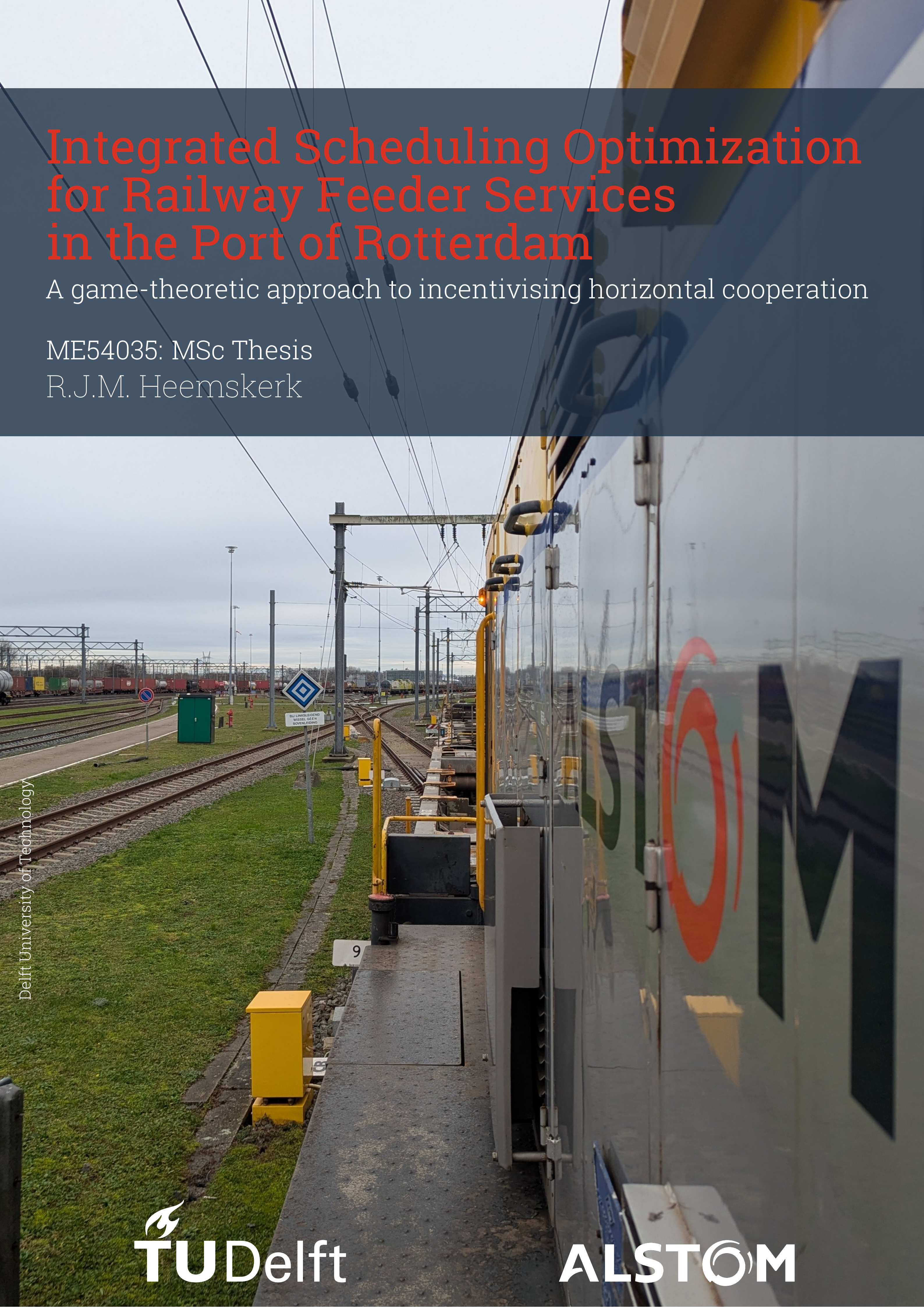
Integrated Scheduling Optimization for Railway Feeder Services in the Port of Rotterdam

A game-theoretic approach to incentivising horizontal cooperation

ME54035: MSc Thesis

R.J.M. Heemskerk



Delft University of Technology

Integrated Scheduling Optimization for Railway Feeder Services in the Port of Rotterdam

A game-theoretic approach to incentivising horizontal cooperation

by

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MSc Thesis

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Preface

This thesis marks the culmination of my MSc Mechanical Engineering, where I specialised in Multi-Machine Engineering. My time in Delft has been a period of limitless development, and this thesis is the final piece to that journey.

Investigating the port railway operations during this thesis has been instructive and challenging. Through this process, I have investigated the possible improvements in railway operations in the port area. With the cooperative approach presented, I believe the full network and all stakeholders can benefit, and I hope to contribute to a more sustainable port.

I could not have come so far without the help of the following people. Firstly, I want to thank Alstom and specifically Peter Aarts for giving me the chance and professional freedom in this project. Then, I am grateful to Frederik Schulte and Rudy Negenborn for their academic guidance. Their critical feedback has been invaluable in shaping this report into what it is today. I also want to thank DB and Casper Wouters for helping understand the operator side of this story, and openly providing the needed data.

On a personal note, I want to thank the people supporting me in the sometimes intense process. To my girlfriend, family, room-mates and friends: thanks for enduring my work hours, my venting, or the constant hum of my running laptop. Your support enabled me to achieve this result.

R.J.M. Heemskerk
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Abstract

The need for international transport of goods has increased for decennia, due to the globalisation of supply chains. The impact on the environment has gotten increased attention in the last few years, with different initiatives aiming to decrease transport emissions. While the EU has released a white paper stressing the need for modal shift towards rail transport, clear results remain absent. Therefore, this thesis explores improving the efficiency of the railway transport in the port area, specifically the port of Rotterdam. The goal is to both improve operational efficiency to decrease direct emissions, and incentivise modal shift towards railway transport.

To achieve these gains, an existing mathematical model is adapted to optimise the schedule for a single railway feeder services operator. A multi-objective function is minimised, to combine orders, reduce locomotive use and improve on time delivery. The model is benchmarked against a greedy algorithm, and structurally outperforms it.

Next, the feeder train services model (FTSM) is then used to investigate cooperative scheduling approaches. Cooperative game theory is used and the FTSM is run with stand-alone and pooled railway operators. For all scenarios tested, cooperating yields benefits, with cost reductions ranging from 25% to 58%, compared to stand-alone operation. The stable coalitions presented by this thesis present further gains in network capacity, as the pooled operators occupy less tracks.

This thesis fills the gap of port-specific railway freight transport, for which it both presents a novel mathematical model, and a cooperative strategy. The scenarios tested show benefits for all stakeholders, providing a solid base for further research and implementation.

Keywords: operations research, port optimisation, freight transportation, cooperative game theory, railway feeder services.

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Nomenclature

Abbreviations

Abbreviation	Definition
AGV	Automated guided vehicle
ALNS	Adaptive Large Neighborhood Search
ALV	Automated lift vehicle
Ba	Barge
BHA	Black Hole Algorithm
CBG	Centraal bediend gebied (Centrally operated area)
Com	Commercial Solver
DES	Discrete Event Simulation
DSS	Decision Support System
FLMT	First and last mile transport
FTSM	Feeder Train Scheduling Model
GA-SQP	Genetic Algorithm-Sequential Quadratic Programming
GR	Group Rationality
HyTabu	Hybrid Tabu Search
ITS	Intermodal Transport System
ITT	Inter Terminal Transport
IR	Individual Rationality
IWT	Inland Waterway Transport
KH	Kijfhoek (Central marshalling yard)
KPI	Key performance indicators
LNS	Large Neighbourhood Search
LR	Literature Review
MC	Monte Carlo simulation
MILP	Mixed-integer linear programming
MIP	Mixed-integer programming
MTS	Multi-trailer systems
NCBG	Niet centraal bediend gebied (Non-centrally operated area)
NSGA	Non-dominated Sorting Genetic Algorithm
PRL	Port Railway Line (Havenspoorlijn)
Q	Queueing
Ra	Rail transport
RL	Reinforced Learning
Ro	Road transport
Sim	Simulation
SOQN	Semi-Open Queueing Network
SQP	Sequential Quadratic Programming
TAS	Truck Appointment System
TEU	Twenty-foot equivalent unit
TV	Terminal Vehicle (e.g., cranes, AGV, MTS)
VRP	Vehicle Routing Problem
Port Locations	
kfhn	Kijfhoek Noord
whz	Waalhaven Zuid
ps	Pernis

Abbreviation	Definition
bot	Botlek
erp	Europoort
erpw	Europoort West
mvt	Maasvlakte
mvtw	Maasvlakte West
mvtaho	Maasvlakte Amaliahaven Oost
mvtahw	Maasvlakte Amaliahaven West
mvtwn	Maasvlakte West Terminal Noord
mvtyn	Maasvlakte Yangtzeehaven Noord

1 Introduction

While railway transport is a proved environmentally friendly alternative to freight transportation by road, the amount of railway transport in the port of Rotterdam has decreased by 12% since 2022 (CBS 2024). The EU has presented its commitment to shifting 30% of road transport to other modes like rail, but clear results remain absent (EP et al. 2018).

The railway movement in the port area, which represents the interface between maritime ships and railway hinterland transportation, currently is an under-researched area. The transportation of freight by trains to and from ships occur in a fragmented market, with decentralized coordination and many inefficiencies. The current way of operating these transports is in rigid schedules and delays are frequent and expensive. Multiple railway operators (>20) handle the freight, causing empty drives and prolonged idling. Core opportunities lie in the significant reduction of operators and/or centralised coordination, posing benefits from a more integrated approach. Gains for the amount of on-time orders, robustness and emissions are probable.

1.1. Problem Description

Freight transport, specifically in the port area of Rotterdam, has been growing for the last decades. On both sides of the port, capacity has been extended. On the sea side, the addition of the second Maasvlakte in 2013 provides massively increased terminal space and freight capacity. On the land side, the Betuweroute was built in 2007, significantly increasing railway capacity towards the hinterland. While the railway infrastructure is there, no significant improvements have been made in the last decade to increase the modal percentage of rail. Terminal operators can optimise loading relatively easily, but due to many factors, railway transport is still often unattractive.

Railway freight transport suffers from multiple problems, where firstly legislation is often considered stricter than other transport modes. Mandatory load and brake checks increase turnaround times, and high trajectory costs further increase prices. The network, with a single track into and out of the port area of Rotterdam, seen in Figure 1.1, presents further difficulties. The non-electrified and non-centrally operated areas (NCBG) towards terminals force locomotive switches for terminal delivery. Furthermore, as no signalling is present in those areas, it is unknown how effectively the reserved timeslots are used. Due to high competition, with more than 20 railway operators serving the port area, schedules are rigid and delays often accumulate.

As modal choice is, in practice, mainly driven by cost and reliability, these factors need to be improved to increase the railway modal share. Therefore, this thesis investigates the possibility of increasing the overall operational efficiency of the port area railway network, by collaboration of railway operators. Collaboration could not only relieve tight schedules in NCBG, but also improves the overall capacity of the network. Furthermore, to ensure operators are willing to cooperate, the financial incentive needs to exist. Therefore, this thesis examines multiple operator games, and checks stability of the cooperation, by using game theory.

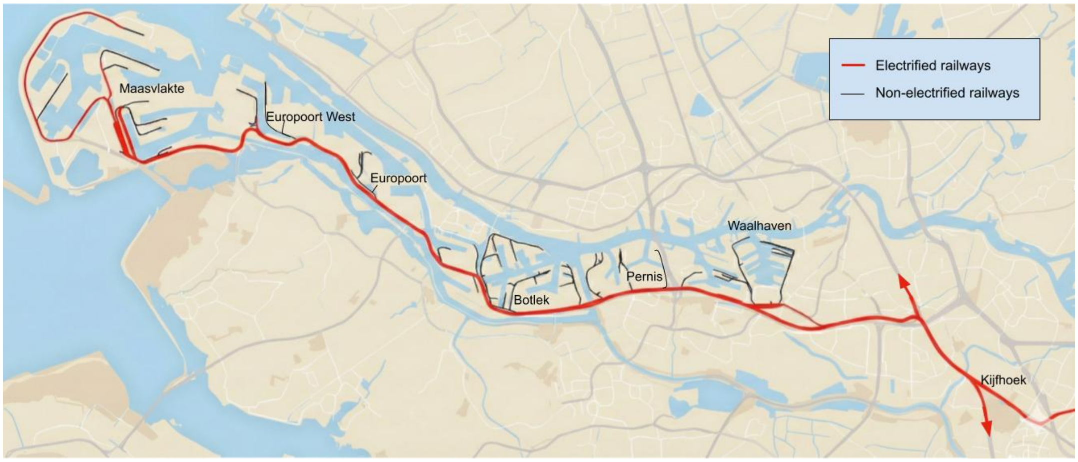


Figure 1.1: The Havenspoorlijn of the port of Rotterdam.

1.2. Involved Stakeholders

The current railway transportation system consists of many stakeholders and to significantly improve operations, their goals and interactions need to be clear. Therefore, in this section the stakeholders are analysed. This is done by taking the perspective of a single railway operator, specifically looking at the power and interest of different stakeholders in fast and efficient railway transportation.

Firstly, the railway operators themselves are very important. As they have the same goal, making as much profit as possible for themselves, they directly compete over the same profits (Gumuskaya et al. 2020). While some operators may cooperate occasionally, it is rare. In this thesis, the term **(railway) operators** is used for this group.

The second major stakeholder group is the clients of the railway transport, which includes both intermodal and terminal operators. Intermodal operators use the intermodal transport chain to move goods, choosing the best path (Hu 2019). Their main power is their choice to move goods over rail or via another mode. Terminal operators yield the same power, but are part of the intermodal chain. In the port area they possess a terminal, in which they tranship goods (Gumuskaya et al. 2020). These stakeholders also have the same interest in the railway transport, which is the on-time delivery of their goods. For that reason, these stakeholders are grouped and called the **railway transport clients**, or **clients** for short.

Next, the port authority has a major role. Its goal is for the whole port to remain competitive with other ports, so to be an efficient and economic system (Gharehgozli et al. 2017). Their interest in efficient railway transportation is therefore large. Furthermore, because the specific port authority in Rotterdam is jointly owned by the municipality and the state, its political power is large, but its practical influence remains limited. In Rotterdam, the port authority is called **Port of Rotterdam**.

The infrastructure manager of the railway network is the next stakeholder. Not only do they manage the construction and maintenance of the tracks, they also determine which train operators get which track at which time (Gestrelius 2022). While a more efficient transportation system decreases the load on the network and the need for expansion, their interest is less significant than the above mentioned stakeholders. The power of the infrastructure manager is often limited, by legally being bounded to a fair allocation between operators. In the Netherlands, **ProRail** manages all rail infrastructure.

These stakeholder currently operate like seen in Figure 1.2. It can be seen operators now act as silos, where inter-operator communication is absent and the result is rigid schedules from the infrastructure manager. The influence of the port authority is not shown, as it is not directly involved in the proces of railway order to delivery. To alleviate the stress on the schedule, and increase railway system capacity, this thesis looks into cooperation of railway operators.

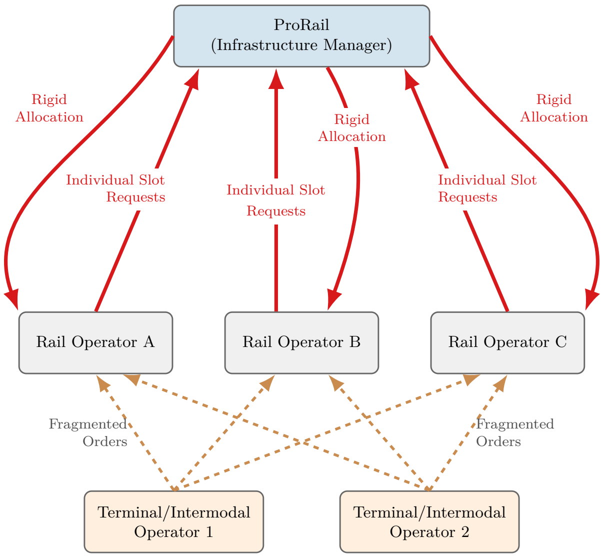


Figure 1.2: The stakeholders in the current system, with their interactions. Clients communicate their orders to the operators, where the operators optimize for their own schedule which results in rigid allocations and non-optimal schedules.

In Figure 1.3, the proposed structure can be seen. A neutral player is added, which acts like a central coordinator, gathering orders and locomotives from the clients and railway operators respectively. It optimises the schedule, and checks availability with the infrastructure manager. Then, the slots are allocated and communicated with the neutral player which puts it forward to the operators. Furthermore, based on their contribution, costs are assigned to the players. To ensure the stability of the coalition, these costs need to be lower than stand-alone and sub-coalition costs. The method to achieve this and the first feasibility checks are the goal of this thesis, where the research questions in the next section form the basis of the research.

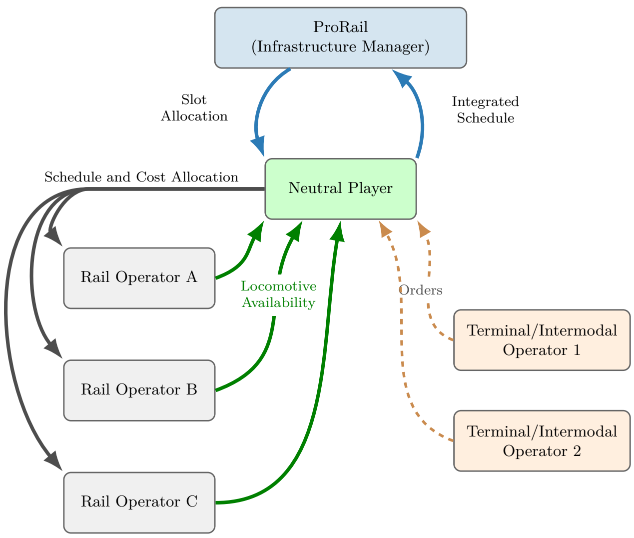


Figure 1.3: The cooperation of the stakeholders of the proposed solution.

1.3. Research Questions

The research addresses the following question:

How can collaborative scheduling optimisation improve the operational efficiency of the railway feeder services in the port area?

- **SQ1:** What is the state-of-art of optimising the port railway first and last mile?
- **SQ2:** How can a mathematical model of the port railway feeder system be formulated to accurately capture its key characteristics and limitations?
- **SQ3:** How can collaborative game theory be implemented to achieve operational efficiency gains, using individual rationality?
- **SQ4:** How does the optimisation performance compare to the decentralized and zonal operation in terms of cost, locomotive usage and network capacity?

1.4. Methods

To answer the different research questions structurally, the methods in which they are answered is explained below.

The literature background of this thesis is explored in **SQ1**. A literature study is done into inter-terminal transport, with a focus on optimisation of the railway transport in port areas. Different subjects are investigated: terminology, the urgency and optimisation methods. The resulting research gap is presented in Chapter 2.

Next, to answer **SQ2**, a mathematical model is made based on a relevant renowned model. Firstly, model requirements are formulated. After that, the chosen relevant model is altered to achieve these requirements and presented in Chapter 3. Lastly, the solution approach for the model is presented and the model is verified to satisfy the requirements in Chapter 4.

SQ3 is answered by using the model in a game theoretic framework, which is introduced in Chapter 5. This chapter shows the conceptual benefits of collaboration.

To further confirm the improvements, multiple experiments are put forward in Chapter 6. The results are presented in Chapter 7. These results quantitatively show the advantages of cooperation, answering **SQ4**.

2
Literature of Port Railway Operations

To provide a theoretical background and a solid base for the mathematical model and the collaborative transport structure, literature is researched. A comprehensive literature review was conducted in Heemskerk (2025). Multiple research questions are answered:

- How do terms like ITT, drayage and first and last mile influence the problem formulation and suitability of existing models?
- What are the operational and economic consequences of the current decentralised planning and operations?
- What is the current state-of-the-art in mathematically optimising railway movements and scheduling?
- How can optimisation of other transport modes, like trucks or inland barges be applied to the railway first and last mile?

2.1. Terminology

Since the specific problem of first and last mile rail transport is not directly addressed in existing literature, this chapter investigates similar research areas. Specifically, as terminology directly influences assumptions in models, different terms are further looked into. Similar research areas include: inter-terminal transport, first and last mile transport, drayage, shunting and feeding services. Considering these multiple alternatives, railway feeder services are the most fitting term which encompasses the activities within the scope of the thesis best.

2.1.1. Inter-Terminal Transport

Firstly, inter-terminal transport (ITT) is a widely studied subject, but mainly considers a different scope regarding vehicle types. Within ITT, most prevalent transport modes are trucks and terminal vehicles like automated guided vehicles (AGVs), automated lift vehicles (ALVs) or multi-trailer systems (MTS). These modalities all have capacity of <10 TEU, which is significantly less than train systems, which have capacity up to 90 TEU (Schroten et al. 2021). The capacity differences have impact on the fleet sizes, which change the problem description significantly.

2.1.2. Shunting

Second, another relevant transportation term for handling trains in the port area is shunting. The process mainly consists of ordering blocks of trains, in a specifically designed marshalling yard. The arrival tracks splits into multiple tracks, in which rows of wagons get sorted by destination (Ambrosino et al. 2021). Sometimes this term gets extended into movement from terminal to terminal, like in the Port of Rotterdam project "PortShuttle". However, in scientific literature it refers to the ordering of wagons, which is fundamentally different from the transportation problem at hand.

2.1.3. First and Last Mile Transport

Thirdly, first and last mile transport (FLMT) is a broad term in literature for the short-haul transportation. It describes the connection from the long-haul, often by maritime shipping or international rail transport, to the final destination. The FLMT can be executed by many modalities, ranging from trucks to even bicycles for parcels. Often, the FMLT is done by a different mode than the main haul (Dotoli et al. 2015). The size of the fleet performing FLMT often is large, and a central hub acts as the centre of the network. Vehicles also have many route options, and scientific literature therefore often focuses on routing. The network of the PRL does not resemble this hub-and-spoke network.

2.1.4. Drayage

Next, a more specific type of FLMT in the port area, is drayage. This is defined as the transport between terminals and receivers, where often trucks pick up containers at the terminal and drop them off at customers. Often it is done by road (Caris et al. 2008). Like FLMT, drayage is often modelled as vehicle routing problems (VRP), focussing on the routing of trucks. Because of the very limited amount of routes in the PRL network, the VRP has limited applicability.

2.1.5. Feeder Services

Lastly, there is the most applicable term, feeder services. While its use in scientific literature is limited, the term describes the "feeding" of maritime barges or terminals. The services support the port area by hauling freight from and to terminals. Specifying the services to rail further increases relevance (SmartPort 2025). It can be seen as another more specific type of FLMT, where the modality is rail and the port area is the location.

In conclusion, port railway feeder services presents itself as the most specific term for the centrally coordinated, high-capacity FLM transport problem.

2.2. Inefficiencies in the Port Area

Currently, the port area of Rotterdam is served by many rail operators (>20), which results in inefficiencies. The multiple different organisations have a different way of operating and do not cooperate, which causes a polycentric, or even decentralised planning. Next to that, they have different objectives either directly competing for the same gain, or conflicting goals, which present difficulties (Maitra 2016; Gumuskaya et al. 2020). The fact that data sharing is essential for efficiency gain, is clear (Crainic et al. 2018). However, due to stiff competition and the sensitivity of the data, data sharing in the transportation sector is not common, causing an even more fragmented chain (EP et al. 2018). An example of the consequences is presented in Chen et al. (2022), where a truck is unable to pickup the correct container due to lack of data sharing. The rail sector is a heavily regulated market, which present a competitive disadvantage towards other modes and also results in innovations rarely happening (Ambrosino et al. 2021).

2.2.1. Operational Consequences

Operationally, the consequences are mainly empty drives and compounding time delays. Before a train can depart after it is loaded, extended safety checks both physically and administratively are required. Combined with brake checks, this results in trains remaining in the port for an additional 2 hours (Ambrosino et al. 2021). Rail operators optimising for their own objectives, in a rigid port system results in further delays for the complete system. Empty drives are common, and when one part of the transport chain is delayed, this often compounds into large delays in further steps, as delays in the rigid schedules have big consequences (Hu et al. 2019). When multiple objectives are combined however, like in the ITT system in Hu et al. (2018), significant operational gains result.

2.2.2. Economic Consequences

These inefficiencies have economical impact as well, not only as result of the delay, but also the resulting mode choice. The direct cost of delays, extra fuel used for empty drives and extra maintenance due to an increased amount of distance covered by equipment are evident. Less apparent are the external cost of these efficiencies. These externalities consist of cost for society, by emitting greenhouse gases, congestion and accidents (Maitra 2016). A large source of emissions is the consequence of the modal choice for trucks instead of the greener alternative of rail or inland barge transport (Ypsilantis et al. 2019). Road transportation, especially for shorter distances (<300km), is faster, more flexible and economical for shippers (Pedersen et al. 2007; EP et al. 2018). The cost-effectiveness of this transport however only is perceived, as resulting costs for four times as much emissions compared to trains and barges, is paid by society (Maitra 2016; Guo et al. 2023).

2.2.3. Political Solutions

To solve the above-mentioned problems, there are two main routes of solutions, political and operational. Multiple policies are discussed and tested in literature, with differing results. The first option is to subsidise construction of railways and road, which could increase network capacity and reduce congestion. However, this could cause induced demand which would still result in congestion, and Guo et al. (2023) found that this would policy would result in losses. Another option considered, is rail transport subsidies. Santos et al. (2015) presents this as the most effective option to enable the modal shift to rail transportation, where it causes a significant increase in rail transport volumes. Next, the internalisation of the external cost (IEC) mentioned earlier, presents itself to be effective in shifting modal flows from road to rail. The European Parliament already has considered an option with the Eurovignette (EP et al. 2018). Furthermore, multiple studies show this IEC-pricing's effectiveness in the modal shift and reducing emissions (Dai et al. 2018; Guo et al. 2023). On the other hand, Santos et al. (2015) mentions the sensitivity of the policy to model assumptions, and care needs to be taken when designing such a policy.

2.2.4. Operational Solutions

Further gains can be achieved by improving operational efficiency, where limited investments in infrastructure can lead to significant gains. While rail transport can be stiff, and a mind shift could be needed for change, synchromodal transport could be a solution (Riessen et al. 2015). Synchromodal transport integrates the transport chain vertically, where shippers can choose their route and modality real-time (Rentschler et al. 2022). This however is a major shift and the change needs cooperative operators to enable it, and is currently limitedly implemented (Duin et al. 2019). Next, the extension of port area further into the hinterland is considered. This concept is known as dry ports, or extended gate when controlled by the port authority (Bouchery et al. 2015; Gumuskaya et al. 2020). It has a rail-road terminal in an area that is not congested by the port, where freight is exchanged from rail to road and back efficiently. Abu-Aisha et al. (2024) shows the effectiveness of these terminals, showing the increase connectivity of the port area. While extended gate and synchromodal transport could provide operational benefits for the railway network, their implementation requires either large financial investments, or full cooperation of many parties. Furthermore, the congested NCBG areas are still not addressed. To the authors knowledge, the port area railway operations have not been optimised for, posing a gap. As the first and last mile is often a burden for long-haul operators, centralising these operations could prove to improve the operational efficiency of the full rail network in the port area.

In conclusion, the port area rail feeder services remain a slow adapting market, but solutions exist and their implementation could achieve significant gain with limited investments. The railway feeder services have not been investigated before, presenting a gap this thesis aims to fill.

2.3. State of the Art Optimisation

As the freight transport in the port area is a complex system with many variables, it is often modelled to simplify and solve. In this section, the different model types are set out and compared, to determine the best model for this thesis.

2.3.1. Location Allocation

Firstly, as port areas are often developed and extended, location allocation is an important problem to be solved. As implied, the objective is to find the most connected, efficient location of hubs. Santos et al. (2015) presents a model that optimises the location of railroad terminals to test the effectiveness of introducing or relocating them. Rattanakunuprakarn (2025) introduces a model that optimises an intermodal system by upgrading road logistics centres to railroad terminals. The goal is to minimise total overall costs, both from using and upgrading the facilities. While these strategic level optimisations offer long term gain, the implementation is slow and requires large capital investments.

2.3.2. Discrete Event Simulation

Next, Discrete Event Simulation (DES) is used to simulate behaviours of systems. While this is not an optimisation algorithm, it can still be used to investigate properties of transportation systems, like by Schroër et al. (2014). In that paper, it is used to simulate terminals in an ITT system, where different demand scenarios are tested with different vehicle configuration, to evaluate the most optimal configuration. In similar way, Duinkerken et al. (2006) tested the differences in using multi-trailer systems, automated guided vehicles and automated lifting vehicles. In both papers the input of the simulation is a fleet of vehicles, making the fleet sizing exogenous, i.e. pre-determined. While simulation can give insight into the behaviour of a system, it is less suited for finding the (near)-exact optimal solution by changing variables like fleet size.

2.3.3. Travelling Salesman Problem

A commonly used model that can be optimised, is the Travelling Salesman Problem (TSP). It consist of a central hub from which a single travelling salesman needs to visit multiple nodes to pick up demand, with unlimited capacity. Malinovskiy (2025) uses a classic TSP to determine the best route for intermediate stop pickups. It mentions TSP often being variated on, like in Braekers et al. (2013), where an asymmetric multiple vehicle TSP is used, to optimise drayage operations. While being the basis of further models, the classic TSP is too simple for the complex behaviour of the port area feeder services.

2.3.4. Vehicle Routing Problem

Another commonly known extension of the TSP is the Vehicle Routing Problem (VRP). In VRP, there is a fleet of vehicles with specific capacities, which need to pickup demand from different nodes and gather it at a central hub. VRP is often used to optimise drayage operations, like in Dotoli et al. (2015). It presents a two-stage model to first determine shortest road route, after which the fleet size is determined. Again, from standard VRP, there are multiple extensions to add, in a simplified way, characteristics like congestion or as in Ypsilantis et al. (2019), a heterogeneous fleet. They present a fleet size and mix vehicle routing problem (FSMVRP), which is formulated to determine the effect of horizontal collaboration for dry ports. While Their demand is consolidated. This model shows large similarities with the railway network in the port of Rotterdam, due to similar vehicle capacities and route options being limited. Furthermore, VRPs often integrate fleet sizing in their objective function, making it endogenous. However, applicability is still limited as there is limited flexibility with origin and destinations being interchanged.

2.3.5. Inter-Terminal Transport

While the VRP mainly focuses on single-commodity and routing, ITT is often multi-commodity and focuses on freight flow. The highly cited model proposed by Tierney et al. (2014) models ITT in a time-space graph, where both congestion and long-term loading and unloading of barges is included. Hu et al. (2019) extends the model to include the consolidated hinterland railway transport. While this thesis does not focus on the containers like in Tierney et al. (2014), the flow of wagons is still very similar in terms of capacity and routing. The addition of congestion and long-term loading further adds to the applicability of the model, adding an option for length dependent coupling of wagons. Finally, the two-stage solution proposal where first flow is solved, after which locomotives are assigned is appropriate for the network in this thesis.

2.3.6. Model Comparison

For visual reference, the main differences between the above-mentioned model types are summarised in Table 2.1. The focuses of the different models are compared, and whether fleet sizing is treated as a fixed input, an exogenous parameter, or an endogenous decision variable. The fleet homo- or heterogeneity is reported on, after which congestion and handling characteristics are shown.

From Table 2.1, it can be seen that only ITT models combine network-based optimisation with endogenous fleet sizing, congestion effects, and handling operations. This makes them particularly suitable for modelling rail-based inter-terminal transport in the Port of Rotterdam.

Model	Optimisation	Decision focus	Fleet sizing	Fleet Composition	Congestion & Handling	Typical Complexity
LA	✓	Facility location	–	–	–	★ – ★★
DES	–	System behaviour	Exogenous	Mixed	✓	Variable
TSP	✓	Single-vehicle routing	Fixed (1)	Uniform	–	★ – ★★★
VRP	✓	Fleet routing	Endogenous	Uniform (*standard*)	Limited	★★★★ (NP-hard)
ITT	✓	Freight flow	Endogenous	Mixed	✓	★★★★★ (NP-hard)

Table 2.1: Comparison of optimisation and simulation model types.

2.4. Cooperative Game Theory

To optimise complex processes with many players, like the problem described in Section 1.1, cooperative game theory can be used to incentivise collaboration. Because players optimise for their own gain, cooperation without incentive in practice never exists. To enable the collaboration of multiple parties, Shapley (1953) introduced cooperative game theory.

The basis of cooperative game theory is the horizontal cooperation of players, where they share resources for mutual gain. A key question then is how to share costs or profits (Guajardo et al. 2016). In this game, the operation of a single player is called stand-alone. The cooperation of all players is called the grand coalition.
Shapley (1953) introduced the four axioms of fair allocation. Firstly, the solution should be efficient, where all costs gathered by the grand coalition should be divided between the players. Next, if two players contribute the same value, they should be rewarded equally. Then a non-contributing player should also not be allocated any cost. Lastly, additivity should be satisfied, where the sum of the allocation of two players is equal to the allocation of a player with the sum of the previous two players' contribution.

2.4.1. Allocation Strategies

To allocate gains between players, the most used is the strategy from Shapley (1953). Next to the Shapley Value, there are multiple other strategies to allocate gain, e.g. proportional, nucleolus and ad hoc methods in transportation (Guajardo et al. 2016).

2.4.2. Stability of the Coalition

To confirm the stability of the coalition, both stand-alone and sub-coalitions' costs need to be compared to grand-coalition costs. Firstly, Individual Rationality (IR) is a term in cooperative game theory that describes the individual parties in a game are to gain from collaboration. Compared to stand-alone operations, being in the grand coalition pays off, where the assigned cost is lower than their original cost. Next to IR, there also is Group Rationality (GR), where in a game of more than two players, a group of players is still better off in the grand coalition. For GR to be valid, the cost of all sub-coalitions are calculated. If the sum of their cost allocation in the grand-coalition is lower than the cost of all possible sub-coalitions, GR is guaranteed. For a game, all solutions that satisfy both IR and GR are part of what is called the Core. For a problem, the Core could be empty, meaning no solutions cause all individuals and sub-groups to be better of in the grand coalition.

2.4.3. Application of Game Theory

While cooperative game theory has presented promising solution to improve operational efficiency of systems, real applications remain limited. In railway operations specifically, the applications are limited to long-distance freight movement. Prokić (2023) discusses the applicability of a game-theoretic approach in EU's railway freight corridors. It proposes the approach as the solution to the lack of cooperation along the corridors. Continuing that approach, a model is proposed in Prokić et al. (2025) with promising results for the improvement of the system.

Lyu et al. (2025) presents the application of cooperative game theory in the context of berth allocation. They present a novel approach to avoid needing to calculate the solution for every coalition.
To the authors knowledge, no other applications of cooperative game theory in the railway sector have been researched. Furthermore, no real-world implementation exists. This thesis aims to fill this gap.

2.5. Conclusion

In conclusion, this paper addresses the research gap regarding railway first- and last-mile transport in port areas, specifically by using exact operational optimisation algorithms to evaluate the cooperation between multiple railway operators. This gap can be seen in Table 2.2 Railway feeder services most accurately capture the characteristics of the problem, where large-capacity vehicles need to be scheduled. While implementation of innovation in this market is slow, major efficiency gains are anticipated. Strategies are applied in other modes, like inland barges, but the effect on railway transport remains unknown. Because the problem is not extensively researched for railway transport, this thesis extends the theory into the freight railway domain. As a basis, the ITT model of Tierney et al. (2014) is used, due to its flexibility and robustness. The solving approach used is exact optimisation, as it provides a straightforward baseline. However, when computation times restrict solutions, (meta-)heuristics can be added. The model enables integrated scheduling for operators, and using it with coalitions could provide the necessary optimisation needed for cooperation. Cooperative game theory could prove to be the strategy for increasing the operational efficiency of the network.
In the next chapter, the model is adapted to accurately replicate the feeder train dynamics.

Table 2.2: Literature overview and research gap. ✓ = fully addressed, ○ = partially addressed, - = not addressed.

Study	**Focus**	**Policy approach**	**Operational optimisation**	**Port area railway focus**	**MILP scheduling**	**Cooperative game theory**
Santos et al. (2015)	Rail subsidies & IEC	✓	-	-	-	-
Guo et al. (2023)	Modal shift policy mix	✓	-	-	-	-
Dai et al. (2018)	Sustainable IEC pricing	✓	○	-	-	-
Tierney et al. (2014)	ITT MILP model	-	✓	-	✓	-
Hu et al. (2019)	ITT–hinterland rail integration	-	✓	○	○	-
Riessen et al. (2015)	Synchromodal transport	○	✓	-	-	-
Duinkerken et al. (2006)	ITT DES	-	✓	✓	-	-
Schroër et al. (2014)	Maasvlakte DES evaluation	-	✓	✓	-	-
Gharehgozli et al. (2017)	Collaborative ITT solutions	-	✓	✓	-	○
Ambrosino et al. (2021)	Rail-sea intermodal terminal	-	✓	○	○	-
Ypsilantis et al. (2019)	Collaborative fleet deployment	○	✓	-	-	○
Gestrelius (2022)	Train timetabling optimisation	-	✓	-	✓	-
Guajardo et al. (2016)	Cost allocation review	-	○	-	-	✓
Prokić et al. (2025)	Rail corridor governance	○	✓	-	○	✓
Lyu et al. (2025)	Port berth allocation	-	✓	○	✓	✓
Shapley (1953)	Cooperative Game Theory	-	-	-	-	✓
This Paper	**FTSM + cooperative game theory, Rotterdam port area**	○	✓	✓	✓	✓

3

Feeder Train Scheduling

To accurately optimise the operations for a given set of orders and locomotives, a mathematical model is made based on an existing model. First, the problem is described, then requirements are formulated, after which the model is chosen. Next, the formulation is altered to accurately capture FTS behaviour. The model is then verified and tested against requirements.

3.1. Problem Definition and Assumptions

3.1.1. General Problem

The Feeder Train Scheduling Problem, has some key distinct characteristics:

- The network consists of a main railway track, which connects multiple railyards.
- The yards are the hub that connects multiple terminals to each other and to the main port railway line. Often, these terminal connections are not electrified tracks.
- The system has multiple railway operators, terminal operators and at least one infrastructure manager, all with their own objective.
- The railway operators serve the terminals, where they feed the freight into and from the terminals.
- The terminal operators mainly seek on-time and reliable delivery of goods.
- The infrastructure manager assigns trajectories and timeslots for train movements.

3.1.2. Port of Rotterdam

These characteristics all occur in the case of the Port of Rotterdam. It has an extensive rail network, spanning from most terminals towards the central marshalling yard ”de Kijfhoek” (KH) with a single main port railway line, the ”Havenspoorlijn” (PRL). Almost all railway transport passes by the KH, either stopping for reclassification or a locomotive change, or directly moving to the hinterland. From the KH, the PRL continues towards the ports, with major terminal areas being the Waalhaven, Pernis, Botlek, Europoort and Maasvlakte. At all these areas, a larger railyard is present, which is connected to the terminals. The port area of Rotterdam can be seen in Figure 1.1.

Electrification

While the energy consumption of diesel trains has remained steady, the amount of electricity used has increased 45% from 2010 to 2022 (International Energy Agency 2023), showing a shift to more electric locomotives. The PRL is electrified with overhead lines, but the last parts to the terminal (up to >10km) are unelectrified, necessitating the use of diesel or hybrid locomotives. The electrification of the port railway lines can be seen in Figure 1.1. Because installing overhead lines on the non-electrified parts is a costly endeavour, this presents problems for the port area.

Signage and Train Protection

Next to electrification, the railways from PRL to the terminals have another essential distinction in the way they are operated. The main PRL is so called ”centraal bediend gebied” (CBG), or centrally operated by ProRail, the infrastructure manager. On these lines, a trajectory can be booked for a specific movement, for example a drive from KH to Botlek. A certain trajectory is reserved and the transport is centrally overseen and monitored. From the main line, multiple split offs are ”niet centraal bediend gebied" (NCBG) which means their are not centrally monitored by the railway operator. In practice, this means there are no safety systems, and the locomotive and its driver are in full control. A "tijdruimteslot", or timeslot can be booked, during which the area is reserved for one operator. Any movement, direction or stop is allowed during the time.

3.1.3. Critical Assumptions

Some critical assumptions are made, to enable the modelling of the system.

- Orders are all known and definitive.
- Distances between nodes are represented as fixed travel times.
- There are no disruptions in the network, all travel times remain constant.
- Time is discretised with uniform intervals
- Coupling and decoupling are proportional to order length.

Firstly, while order scheduling is a fluid process, to schedule with a model it is necessary to know all orders. Therefore, the orders are assumed to be known and definitive. As a result, if there are any changes to the orders closer to the due time, the optimisation can be re-run or adjustments can be made manually. Then, as the port area network is a short-distance network and train speeds are low, the internodal travel times can be assumed to be constant. The real-world differences in travel times stay well within the time steps and have negligible effects. Next, disruptions are kept out of scope. While scheduled maintenance or disruptions could be integrated, they do not contribute to solve the research question. With the above-mentioned assumptions, what is left is a constant network, in which the time can be discretised into uniform intervals. The model then is solvable with linear programming. Lastly, based on expert information, the coupling and decoupling of trains is made proportional to length, as in reality this is the principal contributor to coupling time. Mandatory wagon checks and brake test differ based on total train length. Other contributors that are not included are freight type, coupling mechanism or location of the order within the train.

3.2. Model Requirements and Selection

With the problem definition in Section 3.1, the requirements of the model are formulated. To achieve the most accurate model, multiple requirements in tracking and model behaviour need to be considered.

- **Requirement 1: Objective Function:** The objective function should minimise for, in order of decreasing importance: Non-deliveries, amount of locomotives used, order delay, driving cost, time away from depot and earliness of delivery.
- **Requirement 2a: Locomotive Modelling:** Locomotives have multiple properties, like a daily cost, weight capacity and a depot node.
- **Requirement 2b: Locomotive Flow:** To ensure locomotive flow and consistency, locomotives need to be accurately tracked, where locomotives start and end at their depot.
- **Requirement 3a: Order Modelling:** In the desired model, orders are an input, where every order consists of a length, weight (linear to length), origin and destination node. Furthermore, every order has a releasetime and a duetime.
- **Requirement 3b: Order Flow:** Orders can only move between nodes when a locomotive is present on that arc, and before and after waiting at a node the order needs to be (de)coupled.
- **Requirement 4: Split Delivery:** Orders should be able to be delivered by two different locomotives.
- **Requirement 5: Combined Locomotives:** Locomotives should be able to combine to carry loads above their weight capacity, while length capacity remains constant.
- **Requirement 6: Arcs:** Arcs should have a travel time, length and length of train capacity.
- **Requirement 7: Locomotive Usage:** While locomotives are used as input, the model should be able to decide whether to use them, making the locomotives endogenous.

Considering the objective function, the aim is to deliver all orders, as not fulfilling the request of a client is costly. Next, using less locomotives decreases cost significantly, where availability, renting cost and driver salaries determine the majority of the cost. In logistics, delay is the next most expensive thing. Time away from the depot node of locomotives has less direct cost, but models the operator behaviour of optimising routes, and also models parking cost and fuel usage. Lastly, due to increasing popularity of ”just-in-time”, early delivery is penalised, albeit slightly.

Using the model comparison from Section 2.3, it is clear the ITT model presented in Tierney et al. (2014) is most suitable. The time-space graph used has multiple advantages for the problem presented in this thesis. Firstly, the chosen architecture of integrating time into the arc structure makes the model a robust solution for freight flow. The occupancy of arcs can easily be kept track of. Secondly, the structure of LT nodes can be altered to model the loading and departing processes of trains. Third and lastly, the model has proven to be scalable to real-world sizes, where it's flow-first solution approach can be used to calculate optima quickly (Tierney et al. 2014).
The proven model combines a mixed, endogenous fleet with a time-space graph, enabling both congestion and handling modelling. In the next section, the model is adapted from ITT to feeder train scheduling.

3.3. Time-Space Network Construction

By adopting the model to the requirements of the port area feeder services characteristics, the system can be distilled into a solvable problem. In this chapter, the changes to the base model are discussed.

3.3.1. Base Graph Construction

Like the base model, the time-space graph consists of a base graph $G = (N, A)$ which is extended through all time-intervals τ to $G^T = (N^T, A^T)$. In contrast to the base model, our graph contains two types of nodes, yard nodes and terminal nodes. Yard nodes represent the locations in the port area which contain a yard with multiple tracks, where a train can stay for a longer period of time. Yard nodes are interconnected and enable transport of both locomotives and orders. These yard nodes get at least one duplicate, a terminal node. This node is used to model different terminals present at the yard. The couple capacity can be used for different terminals, to model different (de)coupling times. Locomotives are able to travel from yard node to yard node, traversing every A^M. Orders can move on travel arcs, but also travel between yard and coupling nodes, so called terminal arcs $A^{C\Delta}$.

Stationary Arcs

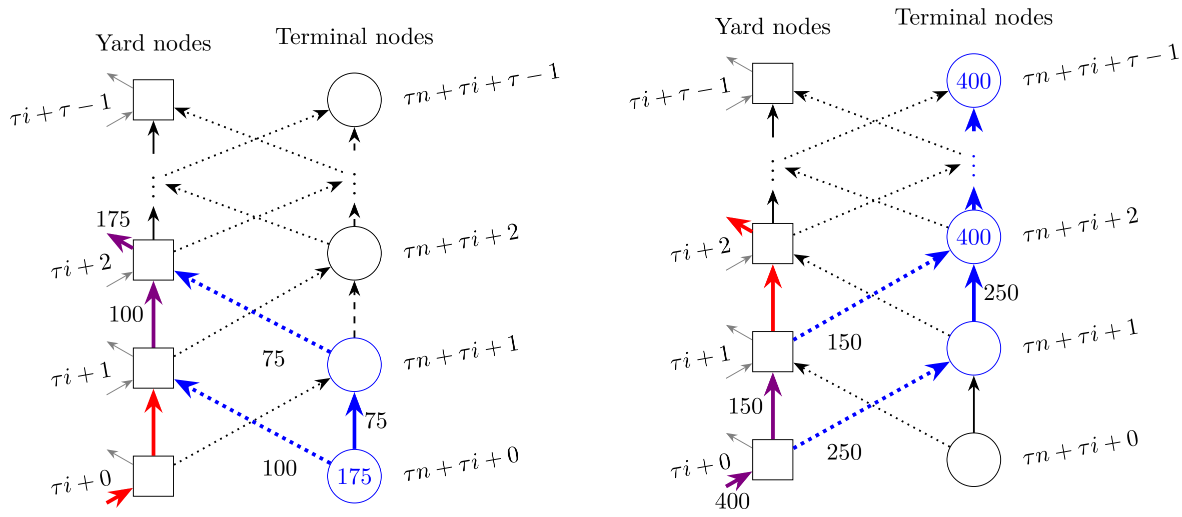
Stationary arcs are used to allow locomotives and orders to stay in the same place for an extended period of time. Both yard and terminal nodes are connected with themselves in the next time step. Because only orders can travel to terminal nodes, only orders can traverse terminal stationary arcs A^{SB}. After being coupled, orders cannot traverse a stationary yard arc A^S without a locomotive. This ensures that before moving through the time-space graph without a locomotive, it needs to be decoupled and vice versa.

Arc Occupancy

While the base model uses the time-space graph to model congestion, this thesis uses it mainly to model arc occupancy. When using this model as optimisation on a lower level, like in a game theoretic network, it can be used in parallel to simulate multiple rail operators and then arc occupancy can easily be kept track of. Congestion, where arcs get a longer travel time like mentioned in Tierney et al. (2014) is often not present in the rail network.

Coupling and Decoupling

To ensure an order is not instantly coupled to a wagon, the coupling arcs A^C are constrained with a length capacity, which acts as the maximum amount of an order that is coupled in that time step. This ensures coupling is length dependent, and includes the real-life checking of wagons and the required brake check. For decoupling, the capacity of the decoupling arcs cap^Δ is higher, as no brake check needs to be performed. While the coupling and decoupling arcs are a direct adaptation from the LT arcs mentioned in Tierney et al. (2014), they have a significant difference which is the fact that couple arcs are connected to their yard node not in the same, but *the next* time step. This increases coupling time but also improves accuracy for the railway network. Another difference is that to couple or decouple an order, a locomotive needs to be waiting at the yard node during the same time. (De)Coupling can be seen in Figure 3.1



(a) Scenario 1: Coupling **(b)** Scenario 2: Decoupling

Figure 3.1: Time-space expansion of a yard node (left) and its terminal node. Green arcs represent a locomotive (x_{ijl}) moving, blue an order (y_{ijd}) and cyan both. An order is coming in from another yard node, and slowly decoupled onto the terminal node. $cap^C = 100$ and $cap^\Delta = 250$. Adaptation from Tierney et al. (2014).

3.3.2. Network Saturation

To model the other operators in the port area, two network saturation factors are used, one to model congestion in the CBG, the other for NCBG. Firstly, the saturation of the travel arcs is modelled with factor ξ_{CBG}, with indicates the fraction of travel arcs randomly pruned from the base graph. The removed arcs model other operators moving over CBG trajectories, blocking it in the schedule of the considered operator. Next, ξ_{NCBG} signifies the factor of arcs pruned in from the terminal arcs. These arcs are not randomly deleted, but an average block time is chosen. Blocks of time are then removed per terminal, modelling the occupancy of the time slots in the NCBG areas. The time-space graph generation process can be seen in Figure 3.2.

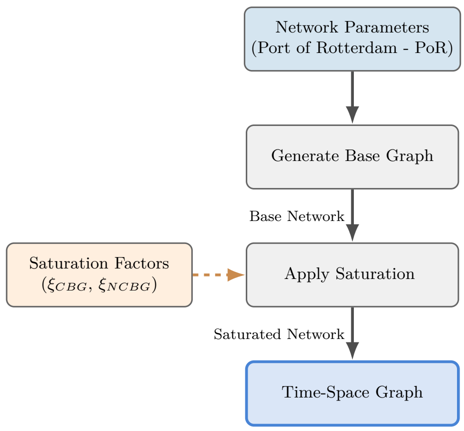


Figure 3.2: The Time-Space graph generation process.

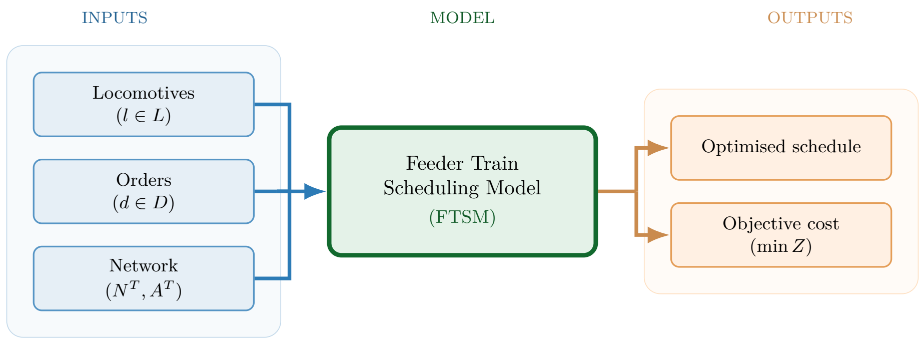


Figure 3.3: The inputs and outputs of the FTSM.

3.3.3. Orders and Locomotives

Orders are used as an input of the system, with key characteristics like start and end node s_d and e_d, release time re_d, and due time du_d. The length and weight of the order len_d & wgt_d are also included. Orders start at a terminal node, from which it has to be coupled and then with a locomotive travel to other nodes. After reaching their desired yard node they get decoupled to their destination, a terminal node again. The properties of locomotives regarded are its weight capacity cap_l^{wgt} and its depot node dp_l. Locomotives start at their depot node, and also return there at the end of the optimisation.

3.3.4. Time-Space Graph Example

In figure 3.4 an example of the time-space diagram can be found. It can be seen that from terminal node A', the order gets coupled to the locomotive at yard node A over two time steps. The locomotive is waiting at the yard node while the order is coupled. After the full order is coupled, both travel from A to B to D.

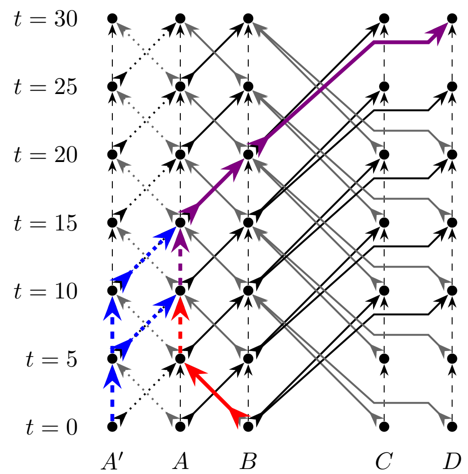


Figure 3.4: An example time-space graph, where solid arcs show a rail connection, dashed arcs represent stationary arcs and dotted lines terminal arcs. Black and grey arrows are arcs in A^M. Red lines show the path of a locomotive, blue shows the path of an order and purple a combined locomotive-order path. Adaptation from Tierney et al. (2014).

3.3.5. MILP Formulation

The following sets, parameters and (auxiliary) variables are used in the MILP model.

Table 3.1: Sets, indices and parameters of the mathematical model.

Symbol	Description	Domain/Unit
Sets and Indices		
L	Set of locomotives	$l \in L$
L^D, L^E	Subsets of diesel and electric locomotives	$l \in L$
D	Set of orders	$d \in D$
T	Set of discrete time steps	$t, \tau \in T$
N	Set of nodes in the base graph	
N^T	Set of all nodes in the time-space graph	$i, j \in N^T$
N^B	Subset of terminal nodes	$i, j \in N^T$
N^M	Subset of yard nodes	$i, j \in N^T$
N_l^L	Subset of nodes that are not the depot for locomotive l	
N_d^D	Subset of nodes that are not the start of end for order d	
A^T	Set of all arcs in the time-space graph	$(i, j) \in A^T$
$A^M, A^{S(B)}$	Subsets of arcs for travelling and waiting (at terminals)	$(i, j) \in A^T$
A^C, A^Δ	Subsets of arcs for coupling and decoupling	$(i, j) \in A^T$
A^L	Subset of arcs for locomotives, including $A^M \cup A^S$	$(i, j) \in A^T$
$A^{C\Delta}$	Subset of terminal arcs, including $A^C \cup A^\Delta$	$(i, j) \in A^T$
$In(j)$ ($End(j)$)	Sets of incoming and outgoing neighbours of node j (at $T[-1]$)	$\{i : (i, j) \in A^T\}$
$Out(j)$ ($Sta(j)$)	Set of outgoing neighbours of node j (at $t = 0$)	$\{k : (j, k) \in A^T\}$
$LIn(j)$ ($LEnd(j)$)	Set of incoming neighbours of node j (at $T[-1]$)	$\{i : (i, j) \in A^L\}$
$LOut(j)$ ($LSta(j)$)	Set of outgoing neighbours of node j (at $t = 0$)	$\{k : (j, k) \in A^L\}$
Parameters		
τ	Discrete time step size	[min]
cap_j^C	Coupling capacity for terminal node j	[m/min]
f^Δ	Coupling to decoupling capacity factor	[m/min]
s_d, e_d	Start and End nodes for order d	[Node ID]
re_d, du_d	Release and Due times for order d	[min]
len_d, wgt_d	Length and Weight of order d	[m, kg]
cap_{ij}^{len}	Length capacity of arc i, j	[m]
cap_l^{wgt}	Weight capacity of locomotive l	[kg]
dp_l	Depot node of locomotive l	[NodeID]
C^{ldaily}	Daily fixed cost for a locomotive	[€]
C^{away}	Cost for a locomotive not being at its depot	[€/min]
C^{delay}, C^{early}	Cost for time delays and earliness	[€/min]
$C^{nondelivery}$	Cost for not delivering an order	[€]
C^{TKM}	Cost per tonne kilometre of moved goods	[€/TonKM]
C^{yard}	Cost for an order waiting at a yard other than its start or end	[€/min]
Auxiliary Variables		
td_d	Time delay of order d relative to its due time	Continuous
ϵ_d	Time earliness of order d relative to its due time	Continuous
α_{lt}	1 if locomotive l is away from its dp_l at t	$\{0, 1\}$
$\gamma_{ij,d}$	1 if order d is on arc $(i, j) \in A^M$	$\{0, 1\}$

Decision Variables

There is one continuous variable y_{ijdl}, which represents the amount of meters of order moved over arc (i, j) by locomotive l. Next, if a locomotive is moving over an arc in A^L, the binary variable x_{ijl} is 1. Furthermore, two binary variables signifying the usage of locomotives u_l and the delivery of orders δ_d are added.

The mathematical formulation is as follows:

Objective Function

$$\min \quad Z = \sum_{l \in L} \sum_{d \in D} \sum_{t \in T} (C^{ldaily} u_l + C^{delay} \tau \cdot td_d + C^{early} \tau \cdot \epsilon_d + C^{away} \tau \cdot \alpha_{l,t} + C^{nondelivery} (1 - \delta_d)$$
$$+ \sum_{ij \in A^M} C^{TKM} \frac{wgt_d}{len_d} \cdot y_{ij,d,l} + \sum_{ij \in A^{C\Delta} \setminus \{s_d, e_d\}} C^{yard} \tau \cdot y_{ij,d,l}) \quad (3.1)$$

1. Locomotive Flow

Firstly, the vehicle movements are constrained. Constraint (3.2) ensures locomotives start and end at their depot, and (3.3) consistent flow across the time-space graph, where for every node (except for depot nodes at start and end of the horizon), flow in is equal to flow out, for every locomotive. Alterations from Tierney et al. (2014) are the variable u_l, to enable endogenous fleet sizing and x gets extended with set L, to track locomotives across the time-space graph.

$$\sum_{j \in LSta(dp_l)} x_{dp_l,j,l} = \sum_{i \in LEnd(dp_l)} x_{i,dp_l,l} = u_l \qquad \forall l \in L \qquad \text{T/O} \quad (3.2)$$
$$\sum_{i \in LIn(j)} x_{ij,l} = \sum_{k \in LOut(j)} x_{jk,l} \qquad \forall l \in L, j \in N_l^L \qquad \text{T/O} \quad (3.3)$$

Next, in constraint (3.4), electric locomotives are prevented from (de)coupling from and to their start and end nodes, modelling the inability to deliver orders to terminals.

$$\sum_{d \in D} \sum_{\substack{(i,j) \in A^{C\Delta} \\ i \in \{s_d, e_d\} \vee j \in \{s_d, e_d\}}} y_{ij,d,l} = 0 \qquad \forall l \in L^E \qquad \text{O} \quad (3.4)$$

2. Order flow

Next, order flow is conserved, where (3.5) and (3.6) set orders flows from starting nodes and to end nodes. Then, (3.7) preserves flow at intermediate nodes. Like in the locomotive constraints, again set L is added to link locomotives to order movements. This is used to enable later constraints.

$$\sum_{j \in Sta(s_d)} \sum_{l \in L} y_{s_d,j,d,l} = len_d \cdot \delta_d \qquad \forall d \in D \qquad \text{T} \quad (3.5)$$
$$\sum_{i \in End(e_d)} \sum_{l \in L} y_{i,e_d,d,l} = len_d \cdot \delta_d \qquad \forall d \in D \qquad \text{T} \quad (3.6)$$
$$\sum_{i \in In(j)} \sum_{l \in L} y_{ij,d,l} = \sum_{k \in Out(j)} \sum_{l \in L} y_{jk,d,l} \qquad \forall d \in D, j \in N_d^D \qquad \text{T} \quad (3.7)$$

To prevent orders from splitting, binary auxiliary variable γ is used in constraint (3.8) for full-order movement. Either $\gamma = 1$ and the full order moves over a locomotive arc, or no part of the order moves.

$$\sum_{l \in L} y_{ij,d,l} = len_d \cdot \gamma_{ij,d} \qquad \forall (i,j) \in A^M, d \in D \qquad \text{O} \quad (3.8)$$

3. Capacities

As length capacity in the rail network is a network constraint, the parameter cap_{ij}^{len} is used in (3.9) to ensure arc length capacity.

$$\sum_{d \in D} \sum_{l \in L} y_{ij,d,l} \leq cap_{ij}^{len} \qquad \forall (i,j) \in A^L \qquad \text{O} \quad (3.9)$$

Equation (3.10) ensures weight capacity, where order weight is assumed to be linear with weight.

$$\sum_{d\in D}\left(\frac{y_{ij,d,l}}{len_d}\cdot wgt_d\right)\leq cap_l^{wgt} \qquad \forall(i,j)\in A^L, l\in L \qquad \text{O} \quad (3.10)$$

The LT arc logic from Tierney et al. (2014) is used to model couple and decouple time in (3.11). The constraint is formulated so that the fraction of couple capacity and decouple capacity used, do not sum up to more than 1. This ensures a locomotive, in a timestep, does not simultaneously (de)couple multiple orders at multiple terminals. Every terminal node has its own capacity. This parameter cap_j^C models different NCBG sizes and per terminal service times. Factor f^Δ is the multiplication for decoupling, as this often takes less time than coupling ($f^\Delta > 1$).

$$\sum_{d\in D}\sum_{jk\in A^C}\frac{y_{jk,d,l}}{cap_j^C}+\sum_{d\in D}\sum_{ij\in A^\Delta}\frac{y_{ij,d,l}}{cap_j^C\cdot f^\Delta}\leq 1 \qquad \forall j\in N^B, l\in L \qquad \text{O} \quad (3.11)$$

4. Locomotive-Order Link

To ensure an order is only moved when a locomotive is available, (3.12) is added.

$$y_{ij,d,l}\leq len_d\cdot x_{ij,l} \qquad \forall(i,j)\in A^L, d\in D, l\in L \qquad \text{T} \quad (3.12)$$

Then, to ensure the locomotive linked to an order waits at a yard for the time the order is (de)coupled, (3.13) and (3.14) are added.

$$y_{ij,l,d}\leq x_{ik,l}\cdot len_d \qquad \forall(i,j)\in A^\Delta,(i,k)\in A^S, d\in D, l\in L \qquad \text{O} \quad (3.13)$$

$$y_{ij,l,d}\leq x_{kj,l}\cdot len_d \qquad \forall(i,j)\in A^C,(k,j)\in A^S, d\in D, l\in L \qquad \text{O} \quad (3.14)$$

Next, to force orders to use the same locomotive on a trajectory, only being able to switch locomotive after decoupling and recoupling, (3.15) is implemented. The locomotive used for the movement of a specific order remains constant over all arc types except those in A^{SB}

$$\sum_{d\in D}y_{ij,d,l}+\sum_{d\in D}y_{ji,d,l}\leq 1 \qquad \forall(i,j)\in A^C\cup A^L, l\in L \qquad \text{O} \quad (3.15)$$

5. Objective Variables

To track how long the locomotives are away from their depot node, auxiliary variable α is introduced and constrained by (3.16)

$$\alpha_{l,t}=u_l-x_{dp_l,j,l} \qquad \forall(dp_l,j)\in A^S, l\in L, t\in T \qquad \text{O} \quad (3.16)$$

For the arrival logic, the time delay is adopted from Tierney et al. (2014) in equation (3.17), and flipped to also include an earliness auxiliary variable in (3.18).

$$td_d=\sum_{du_d\leq t\leq T[-1]}\sum_{i\in In(e_d)}\sum_{l\in L}(t-du_d)y_{i,e_d,d,l} \qquad \forall d\in D \qquad \text{T} \quad (3.17)$$

$$\epsilon_d=\sum_{T[0]\leq t\leq du_d}\sum_{i\in In(e_d)}\sum_{l\in L}(du_d-t)y_{i,e_d,d,l} \qquad \forall d\in D \qquad \text{O} \quad (3.18)$$

Because the variable size is directly influenced by the amount of nodes, time steps, amount of orders and locomotives, the solution space becomes large quickly. Therefore, in the next chapter the solution approach is discussed, where the solver, heuristics and the verification of the model are presented.

4
Solution Approach and Verification

To effectively solve the model presented in Chapter 3, this chapter presents the solution methodology and the model is verified to behave like required in Section 3.2.

4.1. Solution Methodology

To ensure the solution is calculated in a practically usefull time, the solution approach is carefully chosen and discussed below.

4.1.1. Solver

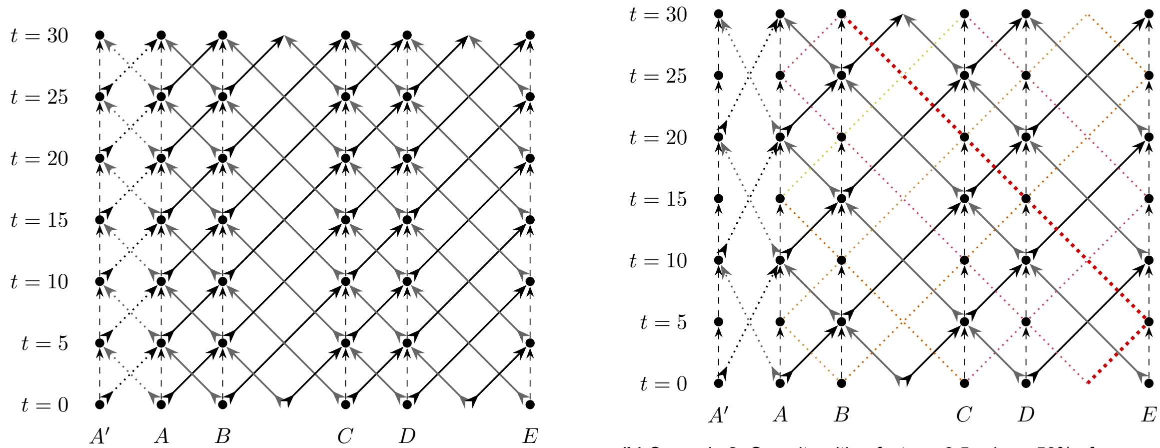
To solve the FTS model from Section 3.3.5, the commercial solver Gurobi is selected. Because the problem is NP-hard, Gurobi's implementation of advanced branch-and-cut algorithms and cutting-plane methods is essential for navigating the complex combinatorics of the time-space expansion. Gurobi provides superior numerical stability compared to open-source alternatives. Furthermore, since the model must be solved iteratively to calculate the characteristic function $v(S)$ for the cooperative game, Gurobi's efficient model-handling in memory significantly reduces the total computation time required for the Shapley value and Nucleolus allocations.

4.1.2. Solution Space Reduction

To decrease computation time, multiple strategies are proposed.

Firstly, the flow-first method proposed in Tierney et al. (2014) can be implemented. In this approach, first only the order flow is solved for, where equations (3.5) to (3.9), (3.11) and (3.15) are enforced. Then, this solution is used as a warm start to the optimisation of the full model, with all constraints active. This method first solves order flow and then assigns locomotives to the order flow. This proves to be an efficient and significantly faster solution approach.

The next option is to reduce the solution space by applying a temporal network sparsity approach. In the time-space graph, arcs are pruned based on the network sparsity factor (σ). The length capacity of the arcs is scaled with $1/\sigma$, to maintain the network capacity. Not only travel arcs are pruned, but terminal connections are also removed and remaining arcs lengthened in time and capacity scaled. Rather than removing arcs randomly, they are pruned systematically along trajectories, preventing artificial waiting at intermediate nodes. As opposed to reducing time-step resolution, this method ensures travel times between arcs remain constant, while the network is significantly decreased in size. An example can be found in Figure 4.1. This method is particularly effective for linear networks like that of the havenspoorlijn. Non-linear networks with branching main lines present difficulties, as branching causes deletion of large amounts of arcs, possibly resulting in disconnecting nodes altogether.



(a) Scenario 1: No sparsity

(b) Scenario 2: Sparsity with a factor = 0.5, where 50% of arcs are removed. Dotted lines are removed and can not be travelled over.

Figure 4.1: The network without and with sparsity, where with a factor of 0.5, 50% of arcs are removed from the network. The amount of trains and capacity per arc is doubled. The arcs are not removed randomly, but per constant trajectory, like the dotted red line in **(b)**

Crucially, the sparsity pruning happens before the saturation factors are applied. The process of making the final time-space graph can be seen in Figure 4.2.

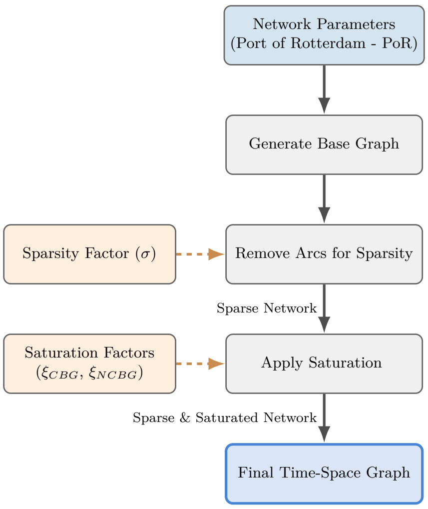


Figure 4.2: The Time-Space graph generation process, including the sparsity method.

Both methods are implemented in the solutions presented in this thesis, to reduce calculation times.

4.2. Model Verification

To verify the workings of the model, the multiple requirements mentioned in Section 3.2 are checked. The following checks need to be successfully passed before using the model in further experiments. In these tests, the heuristics mentioned before are not implemented. First, an experiment is defined and a hypothesis is made. The experiments are executed and the results are compared to the hypotheses.

Verification Network

A simple verification network is made, with 5 connected nodes. The network can be seen in Figure 4.3. Arc capacities are 650 meter, and couple and decouple capacities are $100m/min$ and $250m/min$ respectively.

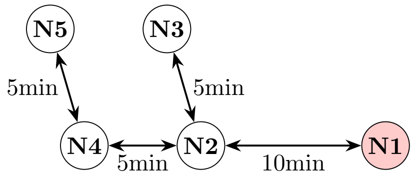


Figure 4.3: The simple verification network.

4.2.1. Experiment 1: Flow and State

Input

To test the flow and state of locomotives and orders, a simple set of orders is made in which one locomotive performs all transportation. It is expected the locomotive combines the delivery of all orders in one trip, where it first delivers O1, then picks up O2, delivers it and lastly delivers O3.

Order ID	Start node		Destination node	Release time	Due time	Length	Weight
O1	1	→	4	0	100	1	1
O2	4	→	2	0	100	1	1
O3	4	→	5	0	100	1	1

Table 4.1: Orders in experiment 1.

Locomotive ID	Depot node	Weight Capacity
L1	1	250

Table 4.2: Locomotives in experiment 1.

Results

It can be seen in Figure 4.4, the expected behaviour is satisfied. The orders are combined, and flow and state of the locomotives are conserved. It can be seen the delivery is optimised to be on-time, shifting them as far to the due time as possible. The optimisation even loads order 2 at node 4 while still having to travel to node 5 and back, enabling delivery closer to the due time.

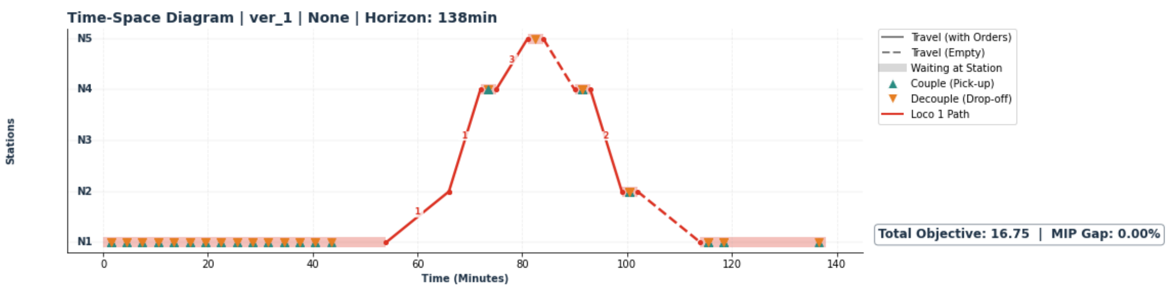


Figure 4.4: Resulting movements from verification experiment 1.

4.2.2. Experiment 2: Capacities

Input

To check if the model respects capacity constraints, multiple orders close to length and weight capacity of the locomotives are used as input. Furthermore, the couple and decouple capacities are the same as Experiment 1.

The experiment in Table 4.3 is specifically designed so that only orders 1 and 2, and 3 and 4 can be moved together, when capacity constraints are correctly implemented. This behaviour is expected, and in combination with the objective function of on time delivery, all deliveries are closest to the due time.

Order ID	Start node		Destination node	Release time	Due time	Length	Weight
O1	2	→	3	0	150	200	150
O2	2	→	3	0	150	200	100
O3	2	→	3	0	150	100	90
O4	2	→	3	0	150	150	160

Table 4.3: Orders in experiment 2.

Locomotive ID	Depot node	Weight Capacity
L1	2	250

Table 4.4: Locomotives in experiment 2.

Results

It can be seen in Figure 4.5 the capacity constraints are respected. Like the experiment was designed for, the orders only move in combination of (3,4) and (1,2). Furthermore, it can be seen the coupling of the orders takes multiple time steps, because of their large length.

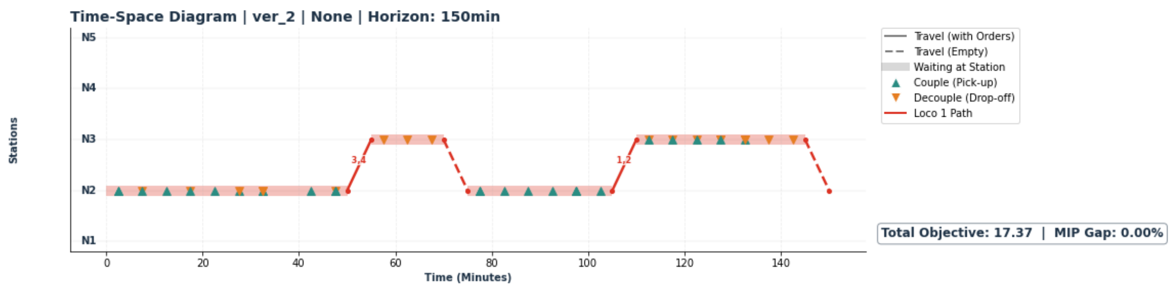


Figure 4.5: Resulting movements from verification experiment 2.

4.2.3. Experiment 3: Objective function

Input

To test the order of the objective function mentioned in the requirements, the orders from Table 4.5 are used as input.

As the round trip from N1 to N3 is 45 minutes with loading and unloading of one order, it is expected O1 will be delivered seperately from the other orders. Dependent on the cost of early delivery and time away from depot, orders are combined or not. When the difference between these two cost is little, only O3 and O4 are expected to be combined, where O4 is delivered early and the locomotive does not wait until its duetime.

Order ID	Start node		Destination node	Release time	Due time	Length	Weight
O1	1	→	3	0	15	100	50
O2	1	→	3	0	100	100	50
O3	1	→	3	0	160	100	50
O4	1	→	3	0	180	100	50

Table 4.5: Orders in experiment 3.

Locomotive ID	Depot node	Weight Capacity
L1	1	250

Table 4.6: Locomotives in experiment 3.

Results

In Figure 4.6 it is seen the orders are indeed delivered separately, optimising for on-time delivery. With order 3 and 4, it can be seen time away from depot is penalised more than the earliness of order 4.

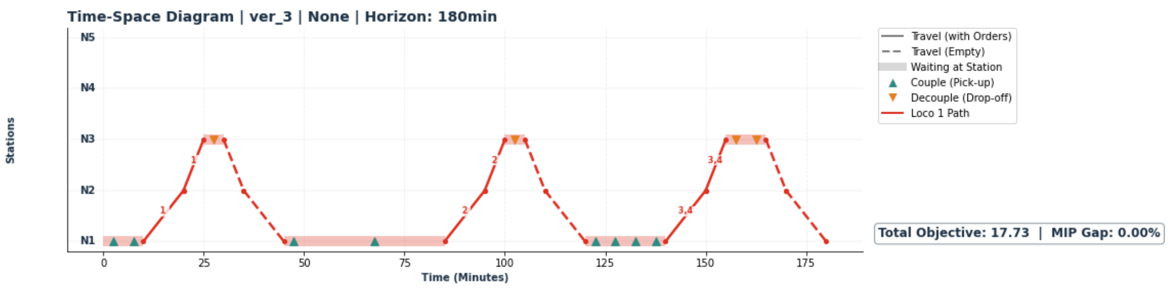


Figure 4.6: Resulting movements from verification experiment 3.

4.2.4. Experiment 4: Split delivery

Input

To show the model is able to deliver an order by two locomotives on two arcs, orders and locomotives are put at the ends of the network and the time horizon is limited to disable locomotives from travelling the full network.

The expected behaviour is that orders are switched between two locomotive at a node in the middle of the network, in this case N2.

Order ID	Start node		Destination node	Release time	Due time	Length	Weight
O1	1	→	5	0	10	10	50
O2	5	→	1	0	10	10	50
O3	1	→	2	0	10	10	50
O4	5	→	2	0	10	10	50

Table 4.7: Orders in experiment 4.

Locomotive ID	Depot node	Weight Capacity
L1	1	250
L2	5	250

Table 4.8: Locomotives in experiment 4.

Results

In the experiment it is seen that the orders indeed exchange locomotive at the intermediate node. It can be seen in Figure 4.7 the orders get decoupled and recoupled to a different locomotive to leave for their respective destination.

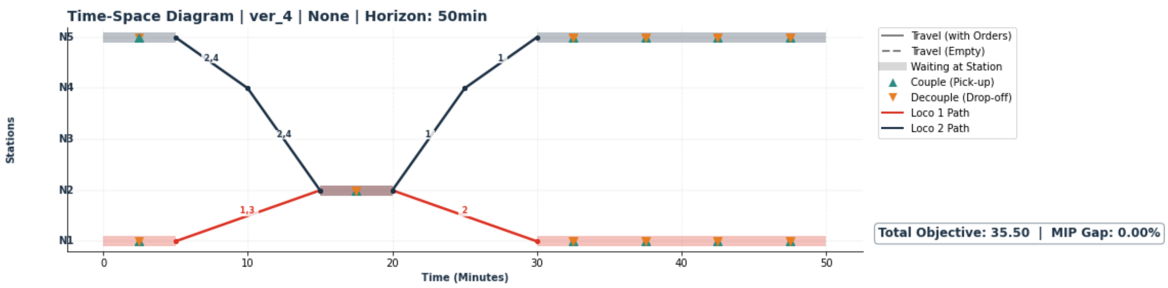


Figure 4.7: Resulting movements from verification experiment 4.

4.2.5. Experiment 5: Combined locomotives

Input

Because some orders, or a combination of two orders can exceed the weight capacity of a locomotive, locomotives can combine. To test this behaviour, experiment 5 is designed with orders from Table 4.9

Order ID	Start node		Destination node	Release time	Due time	Length	Weight
O1	1	→	5	0	70	250	300
O2	1	→	4	0	30	250	300
O3	4	→	1	0	60	450	300

Table 4.9: Orders in experiment 5.

Locomotive ID	Depot node	Weight Capacity
L1	1	250
L2	1	250

Table 4.10: Locomotives in experiment 5.

Results

In Figure 4.8 it can be seen orders O1 and O2 are carried by both L1 and L2, and delivered to N4 and N5. When O1 arrives, L2 leaves to N4, to load O3 and then both locomotives carry O3 to its destination N1.

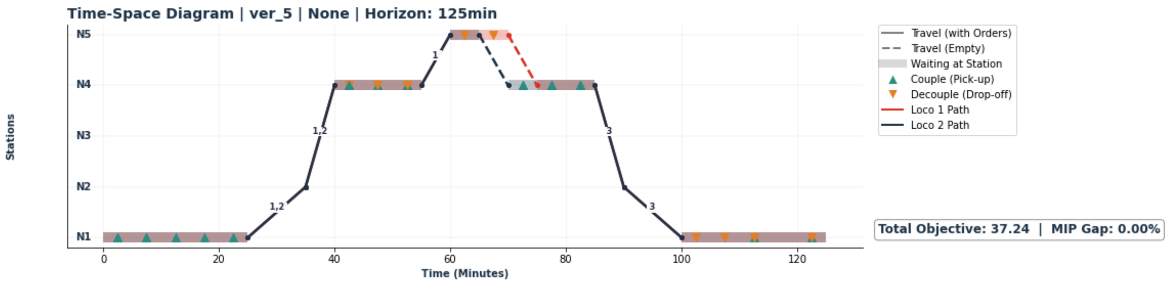


Figure 4.8: Resulting movements from verification experiment 5.

4.2.6. Conclusion

The behaviour from the FTS model in the verification experiments in this chapter prove the workings of the model and compliance with the requirements from Section 3.2. Firstly, requirement 1 is proven in 4.2.3, where the objective function behaves in the required order. Next, requirement 2a, concerning the capacities of the locomotives, is verified in 4.2.2. 2b and 3b are tested in 4.2.1, where locomotive and order flow is shown to be conserved. The last two experiments in Sections 4.2.4 and 4.2.5 show compliance with requirements 4 and 5. As occupied arcs are the output of the model by definition, requirement 6 is also met. Requirement 7 is respected by variable u_l. Therefore it is concluded that all requirements for the model are met and verified, and the FTS model is ready for use in the next chapter, where it will be used as basis for a game theoretic transportation approach.

5

Cooperative Transportation Strategy

With the Feeder Train Scheduling Model (FTSM) from Chapter 3, a cooperative strategy in which multiple railway operators cooperate is tested. Game theory is used to share orders between different operators, and fairly distribute gains. The strategy is compared to a benchmark case, which shows costs and efficiency for the current way of operating.

5.1. The Feeder Train Scheduling Problem as a Cooperative Game

The input of the FTSM can be the demand and the locomotives of a single operator, but can also be used in a cooperative approach. In that case, the coalition determines the demand solved for, with the locomotives of the coalition. In this cooperation, full data and locomotive sharing are assumed.
In Figures 5.1 and 5.2 the resulting terminal occupancy with and without cooperation are shown. By cooperation, order delivery by another operator is enabled, decreasing dwell times of terminals. A single, shared locomotive can execute multiple tasks at the same terminal and over the full network.
As a result of the locomotive capacity sharing, the terminals are only visited by a single locomotive, significantly reducing both used locomotives and occupied terminal time. As locomotive lease is costly, the costs for the coalition will reduce significantly. Furthermore, the decreased time at the terminal will lead to increased network capacity.
While the benefits for the full network are clear, the players need to be incentivised to enter or remain in the grand coalition. To do this, the final cost allocation needs to optimise for every operators' financial gain from cooperating. For this, the FTSM is implemented in the game theoretic framework, presented in the next chapter.

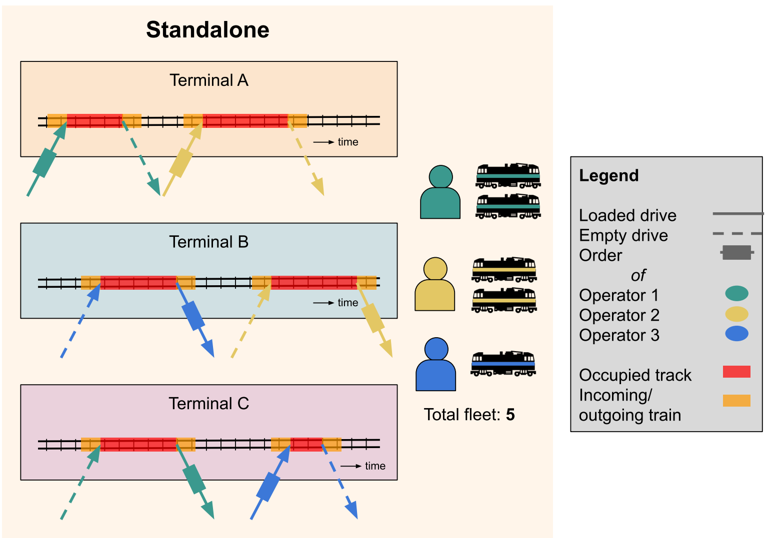


Figure 5.1: Three railway operators acting in silos, optimising for their own gain and not cooperating.

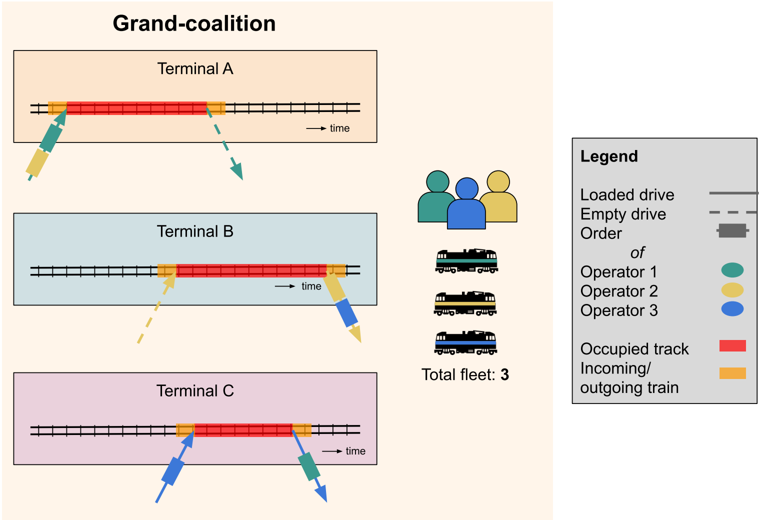


Figure 5.2: The grand coalition with the three players cooperating, where locomotives, orders and costs are shared resources.

5.2. Feeder Train Cooperative Game Framework

The cooperative game is implemented for the specific case of feeder train scheduling in the port area. Using the FTSM from 3, the game is denoted as (P, v).

5.2.1. The Game and its Players

Firstly, the player set is determined, where $P = \{1, 2, ..., p\}$ represents the railway operators that act as players. Every player has its own locomotives and orders, all with their own parameters. Other players, like intermodal operators and terminal operators are considered out-of-scope for this thesis.

These players are considered to be in a coalition, where their orders, locomotive and most importantly costs can be freely transferred, to compensate cooperation. The characteristic function, is $v : 2^P \to \mathbb{R}$. The function $v(S)$ gives the total costs incurred by (sub-)coalition $S \subseteq P$ when combining their resources and demand. The function does not consider any players outside of the coalition.

5.2.2. FTSM in the Framework

To determine all costs for the different coalitions, the FTSM is used. As the input of the FTSM are orders and locomotives, the coalition orders and locomotives are pooled and then used as the input. The orders O_S for coalition S is defined in Equation (5.1), and their fleet F_S in (5.2).

$$O_S = \bigcup_{i \in S} O_i \quad \forall S \subseteq P \tag{5.1}$$

$$F_S = \bigcup_{i \in S} F_i \quad \forall S \subseteq P \tag{5.2}$$

To then calculate coalition cost $v(S)$, the FTSM is used, where the result of the exact optimisation provides the cost. Thus, the characteristic equation becomes Equation (5.3). The visual representation is seen in Figure 5.3.

$$v(S) = \min\Bigg(\quad Z = \sum_{l \in F_S} \sum_{d \in O_S} \sum_{t \in T} \Big(C^{ldaily} u_l + C^{delay}\mathcal{T} \cdot td_d + C^{early}\mathcal{T} \cdot \epsilon_d + C^{away}\mathcal{T} \cdot \alpha_{l,t}$$
$$+ C^{nondelivery}(1 - \delta_d) + \sum_{ij \in A^M} C^{TKM} \frac{wgt_d}{len_d} \cdot y_{ij,d,l} + \sum_{ij \in A^{C\Delta} \setminus \{s_d, e_d\}} C^{yard}\mathcal{T} \cdot y_{ij,d,l} \Big) \Bigg) \tag{5.3}$$

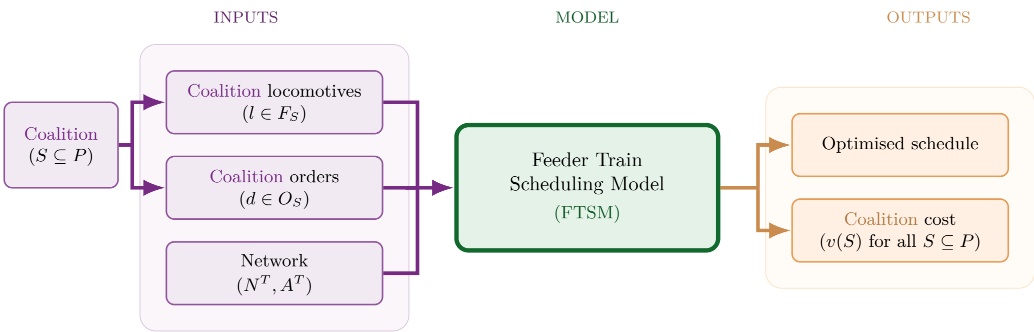


Figure 5.3: The use of the FTSM within the game-theoretic framework, where the locomotives and orders used are those of the coalitions. Adaption from Figure 3.3.

5.3. Profit and Cost Allocation Mechanisms

Using the resulting coalition costs from the FTSM, the saved costs are clear and need to be allocated to determine saved cost. Two strategies are explained below.

5.3.1. Shapley Value

The Shapley value awards the marginal contribution of each player, comparing the coalition cost with and without the player, for all possible coalitions. The gains from the player cooperating determines the cost allocated. In line with common definition, it is formulated as follows (Shapley 1953):

$$\phi_i^{Sh}(v) = \sum_{S \subseteq P \setminus \{i\}} \frac{|S|!(p - |S| - 1)!}{p!} [v(S \cup \{i\}) - v(S)] \tag{5.4}$$

Where ϕ_i^{Sh} is the assigned cost, or Shapley value, for every player i.

The Shapley value allocation is widely considered the most fair allocation, ensuring the marginal contribution of each player is rewarded. However, this fair solution does not always result in a lower cost for each player than its stand alone cost.

5.3.2. Stability and the Core

Though the Shapley value is a trusted method, it does not always guarantee a stable coalition. Therefore, the requirements for a stable game are discussed in this section.

Individual rationality (IR) is the first requirement for a stable game. For a game with cost allocation vector $\phi = (\phi_1, \phi_2, ..., \phi_n)$ where ϕ_i is the cost assigned to player i, IR is guaranteed if:

$$\phi_i \leq v(i) \quad \forall i \in P \tag{5.5}$$

This Equation (5.5) ensures that every player in the coalition, is assigned less costs than it accumulates in stand-alone operation. Next, for any sub-coalition S within P, assigned cost needs to be lower than in the grand coalition. This requirement is called group rationality (GR). The cost allocation satisfies GR when:

$$\sum_{i \in S} \phi_i \leq v(S) \quad \forall S \subseteq P \tag{5.6}$$

$$\sum_{i \in P} \phi_i = v(P) \tag{5.7}$$

Where equation (5.6) ensures the total of assigned cost within a sub-coalition is less or equal to the cost if the sub-coalition would not be part of the grand coalition. Equation (5.7) ensures efficiency, with the total assigned cost to be equal to the total cost from the FTSM.

Solutions that satisfy both IR and GR for all players and sub-coalitions reside in the Core, proving the stability of the coalition.

5.3.3. The Nucleolus

When the above-mentioned core is larger than a singular cost allocation, the nucleolus can be used to determine the allocation. The nucleolus strategy is based on the dissatisfaction of the different players, where it maximises the satisfaction for the grand coalition, by comparing the assigned cost to any sub-coalition. For this, the excess is calculated:

$$e(S, \phi) = v(S) - \sum_{i \in S} \phi_i \tag{5.8}$$

This represents the the excess of every coalition $S \subseteq P$ for a given cost allocation ϕ. In other words, the difference between the cost of the sub-coalition and the assigned cost. The higher the (positive) excess, the more satisfied the members of the sub-coalition are as they save more cost.

Next, a vector is made, sorting all excess values for all possible sub-coalitions (excluding grand-coalition and empty set) in non-decreasing order. The nucleolus maximises the smallest excess, then the second smallest excess and so on, until all excesses have been maximised. This lexicographical maximisation of $E(x)$ over the set of efficient allocations is defined as follows (Guajardo et al. 2016):

$$X = \left\{ \phi \in \mathbb{R}^p : \sum_{i \in P} \phi_i = v(P) \right\} \tag{5.9}$$

The result of this nucleolus method is an allocation that is guaranteed to be in the core, if it exists. In this allocation, all players and sub-coalitions have maximised satisfaction.

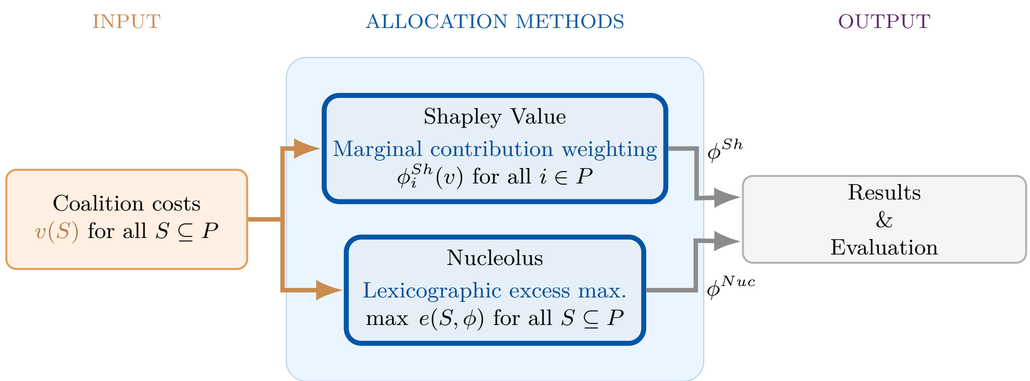


Figure 5.4: The process of calculating the resulting allocation vectors for the Shapley and the Nucleolus method.

The allocation calculation is summarised in Figure 5.4, where the coalition costs calculated with the FTSM are used with the definitions in sections 5.3.1 and 5.3.3 to calculate the resulting cost allocation vectors.

5.4. Implementation Barriers

While being a promising concept, the cooperative transportation strategy has some barriers that need to be considered before real-world implementation is realistic.

Firstly, cooperation in such a grand coalition requires data sharing, and assumes complete information. However, the port area is traditionally a conservative market, and data sharing is highly sensitive. To not deter possible players, confidentiality needs to be ensured, preferably by a neutral player, that is not an existing operator. This neutral player can also ensure the most optimal solution is used, where the shared fleet is used optimally.

The hesitant players need to be convinced to cooperate, with a large enough financial incentive. Therefore, the Core does not only need to be non-empty, but as large as possible. This way, the argument against data sharing does not hold against the gains.

The following chapter presents the experimental framework designed to demonstrate the feasibility of the cooperative game via small-scale tests.

6

Experimental Setup and Parameters

With the working mathematical model and game-theoretic setup, the next step is to represent reality by inputting realistic data. The network, system parameters and order data need to be representative of reality.

6.1. The Network

The network of nodes and arcs is an important input of the model, as the network provides the possibility for locomotives and orders to reach their destination. First, the network of Rotterdam is discussed, after which the time-space graph generation is discussed. Lastly, the modelling of network saturation is explained.

6.1.1. The Port of Rotterdam

The port of Rotterdam, as discussed in Chapter 1 consists of a main Havenspoorlijn, or port railway line (PRL), where the main yards are connected in series. The terminals at those yards, are connected with terminal arcs and represent NCBG. The map of the full port area can be seen in Figure 6.1. For example, the Maasvlakte (MV) area consists of multiple terminals, which are further defined in figure 6.2.

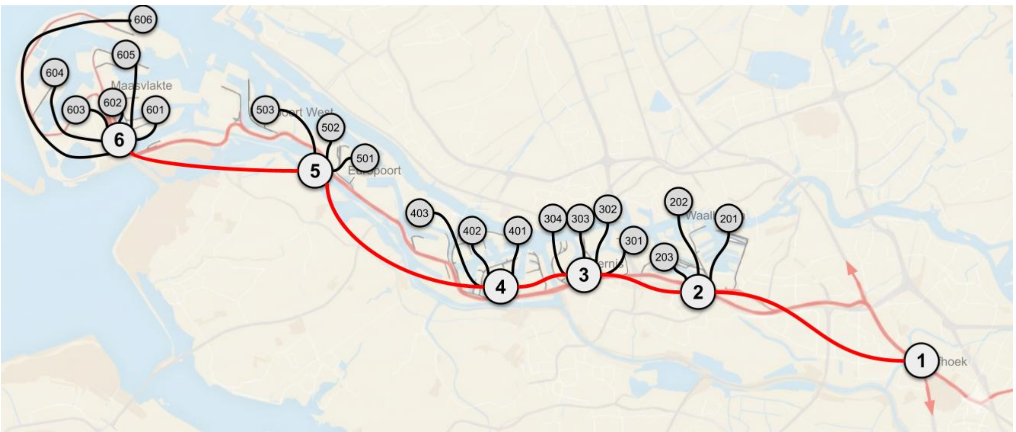


Figure 6.1: The port railway line (PRL) in red, with the terminal connections (NCBG) in black, from Table 6.1.

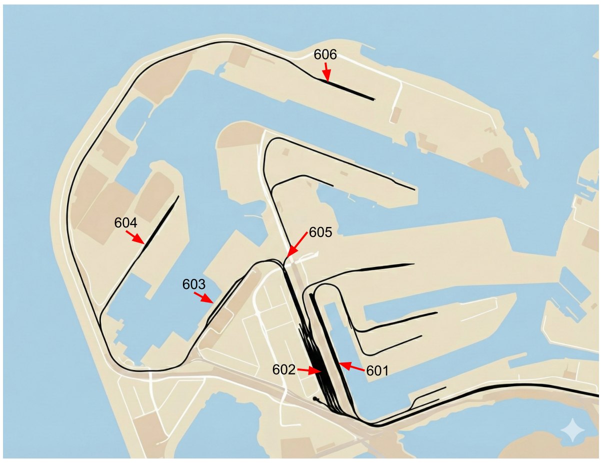


Figure 6.2: The Maasvlakte and its terminals.

Table 6.1: Mapping of Yards to Terminal Abbreviations, Full Names, and IDs

Yard	Abbr.	Full Terminal Name	Node
1	kfh	Kijfhoek	101
2	whz	Waalhaven Noord	201
		Heijplaat	202
		RSCW	203
3	ps	Matrans	301
		1e Petrohaven	302
		2e Petrohaven	303
		Vondelingenplaat	304
4	bot	3e Petrohaven	401
		Botlek	402
		Theemsweg	403
5	erp	Europoort	501
		Beneluxhaven	502
	erpw	Europoort W	503
6	mvt	Maasvlakte	601
	mvtw	Maasvlakte W	602
	mvtaho	MV Amaliahaven O	603
	mvtahw	MV Amaliahaven W	604
	mvtwn	MV W terminal N	605
	mvtyn	MV Yangtzehaven N	606

Based on railway operator data, the travel times for the different inter-yard arcs are presented in Table 6.2. The length capacity of all yards is 740m, while only for terminals at the Maasvlakte length capacity is 740m. Other terminals remain the dated 650m.

Table 6.2: The port of Rotterdam network in formulation, with specific parameters.

NodeID	NodeName	Length_Cap	NumArcs	End1	Trav1	Len1	End2	Trav2	Len2	TermID	couple_cap	cap_term
1	kfh	740	1	2	10	11.5				101	100	650
2	whz	740	2	1	10	11.5	3	6	4.7	201	100	650
										202	100	650
										203	130	650
3	ps	740	2	2	6	4.7	4	6	4.7	301	100	650
										302	100	650
										303	100	650
										304	100	650
4	bot	740	2	3	6	4.7	5	7	10	401	100	650
										402	80	650
										403	100	650
5	erp	740	2	4	7	10	6	15	13.8	501	100	650
										502	100	650
										503	80	650
6	mvtw	740	2	5	15	13.8				601	100	740
										602	100	740
										603	60	740
										604	60	740
										605	60	740
										606	40	740

6.1.2. Time-Space Graph Parameters and Construction

From the network mentioned in Section 6.1.1, the time-space graph is generated. Nodes are extended and connected in time.

Tick Size

An important parameter for accurate cost and computation time is tick size. This determines the total amount of arcs in the network. The calculated optimal cost increases with tick size, as the travel times between arcs are rounded up. Therefore, the time away from depot and time delay become larger. To determine which tick size is appropriate, a sensitivity test is done, of which the results can be seen in 6.3. It can be seen that the objective decreases with tick-size, and computation time increases. A plateau in objective function between tick-size 5 and 8 can be seen. Furthermore, the computation time drops fast from 3 to 4, further dropping until reaching a stable point at 8 minutes per tick. Therefore, for the following experiment tick size is chosen to be 8.

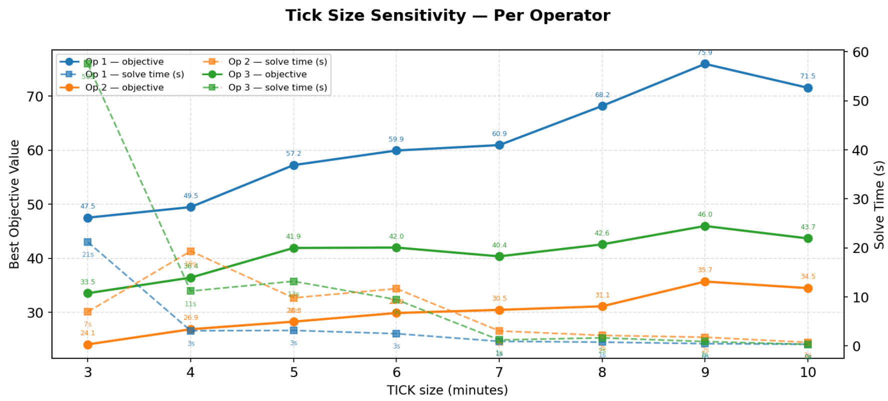


Figure 6.3: Three tick sensitivity tests, with optimal objective and computation time plotted.

Solution Approach

To increase computation speeds, both the flow first and the network sparsity, like discussed in Section 4.1.2, are implemented. The same experiment for tick-size is again executed where the tick-size is varied. It can be seen in Figure 6.4 that when increasing sparsity factor, objective function remains stable until 2, but then increases. Furthermore, while still dropping further, the decrease in computation time is relatively limited upon further sparsity rise. Therefore, for further experiments, a network sparsity of 2 is used, where 50% of arcs are pruned.

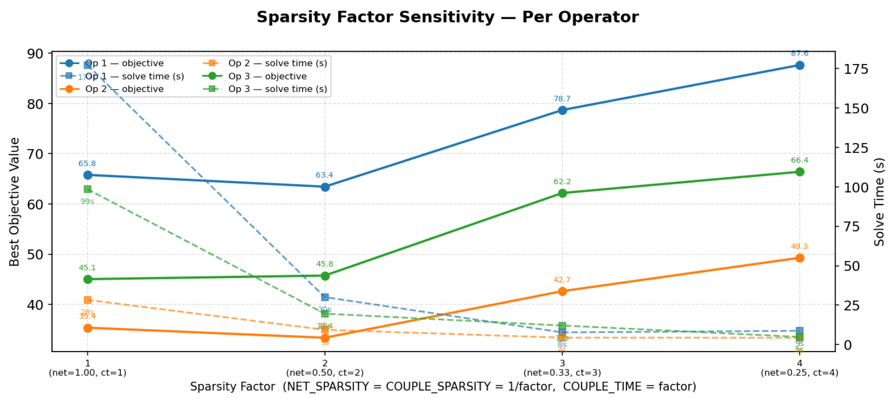


Figure 6.4: Computation time and optimal objective per sparsity factor, for three tests.

6.1.3. Network Saturation Implementation

To model network saturation, arcs are removed from the time-space graph. For both travel and terminal arcs, a percentage of arcs is removed, simulating occupied arcs. For travel arcs, based on the saturation factor random arcs are removed. For terminal arcs, based on the saturation factor, the arcs are removed in blocks. The blocks have a random length, with a mean duration of 30 minutes. Saturation factors for the different experiments can be found in Table 6.3.

Saturation rates	Travel arcs (CBG)	Terminal arcs (NCBG)
Empty (a)	0%	0%
Low (b)	15%	25%
High (c)	30%	50%

Table 6.3: Network saturation rates, based on expert approximations.

6.2. Demand Data Generation

6.2.1. Data Set

To substantiate decisions and input data into the model, a data set is provided by an operator in the port area of Rotterdam. This data set consists of two major sets, arrival and departures for full trains. The data is filtered for either arrival or departures in the Netherlands. The two files then consist of the following columns: row ID, origin point, end point, weight and length, starting and ending date and time. The files are for all transport in a full year, ranging from October of 2024 to September of 2025.

6.2.2. Data Distributions

To generate synthetic data that accurately reflects reality, the underlying patterns are modelled using the following distributions. It can be seen in Figure 6.5 the amount of orders per day is generated from a Poisson fit of the orders per day in the data. Then, all other data is generated from empirical distributions of the real data. The start and end node of trains are paired, where nodes in the port area receive their own system node, and all nodes outside the port area get assigned to the Kijfhoek. As due time is not present in the data, its distribution is taken from train arrival times. To ensure realistic order length and weight, and their ratio, they are determined on the empirical distribution of length, and the distribution of weight to length ratio.

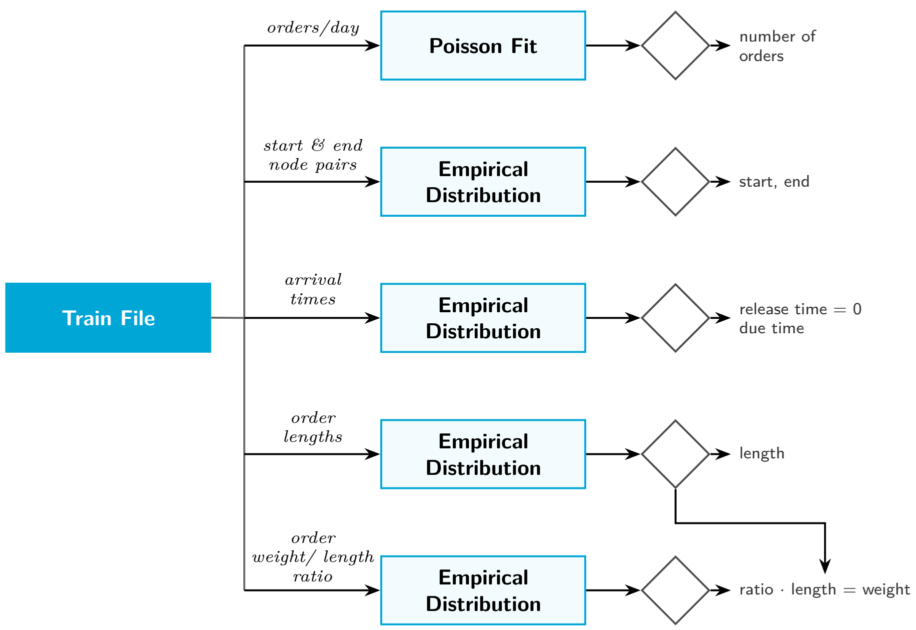


Figure 6.5: Data processing for per operator data generation.

Daily Order Count

The observed daily order count and its distribution fit can be seen in Figure 6.6. The mean amount of orders is $\lambda = 11$. For the experiments, the orders are filtered to be one working shift, from 7:00 to 14:00. The resulting $\lambda_{oneshift} = 4.1$ can be seen in Figure 6.7.

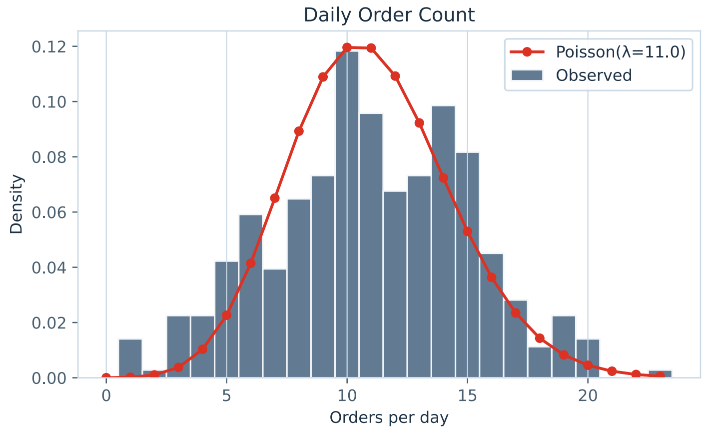


Figure 6.6: The observed amount of orders per day for the operator, with a Poisson fit.

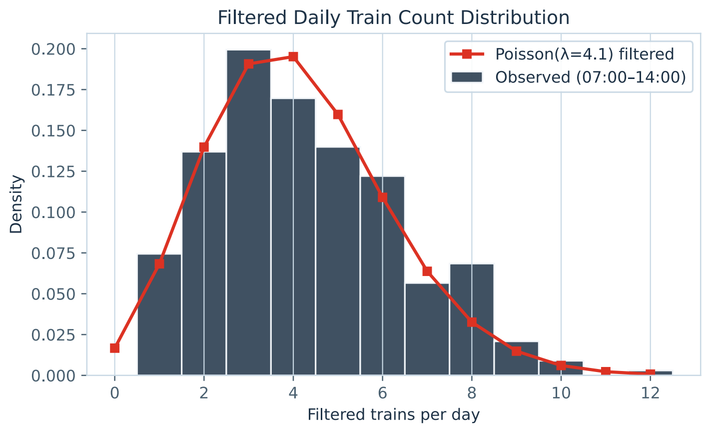


Figure 6.7: The observed amount of orders per day for the operator, in a shift from 07:00 to 14:00.

Duetime

It can be seen in figure 6.8 the delivery of orders is distributed quite evenly. The slight increase in orders between 7:30 and 11:00 is taken into account by the empirical distribution.

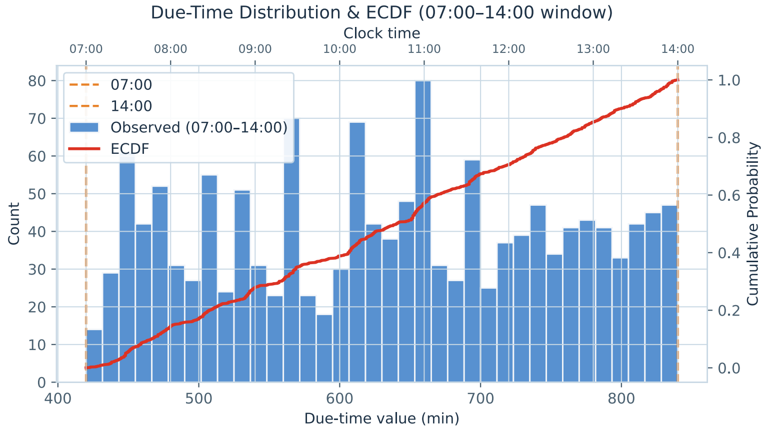


Figure 6.8: Observed arrival times for trains at terminals, used with a ECDF to generate due times.

Order Length and Weight

To determine the order length, the observed data is directly used to sample order lengths. The occurrence of certain order lengths is seen in Figure 6.9.

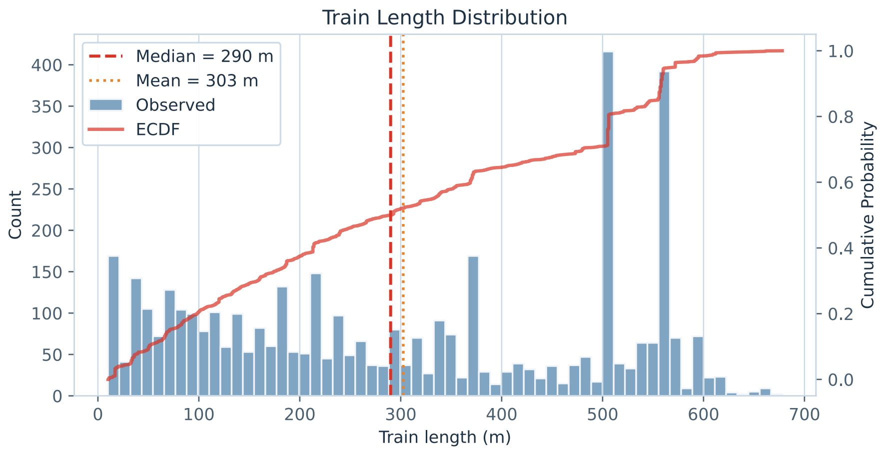


Figure 6.9: Observed order lengths in the operator data, and its ECDF fit.

The then generated order length is used in combinations with the weight to length ratio in the data. This ratio distribution can be seen in Figure 6.10.

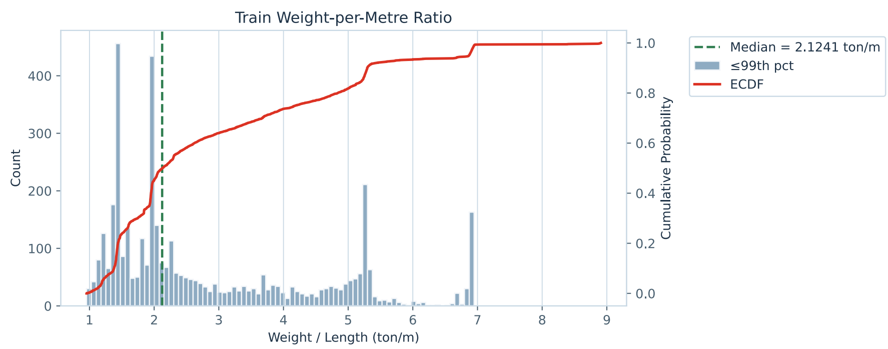


Figure 6.10: Observed weight to length ratios in the data, with ECDF fit.

6.3. Locomotives

Next to the network and orders, the third input of the model is the locomotives of the operators. Two common electric, and two common diesel/HVO locomotives and their properties can be found in Table 6.4.

Table 6.4: Performance Comparison of Common Port Locomotives

Model	Type	Weight (t)	Max Pulling Weight (t)*	Max Speed
Electric Locomotives				
Bombardier TRAXX (BR186)	E	84 t	2,940 t	140 km/h
Diesel Locomotives				
MaK DE 6400	D	82 t	2,810 t	120 km/h
Vossloh 1206	D	80 t	1,800 t	80 km/h

*Max pulling weight based on ”Algemeen” (General) homogeneous train ratings (DB Cargo Concept Tonnentafel v0.5).

6.4. Costs

Based on expert data, the different costs of operation are used as the cost parameters. To incentivise the model to deliver all orders, the penalty or not delivering an order is put at €50.000. Next, based on the approximation that a locomotive driver costs €100.000 per year, and the lease of a locomotive is €35.000 per month, the daily cost of a locomotive is €1500. The energy cost per driven TonKM for diesel and electric locomotives are €0.055 and €0.022 per TonKM respectively. The cost for a locomotive not being at its depot is determined by taking the average route fees in the port area. The parking costs are also determined by the infrastructure manager. Lastly, the delay and earliness costs are estimated, where earliness is penalised less by a factor of 4.

Table 6.5: Cost parameters for the FTSM multi-objective function.

Parameter	Description	Unit	Value[a]
$C^{nondelivery}$	Cost for not delivering an order	€	50.000
C^{ldaily}	Daily fixed cost for a locomotive	€	1500
C^{delay}	Cost for time delays relative to due time	€/min	10
C^{TKM}	Cost per tonne-kilometre of moved goods	€/TonKM	0.055 (D)
C^{TKM}	Cost per tonne-kilometre of moved goods	€/TonKM	0.022 (E)
C^{away}	Cost for a locomotive not being at its depot	€/min	4
C^{early}	Cost for time earliness relative to due time	€/min	2.5
C^{yard}	Cost for an order waiting at a non-terminal yard	€/min	$\approx$ 1.67

[a] *Note:* To ensure numerical stability during optimization, all cost values were scaled by a factor of 0.01 within the MILP solver.

6.5. Benchmarking

6.5.1. Greedy Algorithm

As comparison, a greedy algorithm is introduced, which focuses on just-in-time delivery. The algorithm sorts orders by due time, and starts with the earliest due time. Then, per order, it calculates the job duration, departure time for just-in-time delivery and compares the resulting delays per locomotive. The locomotive with the smallest delay is assigned. The route for the locomotive is added and its location is updated to the destination node after delivery. Before moving to the destination, idle time is checked, and if large enough for travel to depot, it does. After all orders are delivered, all locomotives return to their depot.

Like this, every order is assigned and the resulting cost is calculated. This algorithm, when the horizon is sufficient, results in a schedule where every order is delivered, where orders with earlier due time are prioritized.

Firstly, with the full locomotive set L the objective cost is calculated, after which locomotives are removed from the locomotive set to check if a better objective is possible.

Algorithm 1 Greedy Algorithm for Just-In-Time Locomotive Delivery

```
Input: Full locomotive set L, Set of Orders D
Initialize: BestCost ← ∞, BestSchedule ← null
CurrentSet ← L

while CurrentSet is not empty do
    Sort D ascending by due time
    for each d in D do
        MinDelay ← ∞
        AssignedLoco ← null
                                        ▷ Find the best locomotive for the current order
        for each loco in CurrentSet do
            Calculate JobDuration, DepartureTime for JIT, and Delay
            if Delay < MinDelay then
                MinDelay ← Delay
                AssignedLoco ← loco
            end if
        end for

                                        ▷ Execute delivery and update states
        Assign order to AssignedLoco
        Add route and update AssignedLoco location to destination node
        Check IdleTime of AssignedLoco
        if IdleTime ≥ Time to Depot and back then
            Move AssignedLoco to Depot
        end if
    end for
                                        ▷ Finalize schedule for the current locomotive set
    Return all locomotives in CurrentSet to Depot
    TotalCost ← Calculate objective cost of current schedule
    if TotalCost < BestCost then
        BestCost ← TotalCost
        BestSchedule ← current schedule
    end if
    Remove selected locomotive(s) from CurrentSet
end while

return BestCost, BestSchedule
```

The pseudo code in Algorithm 1 summarises the steps in the process. The resulting 'greedy' schedule consists of single order paths, and orders with more weight than the locomotive capacity cannot be moved. That said, the resulting schedule is a realistic solution to the problem and could definitely work in practice.

6.5.2. Zoning Approach

To further compare the results to a real-world port railway transportation approach, the zoning approach used in the Port of Antwerp is used. In Antwerp, the port area is split up into 9 zones, which all separately get assigned one operator, which provided the most attractive offer.

To test this approach in the Port of Rotterdam, the port is divided into three distinct zones, based on buysness. The first zone consists of the Waalhaven and Pernis, the second zone Botlek and Europoort and finally the Maasvlakte (Figure 6.11). An order belongs to a certain zone when the order moves between the Kijfhoek and the zone, or when it starts in the specific zone. The zone then gets assigned an operator. The zone-orders and the locomotives of the operator then are used as the input of the

FTSM, which calculated the resulting operator cost.

To compare the result to the grand coalition results, the amount of locomotives used and final objective cost of the different zones are summed.

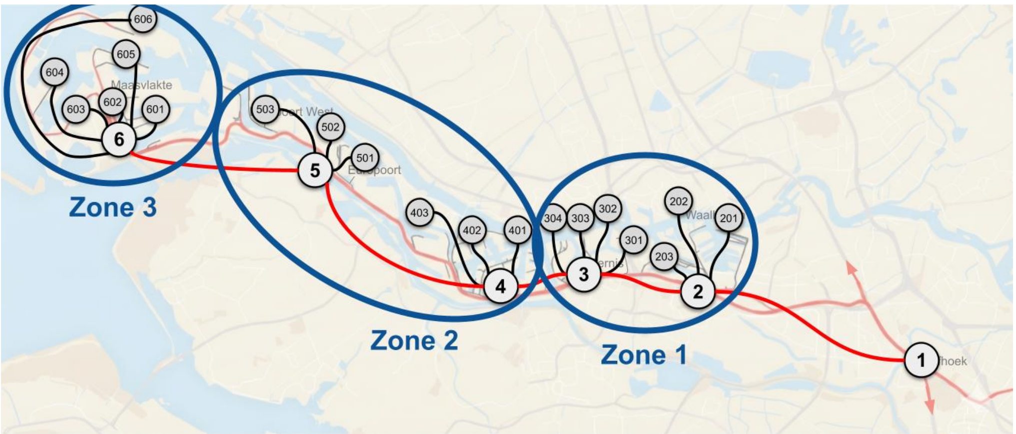


Figure 6.11: The port railway zones for the zonal division approach.

6.6. Experimental Design

6.6.1. Experiment 1: FTSM Benchmark

Firstly, the presented model from Chapter 3 is benchmarked against the state-of-the-art in railway feeder scheduling. As benchmark, the Greedy approach from Section 6.5.1 is used.

Two scenarios are tested, one with homogeneous operators and demand and one with varying operator depot locations. In scenario 1, all operators have similar order amount, with the same distribution over the network. All operators are located at the Waalhaven Zuid. In Scenario 2, the demand is the same as scenario 1, but the depot locations of the operators are the Kijfhoek, the Waalhaven-Zuid and the Maasvlakte. Exact orders and locomotives can be seen in Appendix B.

The goal of experiment 1 is to show the improvements made by the FTSM, where for the different scenarios all stand-alone and coalition costs are calculated, and used to calculate the Shapley and Nucleolus allocations. The cost savings, both with and without cooperation are compared.

6.6.2. Experiment 2: Network Saturation

To investigate the influence of network saturation on the game, both scenario 1 and 2 are used again. Furthermore, a scenario in which the sizes of the operators vary is added. The order count of the second operator is double that of the other two, the locomotive count is 3 and the smaller operators get 2 lower capacity locomotives or a single locomotive. Again, specifics can be found in Appendix B

6.6.3. Experiment 3: Diesel and Electric Operators

As in the railway network, most long-haul orders arrive and leave using an electric locomotive, a scenario is tested where one operators only has electric locomotives. This operator is set to gain as in stand-alone operation, orders cannot be delivered. For the other operators, it will be tested if they still gain from the cooperation.

6.6.4. Experiment 4: Cooperative Approach Benchmark

With the zonal approach discussed in Section 6.5.2 as a benchmark, the cooperative approach using game theory is tested. Scenario 1, 3 and two extra homogeneous scenarios (5 and 6) are used.

The resulting locomotive use and objective cost are compared.

6.6.5. Experiment Overview

The above-mentioned experiments are summarised in Table 6.6.

Table 6.6: Summary of Experimental Design

Exp.	Focus	Scenarios & Setup
1	**FTSM Benchmark**	**S1:** Homogeneous (Waalhaven Zuid). **S2:** Varying depots (Kijfhoek, Waalhaven Zuid, Maasvlakte).
2	**Network Saturation**	**S1, S2** **S3:** Varying operator size.
3	**Fleet Composition**	**S4:** Two diesel and one electric operator.
4	**Cooperative Benchmark**	**S1, S3** **S5, S6** Homogeneous demand and operators.

From these experiments, the following KPI's will be compared:

- Objective cost.
- Allocated cost (Shapley & Nucleolus).
- Amount of locomotives used.
- Time travel arcs are occupied per delivered order.

Firstly, the objective function value will be compared. Being direct cost for the operator, it determines the stand-alone, sub- and grand-coalition cost. Together, they determine if the core is non-empty. Using these cost to calculating the Shapley and Nucleolus allocations, the stability of the coalition using both methods can be investigated. While being part of the objective cost, the resulting number of locomotives used in a solution still presents insightful results. Locomotive lease is the driving operator cost, and clear decrease in numbers therefore is an easily comprehensible result.
Then, used time on the network per order will be compared. As the usage of the current tracks is limited, the time the network is used to deliver an order displays a measure of network occupancy.

In the next chapter, results are presented for the scenarios.

7 Results

In this chapter, the results from the experiments discussed in Chapter 6 are presented. First, the FTSM is benchmarked against the greedy algorithm, after which the influence of network saturation is tested. Then, an only-electric locomotive operator is used to test the influence of deliverability of orders. Lastly, the cooperative approach is compared to the existing zonal approach.

7.1. FTSM Benchmark Results

To compare the FTSM to the greedy algorithm, scenario 1a and 2a are solved with both approaches. The full results can be seen in Tables D.1 and D.3.

7.1.1. Scenario 1a

For scenario 1a, it can be seen FTSM in all tests outperforms the greedy algorithms final objective cost. An average improvement of 17.7% is observed for single operators and 20.5% for the coalitions. Furthermore, the amount of locomotives used is reduced in 3 of 7 tests.

Table 7.1: Scenario 1a results: Comparison between Greedy and FTSM methods for single operators and coalitions. Orders delivered (Ord.), locomotives used (Loc.), final objective cost, gap, and improvement compared to stand-alone cost with the same method.

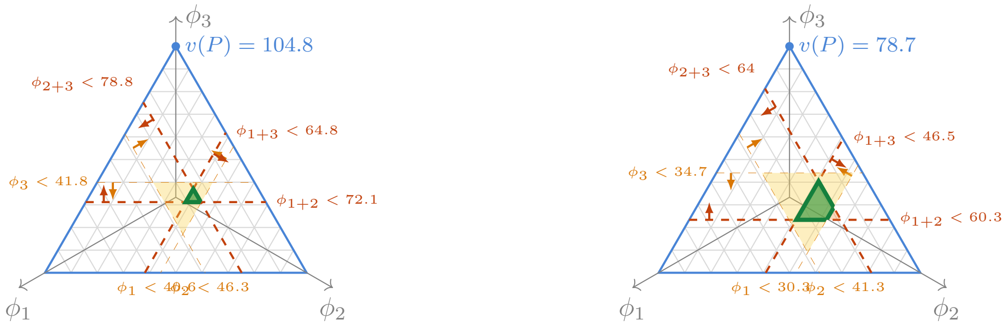
			Greedy			FTSM				
Instance	**# Ord.**	**Avai. locs**	**Ord.**	**Loc.**	**Cost**	**Ord.**	**Loc.**	**Cost (bnd)**	**Gap (%)**	**Improv.**
Single Operators										
1	4	2	4	1	40.6	4	1	30.3	0.0	25%
2	4	2	4	1	46.3	4	1	41.3	0.0	11%
3	4	2	4	1	41.8	4	1	34.7	0.0	17%
Coalitions										
{1, 2}	8	4	8	2	72.1	8	2	60.3	0.0	16%
{1, 3}	8	4	8	2	64.8	8	1	50.3 (46.5)	7.6	22%
{2, 3}	8	4	8	2	78.8	8	1	64.0	0.0	19%
{1, 2, 3}	12	6	12	3	104.8	12	2	78.7 (64.5)	18.1	25%

To present the game-theoretic results, Figure 7.1 is used. In the three-dimensional plot the blue triangle shows the plane of efficient solutions, where all costs are assigned. This blue triangle is called the (positive) imputation triangle. For each player, a line for its stand-alone costs is added in yellow, and the area in which the assigned costs is lower than all players' stand-alone cost is marked to be the IR zone. Then, for every sub-coalition, a line is added in red to signify the border of GR. The area in which IR and GR overlap, is marked in green, and is the core.

It can be seen that for both greedy and FTSM solutions the core is not empty (Figure 7.1). Using the FTSM increases the size of the core significantly however, providing a more stable game. The savings seen in the single operator gains using FTSM, now compound into a larger core.

Next, the allocations calculated and shown in Table D.2. For both the greedy and the FTSM test, the Shapley value satisfies the core bounds. Furthermore, the FTSM provides a further decrease of 7%

in objective value for the grand coalition, compared to the sum of stand-alone costs. This brings the total savings by cooperating to 19% for the greedy algorithm to 26% for FTSM. Using both FTSM and cooperative transport, the operators save 39.9% on average.



(a) Scenario 1a, solved by the greedy algorithm.

(b) Scenario 1a, solved by the FTSM.

Figure 7.1: The imputation triangles for the greedy and FTSM solutions of scenario 1a, with IR area (yellow), GR area (red), and the Core (green).

Table 7.2: Core size bounds, allocation stability, and cost savings compared to stand-alone cost for Greedy and FTSM algorithms (Scenario 1a).

Method	Op.	Core Bounds	Shapley Value			Nucleolus		
			Value	Gain (%)	$\in$ bound?	Value	Gain (%)	$\in$ bound?
	1	[26.0, 40.6]	30.3	25.4	✓	28.1	30.8	✓
Greedy	2	[40.0, 46.3]	40.2	13.2	✓	42.1	9.1	✓
	3	[32.7, 41.8]	34.3	17.9	✓	34.7	17.0	✓
	1	[14.7, 30.3]	20.1	33.7	✓	19.1	37.0	✓
FTSM	2	[32.2, 41.3]	34.4	16.7	✓	36.7	11.1	✓
	3	[18.4, 34.7]	24.2	30.3	✓	22.9	34.0	✓

7.1.2. Scenario 2a

Next, in scenario 2a the operators have different depots. Again, the tests are done for all coalitions, full result tables can be found in Appendix D.

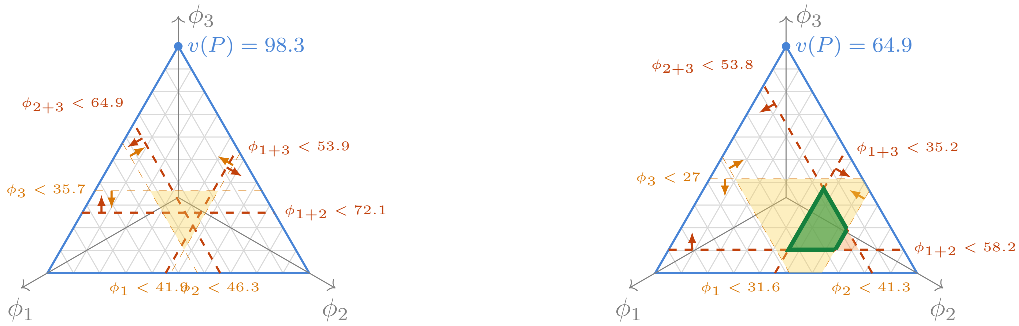
It can be seen in the result Table D.3, the objective compared to scenario 1 has remained stable for the single operator tests of operator 1 and 2, while 3 has decreased its cost. When comparing the sub-coalition results, this advantage operator 3 has can be seen in the sub-coalition cost decrease of {1,3} and {2,3} as well. For this test, it means the assigned new depot is more advantageous.

In scenario 2a, the greedy algorithm solution provides an empty core, seen in Figure 7.2. As the cost of the grand coalition and player 2 have risen, it is impossible to simultaneously satisfy GR for all sub-coalitions.

Using the FTSM however, all coalition costs again drop 19.5% on average. The grand coalition costs drops 34%, providing a large core. Using the benefits of the depot of player 3, the total average savings for each player compared to stand-alone, greedy optimisation reach 48%.

7.1.3. Discussion

In conclusion, the FTSM proves to be a more effective way of planning railway feeder services for the tested scenarios. Over the 14 tests done, the cost savings by using FTSM are 19.5% on average. Furthermore, by combining orders and locomotive capacities, FTSM can realise savings large enough to materialise the core. Next, the superior FTSM is used to investigate the influence of network saturation on the cooperative game.



(a) Scenario 2a, solved by the greedy algorithm.

(b) Scenario 2a, solved by the FTSM.

Figure 7.2: The imputation triangles for the greedy and FTSM solutions of scenario 1a, with IR area (yellow), GR area (red), and the Core (green).

7.2. Network Saturation Results

In the network saturation tests, for different scenarios, the busyness of the network is increased by pruning arcs. In an empty (a), low (b) and high (c) saturation, the homogeneous and different heterogeneous scenarios are tested. The results of the tests are presented in this section.

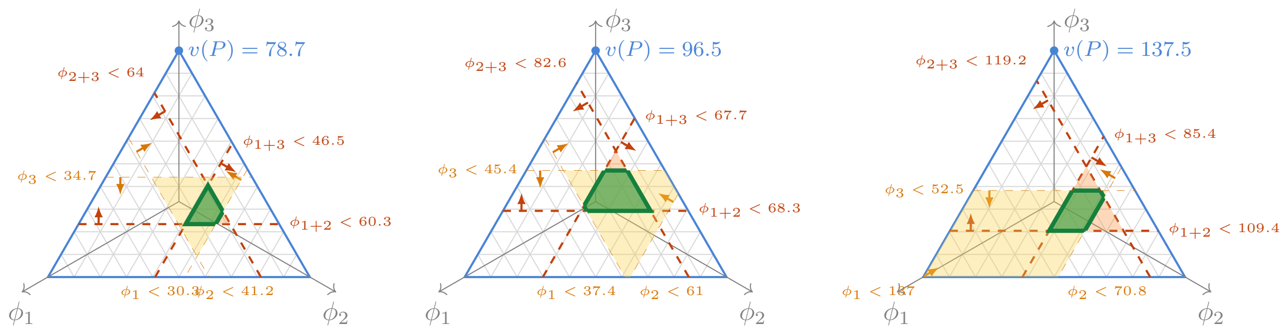
7.2.1. Scenario 1

In the first, homogeneous operator test, the costs for delivering all orders increase with network saturation (Table C.1). Furthermore, more locomotives are needed as paths can be blocked and time slots of NCBG area could not be reached with a single locomotive. Also, as the number of arcs is reduced, computation time and optimality gap drop.

It can be seen in Figure 7.3 the core exists for all tests, showing the area in which IR is guaranteed increasing in size with network saturation. Because an order of operator 1 is not delivered in stand-alone operation, its stand-alone cost is very high, causing every cost allocation for operator 1, even a negative one, to be sufficient for IR.

The Shapley allocation in 1c can be seen to not be in the core, caused by the non-delivery of an order in stand-alone operation. Operator 1 is dependent on the others for the delivery, and its marginal contribution to the grand coalition therefore is negative. Operator 2 and 3 get negative cost assigned, which means operator 1 pays to be a part of the coalition. This allocation violates the GR of {1,2} and {1,3}. The nucleolus provides a cost saving for all operators and sub-coalitions, as expected.

On average, the grand coalition saves 27% (a), 33% (b) and 42% (c) compared to stand-alone operation. This shows an increase in savings when the saturation increases.



(a) Scenario 1a (Empty).

(b) Scenario 1b (Low).

(c) Scenario 1c (High).

Figure 7.3: Comparison of core plots for Scenario 1 scenarios.

7.2.2. Scenario 2

When the depot locations of the operators are changed, cooperation is still beneficial.

Like mentioned in Section 7.1.2, the depot location of operator 3 is more optimal for this demand, seen in the reduction of cost for coalitions with operator 3. Furthermore, the core to imputation triangle percentage remains relatively stable with increasing saturation (Figure C.1). The negative influence of network saturation can especially be seen in the cost of coalition {1,2}, which has a large increase in cost.

Again, in the high saturation scenario, an operator cannot deliver its order, increasing stand-alone cost and forcing the Shapley value out of the core.

The grand coalition saves 38% (a), 39% (b) and 58% (c) for all viable allocations, preserving both IR and GR. The main benefit of this scenario compared to scenario 1 is the depot location of operator 3, decreasing cost for all coalitions with operator 3, also the grand coalition. Therefore, the IR in Figure C.1 can be seen to be larger than from scenario 1.

7.2.3. Scenario 3

Next, the operators are varied in size, where operator 2 has more orders than operator 1 and 3, and also more locomotives. Full demand and locomotives can be found in Appendix B.

For the empty network, cost savings when cooperating are large, the core therefore non-empty and the coalition stable. With this test the size of the core decreases with a higher saturation, in 3c even causing an empty core.

In scenario 3c, mainly because of a large grand coalition cost, the grand coalition is unstable. However, it can be seen in Table C.5 the MIP gap is large, and if with extra computation time the cost could go down, the coalition could become stable. The grand coalition saves 36% (a), 25% (b) and 7.3% (c).

7.2.4. Overall Saturation Results

Over all scenarios, it can be seen that cooperation decreases cost across all tests (Figure 7.4). In experiment 1c and 2c, it can be seen costs are very high, due to the non-delivery of orders. This shows the benefits of cooperating increase with network saturation.
Next, these costs savings need to be allocated. While individual rationality is guaranteed, the core becomes empty in experiment 3c, due to high (non-optimal) grand coalition cost. The non-delivery of an order in stand-alone operation in multiple cases destabilises the grand coalition when using the Shapley allocation, but the nucleolus solution is stable and viable for all non-empty core scenarios.

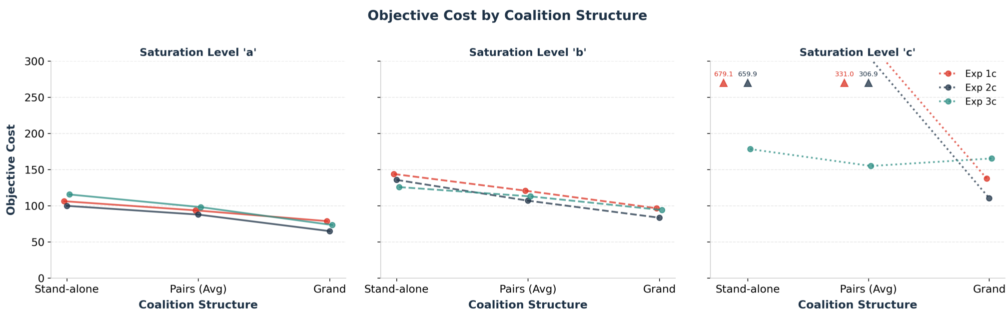


Figure 7.4: The objective cost per coalition size, per network saturation level. The sum of all stand-alone costs, average of sub-coalition plus stand-alone cost of player outside the coalitions and the grand-coalition cost are compared.

Next, it can be seen in Figure 7.5 cooperation structurally decreases the need for locomotives, where the drop is larger in high network saturation cases.
Lastly, the time travel arcs are occupied are also seen to drop with cooperation, again with a steeper slope with higher saturation levels.
In summary, the cooperation provides benefits in all measures, reducing costs and locomotive need, freeing up travel arcs and providing a stable grand coalitions.

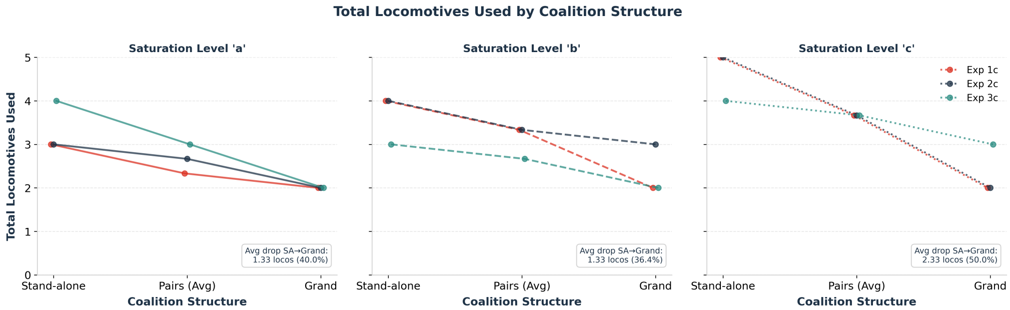


Figure 7.5: The number of locomotives used to deliver the orders, per coalition size, per network saturation level.

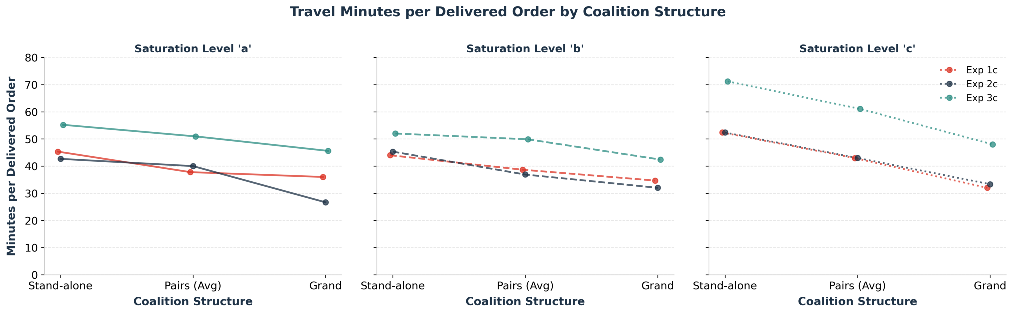


Figure 7.6: The number of minutes travel arcs are occupied per delivered order in the solution, per coalition size, per network saturation level.

7.3. Diesel and Electric Results

In scenario 4, two diesel operators and an electric operator are tested for the different saturation levels, with a non-empty core for all scenarios.

It can be seen in Table C.7 the stand-alone costs of operator 3 are very large, as it cannot deliver orders by itself. It can be seen in Figure C.3, the IR area is very large, due to the non-deliveries of the electric operator. In scenario 4c, an order of operator 1 is also not delivered, even further increasing the benefits of cooperation.

In the allocations, the result is that all Shapley values are not stable, as operator 3 pays to be a part of the coalition, violating GR for its own sub-coalitions. The nucleolus allocation is stable however, providing an average cost reduction of 29% (a), 40% (b), 58% (c) for the diesel operators. As operator 3 cannot deliver its orders without a coalitions, it benefits most from the coalition.

7.4. Cooperative Approach Benchmark Results

Finally, the cooperative approach is compared to the existing zonal approach. For four demand scenarios, the results are compared.

It can be seen in Figure 7.7, the zonal approach for homogeneous scenarios 1, 5 and 6 performs on approximately the same level as stand-alone operation. For the heterogeneous demand scenario (3), the zonal approach outperforms the stand-alone operation by reduction in objective cost of 19%. The grand-coalition decreases the total cost by 24.8% compared to the zonal approach.
Furthermore, the amount of locomotives used in the solutions can be seen to drop more significantly from zonal to grand-coalition (Table 7.3). Lastly, the zonal approach can be seen to only have an average decrease in travel arc usage of %

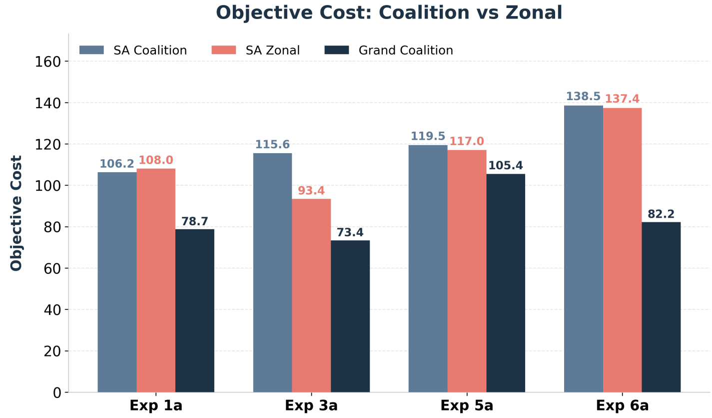


Figure 7.7: The resulting objective cost for the stand-alone (SA), zonal and grand-coalition operation, for the scenarios 1, 3, 5 and 6.

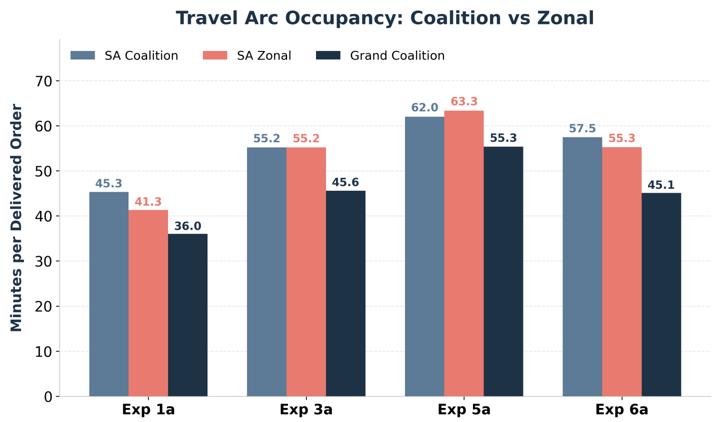


Figure 7.8: The resulting minutes of occupied travel arcs per delivered order for SA, zonal and grand-coalition operation.

Table 7.3: Number of locomotives used for Stand-alone (SA) operation, Zonal approach, and Grand Coalition operations across experiments (Exp.).

	SA	Zonal	GC
Exp. 1a	3	3	2
Exp. 3a	4	3	2
Exp. 5a	4	4	3
Exp. 6a	5	5	2

In conclusion, it is clear the cooperative approach consistently outperforms the zonal approach, both in objective cost as well as in occupied arc times. Because of the network properties, the amount of travel arcs used do not drop when using the zonal approach, defeating its purpose for this network. Furthermore, due to the cooperation all orders in the network can be combined, resulting in benefits in both locomotive use, arc occupancy and most importantly objective cost for operators.

8 Managerial Insights

From the results, some key practical take-aways can be taken, and used for policy-making.

8.1. Key Findings and Stakeholder Advantages

Firstly, the results show and prove the integrated scheduling provided by the FTSM consistently outperforms the greedy scheduling. The reduction results from combining orders and using multiple locomotives to carry heavier loads. The multi-objective optimisation balances the related costs, where the parameters can be tuned to increase the accuracy of the results.

Next, when multiple railway operators cooperate in the port area, the cooperators benefit directly by reduced cost and locomotive dwell time. The orders of the coalition are pooled and schedules integrated, providing reduced locomotive usage and empty drives. Furthermore, the used locomotives are used more effectively. The investigated coalitions are stable, where cooperators are not only better of than operating alone, but also than any sub-coalition. This result, seen in Section 7.2, presents proof and incentive for port-wide cooperation of railway operators.
On top of direct benefits for cooperators, the full railway network, including the port authority and the infrastructure manager, profit by reduced arc usage in the port area and therefore increased network capacity. The port authority enjoys the cost reduction for railway transport, helping its sustainability and modal shift goals. The infrastructure manager can use the increased network capacity as argument to not invest in new tracks, freeing budget for other congested railways. In this cooperation, not only cooperators benefit, but all stakeholders.

Compared to the existing and implemented approach of zoning the port area, the game theoretic cooperation further improves operational efficiency. The zonal approach is used in the port of Antwerp, and though it improves the operational efficiency compared to stand-alone operation, full cooperation is more efficient and provides even more advantages. Not only do the total cost drop, the involved operators all benefit instead of certain operators acquiring the orders and profits. Therefore, the focus of anyone looking to improve the operational efficiency should focus on cooperation instead of zoning.

In the end, the environment and society benefit from the cooperation, where the modal shift towards more sustainable transport is enabled. Using the railway network more effectively increases the amount of goods moved over rail, decreasing externalities of other modes. Society benefits from the sustainability of the railway network, further showing the effective yet unpopular public investment in the railway network, like the construction of the Betuweroute.

8.2. Path to Implementation

While these theoretical results are highly promising, transitioning from a mathematical model to a real-world application requires careful navigation of industry dynamics. To the author's knowledge, executing this would represent the first practical implementation of game-theoretic horizontal cooperation. Overcoming the inherent friction of a highly competitive market demands a strategic approach to implementation.

Firstly, the FTSM operates under the assumption of complete and static order knowledge. In daily operations, ad hoc changes, delays, and dynamic order arrivals are inevitable. Therefore, the FTSM should not be viewed as a fully autonomous scheduling system, but rather as a powerful foundational tool. It can be implemented to generate the optimal baseline schedule, allowing human planners and dispatchers to use it as a starting point and make the necessary real-time operational adjustments.

The traditional reluctance to share data within the port and logistics sector is a significant hurdle to realizing implementation. Operators currently operate in silos and view order data as highly sensitive. Becoming a "first mover" in the cooperation carries a perceived risk of losing competitive advantage. To overcome this challenge, establishing a strictly neutral player and communication is key.

Regarding the communicational challenge to railway operators, there are two main challenges. Firstly, the mathematical proof for the financial benefits needs to be accurately conveyed, to overcome the sector's conservatism. When operators trust the benefits, the resulting cost allocations present the next obstacle. While the Nucleolus allocation successfully guarantees mathematical stability, its implementation is not highly intuitive. The dense mathematical proof needs to be made transparent, understandable business logic. To achieve successful communication and implementation, the port authority, infrastructure manager and the prospective neutral player will likely need to coordinate their efforts closely.

In summary, with the right approach of neutral coordination and communication, this mathematical proof holds the clear potential to transform real-world port operations for the benefit of all stakeholders.

9
Concluding Remarks

9.1. Conclusion

This thesis shows that within the boundaries of the current railway network, major cost savings and operational efficiency gains are possible. Firstly, by scheduling using the proposed approach, orders can be combined and delivered by two locomotives. Compared to a greedy algorithm, daily cost savings in a range of 9 - 34% are achieved, with an average saving of 19.5%. This cost saving can be seen to enable a non-empty core and therefore a stable coalition of three operators.

When the network is increasingly saturated, the objective cost, locomotive use and load on the network drop. With an average cost saving of 34% for the grand-coalition, the core is non-empty in 93% of the tests. While the Shapley value violates group rationality in case of a non-delivery, the Nucleolus is able to transform the cost savings into stable coalitions. The cooperation finally benefits all stakeholders, by decreasing cost, load on the network and thereby enabling a modal shift towards rail.

Compared to the zonal approach that is already implemented in a different port, the Port of Rotterdam benefits most from the proposed cooperative approach. The zonal approach performs similarly to current operation, where the grand-coalition reduces cost by 24.8% over the tested scenarios.

In practice, this thesis provides a clear incentive for railway operators to cooperate, where a neutral planner and locomotive dispatcher plays a key role. The potential gains for a three-operator coalitions are clear, even proven valid for skewed coalitions. With large cost reductions prospective, the operators become better equipped to re-evaluate their conservative data-sharing stance.

9.2. Discussion

Major cost reductions are feasible in the tested hypothetical three player coalitions, however in this thesis there are some critical assumptions that need to be discussed.

The FTSM model presented in the thesis integrates the scheduling of the feeder problem, enabling movement of multiple orders with a single locomotive, or locomotives to combine to carry heavier loads. For this, it is assumed orders are known, and definitive in advance. In real operations however, orders are known at very different times, ranging from a year in advance to ad hoc changes. Next, major assumptions regarding the network are done. This thesis simplifies the railway network in the port area to six hubs, with terminals. The real network however is more complex, with characteristics like yard capacity and exact terminal distances disregarded in the used network. Also, data used to generate the orders used in the experiments is based on the data of a single port area operator. This results in a skewed view on the amount of orders, node pairs and due times. That last property, was not even available in the data, partly due to the earlier mentioned fluid nature of order knowledge. Furthermore, the objective function lacks a cost for the coupling and decoupling of orders, with redundant terminal arcs usage as a result.

In the game-theoretic scenarios, the benefits of cooperation are shown. While major cost reductions are feasible, their realism depend on some key factors. To start, full cooperation of all players is assumed. Data sharing in the model is complete and accurate. However, in the port area, data sharing between competing parties is very rare, and non-cooperation or even sharing inaccurate data could occur. Ensuring this does not happen in the grand coalition is pivotal. Next, the occupancy of arcs is not considered in the results. In reality, when operator 1 occupies a specific NCBG area, the other operators cannot reserve a timeslot. The result of implementing this into the optimisations would be growth of the Core, as stand-alone cost would increase due to more terminal arcs to be occupied. In addition, the tested scenarios have a small horizon, only representing a single locomotive drivers shift. While in theory cooperation would only provide more benefits the larger the horizon, this should be tested.

The two benchmarks done also have side-notes. As the specific problem has not been investigated before, the greedy algorithm is deemed the best there is. This algorithm is not used in practice, as operators plan on full human based processes. The comparison to the zonal approach in is limited by the small instance, as the number of zones in the test now is equal to the number of operators, diminishing gains by the approach. Likely, the zonal approach would perform better in a comparison where the amount of zones is significantly less than the number of operators in stand-alone operation. The grand-coalition is still expected to outperform the zonal approach in that case.

9.3. Future Work

To enable the practical implementation of cooperation of operators in the port area, this thesis already acts as proof that costs will be reduced. Before such a coalition will exits, multiple factors need to be further investigated.

Firstly, the presented model needs to be further validated with reality. Real ad hoc scheduling could be compared to not only ensure the performance of the model, but also realism. Furthermore, the cost (ratios) used in this thesis are based on expert opinion, but could be further increased in accuracy. Also, some orders may have larger costs for delays, terminals could be less or more busy than others and certain goods could take longer to check and therefore couple. These inhomogeneities could be included in the model.

Next, as already shown by the scenario 2 results, the depot location could be influential on the total cost of the operator or coalition. The FTSM model therefore could also be used to test the location of the depot, for more extended demand scenarios. Also, the model is tested using small instances, where a single shift on a single day is used as the horizon, and the order count in runs does not exceed 12. Furthermore, only three operators are used, where the original system has >20 operators acting. Using a high-performance computer, instances could be extended to see what influence that has.

In addition to computer optimisation, some real world test could be done, where trials with real orders and operators could be used to test the cooperation and its results. To achieve the implementation however, a study into the legal feasibility of the approach should be done.

Lastly, the model and game theory optimises for the port railway feeder system. It integrates railway operators, but further integration with both terminal operators and hinterland transport could be included, to see possible further cascading benefits.

AI Statement

AI Statement For this report for the course ME54035: MSc Thesis, I have used Generative AI to:

- Obtain inspiration for the overall structure of the report
- Improve the grammar, style, layout, and/or spelling of the text
- Implement mathematical models into code and/or produce code to process results.

In all cases I have reviewed and corrected the work and remain fully responsible for the content of the report.

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A. Integrated Scheduling Optimization for Railway Feeder Services in the Port Area

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Abstract Due to the globalisation of supply chains, the need for international transport of goods has increased for decennia. The impact of transport on the environment has gotten increased attention in the last few years, with different initiatives aiming to decrease emissions. While the EU has released a white paper stressing the need for modal shift towards rail transport, clear results remain absent. This paper explores improving the efficiency of the railway transport in the port area, specifically Rotterdam. The goal is to improve operational efficiency to both decrease direct emissions, and incentivise modal shift towards railway transport.

To achieve these gains, an existing mathematical model is adapted from ITT to railway feeder services, to optimise for a set of orders and locomotives. A multi-objective function is minimised, to combine orders, reduce locomotive use and improve on time delivery. The model is benchmarked against a greedy algorithm with different scenarios. Next, this feeder train scheduling model (FTSM) is used to investigate cooperative scheduling approaches. Cooperative game theory is used and the FTSM is run with stand-alone and pooled railway operators. Lastly, the cooperative approach is compared to the existing zonal approach.

Compared to the greedy algorithm, FTSM structurally yields less costs for the operators (19,4% cost reduction on average), leveraging the combined orders leveraging the combining of orders and the multi-objective optimisation. For all scenarios tested, cooperating yields benefits, with cost reductions ranging from 25% to even 58%, compared to stand-alone FTSM solutions. The stable coalitions presented by this paper present further gains in network capacity, as the pooled operators occupy less tracks. Compared to the zonal approach, the proposed cooperation yields a cost reduction of 24.8%.

This paper present a novel approach to port railway feeder services, with integrated scheduling and cooperation not only benefitting involved railway operators, but also the port authority and infrastructure manager.

A.1. INTRODUCTION

While railway transport is a proven environmentally friendly alternative to freight transportation by road, the amount of railway transport in the port of Rotterdam has decreased by 12% since 2022 (CBS 2024). The EU has presented its commitment to shifting 30% of road transport to other modes like rail, but clear results remain absent (EP et al. 2018). The pivotal interface of this transport, the railway maritime-hinterland connection in the port of Rotterdam, currently is an under-researched area. The transportation of freight by trains to and from ships occurs in a fragmented market, with decentralized coordination and multiple inefficiencies. The current way of operating these transports is in rigid schedules and delays are frequent and expensive. Multiple railway operators (>20) handle the freight, causing empty drives and prolonged idling. Core opportunities in operational efficiency lie in the significant reduction of operators and centralised coordination, posing benefits from a more integrated approach. Gains for the amount of on-time orders, robustness and emissions are probable.

A.1.1. Problem Formulation

Following the extension in capacity on both sides of the railway network of the Port of Rotterdam, the need for efficient railway operations in the port area has grown. On the sea side, the extension of the Maasvlakte in 2013 and the constant optimisation of terminal operations have increased demand. On the land side, the construction of the Betuwelijn in 2007 increased hinterland railway capacity. Central coordination in the port area remains underdeveloped however, causing the underutilisation of the railway network.

Multiple factors play a role in the lack of development of the railway operations, with strict legislation as a major problem. Mandatory load and brake checks increase turnaround times, and high trajectory costs further increase prices (Krämer

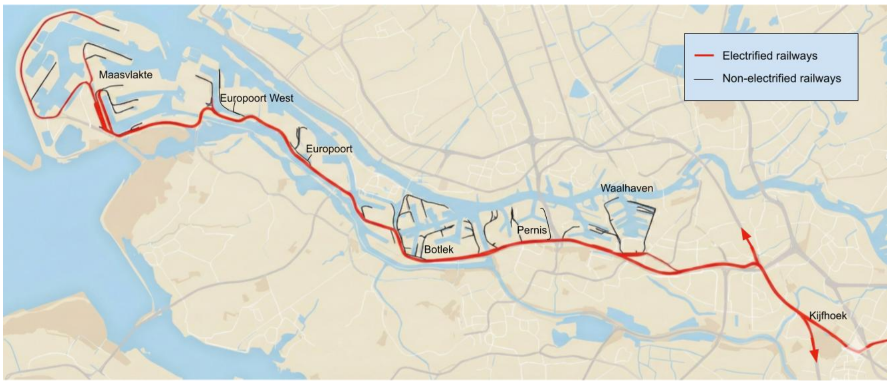


Figure A.1: The Havenspoorlijn of the port of Rotterdam.

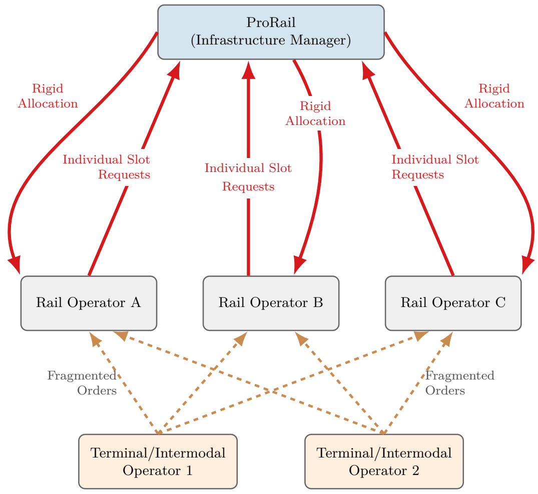
2019). The network, seen in Figure A.1, with a single track into and out of the port area of Rotterdam, presents further difficulties. The non-electrified and non-centrally operated areas (NCBG) towards terminals force locomotive switches for terminal delivery. Furthermore, as no signalling is present in those areas, it is unknown how effectively the reserved timeslots are used. Due to high competition, with more than 20 railway operators serving the port area, schedules are rigid and delays often accumulate. As modal choice is, in practice, mainly driven by cost and reliability, these factors need to be improved to increase the railway modal share. Therefore, this paper investigates the possibility of increasing the overall operational efficiency of the port area railway network, by collaboration of railway operators. Collaboration could not only relieve tight schedules in NCBG, but also improves the overall capacity of the network. Furthermore, to ensure operators are willing to cooperate, a significant financial incentive is required. Therefore, this paper examines multiple operator games, and checks stability of the cooperation, by using cooperative game theory.

A.1.2. Stakeholders

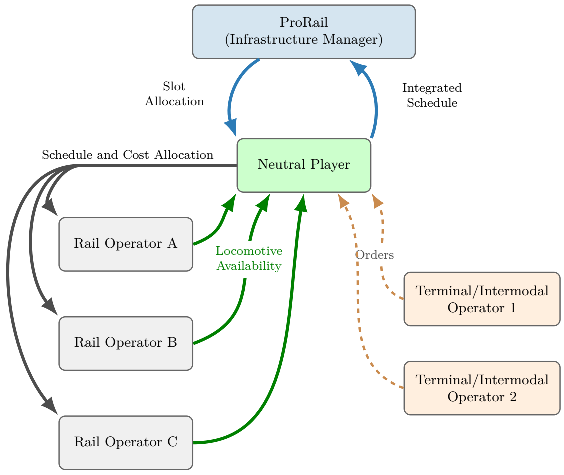
The current railway transportation system consists of many players and to significantly improve operations, their goals and interactions need to be clear. Therefore, in this section the stakeholders are analysed. Firstly, the **railway operators** themselves are very important. In the port area, they directly compete over the same profits (Gumuskaya et al. 2020). While some operators may cooperate occasionally, it is rare. The second major player group is the **clients** of the railway transport, which includes both intermodal and terminal operators. Intermodal operators use the intermodal transport chain to move goods, choosing the best path (Hu 2019). Terminal operators are a link in this intermodal chain, possessing a terminal in which they tranship goods (Gumuskaya et al. 2020). These players also have the same interest in the railway transport, which is the on-time delivery of their goods. Next, the **port authority** (Port of Rotterdam) has a major role. Its goal is for the whole port to remain competitive with other ports, so to be an efficient and economic system (Gharehgozli et al. 2017). Their interest in efficient railway transportation is therefore large. In Rotterdam, due to joint ownership by the municipality and the state, its political power is large, but its practical influence remains limited. The **infrastructure manager** (ProRail) of the railway network is the next stakeholder. Not only do they manage the construction and maintenance of the tracks, they also determine which train operators get which track at which time (Gestrelius 2022). While a more efficient transportation system decreases the load on the network and the need for expansion, their interest is less significant than the above mentioned players. The power of the infrastructure manager is often limited, by legally being bounded to a fair allocation between operators.

Currently, the operations are fragmented, where clients choose an operator, which optimises for their own gain. Their schedule is forwarded to the infrastructure manager, which assign their slots. These silo like data flow causes the resulting schedule to be rigid, the network to be overly saturated and inefficient (Figure A.2a). While the port authority has interest in the improvement of the system, it is not currently involved in the scheduling and railway operations.

In the proposed structure, a neutral player gathers all orders and available locomotives, makes an integrated schedule optimising for the full network, and coordinates this schedule with the infrastructure manager (Figure A.2b).



(a) Current stakeholders and their interaction.



(b) Proposed cooperation structure.

Figure A.3: Current and proposed stakeholder interaction.

A.1.3. Methodology

The following methodology is used to structurally investigate the problem, after which the solution is proposed and tested: first, in Section A.2, the state of the art of the problem is investigated. Different subjects within inter-terminal transport are investigated: terminology, the urgency and optimisation methods. The resulting research gap is presented. Next, a mathematical model is proposed in Section A.3, to solve the scheduling of the port area freight movements by rail. Then, this is used as the basis of a game-theoretic framework (Section A.4), and experiments to test this cooperation are made based on real operator data (Section A.5). Multiple scenarios are tested, where orders and locomotives of three operators are pooled and a schedule is made for the grand coalition. Lastly, the results of the different scenarios are presented and conclusions are drawn in Section A.6.

A.2. LITERATURE OF PORT RAILWAY FREIGHT TRANSPORT

A.2.1. Terminology

Because the specific problem in A.1.1 is not researched in literature, multiple terms to describe the problem are considered. Finally, the term *railway feeder services* is chosen for this paper. While feeder services are mainly used for describing barges ”feeding” large maritime ships, it accurately describes the role of railway operators in the port area. There, the operators act as the interface between hinterland long-haul railway transport, and the maritime ships. The feeding of the maritime ships thus can also be executed by trains.

A.2.2. Current Operations and Solution Approaches

Currently, the railway operations in the port area are inefficient, with many operators (>20) serving the demand on a small network. The main port railway in Rotterdam (havenspoorlijn (PRL)), consists of a single line in, and a single line out of the port. It connects the multiple marshalling yards, which connect to the terminals. The railway operators on this network compete for the same profit, presenting difficulties (Maitra 2016).

Operationally, the consequences are empty drives and compounding time delays. Before a train can depart after it is loaded, extended safety checks both physically and administratively are required. Combined with regulatory brake checks, this results in trains remaining in the port for an additional 2 hours (Ambrosino et al. 2021). Furthermore, empty drives are common, and when one part of the transport chain is delayed, this often compounds into large delays in further steps, as delays in the rigid schedules have big consequences (Hu et al. 2019).

These inefficiencies have both direct and indirect economical impact, by the resulting delay and mode choice. The direct cost of delays, extra fuel used for empty drives and extra maintenance due to an increased amount of distance covered by equipment are evident. Less apparent are the external cost of these efficiencies. These externalities consist of cost for society, by emitting greenhouse gases, congestion and accidents (Maitra 2016; Ypsilantis et al. 2019). The cost-effectiveness of road transport is only perceived, as resulting costs for four times as much emissions compared to trains and barges, is paid by society (Maitra 2016; Guo et al. 2023).

To solve the above-mentioned problems, there are two main routes of solutions, political and operational.

Multiple policies are discussed and tested in literature, with differing results. Guo et al. (2023) investigates subsiding the construction of railways and road, which could increase network capacity and reduce congestion. However, they conclude this could cause induced demand and result in losses. Another option considered, is rail transport subsidies. Santos et al. (2015) presents this as the most effective option to enable the modal shift to rail transportation, where it causes a significant increase in rail transport volumes.

Next, the internalisation of the external cost (IEC) mentioned earlier, presents itself to be effective in shifting modal flows from road to rail. Multiple studies show this IEC-pricing’s effectiveness in the modal shift and reducing emissions (Dai et al. 2018; Guo et al. 2023). On the other hand, Santos et al. (2015) mentions the sensitivity of the policy to model assumptions, and care needs to be taken when designing such a policy.

Further gains can be achieved by improving operational efficiency, where limited investments in infrastructure can lead to significant gains. While rail transport can be stiff, and a mind shift could be needed for change, synchromodal transport could be a solution (Riessen et al. 2015). Next, the extension of port area further into the hinterland is considered. This concept is known as dry ports, or extended gate when controlled by the port authority (Bouchery et al. 2015; Gumuskaya et al. 2020). Abu-Aisha et al. (2024) shows the effectiveness of these terminals, showing the increase connectivity of the port area.

While these operational improvements could provide benefits for the railway network, their implementation requires either large financial investments, or full cooperation of many parties. Furthermore, the congested NCBG areas are still not addressed.

To the authors knowledge, the port area railway feeder operations have not been optimised for, posing a gap. As the first and last mile is often a burden for long-haul operators, centralising these operations could prove to improve the operational efficiency of the full rail network in the port area.

A.2.3. State of the Art Optimisation

While the exact railway feeder problem has neither been described, nor optimised for, inspiration is taken from multiple modelling approaches, comparing their properties and options.

On strategic level, location allocation (LA) is used to determine the ideal hub-location. Santos et al. (2015) provides a model for rail-terminal allocation and Rattanakunuprakarn (2025) shows the influence of upgrading road logistics centres to rail-road terminals. While eventually the favourable location will yield operational benefits, their implementation remains slow and capital intensive. Discrete event simulation (DES) is used to research the behaviour of systems, and can be used to test the influence of different decision making processes. In ITT processes it is used to test different fleet compositions, providing insight in the resulting cost or delays (Duinkerken et al. 2006; Schroër et al. 2014). This however only simulates results, and does not provide an optimal solution.

As basis of many optimisation models, the travelling salesman problem (TSP) does provide the optimal solution to the problem. For a single vehicle, the route between different nodes is optimised. The fleet is singular and flexibility therefore is low.

The vehicle routing problem (VRP) introduces the endogenous sizing of the fleet, providing the required optimisation flexibility. Despite that, it is focussed on routing and due to the limited options in the railway network, it application would be restricting.

Therefore, the inter-terminal model, presented by Tierney et al. (2014) is the most applicable for this problem. The size of the fleet can be optimised by the model and a mixed fleet of locomotives can be used.

However, the model does not track vehicle across the network and consists of low-capacity vehicles, like is needed for the railway feeder services. Therefore, before it can be applied, the model needs to be adapted from the ITT network to the railway feeder services.

In conclusion, the gap this paper aims to fill is the combination of linear operational optimisation integrated with game theoretic collaboration. Improving the railway operations in the port area provides the much needed start in modal shift towards environmentally friendlier freight transportation modes. For this, the next section will present the optimisation model.

A.3. FEEDER TRAIN SCHEDULING

With the model from Tierney et al. (2014) as the basis, an adaptation is presented in this section.

Table A.1: Literature overview and research gap. ✓ = fully addressed, ○ = partially addressed, - = not addressed.

Study	Focus	Policy approach	Operational optimisation	Port area railway focus	MILP scheduling	Cooperative game theory
Santos et al. (2015)	Rail subsidies & IEC	✓	-	-	-	-
Guo et al. (2023)	Modal shift policy mix	✓	-	-	-	-
Dai et al. (2018)	Sustainable IEC pricing	✓	○	-	-	-
Tierney et al. (2014)	ITT MILP model	-	✓	-	✓	-
Hu et al. (2019)	ITT–hinterland rail integration	-	✓	○	○	-
Riessen et al. (2015)	Synchromodal transport	○	✓	-	-	-
Duinkerken et al. (2006)	ITT DES	-	✓	✓	-	-
Schroër et al. (2014)	Maasvlakte DES evaluation	-	✓	✓	-	-
Gharehgozli et al. (2017)	Collaborative ITT solutions	-	✓	✓	-	○
Ambrosino et al. (2021)	Rail-sea intermodal terminal	-	✓	○	○	-
Ypsilantis et al. (2019)	Collaborative fleet deployment	○	✓	-	-	○
Gestrelius (2022)	Train timetabling optimisation	-	✓	-	✓	-
Guajardo et al. (2016)	Cost allocation review	-	○	-	-	✓
Prokić et al. (2025)	Rail corridor governance	○	✓	-	○	✓
Lyu et al. (2025)	Port berth allocation	-	✓	○	✓	✓
Shapley (1953)	Cooperative Game Theory	-	-	-	-	✓
This Paper	**FTSM + cooperative game theory, Rotterdam port area**	○	✓	✓	✓	✓

A.3.1. Feeder Train Scheduling Problem Definition

Accurately optimising the railway feeder problem requires a model which based on a realistic objective function optimises the schedule for a set of orders, with a set of locomotives over a specific network.

The network consist of a port area railway network. Often, the network consist of a main, electrified railway line. This main corridor connects different yards, with multiple non-electrified terminal areas. This necessitates the use of diesel or hybrid locomotives for final delivery to a terminal. As most long-haul transportation in Europe is done by electric locomotives (Krämer 2019), the needed locomotive switch presents itself as a system boundary.

Then, the orders of the clients consists of the following data: origin, destination, due time, length and weight. The clients generally do not only seek on-time delivery, but prefer just-in-time delivery. These are the basic characteristics, where information about goods type, priority or profits are kept out of scope.

The locomotives used have the following properties: weight capacity, depot node (from which they start and where they end) and type D/E (diesel or electric). This last property determines whether a locomotive is able to deliver orders to terminals, which connections often are not electrified.

Next to these characteristics, the following assumptions are done:

- Orders are all known and definitive.
- Distances between nodes are represented as fixed travel times.
- There are no disruptions in the network, all travel times remain constant.
- Order weight is linear with order length.
- Coupling and decoupling are proportional to order length.

A.3.2. MILP Formulation

By adopting the model to the requirements of the port area feeder services characteristics, the system can be distilled into a solvable problem. In this section, the changes to the base model are discussed.

Base Graph Construction.— Like the base model from Tierney et al. (2014), the time-space graph consists of a base graph $G = (N, A)$ which is extended through all time-intervals τ to $G^T = (N^T, A^T)$. Like the base model, our graph contains two types of nodes, yard nodes and terminal nodes. Yard nodes represent the locations in the port area which contain a yard with multiple tracks, where a train can stay for a longer period of time. Yard nodes are interconnected and enable transport of both locomotives and orders. These yard nodes get at least one duplicate, a terminal node. This node is used to model different terminals present at the yard. The couple capacity can be used for different terminals, to model different (de)coupling times. Locomotives are able to travel from yard node to yard node, traversing every A^M. Orders can move on travel arcs, but also travel between yard and coupling nodes, so called terminal arcs $A^{C\Delta}$.

Stationary arcs are used to allow locomotives and orders to stay in the same place for an extended period of time. Both yard and terminal nodes are connected with themselves in the next time step. Because only orders can travel to terminal nodes, only orders can traverse terminal stationary arcs A^{SB}. After being coupled, orders cannot traverse a stationary yard arc A^S without a locomotive. This ensures that before moving through the time-space graph without a locomotive, it needs to be decoupled and vice versa.

To ensure an order is not instantly coupled to a wagon, the coupling arcs A^C are constrained with a length capacity, which acts as the maximum amount of an order that is coupled in that time step. This ensures coupling is length dependent, and includes the real-life checking of wagons and the required brake check. For decoupling, the capacity of the decoupling arcs cap^{Δ} is higher, as no brake check needs to be performed. While the coupling and decoupling arcs are a direct adaptation from the LT arcs mentioned in Tierney et al. (2014), they have a significant difference which is the fact that couple arcs are connected to their yard node not in the same, but *the next* time step. This increases coupling time but also improves accuracy for the railway network. Another difference is that to couple or decouple an order, a locomotive needs to be waiting at the yard node during the same time. Coupling can be seen in Figure A.4.

Network Saturation.— Another adaptation from the base model is the modelling of congestion. In Tierney et al. (2014), congestion is modelled as arcs with longer travel times. Congestion in the railway network is fundamentally different, where travel times remain stable, but arcs may not be available. Therefore, congestion is modelled as follows.
Two network saturation factors are used, one to model congestion in the CBG, the other for NCBG. Firstly, the saturation of the travel arcs is modelled with factor ξ_{CBG}, with indicates the fraction of travel arcs randomly pruned from the base graph. The removed arcs model other operators moving over CBG trajectories, blocking it in the schedule of the considered operator.
Next, ξ_{NCBG} signifies the factor of arcs pruned in from the terminal arcs. These arcs are not randomly deleted, but an average block time is chosen. Blocks of time are then removed per terminal, modelling the occupancy of the time slots in the NCBG areas.

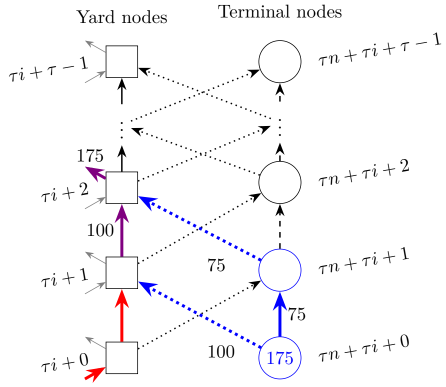


Figure A.4: The coupling of an order of 175m of wagons, with couple capacity 100m per time step. The locomotive (in red) arrives at the yard at the first time step, starts loading the order and leaves the yard node with the full order (in purple) at the third time step. The order moves (in blue) from the terminal node to yard node over two time steps. Figure adapted from Tierney et al. (2014).

Orders and Locomotives.— Orders are used as an input of the system, with key characteristics like start and end node s_d and e_d, release time re_d, and due time du_d. The length and weight of the order $len_d \& wgt_d$ are also included. Orders start at a terminal node, from which it has to be coupled and then with a locomotive travel to other nodes. After reaching their desired yard node they get decoupled to their destination, a terminal node again. The properties of locomotives regarded are its weight capacity cap_l^{wgt} and its depot node dp_l. Locomotives start at their depot node, and also return there at the end of the optimisation.

The following sets, parameters and (auxiliary) variables are used in the MILP model, presented in Tables A.2 and A.3.

Symbol	Description	Domain
Decision Variables		
x_{ijl}	Locomotive l moves over arc $(i,j) \in A^L$	{0,1}
y_{ijdl}	Meters of order d moved over i,j by l	Cont.
u_l	Locomotive l is used	{0,1}
δ_d	Order d is delivered	{0,1}
Auxiliary Variables		
td_d	Time delay relative to due	Cont.
ϵ_d	Earliness relative to due	Cont.
α_{lt}	Locomotive l away from dp_l at t	{0,1}
$\gamma_{ij,d}$	Order d on arc $(i,j) \in A^M$	{0,1}

Table A.2: Decision and auxiliary variables of the model.

Symbol	Description	Domain
Sets and Indices		
L	Locomotives set	$l \in L$
L^D, L^E	Diesel/Electric subsets	$l \in L$
D	Orders set	$d \in D$
T	Discrete time steps	$t, \tau \in T$
N	Nodes in base graph	
N^T	Time-space graph nodes	$i, j \in N^T$
N^B, N^M	Terminal/Yard subsets	$i, j \in N^T$
N_l^L	Non-depot nodes for l	
N_d^D	Non-start/end nodes for d	
A^T	Time-space graph arcs	$(i,j) \in A^T$
A^M, A^S	Travel/Wait arc subsets	$(i,j) \in A^T$
A^C, A^Δ	Couple/Decouple subsets	$(i,j) \in A^T$
In, Out	Neighbors of node j	
Parameters		
τ	Time step size	[min]
cap_j^C	Coupling cap. at j	[m/min]
f^Δ	Couple $\rightarrow$ decouple factor	[m/min]
s_d, e_d	Order start/end	[ID]
re_d, du_d	Order release/due time	[min]
len_d	Order length/weight	[m, kg]
cap_{ij}^{len}	Length capacity of arc i,j	[m]
cap_l^{wgt}	Weight cap. locomotive l	[kg]
C^{ldaily}	Daily fixed cost	[€]
C^{away}	Loc. away from depot	[€/min]
C^{delay}	Delay/Earliness cost	[€/min]
C^{non}	Non-delivery cost	[€]
C^{TKM}	Tonne-KM cost	[€/TKM]

Table A.3: Sets, indices and parameters of the model.

Objective:

$$\min \quad Z = \sum_{l\in L}\sum_{d\in D}\sum_{t\in T}(C^{ldaily}u_l + C^{delay}\tau \cdot td_d + C^{early}\tau \cdot \epsilon_d + C^{away}\tau \cdot \alpha_{l,t} + C^{nondelivery}(1-\delta_d) + \sum_{ij\in A^M} C^{TKM}\frac{wgt_d}{len_d}\cdot y_{ij,d,l} + \sum_{ij\in A^{C\Delta}\setminus\{s_d,e_d\}} C^{yard}\tau \cdot y_{ij,d,l}) \tag{A.1}$$

subject to:

$$\sum_{j\in LSta(dp_l)} x_{dp_l,j,l} = \sum_{i\in LEnd(dp_l)} x_{i,dp_l,l} = u_l \qquad \forall l \in L \quad \text{T/O} \tag{A.2}$$

$$\sum_{i\in LIn(j)} x_{ij,l} = \sum_{k\in LOut(j)} x_{jk,l} \qquad \forall l \in L, j \in N_l^L \quad \text{T/O} \tag{A.3}$$

$$\sum_{d\in D} \sum_{\substack{(i,j)\in A^{C\Delta} \\ i\in\{s_d,e_d\} \,\vee\, j\in\{s_d,e_d\}}} y_{ij,d,l} = 0 \qquad \forall l \in L^E \quad \text{O} \tag{A.4}$$

$$\sum_{j\in Sta(s_d)} \sum_{l\in L} y_{s_d,j,d,l} = len_d \cdot \delta_d \qquad \forall d \in D \quad \text{T} \tag{A.5}$$

$$\sum_{i\in End(e_d)} \sum_{l\in L} y_{i,e_d,d,l} = len_d \cdot \delta_d \qquad \forall d \in D \quad \text{T} \tag{A.6}$$

$$\sum_{i\in In(j)} \sum_{l\in L} y_{ij,d,l} = \sum_{k\in Out(j)} \sum_{l\in L} y_{jk,d,l} \qquad \forall d \in D, j \in N_d^D \quad \text{T} \tag{A.7}$$

$$\sum_{l\in L} y_{ij,d,l} = len_d \cdot \gamma_{ij,d} \qquad \forall (i,j) \in A^M, d \in D \quad \text{O} \tag{A.8}$$

$$\sum_{d\in D}\sum_{l\in L} y_{ij,d,l} \leq cap_{ij}^{len} \qquad \forall (i,j) \in A^L \quad \text{O} \tag{A.9}$$

$$\sum_{d\in D}\left(\frac{y_{ij,d,l}}{len_d}\cdot wgt_d\right) \leq cap_l^{wgt} \qquad \forall (i,j) \in A^L, l \in L \quad \text{O} \tag{A.10}$$

$$\sum_{d\in D}\sum_{jk\in A^C}\frac{y_{jk,d,l}}{cap_j^C}+\sum_{d\in D}\sum_{ij\in A^\Delta}\frac{y_{ij,d,l}}{cap_j^C\cdot f^\Delta}\leq 1$$
$$\forall j\in N^B, l\in L \quad \text{O} \quad \text{(A.11)}$$
$$y_{ij,d,l}\leq len_d\cdot x_{ij,l} \quad \forall(i,j)\in A^L, d\in D, l\in L \quad \text{T} \quad \text{(A.12)}$$
$$y_{ij,l,d}\leq x_{ik,l}\cdot len_d$$
$$\forall(i,j)\in A^\Delta,(i,k)\in A^S, d\in D, l\in L \quad \text{O} \quad \text{(A.13)}$$
$$y_{ij,l,d}\leq x_{kj,l}\cdot len_d$$
$$\forall(i,j)\in A^C,(k,j)\in A^S, d\in D, l\in L \quad \text{O} \quad \text{(A.14)}$$
$$\sum_{d\in D}y_{ij,d,l}+\sum_{d\in D}y_{ji,d,l}\leq 1$$
$$\forall(i,j)\in A^{C\Delta}\cup A^L, l\in L \quad \text{O} \quad \text{(A.15)}$$
$$\alpha_{l,t}=u_l-x_{dp_l,j,l} \quad \forall(dp_l,j)\in A^S, l\in L, t\in T \quad \text{O} \quad \text{(A.16)}$$
$$td_d=\sum_{du_d\leq t\leq T[-1]}\sum_{i\in In(e_d)}\sum_{l\in L}(t-du_d)y_{i,e_d,d,l}$$
$$\forall d\in D \quad \text{T} \quad \text{(A.17)}$$
$$\epsilon_d=\sum_{T[0]\leq t\leq du_d}\sum_{i\in In(e_d)}\sum_{l\in L}(du_d-t)y_{i,e_d,d,l}$$
$$\forall d\in D \quad \text{O} \quad \text{(A.18)}$$

Firstly, the vehicle movement are constrained. Constraint (A.2) ensures locomotives start and end at their depot, and (A.3) consistent flow across the time-space graph. For every node (except for depot nodes at start and end of the horizon), flow in is equal to flow out, for every locomotive. Alterations in these constraints from Tierney et al. (2014) are the variable u_l, to enable endogenous fleet sizing and x gets extended with set L, to track locomotives across the time-space graph. Next, in constraint (A.4), electric locomotives are prevented from (de)coupling from and to their start and end nodes, modelling the inability to deliver orders to terminals.
Then, order flow is conserved, where (A.5) and (A.6) set orders flows from starting nodes and to end nodes. (A.7) preserves flow at intermediate nodes. Like in the locomotive constraints, again set L is added to link locomotives to order movements. This is used to enable later constraints.
To prevent orders from splitting, binary auxiliary variable γ is used in constraint (A.8) for full-order movement.
As length capacity in the rail network is a network constraint, the parameter cap_{ij}^{len} is used in (A.9) to ensure arc length capacity. Equation (A.10) ensures weight capacity, where order weight is assumed to be linear with weight. The LT arc logic from Tierney et al. (2014) is used to model couple and decouple time in (A.11). The constraint is formulated so that the fraction of couple capacity and decouple capacity used, do not sum up to more than 1. This ensures a locomotive, in a single time step, does not simultaneously (de)couple multiple orders at multiple terminals. Every terminal node has its own capacity, cap_j^C, which models different NCBG sizes and per terminal service times. Factor f^Δ is the multiplication for decoupling, as this often takes less time than coupling ($f^\Delta > 1$).
To ensure an order is only moved when a locomotive is available, (A.12) is added. Then, to ensure the locomotive linked to an order waits at a yard for the time the order is (de)coupled, (A.13) and (A.14) are added.
Next, to force orders to use the same locomotive on a trajectory, only being able to switch locomotive after decoupling and recoupling, (A.15) is implemented. The locomotive used for the movement of a specific order remains constant over all arc types except those in A^{SB}.
To track how long the locomotives are away from their depot node, auxiliary variable α is introduced and constrained by (A.16). For the arrival logic, the time delay is adopted from Tierney et al. (2014) in equation (A.17), and flipped to also include an earliness auxiliary variable in (A.18).

A.3.3. Solution Approach

To further decrease computation times, two approaches are adopted.
Firstly, the flow-first approach from Tierney et al. (2014) is implemented. In this approach, first only the order flow is solved for, where equations (A.5) to (A.9), (A.11) and (A.15) are enforced. Then, this solution is used as a warm start to the optimisation of the full model, with all constraints active. This method first solves order flow and then assigns locomotives to the order flow. This proves to be an efficient and significantly faster solution approach.
Next, the time-space graph is reduced in size by pruning trajectories alternately. The linear network of the Port of Rotterdam enable the removal of every other arc, without significant impact on the objective function. The terminal arcs are also pruned, and extended in time.

To verify the model works like required and the results are realistic, multiple tests are designed and executed. The resulting behaviour is validated by experts.

A.4. COOPERATIVE TRANSPORTATION

A.4.1. The Feeder Train Scheduling Problem as a Cooperative Game

The input of the FTSM can be the demand and the locomotives of a single operator, but can also be used in a cooperative approach. In that case, the coalition determines the demand solved for, with the locomotives of the coalition. In this cooperation, full data and locomotive sharing are assumed.
The benefits resulting from cooperation for the full network are twofold. By combining orders of different operators, terminals are not occupied by two operators at two times, but can be served in one time, significantly decreasing the terminal occupance. Next, the amount of locomotives needed in the full network decreases, as empty drives can be filled with order of other operators. Not only does this decrease cost, but it also increases the effective utilisation of assets. Furthermore, the network capacity increases, as less empty drives occupy valuable track time and space.
While the benefits for the full network are clear, the players need to be incentivised to enter or remain in the grand coalition. To do this, the final cost allocation needs to optimise for every operators' financial gain from cooperating. For this, the FTSM is implemented in the game theoretic framework, presented in the next section.

A.4.2. Cooperative Framework

The FTSM is integrated into a game theoretic framework, in which it is used to calculate coalition costs. The framework can be seen in Figure A.5. The cooperative game is implemented using the FTS model and the game is denoted as (P, v).
Firstly, the player set is determined, where $P = \{1, 2, ..., p\}$ represents the railway operators that act as players. Every player has its own locomotives and orders, all with their own parameters. These players form a coalition, where their orders, locomotives and most importantly costs can be freely transferred, to compensate cooperation. The characteristic function, which is minimised, is $v : 2^P \rightarrow \mathbb{R}$. The function $v(S)$ gives the total costs incurred by (sub-)coalition $S \subseteq P$. The

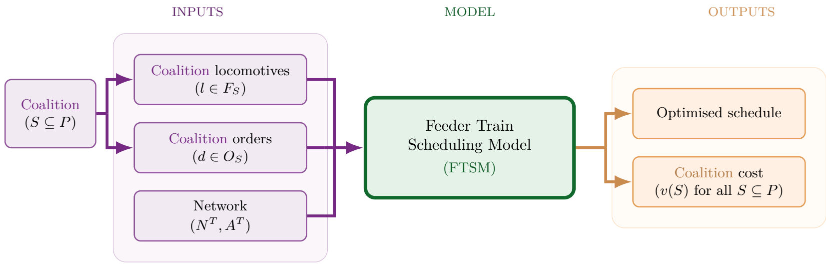


Figure A.5: The game theoretic framework, where coalitions determine the locomotive and order input, and the resulting output using the FTSM are the optimised schedule and resulting coalition cost.

function does not consider any players outside of the coalition. To calculate $v(S)$, the FTSM is used. The optimisation is run and the costs are the optimal cost resulting from the optimisation. The objective function is an adaptation from Equation (A.1). F_S represents the pooled set of locomotives from the players in S, and O_S the combined orders for the coalition.

$$v(S) = \min \Bigg(Z = \sum_{l \in F_S} \sum_{d \in O_S} \sum_{t \in T} \big(C^{ldaily} u_l + C^{delay} \tau \cdot td_d + C^{early} \tau \cdot \epsilon_d + C^{away} \tau \cdot \alpha_{l,t} + C^{nondelivery} (1 - \delta_d) + \sum_{ij \in A^M} C^{TKM} \frac{wgt_d}{len_d} \cdot y_{ij,d,l} + \sum_{ij \in A^{C\Delta} \setminus \{s_d, e_d\}} C^{yard} \tau \cdot y_{ij,d,l} \big) \Bigg) \tag{A.19}$$

The grand coalition is the coalition of all players in the game. As the same network, locomotives and orders are both present in stand-alone operation and the grand coalition, the stand-alone results still belong to the solution space. Therefore, the grand coalition is at least as good as the stand-alone cost, making the game additive. If only a single time slot can be shared, or two orders in the game can be combined, the game is superadditive, always ensuring a better solution than not cooperating.

A.4.3. Cost Allocation

As the grand coalition saves cost, the resulting cost needs to be allocated, to ensure the players benefit fairly. This cost allocation is pivotal in the stability of the coalition, as the final cost savings have a large influence of the satisfaction of the players being in the coalition. Many different allocations exist, but two are considered in this paper.

Shapley Value.— The Shapley Value was presented by Shapley (1953) and looks at the marginal contribution of the players. It compares the coalition cost in- and excluding the player, for all possible coalitions. The gains from the player cooperating determines the cost allocated. In line with common definition, it is formulated as follows:

$$\phi_i^{Sh}(v) = \sum_{S \subseteq P \setminus \{i\}} \frac{|S|!(p - |S| - 1)!}{p!} [v(S \cup \{i\}) - v(S)] \tag{A.20}$$

Where ϕ_i^{Sh} is the assigned cost, or Shapley value, for every player i.

A.4.4. Stability of the Coalition

While the Shapley value rewards marginal contribution, practical implementation also requires the game to be stable and the players to remain cooperating. To achieve this, individual rationality (IR) needs to be guaranteed. For a game with cost allocation vector $\phi = (\phi_1, \phi_2, ..., \phi_n)$ where ϕ_i is the cost assigned to player i, IR is guaranteed if:

$$\phi_i \leq v(i) \quad \forall i \in P \tag{A.21}$$

Furthermore, for any sub-coalition S within P, assigned cost needs to be lower than in the grand coalition. This requirement is called group rationality (GR). The cost allocation satisfies GR when:

$$\sum_{i \in S} \phi_i \leq v(S) \quad \forall S \subseteq P \tag{A.22}$$

$$\sum_{i \in P} \phi_i = v(P) \tag{A.23}$$

Where equation (A.22) ensures the total of assigned cost within a sub-coalition is less or equal to the cost if the sub-coalition would not be part of the grand coalition. Equation (A.23) ensures efficiency, where the total assigned cost is equal to the grand coalition cost. Solutions that satisfy both IR and GR for all players and sub-coalitions reside in the Core, proving the stability of the coalition. The Shapley solution does not always lie in the Core. Due to its intuitive approach and calculation it is still tested. As alternative, the Nucleolus allocation is presented in the next section.

Nucleolus.— The nucleolus strategy is based on the dissatisfaction of the different players. It maximises the satisfaction for the grand coalition players, by comparing the assigned cost to any sub-coalition cost. For this, the excess is calculated:

$$e(S, \phi) = v(S) - \sum_{i \in S} \phi_i \tag{A.24}$$

This represents the the excess of a coalition $S \subseteq P$ for a given cost allocation ϕ. Next, a vector is made, sorting all excess values for all possible sub-coalitions (excluding grand-coalition and empty set) in non-decreasing order. Next, the nucleolus maximises the smallest excess, then the second smallest excess and so on, until all excesses have been maximised. This is called lexicographical maximisation of $E(x)$ over the set of efficient allocations:

$$X = \left\{ \phi \in \mathbb{R}^p : \sum_{i \in P} \phi_i = v(P) \right\} \tag{A.25}$$

As the nucleolus minimises dissatisfaction compared to stand-alone and sub-coalition cost, it per definition lies in the core, if that exists. This property is attractive for implementation.

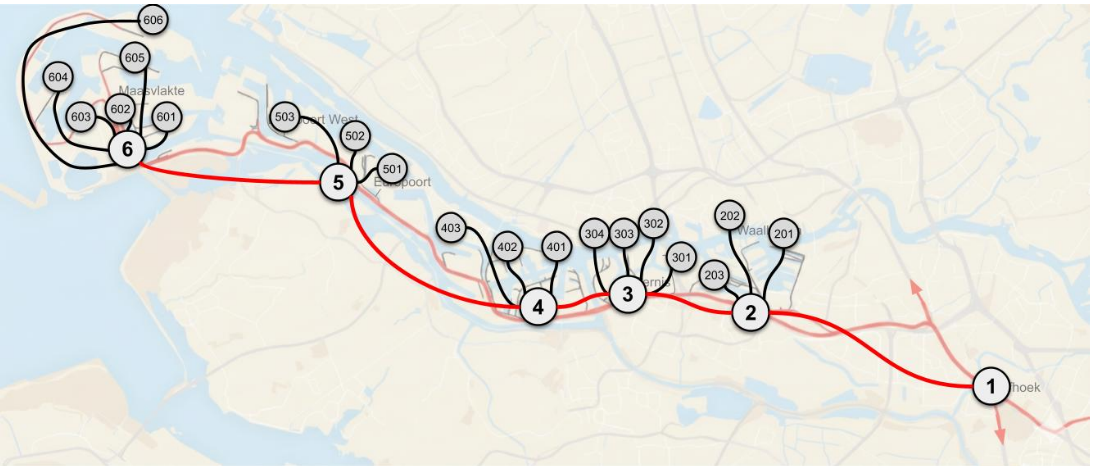


Figure A.6: The port railway line (HSL) in red, with the terminal connections (NCBG) in black, from Table A.4.

A.5. OPTIMISATION EXPERIMENTS

To test both the scheduling and cooperative transportation approaches, this section presents realistic experiments and their results. The solutions are calculated on a device with 12 cores (Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz) and 16GB of RAM.

A.5.1. Setup

The Network.— The network used for the experiments, is the port area of Rotterdam. The simplification of the network can be seen in Figure A.6, with specifics in Table A.4.

Yard	Abbr.	Full Terminal Name	Node
1	kfh	Kijfhoek	101
2	whz	Waalhaven Noord	201
		Heijplaat	202
		RSCW	203
3	ps	Matrans	301
		1e Petrohaven	302
		2e Petrohaven	303
		Vondelingenplaat	304
4	bot	3e Petrohaven	401
		Botlek	402
		Theemsweg	403
5	erp	Europoort	501
		Beneluxhaven	502
	erpw	Europoort W	503
6	mvt	Maasvlakte	601
	mvtw	Maasvlakte W	602
	mvtaho	MV Amaliahaven O	603
	mvtahw	MV Amaliahaven W	604
	mvtwn	MV W terminal N	605
	mvtyn	MV Yangtzehaven N	606

Table A.4: Mapping of Yards to Terminal Abbreviations, Full Names, and IDs

Greedy Benchmarking.— As comparison, a greedy algorithm is introduced, which focuses on just-in-time delivery. The algorithm sorts orders by due time, and starts with the earliest due time. Then, per order, it calculates the job duration, departure time for just-in-time delivery and compares the resulting delays per locomotive. The locomotive with the smallest delay is assigned. The route for the locomotive is added and its location is updated to the destination node after delivery. Before moving to the destination, idle time is checked, and if large enough for travel to depot, it does. After all orders are delivered, all locomotives return to their depot.
Like this, every order is assigned and the resulting cost is calculated. This algorithm, when the horizon is sufficient, results in a schedule where every order is delivered, where orders with earlier due time are prioritized.
Firstly, with the full locomotive set L the objective cost is calculated, after which locomotives are removed from the locomotive set to check if a better objective is possible.

Network Saturation.— Based on expert estimation, the used CBG and NCBG factors for saturation scenarios are 0%,0% for the empty scenario (a), 15%, 25% for the low (b) and 30%, 50% for the high saturation (c).

Experiments.— Four different experiments are designed, all with a different goal.
Firstly, the presented model is benchmarked against the Greedy approach. Two tests are done, with the same demand, but the first with homogeneous operators and the second with varying depot location. The goal of experiment 1 is to show the improvements made by the FTSM, both for stand-alone and coalition operation.
Secondly, in experiment 2 the influence of network saturation is investigated. Scenario 1 and 2 are used again and a third scenario is added, to also research the occurrence of different sized operators.
The third experiment explores the effect of an only-electric long-haul operator on the game. The demand from scenario 1 is used, but now solved for two diesel and a single electric operator.
Lastly, the cooperation strategy is compared to the existing zonal approach already implemented in Antwerp. Demand scenarios 1, 3, and two new scenarios 5 and 6 are solved with both the cooperative game and the zonal approach.
The experiments are summarised in Table A.5

Exp.	Focus	Scenarios & Setup
1	**FTSM Benchmark**	**S1:** Homogeneous (whz). **S2:** Varying depots (kfh, whz, mv).
2	**Network Saturation**	**S1, S2** **S3:** Varying operator size.
3	**Fleet Composition**	**S4:** Two diesel and one electric operator.
4	**Cooperative Benchmark**	**S1, S3** **S5, S6** Homogeneous demand and operators.

Table A.5: Overview of experimental scenarios.

A.5.2. Results

In this section, the results from the scenarios presented in Table A.5 are analysed.

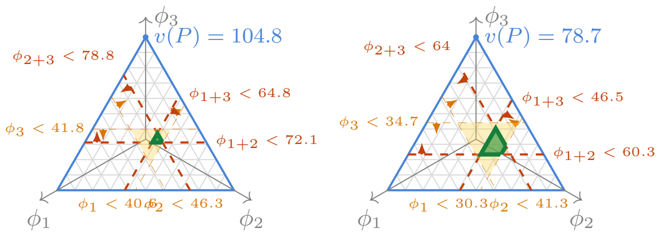
FTSM Benchmark Results.— To compare the FTSM to the greedy algorithm, scenarios 1 and 2 are solved with both approaches. Results are summarized in Table A.6.

For the tested scenarios, the FTSM outperforms the greedy algorithm in all tests regarding final objective cost. An average improvement of 18.5% is observed for the smaller tests and 20.8% for larger test with multiple operator. Furthermore, the number of locomotives used is reduced in 5 out of 14 tests. Due to combined orders and the MILP model, the savings for operators are significant.

	Greedy		FTSM		
Coalition	**Loc.**	**Cost**	**Loc.**	**Cost**	**Imp.**
Scenario 1a (Homogeneous)					
1	1	40.6	1	30.3	25%
2	1	46.3	1	41.3	11%
3	1	41.8	1	34.7	17%
{1, 2}	2	72.1	2	60.3	16%
{1, 3}	2	64.8	1	50.3	22%
{2, 3}	2	78.8	1	64.0	19%
{1, 2, 3}	3	104.8	2	78.7	25%
Average improvement					**19.4%**
Scenario 2a (Heterogeneous Depots)					
1	1	41.9	1	31.6	25%
2	1	46.3	1	41.3	11%
3	1	35.7	1	27.0	24%
{1, 2}	2	72.1	2	60.3	16%
{1, 3}	2	53.9	1	44.5	17%
{2, 3}	2	64.9	2	58.8	9%
{1, 2, 3}	3	98.3	2	64.9	34%
Average improvement					**19.5%**

Table A.6: Combined Scenario results including objective cost improvements.

Using the game theory presented in Section A.4, it is observed that for both solutions the core is non-empty (Figure A.8). The size of the core increases significantly, providing a more stable game. The savings seen in single operator gains using FTSM compound into a larger core. For scenario 2 however, the greedy solution yields an empty core, and the FTSM enables the core to exist.



(a) Greedy (1a). **(b)** FTSM (1a).

Figure A.8: Scenario 1 imputation triangles: blue surface (efficient allocations), orange arrows (IR), red lines (GR), and green area (Core).

Allocations in Table A.7 satisfy the Core bounds. The cost reduction compared to stand-alone operation increased by an average of 8%. Therefore, the coalition is more stable because stand-alone operation would significantly increase costs. In total, using FTSM instead of a greedy algorithm and cooperating in the grand coalition saves 39.5% of total costs. In scenario 2a, operators utilize different depots. The objective for single operator tests of players 1 and 2 remains stable, while operator 3 exhibits cost decreases due to a more advantageous depot location.

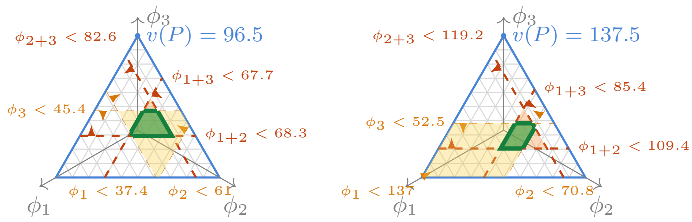
For heterogeneous depots, the core for the greedy algorithm is empty. Using the FTSM, all costs drop 19.5%, and grand coalition costs drop 34%, providing a large core. Total average savings per player reaches 48% compared to stand-alone greedy optimization.

				Shapley		Nucleolus	
Sce.	**Met.**	**Op.**	**Core Bounds**	**Val.**	**$\in$?**	**Val.**	**$\in$?**
1a	Greedy	1	[26.0, 40.6]	30.3	✓	28.1	✓
		2	[40.0, 46.3]	40.2	✓	42.1	✓
		3	[32.7, 41.8]	34.3	✓	34.7	✓
	FTSM	1	[14.7, 30.3]	20.1	✓	19.1	✓
		2	[32.2, 41.3]	34.4	✓	36.7	✓
		3	[18.4, 34.7]	24.2	✓	22.9	✓
2a	Greedy	1	[33.4, 41.9]	32.4	×	31.5	×
		2	[44.4, 46.3]	40.1	×	42.5	×
		3	[26.2, 35.7]	25.7	×	24.3	×
	FTSM	1	[11.1, 31.6]	18.4	✓	17.5	✓
		2	[29.7, 41.3]	32.6	✓	30.8	✓
		3	[6.7, 27.0]	13.9	✓	16.6	✓

Table A.7: Combined allocation stability analysis for Scenarios 1a and 2a.

Network Saturation Results.— In the saturation tests, network busyness is increased by pruning arcs across empty (a), low (b), and high (c) saturation levels.

Homogeneous operator tests (1a to 1c) show that delivery costs increase with network saturation. More locomotives are required as paths are blocked and time slots cannot be reached with a single unit. As arcs are reduced, computation time and optimality gap also drop. Figure A.10 shows the Core exists for all tests. On average, the grand coalition saves 27% (a), 33% (b), and 42% (c), indicating increasing savings as saturation grows.



(a) Scenario 1b (Low). **(b)** Scenario 1c (High).

Figure A.10: Comparison of Core plots for Scenarios 1b and 1c. Increasing network saturation expands the Individual Rationality (IR) area.

For all tested scenarios, cooperating yields lower objective cost, as seen in Figure A.11. As saturation increases, some orders are only delivered by the grand coalition, and the average decrease in objective cost increases with saturation from 32.5% to 56.8% on average.

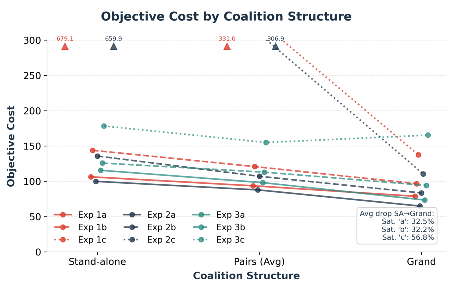


Figure A.11: Objective cost across network saturation levels and coalition sizes.

Furthermore, cooperation both reduced locomotive use (Figure A.12) and the use of the network (Figure A.13). Both these measures further decrease with higher saturation, where the locomotive use on average drops by 1.67, while at high saturation the network usage decreases 36%.

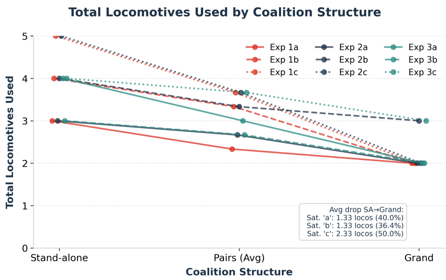


Figure A.12: Locomotive use across network saturation levels and coalition sizes.

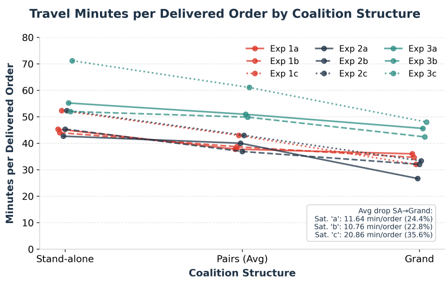


Figure A.13: Travel arc occupancy across coalition sizes.

Fleet Composition Results.— In scenario 4, involving diesel and electric operators, the IR area is large due to non-deliveries. With the core seen in Figure A.14, the nucleolus allocation remains stable, providing an average cost reduction of 29% for diesel operators.

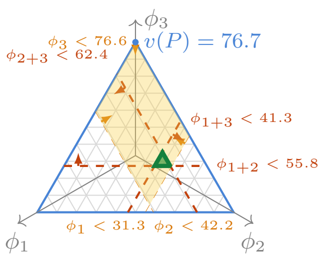


Figure A.14: Scenario 4 (FTSM).

Cooperative Benchmark.— In Table A.8 it can be seen for the zonal approach, the total cost for the operators only drop in scenario 3 compared to stand-alone operation. This lack of improvement causing the incentive for cooperation to fail to materialise, except for the operators that get assigned to a zone. The grand coalition cost however causes significant drops in cost for all operators, 24.8% compared to the zonal approach. Furthermore, the locomotives used and the time needed for order delivery is reduced significantly as well.

Scen.	Metric	SA	Zonal	Grand	Red.*
1	Cost	106.2	108.0	78.7	27.1%
	Locos	3	3	2	33.3%
	Time [min]	45.3	41.3	36.0	12.8%
3	Cost	115.6	93.4	73.4	21.4%
	Locos	4	3	2	33.3%
	Time [min]	55.2	55.2	45.6	17.4%
5	Cost	119.5	117.0	105.4	9.9%
	Locos	4	4	3	25.0%
	Time [min]	62.0	63.3	55.3	12.6%
6	Cost	138.5	137.4	82.2	40.2%
	Locos	5	5	2	60.0%
	Time [min]	57.5	55.3	45.1	18.4%
Avg.	**Cost**		Overall Reduction:		**24.8%**
	Locos		Fleet Efficiency Gain:		**37.9%**
	Time		Avg. Arc Occupancy Red.:		**15.3%**

*Reduction (Red.) compared to Zonal approach.

Table A.8: Comparison table between the cooperative and zonal approach, with stand-alone (SA) operation, zonal solution and the grand coalition operation. Cost, locomotives used and time on travel arcs needed are compared.

A.6. CONCLUSIONS & FUTURE RESEARCH

A.6.1. Conclusion

This paper shows that within the boundaries of the current railway network, major cost savings and operational efficiency gains are possible. Firstly, by scheduling using the proposed approach, orders can be combined and delivered by two locomotives. Compared to a greedy algorithm, daily cost savings in a range of $9 - 34\%$ are achieved. This cost saving can be seen to enabling a non-empty Core and therefore a stable coalition of three operators.
When the network is increasingly saturated, the Core remains non-empty, except for a high saturation, heterogenous size operators. All tests guarantee IR to hold, providing incentive for cooperation. The Shapley value often provides the same reduction in costs for operators compared to the nucleolus allocation. However, a non-delivery in stand-alone operation causes the Shapley value for the other operators turns negative, violating group rationality. Using the nucleolus allocation, the dissatisfaction of all players is minimised. Cost savings of 25% to 58% are reported for the different tests, compared to stand-alone operation.
Compared to the zonal approach used in Antwerp, the cooperation in the grand-coalition benefits the players more, with larger cost reduction and increased network capacity.

In practice, this paper provides a clear incentive for railway operators to cooperate, where a neutral planner and locomotive dispatcher plays a key role. The potential gains for a three-operator coalitions are clear, even proven valid for skewed coalitions. With cost reductions of over 30% prospective, the confidentiality argument for stand-alone operation is expected to be overcome.

A.6.2. Discussion

While this paper shows that major cost reductions are feasible in multiple demand scenarios by cooperating in a three-player coalition, these gains rely on some critical assumptions.
The FTSM is deterministic and assumes full order-knowledge, real-world operations are more fluid however, and require ad-hoc adaptions. Furthermore, the simplification of the port area omits specific yard capacities and the used data is from a single operator.

From the game-theoretic perspective, the framework assumes full cooperation and data-sharing. The port area is notorious for being reluctant to share this information, due to fierce competition. Furthermore, the model is executed for a short time horizon and long term effects are not discussed. Also, arc usage is not adopted from operator to operator in the current solution approach. Occupying arcs used in another solution could prove to increase stability of the coalition, as a larger coalition means less arcs are occupied by players outside of the coalition.

A.6.3. Future Work

To address these shortcomings, the following future work is proposed.

Firstly, the presented model needs to be further validated with reality. Real ad hoc scheduling could be compared to not only ensure the performance of the model, but also realism. Furthermore, the cost (ratios) used in this paper are based on expert opinion, but could be further increased in accuracy. Also, some orders may have larger costs for delays, terminals could be less or more busy than others and certain goods could take longer to check and therefore couple. These inhomogeneities could be included in the model.

Next, as already shown by the scenario 2 results, the depot location could be influential on the total cost of the operator or coalition. The FTSM model therefore could also be used to test the location of the depot, for more extended demand scenarios. Also, the model is tested using small instances, where a single shift on a single day is used as the horizon, and the order count in runs does not exceed 12. Furthermore, only three operators are used, where the original system has >20 operators acting. Using a high-performance computer, instances could be extended to see what influence that has.

In addition to computer optimisation, some real world test could be done, where trials with real orders and operators could be used to test the cooperation and its results. To achieve the implementation however, a study into the legal feasibility of the approach should be done.

Lastly, the model and game theory optimises for the port railway feeder system. It integrates railway operators, but further integration with both terminal operators and hinterland transport could be included, to see possible further cascading benefits.

B. Scenario Demand and Locomotives

Table B.1: Demand specification: Scenario 1, 2 and 4.

Order	Start	End	Release	Due	Length (km)	Weight (t)	Op.
1	501	101	0	445	559	1537.25	2
2	502	606	0	446	37	140.68	3
3	501	502	0	500	126	304.67	1
4	304	302	0	536	247	350.58	1
5	603	605	0	562	120	492.45	1
6	605	502	0	567	97	190.86	2
7	402	605	0	608	186	425.98	1
8	606	502	0	608	213	1111.05	2
9	203	501	0	652	448	1125.60	3
10	101	403	0	710	319	1050.25	2
11	101	601	0	792	94	141.20	3
12	606	603	0	830	546	2011.10	3

Table B.2: Locomotive specification: Scenario 1, 5 and 6.

Loc	Depot	Weight cap (t)	Op.	Engine
1	2	2810	1	D
2	2	2810	1	D
3	2	2810	2	D
4	2	2810	2	D
5	2	2810	3	D
6	2	2810	3	D

Table B.3: Locomotive specification: Scenario 2.

Loc	Depot	Weight cap (t)	Op.	Engine
1	1	2810	1	D
2	1	2810	1	D
3	2	2810	2	D
4	2	2810	2	D
5	6	2810	3	D
6	6	2810	3	D

Table B.4: Demand specification: Scenario 3.

Order	Start	End	Release	Due	Length (km)	Weight (t)	Op.
1	603	401	0	423	119	550.57	2
2	203	101	0	450	505	2510.71	2
3	101	303	0	476	17	77.48	1
4	602	101	0	504	572	1114.46	3
5	202	501	0	564	506	994.71	2
6	101	304	0	652	340	499.59	2
7	603	101	0	658	17	78.36	3
8	501	202	0	747	505	1180.70	2
9	303	502	0	769	594	964.82	2
10	604	603	0	777	111	736.89	1

Table B.5: Locomotive specification: Scenario 3.

Loc	Depot	Weight cap (t)	Op.	Engine
2	2	2810	2	D
3	2	2810	2	D
4	2	2810	2	D
1	2	2810	1	D
5	2	1800	3	D
6	2	1800	3	D

Table B.6: Locomotive specification: Scenario 4.

Loc	Depot	Weight cap (t)	Op.	Engine
1	2	2810	1	D
2	2	2810	1	D
3	2	2810	2	D
4	2	2810	2	D
5	2	2940	3	E
6	2	2940	3	E

Table B.7: Demand specification: Scenario 5.

Order	Start	End	Release	Due	Length (km)	Weight (t)	Op.	Zone
1	501	402	0	450	213	558.13	1	2
2	401	202	0	471	319	761.03	2	2
3	603	606	0	501	23	67.43	3	3
4	606	402	0	592	443	868.50	2	3
5	201	502	0	608	120	168	1	1
6	602	302	0	623	345	470.45	3	3
7	501	101	0	652	616	672.37	2	2
8	606	501	0	672	372	1860	3	3
9	101	403	0	674	153	312.88	2	2
10	101	602	0	756	505	720.65	3	3
11	203	101	0	789	85	96.39	2	1
12	202	602	0	834	214	231.83	1	1

Table B.8: Demand specification: Scenario 6.

Order	Start	End	Release	Due	Length (km)	Weight (t)	Op.	Zone
1	502	302	0	438	544	3781.58	2	2
2	304	101	0	474	594	3039.88	1	1
3	304	101	0	524	556	2500.11	1	1
4	101	403	0	561	67	155.66	1	2
5	402	501	0	649	57	90.06	2	2
6	603	605	0	654	33	91.26	3	3
7	402	601	0	674	186	315.24	1	2
8	602	502	0	702	213	554.79	3	3
9	303	501	0	728	400	1096.67	2	1
10	501	302	0	747	443	815.52	2	2
11	101	402	0	821	146	697.56	3	2

Table B.9: Locomotive specification: Zone_Experiment.

Loc	Depot	Weight cap (t)	Zone	Engine
1	2	2810	1	D
2	2	2810	1	D
3	2	2810	2	D
4	2	2810	2	D
5	2	2810	3	D
6	2	2810	3	D

C. Full Coalition Results

C.1. SCENARIO 1

Table C.1: Scenario 1 results: Comparison of FTSM method for single operators and coalitions across three saturation scenarios. Orders delivered (O), locomotives used (L), cost, gap, and time shown.

			FTSM														
			Empty (a)					Low saturation (b)					High saturation (c)				
	# Ord.	**Avai. locs**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**
Single Operators																	
1	4	2	4	1	30.3	0.0	15.3	4	1	37.4	0.0	3.4	3	2	555.7	0.0	2.5
2	4	2	4	1	41.2	0.0	17.0	4	2	61.0	0.0	9.7	4	2	70.8	0.0	5.0
3	4	2	4	1	34.7	0.0	23.0	4	1	45.4	0.0	10.9	4	1	52.5	0.0	8.0
Coalitions																	
{1, 2}	8	4	8	2	60.3	0.0	6994	8	2	68.3	0.0	56.5	8	2	109.4	0.0	80
{1, 3}	8	4	8	1	50.3 (46.5)	7.6	7200	8	2	67.7	0.0	1844	8	2	85.4	0.0	149
{2, 3}	8	4	8	1	64.0	0.0	1321	8	2	82.6	0.0	1092	8	2	119.2	0.0	876
{1, 2, 3}	12	6	12	2	78.7 (64.5)	18.1	10800	12	2	96.5 (88.1)	8.7	10800	12	2	137.5 (130.7)	5.0	10800

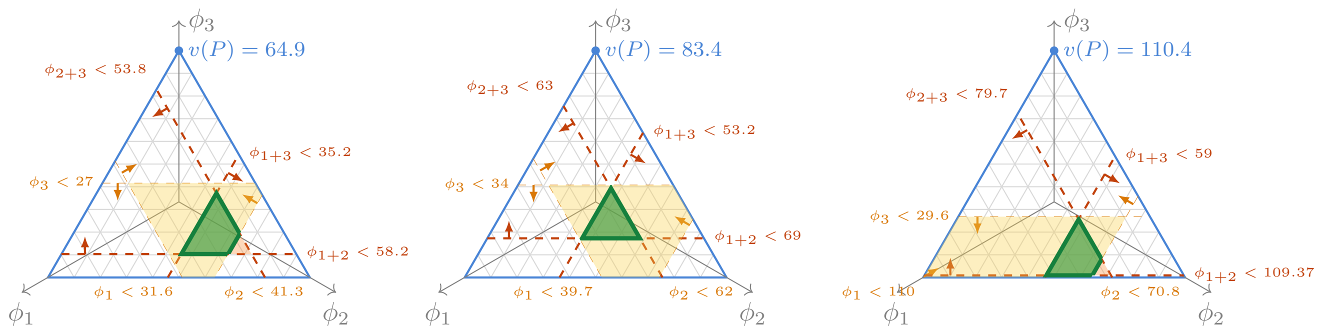
Table C.2: Core bounds, allocation stability, and cost savings for Experiment 1 (Empty/Low/High saturation).

Scenario	**Op.**	**Core Bounds**	**Shapley Value**			**Nucleolus**		
			Value	**Gain (%)**	**∈ Core?**	**Value**	**Gain (%)**	**∈ Core?**
1a (Empty)	1	[14.7, 30.3]	20.1	33.6	✓	19.1	36.9	✓
	2	[32.3, 41.3]	34.4	16.7	✓	36.7	11.1	✓
	3	[18.5, 34.7]	24.2	30.2	✓	22.9	34.0	✓
1b (Low)	1	[13.9, 37.4]	22.0	41.1	✓	22.4	40.1	✓
	2	[28.9, 61.0]	41.3	32.3	✓	37.4	38.8	✓
	3	[28.2, 45.4]	33.2	26.9	✓	36.7	19.1	✓
1c (High)	1	[18.4, 555.7]	203.3	63.4	✓	32.9	94.1	✓
	2	[52.1, 70.8]	-22.3	131.5	×	61.5	13.2	✓
	3	[28.2, 52.5]	-43.4	182.7	×	43.2	17.8	✓

C.2. SCENARIO 2

Table C.3: Scenario 2 results: Comparison of FTSM method for single operators and coalitions across three saturation scenarios. Orders delivered (O), locomotives used (L), cost, gap, and time shown.

			FTSM														
			Empty (a)					Low saturation (b)					High saturation (c)				
	# Ord.	Avai. locs	O	L	Cost	Gap (%)	Time (s)	O	L	Cost	Gap (%)	Time (s)	O	L	Cost	Gap (%)	Time (s)
Single Operators																	
1	4	2	4	1	31.6	0.0	17.5	4	2	39.7	0.0	4.0	3	2	559.6	0.0	3.5
2	4	2	4	1	41.3	0.0	19.4	4	2	62.0	0.0	21.5	4	2	70.8	0.0	7.5
3	4	2	4	1	27.0	0.0	24.7	4	2	34.0	0.0	42.1	4	1	29.6	0.0	7.7
Coalitions																	
{1, 2}	8	4	8	2	60.3 (58.2)	3.4	7200	8	1	69.0	0.0	558	8	2	109.37	0.0	248
{1, 3}	8	4	8	1	44.5 (35.2)	20.9	7200	8	2	53.2	0.0	2990	8	2	59.0	0.0	244
{2, 3}	8	4	8	2	58.8 (53.8)	8.4	7200	8	2	63.0	0.0	941	8	2	92.4 (79.7)	13.8	7200
{1, 2, 3}	12	6	12	2	64.9 (54.8)	15.6	10800	12	2	83.4 (62.1)	25.6	10800	12	2	110.4 (91.0)	17.6	10800



(a) Scenario 2a (FTSM). **(b)** Scenario 2b (FTSM). **(c)** Scenario 2c (FTSM).

Figure C.1: Comparison of core plots for different scenarios.

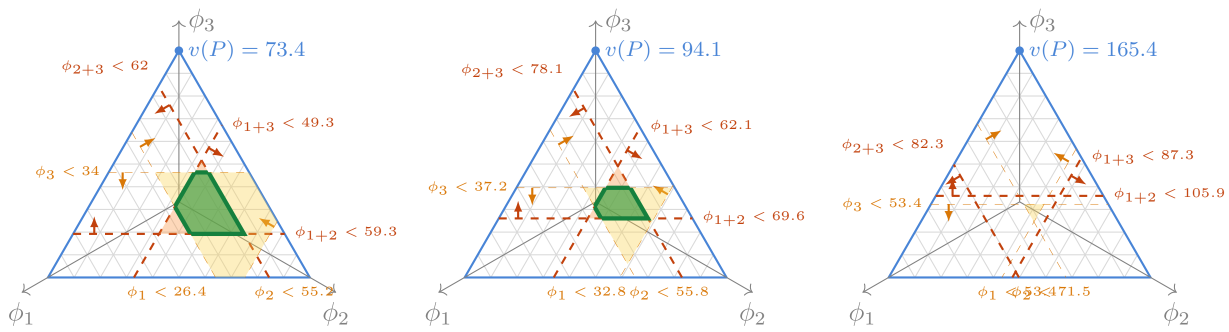
Table C.4: Core bounds, allocation stability, and cost savings for Experiment 2 (Empty/Low/High saturation).

Scenario	Op.	Core Bounds	Shapley Value			Nucleolus		
			Value	Gain (%)	∈ Core?	Value	Gain (%)	∈ Core?
2a (Empty)	1	[11.1, 31.6]	18.4	41.7	✓	17.0	46.3	✓
	2	[29.7, 41.3]	32.6	21.1	✓	35.5	14.0	✓
	3	[6.7, 27.0]	13.9	48.5	✓	12.4	54.0	✓
2b (Low)	1	[20.4, 39.7]	24.4	38.6	✓	26.5	33.2	✓
	2	[30.3, 62.0]	40.5	34.7	✓	36.4	41.3	✓
	3	[14.4, 34.0]	18.5	45.5	✓	20.5	39.6	✓
2c (High)	1	[30.8, 559.5]	208.1	62.8	✓	39.8	92.9	✓
	2	[51.5, 70.8]	-25.9	136.6	×	60.5	14.6	✓
	3	[1.1, 29.6]	-71.8	342.7	×	10.1	65.8	✓

C.3. SCENARIO 3

Table C.5: Scenario 3 results: Comparison of FTSM method for single operators and coalitions across three saturation scenarios. Orders delivered (O), locomotives used (L), cost, gap, and time shown.

			FTSM														
			Empty (a)					Low saturation (b)					High saturation (c)				
	# Ord.	Avai. locs	O	L	Cost	Gap (%)	Time (s)	O	L	Cost	Gap (%)	Time (s)	O	L	Cost	Gap (%)	Time (s)
Single Operators																	
1	2	1	2	1	26.4	0.0	3.5	2	1	32.8	0.0	2.2	2	1	53.4	0.0	2.1
2	6	3	6	2	55.2	0.0	1609	6	1	55.8	0.0	76	6	2	71.5	0.0	142.5
3	2	2	2	1	34.0	0.0	2.9	2	1	37.2	0.0	2.3	2	1	53.4	0.0	2.1
Coalitions																	
{1, 2}	8	4	8	2	62.8 (59.3)	5.7	7200	8	2	72.7 (69.6)	4.2	7200	8	3	116.9 (105.9)	9.4	7200
{1, 3}	4	3	4	1	49.3	0.0	44.1	4	1	62.1	0.0	9.9	4	2	87.3	0.0	11
{2, 3}	8	4	8	2	66.4 (62.0)	6.8	7200	8	2	78.1	0.0	360	8	2	82.3	0.0	416
{1, 2, 3}	10	6	10	2	73.4 (66.7)	9.1	10800	10	2	94.1 (89.0)	5.4	10800	10	3	165.4 (137.4)	17	10800



(a) Scenario 3a (FTSM). **(b)** Scenario 3b (FTSM). **(c)** Scenario 3c (FTSM).

Figure C.2: Comparison of core plots for Scenario 3 scenarios.

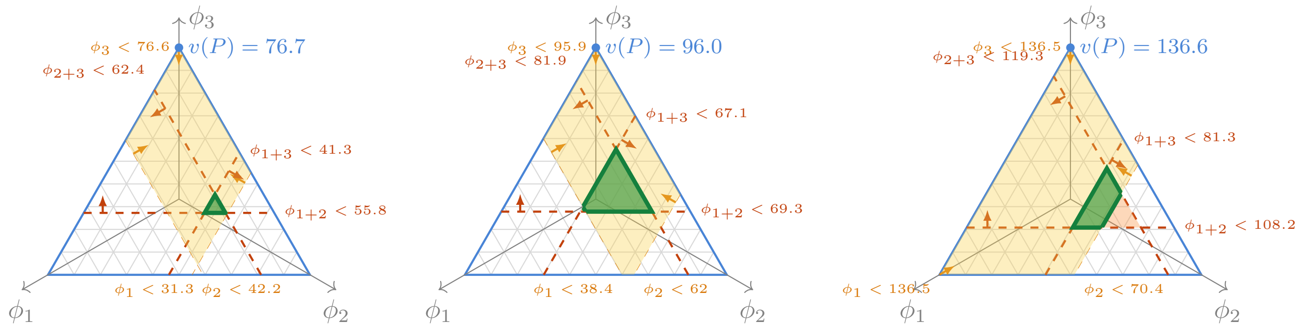
Table C.6: Core bounds, allocation stability, and cost savings for Experiment 3 (Empty/Low/High saturation).

Scenario	Op.	Core Bounds	Shapley Value			Nucleolus		
			Value	Gain (%)	∈ bound?	Value	Gain (%)	∈ bound?
3a (Empty)	1	[11.4, 26.4]	15.8	40.0	✓	18.9	28.3	✓
	2	[24.1, 55.2]	36.6	33.8	✓	31.5	42.9	✓
	3	[14.1, 34.0]	21.0	38.2	✓	23.0	32.4	✓
3b (Low)	1	[16.0, 32.8]	22.7	30.8	✓	24.8	24.2	✓
	2	[32.0, 55.8]	42.2	24.3	✓	38.4	31.2	✓
	3	[24.5, 37.2]	29.2	21.6	✓	30.9	17.1	✓
3c (High)	1	[83.1, 53.4]	56.9	-6.5	×	64.7	-21.2	×
	2	[78.1, 71.5]	63.5	11.3	×	59.7	16.6	×
	3	[59.5, 53.4]	45.1	15.6	×	41.1	23.2	×

C.4. SCENARIO 4

Table C.7: Scenario 4 results: Comparison of FTSM method for single operators and coalitions across three saturation scenarios. Orders delivered (O), locomotives used (L), cost, gap, and time shown.

			FTSM														
			Empty (a)					Low saturation (b)					High saturation (c)				
Instance	**# Ord.**	**Avai. locs**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**	**O**	**L**	**Cost**	**Gap (%)**	**Time (s)**
Single Operators																	
1	4	2	4	1	31.3	0.0	18.2	4	1	38.4	0.0	4.4	3	2	556.7	0.0	2.2
2	4	2	4	1	42.2	0.0	53.0	4	2	62.0	0.0	19.9	4	2	70.4	0.0	4.8
3	4	2	0	0	2001.0	0.0	4.3	0	0	2001.0	0.0	3.6	0	0	2001.0	0.0	2.9
Coalitions																	
{1, 2}	8	4	8	2	60.7 (55.8)	8.1	7208	8	2	69.3	0.0	166.1	8	2	108.2	0.0	2271.7
{1, 3}	8	4	8	1	48.6 (41.3)	15.0	7210	8	2	67.1	0.0	6648.7	8	2	81.3	0.0	116.3
{2, 3}	8	4	8	1	62.4	0.0	6840	8	2	81.9	0.0	2039.9	8	2	119.3	0.0	2745.4
{1, 2, 3}	12	6	12	2	76.7 (58.3)	23.9	10800	12	2	96.0 (84.0)	12.5	10800	12	2	136.6 (130.4)	4.5	10812.3



(a) Scenario 4a (FTSM). **(b)** Scenario 4b (FTSM). **(c)** Scenario 4c (FTSM).

Figure C.3: Comparison of core plots for Scenario 4 scenarios.

Table C.8: Core bounds, allocation stability, and cost savings for Experiment 4 (Empty/Low/High saturation).

Scenario	**Op.**	**Core Bounds**	**Shapley Value**			**Nucleolus**		
			Value	**Gain (%)**	**∈ bound?**	**Value**	**Gain (%)**	**∈ bound?**
4a (Empty)	1	[14.2, 31.3]	-309.2	1087.5	×	16.3	47.9	✓
	2	[35.4, 42.2]	-293.2	794.2	×	37.4	11.4	✓
	3	[20.9, 2001.0]	679.0	66.1	✓	22.9	98.9	✓
4b (Low)	1	[14.1, 38.4]	-303.6	890.1	×	22.9	40.5	✓
	2	[28.9, 62.0]	-284.4	558.5	×	37.7	39.3	✓
	3	[26.7, 2001.0]	684.0	65.8	✓	35.5	98.2	✓
4c (High)	1	[17.3, 556.7]	-122.3	122.0	×	24.9	95.5	✓
	2	[55.3, 70.4]	-346.4	591.8	×	62.9	10.7	✓
	3	[28.3, 2001.0]	605.3	69.7	✓	48.8	97.6	✓

D. FTSM Benchmarking Results

D.1. SCENARIO 1A

Table D.1: Scenario 1a results: Comparison between Greedy and FTSM methods for single operators and coalitions. Orders delivered (Ord.), locomotives used (Loc.), final objective cost, gap, and improvement between approaches shown.

			Greedy			FTSM				
Instance	**# Ord.**	**Avai. locs**	**Ord.**	**Loc.**	**Cost**	**Ord.**	**Loc.**	**Cost (bnd)**	**Gap (%)**	**Improv.**
Single Operators										
1	4	2	4	1	40.6	4	1	30.3	0.0	25%
2	4	2	4	1	46.3	4	1	41.3	0.0	11%
3	4	2	4	1	41.8	4	1	34.7	0.0	17%
Coalitions										
{1, 2}	8	4	8	2	72.1	8	2	60.3	0.0	16%
{1, 3}	8	4	8	2	64.8	8	1	50.3 (46.5)	7.6	22%
{2, 3}	8	4	8	2	78.8	8	1	64.0	0.0	19%
{1, 2, 3}	12	6	12	3	104.8	12	2	78.7 (64.5)	18.1	25%

Table D.2: Core size bounds, allocation stability, and cost savings compared to stand-alone cost for Greedy and FTSM algorithms (Scenario 1a).

Method	Op.	Core Bounds	Shapley Value			Nucleolus		
			Value	**Gain (%)**	**∈ bound?**	**Value**	**Gain (%)**	**∈ bound?**
Greedy	1	[26.0, 40.6]	30.3	25.4	✓	28.1	30.8	✓
	2	[40.0, 46.3]	40.2	13.2	✓	42.1	9.1	✓
	3	[32.7, 41.8]	34.3	17.9	✓	34.7	17.0	✓
FTSM	1	[14.7, 30.3]	20.1	33.7	✓	19.1	37.0	✓
	2	[32.2, 41.3]	34.4	16.7	✓	36.7	11.1	✓
	3	[18.4, 34.7]	24.2	30.3	✓	22.9	34.0	✓

D.2. SCENARIO 2A

Table D.3: Scenario 2a results: Comparison between Greedy and FTSM methods for single operators and coalitions. Orders delivered (Ord.), locomotives used (Loc.), final objective cost, gap, and improvement shown.

			Greedy			FTSM				
Instance	**# Ord.**	**Avai. locs**	**Ord.**	**Loc.**	**Cost**	**Ord.**	**Loc.**	**Cost (bnd)**	**Gap (%)**	**Improv.**
Single Operators										
1	4	2	4	1	41.9	4	1	31.6	0.0	25%
2	4	2	4	1	46.3	4	1	41.3	0.0	11%
3	4	2	4	1	35.7	4	1	27.0	0.0	24%
Coalitions										
{1, 2}	8	4	8	2	72.1	8	2	60.3 (58.2)	3.4	16%
{1, 3}	8	4	8	2	53.9	8	1	44.5 (35.2)	20.9	17%
{2, 3}	8	4	8	2	64.9	8	2	58.8 (53.8)	8.4	9%
{1, 2, 3}	12	6	12	3	98.3	12	2	64.9 (54.8)	15.6	34%

Table D.4: Core size bounds, allocation stability, and cost savings compared to stand-alone cost for Greedy and FTSM algorithms (Scenario 2a).

Method	**Op.**	**Core Bounds**	**Shapley Value**			**Nucleolus**		
			Value	**Gain (%)**	**$\in$ bound?**	**Value**	**Gain (%)**	**$\in$ bound?**
Greedy	1	[33.4, 41.9]	32.4	22.7	×	31.5	24.8	×
	2	[44.4, 46.3]	40.1	13.4	×	42.5	8.2	×
	3	[26.2, 35.7]	25.7	28.0	×	24.3	31.9	×
FTSM	1	[11.1, 31.6]	18.4	41.8	✓	17.5	44.6	✓
	2	[29.7, 41.3]	32.6	21.1	✓	30.8	25.4	✓
	3	[6.7, 27.0]	13.9	48.5	✓	16.6	38.5	✓

E. Zone Results

E.1. SCENARIO 1

Table E.1: Operational results: Comparison between FTSM (Scenario 1a) and the Zonal Approach.

	FTSM						Zonal Approach				
Op.	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**	**Zone**	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**
1	4	1	30.3	0.0%	15.3	**Zone 1**	2	1	23.0	0.0%	6.8
2	4	1	41.3	0.0%	17.0	**Zone 2**	5	1	48.9	0.0%	219.3
3	4	1	34.7	0.0%	23.2	**Zone 3**	5	1	36.1	0.0%	27.4
Total	**12**	**3**	**106.2**	**0.0%**	**55.5**	**Total**	**12**	**3**	**108.0**	**0.0%**	**253.5**
Grand	**12**	**2**	**78.7 (64.5)**	**18.1%**	**14044.0**	**–**	**–**	**–**	**–**	**–**	**–**

E.2. SCENARIO 3

Table E.2: Operational results: Comparison between FTSM (Scenario 3a) and the Zonal Approach.

	FTSM						Zonal Approach				
Op.	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**	**Zone**	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**
1	2	1	26.4	0.0%	3.5	**Zone 1**	5	1	33.9	0.0%	260.5
2	6	2	55.2	0.0%	1609.2	**Zone 2**	1	1	20.8	0.0%	1.8
3	2	1	34.0	0.0%	2.9	**Zone 3**	4	1	38.6	0.0%	63.2
Total	**10**	**4**	**115.6**	**0.0%**	**1615.6**	**Total**	**10**	**3**	**93.4**	**0.0%**	**325.5**
Grand	**10**	**2**	**73.4 (66.7)**	**9.1%**	**10800**	**–**	**–**	**–**	**–**	**–**	**–**

E.3. SCENARIO 5

Table E.3: Operational results: Comparison between FTSM (Scenario 5a) and the Zonal Approach.

	FTSM						Zonal Approach				
Op.	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**	**Zone**	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**
1	3	1	27.7	0.0%	42.2	**Zone 1**	3	1	27.3	0.0%	14.4
2	5	2	54.3	0.0%	524.2	**Zone 2**	4	1	31.1	0.0%	23.6
3	4	1	37.5	0.0%	30.8	**Zone 3**	5	2	58.6	0.0%	548.4
Total	**12**	**4**	**119.5**	**0.0%**	**597.2**	**Total**	**12**	**4**	**117.0**	**0.0%**	**586.4**
Grand	**12**	**3**	**105.4 (60.4)**	**42.8%**	**10800**	**–**	**–**	**–**	**–**	**–**	**–**

E.4. SCENARIO 6

Table E.4: Operational results: Comparison between FTSM (Scenario 6a) and the Zonal Approach.

FTSM							Zonal Approach					
Op.	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**	**Zone**	**O**	**L**	**Cost (LB)**	**Gap (%)**	**Time (s)**
1	4	2	58.7	0.0%	183.0	**Zone 1**	3	2	56.8	0.0%	416.8
2	4	2	51.6	0.0%	1061.2	**Zone 2**	6	2	58.0	0.0%	2194.5
3	3	1	28.2	0.0%	5.4	**Zone 3**	2	1	22.6	0.0%	1.7
Total	**11**	**5**	**138.5**	**0.0%**	**1249.6**	**Total**	**11**	**5**	**137.4**	**0.0%**	**2613.0**
Grand	**11**	**2**	**82.2 (57.5)**	**30.0%**	**10800**	**–**	**–**	**–**	**–**	**–**	**–**