	0.94	11.54	7.02
Verbrugge 2	3.47	17.29	7.47
Verbrugge 3	0.13	15.15	5.76
Vopak	2.16	10.70	5.43
Zeeland Refinery	0.94	10.54	6.02
ZZC	1.13	14.03	5.04

Table 2-3: Terminal travel times

Table 3 shows that most travel times are in the five- to eight-minute range. Very short travel times are observed for inter-terminal transport between Kloosterboer gates 1, 2, and 3, which are on the same complex, and between the neighbouring Verbrugge 3 and Kloosterboer 5 terminals. Access World Terminals, located in the southwestern part of North Sea Port with only one road leading to it, has the highest average travel time. AWT is also part of the longest possible route in the port, extending to and from Verbrugge, requiring a vehicle to traverse the entire port complex.

The travel time from one terminal to another or the Central Gate is under fifteen minutes in 95% of all possible trips. The remaining five per cent of the trips can be executed within eighteen minutes.

Ninety-five per cent of trips between terminals or the Central Gate take under fifteen minutes, with the remaining five per cent taking up to eighteen minutes. Since most trips start or end at the Central Gate, these trips form the core of the transportation cycle. Table 2-4 details the distances and corresponding travel times from the Central Gate to all terminals, assuming a constant speed of 45 km/h.

Terminal	Distance (km)	Time (mm:ss)
Kloosterboer 1	4.84	6:27
Kloosterboer 2	4.97	6:37
Kloosterboer 3	5.06	6:45
Kloosterboer 4	6.68	8:54
Kloosterboer 5	7.02	9:21
AMC	6.69	8:55
ZZC	6.86	9:09
Verbrugge 2	8.20	10:55
Verbrugge 3	7.09	9:27
Verbrugge 1	3.37	4:29
Supermaritime	5.17	6:53
Vopak	3.47	4:37
MSP	3.33	4:26
Zeeland Refinery	2.82	3:45
Access World Terminals	5.68	7:34

Table 2-4: Distances from Central Gate to terminals and the associated travel times

An overview of all inter-terminal travel times can be found in Appendix A.

2.4 Previous research

This subsection focuses on the results of earlier conducted research concerning North Sea Port and the Central Gate.

North Sea Port has already conducted research to gain first impressions on the Central Gate concept. This research focused on three questions:

1. How do different traffic rules (and the possible separation of automatic and manual operations) impact productivity and safety at the Central Gate?
2. How many autonomous vehicles are required when all inbound and outbound transports are decoupled at the CG?
3. How can the number of autonomous vehicles be balanced against the average waiting time?

While the first question is less relevant to this research, the findings on the second and third questions provide valuable input. Both questions considered the number of autonomous vehicles and terminal operating hours as experimental factors. Terminal operations could run for 12 or 24 hours, with the minimum number of autonomous vehicles required for viable operations set at 12.

The preliminary research concluded that increasing the number of autonomous vehicles somewhat increases cycle time, primarily due to the limited number of jobs that can be combined at the same terminal. In this study, combinations were only possible at the same terminal. When outbound call time, the time it takes to pick up a container after it becomes available, is the primary KPI, at least 16 autonomous vehicles are needed for 24-hour operations and 20 for 12-hour operations. Relaxing the outbound call time requirement would reduce the number of autonomous vehicles needed (Distribute, 2021b).

2.5 Conclusions

The Central Gate at North Sea Port Vlissingen will include parking places for up to 450 trucks and trailers, offer rest facilities and lessen congestion on streets within the port area. Located in the southeastern corner of the port, it serves fifteen terminals across nine companies. In most cases, the travel time between terminals or the Central Gate is between five and eight minutes.

The autonomous vehicles used for the transportation of containers can be classified as single-task, single-robot and time-extended assignment problems. The vehicles are homogeneous; each transport requires only one vehicle, and some information is available on when future jobs will arise.

Transportation requests are unevenly distributed throughout the day, with most jobs occurring in the morning and gradually declining. Although 24/7 operations are possible, almost no jobs occur during the evening or night. Additionally, jobs are rare on weekends and are relatively evenly distributed on weekdays.

3. Literature review

This chapter includes a literature review to answer the first two research questions. Section 3.1 focuses on connected and automated driving, the research trends, and possible drawbacks. Section 3.2 delves into the concept of first- and last-mile transport, including the decoupling from the long haul. Section 3.3 describes the shared shuttle service concept and cooperative vehicle routing. Section 3.4 focuses on dynamic routing and its characteristics. Section 3.5 discusses fairness with sub-sections on utility, game-theoretic solution concepts, and fairness measures. Lastly, Section 3.6 introduces three methods for collaboration in allocation and assignment problems and ends with an overview of the most used cost allocation methods.

3.1 Connected Automated Transport

This section covers connected and automated transport and aims to provide a better understanding of automated driving, automated vehicles, how to allocate tasks to them, connectivity, and the drawbacks and challenges of using automated vehicles.

3.1.1 Research trends

According to the Joint Research Centre of the European Commission, four trends are changing road mobility and can radically transform transportation as we know it (Alonso Raposo et al., 2019). These trends are:

- *Automation*: Systems that can perform some parts or all of the dynamic driving tasks.
- *Connectivity:* Using technology enables road vehicles to communicate with each other and the roadside infrastructure.
- *Decarbonisation:* Adopting alternative fuels like electricity, hydrogen, biofuels and natural gas.
- *Sharing:* Providing users with short-term access to transport needs as needed.

Automation and connectivity go hand in hand. An autonomous vehicle without good connectivity lacks a complete overview of the surrounding environment. Good connectivity provides information that automated vehicle sensors can not see. Hence, automation and connectivity have a powerful synergy (Shladover, 2018).

The shift towards automation and connection necessitates designing new vehicles and transportation solutions. This shift presents opportunities to make modes of transport more sustainable by using greener fuels and making them more accessible through sharing. Sharing reduces the environmental impact by distributing fuel consumption across multiple users and minimizing the resources needed.

Expected benefits of connected automated transport are fewer accidents, reduced emissions, decreased congestion, more inclusive transport, enhanced comfort and reduced land use. However, numerous challenging issues need to be resolved before the widespread introduction of automated driving can be realized (European Commission, 2019).

3.1.2 Automation or autonomy

While often interchangeable, "automation" and "autonomy" have distinct meanings. The basic definition of automation is “the use of electronic or machinal devices to replace human labour”, whereas autonomy refers to independence and self-sufficiency. Autonomy should, therefore, only be used when referring to decision-making.

An automated vehicle can be considered autonomous if all functions are performed by systems in the vehicle itself. However, when the vehicle relies on infrastructure to acquire information or to determine manoeuvres, it is considered cooperative rather than autonomous. Due to the interchange of automation and autonomy in writing, one could encounter many situations where autonomy is used to describe automation or vice versa (Shladover, 2018). Nonetheless, distinguishing between these concepts is essential, as a vehicle can cooperate in manoeuvring while being autonomous in determining its speed and when to break.

3.1.3 Automated vehicles

Automated (guided) vehicles are extensively used in manufacturing, warehousing and logistics to transport goods. As part of the fourth industrial revolution, a shift in the usage of automated vehicles is expected. Future fleets are expected to be adaptable to changing circumstances, robust in all situations, and scalable to meet varying demands at any time.

The Fourth Industrial Revolution, Industry 4.0, marks a paradigm shift from centrally controlled to decentralized processes. This shift is characterized by interconnectivity, transparency of information, decentralized decision making and improved technical assistance (Hermann et al., 2016). In the Industry 4.0 paradigm, autonomous vehicles must operate under decentralized control, moving past the current practice of centralized control (De Ryck et al., 2020). In this decentralized situation, the vehicles will communicate directly with each other through an intermediate central broker.

According to De Ryck (2020), decentralized control is a better fit for dynamic environments, allowing quicker adaptation to changes. Nonetheless, coordination will require more time, as each vehicle operates with its individual goals, which may not always lead to a globally optimal solution. The differences between a centralized and decentralized architecture can be found below in Table 3-1.

Centralized approaches	Decentralized approaches
Deeply rooted in the industry	Hardly implemented in practice.
Well-known algorithms	Well-known algorithms
Access to global information	Access to local information
Global optimum	Sub-optimal
Small scaled systems	Large scaled systems
Simple systems	Complex systems
Less robust in dynamic situations	More robust in dynamic situations

Table 3-1: Centralized versus decentralized control architecture (De Ryck et al., 2020)

In their taxonomy of multi-robot systems, Gerkey & Matarić (2004) propose that these systems can be categorized along three axes:

- Single-task robots (ST) or multi-task robots (MT)
  Can a robot execute only one task at a time or multiple tasks simultaneously?
- Single-robot tasks (SR) or multi-robot tasks (MR)
  Can a single robot complete a task, or are multiple robots needed?
- Instantaneous assignment (IA) or time-extended assignment (TA)
  In an instantaneous assignment, the information concerning robots, tasks and the environment only allows for an immediate allocation of tasks to robots without considering possible future assignments. In the time-extended assignment, more information is available, such as the set of all future jobs that need to be executed or a model of how tasks are expected to arrive over time.

Using these axes to classify robot assignment problems results in eight possible combinations. Autonomous vehicles for picking up and delivering containers are single-task robots and single-robot tasks.

In general, AGV systems have five core tasks that need to be executed (De Ryck et al., 2020):

- Task allocation: How can tasks be optimally assigned to a set of AGVs? Task allocation is one of the most challenging tasks as this is an NP-hard problem aiming to minimize the costs associated with the assignment. Desired properties of task allocation algorithms include divisibility, scalability, flexibility, and responsiveness.
- Localization: How to obtain the exact location on a map? Localization is a decentralized task as the equipment for determining the location is onboard the vehicle.
- Path Planning: How can an obstacle-free path from the current location of an AGV be generated to its destination? First, a representation of the clear space must be found. Afterwards, an algorithm can be applied to determine the shortest path within this free space.
- Motion Planning: How to execute a real-time route with dynamic obstacles? It builds on path planning as the created static path is most likely not collision-free. Motion planning aims to prevent collisions and deadlocks.
- Vehicle Management: How to deal with battery constraints, failures and maintenance? Vehicle management is needed as the vehicle status will cause constraints on the ability to perform a task. It may, however, be relevant to include battery management in task allocation as it can impact the overall system performance.

Of these core tasks, only task allocation and vehicle management fall within the scope of this research. The technical aspects of autonomous vehicle systems, such as localization, path planning, and motion planning, will not be discussed.

For the allocation of tasks, De Ryck (2020) states that there are four possible categories into which methods can fall. These categories are optimization-based, market-based, behaviour-based, and field-based, with the latter two seldom used in practice.

Optimization-based approaches use algorithms that search for a solution that maximizes profit or minimizes costs. Theoretically, an exact solution can be found for the problem, but only for small problem instances. Optimization-based approaches give reasonable solutions for small autonomous vehicle systems, but for larger problem instances, it becomes hard to find solutions that approximate the global optimum. Moreover, the computing time will increase with an increase in problem size, and the solution will lack robustness (De Ryck et al., 2020).

Market-based approaches allocate resources based on economic principles. Generally, market-based solutions are robust, scalable and flexible (De Ryck et al., 2020). Agents make a bid based on their available information, with the resource being allocated to the agent with the best bid. Tasks can be offered one at a time, resulting in a single-item auction or a bundle of multiple tasks in which the auction becomes combinatorial (Wooldridge, 2009).

These single-item or combinatorial auctions can take on different forms. English auctions start at a predetermined price, after which agents are invited to bid. Bids are open and must be increased from the previous highest bid. When no agent is willing to raise its offer, the agent with the highest bid pays that amount. Dutch auctions work the other way around; in this type of auction, the auctioneer starts the bidding at an artificially high price, after which the asking price is lowered. If an agent is willing to match the asking price, he is allocated the good or resource.

A more straightforward form of auction is the first-price sealed-bid auction. This auction consists of a single round in which all agents make their bids blind without knowing the other agents' valuations.

The agent with the highest bid is awarded the resource and must pay the amount it offered for it. To win the first-price sealed-bid auction, an agent only needs to bid fractionally more than the second-highest bid. The difference between the highest and second-highest bid can be seen as lost money from the winner's standpoint. This is different in a second-price sealed-bid auction or Vickrey auction in which the highest bidder wins, but the winner pays the amount offered by the number two (Wooldridge, 2009).

Moreover, decisions must be made regarding the level of centralization and frequency of job assignments. Hyland and Mahmassani (2017) provide a taxonomy for classifying autonomous vehicle systems. According to their framework, design decisions need to be made along the following axes:

- Global or local information: Is information known to all agents, or is it kept at a local level?
- Centralized or decentralized decision: Are assignment decisions made by a centralized agent or at a local level?
- Job assignment: When and how often do tasks need to be assigned? A task can be immediately assigned to a vehicle when a new one arises or at fixed time intervals.
- Planning horizon length: At the moment of planning, are expected future jobs taken into account, or are only the jobs known at the moment of assignment taken into account?
- Modelling battery constraints: automated vehicles are powered by electrical energy and will be unavailable when recharging. Battery levels and energy consumption constrain which tasks can be executed.
- Modelling time window constraints: modelling time windows will make the problem more complex. When modelled explicitly, the time window is a hard constraint that must be met. When modelled implicitly, time windows do not have to be strictly met, but missing them incurs a penalty.

3.1.4 Levels of automation

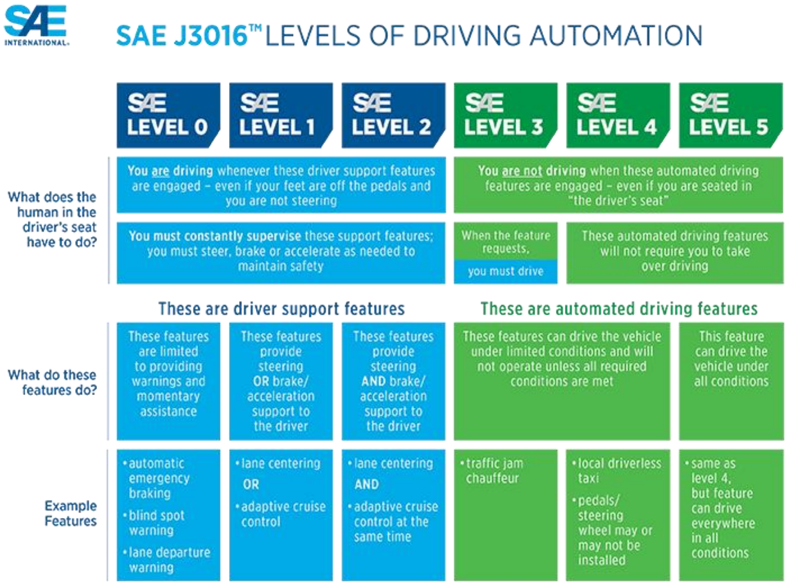

Figure 3-1: SAE Levels of driving automation (SAE, 2018)

When classifying automated road vehicles, there are six levels, from no to full automation, as seen in Figure 3-1. From level 3 onwards, the automated driving functions take over driving actions currently being executed manually. For levels 0, 1 and 2, the automated part is located in driver support functions, and the driver still needs to conduct all the standard tasks, such as steering and braking. At levels 3 and 4, a vehicle can ride fully automated but only under limited circumstances, such as in a disclosed area or under limited traffic. Under all circumstances, the vehicle can drive itself only at the fifth and highest level.

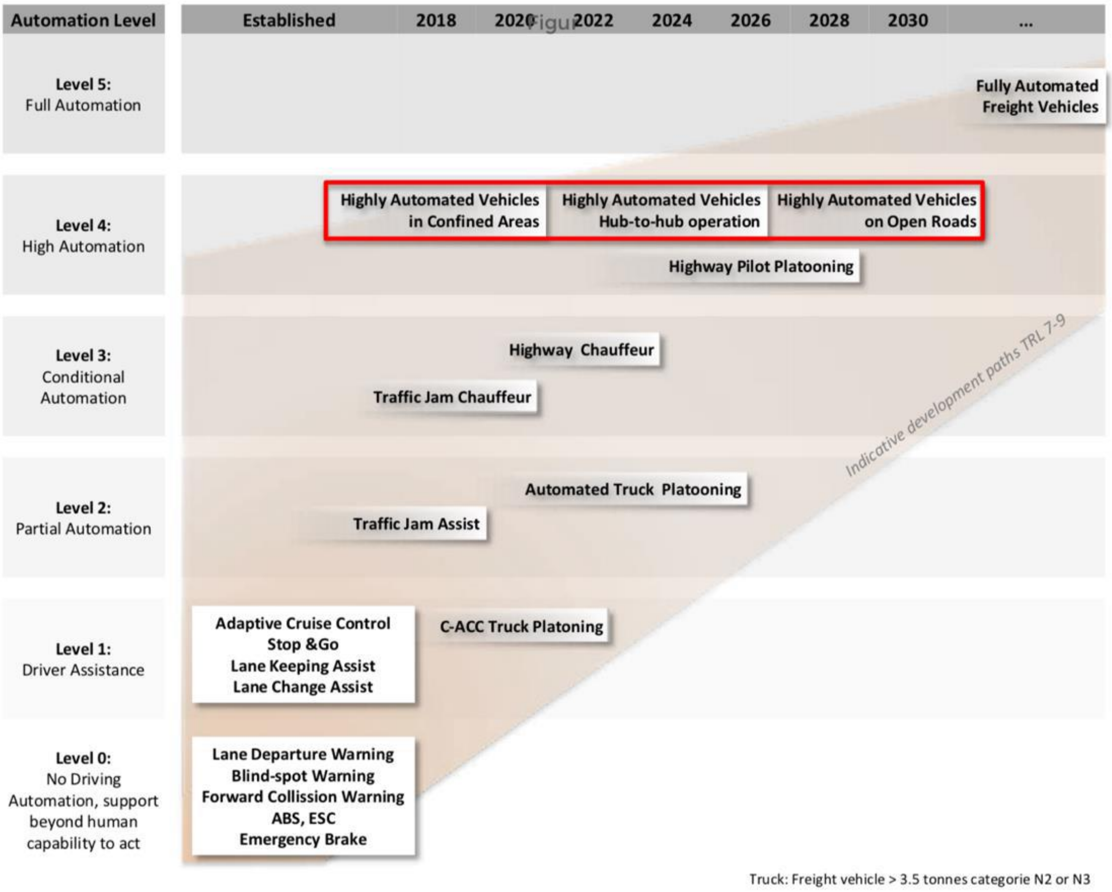

Figure 3-2: Development path of automated freight transport (ERTRAC, 2019)

When specifically looking at the developments of automated driving for freight transport, the time path in Figure 3-2 has been constructed by the European Technology Platform (ERTRAC, 2019). As can be seen, lower levels of automation are already widely studied and even implemented in practice. However, fully automated freight vehicles, operating without human interaction, are not expected to be ready until the next decade.

European regulations mandate that new technologies and functionalities for automated transport are only permitted on public roads once proven safe and reliable. However, testing these systems on public roads is crucial to determining their safety and security. To address this challenge, The Netherlands has introduced regulations that allow testing with connected automated transport on public roads (RDW, 2020). As such, the Netherlands were one of the frontrunners in allowing tests with automated transport.

Flämig (2016) outlines several possible applications of automation in freight transport at level 4 automation, including:

- *Interstate pilot*: On highways, vehicles operate fully automated, though a driver always remains aboard to control unclear traffic situations such as roadworks and minor roads.

- *Vehicle on-demand*: An autonomous decentralized AGV system operating without drivers. The risk of lacking a driver who can take over the vehicle can be mitigated by having different entrances and exits to highways or by creating dedicated lanes. Another option is to use the vehicles only on straightforward roads such as highways and have a backup driver on board the vehicle at rest places. T his system resembles the interstate pilot but reduces the driver's involvement.
- *Follow-me vehicle*: An extension of the interstate pilot, this mode allows the driver to engage in value-added tasks, such as preparing for the next delivery or completing administrative work, when not directly controlling the vehicle.
- *Valet parking:* The vehicle's autopilot navigates to a pre-assigned parking spot. This concept could be instrumental in urban or industrial areas, releasing the driver from the stressful tasks of carefully navigating the vehicle through tight spaces.

The ERTRAC development path shown in Figure 3-2 outlines the following potential scenarios for possible applications of SAE level 4 vehicles (ERTRAC, 2019):

- *Highly automated freight vehicles in confined areas*: A confined area would allow uncrewed remotely controlled vehicles to be utilised. The vehicles could even have their driver's cabins removed. Additionally, specific traffic regulations tuned to the specific environment may be introduced to enhance intermodal transport.
- *Highly automated freight vehicles in hub-to-hub operations*: Vehicles will be used on predefined corridors. These corridors might be specifically designed or modified to accommodate automated freight transport. This scenario could involve either conventional trucks or trucks with removed driver cabins, depending on the level of automation. Significant changes would be needed in road infrastructure, traffic management systems, and logistical coordination to enable this form of transport.
- *Highly automated freight vehicles on open roads and in urban areas:* Here, vehicles must navigate various road types, including highways and narrow city streets, while interacting with a wide range of other road users, such as pedestrians and cyclists. Anticipation is needed to handle vulnerable road users. The ability to anticipate and respond to the behaviour of vulnerable road users is crucial in this context.

These three scenarios where automated freight transport could be applied are mentioned in increasing order of complexity. In confined areas controlled by companies, non-automated travel could be eliminated, allowing for rules and control mechanisms directly aimed at automated modes of transport. In the last scenario, regular traffic continues, and the vehicle needs to be able to deal with all kinds of roads, ranging from highways to narrow streets in the city centre.

In the context of the North Sea Port use case, which is the focus of this research, both confined area operations and hub-to-hub operations are relevant. Terminals within the port represent confined areas, while cross-terminal travel involves open roads. Therefore, this research will focus on vehicles with level 4 automation, especially those suited for suited distances.

An example of a vehicle operating in such areas is the Auto TUG shown in Figure 3-3. The Auto TUG, developed by Terberg Special Vehicles, is an automated yard tractor operating at SAE levels 2 to 3 and intended to reach level 4 autonomy. Another example is the Volvo Vera, which has been used in the port of Gothenburg for many years now.

Figure 3-3: Terberg's Auto TUG and Volvo's Vera with a trailer attached (Terberg Special Vehicles, 2019) (Volvo, 2019).

3.1.4 Connectivity

Robust connectivity is essential to make vehicles independent and self-sufficient—autonomy and connectivity are closely connected. New intelligent transportation systems depend on a smooth information exchange between vehicles and roadside infrastructure. In these systems, vehicles are connected to other vehicles, infrastructure, pedestrians or cyclists and at the most general level, 'everything'. This vehicle-to-everything level can be compared with the Internet of Things concept, in which a vehicle could be connected to any other device (Shladover, 2018).

3.1.5 Possible drawbacks

Though (connected) automated vehicles seem promising for the future of transport, there are some possible drawbacks associated with these vehicles and their development. First of all, there is the issue of user acceptance. People may worry that AVs will not drive as well as human drivers, feel uneasy about being in a vehicle under automated control, and fear that data anonymity cannot be guaranteed (Raposo et al., 2017).

Second, when conventional vehicles still form the main share of transport during the transition period, road safety is not expected to improve. Automated vehicles may drive conservatively for liability reasons, which could encourage human drivers to take more risks, such as overtaking or splitting autonomous platoons. Furthermore, technological issues, such as potential system and network failures, also raise safety concerns.

Lastly, overall road capacity could decrease in mixed traffic conditions because autonomous vehicles may require longer headways. Without changes to the existing infrastructure, less space is available for conventional vehicles (Raposo et al., 2017).

3.2 First- and last-mile logistics

This sub-section is about first- and last-mile logistics. It introduces this part of the transportation journey, how it differs from long-haul transportation, and which applications are used when the first or last mile is decoupled from the long haul.

First- and last-mile logistics is the movement of goods or people from a transportation or logistics hub to the final destination. As the terms themselves say, it focuses on the transport on the first and last leg of the journey. It includes deliveries from and to consumers and businesses, business to business and the transport of people by public transport. Though the distance travelled is low in these stages, the costs of first- and last-mile delivery are high. Depending on the situation, fifteen to seventy per cent of the total supply chain costs can be attributed to these legs (Olsson et al., 2019).

Traffic situations can be pretty diverse compared to long-haul in first- and last-mile applications. Whereas long-haul transport takes place on highways and trunk roads with similar traffic conditions throughout the trip, first- and last-mile transportation can take on many forms. First- and last-mile applications in urban areas will look different than in port areas or near a highway hub.

The term last-mile logistics can be decomposed into multiple concepts. First, last-mile logistics is the process of planning and controlling efficient and effective transportation and storage from the order point to the endpoint. Last-mile distribution is associated with the handling, moving and storing of goods to the point of consumption through various channels. Last-mile fulfilment is strongly associated with last-mile transport. This component is processing orders to prepare them for delivery to the end customer (Olsson et al., 2019).

Disconnecting the long-haul and the first- and last-mile enables the usage of specialized and tailored vehicles for each track of a journey. Multiple aspects may prompt decoupling. First of all, decoupling may be enforced by regulations. Cities, for example, may have imposed low-emission zones. In this case, polluting long haul trucks are not allowed to enter the city centre, thereby requiring transhipment of goods. Second, grouped loads may have to be split to reach the final user, as the long-haul mode of transportation is unsuitable for the last mile. Lastly, streets in city centres are often narrow, have one-way traffic and lack parking space (Crainic et al., 2004). Agile and smaller vehicles can reduce travel time and congestion in these situations.

As decoupling the first- and last-mile from the long haul takes place in multiple different situations, there are also multiple concepts for decoupling points. In urban areas, Crainic (2004) proposes using satellite locations where freight from various external destinations can be transferred to urban-proof vehicles. Freight for one street could be consolidated into a single vehicle, reducing the number of trips to that destination. These satellite locations should not offer storage facilities, with transhipment being the only operational activity.

For first- and last-mile logistics, applications differ clearly between business-to-business (B2B) and business-to-costumer (B2C) (Olsson et al., 2019). Business-to-consumer applications aim to serve multiple customers with one vehicle. Examples of these applications are package delivery and online grocery shopping, with both methods pooling individual orders based on delivery location. B2B last-mile transportation includes different forms; for example, containers are delivered to one central transhipment location at a large industrial complex before being transferred to the end location.

3.3 Shared services

This sub-section is on shared services. It first briefly introduces the concept of ridesharing and its history before focusing on shared applications in a corporate and business context.

Ridesharing is one application in transportation that reduces the total number of kilometres travelled. Ridesharing has been in place since the 1940s when it was introduced in the United States as a form of rationing due to the Second World War. Carpooling, in which people take turns driving each other, became popular in the seventies due to the oil crisis. Though the introduction of the internet has led to the emergence of online platforms where ride-sharing can be arranged, the amount of rideshares for business trips has declined. Online platforms can either consist of service operators with dedicated vehicles and drivers or a matching agent by coupling car drivers and passengers (Furuhata et al., 2013).

The platforms mentioned above are in the customer-to-customer or business-to-costumer segments. Nevertheless, sharing or pooling transport rides could be beneficial for companies. Logistics-sharing solutions and their respective capabilities have the potential to reduce emissions and reduce the transport sector's impact on climate change. Sharing vehicles, vehicle capacity, warehouses, or infrastructure reduces operating expenses, transportation costs per kilometre and personal and maintenance costs (Melo et al., 2019).

When transport planning is entirely outsourced, the company executing these tasks is called a fourth-party logistics provider (4PL). Fourth-party logistics providers do not own their vehicles but are responsible for mainly managing complex supply chains (Saglietto, 2013). When multiple carriers agree to collaborate and use a 4PL, information such as the available capacity and jobs are shared between the provider and coordinating party, but not between the carriers, as it is kept confidential (Dai & Chen, 2012). The other carriers do not gain insights into other companies' jobs.

3.4 Dynamic routing

This sub-section covers dynamic routing and its associated concepts. This section focuses on the degree of dynamism and the characteristics of fleet management problems. These topics are discussed to see whether some of these methods can be applied at NSP. In Section 3.4.3, several examples of dynamic fleet management applications will be given.

Dynamic fleet management focuses on the management of distribution systems. Although no clear unifying definition of dynamic fleet management exists, it refers to environments in which information is dynamically revealed to the decision-maker. Information may not be known at the initial planning stage and may change after the execution of a plan has begun.

Using dynamic fleet management in operations planning processes has two primary supportive functions. First, it involves assigning vehicles (and drivers) to known loads and reassignment as changes in demands, vehicle availability, and traffic conditions become evident. Additionally, vehicles can be repositioned to serve expected future demands. Second, there is the need to manage customer service requests where jobs can be accepted or rejected. It is not always required to serve all demands; they may be rejected and, depending on the problem, be lost forever (Regan et al., 1998).

Dynamic fleet management is one of the earliest dynamic extensions of the general vehicle routing problem. According to Psaraftis (1995), the problem is considered dynamic “if the output is not a set of routes, but rather a policy on how the routes should evolve as a function of those inputs that evolve in real-time”.

Examples of these inputs are demand, travel- and loading times. Firstly, demands are stochastic, with jobs becoming available for transport on short notice. Secondly, travel times can vary due to traffic conditions, congestion or failures. Lastly, the time required for loading and unloading may also vary. Therefore, an essential part of dynamic fleet management is to track changes and deviations in these conditions (Regan, 1998).

The primary decision is what to do with the vehicle once the load is delivered. It can be assigned immediately to another job, repositioned to a different location in anticipation of future demands or kept at the location in anticipation of local demand. In the long run, the goal is to make decisions that yield the most, such as avoiding having a vehicle idle in an area with low demand.

3.4.1 Level of dynamism

This sub-section describes the degree of dynamism and its impact on the algorithms used in fleet management problems.

The dynamics of fleet management depend on when requests arrive and the frequency of planning. Static customers or advanced requests are being received before the routing process starts.

Immediate or dynamic requests, on the other hand, arise during the real-time execution of routes and are not known when the original plan is made (Zeimpekis et al., 2008). The degree of dynamism can then be calculated by dividing the number of dynamic requests by the total number of requests (Larsen et al., 2002).

$$degree\ of\ dynanism = \frac{number\ of\ dynamic\ requests}{total\ number\ of\ request}$$

Equation 3-1: Degree of dynamism

This equation can be refined by considering the moment a request arrives. Intermediate requests have their moment of arrival t_i recorded. By using the request arrival time, the degree of dynamism can be adapted to reflect the average lateness of intermediate requests compared to the latest time they can be received (T). It can be calculated using Equation 3-2, where zero represents an entirely static system, and one represents a completely dynamic system.

$$effective\ degree\ of\ dynanism = \frac{\sum_{i=1}^{n_{imm}} \left(\frac{t_i}{T}\right)}{n_{tot}}$$

Equation 3-2: Effective degree of dynamism

Furthermore, when time windows are applicable, the reaction time plays a vital role in determining the degree of dynamism. Planners prefer a longer reaction time, providing a more extended period to insert the new job.

Based on the level of dynamism, different classes can be established. In weak dynamic systems, around 80% of the jobs are known when constructing routes, resulting in a degree of dynamism of 20%. Examples of these weak dynamic systems are taxi transport for elderly hospital treatments and replenishments of companies with static demands. These problems use re-optimization and insertion as their main algorithms to minimise the routing costs.

In moderate dynamics systems, the degree of dynamism ranges between twenty and eighty per cent and involves multiple stochastic elements. Examples include service and repair operations with planned preventive maintenance and immediate repairs for machine or service breakdowns. At this level of dynamism, routing algorithms should be computationally efficient due to the relatively high number of immediate requests requiring the algorithm to run multiple times. Problems of this class often use local-search-based approaches for insertion and tabu search for route improvement.

One speaks of highly dynamic systems when the degree of dynamism exceeds eighty per cent. Examples include emergency and busy taxi services (Larsen et al., 2002). The primary focus here is to reduce the system response time, which is the sum of waiting time and service or travel time. Additionally, resources are often rerouted from low-demand locations to high-demand areas.

3.4.2 Fleet management characteristics

This sub-section describes how to formulate fleet management problems and their computational difficulties.

What to do with a vehicle depends on the vehicle's state and the chosen decision policy. A policy outlines how to act in a specific situation and state to achieve the best long-term result. A vehicle's state can be described by its location and availability. For example, a vehicle can travel with a load, unloaded, idle, and available or idle and unavailable. The vehicle's status changes when the associated activity is completed (Regan et al., 1998). The policy is also state-dependent, as the decision depends on the vehicle's state. If the vehicle is in an area that has historically been profitable, it is more likely to remain there than in an area with few opportunities. Each decision in a particular state comes with associated benefits and costs, influencing the decision-making process. In the long run, the goal is to find a policy that maximizes overall benefits.

However, evaluating all possibilities is infeasible in most cases because the problems suffer from the three curses of dimensionality (Powell et al., 2012). The first is the large state space, which grows exponentially. In this case, the state space is the number of vehicles ^ the number of locations ^ the number of vehicle statuses. Including an extra dimension of information increases the state space gigantically due to the exponentiation of factors. The second curse is the large outcome space, which becomes problematic when calculating the expected rewards or costs. Lastly, the third curse of dimensionality is the size of the action space, which includes the set of feasible actions that can be taken.

Due to these computational inefficiencies or even impossibilities, flexible operational assignment strategies are used. These strategies allow for the modification of assignments without evaluating all possible scenarios. Unlike inflexible assignment methods, such as first come, first served (FCFS) and nearest origin assignment, dynamic methods support route diversion and load swapping to give preference to high-priority jobs or improve the vehicle's route efficiency (Regan et al., 1998).

Several parameters can describe a specific operational strategy, including the acceptance rule used, the assignment rule employed, the number of vehicles in the fleet, the simulation horizon, the vector of pickup deadlines, the rate of request arrivals per vehicle and a minimum number of simulation realizations.

3.4.3 Examples of applications

This sub-section gives examples of situations in which dynamic fleet management models are used.

Dynamic fleet management applications span a wide range of systems. One example is on-demand aircraft scheduling, where dynamic assignment methods are used, particularly in charter operations, due to their unpredictable flight patterns (Ronen, 2000). Commercial airliners have an easier time because their flights generally follow a timetable, with schedules made months in advance. Most charter operations follow a fractional aircraft ownership model, where companies sell shares to customers, giving them the right to use a jet for a certain amount of flight hours. These flights can be requested just a few hours before departure, making it a highly dynamic problem. Additionally, demand must always be met. If the company has no available aircraft, it must outsource the request to another carrier at much higher costs (Sumarti et al., 2022).

Another application of dynamic fleet management is in load-to-vehicle assignment. Yang et al. (2004) describe a problem where container pick-up and delivery jobs are assigned to vehicles. Part of the job list is known in advance, while other jobs arise when the vehicles are already on route. Once a job arises, the operator has a limited period to decide whether to accept or reject it. Executing a job generates revenue proportional to the travel distance, while rejecting a job incurs costs linear to the travel distance. Additional costs are incurred for missing time constraints and empty travel. The objective is to find a strategy for managing future jobs that maximizes overall revenue. The problem is dynamic because acceptance or rejection decisions are taken instantaneously, without knowledge of future job characteristics. Re-optimization policies continuously seek optimal solutions by factoring in early information about future jobs that have shown the best results (Yang et al., 2004).

3.5 Fairness

This subsection elaborates on fairness. First, a general introduction to fairness in resource allocation is discussed. Subsequent sections will focus on the widely used concept of utility, game-theoretic solution concepts and characteristics of fairness measures.

In social sciences, fairness is often viewed as equality of opportunity. A narrow definition of fairness can be defined as "ensuring that people who are similarly qualified for an opportunity have similar chances of obtaining it". Taking on a broader view, fairness can be defined as ''ensuring that people of equal ability and ambition can realize their potential equally well'' (Barocas et al., 2019).

Fairness becomes especially important in allocation problems, where resources are limited or constrained. Many network allocation methods assume that the social optimum is achieved by optimizing the sum of utilities of individual agents. In such an allocation method, a party can, however, receive a disproportionate amount of resources if it is willing and able to pay for it (Sinha & Anastasopoulos, 2017). Fairness can be factored in through different allocation methods to counter this potential imbalance in allocations.

A compelling resource allocation should be non-negative, bounded by demand and efficient. No user should receive a negative amount, no user should receive more than its demand, and all available resources should be allocated. In computer allocation problems, the most commonly used methods are the weighted proportional rule, max-min fair allocation and α-fair. The weighted proportional allocation is based on a logarithmic utility function and the idea that it captures the individual worth of a resource. A max-min fairness allocation gives the lowest claimer its total demand and evenly distributes the unused resources over others. The α-fairness algorithm is a family of assignment rules with the outcomes depending on the parameter α in the function below (Fossati et al., 2018).

$$\sum_{i=1}^{n} \frac{x_i^{(1-\alpha)}}{1-\alpha}$$

Equation 3-3: Function for the α-fairness algorithm

According to Fossati (2018), an allocation should fulfil three properties. First, all users should receive at least zero. Second, a user should not receive more than its demand. Lastly, the sum of all individual allocations should equal the total available resources.

In the classical approach of measuring a player's satisfaction, user satisfaction is the highest when the user receives precisely the number of resources that they requested and the lowest when receiving nothing. When resources are limited, and a user asks for more than the total available resources, maximum satisfaction can not be achieved (Fossati et al., 2018).

A resource allocation problem can be modelled as a cooperative game that can be captured by a set of users, their claims and the total amount of available resources. Difficulties arise when the total claims exceed the available resources. When there are ample resources, the allocation becomes straightforward.

The following sub-sections will discuss utility, game-theoretic solution concepts and fairness measures. Utility is an often-used concept to model value, and when it can be transferred, game-theoretic solution concepts such as the core and Shapley values can be applied. Lastly, various fairness measures with their properties will be examined.

3.5.1 Utility

Utility is a widely used concept to model worth or value. It assumes that any action's value or costs can be determined. Though infinite utility functions exist, the estimated value should consider two things in robot task allocation. First, the expected quality of executing a task with specific methods and equipment will indicate the benefits of the task. Second, the costs of executing a task should be estimated considering both the method and equipment and resource costs, such as battery usage (Gerkey & Matarić, 2004).

3.5.2 Game-theoretic solution concepts

Assuming that utility can be transferred and taking on a game-theoretic standpoint, stable solutions are obtained when all players are in the core. The core is the set of all feasible allocation vectors for which no players or agents are incentivised to leave. It includes all efficient payoff distributions, meaning all possible resources are allocated, and rational means the allocation to all players in the coalition should be equal to or larger than the value of the coalition. Thus, staying in the coalition is more beneficial than breaking away (Peters, 2008).

Next to the core, the Shapley value is a well-known solution concept that assigns its average marginal contribution to each player. It is calculated by taking the average for each player's marginal contribution over all possible coalitions:

$$\Phi_i = \sum_{S \in N: i \in S} \frac{|S|!(n-|S|-1)!}{n!} [v(S \cup \{i\}) - v(S)]$$

Equation 3-4: Formula for calculating the Shapley value

Equation 3-4 shows the formula for calculating the Shapley value where S represents the subsets, v(S) is the value of a coalition, and n is the number of players. The Shapley value is intuitive but computationally inefficient as n-factorial marginal vectors need to be calculated.

Another game-theoretic solution concept is the nucleolus. The nucleolus can be seen as a measure of regret and minimizes the maximal regret among all coalitions. The allocation makes the most considerable dissatisfaction the smallest and is a unique imputation (Peters, 2008).

3.5.3 Fairness measures

A global fairness measure can be calculated by evaluating individual fairness scores for users. According to Fossati (2018), the presence of other users must not influence fairness evaluation methods, the demand of other users, or the availability of resources. Based on this, alternative satisfaction rates should incorporate demand relativeness and relative null satisfaction. The satisfaction rates should show the same characteristics, whether demand has an order of magnitude in single figures or the thousands. Moreover, a satisfaction rate of zero should be obtained when a user is assigned its minimal right and not when it has allocated nothing. In this case, the satisfaction rate drops below zero if a user gets less than its minimal right.

According to Lan (2010), a fairness measure should fulfil five axioms:

- *Continuity*: A fairness measure is continuous for all agents. A change in the allocation should be reflected in the same direction in the fairness measure.
- *Homogeneity*: A fairness measure is a homogenous function independent of the unit measurement or the magnitude of the resource allocation.
- *Asymptotic Saturation*: A fairness measure for allocation in which each agent gets the same resource allocation will become independent of the number of users.

- *Irrelevance of partition*: When an allocation is partitioned into two parts, the fairness index can be calculated recursively and yield the same result.
- *Monotonicity*: The fairness measure increases monotonically for two agents when the difference between the allocations is near zero.

Jain (1998) introduced a global fairness index independent of the number of users and size of the allocation, which can adapt to changes in an allocation and can be expressed as a percentage. It is defined in the following way:

$$J = \frac{\left[\sum_{i=1}^{n}(x_i)\right]^2}{n\sum_{i=1}^{n}(x_i)^2}$$

Equation 3-5: Formula for calculating the Jain index

with x_i being the amount allocated to user *i*. The value of the Jain index is located in the interval between zero and one. A zero value means the allocation is unfair for all, and a value of one indicates that the allocation is fair to all users.

Fossati (2018) introduces the player satisfaction rate and mood value as possible measures. The player satisfaction rate is based on a player's minimal and maximal rights. The minimal right is defined as the value a user has while acting on its own, and the maximum right is the difference between the grand coalition and the grand coalition minus the player itself. According to these properties, the player satisfaction rate is calculated as follows:

$$Player\ satisfaction\ rate = \frac{x_i - min_i}{max_i - min_i} = \frac{x_i - v(i)}{[v(n) - v(n\backslash i)] - v(i)}$$

Equation 3-6: Formula for calculating the player satisfaction rate

The mood value is derived from the player satisfaction rate, as the mood value is the allocation in which the player satisfaction rate is the same for all players.

$$mood\ value = \frac{E - \sum_{i=1}^{n} v(i)}{\sum_{i=1}^{n}[E - v(N\backslash i)] - \sum_{i=1}^{n} v(i)} = \frac{x_i - v(i)}{E - v(N\backslash i) - v(i)}$$

Equation 3-7: Formula for calculating the mood value

The fairest solution corresponds to the situation in which every player has the same tendency to leave the coalition. In this case, all players have the same satisfaction rate. Compared to the game-theoretic solution concepts of the core and Shapley value, the mood value is less computationally complex, which is a significant advantage (Fossati et al., 2018). Faster computation is especially advantageous when the number of players is high, as only the maximum and minimum rights have to be calculated compared to all individual vectors of the Shapley value.

In an envy-free allocation, every agent is satisfied with his share of the total resources and feels that his share is as good as the shares of other agents. In other words, the agents are not incentivised to acquire other agents' resources. Reaching this state requires strict constraints and may be nearly impossible when many agents are involved (Sinha & Anastasopoulos, 2017).

3.6 Collaborative allocation methods

This sub-section introduces multiple collaborative allocation methods used in transportation in more detail. These methods, which build on the game theoretic concepts of Section 3.5, are the carrier collaboration problem with pick-up and delivery, cooperative vehicle routing, and max-min allocation *methods. In the last section, the most widely used cost allocation methods are discussed, along with their pros and cons.*

3.6.1 Carrier collaboration

In a carrier collaboration problem in pick-up and delivery (CCPPD), multiple carriers collaborate by sharing their transportation resources and vehicle requests. The main goal of this collaboration is to increase vehicle utilization rates and reduce the number of empty backhauls.

In CCPPD, two significant issues must be addressed to achieve successful collaboration: collaborative planning and fair profit allocation. First, a shared plan must be developed that meets all pick-up and delivery demands across all carriers while respecting vehicle capacities and delivery windows. This plan should be designed in such a way that it maximises the overall profit for all carriers involved. Second, the profits must be distributed after the collaborative planning so that no carrier earns less than it would have without the collaboration. This distribution ensures that all carriers are incentivised to continue the partnership (Dai & Chen, 2012).

The contribution of each carrier is evaluated based on the offering and serving of transportation requests. For example, if carrier A outsources a request to carrier B, carrier A retains a portion of the revenue as compensation for offering the request. Carrier B, in turn, receives a share of the revenue as a reward for fulfilling the transportation task. This compensation ensures that both carriers are appropriately rewarded for offering and servicing requests. As carrier collaboration is achieved by sharing transportation requests, the contribution of each carrier should be evaluated based on offering and serving requests. If a carrier outsources a request to another carrier, the offering party should profit by retaining part of the revenue as a reward for acquiring the request. At the same time, the offering party should transfer parts of the revenue to the servicing carrier as a reward for taking on the request (Dai & Chen, 2012).

Determining a fair division of revenue is complex as transportation requests vary in profitability, and determining the costs of serving a request is challenging, especially when multiple requests are combined on a single route. To address these problems, a global view should be taken when evaluating profits.

Dai & Chen (2012) propose a method for evaluating the contribution of each carrier using a parameter w_m, which measures the contribution of carrier m:

$$w_m = \frac{(\theta_1 * c_m + \theta_2 * R_m)}{\theta_1 * \sum_{m=1}^{M} c_m \ + \ \theta_2 * \sum_{m=1}^{M} R_m} \ m = 1, .., M$$

Equation 3-8: Formula for calculating the contribution of a carrier m

In this equation, θ_1 and θ_2 are weight factors to balance the importance of costs and revenue, c_m is the total costs assigned to carrier m, and R_m is the total revenue a carrier generates. The costs and revenues are scaled to the total contributions of all parties to calculate the carrier's contribution. This method will allocate more profit to carriers with higher contribution measures.

3.6.2 Max-min allocation methods

The principle of max-min fairness focuses on ensuring resources are distributed to maximise the minimum allocations. It implies that given the number of jobs to be executed, the number of jobs of a company cannot be increased by simultaneously decreasing the number of jobs of other companies with the same number of jobs or fewer (Ye et al., 2017).

In the max-min minimum cost allocation problem proposed by Ye (2017), the objective is to allocate jobs fairly while minimizing the associated costs. This approach consists of two steps. First, the allocation vectors that are min-max fair are identified. After this, calculate the costs of each vector and select the one that minimizes the costs. A drawback of this method is that it only focuses on the number of assigned jobs without accounting for the size or complexity of a job.

Fossati (2018) builds on the idea of max-min fairness, but unlike Ye's method, it is based on the number of available resources and the demand of each player. This method gives the lowest claimant its total demand (or as much as available), with the remaining resources distributed equally among the other players. The formula for finding the max-min fair allocation of a user can be found below in Equation 3-9.

$$MMF_i(c, E) = \min\left(c_i, \frac{E - \sum_{j=1}^{i-1} MMF_j(c, E)}{n - i + 1}\right)$$

Equation 3-9: Formula for the max-min fair allocation of a user

3.6.3 Cooperative vehicle routing

Though the assignment problem in this research is a dynamic fleet assignment problem, it shares several key elements with the vehicle routing problem (VRP). As such, interesting concepts can be applied to the vehicle routing problem domain.

Generally, a vehicle routing problem aims to minimize the total cost of visiting a set of locations. The problem has a set of locations that need to be visited, a set of depots where the vehicles start and end their trip and a fleet of vehicles. Costs are incurred for making a trip from locations *i* and *j* if that trip is included in the planned route. Each demand location must be visited, and routes must start and end at a depot. These primary constraints can be extended with additional constraints incorporating vehicle capacity limitations, time windows, picking up goods and travel distance restrictions (Goel & Gruhn, 2008).

In most vehicle routing problems, a single company owns the transport vehicles and is responsible for the routing decisions. However, in cases where companies collaborate and form a coalition, a cost reduction can be achieved. Zibaei (2016) presents a model for the cooperative multi-depot vehicle routing problem to minimize the total transportation costs for vehicles in a coalition. The model is first solved by all players acting individually with their dedicated vehicles. Subsequently, all possible coalitions are evaluated. Starting with two-player coaling, then three-player coalitions and so on till all possible coalitions are evaluated. In total, the number of coalitions to be evaluated is 2^n-1.

3.6.4 Cost allocation methods

The cost savings of a collation are the difference between the total costs of the coalition and the sum of the individual costs if the players act independently. If the coalition costs are lower than individual costs, collaboration is incentivised. To make these coalitions stable, cost savings can have to be reallocated to keep all players aboard.

Regarding cost allocation in collaborative problems, the most important aspects are that no player pays more than in an individual scenario, and the allocation is stable. Table 3-2 shows the most widely used cost allocation methods and their pros and cons, according to a review by Guajardo and Rönnqvist (2016). These methods are “traditional” because they can be applied to many problem settings and are not tailored to a specific case. Some of these methods are already partly introduced in Sections 3.5 and 3.6.

Name	Method	Pros	Cons
Core allocation method	Find all subsets where no player will get a better outcome by deviating from the grand coalition.	• Individually rational as each player pays at most its individual costs. • No one can improve by deviating.	• Solving requires a large linear problem. • The core can be empty. In this case, another method is needed to allocate costs.
Shapley value	Assign each player the average of its marginal costs.	• Allocation is efficient, symmetric and additive. • Unique allocation.	• Generally, it does not belong in the core. • The number of marginal vectors grows exponentially.
Nucleolus	Minimizes the maximum excess: the difference between a player's assigned cost and the minimal cost they could have paid.	• Unique allocation • Always located in the core when this is non-empty.	• Calculating it is difficult as it is non-formula-based. Algorithms for calculating it are based on linear programs.
Proportional methods	Assign each player a share of the total costs. Share can be equal for each player or be based on, for example, demand quantities.	• Computational simple. • Multiple inputs can be used as a basis for the shared vector.	• Stability of allocation can be an issue.
Dual or shadow prices	When the cost function is obtained by solving a linear programming model, the underlying dual program can generate a cost allocation.	• The same model can solve both the cost function and cost allocation.	• It is only suitable when a linear program is used.
Marginal separable and non-separable costs	First, find the separatable costs for all players. Assign the player its separable costs and divide the rest over all the players.	• A player does not pay for the non-shared costs of another player.	• It does not always lead to an efficient allocation. • Another method may be required to allocate the non-separable costs.
Stand-alone cost comparison	Each player's cost is first calculated as it would be the only system user. Allocate the total cost so no one pays more than its standalone costs.	• Allocation is individually rational.	• Only gives an upper bound of the costs; another method is required for allocating the costs.

Table 3-2: Most used cost allocation methods

The game-theoretic allocation methods of the core, Shapley value and nucleolus have advantageous properties; however, this comes with high computational intensity. When it comes to the core, it can even be empty, meaning no cost allocation can be obtained using this method. The proportional, marginal and stand-alone allocation methods are computationally fast but do not always lead to an efficient or stable allocation.

3.7 Conclusions

This sub-section summarizes the main findings of the literature review and answers research Question 1.

Automated transport

Automated vehicles are already widely used in manufacturing and warehousing to transport goods. Over the last few years, the development of connected and automated road vehicles has taken place rapidly. Features such as adaptive cruise control and steer/brake support have already been implemented in standard road cars. Highly automated vehicles without drivers are used in enclosed areas and are being tested on open roads. Automation is closely tied to connectivity; automated systems cannot function independently without robust communication between vehicles and roadside infrastructure.

The transportation process can be divided into the first- and last-mile segments and the long haul when transporting goods or containers. Separating the long-haul portion and the first- and last-mile enables the usage of specialized vehicles for each part of the journey. Whereas long-haul transport takes place on highways and trunk roads with similar traffic conditions throughout the trip, first- and last-mile transportation can take on many forms. First- and last-mile applications in urban areas differ from those in port areas or near a highway hub.

Fairness and collaboration

No global definition of fairness exists, as it can be interpreted in multiple ways. Fairness measures should operate independently of the number of agents and the demand size. From a game-theoretic standpoint, fairness can be evaluated using principles such as the core, which includes all allocations in which agents are better off working together than individually, or the Shapley value, which measures each agent's relative contribution (Peters, 2008).

In carrier collaboration, pick-up and delivery requests are shared among carriers, and compensation is provided for taking over jobs (Dai & Chen, 2012). In cooperative vehicle routing problems, collaboration involves forming coalitions among vehicles from different owners. The problem is first solved with all agents acting individually, and then savings from potential coalitions are evaluated. These cooperative VRPs are, however, computationally intensive due to the need to evaluate numerous coalitions and permutations (Zibaei et al., 2016). In the max-min allocation method, the lowest claimant is allocated its total demand with the remaining resources divided over the remaining users (Fossati et al., 2018). If multiple max-min allocations exist, the one with the lowest costs is chosen (Ye et al., 2017).

Concerning cost allocation, game-theoretic-based methods have advantageous properties such as efficiency and uniqueness, but these methods are computationally intense. Proportional or separate cost methods are faster to compute but do not always guarantee an efficient or individual rational allocation.

4. Solution design

This chapter discusses the solution design for the North Sea Port case. It answers the third research question of what a suitable method for implementing a fair-use shuttle service is. First, in Section 4.1, a formal definition of the problem is formulated. Section 4.2 discusses three main principles which are essential for assigning jobs to vehicles. In Section 4.3, the chosen assignment strategy of jobs to vehicles is discussed, while Section 4.4 elaborates on the solution approach. Section 4.5 summarizes the main findings of this chapter and provides an answer to the second research question.

4.1 Problem definition

In this section, the definition of the transportation problem at North Sea Port is given. The flow of transportation at NSP is introduced first before a formal definition of the problem is formulated.

The flow of transportation jobs at North Sea Port occurs in two directions: from the Central Gate to a terminal and vice versa. There is no inter-terminal transport. From the perspective of an AV, several tasks can be performed. First, it can transport a container from one location to another. Second, it can travel empty from one location to another to pick up a container. Lastly, the AV can travel empty to its designated idle area or a terminal in anticipation of future jobs.

Since each trip consists of a limited number of legs and each vehicle can carry only one container, the problem cannot be described as a vehicle routing problem (VRP). Instead, it is more appropriate to call it a dynamic fleet assignment problem, as the vehicles must be matched with the pick-up and delivery jobs.

4.1.1 Formal formulation

The container transportation problem at NSP involves multiple terminals $t \in T$, which each have jobs $j \in J$, which need to be transported to or from the Central Gate. As it operates as a terminal itself, the Central Gate is included in the terminal set T. A job is transported over a route $r \in R$ by a vehicle $v \in V$. A vehicle can only transport one job at a time but can have a list of future jobs it will have to execute.

All jobs $j \in J$ stem from a job distribution across the terminals and differ per hour of the day and whether a job is inbound or outbound. Each job has a time at which information on the job becomes available for planning, the time it becomes available for pick-up and due time. Jobs j are assigned to a vehicle according to an assignment strategy.

All routes r have their travel distances based on the real-life road network; the time it takes a vehicle $v \in V$ to traverse the route depends on the travel speed. Each vehicle v costs a fixed amount per year based on purchasing price, residual value and length of life. Moreover, variable costs are incurred per kilometre travelled.

Summarizing, the problem has the following sets and inputs:

Sets

- T: the terminals and the Central Gate
- V: the autonomous vehicles (experimental factor)
- J: the jobs to be executed
- R: travel routes between terminals

Inputs

- Travel speed
- Decoupling and hitching time of a container
- Container due time window per job
- Early information window
- Vehicle costs
- Job assignment strategy

4.2 Principles to fulfil

This sub-section relates to principles that should be fulfilled regarding the assignment of jobs to vehicles at North Sea Port.

Of the problem inputs mentioned in Section 4.1, the choice of the assignment strategy is an essential decision. It should lead to results that fulfil the following three properties:

1. Guarantee efficient logistics performance.
2. Be deemed fair to all terminals involved.
3. Be adaptable to changes in the system.

The first property is to ensure the system's baseline performance. For sound system functioning, all jobs should be delivered to and picked up from the terminal within a reasonable timeframe: terminal dwell time should not exceed an hour. Based on historical data, container due times are, on average, two hours after it becomes physically available for transportation. Meeting the due times for container pickups helps prevent terminal overflows and delays in subsequent transportation modes.

The second priority is fairness, which is necessary to satisfy and engage all terminals. At the same time, it should be obtained for logistical performance and costs of a terminal. In both cases, sharing should be advantageous over acting alone. Additionally, vehicle assignments throughout the day should be balanced between terminals. It would be unfair if terminal A completed all its jobs first, leaving terminal B to wait and unable to complete any tasks during that time. Such a situation would result in excessive waiting times for Terminal B.

The property of adaptability is essential because the system experiences different dynamics throughout the day and week. The number of jobs to be completed fluctuates during the day and throughout the week, with significantly fewer jobs needing execution on weekends. Additionally, the system should operate independently of the number of terminals and vehicles and be capable of handling varying demand levels at each terminal.

4.3 Job assignment strategy

This sub-section discussed the chosen strategy for assigning vehicles to jobs.

For the job assignment strategy, a centralized approach is deemed the preferred option. In this case, information is globally available on which jobs must be scheduled, which jobs will become available soon, and the statuses and locations of all autonomous vehicles. As all this information is necessary for making sound assignment decisions, a centralized approach seems the way to go.

At NSP, the system has a low degree of dynamism as there is just some stochasticity. As such, the AVs can have a schedule with a sequence of future jobs. When making an assignment decision, all the schedules of all vehicles should be evaluated, and the job should be placed in the best schedule; this can be a vehicle that is not yet available at the moment of deciding. No reassignment of jobs takes place; the order of the vehicle jobs can only be changed by the insertion of another job.

Information on when a job becomes executable is available in advance; this early information can be used in the planning. The estimated arrival time of a trailer is known some time beforehand. Changings in the expected time of inbound containers can be caused by external factors like traffic and roadworks. Nevertheless, it provides a general indication of container release times, enabling the planning of a sequence of transportation jobs.

It is proposed that the assignment decision be made when information on a job becomes available. Because of the low level of dynamism, an insertion algorithm for the job assignment is used. When job information arises, the schedules of all vehicles are evaluated. Per vehicle, all possible insertion places are evaluated. The job is assigned to the vehicle, which yields the earliest completion time for all jobs in its schedule. For an illustration, the pseudocode of this algorithm can be found below in Figure 4-1.

Algorithm 1: job scheduling

```
Input: Job data, vehicle schedules
Output: Vehicle schedule
Initialize trackers
Best solution = ∞
Best vehicle = 0
Best position = 0
For all vehicles v
        For all positions z+1 already in the vehicle job list
                Copy the existing job list
                Insert job at position z
                Update completion times of subsequent jobs
                If total completion time < best solution so far
                        Update best solution
                        Update best vehicle
                        Update best position
                End If
        Next position in the schedule
Next vehicle
Insert job at the best position over all vehicles
Return updated vehicle schedule
```

Figure 4-1: Pseudocode of the job scheduling algorithm

Concerning the property of adaptability discussed in Section 4.3, the method of algorithm 1 works independent of the number of jobs, vehicles and terminals.

4.4 Simulation and cost allocation approach

This section discusses the solution approach related to the simulation model and the cost allocation method, which is two-fold. Section 4.4.1 discusses the first part related to the simulation model, and Section 4.4.2 discusses the second part, which concerns cost allocation. The simulation model is only discussed briefly here, as Chapter 5 is dedicated to its conceptual model.

As mentioned in Section 4.2, a fair solution for all terminals should be obtained in terms of logistical performance and financial costs. As we deal with the assignment of a resource to a job instead of an amount of total available resources, the methods mentioned by Dai & Chen (2012), Fossati (2018) and Ye (2017) in Sections 3.6.1 and 3.6.2 are not applicable. As such, the fairness of the system will have to be evaluated afterwards. A two-way approach is used for this. First, a simulation model is used to gain insights into the logistical performance of the system. After that, based on the output of the simulation model, fairness is evaluated in financial terms by finding a cost allocation in which sharing is profitable for all involved terminals.

4.4.1 Simulation model

Using simulation allows for the evaluation of various configurations of the shuttle service at North Sea Port. The simulation model was constructed object-based, which allows for dedicated attributes per object type and within the model, objects can be followed visually. These two features are helpful for debugging and tracing the logical flow of the model. Moreover, the simulation model is discrete event-based: the simulation moves from one event to another. Between events, no simulation time elapses. As certain events trigger all processes related to autonomous vehicle transportation at NSP, e.g. arrival and departure events of a vehicle at a terminal, simulation is a good tool for modelling the system.

As shown in Figure 4-2, the simulation model output will provide insights into three parts: autonomous vehicle utilization, container dwell time (the time a container spends in the system between becoming available and being delivered at its destination), and attributed travel kilometres per terminal. The terminal kilometres travelled will be used as input for calculating the cost divisions together with the cost structure and the chosen cost allocation methods. Together, these inputs yield a cost distribution per terminal, showing the weekly system costs.

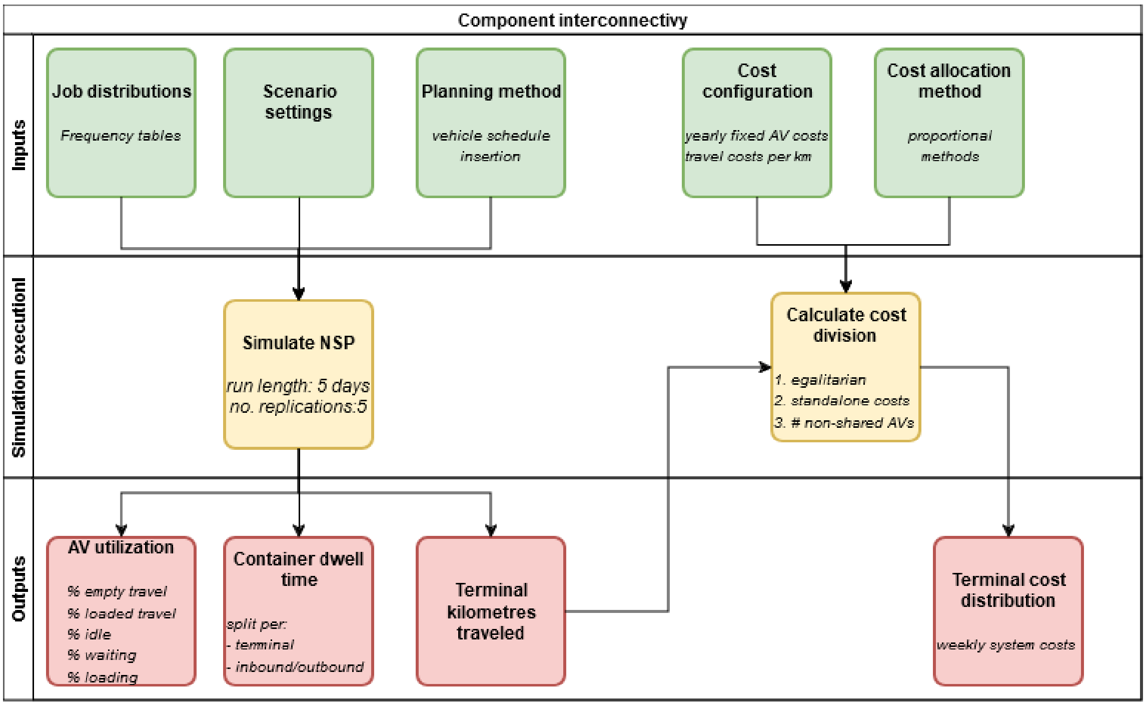

Figure 4-2: Interconnectivity of simulation processes

As the cost calculation only requires basic mathematical calculations, it can be executed by another tool. However, as the cost allocation uses output generated and stored in the simulation model, the cost calculation is executed at the end of a simulation run.

4.4.2 Cost allocation

Concerning cost allocation, the review of Guajardo & Rönnqvist (2016) in Section 3.6.4 showed the most widely used methods. As the problem is solved by simulation and not by a linear program, the dual shadow approach, which switches the constraints and variables of the linear programming model, is not applicable. As discussed in Chapter 3, the game-theoretic solution concepts of the core, Shapley value and nucleolus offer interesting properties but have their drawbacks. As the core is bound by all efficient and individually rational payoff vectors, calculating a core-based cost allocation for this problem requires a large linear programming model. The core can, however, be empty, which means another method is required. Nevertheless, the definitions of efficiency and individual rationality can be applied. In this case, it means all costs should be allocated, and a terminal can not be allocated more than when acting alone.

We decided to use a combination of the proportional, separatable costs and stand-alone cost methods mentioned in Section 3.6.4 to calculate the terminal division. First of all, these three methods are easy to compute. The stand-alone cost method corresponds with the situation in which terminals do not cooperate and do not share vehicles; this method is used to gain insights into the costs per terminal when acting individually. By using a separable cost allocation method, only the fixed costs have to be allocated over the terminals. Variable costs per km are assigned to the terminal that owns the container. When an empty repositioning takes place, the costs are attributed to the terminal to which the vehicle is travelling. This way of allocating empty repositioning costs is deemed to be the best option as this terminal gains from having the vehicle transport its job. The proportional allocation method can be calculated using different input factors. This is beneficial as one method can yield multiple cost allocations.

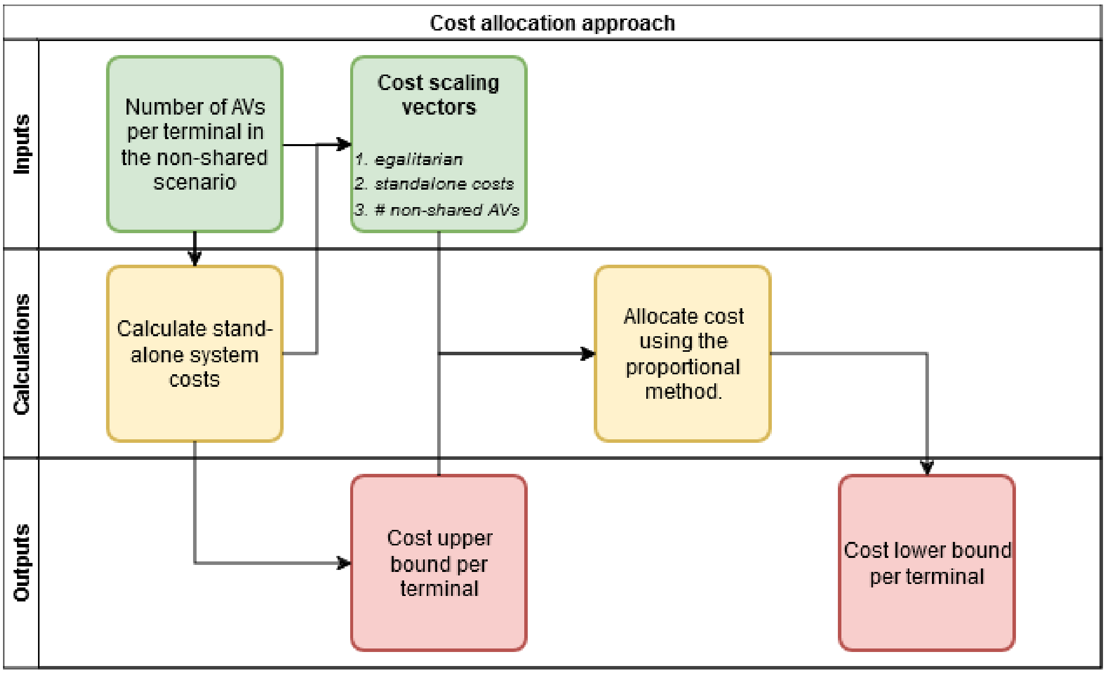

Figure 4-3: Cost allocation approach

Figure 4-3 shows the iterative approach followed for coming to a weekly terminal cost allocation. First, the standalone costs per terminal are calculated. These are the system costs per terminal when each terminal acts alone. As such, no sharing takes place in this scenario, and each terminal has its dedicated vehicles. Calculating the required number of vehicles in both the shared and non-shared scenarios is part of the experimental design. The stand-alone cost allocation is an upper bound of the costs of a terminal. To guarantee a fair and stable solution, no terminal should be allocated more than this value to prevent it from cooperating.

The primary method used for allocating costs is the proportional method. As the name suggests, the proportional method allocates the total costs C(N) according to a fraction α_t such that

$$x_t = \alpha_t * C(N), \forall t \in T, \sum_{1}^{T} a_t = 1$$

Equation 4-1: Proportional cost allocation method

The input fractions α_t can be based on multiple criteria. For North Sea Port, these weights will be based on three factors:

1. Egalitarian method
2. Standalone costs of a terminal
3. Number of AVs per terminal in the non-shared scenario

The easiest of these input fractions is the egalitarian method, which assigns each terminal the same fraction of costs, that is, $x_t = C(N) / n$. This weigh factor does not account for the size of each involved terminal and is not expected to yield a stable solution. The second fraction uses the standalone costs of a terminal to determine the weight factors. The third weight value is a translation of terminal demand, which is frequently used as a weight value. In this case, the scaling vectors are based on the number of autonomous vehicles each terminal requires when acting alone. The third fraction, which deals with the standalone costs of a terminal, is also based on the non-shared scenario. Instead of the number of autonomous vehicles, it uses the total costs of a terminal when operating alone. For the second and third methods, the standalone costs and number of AVs should be normalized to obtain a total weight of one.

Figure 4-4 below shows the pseudocode on how to calculate the terminal cost division.

Algorithm 2: Terminal cost division

```
Input: yearly AV costs, number of AVs in the system, AV kilometre costs, terminal kilometres travelled, allocation method
Output: Weekly costs per terminal
Retrieve input
NoAVs = number of total AVs in the system
NoNonSharedAV(t) = the number of AVs of a terminal in the non-shared scenario
Standalonecosts(t) = costs of a terminal in the non-shared scenario
yearlyCosts = yearly fixed cost of an autonomous vehicle
kmCosts = variable cost per kilometre travelled
Terminalkms(t) = kilometres attributed to terminal t
For all terminals t
        If cost allocation fraction = egalitarian
                Terminalcosts(t) = kmCosts * Terminalkms + noAVs/noTerminals * yearlyCosts /52
        Else If cost allocation fraction = non-shared AV fractions
                Terminalcosts(t) = kmCosts * Terminalkms + NoNonSharedAVs(t)/Σ_1^t NoNonSharedAVs(t) * noAVs * yearlyCosts /52
        Else If cost allocation fraction = stand-alone cost fractions
                Terminalcosts(t) = kmCosts * Terminalkms + standalonecost(t)/Σ_1^t standalonecosts(t) * NoAVs * yearlyCosts / 52
        End If
Next terminal
Return weekly cost per terminal t
```

Figure 4-4: Pseudocode for calculating the cost division using the proportional cost method

4.5 Conclusions

This chapter presented the solution design for the transportation problem at North Sea Port. In the problem, jobs should be assigned to autonomous vehicles in such a way that the solution has good logistical performance, is fair across all terminals and is adaptable to changes in the system. As the degree of dynamism encountered at NSP is low and job information is available early, vehicles can have a schedule with future jobs.

A schedule insertion algorithm will be used to assign jobs to vehicles. Jobs will be assigned to a vehicle at the moment early information on the job arises. All vehicle schedules will be evaluated, and the job will be assigned to the vehicle with the lowest total job completion time.

The solution design follows a two-way approach. First, a simulation model is used to generate insights into the logistical performance of the system. Simulation output is used as input for the second step of the cost allocation. Regarding cost allocation, the terminal costs are first calculated for the situation in which each terminal acts alone. Afterwards, costs are allocated using the proportional method with weight values being egalitarian, based on the standalone costs and the number of terminal AVs in the non-shared scenario.

5. Conceptual model

This chapter presents the conceptual model, a simplified non-software representation of the simulation model. Section 5.1 outlines the requirements for creating a conceptual model, while Section 5.2 focuses on the model-building process using the framework of Robinson. Section 5.3 discusses the main model contents, including the flowcharts that display the model's logic.

5.1 Introduction

This sub-section introduces the conceptual model-building process, detailing the model's goals and requirements.

Robinson (2008a) states that a conceptual model is a simplified non-software representation of a real system. It involves moving from a problem situation through identifying requirements and inputs to clearly defining what is being modelled and how it will be represented. Robinson's (2008b) framework outlines the following critical tasks involved in conceptual modelling:

- Understanding the problem situation
- Determining the modelling and project objectives
- Identifying the model outputs (responses)
- Identifying the model inputs (experimental factors)
- Determining the scope and level of detail and identifying assumptions and simplifications.

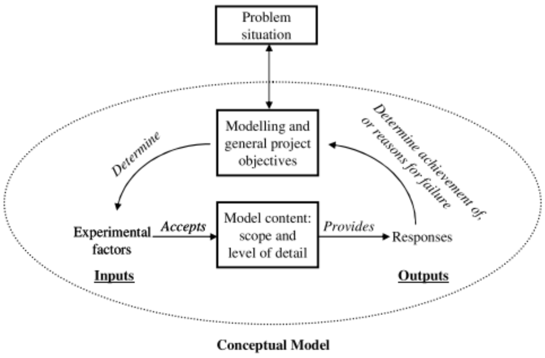

Figure 5-1: Conceptual model framework (Robinson, 2008b)

As shown by the arrows in Figure 5-1, creating a conceptual model is not linear but involves repetition and iteration. A conceptual model must meet the following four requirements:

- *Validity:*
  The perception is that the conceptual model can be accurately translated into a computer based on the modeller's perspective.
- *Creditability*:
  Similar to validity but from the client's standpoint. Since the modeller and the client may have different views on the accuracy and purpose of the model, validity and creditability are treated as separate requirements.
- *Utility*:
  The modeller and client's shared perception is that the conceptual model can be turned into a useful computer model to aid decision-making.
- *Feasibility*:
  The perception is that the conceptual model can be turned into a computer model with the available resources.

5.2 Conceptual model building

This section will describe the conceptual model for the North Sea Port case using Robinson's framework. Section 5.2.1 introduces the problem situation, and Section 5.2.2 focuses on the modelling and project objects. Sections 5.2.3 and 5.2.4 describe the out- and inputs, respectively. Section 5.2.5 discusses the model's scope and level of detail and which agents and processes are included or excluded.

5.2.1 Problem situation

As introduced in Chapters 1 and 2, the proposed layout of the Central Gate is entirely new. The conceptual model must provide a realistic representation of this new situation. Referring to the model requirements discussed in Section 5.1, stakeholders must have confidence in the model's outcomes to gain credibility.

Given the problem description outlined in Chapter 2 regarding the North Sea Port case, the problem situation for this conceptual model is defined as follows: *How can autonomous vehicles be effectively used in a shared situation to achieve logistical performance while ensuring fairness?*

5.2.2 Modelling and general project objectives

The conceptual model translates the problem into specific modelling and project objectives. Since the proposed system does not yet exist, the main objective is to gain insights into the performance of the new situation. The goal is to create a high-level understanding of the system's performance. Naturally, due to the shared vehicles, the question of whether fairness can be achieved is also essential. Finally, the port authority is also interested in comparing the proposed autonomous vehicle system with the current, non-automated setup.

5.2.3 Outputs

- Container dwell time
- Utilization of an AV
  Split in travelling with a load, travelling empty, idle and waiting for a load.
- On-time percentage
  What is the percentage of jobs that are completed within a particular time?
- Kilometres travelled loaded and empty

5.2.4 Inputs

- Number of autonomous vehicles
  - Broken down per terminal in the non-shared base scenario
- Travel distances between terminals and Gate
- Travel speed
- Decoupling and hitching time
- Distribution of jobs
  - Split between inbound and outbound
  - Total hourly demand
  - Hourly division across terminals
  - Assumed that each weekday follows identical distributions
- Early information window
- Assignment strategy
- Mean due time

5.2.5 Scope and level of detail

In the model, the focus is solely on the transportation of containers. Processes at the Central Gate and terminals will be treated as a black box, meaning they will be simplified and modelled with a fixed execution time for each process. Moreover, travel times will be assumed to remain constant during the day, unaffected by peak hours or congestion. These times will be calculated based on distance with a margin that reflects traffic conditions.

Regarding autonomous vehicles, it is assumed that there are no battery limitations and that the vehicles will operate without breakdowns. Decoupling and hitching containers will also be assigned a fixed time as simplification.

As shown in Table 2-1 and Table 2-2, demand at NSP shows different patterns during the day and the week. However, these patterns remain consistent across weeks, and seasonality is not a factor. As such, the model will have a run length of one week.

A fixed travel speed is assumed for the entire trip to calculate the travel times from location A to location B. As such, there is a linear relationship between the travel distance and travel time. A margin can be added to the linear travel times to incorporate different travel conditions, such as congestion and accidents.

Table 5-1 outlines the inclusion or exclusion of each possible simulation component in the model.

Component	**Include/Exclude**	**Reason/comment**
	Entities	
Terminals	Include	
Central Gate	Include	Excluding resting truckers and trucker facilities
Containers	Include	
Cargo type	Exclude	Can, in reality, impose constraints on the decoupling of a trailer and the transport by AV.
Other road vehicles	Exclude	Travel is modelled as a fixed time + random value representing travel conditions as congestion.
Human personnel	Exclude	
	Activities	
Resting trucks at CG	Exclude	No impact on inter-terminal transport.
Container pick up	Include	
Container drop off	Include	
Empty AV travel	Include	
AV Charging	Exclude	Battery constraints are ignored, so no charging is required.
Internal terminal operations	Exclude	
Decoupling/hitching of container	Include	Impact on schedule
Maintenance/failures	Exclude	Possibility for further research
Job deadlines	Include	Modelled as a soft constraint
Customs check	Exclude	CG is modelled as a black box.
	Resources	
Trucks	Exclude	CG arrivals are modelled as a black box

Containers	Include	
AV	Include	
Human personal	Exclude	Irrelevant for fairness, assumed not to impact operations.
LHV	Exclude	There are too few arrivals to be of impact. In reality, it imposes decoupling constraints.
Road infrastructure	Exclude	
Charging stations	Exclude	Battery constraints are ignored, so no charging

Table 5-1: Include/exclude for possible components in the model

5.3 Model contents

This section first discusses two major design decisions, followed by a discussion of the main functions and contents of the model.

As discussed in Section 4.3, there is a low degree of dynamism at North Sea Port, and for that reason, the schedule insertion algorithm of Figure 4-1 was used to assign jobs to vehicles. For this, a centralized approach is used as the planning agent needs to have information on all jobs and the status of autonomous vehicles.

Kloosterboer operates multiple terminals, three of which are located on the same complex and can effectively function as a single terminal. Therefore, these three terminals are modelled as a single terminal. Moreover, the terminal of NSP did not provide data on historical demands and was excluded for that reason.

5.3.1 Type of simulation

This section determines which type of simulation reflects the operations of North Sea Port and calculates the number of replications required.

The simulation model is terminating as it empties during, and no demand is modelled on the weekends. In the simulation model, demand is concentrated during day hours, and no demand occurs during the weekend. As such, the model is treated as a terminating simulation with a run length of a week. Additionally, steady-state cycles can be observed, as shown in Figure 5-2. During peak times, higher AV utilization rates lead to an increase in the overall dwell time of a container.

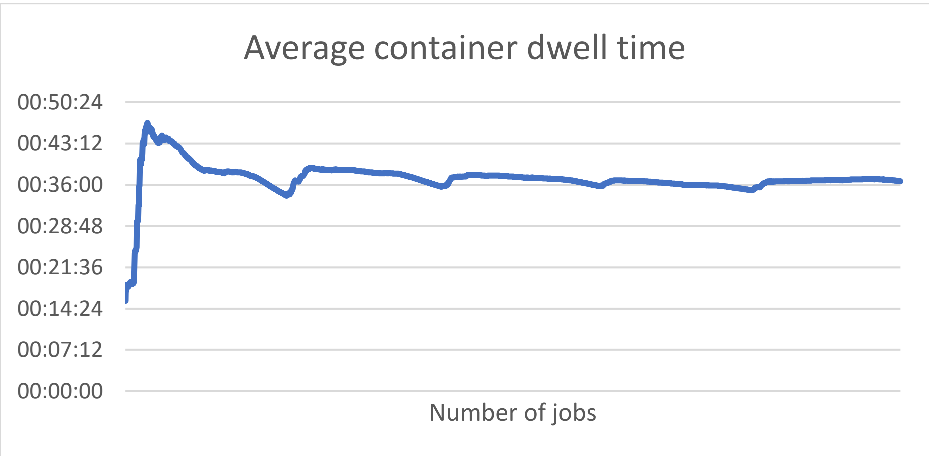

Figure 5-2: Average container dwell time

The number of required replications per experiment is calculated using the fixed-sample size method of Law (2015), as shown in Equation 5-1Equation 5-1: . The average container dwell time was used as input KPI with a simulation run length of a week. The relative error γ allowed is at most five percent and a 95% confidence level was used; The latter results in an α of 1 – 0.95 = 0.05.

$$n^* = min\left\{ i \geq n: \frac{t_{i-1,1-\frac{\alpha}{2}}\sqrt{\frac{S_n^2}{i}}}{|\bar{X}_n|} \leq \frac{\gamma}{1+\gamma} \right\}$$

Equation 5-1: Formula for determining the number of replications (Law, 2015)

When n is five, the left side of the equation is smaller than the right side of the equation and does not jump over again over the allowed relative error when n is increased further. As such, five was found to be the required number of replications.

5.3.2 Job data generation

This section discusses how job data is generated within the model.

Based on the historical job patterns shown in Section 2.3 and hourly patterns over all terminals, input jobs are created at the start of the simulation. First, the number of inbound and outbound jobs per hour is determined. Normal distributions are used with the historical average as the mean and a fraction of that number as the standard deviation. The coefficient of variation can be changed at the main frame of the simulation for experimentation. The outcomes of these random experiments are rounded as the number of jobs can not be fractional. When using low-demand values, it must be ensured that the number of jobs does not become negative. Assigning jobs to a terminal uses an empirical distribution based on historical data of terminal job distribution; these distributions can be found in Appendix B. The arrival time of the job is uniformly distributed within the hour.

5.3.3 Simulation events

This section outlines the primary events within the simulation and identifies the corresponding triggers that initiate these events.

In the simulation model, the most important events are those related to autonomous vehicles. The following situations trigger AV events:

- A job is assigned to an AV while the vehicle has been idle.
- An AV is activated after being idle.
- An AV arrives at a terminal for pick-up or delivery of a job.
- An AV leaves a terminal after delivering or picking up a container.
- An AV has completed the final job on schedule.

The first two events on this list, which both involve idle AVs, are not the same. While both deal with idle AV, assigning a job to a vehicle does not necessarily warrant immediate action. The activation event means the vehicle is activated to go to the location of its first job. As such, the first event involves planning, and the second one involves the execution of a task.

Beyond managing AVs, another critical process is the loading, which is invoked when an AV enters or exits the loading stations. This process ensures containers are 'physically' loaded onto or detached from the AV.

Figure 5-3 and Figure 5-4 show the flowcharts for the arrival and departure events of an AV at a terminal.

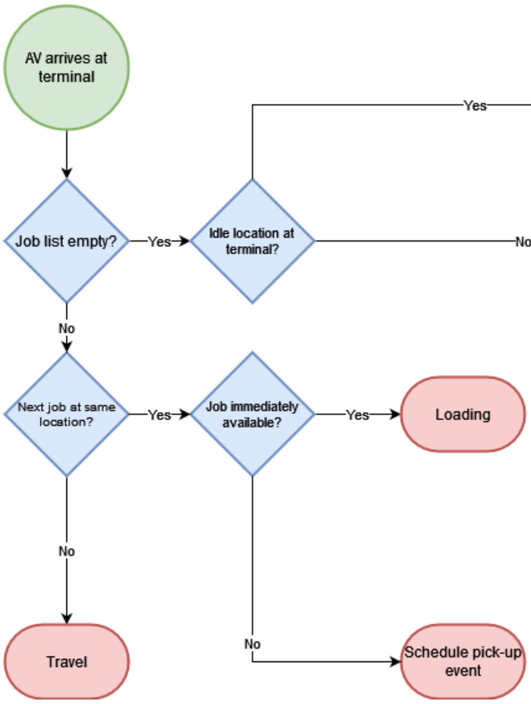

Figure 5-3: AV terminal arrival flow

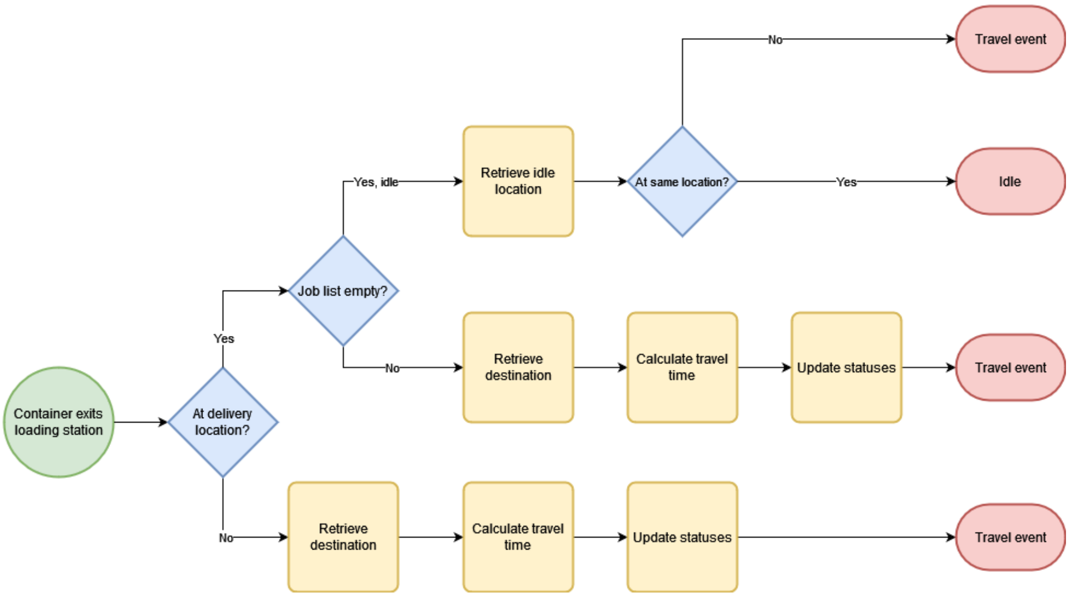

Figure 5-4: AV terminal departure flow

5.3.4 Planning

The planning agent is one of the most critical agents in the model as it determines the job sequence of the vehicles and impacts many performance statistics. The planning uses an insertion algorithm, where all possible positions for the job across all available AVs are evaluated. The job is assigned to the AV, whose schedule results in the lowest make span. The flowchart in Figure 5-5 is a graphical representation of the pseudocode shown earlier in Figure 4-1.

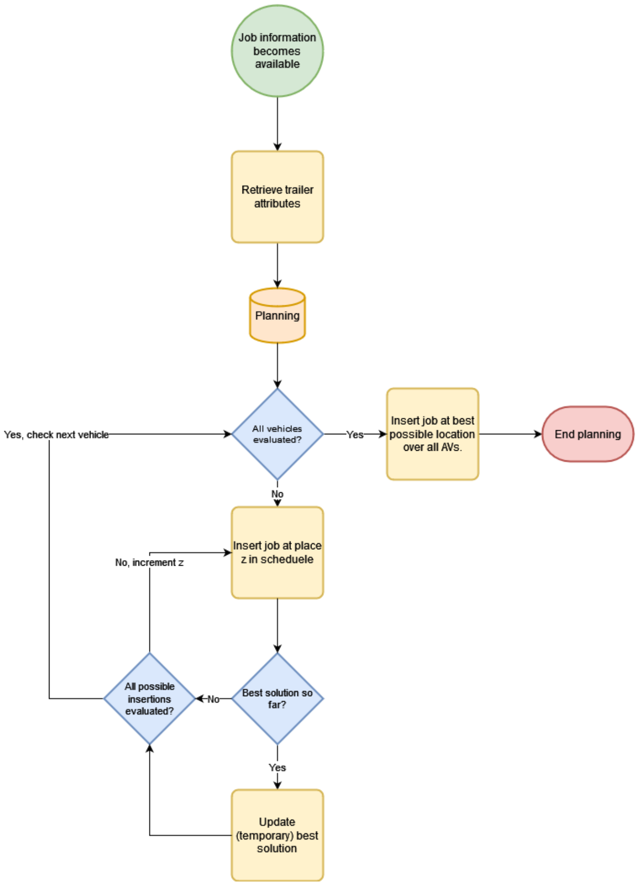

Figure 5-5: Planning flowchart

5.4 Model verification and validation

This sub-section discusses the verification and validation of the conceptual model.

According to Law (2015), verification is determining whether the inputs and assumptions of the conceptual model have been accurately translated into a computer model. This process was carried out by tracking the flow of a container through the system to ensure it was processed correctly, running the simulation in a smaller setting to observe its functionality and using improbable conditions to test its robustness. Moreover, at the end of a simulation run, it is checked whether all are delivered and, as such, have left the system. No problems have

Conversely, validation concerns whether the simulation model accurately represents the real-life system. Since the proposed system configuration of North Sea Port does not yet exist, this validation method is impossible. However, a model can still be considered valid if it proves helpful for decision-making related to the system (Law, 2015). Using this definition, the model is deemed valid as it provides a valuable tool for analysing system performance, and the model output acts as an input for cost allocation.

5.5 Conclusions

In this chapter, we have built the conceptual model, which serves as a non-software representation of a real system (Robinson, 2008a). Since the proposed system does not exist yet, the primary modelling objective is to gain insights into the performance of the new situation.

In order to assess the performance of the proposed system, the container dwell time, utilization rates of autonomous vehicles, and the amount kilometres travelled are suitable for evaluating the logistical performance of the system. Inputs for the model are the number of AVs, travel distances and speed, decoupling and hitching times and job distribution data categorized by hour, terminal, and in/outbound direction.

As the research focuses solely on the assignment and transportation of jobs, many processes, which are in real-life complex, are modelled as a black box. For example, travel conditions are represented by a fixed travel speed. Five replications of the simulation model are required to obtain statistically sound results.

6. Results

This chapter discusses the main results of the research. In Section 6.1, the experimental design will be explained. Section 6.2 discusses the main findings of these experiments, and in Section 6.3, the financial costs per terminal will be allocated.

6.1 Experimental design

This section introduces the experimental design and the baseline experimental settings used when executing these experiments.

Multiple experiments were run to gain insight into the logistical performance of the shared shuttle service at North Sea Port. Table 6-1 shows the executed experiments with a description of the experiment's goal. Experiment 1 aims to determine the minimum number of vehicles required. Experiment 2 builds on this by finding the number of vehicles per terminal when no sharing occurs. Experiment 3 aims to give insights into travel kilometres, which are required later on in the cost allocation. Experiments 4 and 5 look into the impact of changing due times and early information window of jobs.

ID	Experiment	Goal
1	Number of AVs	The goal of this experiment is to determine the number of autonomous vehicles required when these vehicles are being shared among the terminals. It gives insights into both the container dwell time and the autonomous vehicle utilization.
2	No cooperation	This experiment aims to find the number of vehicles required when no sharing takes place. It is executed by searching for the number of vehicles that are required to obtain a container dwell time similar to that in the shared scenario.
3	Inter-terminal travel	This experiment will give insights into empty intra-terminal travel and which combinations of terminals offer a positive synergy.
4	Due time windows	This experiment looks to see the impact of stricter average due times on the average container lateness and on-time percentage.
5	Early information window	This experiment's goal is to see whether changing the early information window of jobs impacts the average container dwell times.

Table 6-1: Experimental design

Each configuration of an experiment was tested five times. As mentioned in Section 5.3.1, five replications of the simulation are required for sound statistical analysis.

The experiments were all run with the computational settings shown below in Table 6-2 unless explicitly stated to be different. Note that when the number of autonomous vehicles is kept stable in an experiment, the result of Experiment 1 is used.

Parameter	Baseline value
Travel speed	45 km/h
Trailer coupling time	6 minutes
Average due time	2 hours
Early information window	2.5 hours
Job distribution coefficient of variation	0.1
AV Idle location	Local
Number of autonomous vehicles	16

Table 6-2: Experimental settings

A local idle location for AVs means that an autonomous vehicle goes idle at the destination location of its last job. Another option for idling would be that it always drives back to the Central Gate and idles over there. The job distribution coefficient of variation is used to determine the standard deviation used to generate the number of jobs within an hour. The number of jobs per hour is generated using a normal distribution; using a value of 0.1 implies that the standard deviation is 0.1 times the mean.

6.2 Logistical performance

This section discusses the results of the experiments executed as mentioned in the experimental design of Table 6-1. Section 6.2.1 will discuss the results of experiment 1, focussing on the number of autonomous vehicles required. Section 6.2.2 presents the results of experiment 2 related to the scenario in which terminals do not cooperate. Section 6.2.3 is on experiment 3, which focuses on the weekly kilometres travelled and the inter-terminal travel. Section 6.2.4 looks into the impact of container due times with experiment 4. Finally, Section 6.2.5 discusses the results of experiment 5 and some other minor observations.

6.2.1 Number of autonomous vehicles

Experiment 1 focused on determining the minimum number of autonomous vehicles (AVs) needed to ensure good logistical performance. In this experiment, the number of AVs varied from 10 to 20, with all other variables held constant.

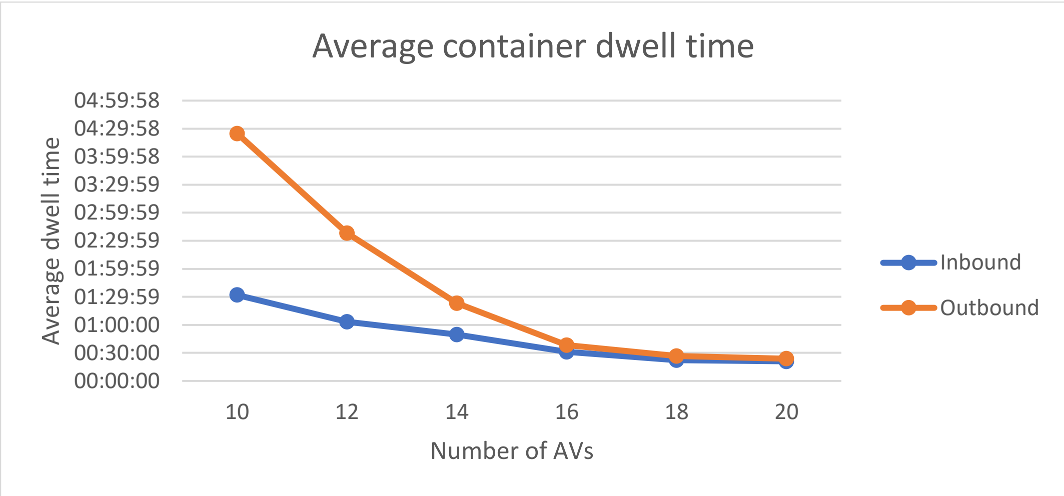

Figure 6-1: Average dwell time of a container against the number of autonomous vehicles

Figure 6-1 plots the average dwell time against the number of AVs. The results show that increasing the number of total AVs from 10 to 16 significantly reduces the average dwell time of containers. Further increasing the number of AVs continues to decrease the dwell time but at a slower rate.

In the experiments with fewer AVs, the dwell time for outbound jobs was significantly higher than that for inbound jobs. This difference is caused by terminals generally having an uneven distribution of jobs between outbound and inbound. As such, an inbound job can be directly coupled with an outbound job, whereas this is not the case the other way around.

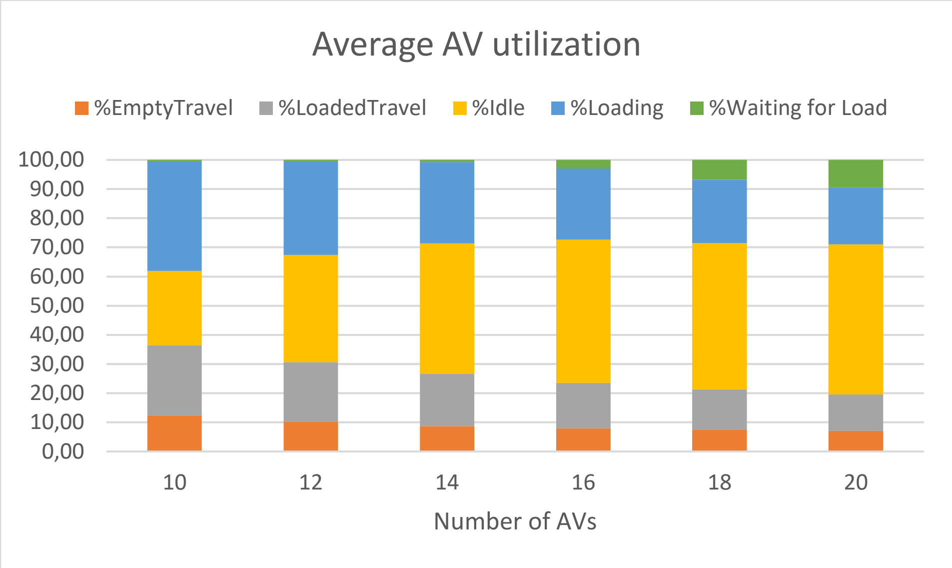

Figure 6-2: Average AV utilization against the number of AVs

Figure 6-2 shows the average utilization of an AV. First of all, across each configuration, the idle percentage is high. No jobs are executed at night, so the AVs are inactive for long periods. Second, in the scenario with fewer AVs, the percentage of time loading is high. As AVs are continuously transporting containers, the time spent loading is high. Third, in the scenarios with 16 or more vehicles, the percentage of time waiting for loading increases significantly. As more AVs are available, each AV has more slack in its schedule and can be sent to terminals before future jobs.

6.2.2 Shared versus non-shared

In Experiment 2, a comparison was made between scenarios where AVs were shared among terminals versus each terminal having dedicated AVs to see whether sharing is logistical and financially advantageous. In the non-shared scenario, each terminal should have a logistical performance comparable to that of the shared scenario. The benchmark is done by having sixteen AVs in the shared scenario as further increasing the number of vehicles showed limited returns on the container dwell as illustrated in Figure 6-1 in Section 6.2.1.

Terminal	#AVs required	Non shared AVs	Shared 16 AVS	Shared 24 AVS
KB123	4	00:30:47	00:33:32	00:19:23
KB4	2	00:28:03	00:34:50	00:21:44
KB5	2	00:31:40	00:34:36	00:22:17
AMC	1	00:36:34	00:36:29	00:21:50
ZZC	1	00:34:01	00:32:11	00:21:52
VB2	4	00:37:03	00:41:19	00:25:13
VB3	3	00:47:49	00:40:11	00:23:32
VB1	3	00:23:08	00:36:24	00:17:49
SUP	1	00:27:23	00:33:59	00:19:49
VOP	1	00:29:24	00:29:41	00:17:20
ZER	1	00:22:32	00:32:34	00:16:53
AWT	1	00:33:12	00:37:18	00:21:01
System	24	00:32:38	00:35:54	00:20:54

Table 6-3: Comparison of average container dwell time between shared and non-shared scenarios

Table 6-3 shows that 24 autonomous vehicles are required to have the same performance level. Adding or removing one AV has more impact than in the non-shared scenario, e.g., for the *KB123* terminal, the average dwell time almost triples to 1.5 hours when going from four to three AVs. Smaller terminals such as *ZER*, *VOP, SUP and AWT* have better average system performance when working alone than in the shared case. Of the larger terminals, *VB1* also has improved dwell time when not sharing a vehicle fleet.

The location of these terminals within North Sea Port most likely causes the lower container dwell. As can be seen in Figure 2-4, these terminals are located close to the Central Gate; as such, the travel time forms just a limited part of the container dwell time. Compared to the other terminals with an improved dwell time, *AWT* is located further away from the Central Gate on the southwestern edge of the port. Being a geographical outlier has a negative impact in the shared scenario as a vehicle will have to travel longer when transporting a container for *AWT*.

Directly comparing the scenario in which terminals have individual vehicle ownership with the 16 AV scenario, however, has drawbacks. In this case, the non-shared scenario has 24 AVs, while the shared scenario has 16. Therefore, in the final column of Table 6-3, the systems time of a shared scenario with 24 AVs is shown. In this case, each terminal performs better in the shared scenario.

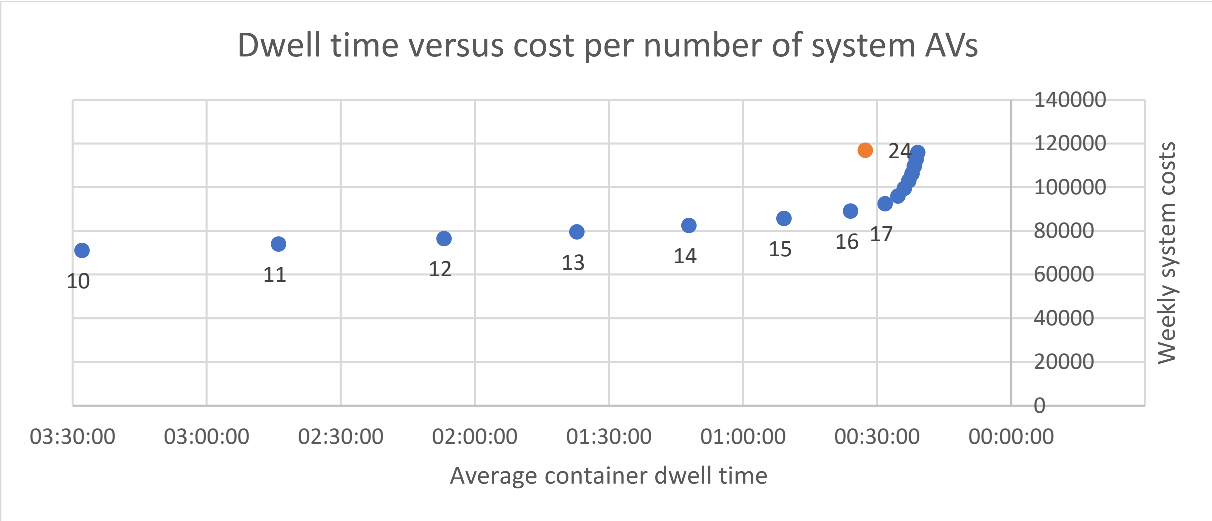

Figure 6-3: Average container dwell time plotted against the system costs

Figure 6-3 shows the system costs against the average container dwell time. The diminishing returns of additional AVs past sixteen vehicles are clearly shown. In this figure, the orange dot corresponds to the non-shared scenario with 24 systems AVs. Whereas sixteen AVs in the shared scenario give comparable performance to the non-shared scenario, 17 shared vehicles have a performance that is strictly better both in costs and average container dwell time.

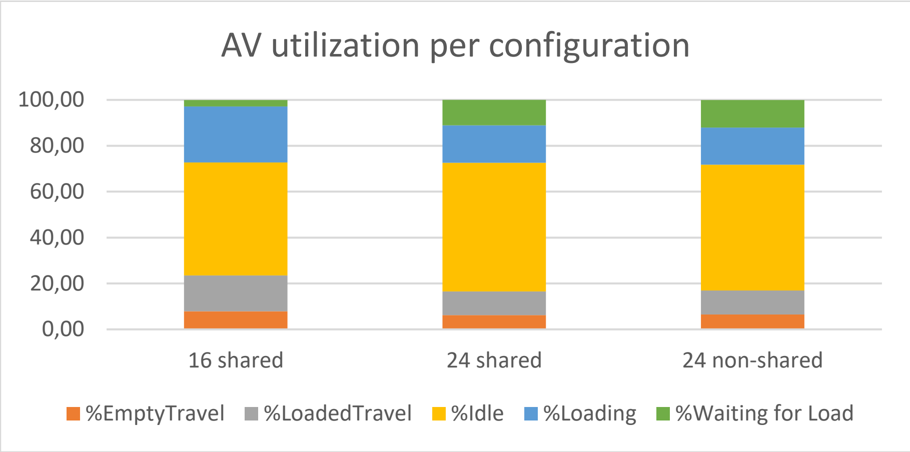

Figure 6-4: Average AV utilization per configuration

When looking at the vehicle utilization rates of the configuration discussed in Table 6-3, the shared and non-shared scenarios with 24 vehicles seem to have similar utilization rates, as shown in Figure 6-4. However, when looking into the average AV utilization per terminal in the non-shared scenario of Figure 6-5, differences can be observed across terminals. Vehicles of *KB123* and *VOP* are loading over 20% of the time compared to loading percentages under 10% for SUP and AWT. Another example of this is the high waiting-for-load percentages of *VB1* and *ZER* compared to low values of *KB123*, *VB2* and *VB3*. When vehicles are shared, the utilization rates are comparable over the vehicles.

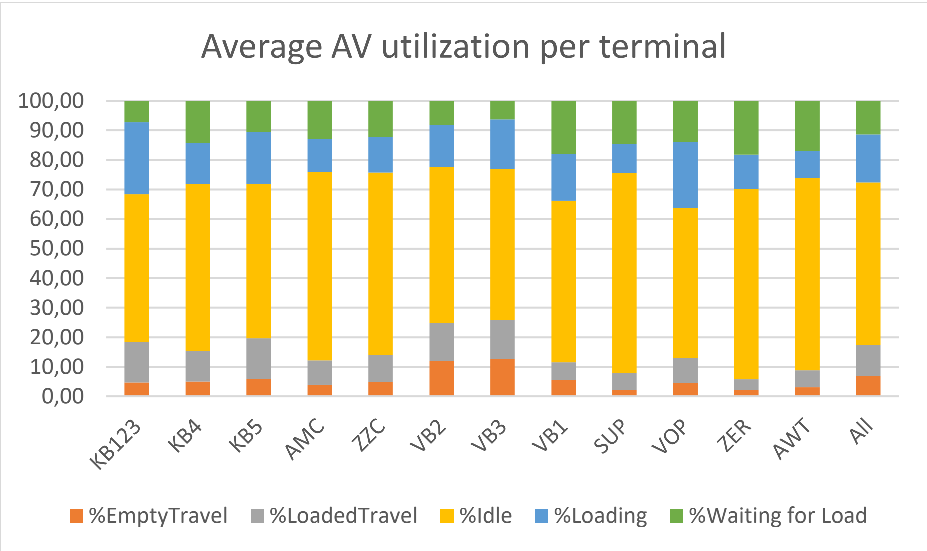

Figure 6-5: Average AV utilization per terminal in the non-shared scenario

Table 6-4 summarizes the main performance statistics for the three configurations. The kilometres travelled will be discussed below in Section 6.2.3, whereas the problem of allocating cost in the shared scenario is discussed in Section **?**.

Configuration	No of AV's	System costs	average dwell time	Total km travelled	Km travelled empty
Non-shared	24	€ 116.932	00:32:38	21543	8312
Shared	16	€ 89.052	00:35:54	19.911	6.680
Shared	24	€ 115.898	00:20:54	21.026	7.795

Table 6-4: Summary of performance statistics

6.2.3 Kilometres travelled

In experiment 3, the number of autonomous vehicles was the experimental factor to see the impact of the total amount of weekly kilometres travelled. As shown in Table 6-5, the number of weekly kilometres travelled at first decreases when the number of AVs increases but increases again when more than 14 AVs are in the system. In these cases, more empty repositions increase the total kilometres travelled. Sharing clearly reduces the total number of kilometres travelled; the non-shared scenario is the only case in which over 8000 kilometres are travelled empty.

Situation	#Avs	Loaded	Empty	Total
Non-shared	24	13231	8312	21543
Shared	10	13231	6884	20114
Shared	12	13231	6555	19786
Shared	14	13231	6480	19711
Shared	16	13231	6680	19911
Shared	18	13231	7037	20268
Shared	20	13231	7459	20689
Shared	22	13231	7669	20900
Shared	24	13231	7795	21026

Table 6-5: Kilometres travelled per week

In the scenario with sixteen AVs, the vehicles travel 13231 km loaded and 6680 km empty. Of these empty kilometres, 1540 are inter-terminal, meaning sharing shows synergy between the terminals. The inter-terminal travel is shown below in Table 6-6

	KB123	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	ZER	AWT
KB123		58,02	54,36	12,95	9,52	231,8	177	110,03	11,2	20,65		7,76
KB4	22		7,35	1,25	1,83	59,21	24,75	10,39	8,29	6,62		
KB5	23,9	9,78		2,1	1,44	40,3	2,58	18,05	1,82	5,39		2,35
AMC	6,77	1,79	3,78		1,16	19,45	9,38	5,42	3,45	1,98		
ZZC	7,28	3,67	3,5	0,87		25,54	10,61	8,39		2,49		
VB2	2,71	0,85	1,06	0,44			2,66	1,69	2,3			
VB3	2,7	0,2	0,22			3,39		1,58	1,98			
VB1	3,46	1,36	1,5	2,71		1,69	7,88		0,39	0,73		0,94
SUP	15,73	3,32	1,82	5,18	1,57	13,78	11,89	26		4,3		6,64
VOP	31,14	11,92	20,48	3,95	3,32	79,08	53,4	32,67	2,15			1,6
ZER												
AWT	17,08	8,3	4,7	2,17		10,38	22,72	39,18	4,15			

Table 6-6: Distribution of empty inter-terminal kilometres

Most trips with empty kilometres start from *KB123* and go to *VB2* and *VB3*. These terminals are located close to each other, and most jobs at *KB123* are inbound, whereas the jobs at *VB2* and *VB3* are primarily outbound, allowing for this synergy.

6.2.4 Due time impact

Experiment 4 looked into the impact of changing the due times of a container. In the simulation model, due times were assigned to each container using a normal distribution. The standard deviation was set to a quarter of the mean due time. Missing due times was not modelled as a hard constraint, though future research could explore incorporating it.

Mean due time	Average lateness	On-time percentage
2:00:00	00:01:11	97.05%
1:45:00	00:01:35	96.14%

1:30:00	00:02:08	94.87%
1:15:00	00:02:53	92.81%
1:00:00	00:04:02	87.96%

Table 6-7: Average lateness and on-time percentage

As can be seen in Table 6-7, the average lateness of all containers ranged between two and four minutes. The lateness was primarily influenced by a few containers delivered over an hour late, while the vast majority were delivered on time. These delayed containers typically had a shorter interval between their availability and due time, as low due times were generated from the normal distribution.

When the average due time was 1.5 hours or longer, the on-time delivery percentage was 95% or higher. Furthermore, no significant differences in average lateness or on-time performance were observed between terminals. This consistent result among terminals is essential as substantial differences in lateness between terminals could unfairly disadvantage an individual terminal. Moreover, the non-shared scenario showed results similar to those of the shared situation.

6.2.5 Other observations

Experiment 5 focussed on adjusting the time window for early information. Adjusting this window did not show a significant impact on the container dwell time. Besides the main results of the five experiments, the following minor observations can be made:

- The workload distribution among the autonomous vehicles showed similar patterns. Only in the scenario when 24 vehicles are used are the final four AVs less active than other vehicles. As such, the final four vehicles can be considered unnecessary and costly.
- The time spent loading and unloading a trailer, which both take six minutes, forms a substantial part of the container dwell time.

6.2.6 Sensitivity analysis

Different input values were used to test the robustness of the system, such as the number of jobs, loading time, and travel speed. The sensitivity analysis yielded the following insights:

- Having fifty per cent more jobs in the system while keeping the number of autonomous vehicles at 16 leads to an average container dwell time of almost three hours. However, this increase can be offset by increasing the number of AVs to 24, resulting in an average dwell time of 33 minutes, comparable to the result of Section 3.2.2. When halving the number of jobs in the system, the number of autonomous vehicles can also be halved to eight.
- Halving the loading time to three minutes resulted in an average dwell container dwell time of 16.5 minutes. On the other hand, doubling the loading time to twelve minutes leads to an increase in the average container dwell time to over three hours.
- Different travel speeds impact the performance indicators, as one would expect. Lower speeds lead to a significant increase in average container dwell time and a higher percentage of time an autonomous vehicle is travelling. The opposite of both is true when travel speeds are increased.

6.3 Cost allocation

In this section, the results of the terminal cost allocation are discussed. Section 6.3.1 allocates the costs according to the design discussed in Section 4.4.2. After that, Section 6.3.2 dives into the financial benefits of cooperating.

6.3.1 Terminal costs

At North Sea Port, the total cost can be divided into fixed AV-related costs and variable costs related to the kilometres travelled. The yearly fixed costs of an AV are calculated assuming a lifespan of five years, a purchase price of one million euros and a leftover value of €200000 at the end of life. As such, the fixed vehicle costs are €160000 per year, which implies a weekly cost of €3077. Variable costs of two euros per kilometre travelled are incurred. When a vehicle travels empty, the costs are allocated to the terminal where repositioning occurs.

Table 6-8 shows the standalone costs of each terminal in the non-shared scenario. In this case, there are a total of 24 AVs in the system. These values act as an upper bound for the cost allocation; no terminal should pay more than this when sharing vehicles.

Terminal	#AVs	Costs
KB123	4	€ 20.286
KB4	2	€ 9.673
KB5	2	€ 9.874
AMC	1	€ 4.329
ZZC	1	€ 4.367
VB2	4	€ 21.803
VB3	3	€ 17.191
VB1	3	€ 13.238
SUP	1	€ 3.950
VOP	1	€ 4.346
ZER	1	€ 3.648
AWT	1	€ 4.227
System	24	€ 116.932

Table 6-8: Standalone costs of each terminal in the non-shared scenario

As mentioned in Section 6.2, the same logistical performance can be obtained with only 16 AVs when sharing vehicles. For allocation of the costs of these 16 AVs, proportional methods are used, as introduced in the solution design in Section 4.4.2. Weight factors are based on the egalitarian method, the standalone costs of a terminal and the number of AVs per terminal in the non-shared scenario. Table 6-9 shows the cost allocation using these three weight factors.

Terminal	Egalitarian	Standalone	#non-shared AVs
KB123	€ 12.234	€ 16.675	€ 16.336
KB4	€ 7.286	€ 7.257	€ 7.286
KB5	€ 7.578	€ 7.634	€ 7.578
AMC	€ 5.276	€ 2.997	€ 3.225
ZZC	€ 5.219	€ 2.943	€ 3.168
VB2	€ 12.239	€ 17.319	€ 16.341
VB3	€ 10.794	€ 13.931	€ 12.845
VB1	€ 8.155	€ 9.628	€ 10.206
SUP	€ 5.015	€ 2.575	€ 2.963
VOP	€ 5.356	€ 3.084	€ 3.305
ZER	€ 4.654	€ 2.088	€ 2.603
AWT	€ 5.247	€ 2.923	€ 3.196
System	€ 89.052	€ 89.052	€ 89.052

Table 6-9: Cost allocations for the shared scenario

As expected, using egalitarian weight factors violates the fairness requirements. In this case, the fixed costs are divided equally among all terminals, not considering the sizes of their demands. In this case, the larger terminals generate considerable savings at the cost of the smaller terminals.

Moving from an egalitarian allocation to one based on the standalone costs or the number of non-shared autonomous vehicles benefits the smaller terminals, which now pay significantly less. In both scenarios, each terminal pays less than in the individual scenarios of Table 6-8. The lowest of these two values can be seen as the lower bound of costs for a terminal; a terminal should pay not less than this value. For summarization, the results of the three allocation methods are shown visually in Figure 6-6.

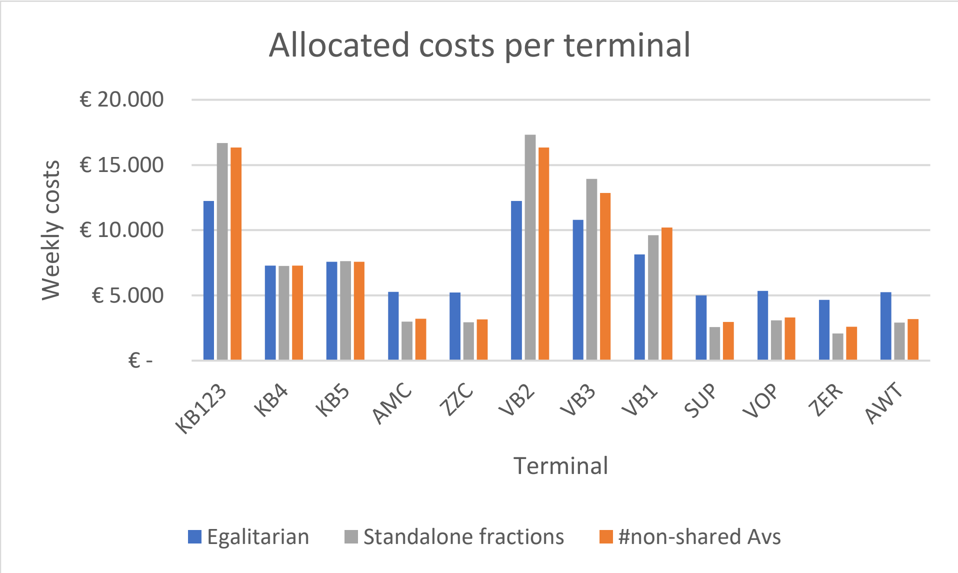

Figure 6-6: Cost per terminal per allocation method

6.3.2 Financial benefits of sharing

By sharing, the number of required autonomous vehicles can be reduced from 24 to 16. This reduction saves the terminals together €27.800 a week. Over a year the savings are almost 1.5 million euros, which is 1.5 times the purchase price of an AV. However, this is in an optimal situation. In reality, the savings will probably be lower by adding more complexity.

Calculating the savings per terminal as a result of sharing yields the results shown in Figure 6-7. The results are based on the proportional allocation method. The highest savings are obtained by the smaller terminals and less by the larger terminals, who, if they want, have the money to invest in AVs themselves. However, even for them, a twenty per cent cost reduction can be achieved.

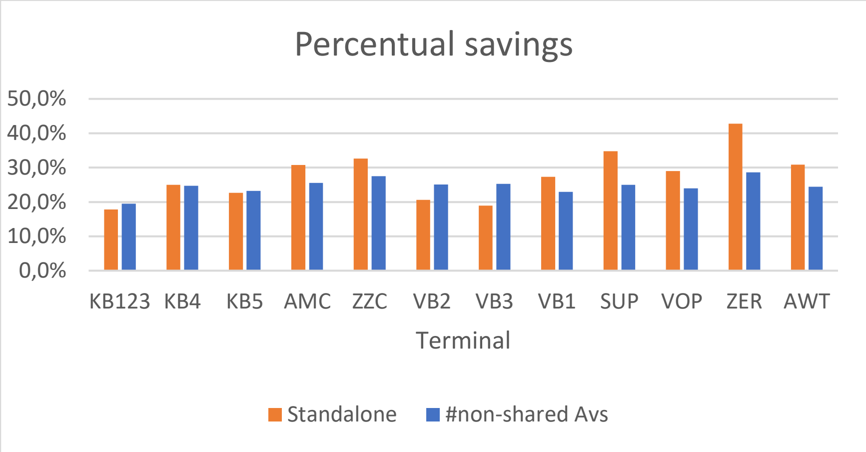

Figure 6-7: Percentual weekly savings per terminal

6.3.3 Game theoretic evaluation

In the solution decision of Section 4.4, it was decided not to use the game theoretic axioms as it would be challenging to incorporate them in the cost allocation directly. However, the concepts of efficiency, individual rationality and coalition rationality can be applied to the allocations of Section 6.3.1. An allocation is:

- Efficient if all costs are allocated.
- Individual rational if the allocated cost do not exceed the standalone costs for all players.
- Coalitional rational if the allocated cost of a subset does not exceed the sum of the standalone costs of that subset. Must hold for all subsets.

Table 6-10 shows per weigh factors used in the proportional cost allocation whether the axioms are met.

Weigh factor	Efficient	Individual rational	Coalitional rational
Egalitarian	✓	×	×
Standalone cost	✓	✓	?
#non-shared AVs	✓	✓	?

Table 6-10: Game theoretic evaluation of the cost allocations

All weight factors used result in an efficient allocation as all costs are allocated. The egalitarian weight factors, which evenly attribute fixed costs over terminals, are both not individually rational and conditionally rational. Smaller terminals are allocated more costs than the upper bound allowed, and this also holds for subsets of smaller terminals. The proportional allocations using the standalone costs or the number of non-shared AVs as weigh factors are individually rational. However, the question remains whether they are coalitional rational. Forming a smaller subset of terminals could require that subset to have more vehicles and thus costs than the sum of the individual subsets.

Lastly, all three weight factors show consistent results independent of the input values used for the fixed and variable vehicle costs. As such, using a different cost configuration does not lead to a different cost division among the terminals.

6.4 Conclusions

To secure logistical performance at North Sea Port, 24 autonomous vehicles are required when all terminals have their own dedicated vehicles. Sharing vehicles can reduce the number of AVs to 16 while keeping a similar average container dwell time. As no jobs occur at night, the vehicles have a high idle percentage.

A combination of stand-alone and proportional methods was used to allocate the costs. No terminal could be assigned more than its standalone cost, representing the costs of working individually. Moreover, each terminal should not be assigned less costs than the results of the proportional methods. These methods lead to the cost bounds shown below in Table 6-11.

Terminal	Upper bound	Lower bound
KB123	€ 20.286	€ 16.336
KB4	€ 9.673	€ 7.257
KB5	€ 9.874	€ 7.578
AMC	€ 4.329	€ 2.997
ZZC	€ 4.367	€ 2.943
VB2	€ 21.803	€ 16.341
VB3	€ 17.191	€ 12.845
VB1	€ 13.238	€ 9.628
SUP	€ 3.950	€ 2.575
VOP	€ 4.346	€ 3.084
ZER	€ 3.648	€ 2.088
AWT	€ 4.227	€ 2.923

Table 6-11: Upper and lower bound of costs for each terminal

The proportional allocation method, using either the standalone costs or the number of non-shared AVs per terminal as input weights, projects the smaller terminals by assigning them less cost than when acting alone, keeping them aboard. At the same time, the larger terminals still obtain savings compared to the non-shared scenario, keeping them also satisfied.

7. Conclusion

This chapter presents a summary of the key findings of this research. Section 7.1 contains the main conclusions, and Section 7.2 discusses the limitations of the research and possibilities for future research.

This research explored the requirements for implementing a shared shuttle service, illustrated through a case study on North Sea Port in Vlissingen. The goal of this research was to answer the main research question:

How can a fair shuttle service be designed for a first- and last-mile shared shuttle service using autonomous vehicles at North Sea Port Vlissingen?

To help answer this question, the following sub-questions were formulated:

1. What are the current processes in place at North Sea Port, and which changes will occur when the Central Gate is implemented?
2. How can first- and last-mile transport be implemented and managed fairly?
3. What is a suitable method for implementing a fair-use shared shuttle service at NSP?
4. How can a simulation model of North Sea Port be designed and evaluated?
5. What performance can be expected of the fleet management algorithm at North Sea Port Vlissingen?

7.1 Conclusions

This section discusses the main conclusions of the research, answering the main research question.

The Central Gate at North Sea Port Vlissingen will include parking places for up to 450 trucks and trailers, offer rest facilities and lessen congestion on streets within the port area. Located in the southeastern corner of the port, it serves fifteen terminals across nine companies. Autonomous vehicles will be used to transport containers from and to the terminals and the Gate.

In recent years, autonomous vehicles have been increasingly used in manufacturing and warehousing operations and are now developing towards use in more complex open-world systems. By decoupling first- and last-mile transportation from long-haul trips, specialized vehicles can be used for all transportation legs. Additionally, shared transportation reduces emissions and costs when rightly distributed. High connectivity and automation levels are required to integrate autonomous vehicles on open roads successfully. The aspect of fairness becomes crucial when resources are limited. Various allocation methods, such as max-min fairness and carrier collaboration, aim to protect the rights of smaller parties. Fairness can also be ensured using game-theoretic solution approaches as the core and Shapley value, though these methods are computationally demanding.

The shuttle service at NSP should balance logistical performance, fairness and adaptability. As the level of dynamism encountered at NSP is low, a schedule insertion algorithm was used to assign jobs to vehicles. When a job becomes available for planning, all possible vehicles and positions in the schedule are evaluated. A job is assigned to the place in the schedule that yields the shortest schedule completion time among all vehicles. A simulation study was conducted to test various configurations at NSP. Key logistical performance indicators include container dwell time, autonomous vehicle utilization and the total amount of kilometres travelled. The number of kilometres travelled is used as input for cost allocation.

When 16 autonomous vehicles are used, the average container dwell time is just over half an hour, with over ninety per cent of the jobs being delivered on time. Through sharing, the total number of system AVs can be reduced from 24 to 16, saving a third of the fixed costs.

The upper and lower bounds of cost per terminal were obtained by calculating the standalone costs of each terminal and using a proportional allocation with multiple weight factors. A terminal shall not be assigned more than it is upper bound and not less than its lower bound to keep the system stable. The proportional cost allocation methods favour smaller terminals as they are assigned more savings than the larger ones. This allocation ensures they are protected against the larger ones who can bear the financial investments of buying autonomous vehicles alone. Figure 7-1 shows that using a proportional allocating method based on the standalone costs or the number of AVs in the non-shared scenario reduces costs for all terminals compared to working alone. When one of these weight factors should be chosen, it is best to use the standalone cost weights as these assign fewer costs to the smaller terminals, which, without sharing, would be less inclined to buy autonomous vehicles.

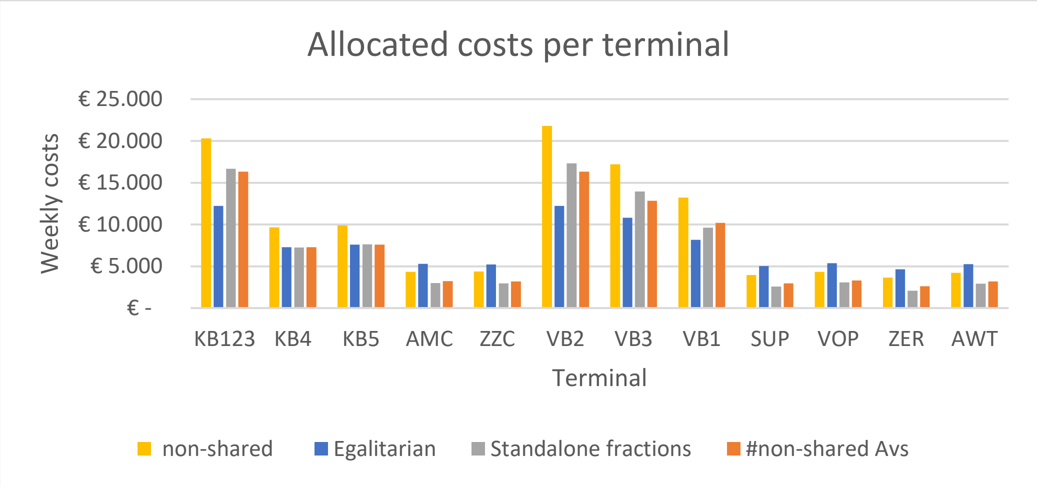

Figure 7-1: Terminal weekly cost for various allocation methods

In conclusion, a shuttle service with autonomous vehicles can be designed fairly at North Sea Port Vlissingen. Using a schedule insertion algorithm for job-to-vehicle assignment and having a total of sixteen autonomous vehicles, the average container dwell time is around half an hour and consistent among the terminals. Vehicle utilization levels show no extremes, and due times are generally met. When allocating costs according to a proportional method, each terminal has financial benefits from sharing vehicles as they all pay less than the situation in which they would have their dedicated vehicles. Smaller terminals are assigned relatively less cost than the larger ones.

7.2 Discussion

This section further discusses the results and limitations of the research that was conducted. It will also discuss possibilities for further research.

North Sea Port

The case study of North Sea Port is a good test of whether a shared service using autonomous vehicles can work as distances within the port are not that large, there are larger and smaller terminals, and demand across terminals shows different patterns over the day and concerning in- and outbound jobs. Sharing not only has financial benefits, but the different in- and outbound job patterns between terminals also showed the logistic upside of sharing.

Though there is a willingness at NSP to use new and greener transportation concepts, implementing the shuttle service in real life faces some major roadblocks. To successfully integrate autonomous vehicles on the open road, high levels of connectivity between vehicles and road infrastructure are required. This required level of connectivity and automation has not yet been obtained. Moreover, though this research has shown that sharing autonomous vehicles is more profitable for all terminals than working alone, buying a minimum of sixteen autonomous vehicles still requires a significant upfront financial investment from all terminals. Together, these two points put a question mark on the implementation of the shared shuttle service at North Sea Port.

Impact of simplifications

To simplify the simulation model representing NSP, multiple processes which impact the performance have been excluded or reduced in complexity to limit the scope of the research. In reality, these simplifications complicate the problem and influence the outcomes. For example, the charging and battery constraint of a vehicle directly impacts the vehicle utilization and the set of executable jobs by a vehicle. Indirectly, this impacts the average container dwell time and even the total number of vehicles required if a vehicle is unavailable for extended periods.

Moreover, travel times, which are part of the container dwell time, can be modelled more stochastically. Multiple average speeds could be used to reflect peak hours with more congestion or quieter hours with less traffic.

Lastly, due times were assigned to a job but without implications for missing them. Penalty costs could be incurred for missing due times. Incurring this will make the job assignment and cost allocation more complex.

Smaller sub-sets

In this research, vehicles were shared between all terminals. However, geographic locations or demand patterns could be used to define smaller subsets for sharing. Due to the problem size, it is advisable not to evaluate all sub-coalitions but first to indicate promising subsets. A possible demand-based subset for NSP was already identified in experiment 3 in Section 6.2.3. Inbound jobs at *KB123* were often combined with outbound jobs at *VB2* or *VB3*. Putting these terminals together in a subset will preserve this positive synergy, but the impact on the remaining terminals must be evaluated.

Degree of dynamism

The job pattern at North Sea Port has a low degree of dynamism. For this reason, a schedule insertion algorithm was used to assign jobs to autonomous vehicles. Implementing a shared service in a system with higher dynamism could require a whole different job assignment method. A different assignment method could also impact the cost allocation.

Cost allocation stability

Cost allocations were based on a simulation run of a week. As historic demand showed similar patterns, it was assumed that demand distributions were constant over weeks. When demand patterns do differ over weeks, it is advised to recalculate the cost allocation weekly to reflect these changes. In this case, it is proposed to use the standalone costs as weigh factors for the proportional allocation method, as these values change with different demands. Updating is still required to obtain a fair cost allocation reflecting the changes in demands.

References

Alonso Raposo, M., Ciuffo, B., Alves Dies, P., Ardente, F., Aurambout, J.-P., Baldini, G., Baranzelli, C., Blagoeva, D., Bobba, S., Braun, R., Cassio, L., Chawdhry, P., Christidis, P., Christodoulou, A., Corrado, S., Duboz, A., Duch Brown, N., Felici, S., Fernández Macías, E., … Vandecasteele, I. (2019). *The future of road transport - Implications of automated, connected, low-carbon and shared mobility*. Publications Office of the European Union. https://doi.org/10.2760/668964

Barocas, S., Hardt, M., & Narayanan, A. (2019). *Fairness in Machine Learning: Limitations and Opportunities*. fairmlbook.org. http://fairmlbook.org

Crainic, T. G., Ricciardi, N., & Storchi, G. (2004). Advanced freight transportation systems for congested urban areas. *Transportation Research Part C: Emerging Technologies*, *12*(2), 119–137. https://doi.org/10.1016/j.trc.2004.07.002

Dai, B., & Chen, H. (2012). Profit allocation mechanisms for carrier collaboration in pickup and delivery service. *Computers and Industrial Engineering*, *62*(2), 633–643. https://doi.org/10.1016/j.cie.2011.11.029

De Ryck, M., Versteyhe, M., & Debrouwere, F. (2020). Automated guided vehicle systems, state-of-the-art control algorithms and techniques. *Journal of Manufacturing Systems*, *54*(December 2019), 152–173. https://doi.org/10.1016/j.jmsy.2019.12.002

Distribute. (2021a). *About Us - Distribute*. https://www.distribute.company/about-us/

Distribute. (2021b). *SIMULATION STUDY CENTRAL GATE*.

ERTRAC. (2019). *Connected Automated Driving Roadmap Status: final for publication*. https://connectedautomateddriving.eu/wp-content/uploads/2019/04/ERTRAC-CAD-Roadmap-03.04.2019-1.pdf?fbclid=IwAR3ynV7OpUc07zO3Y1PqQKe4S5xgY_sW8kMbnocwTZ7S78Cfz8upjPKRKpo

European Commission. (2019). *STRIA Roadmap on Connected and Automated Transport: Road, Rail and*. http://europa.eu

Flämig, H., Maurer, M., Gerdes, J. C., Lenz, B., & Winner, H. (2016). Autonomous driving: Technical, legal and social aspects. In *Autonomous Driving: Technical, Legal and Social Aspects* (pp. 1–706). https://doi.org/10.1007/978-3-662-48847-8

Fossati, F., Hoteit, S., Moretti, S., & Secci, S. (2018). Fair resource allocation in systems with complete information sharing. *IEEE/ACM Transactions on Networking*, *26*(6), 2801–2814. https://doi.org/10.1109/TNET.2018.2878644

Furuhata, M., Dessouky, M., Ordóñez, F., Brunet, M. E., Wang, X., & Koenig, S. (2013). Ridesharing: The state-of-the-art and future directions. *Transportation Research Part B: Methodological*, *57*, 28–46. https://doi.org/10.1016/j.trb.2013.08.012

Gerkey, B. P., & Matarić, M. J. (2004). A formal framework for the study of task allocation in multi-robot systems. *International Journal of Robotics Research*, *23*(9), 939–954.

Gerrits, B. (2023). *Self-Organizing Logistics : Towards a unifying framework for automated transport systems* [University of Twente]. https://doi.org/10.3990/1.9789036555555

Goel, A., & Gruhn, V. (2008). A General Vehicle Routing Problem. *European Journal of Operational Research*, *191*(3), 650–660. https://doi.org/10.1016/j.ejor.2006.12.065

Guajardo, M., & Rönnqvist, M. (2016). A review on cost allocation methods in collaborative transportation. *International Transactions in Operational Research*, *23*(3), 371–392.

https://doi.org/10.1111/itor.12205

Hermann, M., Pentek, T., & Otto, B. (2016). Design Principles for Industrie 4.0 Scenarios. *2016 49th Hawaii International Conference on System Sciences (HICSS)*, 3928–3937. https://doi.org/10.1109/HICSS.2016.488

Hyland, M. F., & Mahmassani, H. S. (2017). Taxonomy of shared autonomous vehicle fleet management problems to inform future transportation mobility. *Transportation Research Record*, *2653*, 26–34. https://doi.org/10.3141/2653-04

Jain, R., Chiu, D., & Hawe, W. (1998). *A Quantitative Measure Of Fairness And Discrimination For Resource Allocation In Shared Computer Systems*. *January*. http://arxiv.org/abs/cs/9809099

Lan, T., Kao, D., Chiang, M., & Sabharwal, A. (2010). An axiomatic theory of fairness in network resource allocation. *Proceedings - IEEE INFOCOM*. https://doi.org/10.1109/INFCOM.2010.5461911

Larsen, A., Madsen, O., & Solomon, M. (2002). Partially dynamic vehicle routing - Models and algorithms. *Journal of the Operational Research Society*, *53*(6), 637–646. https://doi.org/10.1057/palgrave.jors.2601352

Law, A. M. (2015). *Simulation Modeling and Analysis, FIFTH EDITION*. McGraw-HIll Euducation. www.averill-law.com

Melo, S., Macedo, J., & Baptista, P. (2019). Capacity-sharing in logistics solutions: A new pathway towards sustainability. *Transport Policy*, *73*(July 2018), 143–151. https://doi.org/10.1016/j.tranpol.2018.07.003

North Sea Port. (2019). *Central Gate: Pre-terminal function*.

North Sea Port. (2020). *Over ons - North Sea Port*. https://www.northseaport.com/over-ons

Olsson, J., Hellström, D., & Pålsson, H. (2019). Framework of last mile logistics research: A systematic review of the literature. *Sustainability (Switzerland)*, *11*(24), 1–25. https://doi.org/10.3390/su11247131

Peters, H. (2008). *Game Theory A Multi-Leveled Approach*. Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-69291-1

Powell, W. B., Simao, H. P., & Bouzaiene-Ayari, B. (2012). Approximate dynamic programming in transportation and logistics: a unified framework. *EURO Journal on Transportation and Logistics*, *1*(3), 237–284. https://doi.org/10.1007/s13676-012-0015-8

Psaraftis, H. N. (1995). Dynamic vehicle routing: status and prospects. *Annals of Operations Research*, *61*, 143–164.

Raposo, M. A., Ciuffo, B., Makridis, M., & Thiel, C. (2017). From connected vehicles to a connected, coordinated and automated road transport (C2ART) system. *5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2017 - Proceedings*, 7–12. https://doi.org/10.1109/MTITS.2017.8005649

RDW. (2020). *Practical testing of Connected automated vehicle in the Netherlands | RDW*. https://www.rdw.nl/over-rdw/information-in-english/about-rdw/connected-automated-vehicle/practical-testing-of-connected-automated-vehicle-in-the-netherlands

Regan, A. C., Mahmassani, H. S., & Jaillet, P. (1998). Evaluation of dynamic fleet management systems simulation framework. *Transportation Research Record*, *1645*, 176–184. https://doi.org/10.3141/1645-22

Robinson, S. (2008a). Conceptual modelling for simulation Part I: Definition and requirements. *Journal of the Operational Research Society*, *59*(3), 278–290. https://doi.org/10.1057/palgrave.jors.2602368

Robinson, S. (2008b). Conceptual modelling for simulation Part II: A framework for conceptual modelling. *Journal of the Operational Research Society*, *59*(3), 291–304. https://doi.org/10.1057/palgrave.jors.2602369

Ronen, D. (2000). Scheduling Charter Aircraft. *The Journal of the Operational Research Society*, *51*(3), 258. https://doi.org/10.2307/254083

SAE. (2018). Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. In *SAE Standard J3016* (Issues 2014-01–16). https://doi.org/https://doi.org/10.4271/J3016_201806

Saglietto, L. (2013). Towards a Classification of Fourth Party Logistics (4PL). *Universal Journal of Industrial and Business Management*, *1*(3), 104–116. https://doi.org/10.13189/ujibm.2013.010305

Shladover, S. E. (2018). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *22*(3), 190–200. https://doi.org/10.1080/15472450.2017.1336053

Sinha, A., & Anastasopoulos, A. (2017). Incentive mechanisms for fairness among strategic agents. *IEEE Journal on Selected Areas in Communications*, *35*(2), 288–301. https://doi.org/10.1109/JSAC.2017.2659061

Sumarti, N., Brahmandita, I. B. P., & Aqsha, M. A. (2022). A Simulation of Optimal Model on Fractional Aircraft Ownership (FAO) Management. *Mendel*, *28*(2), 1–8. https://doi.org/10.13164/mendel.2022.2.001

Terberg Special Vehicles. (2019). *An Autonomous Tractor Partnership - Terberg*. https://newsmedia.terberggroup.com/en/special-vehicles/overview/press-releases/special-vehicles/an-autonomous-tractor-partnership/

Volvo. (2019). *Vera's first assignment: Volvo Trucks presents an autonomous transport between a logistics centre and port*. https://www.volvotrucks.com/en-en/about-us/automation/vera.html

Wooldridge, M. (2009). *An Introduction to MultiAgent Systems* (2nd ed.). John Wiley & Sons.

Yang, J., Jaillet, P., & Mahmassani, H. (2004). Real-time multivehicle truckload pickup and delivery problems. *Transportation Science*, *38*(2), 135–148. https://doi.org/10.1287/trsc.1030.0068

Ye, Q. C., Zhang, Y., & Dekker, R. (2017). Fair task allocation in transportation. *Omega (United Kingdom)*, *68*, 1–16. https://doi.org/10.1016/j.omega.2016.05.005

Zeimpekis, V., Tarantilis, C. D., Giaglis, G. M., & Minis, I. (2008). Dynamic Fleet Management. In *Dynamic Fleet Management*.

Zibaei, S., Hafezalkotob, A., & Ghashami, S. S. (2016). Cooperative vehicle routing problem: an opportunity for cost saving. *Journal of Industrial Engineering International*, *12*(3), 271–286. https://doi.org/10.1007/s40092-016-0142-1

Appendix A: Travel distances and times

From/to	CG	KB1	KB2	KB3	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	MSP	ZER	AWT
CG		4,84	4,97	5,06	6,68	7,02	6,69	6,86	8,20	7,09	3,37	5,17	3,47	3,33	2,82	5,68
KB1	4,84		0,21	0,23	2,72	2,98	2,58	1,04	4,23	3,06	5,46	6,85	3,16	3,11	4,47	8,59
KB2	5,14	0,31		0,12	2,82	3,32	2,82	2,80	4,51	3,38	5,77	7,15	3,46	3,40	4,77	9,49
KB3	5,04	0,20	0,39		2,97	3,17	2,69	1,06	4,42	3,13	6,38	6,96	3,36	3,30	4,67	9,39
KB4	6,68	2,88	2,59	2,68		1,04	0,56	1,31	2,13	0,99	6,78	8,29	3,31	4,90	6,25	10,37
KB5	7,02	3,32	3,02	3,14	1,05		1,05	1,03	1,32	0,10	7,52	9,08	5,39	5,36	6,71	11,76
AMC	6,69	2,89	2,59	2,71	0,57	1,05		1,45	2,22	1,02	6,78	8,63	4,94	4,90	6,25	10,86
ZZC	6,86	1,04	1,22	1,34	1,31	1,03	1,45		2,20	0,98	5,99	7,84	4,15	4,12	5,47	10,52
VB2	8,20	4,53	4,23	4,35	2,13	1,30	2,21	2,24		1,21	8,45	11,48	6,59	6,56	7,91	12,97
VB3	7,09	3,30	3,00	3,12	0,99	0,10	1,02	1,04	1,21		7,88	9,91	5,34	5,31	6,66	11,36
VB1	3,37	5,49	5,19	5,31	8,66	7,52	6,78	5,99	8,45	7,88		1,94	3,63	3,47	0,71	2,36
SUP	5,17	7,30	7,00	7,12	8,29	9,08	8,63	7,84	11,48	9,91	1,94		5,38	5,26	2,60	4,15
VOP	3,47	3,63	3,33	3,45	3,31	5,39	4,94	4,15	6,59	5,34	3,63	5,38		1,62	2,97	8,02
MSP	3,33	3,47	3,17	3,29	4,90	5,36	4,90	4,12	6,56	5,31	3,47	5,26	1,62		2,90	7,99
ZER	2,82	4,91	4,61	4,73	4,67	6,25	6,71	6,25	7,91	6,66	0,71	2,60	2,97	2,90		2,66
AWT	5,68	10,00	9,70	9,82	10,37	11,76	10,86	10,52	12,97	11,36	2,36	4,15	8,02	7,99	2,66	

Figure A-1: Travel distances between terminals in kilometres

From/to	CG	KB1	KB2	KB3	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	MSP	ZER	AWT		
CG		6,45	6,62	6,75	8,91	9,36	8,92	9,15	10,93	9,45	4,49	6,89	4,63	4,44	3,76	7,57		travel to/from CG
KB1	6,45		0,28	0,306667	3,63	3,97	3,44	1,39	5,64	4,08	7,28	9,13	4,21	4,15	5,96	11,45		Same complex (KB1-KB2-KB3)
KB2	6,85	0,413333		0,16	3,76	4,43	3,76	3,73	6,01	4,51	7,69	9,53	4,61	4,53	6,36	12,65		Same complex (VB3-KB5)
KB3	6,72	0,266667	0,52		3,96	4,23	3,59	1,41	5,89	4,17	8,51	9,28	4,48	4,40	6,23	12,52		
KB4	8,91	3,84	3,45	3,57		1,39	0,75	1,74	2,84	1,32	9,04	11,05	4,41	6,54	8,34	13,82		
KB5	9,36	4,43	4,03	4,19	1,39		1,40	1,37	1,76	0,13	10,03	12,11	7,19	7,15	8,95	15,68		
AMC	8,92	3,85	3,45	3,61	0,76	1,40		1,93	2,96	1,36	9,04	11,50	6,58	6,54	8,34	14,47		
ZZC	9,15	1,39	1,62	1,78	1,74	1,37	1,93		2,93	1,30	7,99	10,45	5,53	5,49	7,29	14,03		
VB2	10,93	6,05	5,65	5,81	2,84	1,73	2,95	2,99		1,61	11,26	15,31	8,79	8,74	10,54	17,29		
VB3	9,45	4,40	4,00	4,16	1,32	0,13	1,36	1,38	1,61		10,50	13,22	7,13	7,08	8,88	15,15		
VB1	4,49	7,31	6,91	7,07	11,54	10,03	9,04	7,99	11,26	10,50		2,59	4,84	4,62	0,94	3,14		
SUP	6,89	9,74	9,34	9,50	11,05	12,11	11,50	10,45	15,31	13,22	2,59		7,17	7,01	3,47	5,53		
VOP	4,63	4,84	4,44	4,60	4,41	7,19	6,58	5,53	8,79	7,13	4,84	7,17		2,16	3,96	10,70		
MSP	4,44	4,63	4,23	4,39	6,54	7,15	6,54	5,49	8,74	7,08	4,62	7,01	2,16		3,86	10,65		
ZER	3,76	6,54	6,14	6,30	6,23	8,34	8,95	8,34	10,54	8,88	0,94	3,47	3,96	3,86		3,55		
AWT	7,57	13,33	12,93	13,09	13,82	15,68	14,47	14,03	17,29	15,15	3,14	5,53	10,70	10,65	3,55			

Figure A-2: Inter-terminal travel times in minutes assuming a fixed speed of 45 km/h

Appendix B: Terminal job intensities

Hour	KB123	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	MSP	ZER	AWT
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
7	0.00	0.00	0.00	0.18	0.35	0.38	0.41	0.44	0.62	0.65	0.65	0.82	1.00
8	0.14	0.18	0.23	0.25	0.26	0.49	0.71	0.93	0.94	0.96	0.96	0.98	1.00
9	0.22	0.30	0.37	0.39	0.41	0.57	0.72	0.88	0.90	0.96	0.96	0.98	1.00
10	0.19	0.25	0.32	0.34	0.36	0.53	0.71	0.89	0.91	0.96	0.96	0.98	1.00
11	0.20	0.27	0.34	0.36	0.37	0.55	0.73	0.91	0.92	0.97	0.97	0.98	1.00
12	0.19	0.25	0.31	0.33	0.34	0.53	0.72	0.91	0.93	0.97	0.97	0.98	1.00
13	0.16	0.21	0.27	0.30	0.34	0.51	0.69	0.86	0.90	0.93	0.93	0.97	1.00
14	0.17	0.22	0.28	0.32	0.35	0.52	0.69	0.85	0.89	0.93	0.93	0.96	1.00
15	0.21	0.28	0.35	0.36	0.37	0.56	0.74	0.93	0.94	0.98	0.98	0.99	1.00
16	0.22	0.30	0.37	0.37	0.37	0.56	0.76	0.95	0.95	1.00	1.00	1.00	1.00
17	0.25	0.34	0.42	0.42	0.42	0.60	0.77	0.95	0.95	1.00	1.00	1.00	1.00
18	0.25	0.34	0.42	0.42	0.42	0.59	0.76	0.93	0.93	1.00	1.00	1.00	1.00
19	0.20	0.26	0.33	0.33	0.33	0.55	0.76	0.98	0.98	1.00	1.00	1.00	1.00
20	0.00	0.00	0.00	0.00	0.00	0.31	0.61	0.92	0.92	1.00	1.00	1.00	1.00
21	0.00	0.00	0.00	0.00	0.00	0.28	0.56	0.85	0.85	1.00	1.00	1.00	1.00
22	0.00	0.00	0.00	0.00	0.00	0.16	0.32	0.47	0.47	1.00	1.00	1.00	1.00

23	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.05	0.05	1.00	1.00	1.00	1.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00

Table B-1: Cumulative outbound job terminal intensities

	KB123	KB4	KB5	AMC	ZZC	VB2	VB3	VB1	SUP	VOP	MSP	ZER	AWT
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
7	0.00	0.00	0.00	0.19	0.39	0.39	0.39	0.39	0.58	0.61	0.61	0.81	1.00
8	0.33	0.43	0.54	0.61	0.67	0.69	0.72	0.74	0.80	0.87	0.87	0.94	1.00
9	0.37	0.50	0.62	0.66	0.70	0.73	0.76	0.79	0.82	0.92	0.92	0.96	1.00
10	0.39	0.52	0.65	0.69	0.72	0.74	0.76	0.78	0.82	0.92	0.92	0.96	1.00
11	0.42	0.56	0.70	0.73	0.77	0.78	0.79	0.81	0.84	0.93	0.93	0.97	1.00
12	0.43	0.57	0.72	0.75	0.78	0.79	0.80	0.82	0.85	0.94	0.94	0.97	1.00
13	0.42	0.56	0.71	0.74	0.77	0.78	0.79	0.81	0.84	0.93	0.93	0.97	1.00
14	0.35	0.46	0.58	0.64	0.71	0.72	0.73	0.74	0.80	0.87	0.87	0.93	1.00
15	0.36	0.48	0.59	0.66	0.72	0.73	0.74	0.75	0.81	0.88	0.88	0.94	1.00
16	0.38	0.51	0.63	0.69	0.74	0.75	0.76	0.77	0.82	0.89	0.89	0.95	1.00
17	0.52	0.69	0.86	0.86	0.86	0.88	0.89	0.91	0.91	1.00	1.00	1.00	1.00
18	0.50	0.67	0.84	0.84	0.84	0.85	0.86	0.88	0.88	1.00	1.00	1.00	1.00
19	0.53	0.71	0.89	0.89	0.89	0.91	0.93	0.95	0.95	1.00	1.00	1.00	1.00
20	0.23	0.31	0.39	0.39	0.39	0.48	0.58	0.68	0.68	1.00	1.00	1.00	1.00
21	0.00	0.00	0.00	0.00	0.00	0.07	0.14	0.21	0.21	1.00	1.00	1.00	1.00
22	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	1.00	1.00	1.00	1.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00

Table B-2: Cumulative inbound job terminal intensities