Master Thesis
Industrial Engineering and Management

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DEVELOPING A CAPACITY ALLOCATION POLICY AT RAILWAY YARDS FOR PRORAIL

Colophon

This version is a publicly available version and confidential information is left out and replaced with fictional data. Names of rail operators are referred to as ''Rail operator A''. Most results are modified to prevent tracking the identity of rail operators.

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Preface

Dear reader,

This thesis marks the end of my time as a student Industrial Engineering and Management at the University of Twente. You are about to read my master thesis ‘’Developing an allocation policy for ProRail”. I would like to thank several persons contributing to this research.

I want to say a big thank you to my supervisors Yoran de Weert and Sybren Hazenberg of ProRail. They have been really helpful and supportive throughout this research. We had some great meetings where they were always ready to answer my questions and give me valuable feedback. It was not all work though – we also had some fun conversations. Their advice made this research much better.

I also want to thank the colleagues for their help during my research and answering my questions quickly. A special thank you goes to Petra Luiken, the manager of Team Emplacementen, for making it possible for me to do this research at ProRail in Utrecht.

Furthermore, I want to thank my supervisors Engin Topan and Alessio Trivella of the University of Twente. Engin was always helpful and quick with answering to my questions. I enjoyed our meetings and I am thankful for this extensive feedback and insights. I would like to thank Alessio as well for guiding me in the right direction.

Finally, I would like to thank my family and friends. My family has always been there for me during my study period and I have had a great time with my friends at the university.

I hope you enjoy reading my thesis!

Ismail Yagci
Enschede, March 2024

Management Summary

Problem Context

ProRail is a railway company mainly responsible of the regulation of all train-related traffic, maintenance of existing railway and the allocation of capacity of trains of rail operators. This research is conducted at the Capacity Allocation Traffic (CAT) department within team Emplacementen at ProRail in the Netherlands. This team is responsible for allocating capacity at railway yards. This research focuses on a single railway yard, which is the passenger railway yard of Watergraafsmeer located in Amsterdam.

ProRail has identified a critical issue in capacity allocation within the rail network, wherein rail operators frequently request more capacity than available, leading to conflicts and logistical challenges. This imbalance in capacity allocation has resulted in complaints from rail operators, submitted to the Autoriteit Consumenten Markt (ACM), which aims to ensure fair competition and protect consumer interests. The core problem identified is that ProRail allocates capacity based on requests rather than actual needs, leading to inefficiencies and conflicts. In addressing this issue, ProRail aims to improve the allocation process to better align with the actual needs of rail operators. The main research question that this research aims to answer is:

"What capacity allocation policy at railway yards can ProRail apply to meet the needs of rail operators?"

Methodology

In this research, we aim to develop an allocation policy for fourteen tracks at railway yard Watergraafsmeer. The essence of a policy lies in determining the allocation of rail operators to specific tracks. This policy should be applied over the course of a year, representing an annual allocation. Therefore, we utilized historical data of registered occupations on the tracks at Watergraafsmeer, representing the year X. We transformed the data, categorizing trains occupying a track as arriving demand to be allocated within the railway yard.

A mixed integer programming model is formulated to allocate the rail operators to the tracks. This model determines the allocation of arriving demand onto the tracks, with the objective of minimizing the number of rejected demand from rail operators. This is the first objective that we have to meet. Two key aspects incorporated into the model are the principles of time blocks and ad-hoc tracks, as these elements will determine the policy and will also be part of the instances for running the model.

Time blocks are formulated as a constraint in the model, representing predefined minimum non-decomposable time units during which trains belonging to the same rail operator can be allocated. Ad-hoc tracks are additional reserve tracks designed to accommodate trains that cannot be allocated to the regular tracks. When a train is allocated to an ad-hoc track, it counts as a half rejection in our model, which is determined by applying a weight in the objective function.

Furthermore, the development of an allocation policy involves creating instances, each representing a policy to assess the potential influences of capacity allocation policies. These instances, representing plausible outcomes of the allocation policy, is tested using the model. For the instances, we split up the data in smaller segments, representing two weeks in February. We developed 12 instances based on time blocks and ad-hoc tracks, analysing each instance for feasibility and optimality. The instance leading to the best outcome in terms of objective value is selected for further refinement.

We establish the allocation policy based on the schedule obtained as a result. Subsequently, our second objective takes precedence. In accordance with expert opinion, our aim is to maximize the number of dedicated tracks for rail operators. This entails implementing a greedy algorithm, utilizing swap operations within the schedule of the selected instance. We require this algorithm as it generates a greater number of dedicated tracks compared to the MILP. Additionally, we formulate an alternative policy alongside the original policy derived from the instance.

Furthermore, we test the policies derived from the model the expert opinion with two existing policies, namely the annual allocation of year X and a variant of this with mixed tracks. We have multiple rail operators, which are Rail Operator A, B, C, D, E and F. We utilize a First Come First Serve rule (FCFS) to minimize the number of rejected trains. We test this by utilizing the complete year of X as input data, comprising a total of 30000 trains. We utilize a larger dataset compared to what was used for the MILP to evaluate the practical utility of a policy over a one-year period. A sensitivity analysis is conducted by modifying one parameter from the model, which are the durations of trains occupying a track.

Results

We have run our MILP with the 12 instances for the weeks in February and the objective values ranges between 55 and 64 rejections, based on a total demand of 1558 trains. Over 90% of the trains are accepted for each instance.

We choose instance 5 as our preferred instance, with an objective value of 56.5 and a time block length of 4 hours and 1 ad-hoc track.

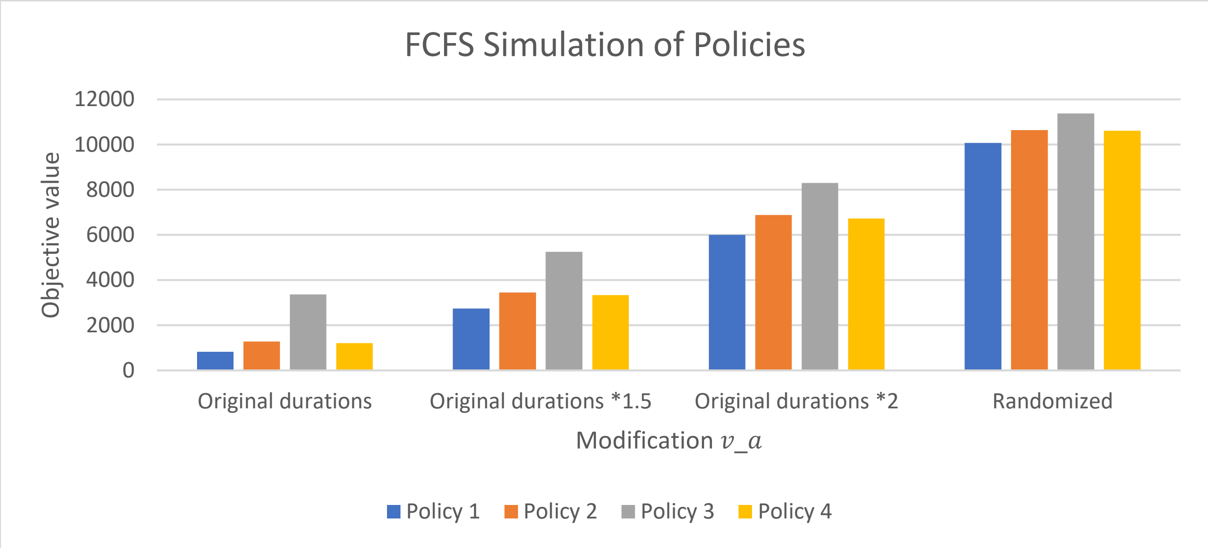
The policy devised from instance 5 incorporates 9 mixed tracks for both Rail Operator A and B, 4 mixed tracks for C and D and 1 mixed tracks for E and F on the ad-hoc track. Despite being rejected by the model, we opt to assign Rail Operator F to the ad-hoc track to ensure a more balanced allocation.

In pursuit of our second objective to maximize the number of dedicated tracks, we analysed instance 5 and applied our greedy algorithm through swap operations. As a result, we formulated an alternative policy with an increased number of dedicated tracks, totalling five: one for Rail Operator A and four for Rail Operator B. Additionally, there are eight mixed tracks for Rail Operator C and D, along with one ad-hoc track for Rail Operator E and F.

For our sensitivity analysis, we formulated four settings for the duration parameter. The objective of the analysis is to determine which policy configuration results in the lowest number of rejections. We utilize durations of trains (length of stay) as a parameter to assess the robustness of each policy and understand its impact on the number of rejections. By varying durations, we can gauge how sensitive each policy is to changes. One of the configurations involves randomized durations, which are randomly generated durations aimed at assessing their impact alongside the durations utilized in the model, as well as their variants multiplied by a factor 1.5 and 2.

We test these configurations across our four policies: the policy derived from the model (Policy 1), expert opinion (Policy 2), the current allocation policy of year X (Policy 3) and the variant with mixed tracks (Policy 4). We are examining whether both the model's policy and the expert opinion's policy outperform our current policy. With a total demand of 30000 trains from the year X, we allocate trains using a FCFS approach and evaluate the objective value for each policy and configuration.

The results of the sensitivity analysis, depicted in M. 1, illustrate the variation in objective values per policy and configuration of the duration. Under the original durations, the objective value ranges from approximately 800 to 3500 rejected trains. Conversely, implementing randomized durations consistently resulted in objective values surpassing 10000 rejections. Notably, Policy 1 exhibits the best performance in terms of objective values, with both Policy 1 and 2 outperforming the current allocation policy (Policy 3).



M. 1 Results of FCFS simulation

Conclusion, Discussion and Recommendations

A key finding was that instance 5 with a time block length of 4 and 1 ad-hoc track came as most effective in terms of objective value. Policy 1, based on model outcomes, outperforms the current policy (Policy 3) showing the best objective value in our sensitivity analysis. However, Policy 2, based on expert opinion, may be preferable from a rail operator perspective as it produces more dedicated tracks.

Constraints within the model posed challenges regarding performance and memory issue with large data instances, especially Constraint (2). Data limitations, including incomplete records of train lengths presented further obstacles. We also noted significant disparities among rail operators, with Rail Operator A and B exhibiting considerably higher demand compared to E and F, which have relatively minimal demand.

ProRail is advised to implement Policy 2, which is the policy from the expert opinion, offering more dedicated tracks. It is recommended to improve data accuracy and improve performance of model by reformulate constraints, especially Constraint (2). Moreover, we suggest to improve our model incorporating train characteristics to prioritize different types of trains.

This research enhances theoretical understanding and practical applications in railway yard allocation. By introducing a tailored MILP model for the TAP, it fills gaps in the literature and offers valuable insights for ProRail’s operations. The model can be adapted for other railway yards, aiding in the formulation of allocation policies specific to each yard’s needs.

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1. Introduction

In this chapter, an introduction of this research is given. We start with a concise description of ProRail in Section 1.1 with an elaborate explanation on the area that is discussed in Section 1.2. In Section 1.3, the problem identification with the formulated core problem are described. Subsequently, the research design is introduced in Section 1.4. The sub-research questions are formulated based on the main research question, that is introduced as well. Finally, we will also determine the scope of this research in Section 1.5.

1.1 ProRail

ProRail is a railway company with the Dutch State as its sole shareholder under the name Railinfratrust bv, operating in the Netherlands with its headquarter located in Utrecht. They have a five key activities of which they are responsible of, including management of stations, maintenance of existing railway, construction of new railway and stations, informing passengers and operators, the regulation of all train-related traffic and guaranteeing its safety and the allocation of capacity to passenger trains or cargo train on the track (ProRail, 2023). To provide a better understanding of how the regulation of traffic and capacity allocation is for ProRail, it is considered that in total 7.000 kilometres of track is allocated and 160 million kilometres of track is travelled per year (ProRail, 2023).

ProRail aims to improve the railway network of the Netherlands to maintain its operability. However, recent developments in the world such as the Corona pandemic had a massive impact, resulting in low numbers of passengers travelling by train. Moreover, it is expected that passenger and cargo transport will grow in the next years (ProRail, 2023). ProRail foresees a 30% rise in traffic, translating to approximately 1.5 million passengers daily passengers by the year 2030.

From an organisational perspective, approximately 5200 employees are working throughout the Netherlands distributed among multiple offices and traffic control stations. It comprises several departments including ICT, Finance and Control, Asset Management, Safety and Capacity Management (CM). The latter will be introduced in Section 1.2 and analysed explicitly in the next chapter, being the department that is central of this report.

1.2 Capacity Management

ProRail has multiple key activities and responsibilities to execute and one of them is the organisation of capacity on the track for the present and the future. The responsibility of capacity allocation has been delegated to the Capacity Management. They have the knowledge about the necessary capacity and the current infrastructure. Besides, this department plays an advisory role towards the Ministry of Infrastructure and Water Management.

Concretely, CM translates the daily needs and long-term plans of (local) governments, rail operators and passengers into a realistic policy and seeks to optimize the utilization of the railway network that meets the demand of the aforementioned groups. Two aspects within CM can be distinguished, namely allocation of maintenance activities and traffic allocation. Yearly, they determine the capacity that is required within the limits of the available infrastructure and allocate the capacity. The task to allocate all traffic-related activities is assigned to a subdepartment within CM, which is called

Capacity Allocation Traffic (CAT). Within CAT, the team *Emplacementen* [1] focuses on the capacity allocation for railway yards.

Each year in April, the rail operators can apply their requests for capacity to which CM creates a planning of the available capacity among the train paths and railway yards, also referred as time table. This new planning of the train table ultimately starts in December. In accordance with governments and several railway companies, the desired functionalities and utility of the railway network and transfer capacity will be specified.

CM also cooperates with their customers and there is a distinction between internal and external customers. The latter are railway companies, specifically cargo rail operators, passenger rail operators alongside logistical partners as ports and maintenance companies. Additionally, the government again is included as well. Internal customers are the departments within ProRail that are closely connected to CM, which are Asset Management, Projects and Traffic Control. In the allocation of capacity, CM does not differentiate when determining which entities will receive the capacity.

In this research, the focus lies on railway yard Watergraafsmeer, which is located in Amsterdam. A railway yard is an area having a network of tracks and sidings for storage and maintenance. This terrain is one of most important locations in the Netherlands (ProRail, 2023). It is of great importance to run the timetable as good as possible, since it can impact not only the city of Amsterdam, but also the rest of the Netherlands. Subsequently, the high-speed rail line starts in Amsterdam and runs to the Belgian border, connecting to the high-speed network toward Belgium and France. It also acts as a connection to the United Kingdom through the Eurostar train services. Lots of trains pass the night here after service. Besides, the trains are getting cleaned from both the inside and outside and supplied of all the necessary products, such as sanitary products. In Section 2.2, the procedure of allocating capacity at Watergraafsmeer is elaborately described. Moreover, in Section 1.3.1, we will identify the problem of this research occurring at railway yard Watergraafsmeer.

1.3 Problem description

In this section, the problem raised by ProRail is discussed. Next to that, the context of the problem is explained with the use of a problem cluster and the core problem is formulated.

1.3.1 Problem identification

ProRail observes that rail operators apply most of the time for more capacity than available and this results in conflicts. Employees at Capacity Allocation Traffic and rail operators are indicating that the tracks are scarce, leading to the fact that some rail operators could not be allocated to tracks they requested for. On the other hand, rail operators observed in practice that tracks were empty and it was not possible to fulfil wishes of some rail operators to allocate them at preferred tracks. As a consequence of the observations rail operators, complaints are made about this when they notice that the allocation is incorrectly conducted. These complaints are submitted to the Autoriteit Consumenten Markt (ACM), which is an organisation that has the goal to ensure fair competition between businesses and aims to protect consumer interests (ACM, 2023). The capacity on the yard is scarce and therefore operators need capacity on other railway yards. Although it is nearly impossible to satisfy the needs of all passenger operators, improvements in the capacity allocation on Watergraafsmeer may lead to fewer redundant train movements.

[1] Team within Capacity Allocation Traffic responsible for allocating capacity at railway yards in the Netherlands

Another problem is that the timetable is prone to a lot of changes, due to delay of rail operators at other areas or rail operators figure out that they do not need capacity anymore. Consequently, ProRail observes that it is challenging to anticipate on changes in the capacity allocation planning and satisfy all parties included in the allocation process. At the moment, all rail operators can request their required capacity, which is logistically speaking a form of waste in the process of allocating. Therefore, this problem is less related to the main cause occurring at ProRail and is left out of the problem cluster (Heerkens & Van Winden, 2017). As we highlighted, ProRail foresees an increasing demand for capacity in the (near) future, necessitating an improvement in the way ProRail allocates capacity compared to the current situation.

1.3.2 Problem cluster

In Figure 1, the relation between the problems is depicted visually. As shown in the legend below, the green square represents the core problem that is solvable, while the red square is a core problem that is difficult to solve. The yellow square is the action problem of this research.

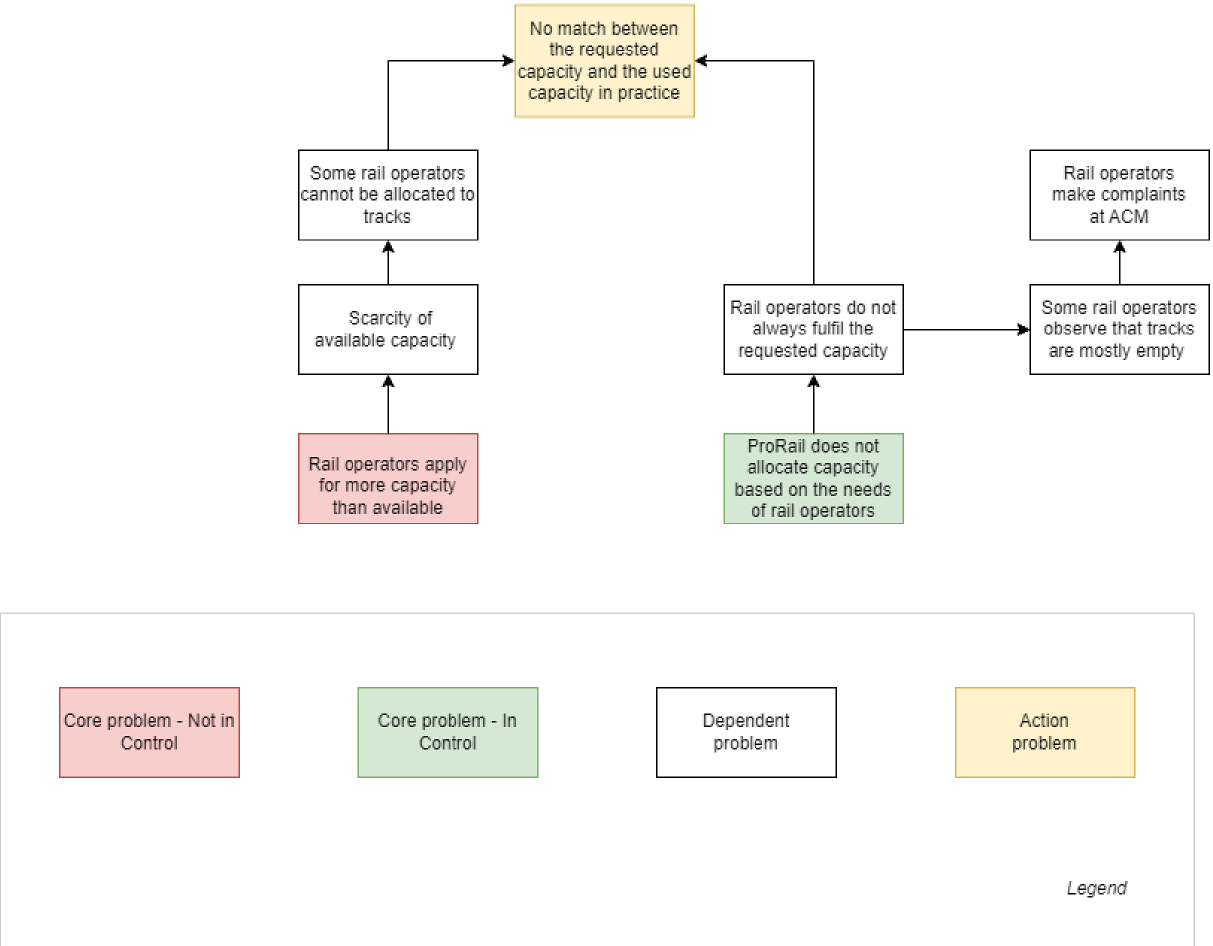


Figure 1 Problem cluster of this research

We already indicated that rail operators do not always fulfil the requested capacity and the cause of this problem has been marked as the core problem. Hence, the core problem of this research is formulated as follows:

"ProRail does not allocate capacity based on the needs of rail operators but on the requests"

ProRail is currently focusing on how to allocate rail operators based on the requests and seeks to gain insight in the usage of capacity in reality. Subsequently, the action problem, which is a discrepancy between the norm and reality, of this research is defined as the fact that there is no match between the requested capacity of rail operators and the used capacity in practice. It occurs that rail operators seem to need the capacity they have been asking for, resulting in conflicts with other parties that were not allowed to receive capacity beforehand. In the next section, the research design and approach is described.

1.4 Research design

This section covers the approach to solve the core problem and the research goal. First, the objective of this research is defined, and the practical contributions are outlined. Additionally, the research questions are formulated that break down the core problem.

1.4.1 Research goal

This research aims to develop an optimal allocation policy for ProRail to allocate capacity to rail operators at Watergraafsmeer. It is paramount for ProRail to justify decisions towards rail operators that feel affected. We intend to allocate rail operators to the tracks. The definition of common type of tracks will be provided in Section 2.2.

1.4.2 Research questions

To tackle and solve the core problem, several research questions are formulated and eventually answered. The structure of the research questions is based on the Managerial Problem-Solving Method (MPSM) of Heerkens & Van Winden (2017). The methodology of this research is shown in Table 1.

Table 1 Research methodology

Managerial Problem-Solving Method			**Outline**	
Phase	Description	Question	Chapter	Description
1	Defining the problem	-	1	Introduction
2	Formulating your problem-solving approach	-	1	Introduction
3	Analysing the problem	1	2	Current situation
4	Formulating (alternative) solutions	2 3	3 4	Literature review Solution design
5	Choosing a solution	4	5	Results
6	Evaluation	5	6	Conclusion Discussion Recommendations

The idea behind the research questions is that each question focuses on a chapter and that helps to answer the main research question. The fifth research question will be addressed in Chapter 6 and concludes this research.

Hence, the following main research question is formulated:

What capacity allocation policy at railway yards can ProRail apply to meet the needs of rail operators?

The following research questions are formulated that are addressed in each chapter. These are structured and explained below.

1. **What is the current situation of the capacity allocation process at Watergraafsmeer?**
   - *How is the current process organised in general?*
   - *What is the outline of railway yard Watergraafsmeer?*
   - *What is the current utilisation of tracks at Watergraafsmeer?*

In Chapter 2, the current process of capacity allocation is described. Interviews with employees at Team Emplacementen are held to gain insight and to collect the relevant information. A visual overview is given in the form of a timeline. Hereafter, a description of the railway yard Watergraafsmeer is given. Again, interviews are held with employees to get a better understanding of the operations at this railway yard. Furthermore, an analysis will be provided of the amount of time a track is occupied with available data of 2021 and 2022 of Watergraafsmeer.

2. **What is known in the literature about capacity allocation at railway yards?**
   - *What type of models are suggested and available in scientific literature to allocate capacity at railway yards?*
   - *What solution methods are known in general to allocate capacity in rail transport?*

This research question aims to find the relevant literature for this research. To start with, we want to understand what model would fit best to allocate capacity of rail operators. Moreover, we will delve into the type of methods to allocate capacity in general.

3. **How can we create a model to allocate capacity at railway yard Watergraafsmeer?**
   - *What are the parameters, variables and the objective function of the chosen model?*
   - *How can we incorporate the characteristics of Watergraafsmeer to the model?*
   - *What are the restrictions and assumptions that must be taken into account?*
   - *What steps do we take to develop an allocation policy?*

To gain insight into the solution design of this research, we will provide a textual formulation of the model tailored to railway yard Watergraafsmeer. Additionally, we will point out the limitations of the model by formulating constraints and assumptions that needs to be implemented in the model. Furthermore, we include the parameters, variables and constraints to the needs of ProRail. Finally, we will present the methodology for the development of an allocation policy.

4. **How can we test the solution proposed based on the formulated model and what are the insights that we can develop?**
   - *What are the results of the instances of the model?*
   - *What are the insights that we can develop from the results?*

Based on the formulated model, we will proceed to test various instances of the model. We will present key figures and tables to highlight important results derived from these instances. Subsequently, we will assess the robustness of the solution through sensitivity analysis, providing a brief discussion of our findings. Additionally, we will extract valuable insights from the outcomes generated by the model.

5. **How should the results be interpreted and what conclusions can we draw from this research?**
    - *What conclusions and recommendations can be derived from the obtained results?*
    - *What are the limitations?*
    - *What are suggestions for future research?*
    - *How does this research contribute to theory and practice?*

The final research question focuses on the interpretation of the results. We will formulate relevant conclusions drawn from the thesis, discussing our approach to reaching the solution and highlighting limitations encountered during this research. Recommendations will be provided, along with suggestions for future research. Additionally, we will discuss the contribution of this research to both theory and practice.

1.5 Scope

This research is considered as a case study for specifically railway yard Watergraafsmeer. The implementation will be out of scope but could be discussed. Next, we will focus on the capacity allocation procedure for traffic, which has been introduced briefly in Section 1.2 and will be described elaborately in Chapter 2. The infrastructure of railway yards consists of *Centraal Bediend Gebied (CBG)*, which refers to centralized traffic control, and *Niet-Centraal Bediend Gebied (NCBG),* which is non-centralized traffic control. CBG is an area on the railway network from which the track occupation is detected from one system and the control of those objects on the track is regulated from a centralized point of view (ProRail, 2023). NCBG is the variant from which traffic control is not executed from a centralized point of view, but locally under the supervision of a rail traffic controller, who communicates with rail operators and actively guides them (ProRail, 2023). Given the absence of detailed monitoring of movements, the data on occupied tracks at NCBG can be inconsistent or even unavailable. As a result, the focus remains on allocating capacity solely within CBG. The explanation of what tracks at Watergraafsmeer are within CBG is discussed in Section 2.2.

1.6 Summary Chapter 1

In this chapter, we provided an introduction to the company and its relevant department, outlining the problem that has arisen. We explained the core business of the department with numerous examples. Additionally, we described the problem identification and presented a problem cluster to highlight the core problem and the corresponding action problem that needs addressing. Our core problem is identified as the mismatch between the requested capacity and actual usage. The action problem stems from the observation that rail operators request more capacity than is available, leading to the issues we have outlined.

Moreover, our main research question aims to develop an allocation policy for railway yard Watergraafsmeer. We defined the scope to establish the boundaries and extent of this research. The research design outlines our approach to solving our core problem by formulating sub-questions. Chapter 2 will delve into describing the current process at CAT, while Chapter 3 will focus on the literature search to find relevant information. In Chapter 4, we will detail the solution design and our approach to obtaining results. Chapter 5 will present the results, and we will conclude this research by providing recommendations, discussing our findings, and make suggestions for future research.

2. Current Situation

In this chapter, the current situation at CAT at ProRail is explained in detail. The following research question will be answered:

What is the current situation of the capacity allocation process at Watergraafsmeer?

In Section 2.1, the main procedure of capacity allocation is described. Furthermore, a current overview of capacity allocation at the railway yard Watergraafsmeer is shown and discussed elaborately. In Section 2.2, an overview of the operations at Watergraafsmeer is discussed and the corresponding rail operators and in Section 2.3 the current utilisation of tracks is explained and the degree of occupancy of tracks.

2.1 Capacity allocation procedure

In this section, the capacity allocation procedure is described in general. ProRail distinguishes several types of processes, namely the Mid-Long Term (MLT), the annual allocation itself and the allocation in the ad-hoc phase. We discuss each process in the following sections. Figure 2 shows a timeline to indicate the duration of the several procedures. The time is measured in months and the timeline is in chronological order starting from the top X - 84 to the bottom, marked as X representing the starting moment of a new time table. The numbers represent the number of months. Further details of Figure 2 will be discussed in Section 2.1.2.

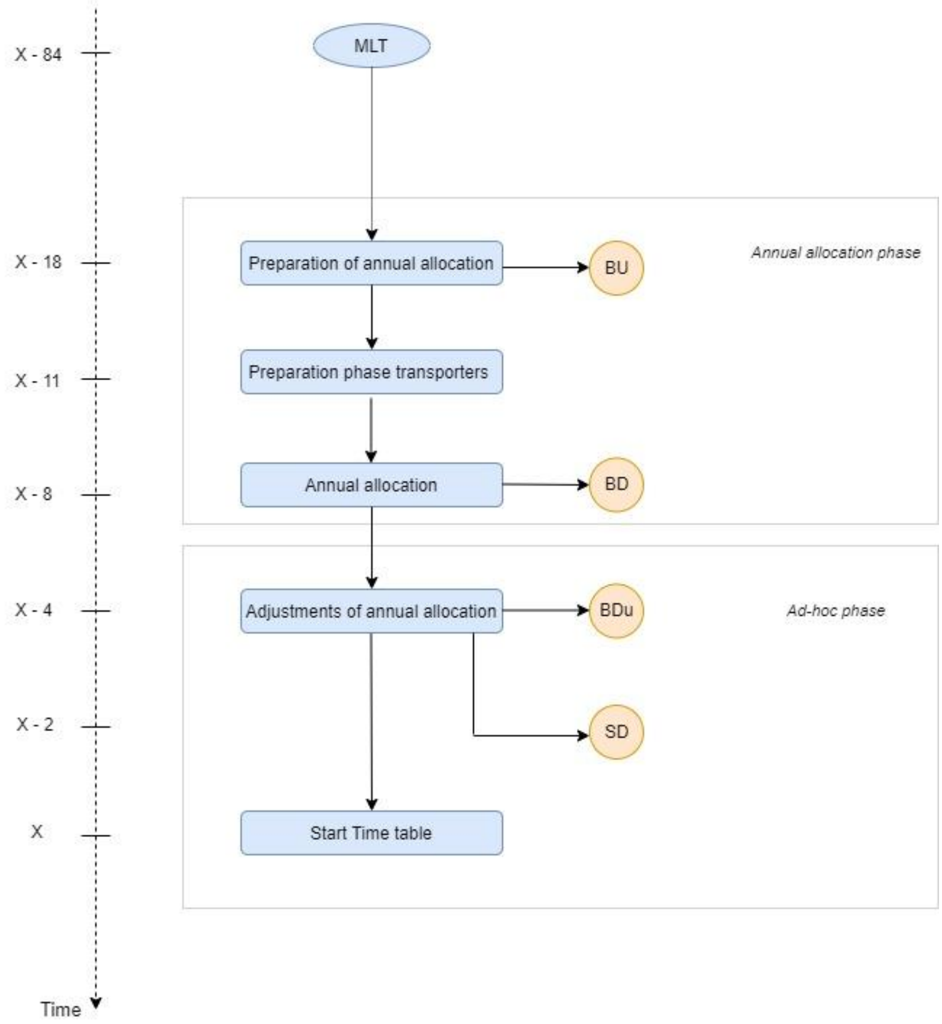


Figure 2 Timeline of current capacity allocation procedure

2.1.1 Mid-Long Term Forecast

The MLT stand for Mid-Long Term forecast. This stage represents the predictions and expectations that might occur in the mid-long term, ranging from 18 months from the initial preparation of a time table. Several projects are carried out by ProRail to realise improvements.

2.1.2 Annual allocation

This phase starts roughly 18 months from the actual timetable. The first subprocess is the so-called preparation of the annual allocation, in which ProRail and the rail operators have preliminary talks about the amount of capacity rail operators expect to require. Besides, the set-up of the BU (basis uren) is realised. The latter refers to a schedule in which the number of trains per hour are scheduled on a specific route. Moreover, the infrastructure managers cooperating in the rail freight sector present in favour of the rail freight rail operators the supply of the so-called Pre-Arranged Paths (PAPs). These paths are predetermined specifically for rail freights to destinations abroad (ProRail, 2023). Hence, ProRail allocates capacity on train paths only.

The period between the preparation of the annual allocation and the annual allocation does not have a formal status, which is from X-11 until X-8. Rail operators make preparations to apply their requests for capacity until the deadline.

The annual allocation itself starts eight months before the timetable. The design of the timetable will be determined based on the applications of rail operators. All requests are collected and checked whether conflicts appear. In this stage, the set-up of the BD (basis dagen) is delivered. BD refers to the schedule consisting of seven days of each 24 hours in a regular week.

During the annual allocation process, the train paths, the parking capacity, trains that need to pass a bridge opening, the weekly withdrawals and the incidental withdrawals are scheduled. The weekly maintenance timeslots are short, planned periods in the week in which small maintenance activities are executed. The capacity allocated for these activities can be done without consultation of other rail operators. The incidental withdrawals are the out-of-service periods in which larger operations on tracks are executed. All the mentioned elements are part of the BD and will be officially included. A special category of applications are the so-called ''late requests'', which are basically the requests received after the deadline (X-8) but before the capacity has been allocated ultimately (X-4). These requests will be processed based on a First-Come-First-Serve principle. It is possible that changes may be implement if it necessary to improve the flow and reduce conflicts and if the transporter who received capacity agrees with the adjustments that is taking place. Approximately a month before the publication of the time table, a draft version is handed out. The reason for this is to give rail operators a final opportunity to respond whether they agree with the allocation and also to implement small changes.

2.1.3 Allocation in the ad-hoc phase

The ad-hoc phase concerns the additions and changes in the annual allocation. This phase is starting from X-4 and it continues a whole year of the timetable, which is X + 12. The requests are handled based on a first-come-first serve principle. Hence, the applicant that requested first, will receive the capacity. Again, it is not allowed to have conflicts in the schedule when changes are applied. Furthermore, rail operators have the possibility to determine to what extent a change should be made. When a frequent change needs to be applied, for instance each Monday afternoon for the rest of year, then this is marked as a BDu (basis dagen update). This is not characterised as a fully-fledged process, but more as a method to highlight adjustments. When an adjustment in the time table has to be made for specific days, such as unique holidays, the change will be applied in the SD (specifieke dagen). The SD is a method as well, focusing on changes with respect to unique events.

There are namely six periods consisting of approximately two months that a frequent change can be applied. The first BDu period already starts after the annual allocation of the new time table is published (X – 4). For instance, an adjustment made during the third BDu period means that changes are only applied after this period for the rest of the year. A SD adjustment can be made every week or every two weeks, dependent on the frequency of conflicts that can appear. As a result, the number of SD week adjustments within a BDu period varies from four to twelve weeks. Although, when a fast change needs to be made within the same week, CM is only eligible to apply changes when that change is implemented 48 hours or later after a BDu period started. If that adaptation has to be made 48 hours or earlier, Traffic control of ProRail deals with these changes. The procedures and operations of traffic control will be disregarded for this research and is out of scope.

2.1.4 Capacity allocation at railway yards

The capacity allocation of railway yards slightly differs from train paths, since these yards are mostly meant to park trains after service or perform maintenance to trains, whereas train paths is the capacity needed within the infrastructure to run a train between places over a certain time period. ProRail announces the available capacity to rail operators during the preparation phase for rail operators (between X – 11 and X – 8), which is before March. Each railway yard consists of multiple tracks having different functionalities. An overview of tracks per railway yard is shown in the Sporendatabase, which is a catalogue with the relevant information per track. The functionality of a track indicates to what purpose a track can be used. Some tracks could have two functionalities where functionality one represents the primary purpose and functionality two is the secondary purpose.

ProRail takes the functionalities into account when allocating the tracks. In favour of the optimal utilization of tracks, it is possible that ProRail decides to deviate from the listed functionalities. To avoid unused capacity, an agreement can be concluded between different rail operators to share usage.

Capacity requests for the annual allocation are made by means of the so-called *volume-infra-inzetten* (VII) in Donna. Donna is an application used to schedule and request train paths, shunting tracks and parking capacity in favour of the BU, BD and SD. The VII are the theoretical reservations of capacity consisting of the corresponding track and the length of duration by rail operators in the application. Every rail operator entitled can apply for capacity without any restriction or limitation. As mentioned in Section 1.2, the employees working at team *Emplacementen* will check for conflicts at the requests and try to solve this whenever possible.

In addition to creating a new time table for the upcoming year, improvements are being made to the current year's schedule as well. Rail operators often make ad-hoc requests, which can potentially lead to conflicts in the schedule. With Donna, it is possible to identify the type of conflict that has occurred and determine if it can be resolved by reassigning a rail operator to a different track. To address our specific problem, our attention is directed towards the annual allocation phase, specifically aimed at refining the process of generating an annual allocation.

2.2 The Case: Watergraafsmeer

In this section, we will discuss the design and the operations at Watergraafsmeer. First, we will focus on the railway yard itself and secondly about the involved rail operators making use of the tracks.

2.2.1 Overview of Watergraafsmeer

The railway yard of Watergraafsmeer was founded in 1904 and merely played a role in shunting rail freights. Later on, it mainly became a railway yard for passenger trains. The yard is equipped with facilities to execute maintenance and cleaning activities to trains. Figure 3 shows the outline of the railway yard Watergraafsmeer.

The designated places for that are present such as a workshop and a train wash facility. One of the designated places is a maintenance depot called *Nedtrain,* mostly referred as *NS Onderhoud en Service* (NS O&S), which is belonging to NS. Nedtrain is a subsidiary of NS and is responsible for maintenance, overhaul and cleaning of trains (NS, 2023). It has various locations throughout the Netherlands, including a significant facility at Watergraafsmeer. The tracks connected to this location are only in use of rail operators of NS.

Another facility belonging to NS and connected to Nedtrain is the *Kuilwielenbank,* which is a specific facility for measuring and checking train wheels. It consists of a measuring system to check train wheels accurately on wear, dimensions and other possible defects. The Kuilwielenbank contributes to the quality and safety of train wheels and ultimately on the rail traffic in general.

Furthermore, the Technical Centre at Watergraafsmeer is another facility for train maintenance and repair and part of NS O&S. It mainly provides comprehensive technical services for trains. Moreover, it plays a crucial role in the maintenance and reliability of trains and ensures the good condition meeting the required safety standards.

Looking at the tracks at Watergraafsmeer, the following tracks can be distinguished and an overview of common types of tracks is shown in Table 2.

Table 2 Common types of tracks at Watergraafsmeer

Track type	Definition
Parking track of passenger trains	Track used to park trains after service
Infrastructure track	Special track used for transportation of equipment to execute maintenance activities in favour of the infrastructure
Shunting track	Track used to sort and classify trains based on their destinations or specific routes. It also provides the flexibility to reorganize and rearrange trains, enabling efficient distribution and optimization of rolling stock.
Service track	Track used to provide the support for cleaning the interior and exterior of the trains, including windows, floors, seats, toilets and other surfaces after the regular operational service.

These type of tracks are all spread across the railway yard. We mentioned in Section 2.1.4 that tracks can have one or two functionalities. Besides, we also want to focus on the tracks locating in CBG area, as indicated by a red circle in Figure 3 in Section 1.5. The tracks at Watergraafsmeer in CBG are the so-called C-tracks, to which fifteen of them are in total. In Table 3, we provide an overview of these tracks with the corresponding functionalities and effective length in meters derived from the current version of the Sporendatabase (ProRail, 2023).

Table 3 Functionalities and effective length of C-tracks Watergraafsmeer

Track	Functionality 1	Functionality 2	Effective length (m)
C1	Shunting track	Service track	330
C2	Parking track	Service track	350
C3	Parking track	Service track	425
C4	Parking track	Service track	470
C5	Parking track	Service track	430
C6	Parking track	Service track	455
C7	Parking track	Service track	337
C8	Parking track	Service track	337
C9	Parking track	Service track	337
C10	Parking track	Service track	337
C11	Parking track	Service track	337
C12	Parking track	Service track	337
C13	Parking track	Service track	337
C14	Parking track	Service track	337
C15	Shunting track		518

Based on the given information in Table 3, we observe that there are two tracks used as shunting track, which are C1 and C15. This means that these two tracks are not allowed to park trains initially.

ProRail may deviate from the stated functionalities if there are valid reasons. Traffic Control must agree with this adjustment, as there is less room for adjustments in the planning. In a later stage of this research, these two tracks will not be included in the analysis to define a capacity allocation policy, as we aim to allocate rail operators to the tracks highlighted in Table 3.

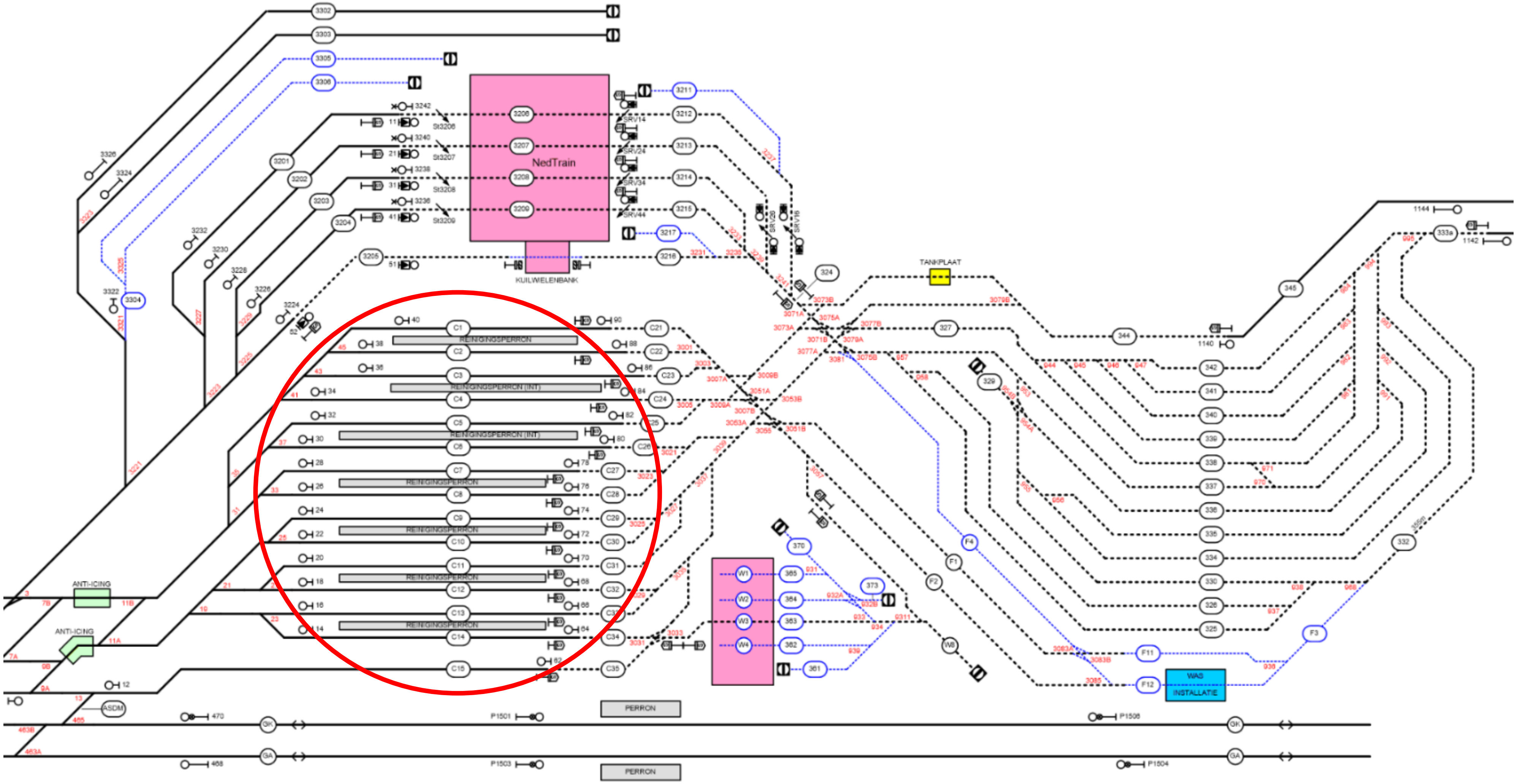


Figure 3 Current overview of the tracks at railway yard Watergraafsmeer

The C-tracks are shown in the left corner immediately below the facility of Nedtrain. We marked this location with a red circle. They are located from the top (C1) to the bottom (C15). The tracks represented as dotted lines are tracks within NCBG area and the tracks with straight lines are within CBG area.

2.2.2 Rail operators

Rail operators are responsible for the efficient and safe movement and organization of trains within railway yards. They ensure the efficient movement of train within the yard and a few activities they execute are sorting, assembling and dissembling the train. They have to follow communication procedures and protocols. At Watergraafsmeer, this includes moving the train from CBG area to NCBG area. We distinguish several rail operators that actively utilize the tracks at Watergraafsmeer in the timetable of Year X. Table 4 lists the current rail operators at Watergraafsmeer.

Table 4 Rail operators at Watergraafsmeer in year X

Rail operator	**Explanation**
A	Information is left out due to confidentiality!
B	Information is left out due to confidentiality!
C	Information is left out due to confidentiality!
D	Information is left out due to confidentiality!
E	Information is left out due to confidentiality!
F	Information is left out due to confidentiality!

2.3 Current utilization of tracks

In order to assess the utilization of tracks by rail operators at the C-tracks at Watergraafsmeer, an analysis was conducted using available datasets. The analysis excluded the C1 and C15 tracks. The datasets comprised the start time and end time of track occupation by rail operators, encompassing both daytime and night-time periods from December 2021 to November 2022. To focus solely on daytime utilization, the duration of track occupation was calculated specifically for a 12-hour period during the day. This 12-hour period stretches out from 7:00 until 19:00. This period has been chosen because it fits merely with the planning of the rail operators themselves. When the duration of track occupation in hours has been calculated, we sum up all durations for each track. The total number of hours of track occupation per track is obtained during daytime for the time period of the mentioned 11 months.

The results are visually represented in a bar graph in Figure 4, where each track represents a bar. The height of each bar corresponds to the percentage of the total time a track can be occupied, so by dividing the total number of hours a track was occupied by the total number of daytime hours within December 2021 and November 2022.

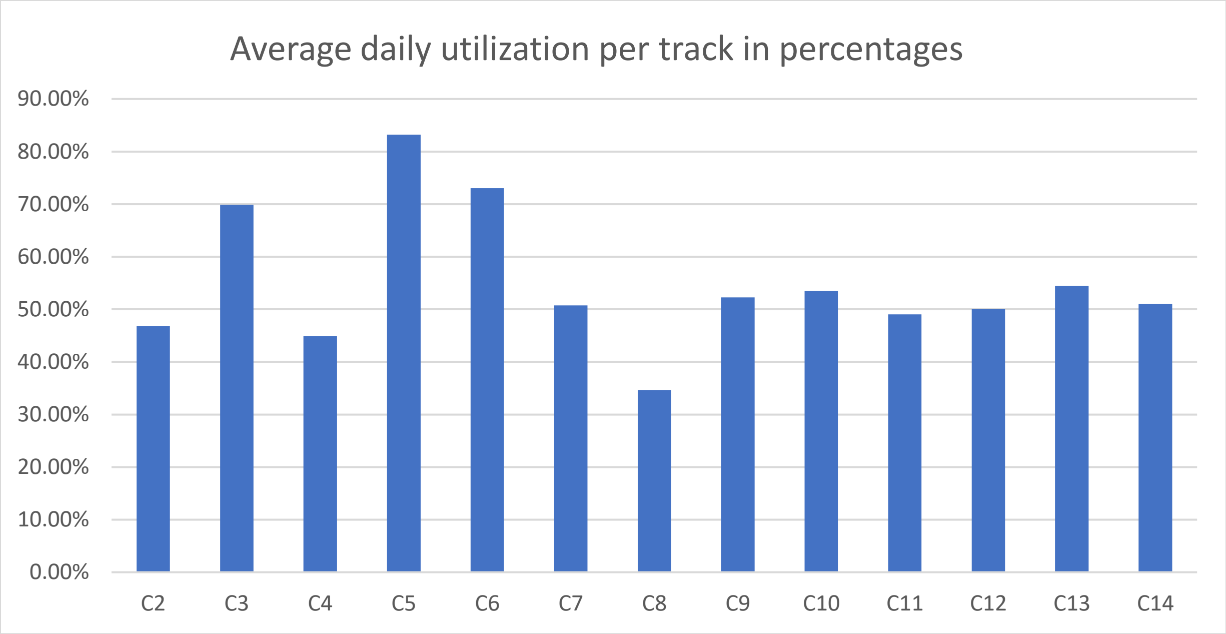


Figure 4 Average daily utilization per track between 7:00 and 19:00 in percentages (Dec'21 - Nov'22)

The same procedure has been executed for the time period of February 2023 until May 2023. Its result is plotted in Figure 5. The figures suggest that tracks with a higher percentage reflect higher rates of occupation, whereas a lower percentage suggests that tracks are less occupied. It stands out that both line graphs have a similar shape and in both cases, C8 has a low utilization compared to other tracks.

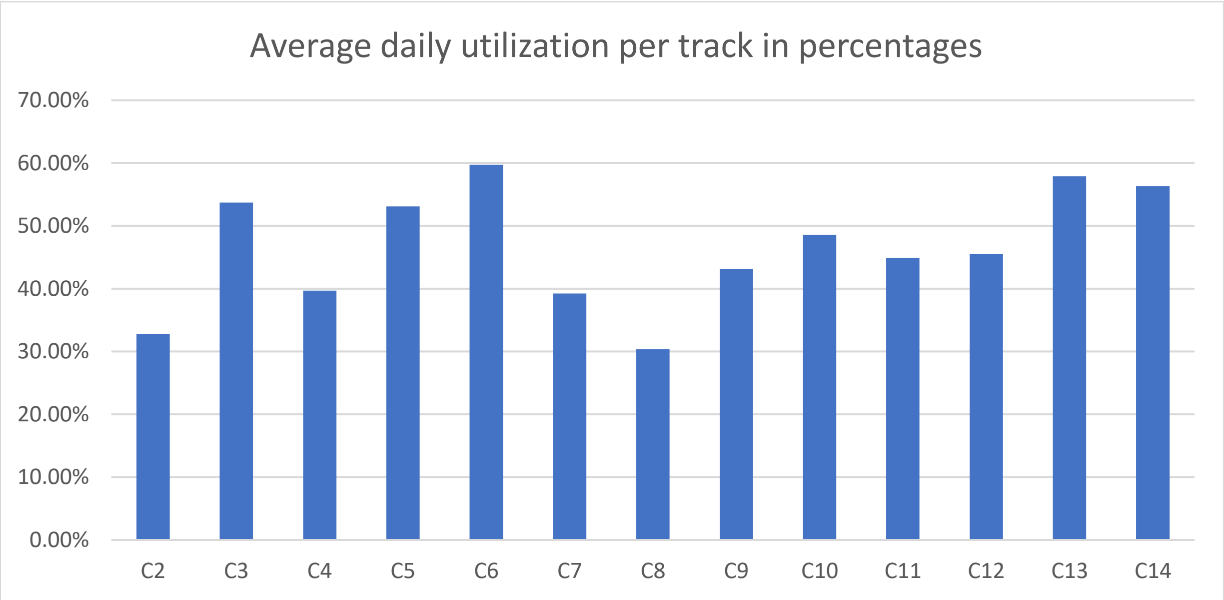


Figure 5 Average daily utilization per track between 7:00 and 19:00 in percentages (Feb'23 - May'23)

Additionally, we have examined the extent of unoccupied tracks in both datasets. To accomplish this, we determined the percentage of unoccupied tracks for each weekday. The restriction is that a train has a minimum parking duration of 6 hours. Therefore, we calculated the average for each weekday within the corresponding time period covered by the dataset. This provided us with the average duration of unoccupied tracks per weekday. Furthermore, we segregated the results to both datasets shown in Table 5 and 6.

Table 5 Occupation rates during the week (Dec'21 - Nov'22)

Track/Weekday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
C2	27%	47%	47%	40%	33%	38%	31%
C3	13%	13%	13%	7%	20%	44%	19%
C4	27%	20%	20%	40%	60%	63%	44%
C5	13%	20%	13%	13%	20%	44%	13%
C6	27%	13%	13%	33%	33%	25%	19%
C7	33%	27%	40%	27%	40%	31%	25%
C8	40%	53%	53%	40%	47%	31%	31%
C9	13%	0%	33%	13%	20%	19%	31%
C10	20%	13%	13%	7%	7%	25%	25%
C11	53%	53%	53%	47%	40%	13%	31%
C12	67%	47%	27%	40%	33%	13%	25%
C13	27%	40%	33%	13%	27%	0%	19%
C14	27%	20%	13%	20%	13%	13%	13%

Table 6 Occupation rates during the week (Feb'23 - May'23)

Track/Weekday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
C2	22%	37%	37%	31%	46%	39%	15%
C3	2%	2%	2%	0%	4%	13%	0%
C4	15%	26%	17%	24%	57%	50%	15%
C5	0%	0%	2%	0%	2%	4%	0%
C6	4%	7%	2%	0%	13%	7%	2%
C7	15%	15%	9%	4%	22%	7%	9%
C8	48%	33%	43%	40%	48%	41%	11%
C9	4%	0%	7%	0%	7%	15%	13%
C10	7%	4%	2%	0%	9%	22%	15%
C11	33%	61%	50%	44%	46%	30%	22%
C12	39%	39%	57%	42%	22%	30%	20%
C13	46%	33%	37%	44%	35%	28%	9%
C14	28%	30%	30%	29%	22%	35%	17%

We distinguish the occupancy rates by marking the green percentages as mostly unoccupied while the red percentages indicate highly occupied tracks. Focusing on Table 5, the Thursday is considered as a weekday that almost all tracks are occupied more than half of the time. Track C5 is the track that shows for all weekdays that is the occupancy rate is approximately 0%, indicating that it is occupied throughout the week. Track C9 has relatively low unoccupied percentages on weekdays, with Monday, Tuesday and Thursday of 4%, 0% and 0% respectively. Track C11 consistently shows high unoccupied percentages on weekdays, indicating a significant amount of free time during those days.

Table 5 shows that in general there is a lot of variation between the tracks and also per day. For instance, track C12 is often more unoccupied during the week days compared to the weekend days. Next to that, we observe that C4 and C11 have more peaks, resulting in percentages of 50% or higher, indicating that tracks are for more than of the time unoccupied. C13 and C14 have lower percentages, namely not higher than 40%, so that these tracks are more often occupied.

2.4 Summary Chapter 2

We conclude Chapter 2 by answering the research question. To start with, we provided an explanation of the current process of capacity allocation in general, including a brief explanation for railway yards and presented a timeline to illustrate the duration of each subprocess.

Subsequently, we outlined the railway yard Watergraafsmeer and its designated tracks. Watergraafsmeer encompasses multiple tracks, some within CBG and others within NCBG. Our focus is on the CBG area and especially on the C-tracks, ranging from C1 till C14.

Furthermore, we illustrated the current utilization of tracks based on datasets of the year 2022 (covering December 2021 and November 2022) and the initial months of 2023 (from February 2023 and May 2023) from 7:00 AM until 19:00 PM. We noted that in both cases, C8 exhibited relatively low utilization compared to other tracks. Additionally, we analysed the extent of unoccupied slots per day for both datasets. In 2022, tracks C5 and C9 were frequently occupied, while track C11 on the other hand remained largely unoccupied, particularly during working days. In the first months of 2023, C13 and C14 were predominantly occupied, while C12 remained mostly unoccupied. The findings are visualised in Table 5 and 6.

There are notable differences in track utilisation and time periods. The analysis highlights tracks with consistently low utilisation, such as C8 in both datasets and C11 during working days in 2022, while C5 and C9 were frequently occupied. These findings present opportunities for optimization by implementing improvements to better utilize underutilized tracks.

Moving forward, we will conduct a literature review to gain insights into effective approaches for capacity allocation at railway yards, formulation of models and how to solve them.

3. Literature review

We will provide an elaborate literature review and we aim to answer the following research question:

What is known in the literature about capacity allocation in rail transport?

In Section 3.1, an overview is given of different types of models in literature. This will form the basis of the solution design. Section 3.2 will cover several solution methods that are suggested to solve models. Section 3.3 will address how one can model uncertainty to cope with changes. Finally, Section 3.4 provides an overview of validation methods to assess the accuracy of a model.

3.1 The concept of shunting

According to Lentink et al., (2006) and Freling et al., (2005), the process of parking train units at a yard together with several related processes is called ‘’shunting’’. One issue discussed is the fact that train units are strongly restricted in their movements by the railway infrastructure. Arrivals and departures are typically mixed in time. During the night, the goal of shunting is to select the positions and compositions of the trains at the shunt yard in such a way that the operations in the next morning can start up as smoothly as possible.

Futher elements that are involved in shunting is shown in Figure 6.

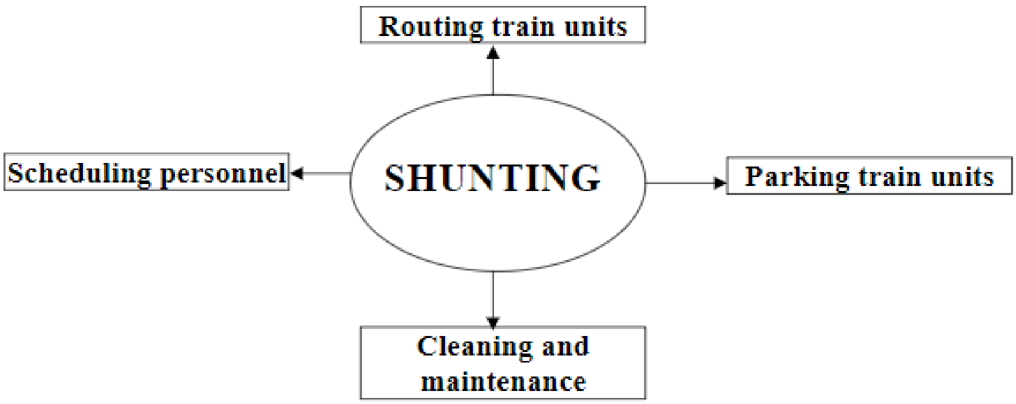


Figure 6 Elements of shunting (Lentink et al., 2006)

The concept of shunting is a broad concept as one can observe from Figure 6. We are mainly interested in parking train units as one of the elements of shunting, since we deal with (parking) tracks (C1 until C14) at Watergraafsmeer and an efficient planning an allocation of rail operators to these tracks. In the context of planning and scheduling rail operations, Marinov et al. (2013) distinguishes three types of management levels:

- The strategic level encompasses long term planning of several decisions including redesign, reconstruction of the physical tactical network and relocation of railway facilities.
- The tactical level is focusing more on medium term planning. At this level, timetables and schedules are developed.
- The operational level is for short term planning, which might be executed over the same day of service delivery. Furthermore, timetables and schedules are implemented on a ‘’day-to-day’’ basis in order for the system to provide the service. Kamenga et al. (2021) even splits the latter in *pre-operational* and *real-time* planning phases. However, the definition of the

precise timing of these phases slightly differs per study. An example is France, which associates this as from six days to four hours before operations (Kamenga et al., 2021). The latter then starts and continues until operations are actually performed.

To come up with a concrete approach of trains or units of trains are allocated to tracks, we would like to formulate a model that supports this approach and can help to provide insights. The problem introduced by Haahr et al. (2017), Freling et al. (2005) and Lentink et al. (2006) is the so-called *Train Unit Shunting Problem (TUSP),* focusing on shunting operations planning. Primarily, the goal is to optimize the shunting operations, minimizing the time and resources needed including the assembly, disassembly and rearrangement of train units. Its objective is to develop strategies or algorithms that enable the efficient shunting of train units within a railway yard.

The theory discussed from the several authors are all derivations from the Train Unit Shunting Problem and are mostly at the *Operational Level*. Freling et al. (2005) discusses a few characteristics for this problem, which are:

- Arrivals and departures of train units may be mixed in time. Within the planning horizon, this may imply that the first departure may take place before the last arrival
- (Shunt) units may have different subtypes and lengths. As a result, the type may restrict the set of (shunt) tracks where a (shunt) unit can be parked.
- The tracks may have different types and lenghts. The type of a track determines how a unit can approach the track. Some of the tracks can be approached from one side or both sides, respectively called *Last In First Out (LIFO) tracks* and *free tracks*.
- The timetable contains fixed arrival and departure times, but often flexible arrival and departure times from the shunt tracks.

3.2 Capacity allocation models in railway systems

For the capacity allocation of rail operators at Watergraafsmeer, we aim to develop a model that optimizes the annual capacity allocation based on the needs of rail operators. Models are used to predict or compare the future performance of a new system, a modified system, or an existing system under new conditions (Carson, 2002). As we are doing so, we need to understand how to formulate a model on railway yards, especially to park trains on the specified tracks mentioned in Section 2.2.1.

Practical instances often render the TUSP too large to solve as a single integrated optimisation problem. According to Gilg et al. (2018), this problem can be decomposed into two subproblems:

1. The assignment of arriving parts to departure parts which form a train.
2. The assignment of trains to tracks.

The first subproblem is identified as a *Matching Problem* (Haahr et al., 2017). This problem pairs the arrivals and departures of train units at depot or yard. The resulting matching implictly specifies how long individual units will spend in the depot or yard. The second subproblem is indicated as the *Parking Problem* or better known as the *Track Allocation/Assignment Problem (TAP)* (Haahr et al., 2017), (Gilg et al., 2018), (Freling et al., 2005)*,* (Lentink et al., 2006)*.*

The Matching Problem is formulated as a *Mixed Integer Programming (MIP)* model by Freling et al. (2005) and Lentink et al. (2006), in which the supply and demand of train units are matched. Each arriving train (shunt) unit is assigned to a departing (shunt) unit. Ultimately, the pair of matchings results in so-called *blocks*, which is an entity of one or more train units that remain together for the entire planning period and thus a combination of an arriving train and an identical departing train.

Both papers point out that the combination of an arriving part and a departing part is feasible if the units in both parts are the same, these units are in the same order, and the departing part leaves the station after the arrival of the arriving part. The decision variables are defined as binary, which are three of them indicating whether an arriving part is used, a departing part is used and whether the arriving part is assigned to a departing part. The objective of this model is to minimize the weighted sum of the number of parts incurring a penalty cost.

For the second subproblem, Freling et al. (2005) and Lentink et al. (2006) proposed an integer programming model that is aimed at assigning blocks to (shunt) tracks. The TAP is formulated as a Set Partitioning Problem. Let S be the set of (shunt) tracks and K^s be the set of assignments on tracks $s \in S$ and K_b^s the set of assignments on track $s \in S$ containing block $b \in B$. The decision variables are declared as follows:

$$x_k^s = \begin{cases} 1 \; if \; assignment \; k \; \in \; K^s \; is \; used \; on \; (shunt) \; track \; s \; \in \; S \\ \qquad\qquad\qquad 0 \; otherwise \end{cases}$$

$$y_b = \begin{cases} 1 \; if \; block \; b \; \in \; B \; is \; not \; parked \; on \; any \; (shunt) \; track \; s \; \in \; S \\ \qquad\qquad\qquad 0 \; otherwise \end{cases}$$

Two binary decision variables are defined including, whether an assignment is used on a track and whether a block is not parked on any (shunt) track.

Gilg et al. (2018) formulates the TAP model using a departure and conflict model. The departure model is used to focus on the departure time of one train on a given track and identify possible relations to other currently parking trains. One decision variable considered is a basic binary decision variable and is stated as follows:

$$x_{i,s} = \begin{cases} 1 \; if \; train \; i \; is \; assigned \; to \; track \; s \; \in \; S \\ \qquad\qquad 0 \; otherwise \end{cases}$$

The other decision variable is a bit specific and contains more indices regarding the side of the track that a train can leave. Gilg et al. (2018) consider free tracks and introduce the indices *p* and *q,* marking the side *p* to enter a track and leave the track from side *q*. The following binary decision variable is formulated:

$$x_{i,s,p,q} = \begin{cases} 1 \; if \; train \; i \; enters \; track \; s \; from \; side \; p \; and \; leaves \; from \; side \; q \\ \qquad\qquad\qquad 0 \; otherwise \end{cases}$$

When considering the constraints, the assignment principle is feasible if the following conditions hold according to Freling et al. (2005) and Lentink et al. (2006):

- No crossings. This only occurs when a train unit is obstructing the arrival or departure of another train unit.
- The total length of the units on the tracks never exceeds the length of the track.
- All blocks of the subsets are allowed to park on the track.

Jacobsen & Pisinger (2011) discuss the shunting planning problem, which is meant to produce a shunting and work plan for a time horizon of 2-3 days. This model is simplified, since they work with discrete time units of one quarter of an hour. Assumptions of this model are that each train unit arrives at a nearby station, from where it has to be shunted to a depot track. Upon completion of the repair, the train unit will be delivered to a given location which may not be the same as the arrival location. Upon arrival, the train unit is shunted into the workshop for repair. When repair is completed, the train unit is is removed from the workshop and again parked at a depot track. Around delivery time, the train is shunted to the place of departure. Additionally, all shunting tracks are *LIFO* tracks and it is possible to collect any train unit at a depot track at time within 15 minutes, which represents one time unit.

The model should meet the following constraints:

- A train unit cannot be parked before it arrives at the collect track.
- Train units should be collected in the order they arrive.

The constraints formulated by Gilg et al. (2018) implies that each train is assigned to at most one track, the length of the train units should not exceed the track length and departure constraints are formulated, which suggests the the direction a train should leave the track (considering LIFO tracks or free tracks).

Regarding the objective function, Jacobsen & Pisinger (2011) composed an objective function of several penalty terms which are set to minimize. Consequently, a penalty is given if the deadline is not met, if the train is not collected at arrival or the train have not passed on time. Gilg et al. (2018) delineates the objective function aimed at maximizing the number of assigned trains to tracks. The outline of the objective function is as follows:

$$\max \sum_{i,s} x_{i,s} + \sum_{i,s,p,q} x_{i,s,p,q}$$

The conflict model determines where forbidding infeasible assignments of two trains on the same track appear. The objective function and the length constraints hold the same principle as in the departure model.

3.2.1 Conclusions from capacity allocation models

It becomes clear that the problem discussed in Chapter 1 can be related to the Train Unit Shunting Problem, which is divided into two subproblems. The first subproblem is the Matching Problem and the Track Assignment Problem, the second subproblem, is the subproblem of higher interest for ProRail. The models of Gilg et al. (2018), Jacobsen & Pisinger (2011), Freling et al. (2005) and Lentink et al. (2006) are formulated as Mixed Integer Programming models, with each of them discusses a different variant based on the characteristics and topic of the papers.

The models discussed in the papers cannot be directly adopted and applied to the problem we formulated. For instance, the objective functions are different or too general to be applied and therefore an objective function based on the needs of ProRail should be formulated. Decision variables can be adopted, for instance the binary decision variable that is stated by Gilg et al. (2018) of how a train is assigned to a track, but must be modified to the case of Watergraafsmeer. The same principle holds for constraints that are formulated. We do not have to deal with LIFO tracks, but only with free tracks, as the tracks are approachable from two sides. Therefore, it makes it reasonable to apply and formulate a MILP model with self-added parameters and constraints that is applicable to Watergraafsmeer.

3.3 Solution methods

In this section, we present solution methods to solve a capacity allocation model. We provide examples based on the theory discussed in Section 3.2, as these papers also provide solution methods to their cases.

3.3.1 Overview of solution methods

Considering the TAP, Kamenga et al. (2021) proposes a greedy heuristic, which assigns parking time slots to trains in the (shunting) yards. This assignment takes into account the constraints on parking time slots imposed by the input solution. This input solution involves the maintenance schedule and the coupling and uncoupling operations planned impose the assignment of shunting tracks to specific trains at some time instant. When the constraints are set, the greedy approach assigns the remaining parking time slots, which is referred to as ''unassigned slots''.

Freling et al. (2005) proposed a programming model for the TAP, which is solved by applying column generation. Column generation is a method to avoid considering all variables of a problem explicitly (Junker et al., 1999). Examples are linear programs with an extremely large number of variables. Subsequently, this problem can be solved by only considering a small subset *X'* of the set of variables *X*. The resulting problem is denoted as the *master problem*. The question that is posed after it is solved is: ''Are there any variables in *X* or *X'* which can be used to improve the solution?''. Accordingly, duality theory provides a necessary condition that a variable with negative reduced costs is the right choice and the simplex algorithm is used to find a variable by calculating the reduced costs of all variables (Junker et al., 1999). Then, the idea behind column generation is to find variables with negative reduced costs without enumerating all variables.

Jacobsen & Pisinger (2011) present three metaheuristics for the shunting planning problem, which are Guided Local Search (GLS), Guided Fast Local Search (GFLS) and Simulated Annealing (SA). GLS is used as an iterative method, where each iteration represents a local search. Originally, GLS is used to solve constraint satisfaction problems, where it is difficult to find a feasible solution. This method defines solution features which characterize a given solution. When a local minimum is reached, GLS modifies the function in order to escape the local minima and perform a new local search.

We proceed with the algorithm's steps in the following manner:

1. **Initialisation**: Begin by selecting an initial solution x_0.
2. **Iteration control**: Iterate over a predefined number of iterations M.
3. **Penalty adjustment**: Initialize penalty parameter p_i to zero.
4. **Local search**: Perform a local search operation to enhance the current solution x_k.
5. **Utility calculation**: Compute the utility of each constraint based on the current solution.
6. **Penalty update**: Adjust penalty parameter p_i based on constraint utility.
7. **Iteration update**: Increment the iteration count k.
8. **Termination**: Continue iterating until a predfined stopping criterion is met.
9. **Result retrieval**: Return the best solution found thorughout the iterations with respect to the objective function value.

Figure 7 shows the outline of how the GLS algorithm can be implemented.

Algorithm *GLS*

Choose an initial solution x_o i S

Set $k: = 0$

for $i = 1$ **to** M **do**

  $p_i = 0$

while not stop-criterium

  $h = g + \lambda \cdot \sum_{i=1}^{M} p_i I_i(x_k)$

  $x_{k+1} = local\_search(x_k, h)$.

  for $i = 1$ **to** M **do**

    $util_i = I_i(x_{k+1}) \cdot \frac{c_i}{1+p_i}$

   for each i, where $util_i$ is maximal

    $p_i = p_i + 1$

   $k = k + 1$

Return the best found solution with regard to g.

Figure 7 Outline of the GLS algorithm

The principle of GFLS is the combination of GLS and Fast Local Search (FLS). FLS indicates that the neighborhood of a solution is broken down to a number of subneigborhoods. To each of these, an indicator variable is attached called an activation bit. If an activation bit is equal to 1, the subneigborhood is active, otherwise inactive. The idea behind this method is to scan the neighborhoods in a given order, and only scan the active neighbourhoods. Initially, all neighbourhoods are active. If a subneigborhood is examined and does not contain a better solution, this subneigborhood becomes inactive. Otherwise, it remains active and the current solution is set to the new better solution. Now, depending on the new solution, we activate the inactive neigborhoods where we expect to find a new better solutions. The process continues and when all activation bits are 0, the process stops, and the current best solution is returned as local minimum.

The third metaheuristic dicussed is Simulated Annealing. We will provide the algorithm's steps as follows:

1. **Initialization**: Choose an initial solution i from the solution space S.
2. **Temperature initialization:** Choose a start temperature T for the annealing process.
3. **Annealing process:** While a predefined stopping criterion is not met;
4. Choose a random neighbouring solution j from the neigbourhood $N(i)$ of solution i.
5. If the objective function value of solution j, $f(j)$, is better than that of solution i, $f(i)$, accept solution j.
6. Otherwise, calculate the acceptance probability p based on the the objective function values and temperature.
7. Generate a random probability p between 0 and 1.
8. If p is less than or equal to $e^{\frac{f(j)-f(i)}{T}}$, accept solution j.
9. Update the temperature T using a cooling schedule.
10. **Termination**: Return the final solution found.

Figure 8 present the outline of how SA can be implemented.

```
Algorithm SA
Choose an initial solution i in S
Choose a start temperature T
while not stop criterium
    Choose a random j ∈ N(i)
    if f(j) ≤ f(i) then  i = j
    else
        p = rand(0,1)
        if p < e^(-(f(j)-f(i))/T) then  i = j
    T = newtemperature(T)
Return i
```

Figure 8 Outline of the SA algorithm

Gilg et al. (2018) provided two integer programming models for the TAP, which are a departure model and a conflict model and both models share the same set of decision variables and certain constraints. Solving the TAP using both models results in a feasible parking assignment. These proposed integer programming models have been solved with the commercial solver Gurobi. Freling et al. (2005) showed that its MIP formulation can be solved efficiently using CPLEX.

As we presented multiple solution methods including the use of (meta)-heuristics or a commercial solver, the difference between these approaches is mostly because heuristics are used to find quick solutions, which outperforms commercial solver in terms of computational time. Commercial solvers on the other hand are used for their reliability and robustness and helpful for smaller problem instances.

3.3.2 Conclusions of solution methods

In Section 3.3.1, we have listed various methods to solve a model. One possibility is to solve models using heuristics, such as Simulated Annealing and Local Search algorithms. Another possibility is to apply a commercial solver as Gurobi and CPLEX, as mentioned by respectively Gilg et al. (2018) and Freling et al. (2005). As we discussed two different approaches for solving a model, each with distinct advantages, opting for a commercial solver proves sufficient. This choice is justified by the reduced complexity of the TUSP, achieved by solving an instance of this problem in the form of a modified TAP.

3.4 Summary Chapter 3

This chapter concludes the literature review and provides the answer to the research question. The main goal is to gain insight in what approach should be taken to come up with an ultimate solution for the capacity allocation problem at Watergraafsmeer. We introduced the problem context from literature as the *Train Unit Shunting Problem*, which is divided into subproblems to effectively solve the problem. The focus will lie on the *Track Assignment Problem,* to which we will formulate a modified version of by adding decision variables, parameters and constraints.

We presented different methods to solve the TAP. One option is to implement heuristics (Guided Local Search or Simulated Annealing) and the other option is to make use of a commercial solver (Gurobi or CPLEX). Table 7 provides a summary of solution approaches in the literature review.

Table 7 Summary of solution approaches literature review

Paper	Solution Approach	Objective	Constraints
Lentink et al. (2006)	Mixed Integer Programming (MIP) model for Train Unit Shunting Problem (TUSP)	Minimize weighted sum of penalty costs for train unit assignments	- No crossing of train union - Total length of union on tracks does not exceed track length
Freling et al. (2005)	MIP model for Track Assignment Problem (TAP)	Minimize the costs of a shunt plan	- No crossings - Total length of union on tracks does not exceed track length - All blocks are allowed to park at the track
Gilg et al. (2018)	Integer programming models for TAP, including departure and conflict models	Maximize number of assigned trains to tracks	- No crossing of train union - Total length of union on tracks does not exceed track length - Departure constraints
Jacobsen & Pisinger (2011)	Metaheuristic algorithms (Guided Local Search, Guided Fast Local Search, Simulated Annealing) for shunting planning problem	- GLS and GFLS: iteratively improve the current solution by exploring the neighbourhood of the solution space. - SA: find the optimal or near-optimal solutions by simulating the annealing process.	- GLS and GFLS: Feasibility of solutions. - SA: Solution feasibility, temperature schedules and acceptance criteria.
Kamenga et al. (2021)	Greedy heuristic for parking time slot assignment shunting yards	Maximize the utilization of available track resources while minimizing the number of unassigned slots	- Each train is assigned a slot on the track necessary to carry out each operation - Each train must be assigned a slot on the same track for uncoupling and coupling operations
Own work	MILP model derived from the TAP with featuring distinct objective function, decision variables, parameters and constraints	Minimize the number of unassigned trains of rail operators	- Each track can be occupied by one train at any given time. - Each train has a length of stay and no overlapping is allowed on tracks.

4. Solution Design

This chapter addresses the following research question:

How can we create a model to allocate capacity at railway yard Watergraafsmeer?

This chapter focuses on the mathematical formulation of the model intended to address the problem at hand. In Section 4.1, we presents our research methodology, providing an explanation of the steps involved. Section 4.2 introduces the essential sets, parameters, decision variables, objective function and constraints of the model, applicable to railway yard Watergraafsmeer. Section 4.3 will provide a detailed illustration of the model in action. Section 4.4 explains the steps for data processing.

4.1 Experimental design

As we start on the development of a capacity allocation policy for Watergraafsmeer, our goal in here is to create instances that show the potential influence on capacity allocation. Each instance represents a plausible outcome of an allocation policy and will be tested using a MILP model. To achieve this, we have outlined a series of steps to a establish a comprehensive and feasible capacity allocation policy for ProRail. The essence of a policy lies in determining the allocation of rail operators to specific tracks.

In our approach, we aim to achieve two objectives. The first objective focuses on minimizing the number of rejected trains from rail operators. This entails optimizing the allocation process to ensure that as few trains as possible are left rejected. For the MILP, we will utilize a smaller segment of input data representing the first two weeks in February of the year X. Further details on this choice will be provided in Section 5.1.

The secondary objective is to maximize the number of dedicated tracks for rail operators. This involves the allocation of rail operators to tracks for their exclusive use. We omit this objective from the MILP due to its computational complexity, which could significantly increase the runtime of the model. Figure 9 provides a visual representation of the initial steps in our approach, illustrated through a swim lane diagram.

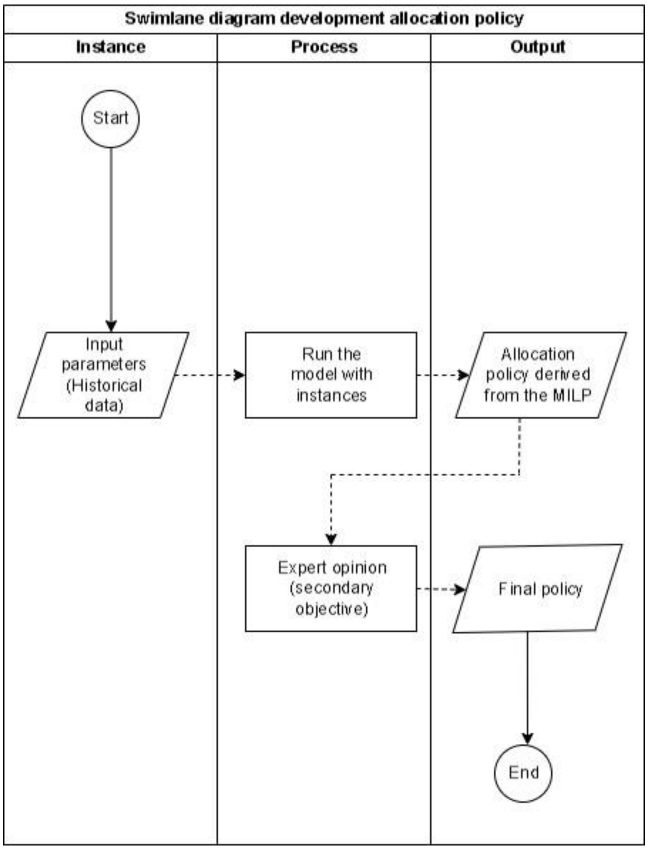


Figure 9 Swimlane diagram of development allocation policy

Below, we elaborate on these steps:

1. **Instance development**
   - Our approach involves the creation of multiple instances based on the length of time blocks and the number of ad-hoc tracks.
   - These instances will be tested using our model to measure the impact on capacity allocation.
2. **Determine policies**
   - To arrive at a feasible capacity allocation policy, we will analyse each instance.
   - We will choose the instance that produces the optimal objective value from the model (first objective)
   - We will analyse the allocation of rail operators and formulate an appropriate policy
   - The subsequent step involves addressing the second objective, which entails assessing the presence of dedicated tracks for rail operators. The secondary objective is informed by expert opinion. We further refine the policy derived from the model runs, and in conjunction with expert input, we employ a greedy algorithm utilizing swap operations to maximize the creation of dedicated tracks. This additional step occurs subsequent to the model runs, addressing our secondary objective. By omitting this objective, we effectively achieve our secondary objective. Ultimately, we obtain the policy derived from the model, while also incorporating a supplementary policy based on expert insights.

3. **Policy evaluation**
   - In this phase, we evaluate our derived allocation policies both from the model and the expert opinion, in addition to two existing allocation policies. These existing policies include the annual allocation of year X and an adjusted one of X. For each of the four policies, we utilize demand data from the whole year of X to allocate rail operators to tracks according to principles outlined in each policy. We have a total of 30000 trains. The allocation of trains from rail operators follows a First Come First Serve (FCFS) principle, and we aim to assess the objective of minimizing the number of rejected trains for each policy. FCFS represents a distinct approach from the one utilized in the model, where our focus lies specifically on the arrival time of trains. Hence, for each policy, we apply the FCFS approach and evaluate the resulting objective value. We employ the two existing as benchmarks and evaluate them alongside the policies derived from the model runs and expert opinion. Utilizing the FCFS rule serves as baseline for comparison against more complex models, given that our model does not solely rely on this principle.
4. **Sensitivity analysis**
   - For our sensitivity analysis, we adjust the initial set of activity durations that we are using in our model to examine how our policies respond to a range of activity duration configurations. We will categorize four types of configurations: the initial set of durations, two modified sets where durations are increased with 1.5 and 2 respectively, and a random configuration. This random configuration is utilized to evaluate the extent of change in our solution's performance. Increasing durations in our analysis serves to assess the flexibility of the proposed policies and replicate real-world conditions, including delays, an aspect we currently overlook. Further elaboration on this will be provided in Section 5.3. Varying these parameter values enables us to gain insights into the sensitivity of our outcomes, offering insight into how adjustments in input values impact the proposed allocation policy. We will employ the full dataset of year X, consistent with our methodology for policy evaluation. Figure 10 illustrates the steps for the sensitivity analysis.

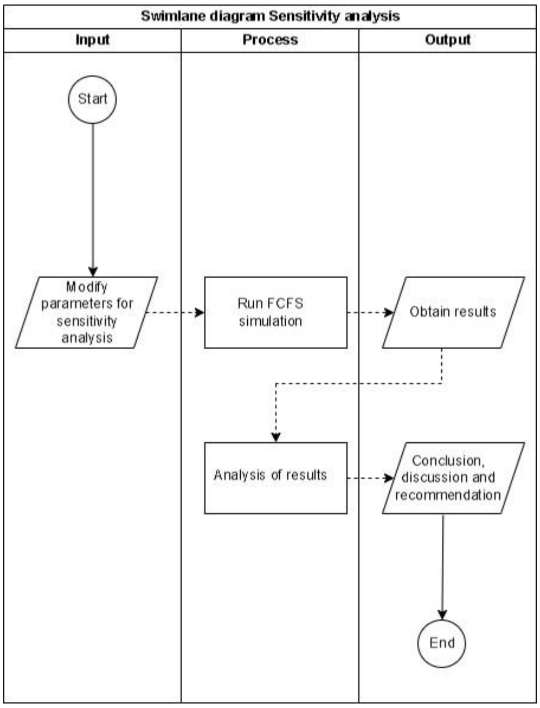


Figure 10 Swimlane diagram sensitivity analysis

4.2 Model description

This section provides the outline of the mathematical formulation to allocate capacity at railway yards in general. We aim to highlight the characteristics that are applied to the model.

4.2.1 Model introduction

To construct a formulation, it is imperative to identify the key elements pertaining to railway yards. Subsequently, we have integrated the following components into the MILP model. Primarily, the model is composed to allocate capacity fairly to match the demands of rail operators. In the context of this thesis, we consider a set of rail operators arriving at tracks for allocation.

Each train from a rail operator undergoes a specific activity, each with a predetermined length of stay. We operate under the assumption that a track can be occupied by only one train from a given rail operator at any given time, thus disregarding shared usage during the same time period. Our model is extended by introducing the concept of fixed *time blocks*. These time blocks with predefined durations aim to streamline the acceptance and allocation of trains from the same rail operator within a time block. This approach reduces the (potential) operational challenges associated with having numerous different rail operators on a single track.

In addition to the core principles of the model, our model includes specific constraints that must be adhered to. We provide an explanation and an overview of the model in the next section.

An addition to the model is the inclusion of *ad-hoc tracks*, which have a unique status. These tracks, exempt from time blocks, can be utilized when regular tracks are occupied. A penalty is incurred when a train is assigned to an ad-hoc track.

4.2.2 Assumptions and restrictions

In the previous section, we introduced our model incorporating specific restrictions. The model is to be utilized for railway yard Watergraafsmeer. Therefore, we need to make assumptions.

1. Due to the absence of information on train lengths, it is assumed that a rail operator allocated to a track fits the track, regardless of the train's length.
2. When a train of a rail operator occupies a track, it remains at that track for the entire duration, with no consideration for moves to other tracks in the meantime.
3. Each arriving train is equally important, regardless of type of activity, length of stay or type of rail operator.

4.2.3 Model formulation

We have a set of rail operators, denoted as $\mathcal{O}$ = {1, …, O} to be allocated on tracks $\mathcal{S}$ = {1, …, S}. Each rail operator is assigned to one or more available time blocks, represented by $\mathcal{B}$ = {1, …, B} consisting of multiple time periods $\mathcal{T}$ = {1, …, T}. In our model, we define time periods in terms of hours, while a time block consists of one or several consecutive hours. Each rail operator brings trains with predetermined lengths of stay to be occupied on the tracks, and we categorize these activities as A = {1, …, A}, based on their lengths of stay. A new subset, $G \subset \mathcal{S}$, is introduced to identify ad-hoc tracks.

The key parameter is the demand parameter $\delta_{o,a,t}$ serving as input for the model. In essence, it represents the quantity of arriving trains, manifesting as a numerical value. An arriving train is characterised by its rail operator, activity duration and time period in which it arrives. The activity duration is defined by parameter v_a, indicating the duration of activity a. Each rail operator has been assigned an activity based on the available data. These activities correspond to the length of stay. Each activity is associated with a numerical value. We will delve deeper into this concept in Section 5.1. For a detailed explanation of how these durations were determined, we refer to Appendix B. When allocating a train, we determine the number of time blocks it should be assigned based on the durations. These time blocks are consistent and remain the same for every t = 1, … ,T.

When demand arrives at the railway yard, our focus lies primarily on the rail operator to which the train belongs, rather than on the specific train itself. Given that we do not consider the lengths of trains and tracks, we make the assumption that all tracks are sufficiently long to accommodate any train for allocation.

Our decision variables involve the acceptance and allocation of trains of rail operators. The Z-variable ($Z_{o,a,s,t}$) is binary and indicates whether a train from the corresponding rail operator *o* for activity *a* is accepted on a track *s* during a specific time period t. Essentially, we determine the acceptance time for each arriving train, which signifies the beginning its allocation period. This time period marks when a train will commence occupying the track for its designated duration. The X-variable ($X_{o,s,t}$) denotes the allocation of the accepted train. This variable is set to 1 for each time period when the corresponding train occupies a track according to its length of stay.

The Z-variable plays a crucial role in determining whether an arriving train is accepted and establishes the starting time of its allocation. On the other hand, the X-variable specifies the time periods during which the accepted train occupies a track. are marked to be occupied for that accepted train. This separation of variables allows for a clear distinction between the decision to accept and the actual allocation.

Sets	**Description**
$\mathcal{O}$	Set of rail operators
$\mathcal{S}$	Set of tracks
$\mathcal{T}$	Set of time periods
$\mathcal{B}$	Set of time blocks

A	Set of activities
G	Set of ad-hoc tracks $g \subset \mathcal{S}$

Parameters	**Description**
$\delta_{o,a,t}$	Number of trains arriving of rail operator $o \in \mathcal{O}$ with activity $a \in \mathrm{A}$ at the beginning of time period $t \in \mathcal{T}$
ℓ_b	Length of a time block $b \in \mathcal{B}$
v_a	Duration of activity $a \in \mathrm{A}$
Penalty	Penalty incurred when trains are allocated on ad-hoc track

Decision variables	**Description**
$X_{o,s,t}$	$X_{o,s,t} = \begin{cases} 1 \text{ if train of rail operator } o \text{ is allocated to track } s \text{ at time period } t \\ 0 \text{ otherwise} \end{cases}$
$Z_{o,a,s,t}$	$Z_{o,a,s,t} = \begin{cases} 1 \text{ if train with activity } a \text{ of rail operator } o \text{ is accepted to track } s \text{ arrives at time period } t \\ 0 \text{ otherwise} \end{cases}$

Objective function

We aim to minimize the number of trains of rail operators that are not accepted from the demand and thus are unmet by representing the difference between the total demand arriving and the total number of rail operators accepted on the tracks. A penalty parameter is added only when ad-hoc tracks are present. We formulate our objective function with the addition of ad-hoc tracks.

$$\min \sum_{o \in \mathcal{O}} \sum_{a \in \mathrm{A}} \sum_{t \in \mathcal{T}} \delta_{o,a,t} - \sum_{o \in \mathcal{O}} \sum_{a \in \mathrm{A}} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} Z_{o,a,s,t} * (\mathbf{1} + Penalty\ \mathbf{1}|_{s \in G})$$

Constraints

Constraint (1) ensures that the number of accepted trains should not exceed the demand. It creates the situation that the number of accepted trains summed over the tracks *s* is at most equal to the demand that arrives at each time period. Additionally, this constraint accepts up to δ trains, but also fewer trains if it does not fit all the tracks.

$$\sum_{s \in \mathcal{S}} Z_{o,a,s,t} \leq \delta_{o,a,t} \quad \forall o \in \mathcal{O}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \quad (1)$$

Constraint (2) ensures that there are no overlaps between trains occupying the same track at the same time and that once a rail operator has been allocated to a track, no other rail operator can use the same track during the allocated time periods. The left-hand side represents the maximum time period when rail operator o with activity a on track s is not present. If $Z_{o,a,s,t} = 0$, indicating that rail operator o is not accepted, then the entire expression evaluates to $M + 1$, which represents the maximum possible time period. If $Z_{o,a,s,t} = 1$, indicating that rail operator o is accepted on track s at time period t, then the entire expression evaluates to 1, indicating that the maximum time period is 1. The right-hand side represents the total number of trains from all rail operators occupying track s at time period t. If this summation is greater than or equal to the maximum time period on the LHS, it ensures that no overlapping trains are present on track s at time period t.

$$((1 - Z_{o,a,s,t}) * M) + 1 \geq \sum_{o' \in \mathcal{O}} \sum_{a' \in \mathrm{A}} \sum_{t' \in \mathcal{T}} Z_{o',a',s,t'} \, \forall o \in \mathcal{O}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \forall a \in \mathrm{A} \quad (2)$$

Constraint (3) is designed to guarantee that a train can be accepted (indicated by $Z_{o,a,s,t} = 1$) only if the track is allocated to that corresponding rail operator for the entire duration of the train's intended stay. This is expressed by $X_{o,s,t'} = 1$ for all time periods t' within the predetermined duration v_a. The left-hand side represents the duration of time that rail operator o with activity a occupies track s at time period t.

If $Z_{o,a,s,t} = 1$, indicating that rail operator o is accepted on track s at time period t, then the entire expression evaluates to the predetermined duration v_a. If $Z_{o,a,s,t} = 0$, the expression evaluates to 0, indicating that the rail operator is not accepted onto the track during that time period. The right-hand side represents the total number of time periods within the duration v_a for which rail operator o is allocated to track s. If this summation is equal to v_a, it ensures that the track is allocated exclusively to rail operator o for the entire duration of its intended stay.

Essentially, this constraint ensures exclusivity, signalling that no other trains can be accepted or allocated to the same track during the entire length of stay of the initially accepted train.

$$Z_{o,a,s,t} * v_a \leq \sum_{t'=t}^{t'=t+v_a-1} X_{o,s,t'} \quad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \qquad (3)$$

Constraint (4) serves as an important rule within the model, ensuring the exclusive occupancy of tracks by rail operators at any time period. This constraint indicates that only one train of one rail operator can occupy a track during a specific time period. It prevents overcrowding and ensures that each track is utilized without conflicts or congestion.

$$\sum_{o \in \mathcal{O}} X_{o,s,t} \leq 1 \quad \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \qquad (4)$$

Constraint (5) plays a role in maintaining the consistency and structure of time blocks within the model. Its purpose is to ensure that the time blocks are fixed and have the same length. Each rail operator is assigned to a specific time block b, and this constraint guarantees that the rail operator blocks the track for consecutive ℓ_b periods.

$$\sum_{t'=b}^{t'=b+\ell_b-1} X_{o,s,t'} = \ell_b * X_{o,s,b} \quad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall b \in \mathcal{B} \quad (5)$$

Each track in the railway yard has a platform. Some tracks have broader platforms due to additional facilities. An example is track Y. (Name of rail operator and specific track is not mentioned due to confidentiality) To model this, constraint (6) is introduced:

$$Z_{o,a,Y,t} = 0 \quad \forall a \in \mathrm{A}, \forall t \in \mathcal{T}, \forall o \in \mathcal{O}, o \neq' RailOperator' \qquad (6)$$

Constraint (7) is an additional constraint incorporated into the model to reflect specific demand patterns observed in the realization data. This constraint restricts certain demand to tracks C4 or C5 exclusively, based on realization data. It ensures that trains already occupying tracks C4 or C5 must be allocated on C4 or C5. In other words, once we see in the data that a train occupies track C4 or C5, it cannot be allocated to another track. This restriction ensures that the occupancy of tracks C4 and C5 remain exclusive to the trains registered in the data.

$$Z_{o,a,4,t} + Z_{o,a,5,t} \leq 1 \quad \forall o \in \mathcal{O}, \forall a \in \mathrm{A}, \forall t \in \mathcal{T} \qquad (7)$$

Constraint (8) and (9) are inequality constraints for both binary variables.

$$X_{o,s,t} \in \{0,1\} \quad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \quad (8)$$

$$Z_{o,a,s,t} \in \{0,1\} \quad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \quad (9)$$

This formulation provides a comprehensive overview of the model for railway yard Watergraafsmeer. A base model, excluding Constraint (6) and (7), is available in Appendix A. Appendix B elaborates the structure of the dataset that is used for the model. This is the parameter--the number of arrivals of trains of rail operators serving as the demand input for the model.

4.3 Model illustration

In this section, we illustrate the working of the model using small test instances with arbitrary numbers. We consider a time horizon of $\mathcal{T} = 16$. There are $\mathcal{S} = 3$ tracks, one of which is an ad-hoc track. Two rail operators ($\mathcal{O} = 2$), and three activities ($\mathrm{A} = 3$) are considered. We set the length of a time block to 4 hours ($\mathcal{B} = 4$). The duration of each activity is outlined in Table 8 and the rail operator names in Table 9.

Considering Table X and X, we find that the durations for activities within set *A* are consistent for both rail operators. For instance, activity 1 has a duration of 1 hour for both Rail Operator A and B. This consistency extends across the entire set *A*, ensuring that each activity is completed within the same timeframe for both operators.

Table 8 Activity durations

A	Duration
1	1
2	2
3	3

Table 9 Rail operators

$\mathcal{O}$	Rail Operator Name
1	A
2	B

We start by populating our demand parameter $\delta_{o,a,t}$, which represents the demand for each rail operator, activity and time period.

The demand is summarized in Table 10.

Table 10 Demand of rail operators

Demand ($\boldsymbol{\delta_{o,a,t}}$)		
Rail operator ($\mathcal{O}$)	Activity (A)	Time period ($\mathcal{T}$)
A	1	1
A	2	1
B	2	2
A	3	3
B	1	3
B	2	3
A	3	5
B	2	5
A	1	6
A	3	7
B	2	7
A	1	8
B	2	10
A	3	10
A	2	10
B	1	10
B	3	11
B	1	11

The objective function determines the number of rejected trains from the demand. A penalty of 0.5 is assigned to allocation on-ad-hoc tracks. The results are summarized in the Z-table and X-table, which are the accepted rail operators (Z-variable is 1) and the allocated rail operators (X-variable is 1) respectively. The Z-table provides an overview of accepted trains on tracks. Each cell in the table represents a time period and track combination, indicating which rail operator and activity are accepted for that time period. The format ''A-2'' denotes that rail operator A with activity 2 has been accepted, with the duration specified in Table 8.

The X-table presents an overview of the allocation trains on tracks for each time period. Similar to the Z-table, each cell represents a time period and track combination. The cell value indicates the rail operator allocated to that time period. If multiple trains from the same rail operator are accepted in the same time block, they are shown consecutively in the same column, signifying that the entire time block is allocated to that rail operator.

The Z-table and X-table collectively summarize the results of our decision variables $Z_{o,a,s,t}$ and $X_{o,s,t}$, providing a clear depiction of the acceptance and allocation of trains across tracks and time periods.

The test instance is implemented in Python 3.9.12 using Gurobi as the engine solver. The demand consists of 18 trains in total, with three tracks available. The first column indicates the time periods represented as hours, the other columns represent the tracks. Track 3 functions as the ad-hoc track. Both rail operators are treated equally, indicating that no priority is given to either one. We will exclude Constraint (8) and (9), as these constraints are specifically added for the case of Watergraafsmeer. Our focus here is solely on illustrating the functioning of the base model in a general context. Table 11 and Table 12 illustrate the results of the Z-table and X-Table respectively.

Table 11 Z-Table of test instance

Overview of accepted trains			
Time period/Track	1	2	3
1	A- 2		A - 1
2		B - 2	
3	A - 3	B - 2	B - 1
4			
5		B - 2	A- 3
6	A - 1		
7	A - 3	B - 2	
8			A - 1
9			
10	A - 2	B- 1	
11		B - 3	A - 1
12			
13			
14			
15			
16			

Table 12 X-Table of test instance

Overview of allocated trains			
Time period/Track	1	2	3
1	A	B	A
2	A	B	
3	A	B	B
4	A	B	
5	A	B	A
6	A	B	A
7	A	B	A
8	A	B	A
9	A	B	
10	A	B	
11	A	B	A
12	A	B	
13		B	
14		B	
15		B	
16		B	

The objective value for this test instance is 5.5. This value is derived from a combination of rejections. Specifically, there are 3 complete rejections and 5 half rejections (allocation on ad-hoc track). We observe that 2 trains of B, both labelled as B – 2, are fully rejected, as well as 1 train of A, which is A – 3. Subsequently, there are 5 trains allocated on the ad-hoc track, with 4 belonging to A and 1 to B, resulting in a total of 5*0.5 = 2.5 rejections. Thus, the objective value comprises 3 complete rejections and 5 half rejections, totalling 5.5.

4.4 Data processing

The demand parameter introduced in Section 4.1.3 is not an exact representation but rather an estimation from the available data. This implies that the actual demand might have been higher, but due to the absence of comprehensive data collection by ProRail on the number of trains allocated to tracks and that rail operators know in advance that there is no demand at certain times, tracks are basically allocated as a whole to rail operators upon request, without detailed information on the specific trains.

Within our dataset, we identified two aspects contributing the uncertainty of the demand parameter. To start with, while tracks are observed to be occupied by trains, determining the rail operator that occupies a track remains in some cases uncertain. The dataset contains a column with the corresponding name of the rail operator occupying the track such as A, B, C, D, E, F and ''?''(indicating unknown). The ''?'' signifies cases where the corresponding rail operator has no planned destination upon leaving the track, resulting in the train dispatcher manually marking a ''?''. To mitigate this uncertainty, we propose refining the dataset by replacing the ''?'' with the actual rail operator that received the track. For instance, if B has been allocated to C9, and a ''?'' is recorded on this track, we would update it to B.

To enhance the accuracy of our demand estimation from the year X data, we assessed which tracks could be definitively assigned to a particular rail operator. The annual allocation for year X provides valuable insights into this, revealing that not all tracks have a straightforward dedication to a single rail operator. The annual allocation for year X is presented in Table 13. This helps us to a more accurate estimation of the demand parameter in our model.

Table 13 Annual allocation of year X at Watergraafsmeer

Track	Rail operator
C1	C and D
C2	B
C3	A and F
C4	C and E
C5	D
C6	D
C7	F
C8	A and B
C9	B and E
C10	E
C11	C
C12	A
C13	F
C14	B

As indicated in Table 13, there are five tracks that are shared by two distinct rail operators. Formally speaking, ProRail is obligated to perceive both companies as different railway undertakings (RUs), and thus solve conflicting capacity requests. In practice, shared tracks do not always result in issues. However, upon analysing requests, it became evident that A desires exclusive access to both tracks for the entire year. This implies that A has forgone certain trains, rejecting them due to unavailability of allocation. To address this, we aim to generate additional demand during the time periods when A lacks the capacity to allocate their trains, precisely when B and F have been assigned to both track. Our approach is outlined below:

- **Estimation in Python**
    - We create an estimation of the number of trains that could be allocated during the period when rail operator C does not have access to the shared tracks.
    - The estimation includes both the number of trains and their respective durations.
- **Random Generation**
    - We employ Python to generate random rows in the dataset, reflecting the potential demand.
    - This includes specifying a mean and standard deviation for the number of trains, as well as mean and standard deviation for the duration.
    - This random row generation is performed separately for Fridays and Sundays.
- **Data Population**
    - We utilize a function for both the number of trains and their durations with specified mean and standard deviation inputs.

By executing this approach, we have effectively created an estimation of the demand that could potentially be allocated to the shared tracks.

4.5 Summary Chapter 4

Chapter 4 concludes the solution design of our research. Section 4.1 outlined the approach of our research, detailing the path we are taking to formulate an allocation policy for Watergraafsmeer. We visualised this approach in the form of swim lane diagrams to illustrate the steps. We elaborated on each step, providing a clear understanding of our methodology. Chapter 5 will delve into the results obtained from our model and the FCFS simulation, bringing insights into the effectiveness of the proposed allocation policy.

In Section 4.2, we introduced the model that forms the backbone of our implementation. Building upon this, we extended the model by incorporating strategic rules in the form of constraints. A comprehensive list of assumptions was outlined. Moreover, we described the working of the model with a simple test instance in Section 4.3. Additionally, we looked closely at the input data and we processed the data for the model in Section 4.4.

5. Numerical study

This chapter covers the computational results of the experiments that we designed and we will answer the following research question:

How can we test the solution proposed based on the formulated model and what are the insights that we can develop?

Section 5.1 outlines the experimental set-up, detailing the various instances considered. Following this, we will present the computational results derived from the model, providing a comprehensive overview of key findings in Section 5.2. Additionally, we will delve into the expert opinion step, discussing the outcomes. In Section 5.3, we conduct the sensitivity analysis and we will provide the results.

5.1 Experimental design

This section describes the experiments carried out in this research. To start with, we elaborate on the details involved in setting up the experiments. Following that, we present and analyse the outcomes derived from the various instances.

Our testing process involves an analysis of two key aspects: the duration of the time block and the quantity of ad-hoc tracks. For each element, we perform runs on a select set of instances. The combination of these two aspects forms distinct instances, as depicted in Table 14.

Table 14 Experimental set-up instances

Instance	Length of time block	Number of ad-hoc tracks
1	1	0
2	1	1
3	1	2
4	4	0
5	4	1
6	4	2
7	6	0
8	6	1
9	6	2
10	8	0
11	8	1
12	8	2

For each model run, we tailor the input settings based on the specific instance under examination. For instance, to yield results for instance 1, we set the time block length to 1 and the number of ad-hoc tracks to 0, signifying the application of time blocks to all tracks.

Concerning ad-hoc tracks, we stipulate that a penalty is imposed when a train of a rail operator is allocated to an ad-hoc track. Across all instances, we consistently set the penalty value at 0.5.

We conducted data analysis to estimate activity durations for rail operators. This involved collecting data for the year X and examining the duration of each train. To gain insights, we created histograms to visualise the frequency distribution of durations for each rail operator. A detailed description is provided in Appendix B. Based on our analysis, we determined a set of durations for each rail operator, which is illustrated in Table 15.

Table 15 Activity durations for the model

Activity	Rail operator	Duration
1	A	1 hour
2	B	3 hours
3	B	9 hours
4	C	8 hours
5	C	96 hours
6	D	1 hour
7	D	4 hours
8	E	1 hour
9	E	4 hours
10	F	6 hours
11	F	8 hours
12	F	10 hours

In total, we have 24 activities defined in the model. However, Constraint (7) restricts specific demand to tracks C4 or C5 based on realization data. For instance, trains occupying track C4 or C5 should only be allocated to those respective tracks and cannot be assigned to other regular tracks. Consequently, registrations on track C4 and C5 are assigned different activity numbers, ranging from 13 to 24, corresponding to the same durations as activities 1 to 12. Therefore, the duration of activity 1 is equal to 13 and so forth.

In relation to our input data for the instances, we segment the data of year X into smaller parts, testing only select cases from that year. We generate various schedules, covering the period of February 1st 00:00 AM until February 16th 07:00 AM, encompassing a total of 368 hours and accommodating a demand of 1558 trains.

Based on our dataset and monthly considerations, we have defined our time horizon for the set $\mathcal{T}$, where time periods are treated as hours with specified start and end times.

This period was strategically chosen, with a particular emphasis on data expansion between December of the year X and March of the year Y. We inquired opinions from experts highlighting that February poses logistical challenges in the annual allocation. The idea behind this inquiry was to explore and assess instances during this period, given its logistical complexities.

We generated two types of schedules, namely a schedule of accepted trains (Z-table) and the allocated trains (X-table). The Z-table furnishes the information on whether an arrived train is accepted, while the X-table shows all the time periods during which the accepted train occupies the track. We introduced an illustration of both tables in Section 4.3.

We have a total of 12 instances. All model instances were executed on a Lenovo ThinkPad P15v laptop, which has a Intel®Core™i7-10750H processor with 2.60 GHz and 16.0 GB RAM memory. The model instances were implemented in Python with version 3.9.12 and we used Gurobi as a solver engine with version 10.0.2, which is an engine specially used to run Mixed Integer Programming models.

5.2 Instances

This section covers the computational results of our model. To commence with, we describe the results from the model and we will derive our allocation policy. Subsequently, the idea behind the expert opinion step is explained and then we will describe the process of our FCFS simulation and show the results.

5.2.1 Model results

The solver was able to find optimal solutions for all instances. In each case, the generated schedule is based on the characteristics specific to each dataset. We highlight the results for the month February in Table 16. We also tested additional instances for months of April and June, as referenced in Appendix E. We do not observe significant differences for the other months; similar patterns are evident in terms of objective values across the instances. For every instance, the following information is provided:

- **Objective value:** This is the value of the objective function for this instance. It is the number of rejected trains for this period, and calculated as in the objective function formulated in Section 4.1.2.
- **Gap:** This is a measure of how close the best solution found is to the optimal solution. A small gap indicates that a solution has been found that is close to the optimal solution.
- **Runtime:** This refers to the amount of time it takes to solve from start to finish. It is expressed in seconds.

Table 16 Computational results of February

Instance	Instance type	Input data	Objective value	Percentage of accepted demand	Gap (%)	Runtime (seconds)
1	Time block = 1 and ad-hoc = 0	February	55	92.94%	0.00	1087.05
2	Time block = 1 and ad-hoc = 1	February	55	92.94%	0.00	1676.15
3	Time block = 1 and ad-hoc = 2	February	57.5	92.62%	0.00	1902.22
4	Time block = 4 and ad-hoc = 0	February	58	92.55%	0.00	1796.57
5	Time block = 4 and ad-hoc = 1	February	56.5	92.75%	0.00	1129.47
6	Time block = 4 and ad-hoc = 2	February	61.5	92.11%	0.00	1827.43
7	Time block = 6 and ad-hoc = 0	February	60	92.30%	0.00	1657.91
8	Time block = 6 and ad-hoc = 1	February	59	92.43%	0.00	1660.03
9	Time block = 6 and ad-hoc = 2	February	63.5	91.85%	0.00	1643.53
10	Time block = 8 and ad-hoc = 0	February	60	92.30%	0.00	2005.72
11	Time block = 8 and ad-hoc = 1	February	59	92.43%	0.00	1851.63

12	Time block = 8 and ad-hoc = 2	February	64	91.78%	0.00	1925.82

Upon reviewing the results in terms of objective value and assessing them by type of time block, we find that the objective values range from 55 to 64, out of 1558 trains, with corresponding gap percentages of 0.00%. The runtimes vary significantly among instances, with values ranging approximately 1087.05 seconds to 2005.72.

We are directing our attention to a particular instance where the objective values are at their lowest, excluding those with a time block length of 1. Although instances with a time block of 1 yield better solutions, it is impractical to allocate a different rail operator for each hour. Our focus lies in scrutinizing the trains rejected in instance 5, particularly when instances with a time block of 1 are omitted. A larger time block facilitates a smoother schedule and minimizes the need for frequent switches between rail operators, thus mitigating logistical issues.

In general, we notice that decreasing the time block length leads to a reduction in the objective value, providing flexibility in train allocation. However, as mentioned, this also leads to more frequent changes in the occupation of rail operators on tracks, posing logistical challenges, leading to the decision to choose instance 5.

The total demand for the month of February amounts to 1558 trains, broken down by rail operator as follows: A with 440 trains, B with 400 trains, C with 220 trains, D with 170 trains, E with 68 trains and F with 260 trains. Analysing the rejections per rail operator for instance 5, we obtain the following results illustrated in Table 17.

Table 17 Rejections per rail operator for instance 5

Rail operator	**Total demand**	**Complete Rejections**	**Ad-hoc track (0.5 rejection)**	**Total Rejections**
A	440	23	5	25.5
B	400	5	3	6.5
C	220	2	1	2.5
D	170	6	0	6
E	68	4	4	6
F	260	9	2	10

In instance 5, the majority of rejected trains are from rail operator A was rejected. For D, all rejections resulted in complete rejections.

Focusing on instance 5 and its schedule, we observe that the majority of allocations come from A and B, followed by C and F with E having the lowest, which we see in Table 17 as well. Our policy is formulated in Figure 11 as follows:

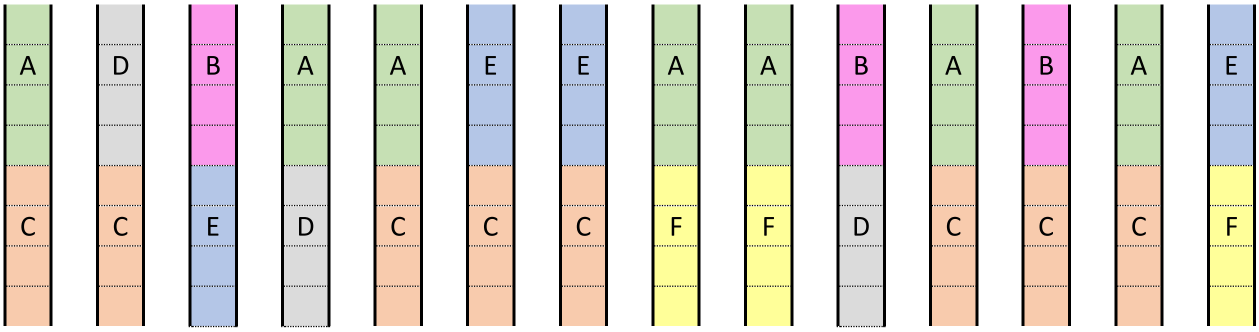


Figure 11 Allocation policy of model run

Our allocation involves a mixed approach for all tracks, which are allocated on the 13 regular tracks, while E and F allocations are handled through the ad-hoc track. The figure indicates that in the case where two rail operators are allocated to a track, 50% of this track is dedicated to one operator and the other 50% is allocated to the other This forms our policy from the model runs.

5.2.2 Expert opinion

After formulating our policy based on the model results, we embarked on achieving our second objective. To accomplish, we sought the expertise of a capacity allocation specialist at ProRail. Together, we determined that establishing dedicated tracks would be pertinent. The idea behind the dedicated tracks involves allocating a track to a single rail operator. We examined closely the policy outlined in Section 5.2.1.

Subsequently, we employed a greedy algorithm, manifested as swap operations, to reallocate rail operator allocations. This approach aimed to create a more balanced distribution of rail operators, facilitating the establishment of dedicated tracks and mitigating logistical complexities.

Our evaluation focused on the feasibility of reallocating rail operator allocations to establish dedicated tracks. Through swap operations, we explored alternative solutions while upholding the original objective value. Appendix C provides a comprehensive description of the swap operations.

We iteratively performed swap operations until no further optimizations were feasible. Ultimately, we successfully dedicated five tracks to one rail operator, resulting in one dedicated track for B, C and D and two for A, allocated eight tracks in a mixed fashion for all rail operators, and designated one track, the ad-hoc track, for both E and F. Our second policy based on expert opinion is outlined in Figure 12.

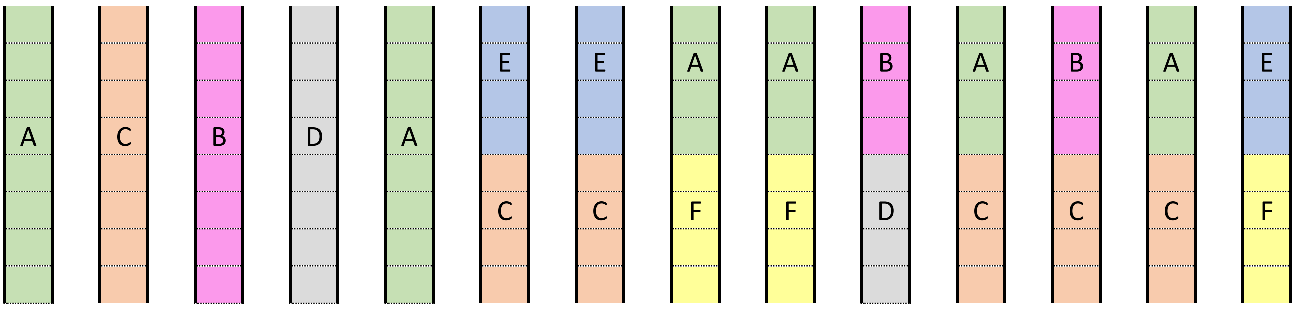
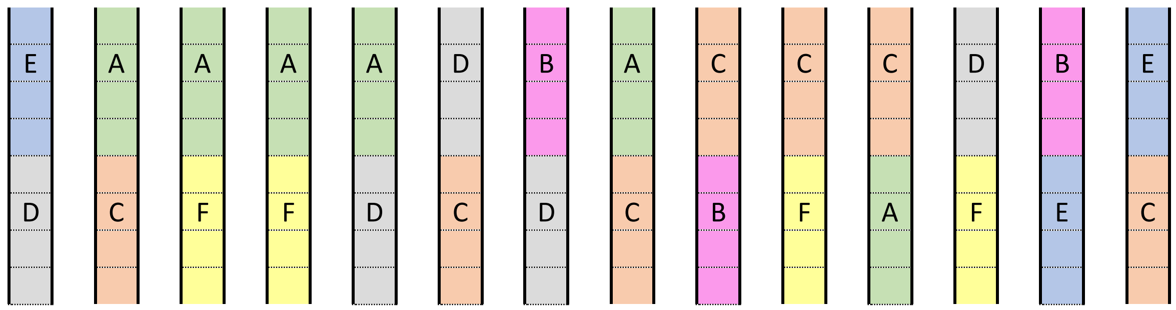


Figure 12 Allocation policy after expert opinion



5.3 Sensitivity analysis

For our sensitivity analysis, we will compare the policies formulated from the model runs and the expert opinion with our current policy, which is based on the annual allocation of year X as outlined in Table 13 in Section 4.3. Figure 13 illustrates our current allocation policy.

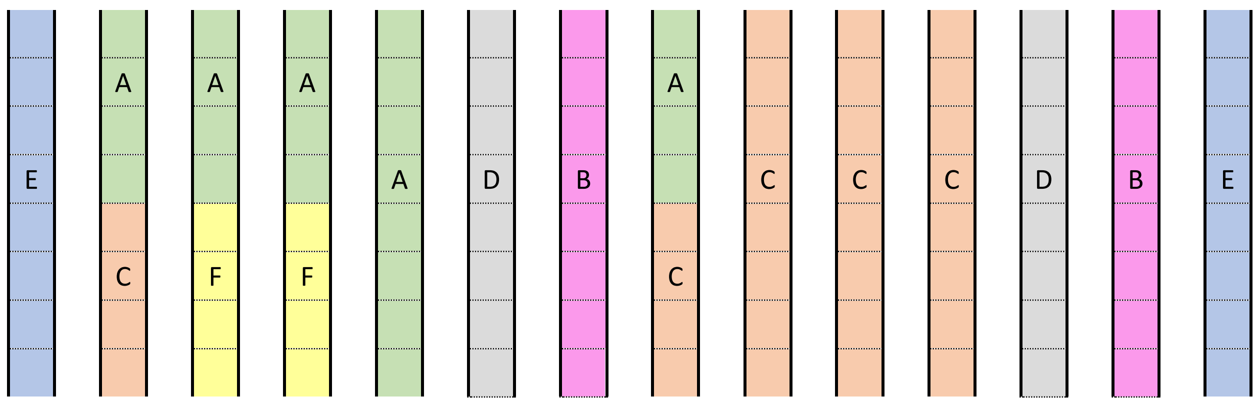


Figure 13 Current allocation policy

This policy reflects that rail operator A, B, C, D and E each have dedicated tracks, with C having the most dedicated tracks among them. We observe that rail operator A shares their tracks with C and F.

Additionally, we introduce a variant of our current policy that includes mixed allocations, thus we apply mixed tracks for all operators. The variant of the current policy is depicted in

Figure 14.

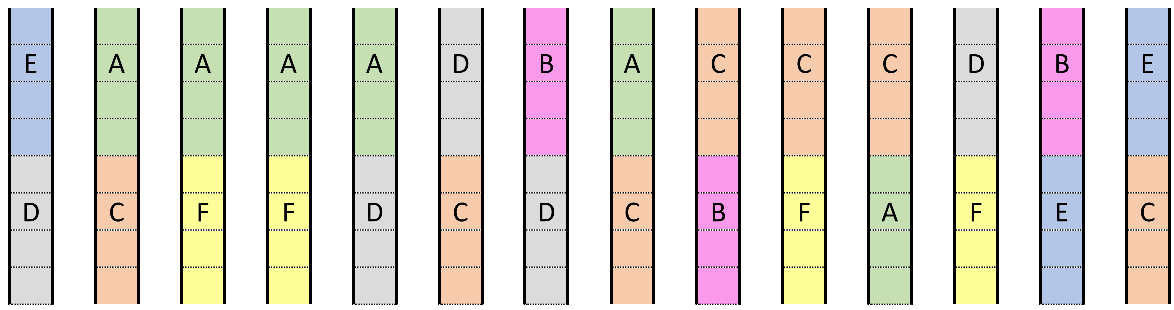


Figure 14 Variant of the current allocation policy

For a comprehensive overview, we list our four policies as follows:

- **Policy 1**: Allocation policy of model based on instance 5, as shown in Figure 11.
- **Policy 2**: Allocation policy after swap operations (expert opinion), depicted in Figure 12.
- **Policy 3**: This is our current allocation policy of year X, displayed in Figure 13.
- **Policy 4**: The variant of the current allocation policy presented in Figure 14.

We aim to allocate rail operators for the year X, representing a total demand of 30000 trains. Our objective is to assess each policy's effectiveness by evaluating the number of rejected trains. Policy 3 and 4 are tested against Policy 1 and 2, respectively, derived from the model runs and the expert opinion.

Regarding the policy evaluation, under each policy, a rail operator can only be allocated to a track designated for them. If a demand arises and all tracks available to that rail operator are occupied, the demand is rejected. To ensure fairness and equality in allocation, we apply a First Come First Serve (FCFS) principle. This principle prioritizes allocation based on arrival, thus ensuring fairness among rail operators.

To conduct our sensitivity analysis, we systematically modified one parameter: the activity durations v_a while keeping the others constant. We tested four configurations:

1. Original durations: Durations used for the model, listed in Table 15.
2. Increased durations (1.5x): Durations multiplied by a factor of 1.5.
3. Increased durations (2x): Durations multiplied by a factor of 2.
4. Randomized configurations: Introducing random durations, as detailed in Table 18.

We incorporate varied configurations with increased durations in our analysis to evaluate the adaptability of the proposed policies and simulate real-world conditions. The random configuration is chosen to determine whether the solution undergoes significant changes.

Table 18 Randomized durations for FCFS simulation

Activity	Rail operator	Duration (hours)
1	A	21
2	A	4
3	A	1
4	B	24
5	B	9
6	C	8
7	D	7
8	D	5
9	D	24
10	E	4
11	F	22
12	F	24

Our goal is evaluate the performance of each policy under these configurations to assess their robustness.

The outline of our FCFS simulation principle is outlined below. A comprehensive explanation of the Python implementation of FCFS is provided in Appendix D.

1. Combining activities with activity durations
    - Activities are combined with their respective durations to form a list.
2. Sorting activities
    - The list of activity durations is sorted based on the starting time of each activity in ascending order
    - Considering the model constraints, the number of activities is reduced to 12, contrasting with the 24 used in the model.

Since were are focusing on a single parameter, we aim to discern the variance between the original durations utilized in the model and the modified versions.

The results of our sensitivity analysis are depicted in Figure 15.

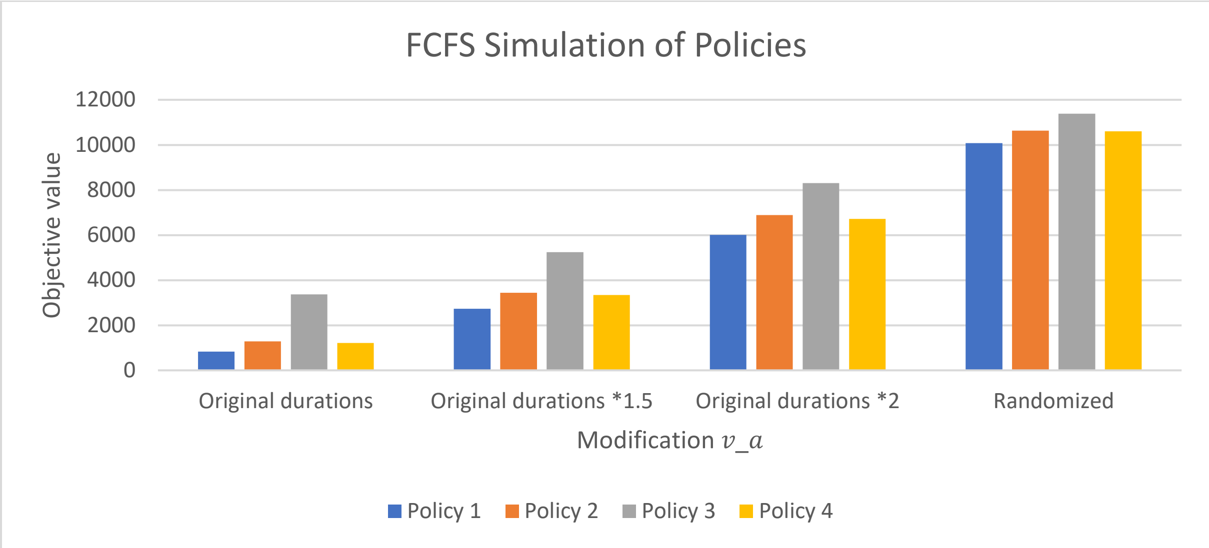


Figure 15 Bar chart of results FCFS simulation

In this figure, we showed the objective value per policy and per modification of our parameter. We notice that the objective value varies for the original durations, ranging from approximately 800 to 3500. However, for the randomized durations, the objective value consistently exceeds 10.000 rejections across all ranges.

We observe that policy 1 from our model performs the best in terms objective value across all modifications and policy 2 from expert opinion performs worse than policy 1. This is caused by that durations of a single train is not considered. With other words, when allocating rail operators to tracks, only the arrival time period is important and it possibly hinders trains with longer durations. With the model, we allocate rail operators optimally independent of arrival time period to meet the objective of the model. Since we only focused on the FCFS principle, the objective values are slightly higher. In essence, all trains of rail operators are equally treated in the allocation process with FCFS. In general, we see that both policies formulated outperform our base allocation policy of year X.

By employing our approach and opting for Policy 1, we can achieve a reduction by 75% for the original durations. Similarly, Policy 2 yields an improvement of approximately 62%. For the other configurations, we still observe an improvement, albeit varying. For the random configuration, the improvement ranges from 6 to 10%. In the case of 1.5x increase, the improvement from 35% to 48%, while for a 2x increase it ranges between 17% and 28% compared to Policy 3.

5.4 Summary Chapter 5

This chapter concludes the results obtained from both the model and the FCFS simulation. Section 5.1 discussed our implementation of the model in Python and the settings of our input data. Following that, Section 5.2 presented the computational results, listing the results of the month February in terms of the objective value. Across the dataset, we observed that instance 5 featuring a time block of 4 and 1 ad-hoc track yielded the best objective value. Upon analysing the X-table of this instance, we noted that 13 tracks could be allocated with a mix of all operators, assigning E and F to the ad-hoc track.

The subsequent step involved the consultation of expert opinion to meet our second objective. We applied swap on our policy of the model to devise an alternative policy maximizing dedicated tracks without impacting the objective value. Through this process, we discovered it was feasible to establish five dedicated tracks, one for B, C and D and two for A, allocate eight mixed tracks for all operators and designate one ad-hoc track for E and F.

The final step was the sensitivity analysis conducted in Section 5.3. Here, we modified a single parameter used in our analysis, namely the predetermined activity duration. We compared the two policies derived from the model results and the expert opinion against policy 1, the annual allocation of year X, and the variant with mixed track for all operators, which was policy 2. Utilizing our FCFS simulation, we tested the number of rejections per policy and per modification. Our visualisation of the results revealed that policy 1, derived from our model, performed the best.

6. Conclusion and Discussion

This chapter concludes this research and we will our answer our final research question:

How should the results be interpreted and what conclusions can we draw from this research?

We list our main conclusions in Section 6.1. Section 6.2 is devoted to discuss our findings in our research and the limitations we faced. Moreover, Section 6.3 describes the recommendations and the possibilities for future research for ProRail. Finally, in Section 6.4 we describe the contributions of this research both to theory and practice.

6.1 Conclusions

This research conducted at ProRail aimed to provide insights into an allocation policy for railway yard Watergraafsmeer. The research question formulated at the beginning of this thesis was as follows:

What capacity allocation policy at railway yards can ProRail apply to meet the needs of rail operators?

During this research, we developed a model aimed at allocating rail operators on the C-tracks at Watergraafsmeer. This model is based on a Track Assignment Problem, but we incorporated different elements to arrive at a final model. We utilized the principle of time blocks, wherein trains of the same rail operator can be allocated if there is available space. Additionally, we introduced the concept of ad-hoc tracks, which are tracks that can be used only if the regular tracks do not provide any possibility for train allocation. The model utilizes historical data as input.

From the results of the model, we observe that the best objective values occur with instances featuring time block length of 1. However, it is less than ideal to permit the possibility of a different rail operator every hour. Instead, it is preferable to have longer time blocks in which multiple trains from a single rail operator can be accommodated and makes it preferable due to clearance. Therefore, we notice that instance 5 with a time block length of 4 and 1 ad-hoc track yield the best result in terms of objective value with longer time block lengths. The results were utilized to analyse and formulate an allocation policy that would define how rail operators are allocated based on the demand. We observed that a mix of all operators are allocated on 13 regular tracks, and we noticed that rail operators E and F are deemed sufficient to be allocated on one track. We conclude that it is appropriate to allocate all operators on the regular track and to use the ad-hoc track for E and F.

The expert opinion step involved iterative swap operations until no new swaps could be made. We determined that we could increase the number of dedicated tracks, and for each dataset, we found the same solution. In total, 5 dedicated tracks, 8 mixed tracks for all operators, and 1 track for E and F were assigned. This policy is more preferable for rail operators, as they prefer to have a dedicated track for themselves.

The sensitivity analysis evaluated four allocation policies for the year X. We noticed that Policy 1, derived from the model outperformed others consistently and that Policy 2, the expert opinion-based policy performed less effectively, likely due to its reliance solely on arrival time periods, potentially hindering trains with longer durations. In summary, our approach demonstrates substantial reductions in train rejections through the adoption of Policy 1, showcasing a 75% decrease for original durations compared to Policy 3, and Policy 2 achieving 62% improvement. For the other configurations, albeit to a lesser extent compared to the original durations.

6.2 Discussion

In this section, we delve into the interpretation of the solution design and the approaches undertaken in this research alongside the results obtained.

6.2.1 Interpretation of solution design

In the course of this research, we encountered several challenges that required careful consideration. We would like to provide insights into the development of our model first. Despite an extensive review of existing literature, we found no suitable model that could be directly applied to our specific situation. Consequently, we formulated our model as a Mixed Integer Programming problem, considering its applicability to the Track Assignment Problem.

Another approach that we explored but ultimately did not include in our is the Bin Packing Problem (BPP). This algorithm typically involves packing items of different sizes into a (in)finite number of bins or containers, aiming to minimize the number of bins or containers utilized. The BPP comes in various variants based on dimensions, such as 1-dimensional, 2-dimensional and 3-dimensional versions. Drawing parallels to our situation, trains can be likened to items, and tracks to bins. However, the incorporation of time blocks in our model sets it apart from traditional BPP variants. Additionally, accommodating time periods during which trains arrive and must be allocated poses a unique challenge not directly addressed by conventional BPP formulations.

Overall, while the principles of BPP provided valuable insights, the specific requirements and complexities of our problem necessitated the development of a tailored approach, leading us to devise the MILP model adapted to the TAP.

6.2.2 Limitations

Focusing on the model itself and the structure, we identified that Constraint (2) significantly impacted the performance of the model. Particularly as we extended our time horizon, we encountered memory issues when the model instance grew too large. Consequently, we opted to partition the data into smaller segments, selecting a subset of interesting instances to facilitate a proper estimation. While our goal remained consistent throughout, aiming to devise an annual allocation policy, we encountered computational constraints when working with a larger dataset. Given the complexity of the of the problem, we originally intended to utilize a larger dataset with different periods throughout the year. However, due to computational limitations, we opted for a smaller dataset.

Regarding the input data utilized for the model, numerous assumptions were necessary to emulate reality as closely as possible . We previously addressed the uncertainty present in the data. However, due to suboptimal data structuring at ProRail, such as inconsistent formatting of data types, redundant information and incomplete datasets, we encountered several challenges. Notably, the absence of well-registered data on train lengths posed a significant obstacle. Therefore, we assumed that all train allocated to tracks would fit, despite known differences in track lengths at Watergraafsmeer. Selecting a dataset that adequately represents the demand of all rail operators proved challenging due to these discrepancies.

As a strategic decision within our model, we designated that rail operator C would consistently be allocated to track Y. Additionally, we specified that trains allocated to either C4 or C5 could be reassigned to either of these tracks based on the available data, resulting in the classification of these trains with different activity numbers (13 to 24). Another factor we did not incorporate due to lack of train lengths is the restriction against accepting two separate trains from the same rail operator simultaneously at the same track, particularly on longer tracks. While this measure could potentially reduce the number of rejected trains, the absence of insights into train lengths precluded its implementation. From a modelling perspective, the tracks are the same. However, we have opted for a pragmatic approach to devise an allocation policy that can be used in practice.

6.3 Recommendations for ProRail

The results obtained from the model and sensitivity indicate that Policy 1 exhibits a superior objective value compared to Policy 3, the current allocation policy. Therefore, it would be reasonable to implement Policy 1 as the allocation policy for railway yard Watergraafsmeer.

However, from a rail operator perspective, Policy 2 might be preferred due to the higher number of dedicated tracks. Thus, we recommend implementing Policy 2 for the annual allocation of the C-tracks at Watergraafsmeer.

Another recommendation is to adopt the base principles of the formulated model. While the current runtime of the model for large test instances is low, indicating efficiency, improvements should still be considered. One potential improvement could involve reformulating Constraint (2) to accommodate larger time horizons. When expanding our set T, this constraint triggers memory exhaustion due to extensive loops. By enhancing the efficiency of this constraint more efficient, we can accommodate larger datasets, enabling the execution of the model on substantial instances.

In the current approach, all trains are considered equal due to the chosen objective. However, it may be useful to distinguish between different types of trains and taking into account the duration of each train. Implementing a more detailed approach where different trains are assigned different priorities based on their characteristics could lead to a more optimal allocation.

Alternatively, exploring different approaches, such as formulating a heuristic, could be beneficial. Heuristics are generally faster in finding solutions, albeit potentially sacrificing optimality. Additionally, various factors can contribute to deviations in the actual occupancy of tracks, making the utilization of heuristics a favourable approach.

For the extension of the model by incorporating train lengths, it is essential for ProRail to maintain accurate records of the types trains occupying the tracks. The absence of relevant train information introduces uncertainty into the model. Additionally, it is crucial to address the lack of sensors in the NCBG area, which prevents the registration of train occupations. The actual demand for trains at Watergraafsmeer and the timing of this demand is unknown. Improving data collection processes and ensuring the availability of train-related information is integral to the allocation of trains, as this information is necessary for accurately determining the demand parameter.

For future research, it would be intriguing to explore the application of priority rules for trains based on factors such as duration, train type and the number of trains per rail operator, especially when train-related information is readily available. Additional recommendations for future research include evaluating the consequences of rejected demand. While it may be feasible to redirect trains to alternative railway yards in certain cases, such actions may not always be preferable. Furthermore, it is essential to investigate the implications of delays, particularly when trains arrive later than scheduled. Additionally, exploring scenarios where capacity is requested and allocated but remains unused presents another avenue for inquiry. This excess capacity could potentially be reallocated to accommodate another rail operator's needs, justifying the need for additional research.

6.4 Contribution

The theoretical contribution of this research is explained in Section 6.4.1 and the practical contribution in Section 6.4.2.

6.4.1 Contribution to theory

This research contributes to advancing the theoretical understanding of optimization models in logistics and transportation management, particularly in the domain of railway yard allocation. By developing a customized MILP model tailored to the TAP, this research extends existing theoretical frameworks found in literature. The incorporation of innovative elements such as time blocks and ad-hoc tracks into the model enriches theoretical discussions for complex logistical challenges. These aspects fill a gap in literature, as such comprehensive models were previously absent.

6.4.2 Contribution to practice

In terms of practical implications, this research provides valuable insights and recommendations for enhancing railway yard allocation approaches. The primary practical contribution to the company is the MILP model formulated, which can be utilized to determine the allocations of trains from various rail operators to railway yards. Given the absence of such models at ProRail, the utilization and improvement of the developed model can significantly benefit operations. Moreover, the base model serves as a valuable template for adaptation to other railway yards, including those dedicated to cargo transport. This allows for the formulation of allocation policies specific to each railway yard's requirements, considering their unique characteristics and operational constraints.

ProRail recognizes the high practical value of this research, as it provides essential insights into addressing the complexities of railway yard allocation. By leveraging the findings of this research, ProRail can enhance its operational efficiency and effectiveness in managing railway yard allocations.

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Appendices

Appendix A Base model

We have a base model applicable to multiple railway yards in the Netherlands. This model allocates rail operators $\mathcal{O}$ to tracks $\mathcal{S}$ based on available time blocks $\mathcal{B}$ consisting of multiple time periods $t \in \mathcal{T}$. Each operator brings trains with predetermined activity durations v_a from the set $a \in \mathrm{A}$, and our key parameter is the demand parameter $\delta_{o,a,t}$. The length of the time blocks is determined by ℓ_b. Trains arrive characterised by operator, activity duration and time period. Decision variables involve train acceptance ($Z_{o,a,s,t}$) and allocation ($X_{o,s,t}$).

$$\min \sum_{o \in \mathcal{O}} \sum_{a \in \mathrm{A}} \sum_{t \in \mathcal{T}} \delta_{o,a,t} - \sum_{o \in \mathcal{O}} \sum_{a \in \mathrm{A}} \sum_{s \in \mathcal{S}} \sum_{t \in \mathcal{T}} Z_{o,a,s,t} \qquad (\boldsymbol{A.1})$$

s.t.

$$\sum_{s \in \mathcal{S}} Z_{o,a,s,t} \leq \delta_{o,a,t} \qquad \forall o \in \mathcal{O}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \quad (A.1a)$$

$$((1 - Z_{o,a,s,t}) * M) + 1 \geq \sum_{o' \in \mathcal{O}} \sum_{a' \in \mathrm{A}} \sum_{t' \in \mathcal{T}} Z_{o',a',s,t'} \qquad \forall o \in \mathcal{O}, \forall t \in \mathcal{T}, \forall s \in \mathcal{S}, \forall a \in \mathrm{A} \quad (A.1b)$$

$$Z_{o,a,s,t} * v_a \leq \sum_{t'=t}^{t'=t+v_a-1} X_{o,s,t'} \qquad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \quad (A.1c)$$

$$\sum_{o \in \mathcal{O}} X_{o,s,t} \leq 1 \qquad \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \quad (A.1d)$$

$$\sum_{t'=b}^{t'=b+\ell_b-1} X_{o,s,t'} = \ell_b * X_{o,s,b} \qquad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall b \in \mathcal{B} \quad (A.1e)$$

$$X_{o,s,t} = 0 \text{ or } 1 \qquad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T} \quad (A.1f)$$

$$Z_{o,a,s,t} = 0 \text{ or } 1 \qquad \forall o \in \mathcal{O}, \forall s \in \mathcal{S}, \forall t \in \mathcal{T}, \forall a \in \mathrm{A} \quad (A.1g)$$

The objective function **A.1** minimizes the unmet demand. Constraint A.1a ensures that train acceptance is not exceeding demand and also indicates that it is okay to accept less trains. Constraint A.1b prevents train overlap and A.1c ensures exclusive track occupancy. Constraint A.1d allows only one train per track per time period and our time block consistency is formulated by Constraint A.1e. Constraints A.1f and A.1g model the variable types, which are binary variables.

Appendix B Data analysis

In the process of selecting the input data for our model, we have opted for the annual allocation data (registered occupations on tracks) from the year X. The reason behind this choice lies in the absence of major fluctuations attributed to external factors, such as disruptions caused by the corona pandemic. Focusing on this year allows us to create a more consistent baseline for our analysis. We are analysing a total of 30000 trains, with the distribution per operator as follows: 2500 for A, 9000 for B, 6000 for C, 2000 for D, 400 for E and 10100 for F.

The input parameter of the model, denoted as $\delta_{o,a,t}$, is of huge importance of our approach. For instance, we have to come up in this context the predetermined durations of our set of activities. Notably, these durations vary across different rail operators. Each rail operator employs distinct approaches in executing activities. To address this, we conducted an analysis of the data for each rail operator, leveraging histograms for each of them. These histograms offer insights into the frequency distribution of activity durations throughout the year.

The figures illustrate the frequencies of occupations for each rail operator. As we indicated that B and F exhibit significantly larger numbers, we observe multiple peaks in the histograms as well.

The year X has six different rail operators, of which two of them had consistently large number of occupations, B and F, and one relatively low compared to the latter, which is E. The following figures show the frequencies of occupations for the whole year for each rail operator.

The figures are left out due to confidentiality!

Based on the observed peaks we observe in the figures, we have established a set of activities for each rail operator, each with a predetermined duration. Table 19 outlines the specific activities along with their corresponding durations, which will be utilized as input for our set A.

Table 19 Complete set of durations per rail operator

Activity	Rail operator	Duration
1	A	1 hour
2	B	3 hours
3	B	9 hours
4	C	8 hours
5	C	96 hours
6	D	1 hour
7	E	4 hours
8	E	1 hour
9	F	4 hours
10	F	6 hours
11	F	8 hours
12	F	10 hours
13	A	1 hour
14	B	3 hours
15	B	9 hours
16	C	8 hours
17	C	96 hours

18	D	1 hour
19	E	4 hours
20	E	1 hour
21	F	4 hours
22	F	6 hours
23	F	8 hours
24	F	10 hours

The durations are strategically chosen based on the characteristics of each rail operator's operations. The inclusion of a diverse set of activities allows for a stronger representation of the demand and operational patterns. In total, we have 12 activities defined in the model. However, Constraint (7) restricts specific demand to tracks C4 or C5 based on realization data. For instance, trains occupying track C4 or C5 should only be allocated to those respective tracks and cannot be assigned to other regular tracks. Consequently, registrations on track C4 and C5 are assigned different activity numbers, ranging from 13 to 24, corresponding to the same durations as activities 1 to 12. Therefore, the duration of activity 1 is equal to 13 and so forth.

Appendix C Greedy algorithm expert opinion

In our expert opinion step, we employ a swap operations to rearrange and optimize the sequence of trains, addressing practical challenges encountered. Swap operations play a crucial role in refining schedules by rearranging the placement of allocated trains. The objective of swap operations is to enhance the overall schedule by exchanging the position of two allocated trains.

One critical condition for performing swap operations is ensuring that the two trains being swapped do not overlap with other allocated trains. Additionally, it is essential to consider the allocation of trains within a time block when swapping. Specifically, it is imperative not to swap a train belonging to one rail operator while a different rail operator is already allocated within the same time block. Furthermore, when conducting a swap for a train allocated at a particular time period, it is necessary to ensure that the train is moved to another track at the same time period without overlapping with existing allocations. This consideration of time periods ensures that there are segments within the schedule where trains can be relocated without conflicting with already allocated trains. Swapping trains to another track allows for better utilization of tracks and leads to a more efficient schedule.

The process of performing a swap operation typically involves the following steps:

1. **Identifying Candidate Trains**
- We identify pairs of tasks that are potential candidates for swapping.
2. **Checking Preconditions**
- Before performing a swap, we verify that the selected trains meet the necessary preconditions. This includes that the two trains being swapped do not overlap with other allocated trains. Additionally, a train from one rail operator cannot be swapped to another track while a train of a different rail operator is already allocated within the same time block. Furthermore, when swapping a train allocated at a particular time period, it is necessary that the train is moved to another track at the same time period without overlapping existing allocations.
3. **Executing the Swap**
- If the preconditions are met, we execute the swap operation by exchanging the position of the two trains. This process updates the schedule to reflect the new sequence of train allocation.
4. **Termination:** Continue until no further swap operations are feasible.

Appendix D FCFS rule

The First Come First Serve rule is implemented in Python and it takes into account factors such as the duration of each activity, track allocations for specific rail operators, and the availability of tracks at different time periods. We outline the steps in the case of randomized durations.

We consider the following steps:

1. **Initialization**

- The script begins by defining a *''duration_mapping''*, which specifies the duration of each activity. This mapping serves as a reference for the duration of activities.
- It calculates a *"target_sum",* by summing up the durations of all activities in the mapping.
- Next it generates *''random_durations",* which assigns pseudo-random durations to each activity. These pseudo-random are used to mimic real-world variations in activity durations.
- The script adjusts the pseudo-random durations to match the "target_sum", ensuring that the total duration of activities remains consistent with the original durations of activities utilized in the model.

2. **Track Allocation**

- The script defines "track_allocations", which specifies the tracks available to each rail operator for performing activities.
- It extracts activities, time periods and operators from a DataFrame, which represents the input data used for the FCFS simulation.
- Processing times are assigned to each activity based on the duration mapping.
- The activities are combined with their processing times and sorted based on their starting time.
- It initializes "track_schedule", "available_tracks" and "rejections", to keep track of allocated trains, available tracks and rejected trains respectively.
- The script iterates through the sorted activities:
    - For each activity, it checks the available tracks that the corresponding rail operator can access.
    - It ensures that there are no overlaps with already allocated trains on the same track before allocating the train.
    - If a suitable track is found, the train is allocated to that track. Otherwise, the activity is rejected due to a lack of available tracks.

3. **Data Presentation**
    - After the allocation process, the script converts the tracks schedules and rejections into DataFrames for better presentation and analysis.
    - The track schedule DataFrame is sorted based on time periods to visualise the sequence of trains on each track.
    - The sorted track schedule and the list of rejected trains are then displayed to provide insight into the scheduling process and any constraints encountered.

Appendix E Results Tables

In this appendix, we present the results obtained for the dataset of April and June. The explanations provided are similar to those given for the dataset of February. We selected April with the commencement of a new annual allocation and tested June to represent a summer period. The demand is listed in Table 20 and the results of April in Table 21.

Table 20 Input data for April and June

Month	Period	Time horizon (hours)	Demand
April	April 1st 00:00 AM until April 9th 07:00 AM	200	447
June	June 1st 00:00 AM until June 9th 07:00 AM	200	373

Table 21 Computational results of April

Instance	Instance type	Input data	Objective value	Percentage of accepted demand	Gap (%)	Runtime (seconds)
1	Time block = 1 and ad-hoc = 0	April	11	97.54%	0.00	89.10
2	Time block = 1 and ad-hoc = 1	April	10.5	97.65%	0.00	98.54
3	Time block = 1 and ad-hoc = 2	April	13.5	96.98%	0.00	104.22
4	Time block = 4 and ad-hoc = 0	April	14	96.87%	0.00	84.69
5	Time block = 4 and ad-hoc = 1	April	13	97.09%	0.00	90.64
6	Time block = 4 and ad-hoc = 2	April	16.5	96.31%	0.00	91.50
7	Time block = 6 and ad-hoc = 0	April	19	95.75%	0.00	84.22
8	Time block = 6 and ad-hoc = 1	April	18	95.97%	0.00	92.83
9	Time block = 6 and ad-hoc = 2	April	20.5	95.41%	0.00	89.16
10	Time block = 8 and ad-hoc = 0	April	19	95.75%	0.00	88.27
11	Time block = 8 and ad-hoc = 1	April	18	95.97%	0.00	100.20
12	Time block = 8 and ad-hoc = 2	April	20.5	95.41%	0.00	98.50

When focusing on the instance with the lowest objective values without a time block length of 1, we aim to examine the rejected trains for instance 5. Referring to Table 21, we find that the total demand for the month of April amounts to 447 trains, broken down by rail operator as follows: A with 100 trains, B with 50 trains and C with 297 trains. Analysing the rejections per rail operator for instance 5, we obtain the following results shown in Table 22:

Table 22 Rejections per rail operator for instance 5

Rail operator	Total demand	Complete Rejections	Ad-hoc track (0.5 rejection)	Total Rejections
A	100	3	9	7.5
B	50	2	3	3.5
C	297	2	0	2

In instance 5, we observe that a small portion of the demand for all operators have been completely rejected. Specifically, 3% of A's demand, 4% of B's demand and approximately 0.5% of C's demand have been rejected outright.

Table 23 provides the results of the instances for the month June.

Table 23 Computational results of June

Instance	Instance type	Input data	Objective value	Percentage of accepted demand	Gap (%)	Runtime (seconds)
1	Time block = 1 and ad-hoc = 0	June	4	98.93%	0.00	83.95
2	Time block = 1 and ad-hoc = 1	June	4	98.93%	0.00	88.44
3	Time block = 1 and ad-hoc = 2	June	6.5	98.26%	0.00	88.18
4	Time block = 4 and ad-hoc = 0	June	5	98.66%	0.00	82.41
5	Time block = 4 and ad-hoc = 1	June	5	98.66%	0.00	88.45
6	Time block = 4 and ad-hoc = 2	June	7.5	97.99%	0.00	83.92
7	Time block = 6 and ad-hoc = 0	June	11	97.05%	0.00	86.00
8	Time block = 6 and ad-hoc = 1	June	10	97.32%	0.00	80.07
9	Time block = 6 and ad-hoc = 2	June	11.5	96.92%	0.00	86.05
10	Time block = 8 and ad-hoc = 0	June	11	97.05%	0.00	84.07
11	Time block = 8 and ad-hoc = 1	June	10	97.32%	0.00	88.41
12	Time block = 8 and ad-hoc = 2	June	12	96.78%	0.00	88.16

For the month June, we focus on both instance 4 and 5, having the same objective value. Referring to Table 23, we find that the total demand for the month of June amounts to 373 trains, broken down by rail operator as follows: D with 270 trains and F with 103 trains. Analysing the rejections per rail operator for instance 4 and 5, we obtain the following results shown in Table 24.

Table 24 Rejections per rail operator for instance 4 and 5

Rail operator	Total demand	Complete Rejections	Ad-hoc track (0.5 rejection)	Total Rejections
D	270	0	5	2.5
F	103	1	3	2.5

These results indicate a relatively low rejection rate for both D and F, with D experiencing no complete rejections and F having just one. The majority of rejections for both operators occurred on the ad-hoc track, amounting to 2.5 total rejections each.

Table 25 provide the results of the objective value of the sensitivity analysis conducted in Section 5.3.

Table 25 Numerical results of FCFS simulation

Policy	Policy type	Original durations	Original durations *1.5	Original durations *2	Randomized
1	13 mixed and 1 ad-hoc track	832	2738	6005	10080
2	5 dedicated, 8 mixed tracks and 1 ad-hoc track	1280	3445	6889	10635
3	Annual allocation year X (original)	3367	5245	8308	11381
4	Annual allocation year X (mixed)	1213	3336	6724	10609