Integration of Condition Based Maintenance in the Preventive Maintenance Planning of Rolling Stock

Master Thesis

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by

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Preface

Dear reader,

This piece of work has been the final undertaking in my journey for getting my Master's degree. I truly enjoyed working hard for this and I'm proud that it's finished.

I'm really thankful and happy that I had the opportunity to do this project at the company Ricardo Rail. I had the best support throughout my internship at Ricardo Rail from my supervisor Maarten de Vries and teamleader Boudewijn van Os who made me really part of the company. I was lucky to also do this project for NS, a client of Ricardo Rail, where I gained a lot of knowledge thanks to Timo, Gerard and the people I interviewed at the maintenance depot Leidschendam. I've learned a lot from the professional work environment, but I also had lots of fun at the office and during events with all of my colleagues.
I also want to thank Vasso Reppa for supervising me throughout this project and helping me to realise this graduation project at a company.

Throughout my studies in my private environment, I always had good company around, especially at the Koornmarkt 40 in Delft, my home at the first floor above my grandmother, where I lived with my girlfriend Sem throughout this time. But I also always had the best support and encouragements from my parents, my brothers and sister.
Furthermore, in university, I was constantly supported by Karel, Idriss, Daniel, Mark, and Charlie, with whom I could always discuss my technical ideas and who always found time to offer advice. I'm proud that we made it through university together for 7+ years.

This thesis represents the completion of my academic specialization in maintenance engineering. There are still so many things to learn, but it's funny that this thesis is the physical proof that I already learned a lot.

Enjoy reading my thesis,

J. van Geest
Koornmarkt 40, Delft, June 2023

Executive Summary

Traditionally, rolling stock maintenance consists of Preventive Maintenance (PM) and Corrective Maintenance (CM). Rolling stock requires PM after running a specified mileage and/or after a specified time period since its previous Preventive Maintenance routine (Wagenaar et al., 2017). PM of rolling stock is usually performed at a maintenance depot, so the rolling stock has to be scheduled out of operation in order to *shunt* (moving a railway vehicle) to the depot for PM. A rolling stock maintenance planning should thus be established in order make efficient decision-making for maintenance while complying with the required availability of rolling stock for passenger operations. The efficiency of the rolling stock PM planning can be quantified by the *mileage losses*. The usage of a rolling stock is related to the mileage (Lai et al., 2015), hence why PM has to be performed every time that a rolling stock ran a certain mileage. This is considered to be the maximum usage that the rolling stock can safely run according to experts. If a rolling stock undergoes PM when the mileage since previous PM is less than the allowed mileage threshold, this remaining mileage is considered as a loss. The mileage loss can be expressed into costs, the *mileage costs*, which are desired to be minimal.

Recently with the use of sensors, microprocessors and an online network that can be used for *condition monitoring*, the health state of a component or sub-system can be retrieved in real-time by detecting faults based on monitoring data (Brahimi et al., 2020). In addition to obtaining the current health state with the use of online condition monitoring, also the degradation evolution of the system can be approximated and CM can be avoided.
When an anomaly is detected with the use of condition monitoring, the health of the system is degrading. This detected anomaly can be isolated and diagnosed, this is defined to be a *fault*. From the moment in time that a fault is detected, the component or system will further degrade until failure. The estimated time between the point in time of fault detection until the time of failure, is defined as the Remaining Useful Life (RUL). The length of the RUL in time units is established by a prognosis. Planning rolling stock maintenance according to this prognosis to failure is referred to as Condition-Based Maintenance (CBM). The maintenance planner can act and rearrange the current maintenance planning in response to a failure prognosis. CBM is thus anticipated to mitigate the disruption of the maintenance planning in comparison to CM.
Ricardo Rail is a consultancy company that participates in this study. Nationale Spoorwegen (NS) is a client of Ricardo Rail, which is a Dutch train operating company that is involved due to a mutual interest in the development of CBM. The newest light-train rolling stock type of NS with its maintenance strategy will be used as case study for this study.

NS expressed interest in optimizing maintenance operations by integrating CBM in the rolling stock PM planning. However, it is unknown whether the integration of this new maintenance approach with the current maintenance strategy is complementary. It will be studied what the impact of CBM is on the decision-making of rolling stock maintenance planning. The main research question is formulated as follows:

What is the impact of integrating Condition Based Maintenance in the Preventive Maintenance planning decision-making?

The state of the art consists of a sufficient amount of research optimizing the rolling stock maintenance planning, based on PM conditions and passenger operations. The objective is to minimize the mileage losses and overall maintenance costs with a MILP optimization model that is solved with a solver algorithm. The challenge is often in these studies to comply with passenger operations while performing efficient PM.
Alternatively, a few studies can be found that integrate a prognostic model of the health of rolling stock into the maintenance planning. The objective in these studies is to exploit the degradation of the rolling stock and maintain the asset right before failure in order to perform efficient maintenance. However,

these studies do not consider if planning maintenance based on the actual degradation actually improves the maintenance planning or study the opportunity of performing CBM in combination with PM. The rolling horizon framework is suggested from literature for simulating rearrangements in maintenance planning decision-making in response to unforeseen events. The maintenance planning optimization methodology from literature will be used for the formulation of the optimization problem.

Passenger operations and maintenance operations are managed independently at NS, hence there is a timetable for passenger operations and a separate planning for maintenance. Maintenance is carried out in a maintenance depot outside the passenger transport railway network, so logistics activities must be initiated in order to shunt a train from the railway network to the NS maintenance depot. NS performs ”short cycle” PM every 108 [days] and/or 45,000 [km] that a rolling stock has been in operation, whatever threshold comes first. A standardized cluster of PM activities is performed per rolling stock at the maintenance depot of NS, which takes 3 days.

The decision-making for maintenance is constrained by the depot capacity and the required amount of rolling stock available for passenger operation. CM is also performed at the maintenance depot of NS at a designated track. It is a challenge to plan CM, because a failure occurs unexpected, so CM brings an extra workload to the maintenance depot and another rolling stock should replace the failed rolling stock in order to comply with the required availability for passenger operations.
If NS would monitor the health of the rolling stock and plan maintenance based on prognostic data, so performing CBM, this creates flexibility for the maintenance planner to pick the most ideal timing. Consequently, less disruptions in the planning take place of this type of maintenance, because it is foreseen.
Additionally, while assuming that the RUL gives the maintenance planner flexibility for planning the maintenance, it becomes reasonable to see this as an opportunity to combine PM with CBM. When PM has to be performed in the near future and a failure is predicted simultaneously, the two maintenance activities can be combined, saving shunting costs because of this economic dependence. Consequently, a trade-off can be made. Either separating PM and CBM, requiring the rolling stock to visit the depot twice with minimal mileage loss. Or combining PM and CBM by scheduling earlier PM, which results in mileage losses but saves costs because the rolling stock only needs to visit the depot once. It is expected that the more *combinations of CBM with PM* can be made, the more efficient the PM planning becomes.

In this study, a rolling stock maintenance planning optimization approaches are formulated as a deterministic MILP problem. Under several assumptions, a mathematical model is formulated that rolling stock should perform PM before reaching the mileage or time threshold. The objective of the maintenance approaches is to minimize the maintenance costs. These costs associated with maintenance are considered to be: Shunting costs, PM costs, CM costs and CBM costs. The model aims to perform PM only when the maximum mileage threshold has been reached so that the mileage losses are minimal while simultaneously performing CBM and CM.
First of all, a rolling stock PM planning optimization method is established based on the way of practice at NS. The first approach, ”approach 1”, only considers PM that should be planned while making a minimum amount of mileage losses. NS does not plan PM according to an optimization tool yet, so this optimization method is beneficial for optimizing the PM planning under the assumptions that are defined in this study.
Secondly, two approaches are formulated building on approach 1, but contain additions that concern the integration of CM and CBM. The addition of this approach is that disruptive CM and CBM will be included in the existing PM planning. When discussing disruptions, this refers to instances of CM or CBM. It was a challenge to model the unexpectedness of failures in the planning model with CM, or how failures could be predicted with CBM. It took therefore three approaches to successfully integrate CBM or CM in the rolling stock maintenance planning optimization model.

A rolling horizon framework is used in order to come to the satisfactory optimization method. The approach that is referred to as ”approach 3” minimizes the overall maintenance costs. This approach is in line with the state of practice, because with this method, a planning is made per week and will be rearranged when disruptions happen during the execution.

Approach 3 can be used for achieving three different types of results:

- The rolling stock PM planning optimization integrating CM.
- The rolling stock PM planning optimization integrating CBM.
- The rolling stock PM planning optimization integrating CBM and additionally CBM can possibly be combined with PM in one routine.

The formulated approaches are evaluated on their sensitivity and the performance of the three different types of results are compared. The results are quantified according to the defined KPI's. These KPI's are the *mileage losses*, the amount of successful optimization computations, referred to as the amount of *feasible solutions*, the *amount of combinations of CBM with PM* and the overall *maintenance costs*.

The performance of the maintenance planning optimization approach 3 is evaluated in order to quantify the difference in the disruptive impact of CM versus CBM. The results demonstrate that a rolling stock PM planning integrating CBM is superior to a PM planning integrating CM, because 27 more feasible solutions out of 180 are found. The results of the optimizations integrating CM demonstrate that more mileage losses are made than for CBM. Moreover, the integration of CBM performs really well, because more than 50% of the times, no mileage losses are made in the planning.
The performance of the maintenance planning optimization approach 3 is evaluated when CBM can be combined with upcoming PM routines. The RUL length for CBM is iterated for this performance evaluation such that a failure may be predicted 7, 14, and 21 days in advance. Also the amount of disruptions in the planning is iterated from 4 to 12. Results show that combining CBM with PM is cost efficient, because extra shunting costs are saved. More costs can be saved the longer the RUL and the more disruptions occur in the maintenance planning. The maximum amount of costs were saved, which is 0.86% of the maintenance costs, with the longest assessed RUL length of 21 days and the most interruptions of 12.

In this study, an optimization method is established that minimizes the mileage losses in the PM planning which can be used as optimization tool for NS. With a rolling horizon framework, the integration of disruptions in the rolling stock PM planning is modeled that can act on unforeseen events and rearrange the planning accordingly.
From the results of optimization approach 3 can be concluded that planning maintenance according to prognostic information results in less mileage losses than a PM planning that is disrupted by CM. This is because CM must be conducted instantly at a time that is difficult to arrange. CBM is more feasible to plan and CBM creates the possibility to combine the depot visit for CBM with PM as well. This has been proven by the model to be cost efficient.

All in all, the model presents an integral simplified version of the NS rolling stock maintenance planning case. For the formulation of this model, assumptions and concessions are made to be able to model the case. As a consequence, the results of the model may therefore deviate from reality.
It is therefore recommended to upscale the fleet model to the actual fleet size, model the required amount of rolling stock for operations variable based on the actual requirements based on peak hours and peak days and approach the maintenance depot capacity constraints more precisely. Also, it is recommended to research how uncertainties of prognostic information influence the decision-making of CBM and how this can be integrated in the planning optimization model.
Nonetheless, this study demonstrates that the integration of CBM to the PM planning is beneficial and it is therefore recommended to perform more research on this subject. It is shown that combining CBM with PM in one routine is cost efficient. Also, based on the results of this study, it is recommended to develop prognostic models to predict failures far in advance, because the longer the RUL of the prognostic models, the more efficient the integration of CBM into the PM planning can be.

List of Abbreviations

BIP	:	Binary Integer Programming
CBM	:	Condition Based Maintenance
CM	:	Corrective Maintenance
FMECA	:	Failure Mode Effects and Criticality Analysis
HVAC	:	Heating, Ventilation, Air Conditioning
ILP	:	Integer Linear Programming
IP	:	Integer Programming
KPI	:	Key Performance Indicator
MBN	:	Materieel Besturingscentrum Nedtrain
MILP	:	Mixed Integer Linear Programming
NS	:	Nationale Spoorwegen
OM	:	Opportunistic Maintenance
PdM	:	Predictive Maintenance
PM	:	Preventive Maintenance
RUL	:	Remaining Useful Life
SDM	:	Storing Defect Materieel
SNG	:	Sprinter Nieuwe Generatie

Contents

1 Introduction

1.1. Background

Maintenance is performed on rolling stock in order to ensure reliable and safe passenger transportation without failures during operation (Zhong et al., 2019). The life cycle of rolling stock includes a significant amount of maintenance costs, hence maintainers strive to perform maintenance as cost efficient as possible. Meanwhile train operators require a high availability of rolling stock for passenger transportation.
Currently, decision-making for rolling stock maintenance planning and activities is based on standardized frameworks such as Failure Modes Effects and Criticality Analysis (FMECA) that determines the maintenance frequency of components while ensuring reliability (de Vos and van Dongen, 2015). The result is a Preventive Maintenance (PM) planning that is usually developed by maintenance experts (Bougacha et al., 2020; Ma et al., 2016; Zomer, 2020). **This predetermined PM might lead to unnecessary maintenance routines and component replacements, because the actual rolling stock condition is not taken into consideration while making maintenance decisions.**

Recently with the use of sensors, microprocessors and an online network, maintenance decision-making can be based on the estimated health condition of the asset (Nappi et al., 2020). This is arguably more efficient since unlike PM, maintenance activities can be suggested when they are certainly required. Preventive Maintenance inspections become unnecessary, because the deterioration of the asset is consistently monitored. The *condition monitoring* can be further exploited when predictions of failures are made based on the condition monitoring measurements. Besides, Corrective Maintenance can be avoided, because failure can be foreseen. Predictions of the time to failure are in this context referred to as *prognostics* and expressed as the *Remaining Useful Life* (RUL) (Nappi et al., 2020). With these developments as starting point, the implementation using prognostics in practice for rolling stock maintenance decision-making can be anticipated.
The dutch railway operator ”Nationale Spoorwegen” (NS) is interested in using condition monitoring and prognostic for maintenance decision-making on their newest rolling stock fleet, the ”Sprinter Nieuwe Generatie” (SNG), which is full of capable equipment to perform condition monitoring. These condition monitoring measurements can subsequently be used for conducting prognostics. Also, track-side condition monitoring equipment is already in use, and the readings are being used at the maintenance depot to determine the health or degradation for example of the wheelsets or the axle bearings. Whilst prognostics and condition monitoring are almost ready for use, the optimum course of action is still uncertain. Specifically how to act on this new information with the current maintenance policy is therefore unclear. To assess the viability of this new maintenance strategy and to assess whether using prognostics for maintenance decision-making is beneficial, its integration with the existing Preventive Maintenance strategy of NS should be researched.

This study addresses rolling stock maintenance, which is specific per train operating organization. There is no one maintenance strategy solution that suits all for rolling stock maintenance and is therefore a thoroughly discussed subject. Due to the involvement of train operator NS in this graduation

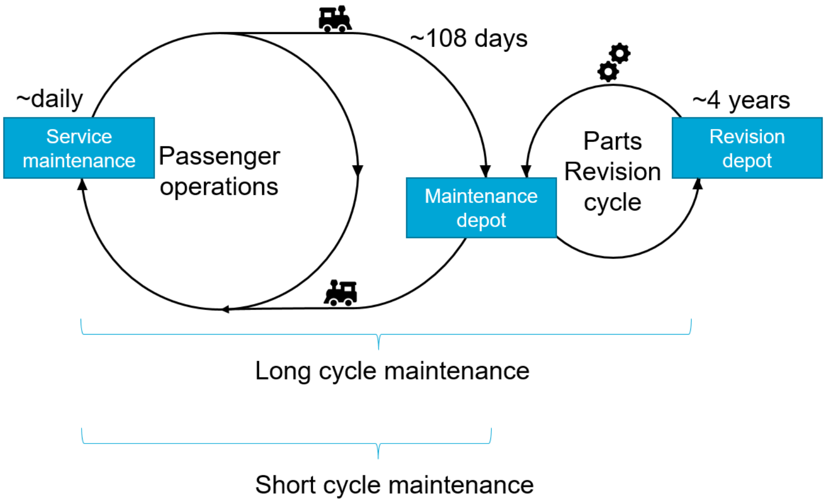


Figure 1.1: Rolling stock Preventive Maintenance cycles at NS

project, their maintenance strategy will be presented and used as a case study throughout. This study contains confidential information that is enclosed in appendix B, which will be referred to as the *confidential annex*. All maintenance costs are therefore multiplied with multiplication factor Y throughout this report, the exact value can be found in confidential annex B section B.3. Also figures with actual costs can be found in this confidential annex.

At NS, passenger operations and maintenance operations are managed independently, hence there is a timetable for passenger operations and a separate planning for maintenance. Still, in order to decide which rolling stock can undergo maintenance and which rolling stock must be available for passenger operations, the parties must communicate.
Maintenance is carried out in a separate maintenance depot, so logistics activities must be initiated in order to transfer a train to the NS maintenance depot. These logistic operations are managed by the fleet operator. The logistics between passenger operations and the maintenance depot are beyond the scope of this study, because the maintenance operator has no influence over logistical decisions at NS.

The rolling stock maintenance organization at NS is centered around distance- and time based periodic Preventive Maintenance. So maintenance experts have decided that rolling stock may run until a time threshold of 108 days has been reached, or the mileage of 45,000 km has been reached since the last PM, whatever threshold comes first. There are different classifications of PM considered by NS. Three main maintenance categories listed below and can be seen in figure 1.1.

- **Daily or weekly maintenance service operations**. Consisting of tasks like cleaning, short safety checks and visual inspections. The duration of this type of maintenance takes a few hours. These activities are performed at shuntyards within the railway network.
- **Short cycle maintenance**. For this type of maintenance rolling stock is unavailable for passenger operations and goes to the designated maintenance depot for maintenance. The maintenance activities include technical checks, inspections and component repairs when a fault has been diagnosed so that failures are prevented. This type of maintenance operation takes place approximately every three months and takes a few days time.
- **Long cycle maintenance**. For this type of maintenance, the rolling stock will be unavailable for passenger operations and goes to a designated maintenance depot every 4 years. For long cycle maintenance, the rolling stock might need to be partly disassembled for large revision projects. The rolling stock will be unavailable for weeks up to months.

The scope of this study is short cycle maintenance at the maintenance depot, because NS aims to perform short cycle maintenance based on the actual condition of the rolling stock. Consequently, when discussing PM, this refers to short cycle Preventive Maintenance of NS.

Mileage losses The amount of mileage that a rolling stock runs can be related to the amount of usage of that rolling stock. Therefore, at NS, the usage threshold for PM is expressed in mileages, 45,000 [km]. The value of the mileage threshold is determined by maintenance experts. This is considered to be the maximum usage that the rolling stock can safely run ensuring a minimum amount of failures. Since the decision-making of rolling stock PM is constrained by this threshold, the rolling stock should outrun the full 45,000 [km] for maximum exploitation. Therefore, the efficiency of the PM planning is expressed at NS in *mileage losses*. Mileage losses are defined to be the remaining amount of mileage that the rolling stock potentially could have run if the rolling stock did not go to the maintenance depot for PM prematurely. This mileage threshold should however be reached within the time threshold of 108 [days] since the last time that the rolling should went to the maintenance depot for PM. The mileage that the rolling stock ran since the last time that PM is performed, can be referred to as the *accumulated mileage*, because the mileage is a cumulative. Similarly, the time in since the last time that PM is performed can be referred to as the *accumulated time*.
Figure 1.2 B explains this by showing that more PM is performed when the mileage losses are made. The mileage losses are shown in red in figure 1.2.
When more mileage losses are made, more PM is performed over a longer period of time, resulting into more maintenance costs. Components are prematurely maintained resulting into unnecessary and costly replacements.

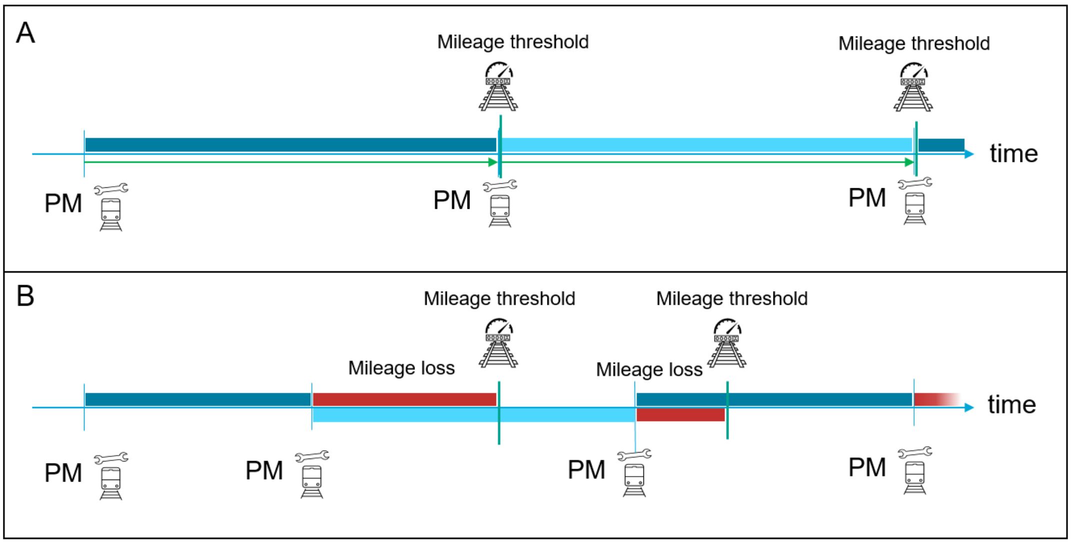


Figure 1.2: Two figures illustrating the timeline of a rolling stock and how the decision-making of PM influences the efficiency of the PM planning
A) situation where PM is planned exactly when the mileage threshold is reached
B) situation where PM is planned before the mileage threshold is reached resulting into mileage losses and more PM

1.2. Maintenance

Consistent use of maintenance terminology is essential for understanding how decisions are made in the context of planning rolling stock maintenance. Therefore, maintenance terminology definitions according to standards and the state of the art are addressed in this section. These definitions will be used consistently throughout the report.

Following the NEN-EN13306 standard (*Maintenance - Maintenance terminology*, 2019), *maintenance* is defined as:

”Combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function.”

From which *technical maintenance actions* are defined as: ”observation and analyses of the item state by e.g. inspection, monitoring, testing, diagnosis, prognosis, etc. and active maintenance actions as repair, replacement ...” (*Maintenance - Maintenance terminology*, 2019). Thus, ”Performing maintenance actions” has various meanings and should be used carefully whilst providing context.

- *A failure* is defined to be the loss of the ability of a component or system to perform a required function (*Maintenance - Maintenance terminology*, 2019).
- A *fault* is defined to be a deviation of a characteristic property or parameter in the system which occurs before failure (Brahimi et al., 2020). A fault could indicate the deterioration of a system that leads to failure over time and over cumulative usage if it would be neglected.

Maintenance actions are performed in order to avoid failures and a detection of a fault could give reason to actively perform maintenance as a repair or refurbishment.

Maintenance categories Maintenance is generally categorized in two categories:

- Corrective Maintenance
- Preventive Maintenance

Further maintenance categories are standardized and can be seen in figure 1.3

Corrective Maintenance (CM), has to be performed after a failure has been observed, so the asset or component is not able to perform the required function anymore. Corrective Maintenance is therefore a reactive action to a failure, which consists of e.g. restoring or repairing the system to a state in which it can perform its function again (*Maintenance - Maintenance terminology*, 2019). An unexpected failure results in service disruption and may initiate damage to connected components because of so-called stochastic dependencies (Fumeo et al., 2015; Ghamlouch and Grall, 2018). So if a system runs until failure, it will incur additional costs. Therefore, Corrective Maintenance is considered expensive, because additional costs could have been prevented when maintenance was performed before failure at a convenient time (Fumeo et al., 2015).

Preventive Maintenance (PM) is performed before failure, when the system is still able to perform its required function. The goal of performing PM is to mitigate degradation and reduce the probability of failure (*Maintenance - Maintenance terminology*, 2019). Degradation is defined as the deterioration of a physical condition because of usage and aging. Preventive Maintenance actions consist of e.g. inspections in order to observe of degradation and possible restoration and repair of observed faults.

Condition Based Maintenance (CBM) is defined to be Preventive Maintenance based on the observation of degradation. Predictive maintenance (PdM) is standardized as CBM, but based on a prognosis of degradation evolution rather than the only the current health status as can be seen in figure 1.3. However, for this study PdM is referred to as CBM and it is assumed that in the scope of this study CBM is based on both observation of degradation and prognostics because of online condition monitoring. Therefore, the term CBM will be used for this type of maintenance throughout this study.

Maintenance planning The decisions for planning Preventive Maintenance are often risk-based, so when the system is statistically probable to fail (Fumeo et al., 2015). The optimal timing for PM is when the system still can function, but degradation is observed and faults may be present indicating that the time to failure is relatively short. The maintenance frequency for PM is traditionally time or distance based, because this can be related to the usage of the rolling stock.

1.3. Online Condition Monitoring and Prognostics

Online condition monitoring With the introduction of online condition monitoring, the health state of a component or sub-system can be retrieved in real-time by detecting faults based on monitoring data (Brahimi et al., 2020). *Online condition monitoring* is defined as the method for measuring system characteristics through microprocessors and sensors whose values can be acquired in real-time. Brahimi et al. (2020) describes that the characteristics of the measured system can be processed in a **diagnostic module** so that a fault can be detected and located to a specific component. The output

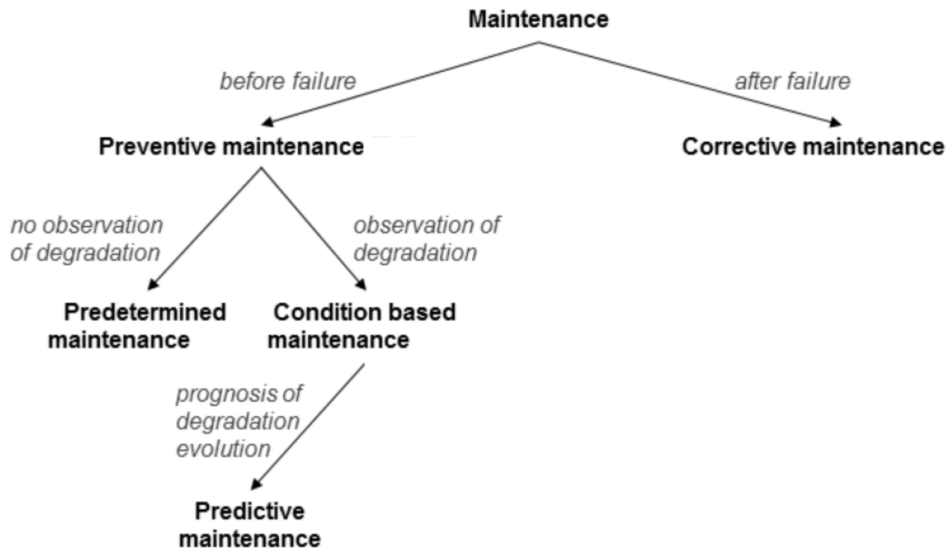


Figure 1.3: Overview (simplified by leaving irrelevant terms out) of maintenance terminology from standard NEN-EN13306 (*Maintenance - Maintenance terminology*, 2019)

of a diagnostic system is thus the fault identification and the cause.

Generally, diagnostics methods can be categorized as *data-driven* and *model-based* (Brahimi et al., 2020; Diego Galar et al., 2013; Gálvez et al., 2022; Villarejo et al., 2016).

- *Data-driven* models for performing diagnostics use available data consisting measurement signals from multiple sensors placed at various locations or other observable condition indicators (Diego Galar et al., 2013). The goal of the data-driven models is to find relations between data that can be correlated to faults (Brahimi et al., 2020; Sysyn et al., 2020). The disadvantage of this method is that the model relies on these correlations in the system that have to be identified from training data which has to be executed and validated beforehand (Diego Galar et al., 2013). Weight parameters are used to build data-driven models, which are then trained using historical sensor data (Gálvez et al., 2022). The advantage of this method is that successful fault diagnosis can be established without a deep physical knowledge of the system (Diego Galar et al., 2013).
- *Model-based* techniques with diagnostics as an output are utilized when there is a deep understanding of the physics governing the system to be monitored. A mathematical model is established that simulates the physical system. The model requires validation before the output can be considered as reliable. Another challenge is to observe complementary variables that can be used as input for the model so the physical state can estimated as output (Diego Galar et al., 2013). A disadvantage of this method is that unidentified fault mechanisms that are therefore not included in the physical model cannot be dealt with (Villarejo et al., 2016).

A third option is hybrid model-based that utilizes a combination of data-driven and model-based techniques. A hybrid model can be used to compensate with a lack of data or improve the fault isolation because of the system knowledge (Gálvez et al., 2022).
Overall, it seems more reliable to use a hybrid model since it integrates two technique that are complementary. For safety reasons, a hybrid model may be more robust because it does not only rely on data or on a physical model.

Prognostics In addition to obtaining the current health state with the use of online condition monitoring, also the degradation of the system can be approximated. When an anomaly is detected by exceeding the *faultiness threshold* with the use of condition monitoring, the health of the system is degrading, so a fault occurs. As a result, the fault can be online identified, the *diagnosis*. From this point in time, the component or system will further degrade until failure. The time between the point in time of fault detection until the time of failure, is defined as the *Remaining Useful Life* (RUL). This framework is illustrated in figure 1.4. Computing *prognostics* is defined as estimating the remaining

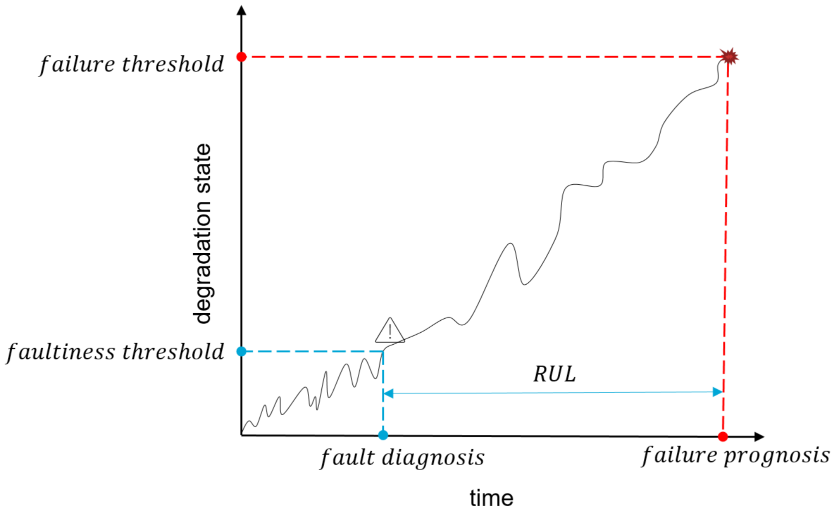


Figure 1.4: Prognostics based on the degradation of an asset

time to failure by making a future prediction of the health state of a component, often executed through a degradation- or prognostic model. Prognostics models can also be categorized in data-driven or model-based techniques (Villarejo et al., 2016).

In literature, examples can be found of prognostic models such as Rivas et al. (2022), whom compute a RUL with a data-driven approach of a turbofan engine, that is part of a larger multi-unit system. They chose to delimit the prognostic model to a specific sub-system that is monitored, so a single RUL prediction is made from the data of the sub-system. This can be compared to the study of Gálvez et al. (2022) who compute the RUL of a HVAC (Heating Ventilation Air Conditioning) system with a hybrid model-based approach. The HVAC is a sub-system of the complex rolling stock multi-unit system and the HVAC itself consists of multiple components as well. Within a multiple unit system, the degradation of the components are often highly dependable because of operational interaction (Boekweit, 2021). However, there are boundaries between independent sub-systems. Computing a prognosis for the HVAC is therefore logical, because the system does not affect other sub-systems on a rolling stock asset.
Defining the sub-systems from which prognostics have to be computed that contribute to the indication of the health of the complete system is therefore critical. The suitability of the prognostics model also depends on the definition of the system level.
Figure 1.5 from Villarejo et al. (2016) illustrates which prognostics model is generally appropriate for the system level.
It has become evident that condition monitoring contributes to better decision-making with diagnostic modules and prognostic modules. Figure 1.6 illustrates the framework how these methods are used for maintenance decision-making.

NS rolling stock prognostic development The newest light-train rolling stock type of NS, ”Sprinter Nieuwe Generatie” (SNG) contains a lot of condition monitoring equipment providing valuable asset data. This asset data can be analyzed, resulting into accurate predictions when a failure is likely to occur. Currently, there is ongoing development on prognostic models for this type of rolling stock. The prognostic models will be conducted on component-, sub-system and system levels. For the scope of this study, it is assumed that prognostic information is available on system level and can be used for maintenance decision-making. It is also assumed that prognostic information is provided in the form of a Remaining Useful Life. A fault can be detected when there is a deviation from the standard behaviour, this deviation can be related to the overall degradation. It is assumed that a failure prognosis can only be conducted after the fault detection, so that it is in accordance with figure 1.4.

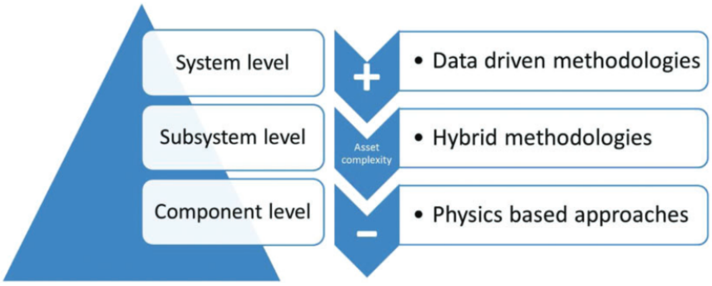


Figure 1.5: Suitability of the prognostics technique for the system level (Villarejo et al., 2016)

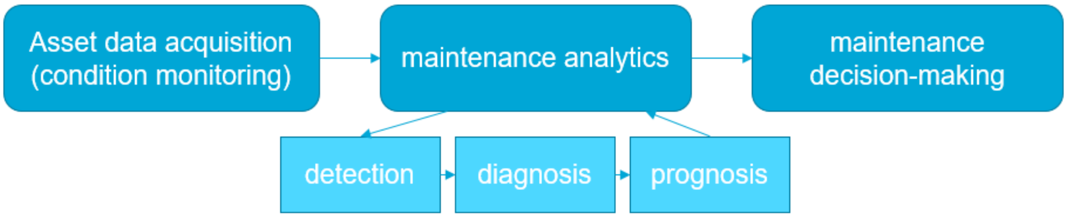


Figure 1.6: Predictive maintenance framework based on Tiddens et al. (2020) and Jardine et al. (2006)

1.4. Research Scope and Questions

The background about rolling stock maintenance presents ongoing development in maintenance methods and the stakeholders are introduced. The motivation of this study can be formulated as follows:

Rolling stock maintenance operators have expressed interest to optimize maintenance operations by using condition monitoring and prognostics for decision-making of rolling stock. However, it is unknown whether the integration of this new maintenance approach with the current maintenance strategy is complementary.

Ricardo Rail is participating in this graduating project. The company provides consultancy services on rolling stock maintenance, purchases and operational excellence, amongst many others. Nationale Spoorwegen (NS) is a client of Ricardo Rail. NS is a Dutch train operating and maintainer company that is involved due to a mutual interest in the development of rolling stock maintenance. Currently, NS performs Preventive Maintenance based on the mileage and/or the time in operation. So the decision-making for maintenance is currently not based on the actual condition of the assets.

The objective of this study is to investigate the impact on the rolling stock Preventive Maintenance planning when Condition Based Maintenance is integrated in the maintenance planning instead of Corrective Maintenance. This approach for maintenance decision-making is relatively new and might conflict the current time and mileage-based and time-based maintenance strategy. The performance of this integration can be investigated by evaluating the maintenance costs.
Moreover, the feasibility of maintenance decision-making based on prognostics will be studied by evaluating the flexibility of the current Preventive Maintenance planning with respect to the maintenance depot capacity, resources and the required amount of available rolling stock for passenger operations. While considering these factors, it can be determined whether the rolling stock maintenance planning can be effectively rearranged so that new maintenance decisions can be made due to the newly retrieved prognostic failure information. Ultimately, the outcome of the study results in a proposal for integration of Condition Based Maintenance. The main research question is:

What is the impact of integrating Condition Based Maintenance in the Preventive Maintenance planning decision-making?
This research question is addressed by answering the following sub-questions.

1. What is the current state of the art for rolling stock maintenance planning optimization methods?

2. What is the current state of practice for rolling stock maintenance planning?
3. How to formulate an optimization problem for rolling stock Preventive Maintenance planning considering the mileage costs and what are the associated decision-variables and constraints?
4. How to design a rolling stock Preventive Maintenance planning algorithm for integrating Corrective Maintenance or Condition Based Maintenance?
5. How to evaluate the performance of the rolling stock Preventive Maintenance planning algorithm considering the integration of Corrective Maintenance or Condition Based Maintenance?
6. What suggestions could be made to NS for improving the maintenance planning based on the results of the rolling stock maintenance planning algorithm?

Currently, the state of the art of rolling stock maintenance planning optimization largely consists of optimal decision-making in Preventive Maintenance planning. The objective of these studies is often is to merge the maintenance planning with the passenger operation schedule. Or methods are established solely focusing on prognosis estimation after fault diagnosis.
Rolling stock maintenance planning decision-making based on prognostics prevents unnecessary component replacements and failures can be predicted in advance so that corrective repairs are excluded. Hence, it is highly desired to implement maintenance decision-making based on the actual degradation of rolling stock in the current maintenance planning. However, the integration of Condition Based Maintenance in the rolling stock Preventive Maintenance planning is yet to be studied in literature. It is unknown if this improves the maintenance decision-making and whether it results in a feasible rolling stock maintenance planning. This study will contribute to the yet to be established integration of Condition Based Maintenance into the Preventive Maintenance planning of rolling stock.

1.5. Approach and Structure

This study addresses the main research question and sub- research questions 1 to 6. In chapter 2, the state of the art of rolling stock maintenance planning optimizations is addressed that answers research question 1.
In chapter 3, research question 2 is addressed by evaluating and discussing the short cycle maintenance strategy of NS. The maintenance strategy of NS will be used as case study during this study and confidential information that is used is enclosed in confidential annex B. Therefore, information with regards to maintenance decision-making is retrieved from NS and this will be considered as the state of practice. This information consists of Key Performance Indicators, maintenance costs and the rolling stock maintenance approach. In this chapter, it will also be described what the opportunities are of Condition Based Maintenance.
According to optimization methods from the state of the art and the state of practice, a maintenance planning optimization approach will be formulated in chapter 4 that ultimately answers research question 3. Also in chapter 4, three optimization approaches are established. It took three iterations to answer research question 4 by formulating the approach that is able to investigate the impact of the integration of Condition Based Maintenance to the rolling stock Preventive Maintenance planning. This approach is verified among other related verification checks further in this chapter.
In chapter 5, research question 5 will be addressed by structurally evaluating the results of the rolling stock maintenance planning optimization approaches. The Key Performance Indicators based on the state of the art and state of practice and experience will be used to evaluate the performance of the approaches. Results are presented as sensitivity checks of parameters and performance comparisons.
In chapter 6, conclusions are made based on the results from chapter 5 with regards to the performance of the maintenance planning optimization approaches and how prognostics impact this. In chapter 6, the limitations of the approach are discussed and future recommendations are provided. A proposal for NS in provided that answers research question 6.

2
State of the Art

In this chapter, the state of the art of rolling stock maintenance planning is presented. The goal of this chapter is to lay out context and demonstrate how rolling stock maintenance planning has been researched. A distinction will be made in the state of the art in order to make a valid comparison of the literature. The first section of the literature review addresses rolling stock Preventive Maintenance planning optimization methods. The second section of the literature review discusses optimization techniques for rolling stock maintenance planning that integrates some type of prognostics. Based on this review, the formulated research question 1 will be addressed:

1. *What is the current state of the art for rolling stock maintenance planning optimization methods?*

The mathematical framework and programming tools commonly used in the state of the art of rolling stock maintenance planning optimization are addressed. With the systematic literature review in this chapter, the state of the art of rolling stock optimization can be discovered and gaps can be identified.

2.1. Rolling stock maintenance planning optimization techniques

The Preventive Maintenance planning for rolling stock is usually developed by maintenance experts (Bougacha et al., 2022). Preventive Maintenance activities for rolling stock are often performed after a certain amount of usage that is expressed in time and mileage that the rolling stock has been running since PM is performed. Therefore, the rolling stock fleet's operating time and mileage are monitored, since safety is intended to be ensured by not exceeding the predetermined time and/or mileage threshold (Wagenaar et al., 2017). While sufficient rolling stock is available for operation and while the workload for the maintenance depot is manageable, the traditional objective of developing a maintenance planning is to maximize the distance/time before PM needs to be performed. Since it can be estimated how much kilometers every rolling stock runs on average per day, it can be easily predicted when a rolling stock is about to exceed the mileage threshold. As a result, the PM planning can be established in advance. The maintenance planner can make a weekly planning for PM at the maintenance depot making decisions based on the mileage of the fleet. So the rolling stock will be maintained at the designated time that the maintenance planner found optimal.

The disadvantage of making a Preventive Maintenance planning based only on the mileage and operational time, is that unexpected or unforeseen ”disruptive” events during operation may impact the planning so that it becomes invalid (Bakon et al., 2022). These disruptive events are initiated because of failures of rolling stock. As a result, the rolling stock has to be repaired for which Corrective Maintenance will be planned. Therefore, Corrective Maintenance is considered to be disruptive in the maintenance planning. Also maintenance that has to be performed due to newly acquired prognostics is considered to be disruptive, because it disrupts the initial maintenance planning.
Therefore, in order to integrate disruptive events in a PM planning, the planning should be able to rearrange maintenance activities and act on these disruptions in real-time.

There are several objectives that may be discovered for optimizing the maintenance planning as a result of complex organizational issues that are involved. Performance indicators managed by various stakeholders must be balanced to optimize the maintenance planning. Hence, many scheduling optimization models are developed in past decades to solve complex scheduling problems (Fazel Zarandi et al., 2020). The rolling stock maintenance planning optimization models that are analyzed for this study are formulated in a mathematical model, translated into Mixed Integer Linear Programming and executed by a solver algorithm.

Mathematical Model Rolling stock is a moving asset in a network, so Research Operations (Hillier and Lieberman, 2015) are often applied to simulate and optimize railway operations, including maintenance planning (Huisman et al., 2005). When an optimization problem is defined, this can be reformulated into a mathematical model for analysis. Under the condition that the problem is well-defined, a model is a realistic representation of an integral part of an operation.
In this case, the defined problem is that the Preventive Maintenance planning is not optimal. Hence, the operation of making a planning for maintenance is formulated considering the key contributions as input for such an operation. From the model formulation, a mathematical model can be formulated expressed in terms of mathematical symbols and expressions (Hillier and Lieberman, 2015). **Decision-variables** are variables whose values have not yet been determined by the model. These are quantifiable decisions, and the values of these decision-variables result into the performance of the operation. An example of a maintenance decision for rolling stock is whether to maintain a unit of rolling stock or not, which is a binary choice expressed as $\{0, 1\}$. The **objective function** is a mathematical function of the decision-variables that is used to express the operation's performance measurement. In the case of maintaining rolling stock, the objective can be to minimize maintenance costs or to maximize the availability. The objective function is then often the sum of all costs or values that relate to availability. The quantifiable boundaries of the performance of the model are defined by the **constraints**. Constraints are functions of decision-variables and **parameters** that make the mathematical solution bounded. These constraints are expressed as inequalities or equations. Parameters define for example the capacity of the maintenance depot. The pre-defined parameters are constants during the operation that can be used to bound the decision-variables in the constraint functions. Parameters define for example the capacity of the maintenance depot, the rolling stock fleet size or costs. Constraints express *how* the capacity of the maintenance depot can not be exceeded or how decision-variables cannot exceed a boundary for example.
If the **objective function** is well-defined, by minimizing or maximizing the function, the model is capable of optimizing the formulated operation. The output of the model is a set of decision-variables that correlate with the optimized operation.

(Mixed) integer (linear) programming The mathematical model can be converted to a computer programming language. (Mixed) integer (linear) programming is a tool which describes a problem of concern with a mathematical model which is described previous section. *Programming* refers to computer programming and *linear* refers to the linear structure of the mathematical model (Hillier and Lieberman, 2015). However, this tool is used to solve linear or nonlinear problems. When integers are used, it is integer (linear) programming (IP or ILP). When both integer and continuous variables are used, this is Mixed Integer (linear) Programming (MILP or MIP). IP problems can also be called Binary Integer Programming (BIP) when the integers used are binary. Integers are very usable for planning problems, because vehicles, people and capacity are assigned for example to the problem that can only be expressed as integers. Integer programming uses a linear programming mathematical model to describe the problem, its objective and constraints. IP is Non-deterministic Polynomial-time hard (NP-hard) which indicates the computational complexity which is high in this case. Polynomial-time is defined by Aung et al. (2019) as:
"*An algorithm for some type of problem where the time required to solve any problem of that type can be bounded above by a polynomial function of the size of the problem.*"
NP-hard problems have a long computation time per iteration and are considered "expensive" to solve. Several solver algorithms can be found in Operation Research and depending on the type of formulation, whether the problem is linear, or nonlinear, a fitting solver can be used. So a **solver** algorithm can be used for finding the solution set of decision-variables.

2.2. Rolling stock Preventive Maintenance planning state of the art

Several studies have focused on optimizing rolling stock maintenance operations. A systematic review of rolling stock maintenance planning showcases the techniques and tools that are used for such problems. A search is conducted in the Scopus database to discover the literature analytically. Scopus is a database linked to scholarly literature. The search query is shown in table 2.1. The query is structured in a way that ”rolling stock” has to be included in the study for maintenance planning or scheduling. The search results will include optimization techniques because the keyword ”optimization” is present. Since the maintenance decision-making is the objective for this assignment, studies with the terms ’routing’, ’allocating’ and ’location’ in the title, abstract or as keyword are excluded. If these term are not excluded, the search would result into undesirable results such as optimization methods that study the shortest route to the maintenance depot for example or location choice (Giacco et al.; Luan et al.).

From the results of the search query, articles are further selected when they satisfy the criteria.

- It includes an optimization problem for rolling stock maintenance planning.
- The research includes an elaborated formulated mathematical optimization model.
- Routing and timetabling rolling stock in the railway network is not the main objective.
- Preferably includes a case study.

Search Query	ALL(”rolling stock”) AND TITLE-ABS-KEY(”maintenance” AND (”planning” OR ”scheduling”)) AND TITLE-ABS-KEY(”optimization”) AND NOT TITLE-ABS-KEY(”routing” OR ”allocating” OR ”location”)
amount of results	117
usable articles	9

Table 2.1: Search query and findings for rolling stock maintenance planning optimization

The subject is the study should be rolling stock and a mathematical optimization method should be formulated in the article. The optimization should be focused on maintenance decision-making. From the 117 results, only 9 are relevant studies that contain an optimization method for rolling stock maintenance planning.

A classified overview of the 9 articles can be found in table 2.2. The studies are classified by the *decision horizon*, which is defined to be time period over which the rolling stock maintenance planning is optimized. It can be assumed that the longer the PM interval, the more PM activities have to be performed (Li et al., 2016). As a result, the duration of the decision horizon indicates the kind of maintenance level, because, for instance, if the decision horizon is one week, monthly or yearly maintenance cannot be taken into account in that study. The table classifies the articles by whether the maintenance planning is integrated with the timetable, because this indicates how planning maintenance is constrained by passenger operations. When maintenance is integrated with timetabling, short inspections are generally performed between operational tasks which is the case for the studies that integrate maintenance planning with timetabling. Therefore, among the 9 articles, a decision horizon of a week corresponds to an integration with the timetable and longer cycle maintenance correlates to no integration with the timetable.

The 9 articles consider a timeline or decision horizon during which rolling stock is operating and therefore accumulate their mileage. The majority of studies use a predetermined mileage value as threshold. Before this threshold, PM have to be performed. This mileage threshold is therefore the main driver for performing maintenance and thus identify the maintenance approach. In order to comply with this PM approach, constraints are defined in the mathematical models. The objectives of the maintenance planning are listed, because is showcases what is considered for the decision-making for maintenance. Common objectives found are:

- Minimize *maintenance costs*:
  The costs associated with maintenance are costs such as labor, repairs, and spare parts.

- Minimize *unavailability*:
  Unavailability is quantified by Rudek and Rudek (2021) as the amount of days that a rolling stock undergoes maintenance and Mira et al. (2020) quantifies unavailability as the days at the maintenance depot, similar as Ma et al. (2016) who defined it as the days that rolling stock is not in operation because of maintenance.

- Minimize *manoeuvring*:
  The amount of action (mileage) that a rolling stock needs to perform to go from operation to the maintenance depot is included in the studies of Lai et al. (2015), Méchain et al. (2020), and Mira et al. (2020). Manoeuvring rolling stock can also be called *shunting* in railway terms. These studies sometimes simplify maneuvering as a constant mileage that it takes to the maintenance depot. Other times, manoeuvring is formulated to be a very detailed operation and the amount of shunting actions to the depot depends on where the rolling stock is in the railway network.

- Minimize *mileage losses*:
  If a rolling stock undergoes PM when the mileage since last PM is less than the allowed mileage before PM is required, this remaining mileage is considered as a loss which is desired to be minimal. On the contrary, the *accumulated mileage* is the mileage since last PM which should be maximized before going to the required PM. This objective indirectly results in cost savings, because when the accumulated mileage is maximized or mileage loss is minimized, the PM is performed less frequently, lowering maintenance costs, as the model ofLin and Zhao (2021).

The yet to be discussed objectives from table 2.2 are found in the studies of Li et al. (2016), Ma et al. (2016), and Sriskandarajah et al. (1998). Li et al. (2016) formulates a maintenance planning optimization integrated with the timetable while also optimizing the procurement of rolling stock. So, when less rolling stock units are required for a feasible operation, this will save overall costs. The objective is therefore to minimize the amount of rolling stock required for the complete operation.
Furthermore, the model of Sriskandarajah et al. (1998) allows the rolling stock to undergo maintenance far before the mileage threshold for maintenance or even after this threshold. This phenomena should not occur and is therefore penalized in their formulated model by applying an extra cost in the objective function. The objective function should be minimized in their study and a penalty would result into a sub-optimal solution.
Ma et al. (2016) maximizes the amount of maintenance in the decision horizon, while having enough rolling stock available for operation. The decision horizon is not long enough to finish all of the predefined PM. The model will therefore optimize the maintenance decision-making.

The solution approach for each study indicate the options that maintenance planning optimization can use. The algorithms are not further elaborated in the articles. However, Lai et al. (2015) and Lin et al. (2019) compare the performance of different solver algorithms on the same model.

The reviewed articles are considered to be the state of the art for rolling stock Preventive Maintenance planning. All studies except for Rudek and Rudek (2021) and Sriskandarajah et al. (1998) contain a MILP mathematical model from which the decision-variables, parameters, constraints and objective functions can be used as inspiration for further development of rolling stock maintenance planning optimizations.

author	year	decision horizon	integrated with timetable	objective	solution approach/ algorithm
Lai et al.	2015	1 week	yes	multi-objective: minimize mileage losses minimize manoeuvring minimize maintenance costs	manually, heuristics
Li et al.	2016	1 week	yes	multi-objective: maximize accumulated mileage/time, minimize required RS for the operation	heuristics, particle swarm
Lin and Zhao	2021	1 week	yes	minimize mileage losses	gurobi
Lin et al.	2019	1 year	no	minimize maintenance costs	simulated annealing gurobi
Ma et al.	2016	1 year	no	multi objective: maximize maintenance performance, minimize unavailability	backtracking algorithm ordering heurstics
Méchain et al.	2020	1 year	no	multi objective: minimize manoeuvring, minimize mileage losses, minimize maintenance costs	unknown
Mira et al.	2020	2 days	yes	multi objective: minimize unavailability, minimize costs, minimize maneuvering	Xpress software
Rudek and Rudek	2021	7, 8, 15, 16 years	no	minimize unavailability	heuristics, RND
Sriskandarajah et al.	1998	1 year	no	minimize costs for too late or too early	genetic algorithms

Table 2.2: Rolling stock Preventive Maintenance planning research categorization

2.3. Rolling stock maintenance planning based on prognostics state of the art

Literature studies that consider rolling stock maintenance planning that are able to rearrange when prognostics indicate that a failure will occur if the asset will not be maintained in the near future are reviewed in this section. Supplementary terms from the state of the art of rolling stock maintenance planning based on prognostics will be introduced in order to understand the methods from these studies.

Condition monitoring data is used as input for prognostic models. The output of prognostic analyses in this study is considered the Remaining Useful Life (RUL). This remaining life can be expressed in time units to failure or usage to failure. Prognostic models process online asset data into fault isolation and failure prediction on multiple system levels. The outcome of these models can be used for supporting decisions in maintenance planning. *Decision-making* is the process of selecting the best choice from a set of options that are carefully considered (Bougacha et al., 2020). Decisions which are logically chosen because of received prognostic information can be defined as *post-prognostic decisions*. In the context of rolling stock maintenance, post-prognostic decisions are performed with the objective to intervene on an as-needed basis while undesirable failure events are avoided (Tiddens et al., 2020). Consequently, the when the RUL is expressed in time unit, this is the decision horizon time period in which decisions can be made to maintain an asset to prevent a failure.

Earlier is described that conducting maintenance based on the prognosis of failure will be referred to as Condition-based maintenance (CBM). CBM is considered to be very effective, because the demand for maintenance is known in advance and the maintenance mechanics are informed about faults due to the fault isolation. The component that needs maintenance is thus known and spare parts can be ordered in advance, since it is known which parts contain faults in the system (Rivas et al., 2022). When CBM is efficiently implemented, the interval between maintenance interventions can be maximized, resulting in less inspections, less repair downtime and less need spare parts inventory (Rivas et al., 2022).

Literature is available researching how rolling stock maintenance decision-making is enhanced with considering prognostic data. The literature addresses how prognostic information is integrated in rolling stock maintenance planning optimization models. Prognostic information can only be acquired in real-time, so a maintenance planning model that integrates prognostic information should be able to act to new information. Still, model wise, these optimization models are comparable to the rolling stock maintenance planning models from section 2.1, because the majority of the found studies consist of a MILP formulation. According to table 2.3, where the search query for finding appropriate studies is written, a search is conducted in the Scopus database. Because of the way the search query is set up, ”rolling stock” must be taken into account for planning or scheduling maintenance. In order to be in line with the previous literature search, ”optimization” is included and studies with the terms ”routing”, ”allocating” and ”location” in the title, abstract or as keyword are excluded. In order to find results that address prognostics, ”prognostics”, ”RUL” and ”condition-based” are the search terms added in comparison to the query for finding rolling stock Preventive Maintenance planning studies.

The problem of searching literature on post-prognostic decision-making for maintenance planning specifically applied to rolling stock, is that it is very limited. The results are critically filtered on whether an optimization is performed on the maintenance planning. Out of evaluating 140 results, only 5 articles are selected as compatible for this review.

Search Query	(”rolling stock”) AND (”maintenance” AND (”planning” OR ”scheduling”)) AND (”optimization”) AND (”prognostic” OR ”Remaining useful life” OR ”RUL” OR ”conditionbased”) AND NOT (”routing” OR ”allocating” OR ”location”)
amount of results	140
usable articles	5

Table 2.3: Search query and findings for post-prognostic rolling stock maintenance planning

author	year	decision horizon	integrated with timetable	objective	solution approach/ algorithm	prognostic level	prognostic integration method
Bougacha et al.	2022	1-60 days	yes	minimize maintenance costs, missed operational tasks corrective maintenance	genetic algorithm, heuristics	component	rolling decision horizon
Crespo Márquez	2022	52 months	no	maximize component degradation before maintenance	Vensim	component	component degrade stochastically to higher risk levels
Herr, Nicod, Varnier, Zerhouni, Cherif, et al.	2017	unknown	yes	maximize component degradation before maintenance	unknown	system	degrading rolling stock because of operational usage
Herr, Nicod, Varnier, Zerhouni, and Dersin	2017	20-90 days	yes	maximize component degradation before maintenance	Gurobi	system	degrading rolling stock because of operational usage
Rokhforoz and Fink	2021	50 days	yes	minimize maintenance costs	hierarchical algorithm	sub-system	every time the next decision horizon starts, random variables determine if a fault is detected

Table 2.4: Overview of rolling stock maintenance based on prognostics planning studies

2.3.1. Rolling stock maintenance planning studies integrating prognostics

The articles that consider rolling stock maintenance planning based on prognostics from table 2.3 are analyzed in order to learn how prognostic information is utilized to improve rolling stock maintenance decision-making. The articles will be analyzed on different aspects:

- The maintenance planning optimization with the optional formulated mathematical model will be discussed. Especially the objective of the optimization model.
- Whether the problem of computing prognostics is conducted on a component, sub-system or system level.
- How prognostics are integrated into the maintenance planning and how the planning is getting rearranged.

Similarly to the literature review from section 2.1, the 'decision horizon' length is listed in table 2.4, because this indicates the type of maintenance level and scale of the optimization model.
Planning optimizations integrated with the operational timetable brings more complexity, but also show the dependence of rolling stock maintenance with passenger operations. The objective formulation of the optimization highly depends on this aspect.
From the 'solution approach/algorithm' can be learned which optimization method is appropriate for the optimization problem and which algorithm can be used. This is not always described in the articles. All studies include a MILP mathematical model, except for Crespo Márquez (2022).
The 'prognostic level' describes whether the prognostics are on a system, sub-system of component level. This study aspect learns how the prognostic method influences the maintenance decision-making.
The method how the optimization problem integrates prognostics of the studies will be reviewed and discussed in this section

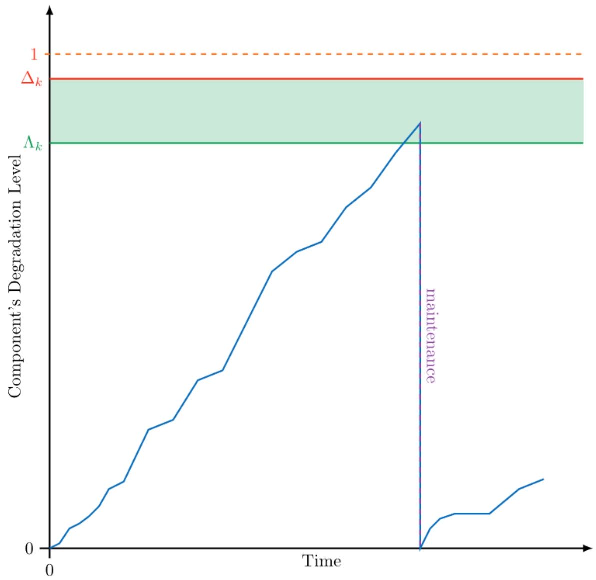


Figure 2.1: Degradation model of a rolling stock component over time (Bougacha et al., 2022)
Δ_k represents the failure threshold and Λ_k represents the lower bound threshold for maintenance

System levels Prognostics can be computed for various system levels. Not every sub-system or components is evenly critical in a complex multi-unit system such as a rolling stock unit. It is therefore relevant to find out on which level(s) prognostic information is relevant and how this can be logically applied for maintenance decisions. Also how the criticality of components in the multi-unit system is considered in the decision-making process. The studies of Herr, Nicod, Varnier, Zerhouni, Cherif, et al. (2017) and Herr, Nicod, Varnier, Zerhouni, and Dersin (2017) neglect this and assume that the whole rolling stock fails when the failure threshold of the prognosis has been exceeded. Although Bougacha et al. (2022), Crespo Márquez (2022), and Rokhforoz and Fink (2021) are considering individual components of sub-system of the rolling stock, it is still assumed that the whole rolling stock fails when any failure threshold has been reached.

Prognostic inputs The studies of Bougacha et al. (2022), Herr, Nicod, Varnier, Zerhouni, Cherif, et al. (2017), Herr, Nicod, Varnier, Zerhouni, and Dersin (2017), and Rokhforoz and Fink (2021) consider similar prognostic inputs to the model. The study assumes that parallel to the maintenance planning optimization, the component or system degrades as illustrated in figure 2.1. When a failure is predicted, thus exceeding the lower bound threshold for maintenance, the rolling stock should be planned for maintenance. The RUL is thus expressed in time units.

Methods from of rolling stock maintenance planning integrating prognostics The research of Bougacha et al. (2020) is the most valuable for this study. They proposed a MILP mathematical model for the maintenance planning decision-making of rolling stock, integrating maintenance interventions based on prognostic information with a periodically PM planning. This study is actually based on the studies of Herr, Nicod, Varnier, Zerhouni, Cherif, et al. (2017) and Herr, Nicod, Varnier, Zerhouni, and Dersin (2017), which are also relevant. Simultaneously, the rolling stock is assigned to passenger operation tasks, thus the model is integrated with a timetable.
It is assumed that prognostic information is available on a component level. A deterioration curve as a function of time is used to initialize the prognostic characteristics of components, which can be seen in figure 2.1. Since the times that component failures are known, their model decides to plan maintenance right before this failure threshold. When this is infeasible to plan, the rolling stock fails and it is assumed that CM has to be performed at the expense of higher maintenance costs.

Bougacha et al. (2022) includes the *rolling horizon* principle, which is used in order to integrate prognostic information in the maintenance planning. Because in a real-world application, the maintenance

schedule is periodically updated (Mira et al., 2020), therefore Bougacha et al. (2022) proposed to simulate periodic planning by executing the maintenance planning optimization with a *rolling horizon*. This framework will be further addressed in the next section.
Planning maintenance is based on the Preventive Maintenance threshold on a component level or based on the degradation of a component. The objective is to minimize maintenance costs, minimize missed operational tasks and minimize Corrective Maintenance.

- Early PM is penalized similar as mileages losses which are directly related to costs in their model.
- Early CBM is also penalized when the prognostic model indicates that the component can still function for some time.

It is assumed that CM is always more expensive than performing early PM or CBM. The capacity of the maintenance depot is defined to not maintain more than a certain amount of rolling stock at a time and secondly, no more than a predefined amount of components can be maintained at the same time. CM is integrated in the algorithm by allowing it to miss the PM or CBM threshold, resulting into expensive CM.
However, the decision horizon length is yet to be determined and the goal of this study is to optimize this. Therefore, the decision horizon length is getting iterated throughout the study in combination with the fleet-size.

Crespo Márquez (2022) proposed a continuous time simulation model of wherein the degradation of bearing (a component) of a rolling stock is modelled. The model is formulated to be a *state machine*. The lifespan of a rolling stock bearing is modeled to be in three states: brand new, degraded and likely to fail. The state transitions are randomly generated in the simulation environment. The states of the state machine thus provide prognostic information about the bearings, because every state in the state machine represent what the remaining life is. According to the health state of the bearings, maintenance is planned while being constrained by maintenance depot capacity.
Their main conclusion is that the time from that bearing is likely to fail to actual failure, highly impacts the decision-making. Because a small RUL, for example, gives less time to act, while a long RUL provides flexibility to act as optimal as possible (Crespo Márquez, 2022).

The proposed model in the study of Rokhforoz and Fink (2021) assumes that the rolling stock are capable of conducting a prognosis. It is assumed that prognostic information cannot be retrieved online. Instead of online, every month the maintenance planners receive an update on the condition of the rolling stock fleet, including a prognosis when which train is likely to fail. The model of Rokhforoz and Fink (2021) decides to perform maintenance on certain rolling stock based on the monthly failure prognosis, while the rest of the fleet is planned for passenger operations every month. The prognosis is expressed as the RUL, however, it is assumed that the RUL is uncertain. So, the failure time of a certain rolling stock is simulated as a random variable. The study is formulated as a MILP model, however, the model is multi-level. One level optimizes the rolling stock passenger operations with the available amount of rolling stock, while the second level optimizes the maintenance planning of the rolling stock based on the failure prognosis per train wagon. The model integrates prognostics by optimizing two levels independently. The maintenance planning will be rearranged based on the prognostics obtained in the second level. This multi-level approach is rather complex to model and not in line with the state of the art and will therefore not be further utilized.

2.3.2. Rolling horizon

A rolling horizon framework to plan rolling stock maintenance is found in the studies of Bougacha et al. (2022) and Lai et al. (2015). The framework of planning according to a rolling horizon framework is illustrated in figure 2.2 where every planning result that will be implemented is represented by a dark color, while the light color represents the decision horizon that symbolizes the foreseeability in days (x-axis) for the planner. Per optimization, a daily planning is executed, considering events that occur 7 days in advance. An optimization is carried out in each round (y-axis), and this process is repeated until the whole planning has been established.

Outside of the context of rolling stock maintenance planning, this concept is used for more comparable problems in literature. The study of Consilvio et al. (2020) used a rolling horizon for simulating planning railway maintenance based on prognostic information. A rolling horizon framework is used to act on newly available real-time information and unexpected faults or delays and rearrange the maintenance planning accordingly (Consilvio et al., 2020). Furthermore, in aircraft maintenance planning, a rolling horizon framework is used to plan aircraft component replacement based on the predicted criticality (de Pater et al., 2021). Not only maintenance can be planned and rearranged with a rolling horizon, it is also used to rearrange the rolling stock timetable for passenger operations when disruptions occur while executing the predefined timetable (Nielsen et al., 2012).

From this can be concluded that this framework is frequently used in literature to model time plannings while unexpected events may happen and rearrangements are required.

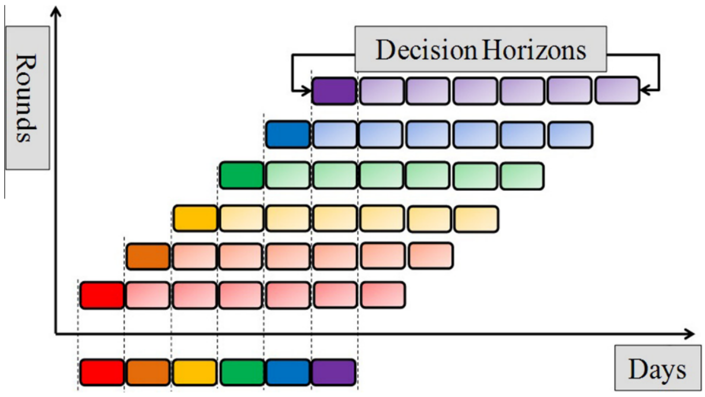


Figure 2.2: Rolling horizon framework used for rolling stock maintenance planning (Lai et al., 2015)

2.3.3. Discussion on the rolling stock maintenance planning integrating prognostics

It can concluded that only a few studies considered rolling stock maintenance planning based on prognostics. The five studies on integrating prognostics that are reviewed found a method to integrate the prognostics into the maintenance planning optimization. The methods found are able to rearrange the maintenance planning according to prognostics. The prognostic degradation models in the studies are simplified and make the optimization problem nonlinear. It can be argued that the found degradation models can be simplified into a constant standard RUL expressed in time units when a failure is detected, regardless of the component or subsystem, since a component failure is considered to result into a rolling stock failure. The multi-level planning approach of Rokhforoz and Fink (2021) can be very complex to implement and reproduce. The approach of a state machine from Crespo Márquez (2022) is not in line with the state of the art of rolling stock Preventive Maintenance planning, because it does not contain a MILP model. From this can be concluded that the approach of Bougacha et al. (2022) and Herr, Nicod, Varnier, Zerhouni, and Dersin (2017) can be used for the rolling stock maintenance planning integrating prognostics. However, a few gaps can be identified:

- It is not considered in literature to integrate the decision-making of rolling stock maintenance based on prognostics within a Preventive Maintenance planning or study the feasibility of proceeding CBM in combination with PM.

- It is not considered if maintenance based on prognostics is more cost efficient to plan in comparison to CM.

The impact of maintenance planning decision-making based on prognostics is not analyzed in literature and should therefore be further researched in this study.

2.4. Concluding Remarks

This chapter, the state of the art of rolling stock maintenance planning optimizations is addressed. A distinction is made between Preventive Maintenance planning optimizations and planning optimizations that integrate prognostics, which helps to find appropriate methods to optimize a rolling stock Preventive Maintenance planning decision-making that can integrate CM and CBM. It became clear that MILP is often used as mathematical framework to optimize the rolling stock maintenance planning. With the literature reviews of rolling stock maintenance planning optimization, research question 1 is addressed.

1. *What is the current state of the art for rolling stock maintenance planning optimization methods?*

A literature gap is identified for the rolling stock maintenance planning optimization methods integrating prognostics. The objective found in the studies is to exploit the degradation of the rolling stock and maintain the asset right before failure in order to perform efficient maintenance. The degradation to failure is provided by the prognostics in the form of the RUL. The RUL is generally expressed in time units to failure. However, these studies do not consider if planning maintenance based on the actual degradation actually enhances the maintenance planning or to study the feasibility of proceeding CBM in combination with PM.

A rolling horizon framework is suggested from literature for simulating rearrangements in maintenance planning decision-making in response to unforeseen events. The maintenance planning optimization methodology from the literature review will be used for the formulation of the optimization problem. The following chapter, the state of practice will be addressed.

3
State of Practice

In this Chapter, the current state of practice of the maintenance organization of NS will be explained. Therefore, research question 2 is addressed:

2. *What is the current state of practice for rolling stock maintenance planning?*

The methodology and motivation of the current maintenance pr active will be described and compared to the state of the art. Consequently, the state of practice of NS may be optimized with an optimization method found in the state of the art. This chapter provides background for the case study that will be performed in the upcoming chapters.

3.1. Rolling stock system breakdown

In order to categorize rolling stock maintenance activities, NS classified the rolling stock multi-unit system into sub-systems. As a result, maintenance tasks can be assigned to specific sub-systems. The classification is inspired by the BS EN 15380 standard *Railway applications — Classification system for railway vehicles Part 5: System Breakdown Structure (SBS)*, 2014.
BS EN 15380-5 provides the classification of railway vehicles in order to make the multi-unit system manageable and recognizable. Note that BS EN 15380 also contains the *Product Breakdown Structure* and the *Function Breakdown Structure*. These structures describe different views of railway vehicles (*Railway applications — Classification system for railway vehicles Part 5: System Breakdown Structure (SBS)*, 2014). However, the BS EN 15380-5 standard structure is used for maintenance classification. Figure 3.2 showcases the top level sub-systems of the railway vehicle, by ten sub-systems. Figure 3.1 showcases comparable sub-systems used for the classification of the NS railway vehicles which are also used for assigning maintenance tasks. The so-called SDM (Storing Defect Materiaal, translated to ”rolling stock failure defect”) codes classification of the NS consists of more sub-systems than the standards, because first level system ’Propulsion and Braking’ (H) from BS-EN-15380 for example is divided into two: codes 01 ... (traction/propulsion) and 02 ... (braking). The translation and overlap between the two classifications is illustrated in table 3.1. Note that the sub-system names in table 3.1 are solely the top-level systems, lower level sub-systems are further specified.

3.2. Maintenance activities classification

NS uses the classification system from figure 3.1 for locating and specifying maintenance activities, this is further translated in table 3.1. For this project, only the ”short cycle maintenance” activities will be reviewed. ”Short cycle maintenance” is classified by NS to be PM tasks from 108 days up to 3 years intervals. There is a list of PM activities set up for a specific rolling stock type, classified according to the sub-(sub-)systems. The list consists of activities that have to be performed with an interval of approximately 3 months (specifically 108 days), 6 months 9 months, 1 year, 1 and a half year and 3 years. The PM activities vary each time because not every item requires PM every 108 days, so some components can be longer in operation than 108 days without requiring PM, so the time threshold may be higher for some components.

	Tractiesytemen
0110	Tractieregeling / chopper
0120	HS-tractie
0130	Tractiemotor/VTT
0140	Mechanische overbrenging
0150	Zandstrooiinstallatie
	Remsystemen
0210	EP-P-rem
0220	ED-rem
0230	Magneetrem
0240	Noodrem
0250	Dodeman
0260	Anti-blokkeer
0270	Handrem/parkeerrem
	Koppelingssystemen
0310	Stoot- en trekwerk + korte kopp
0320	Automatische koppeling
0330	Overgangsinrichting
0340	Doorloopkop
	Buitendeuren
0410	Buitendeuren
0420	Centrale deurbediening
0430	Invalidenlift
0440	Cabine-buitendeur
	Veiligheidssystemen
0510	ATB
0520	Snelheidsmeting (faively)
0530	Typhoon
0540	Veiligheidsmiddelen
	Cascodelen
0610	Casco + buitenramen
0620	Cabine
0630	Overige technische ruimtes
	Loopwerk
0710	Motordraaistel
0720	Motorwielstel
0730	Loopdraaistel
0740	Loopwielstel
0750	Luchtveerbalk
0760	Wielflenssmering
	Klimaatsysteem
0810	verw./vent. Reizigersruimtes
0820	verw./vent. dienstruimtes

	Verlichtingssystemen
0910	Hoofdverlichting reizigers
0920	Leesverlichting
0930	Verlichting dienstruimtes
0940	Front- en sluitseinen
	Communicatiesystemen
1010	Omroepinstallatie
1020	Telerail
1030	Bestemmingsaanduiding
1040	Treintelefoon reizigers
1050	Tracking en Tracing
	Interieur
1110	Binnendeuren
1120	Banken/stoelen
1130	Overige binnenaankleding
	Sanitair
1210	Sanitair
	Energievoorzieningssystemen
1410	Hoofddieselmotor
1420	Brandstofsysteem hoofddiesel
1430	Smeeroliesysteem hoofddiesel
1440	Koelwatersysteem hoofddiesel
1450	Luchtin- en uitlaatcircuit hoofddiesel
1460	Hulpdieselmotor
1470	Brandstofsysteem hulpdieselmotor
1480	Smeeroliesysteem hulpdieselmotor
1510	HS-voorziening Hoofdgenerator
1610	Boordomzetter/Motorgenerator
1620	LS-voorziening
1630	Batterij
1710	Motorcompressor
1720	Luchtvoorziening
1810	Hydrostatische installatie
	Besturings-/diagnosesystemen
1910	Besturingssysteem
1920	Radiobesturing
1930	Multiplebedrijf (6400)
1950	Diagnosesysteem
1960	Autom Rit Registr (ARR)
	Overige systemen
9999	Overige systemen

Figure 3.1: Classification of the rolling stock unit structure from NS in Dutch

Ident of 1st level systems	1st level systems
B	Car body
C	Doors/Loading
D	Guidance
E	Interiors
F	Lighting
G	Energy supply
H	Propulsion and braking
J	Information and communication
K	Train control
L	Coupling and interconnection

Figure 3.2: Classification of the rolling stock unit structure by standard BS-EN-15380 *Railway applications — Classification system for railway vehicles Part 5: System Breakdown Structure (SBS)*, 2014

In order to equally distribute the workload of PM activities every 108 days interval, a cluster of PM activities is arranged. The PM throughput time is therefore consistent for all individual PM clusters. The sequence of PM activities for a maintenance mechanic is a mix of activities located at various sub-systems and the cluster of PM activities is different every 108 days, because the time threshold for PM varies per component. The maintenance planner does take into account whether certain PM activities can be combined and if it is opportunistic to perform adjacent to another. The sequence of clustered PM activities taking a constant workload can be referred to as the *PM routine*. The duration of this PM routine at NS is standardized.

In the state of the art of PM planning optimizations, PM routines are generalized and a predetermined duration of PM routines is considered, regardless of the activities that have to be performed. These studies are in line with the state of practice where a PM routine is also a cluster of PM activities that have to be performed periodically (Lai et al., 2015; Lin and Zhao, 2021; Lin et al., 2019; Ma et al., 2016; Méchain et al., 2020; Mira et al., 2020).

The state of practice of planning PM activities of NS demonstrates that PM routines are not designed for a specific rolling stock sub-system or activities that have equal time intervals. The result is the contrary, PM routines consist of a cluster of PM activities performed by various maintenance mechanics on various sub-systems that can have a 108 days up to 3 years interval. Nonetheless, the consistency of PM routines is that they are designed to endure a similar throughput time. This is in line with the majority of the state of the art where PM is also considered as a cluster of PM activities that also endure a similar throughput time.

3.3. Preventive Maintenance routines at the NS maintenance depot

The mileage and operational days of every rolling stock item is monitored. Based on these values, rolling stock PM decision-making is performed. Rolling stock is scheduled for PM before that the time or mileage threshold is exceeded. At NS, the smallest time threshold for performing PM every 108 days is established by maintenance experts. A second threshold is distance or mileage. For reliability, NS considers the mileage threshold of 45,000 [km] to be the maximum mileage a rolling stock can run

Classification name	SDM code	Standard ident	First level system
Tractiesystemen (Traction systems)	1	H	Propulsion and braking
Remsystemen (Braking systems)	2	H	
Koppelingssystemen (Coupling systems)	3	L	Coupling and interconnection
Buitendeuren (Exterior doors)	4	C	Doors
Veiligheidssystemen (Safety systems)	5	K	Train control
Besturings-/Diagnosesystemen (Control/ Diagnose systems)	19	K	
	19	X	Diagnostics
Cascodelen (Car body)	6	B	Car body
Loopwerk (Running gear)	7	D	Guidance
Verlichtingssystemen (Lighting)	9	F	Lighting
Communicatiesystemen (Communication system)	10	J	Information and communication
Klimaatsysteem (HVAC)	8	E	Interiors
Interieur (Interior)	11	E	
Sanitair (Toilet facilities)	12	E	
Energievoorzieningen (Energy supply)	14	G	Energy supply

Table 3.1: Classification translation from SDM codes to the BS-EN-15380 standard

without requiring PM.
A higher level controller in the organization, the MBN (”Materieel Besturingscentrum Nedtrain” translated to ”rolling stock controlling center of NS”), monitors the mileage and operational time data and decides which rolling stock unit should undergo PM. The maintenance planner at the maintenance depot receives arrival and departure times from the MBN. The rolling stock must finish the PM routine before the departure time in order to comply with the MBN.

The PM activities cannot be performed at one place inside the depot. During the standardized PM routine, a rolling stock should therefore be shunted from a certain location at the depot to another location. Three key locations within the depot are available to perform PM activities:

- Bio track (Biospoor): At the Bio track the toilets are emptied and cleaned. In general, 8 hours are scheduled for this activity. However, when there are no anomalies, this takes less time and when it is possible to go to the next step, the rolling stock is getting shunted. During this PM activity, the wheels are checked on roundness and wear. When this is good, the rolling stock unit is ready for the general PM routines, otherwise, the wheels are getting machined in the *kuilwielenbank* (”underfloor wheel lathe”).
- Kuilwielenbank: At the kuilwielenbank, the wheels can be machined like a lathe. Irregularities are grind off and the wheels are turned until all the wheels have comparable sizes. After this activity, the rolling stock unit is ready for the general PM routine.
- Maintenance track with balcony: At the maintenance track with balcony, the rolling stock unit can be maintained under-, -in and above the rolling stock. Not all PM activities can be performed at

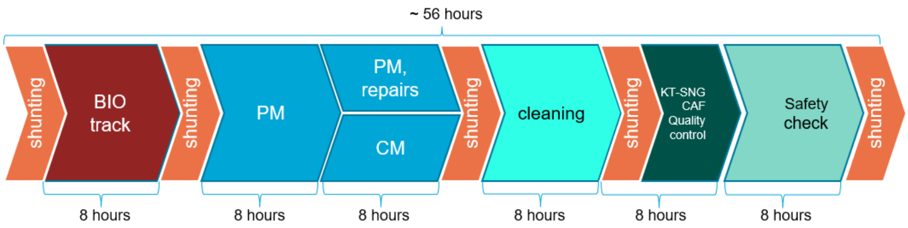


Figure 3.3: Standardized Preventive Maintenance routine

once, because for some PM activities, electric power should be applied via the catenary wires. So the pantograph is in contact with the catenary wire above the roof of the rolling stock. Therefore, due to safety issues, no PM can be performed on the roof via the balcony when electric power is applied.

- Cleaning track: Cleaning equipment is accessible at the cleaning track for cleaning the rolling stock. During this routine, the rolling stock unit can be checked for safety as well.

PM at the depot of NS is performed in shifts of 8 hours, because maintenance mechanics work in that manner. Figure 3.3 demonstrates the throughput of the rolling stock during a standardized PM routine. The different colors represent the different actions and locations that are listed above. The figure is therefore divided in blocks and illustrates when the rolling stock requires shunting in order to go to a different location within the maintenance depot for remaining PM activities. The actual duration of the routine is variable, because it depends on the available mechanics, amount of rolling stock arrivals and available train drivers to perform shunting. However, it is assumed that for this project, the total PM routine is standardized to take 3 days. As earlier described, the PM activities that are performed at every key location may vary every PM routine. Nevertheless, the PM routine is designed to take always 3 days.

The NS maintenance depot has a capacity of three balcony maintenance tracks where PM can be performed. These balcony tracks are only needed for two 8-hours shifts adjacent to one another. This is illustrated in light blue in figure 3.3. In order to avoid that more than three specialized PM tracks have to be used at the same time, at NS, the capacity is constrained by the amount of arrivals at the same time. As a result, it will never occur that rolling stock have to queue for the specialized tracks when three or less rolling stock begin PM in two time slots time. After this maximum arrival, one time slot should be left open when no rolling stock can arrive for PM, because the tracks are occupied for a double shift. Figure 3.4 illustrates this principle, where the chain of blocks represents the PM routine from figure 3.3. The light blue blocks represent the shifts that require the specialized track. As an example, the red cross indicates that too many rolling stock start within two time slots, because at $k = 5$ because too many rolling stock require the balcony track.

3.4. Corrective Maintenance at the NS maintenance depot

Corrective Maintenance is unplanned maintenance when a failure occurred. At NS, the moment when CM is performed depends on the criticality of the failure. The criticality of the failure is classified by NS, based on the the so-called ”Q-profile”. The Q-profile is a predefined chart that determines according to the type of failure in combination with the SDM-code the criticality. Hence, a non-critical component failure may occur that does not require CM up to 21 days, or a severe failure may happen that needs to be repaired immediately. For the scope of this project, only immediate CM as a result of a critical failure is considered. Because practically, immediate CM cannot be planned in advance, this is in contrast to when a rolling stock is allowed to continue operating while experiencing a non-critical failure. These non-critical failures may remain unfixed until the next PM routine.
Critical immediate CM has to be repaired at the maintenance depot. However, CM has to be performed at the NS maintenance depot where PM is performed on other rolling stock units at the same time. CM is therefore performed at the expense of the workload of maintenance mechanics that are already scheduled to perform PM. The throughput time for CM varies and depends on the type of failure, NS aims to perform this in 1 day, but this can deviate when larger repairs are needed. Since the mainte-

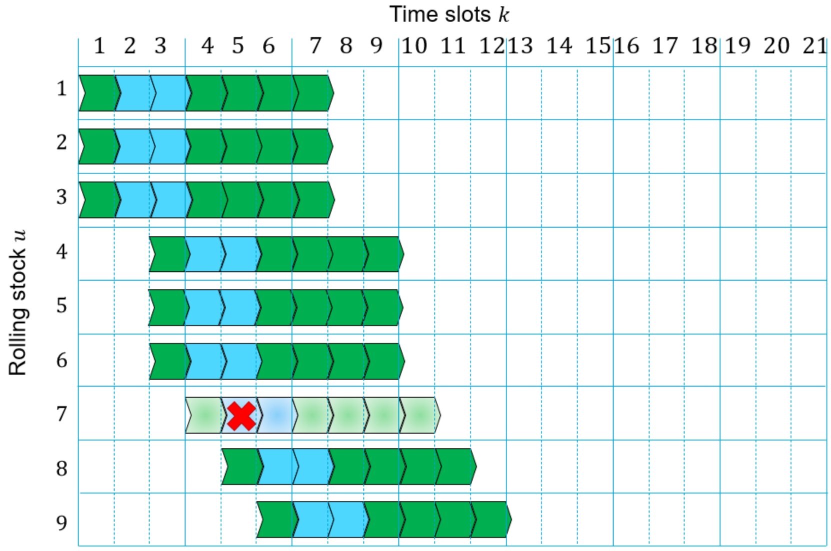


Figure 3.4: Simplified PM planning for 9 rolling stock (y-axis) in 21 time slots (x-axis) where the depot capacity constraint is illustrated

nance depot is using its full capacity already for PM, it is challenging for the maintenance planner to plan CM in between. However, in practice, there continues to be a little room for flexibility in the planning, making it feasible to plan for CM. Besides, at the maintenance depot, there is a dedicated track preserved solely for CM in order to be always able to accommodate a failed rolling stock. Although, this track does not have always all of the tools to repair every type of failure and CM still has to be performed at another specialized track where it disrupts the regular PM planning.

3.5. Rolling stock maintenance planning decision-making at NS

NS is an organization with sub-organizations. For this research the stakeholders in the organization of NS to be considered are the train operator planner and the maintenance planner. The two stakeholders perform their operations according to different KPI's that are listed as follows:

- The maintenance planner at NS aims to perform maintenance as cost- and time efficient as possible while utilizing the available resources in the most effective manner.
  Therefore, at NS, similar to the state of the art, the KPI that is utilized to assess the PM planning performance is the amount of **mileage losses** that are made.
- The train operator aims to have as many rolling stock available for operation creating flexibility and cost efficient passenger operations. So the **availability** of rolling stock is an important KPI for the train operator. Besides, the train operator would benefit from minimal maintenance, because it directly results into more availability.

Additionally, balancing the PM workload is highly desirable for the PM planner. In order to balance the workload for the maintenance depot, the number of trains each week or to be maintained each day should be allocated equally. For that reason, the deployment of rolling stock in passenger operation should be evenly dispersed so that the asset is exploited equally in order to achieve a steady flow of rolling stock needing PM. Since the train operator planner is responsible for rolling stock deployment, a consistent flow of rolling stock entering and exiting the maintenance depot must be ensured through communication between the train operator and the maintenance planner. This proves the dependency of communication between passenger operations and maintenance operations for efficient rolling stock maintenance planning.

Bakkenstand The unavailability of rolling stock at NS is expressed as the "bakkenstand". This value represents the number of train carriages from the whole fleet that is not required for passenger operation. This can be rather complex because the SNG fleet that is considered as case for this study exists of 3 carriage trains and 4 carriage trains. For the sake of simplicity, the two train-sets types will not be distinguished for the problem formulation. The maximum allowed number of unavailable carriages is based on data from NS and can be found in the confidential annex B. How this is computed and expressed in percentages can also be found in the confidential annex, this value is expressed in this study as parameter $O_{percentage}$% as described in confidential annex B section B.2. The "bakkenstand" represents the amount of rolling stock that is required in operation to perform optimal passenger transport. Note that this value is an average amount over a month. Actually, the required affability of rolling stock for passengers operations dynamically changes depending on peak hours, and peak days. Out of the 190 trains-sets, on average, a certain amount of rolling stock (see confidential annex B section B.2) do not have to be deployed. Performing PM is only useful when the train has been in operation for the given amount of time and mileage threshold, that can only be controlled by the train operator. If the rolling stock assets that do not need to be deployed have been the same train sets for a long time period, when the PM time threshold of 108 days is reached for these train sets, they will be maintained earlier than necessary, resulting into mileage losses. From this can be concluded that efficient PM decision-making is highly dependent on the (even) deployment of rolling stock decided by the train operator.

3.6. Opportunistic Maintenance

Complex multi-component systems are difficult to maintain, because of the interdependence of components their states and functions. A rolling stock is considered a multi-component system, which became evident from the SDM classification and standard *Railway applications — Classification system for railway vehicles Part 5: System Breakdown Structure (SBS)*, 2014. This implies that a different approach should be applied to these systems for performing efficient maintenance. However, instead of assessing maintenance tasks to individual components, the dependencies of components can be exploited if tasks are grouped (Boekweit, 2021). Opportunistic maintenance (OM) refers to the practice of taking advantage of the occasion when a particular component is being maintained by additionally maintaining neighbouring components for example. Three classes of dependencies can be considered for OM, economic, structural and stochastic (Ghamlouch and Grall, 2018).

Economic dependence When a maintenance task share the same costs with another task, these can be economic dependent. For example, when the same setup for maintenance is required for multiple maintenance tasks, grouping them to one routine saves costs (Boekweit, 2021). Or when in a geographically distributed system, the item has to travel to the depot for maintenance that brings extra costs, it is convenient to group maintenance tasks.

Structural dependence Structural dependent components should always be maintained simultaneously (Ghamlouch and Grall, 2018). This applies to maintenance tasks where multiple components have to be dissembled in order to perform a specific maintenance task. So these components are then physical dependent.

Stochastic dependence Because of operational interaction between components, when component failures occur, it might influence other components. Consequently, the probability of another component failure increases. Stochastic dependence implies that a component its state may influence the health status of other components in the system (Boekweit, 2021; Ghamlouch and Grall, 2018).

So by understanding the dependencies of a multi-component system to be maintained, the maintenance operation could be performed more efficiently. For the multi-unit geographically distributed rolling stock having economic, structural and stochastic dependencies, an OM approach is therefore very reasonable.

3.7. Condition Based Maintenance opportunities at the NS maintenance depot

CBM that will be planned according prognostics from a prognostic model is not yet implemented at NS. It is therefore unknown how this will be organized at the maintenance depot. This leaves room for creativity and multiple options on how to deal with this approach for maintenance decision-making. The state of the art describes that due to CBM, individual components replaced on an as needed basis so that the component degradation is maximized without failing during operation (Bougacha et al., 2022; Crespo Márquez, 2022; Herr, Nicod, Varnier, Zerhouni, Cherif, et al., 2017; Herr, Nicod, Varnier, Zerhouni, and Dersin, 2017). The maximum component degradation before maintenance cannot be estimated in this research since no prognostic model will be developed. Still it will be assumed that prognostics are expressed as a remaining useful life (RUL) in time units.

Prognostics give insight to the maintenance operator on which component or sub-system is going to fail. The maintenance activities can be prepared before the rolling stock arrives at the maintenance depot, because the fault is already diagnosed. It is not necessary to conduct an investigation to identify the failure in order to carry out CBM, so maintenance activities may be completed immediately. It is therefore expected that the throughput time of CBM is quicker than for CM and therefore costs less.

Combining CBM with PM While assuming that the RUL gives the maintenance planner flexibility for planning the maintenance, it becomes reasonable to see this as an opportunity to also plan the PM routine after the CBM routine. It is appropriate to view this as an opportunity, given that the RUL allows the maintenance planner freedom for arranging the current maintenance planning. When PM has to be performed in the near future, the two maintenance activities can be combined, saving shunting costs because of this economic dependence. Consequently, a trade-off can be made. Either separating PM and CBM, requiring the rolling stock to visit the depot twice with minimal mileage loss. Or combining PM and CBM by scheduling earlier PM, which results in mileage losses but saves costs because the rolling stock only needs to visit the depot once.
From interviews with NS maintenance depot planners, it became evident that it is completely unrealistic to see a CM routine at the depot also as an opportunity to perform PM when the mileage of the rolling stock is near the threshold. The argument for this is that it is considered a tough challenge to plan CM within the already dense PM planning, so planning an extra PM routine in the current planning as well is seen as being too opportunistic.

3.8. Maintenance cost specification

The objective to minimize costs is common for rolling stock maintenance planning optimizations, is be demonstrated from the literature. Also, rolling stock maintenance is desired to be as cost efficient as possible. It should therefore be specified which costs are associated with maintenance of rolling stock. Costs of maintenance operations are difficult to specify because it includes logistic operations, spare parts and the maintenance facility costs for example that are not in the scope of this research. Additionally, the financial losses associated with unavailability of rolling stock due to maintenance can be assessed as well. These costs are very difficult to approach because it is completely dependable on the dynamically changing required availability for passenger transport and therefore out of this scope. Other costs that can be classified as maintenance costs are labor costs. Labor costs consist of wages of mechanics and specialized mechanics to perform specialized maintenance. Since the organization of the depot is out of this scope, the labor costs are simplified and will be considered in the generalized PM or CM costs.
Spare parts costs are considered by Bougacha et al. (2022) and Doganay and Bohlin (2010) who consider maintenance on component level. If spare part costs are considered, the component failures and spare part inventory should be analyzed as well. Because of the complexity and corresponding additional knowledge about spare parts and inventories, this is considered to be out of the scope of this research.
On the contrary, in order to determine the cost savings if fewer PM is required at the depot when maintenance is based on prognostic information, the logistic operations, or so-called shuntings (the transportation of the rolling stock from one location in the railway network to the maintenance depot), must be estimated.
Furthermore, PM and CM routine costs may be generalized and costs due to mileage losses can be estimated. From cost overviews of NS and model comparisons to literature, the considered cost for the rolling stock maintenance planning optimization problem are in table B.1.

Associated maintenance costs:	costs: [euros]	for every:
Shunting costs	see	two-way shunting
Preventive Maintenance routine costs	confidential	routine
Costs induced by mileage losses	annex	km
Corrective Maintenance routine costs	B section B.3	routine
Maintenance due to prognostics Routine costs		routine

Table 3.2: Maintenance costs overview considered in the maintenance planning model

Shunting costs Shunting brings costs like power, a train driver, the permission for utilizing a path to the depot and service costs. So when a rolling stock makes more trips to the maintenance depot for maintenance, this brings more costs. Shunting costs can also be found in the studies of Lai et al. (2015), Méchain et al. (2020), and Mira et al. (2020). In some studies, longer shunting paths are assumed to cost more, depending on the logistical measures, but that will not be considered in this problem. The shunting costs that are specified by NS are estimated to be $C_{shunting}$ euros (see confidential annex B section B.3). This is considered for arriving and departing to and from the depot.
The shunting costs for PM are not specified at NS, but are assumed to be the same as for CM.

Costs induced by mileage losses: The costs for rolling stock Preventive Maintenance are expressed in costs per mileage in monetary units. Also, Lin et al. (2019) computes the maintenance costs per mileage. In this case, the costs are caused by not sufficiently utilizing the remaining mileage up to the mileage threshold. NS applies the same methodology for decision-making on PM, because it similarly expresses PM costs in terms of costs per kilometer. It is fair to take additional costs into account when premature maintenance is performed, as is done in literature and in a similar method at NS. The costs are based on data from NS and estimated to be $C_{mileage}$ (see confidential annex B section B.3) euro per [km], that is referred to as *mileage costs*.

Preventive Maintenance routine costs: Preventive Maintenance costs are determined based on the maintenance operations and cost data of NS. This information is retrieved through interviews and cost analyses found in NS databases. The PM costs includes labor, spare parts, depot facility and other supplementary costs. This is simplified and generalized that every PM routing costs C_{PM} euros (see confidential annex B section B.3) excluding shunting costs.

Corrective Maintenance routing costs: The CM costs includes additional planning costs because the maintenance planning at the depot has to be rescheduled. Additionally, labor and repair expenses are paired with CM along with replacement costs for another rolling stock taking over the passenger operation. NS provides a costs overview from which it can be assumed that CM costs are estimated to be C_{CM} euros (see confidential annex B section B.3). The shunting costs to the depot are excluded because this is taken separately.

Condition Based Maintenance routine costs: CBM is planned according to prognostics expressed as the RUL in time units. This type of maintenance is not yet implemented by NS and therefore, there are no costs estimations made by the operator. Bougacha et al. (2022) estimated the costs of this type of maintenance by the repairing/replacement costs on a component level of the component that is condition monitored. However, for this project, the prognostics are assumed to be on a system level and unrelated to individual components.
It remains therefore an open discussion what the costs are of performing CBM. For this study, it is assumed that this type of maintenance routine is comparable to a CM routine. CM is performed after failure of the asset that has to be maintained whereas CBM is conducted before failure. It may be assumed that CBM costs less because the asset has not failed yet and the fault can be repaired in its infant state. Nevertheless, it may be argued that the same kind of repair is required.

Since CBM is more flexible planning wise, CBM may be combined with PM routines, saving costs due to opportunistic maintenance. PM costs are estimated by NS including repairs that are performed because of a faulty component that is identified during a preventive check. The same faultiness was found if that component was condition monitored, but online and without a preventive check. As a result, PM routines would cost less if CBM would be implemented in the maintenance strategy, because repairs are rather performed according to condition monitoring than in response to a preventive check. So repair costs are shifting from PM to CBM. Therefore, it is unfair to assume that CBM costs the same as CM, because it is assumed that PM costs reduce with the implementation of CBM. Subsequently, costs for CBM are assumed to be less than CM, so C_{CBM} euros (see confidential annex B section B.3), while PM routine costs remain the same with the integration of both routines. The shunting costs to the depot are excluded because this is taken separately.

The described costs will be used for the model optimization objective function that will minimize the costs, resulting in the most cost efficient maintenance planning under the given constraints.

3.9. Concluding Remarks

By describing the current state of practice, research question 2 is addressed:

2. *What is the current state of practice for rolling stock maintenance planning?*

It can be concluded that NS performs maintenance activities on a sub-system level in accordance with the standardized classification of the rolling stock unit breakdown. These individual PM activities are clustered based on their PM time threshold, so that all PM routines have a similar throughput. From this can be concluded that NS makes use of opportunistic maintenance, because convenient PM activities are clustered.
PM routines are planned based on the offer of rolling stock to the maintenance depot and required availability for passenger operations, resulting into a dense planning. CM is therefore very **disruptive** to the PM planning, because the maintenance depot planning has to be rearranged in order to fit in a CM repair.
CBM is not yet implemented at NS, but it can be expected that the throughput time of CBM is quicker than for CM, because it is known in advance what is going to fail and therefore costs less.
Thereafter, since CBM can be planned in advance, this creates the opportunity to combine CBM with an upcoming PM routine, saving shunting costs. An optimization approach based on the state of the art may now be developed for the maintenance practice at NS in accordance with the disclosed state of practice of this chapter. Maintenance costs are specified that are used for the maintenance planning optimization that will be formulated in this study. This is crucial, because it allows the optimization to base decisions on the actual cost ratios of PM activities so that realistic decisions can be made that provide practical insights. This will be performed in the following chapter.

4 Rolling Stock Maintenance Planning Optimization Approaches

In this dhapter, the rolling stock maintenance planning optimization approaches that are formulated in accordance with the state of the art, state of practice and the maintenance operations of NS will be presented. From the scope and assumptions, the optimization problem can be formulated. Subsequently, the mathematical model will be formulated that will be able to solve the problem with an optimization solver algorithm. As a result, the following research questions will be addressed:

3. *How to formulate an optimization problem for rolling stock Preventive Maintenance planning considering the mileage costs and what are the associated decision-variables and constraints?*

4. *How to design a rolling stock Preventive Maintenance planning algorithm for integrating Corrective Maintenance or Condition Based Maintenance?*

Research question 3 will be addressed by formulating an optimization method that can optimize the PM planning based on the way of practice of NS that is described in the previous chapter. This model will be referred to as ”approach 1”.
Research question 4 will be addressed by formulating ”approach 2” considering, PM, CM and CBM. It becomes apparent that approach 2 is not satisfactory for answering research question 3, so a third approach, ”approach 3”, is formulated. Approach 3 is able to plan maintenance with a rolling horizon framework that is discovered in the state of the art. With this approach, a satisfactory model is computed that is able to integrate CM or CBM representing the current state of practice. The model will be verified in this chapter in order to prove the correctness of the model so that it can be further evaluated.

4.1. Scope and Assumptions

The rolling stock maintenance planning optimization problem is a complex problem, because there are several processes on different levels that can be optimized. The state of the art shows how the planning could be optimized integrated with the operational timetable or logistics are taken into account for the maintenance planning optimization. This study will focus solely on the optimization of the rolling stock maintenance planning decision-making. Implying that the rolling stock will be maintained without taking into account the viability of the logistics nor the individual maintenance activities at the maintenance depot.

The approach for this optimization planning will be described by formulating assumptions. Assumptions will be made that simplify and bound the maintenance planning.

- Detailed shunting operations to the maintenance depot is not considered.
- No restrictions on the availability of spare parts.
- Maintenance is performed perfectly.

- In comparison to the maintenance decision-making at NS, for the model, the rolling stock can be during the week without being restricted to strict arrival and departure times to and from the maintenance depot. This is noteworthy because in practice, the MBN, the train operator, decides when trains can be withdrawn out of operation to the maintenance depot.
- The cumulative operational time is still accumulating when the rolling stock is not in operation, so when the rolling stock is standby.
- It is assumed that every rolling stock in operations builds up the same amount of cumulative mileage while in operation per day which is 475 [km].
- Based on the 'bakkenstand', (see confidential annex B) a certain percentage of the rolling stock fleet should be in operation at all times.
- The duration of a PM routine is based on the standard PM routine of NS. The PM routine is modeled because of the discretization per day to take 3 days time.
- The limiting factor of the capacity of the maintenance depot is assumed to be the a maximum amount of arrivals over a certain amount of days.
- The rolling stock is not allowed to undergo PM if the rolling stock has been running less than 94% of the mileage threshold. This implies that rolling stock has to run at least 94% out of 45,000 [km], which is 42,800 [km].

4.2. Rolling stock Preventive Maintenance planning problem formulation

Based on the state of the art, it became apparent that formulating a deterministic MILP problem is the most appropriate method for modeling a rolling stock maintenance planning optimization. The outcome of such optimization problem will describe the PM decision-making of the rolling stock maintenance planning. The goal is to comprehend and quantify the decision-making of the model in order to describe the effects of different input parameters.
The objective of the maintenance planning model will be explained and how this affects the final maintenance decision-making. The method and considerations for the formulation of the maintenance planning model will be chosen Finally, results of the optimization can be discussed according to the yet to be defined Key Performance Indicators.

For the model formulation, a rolling stock fleet maintenance planning problem is defined using a discrete time model where each time slot k is 1 day. In the model, U rolling stock are considered. Passenger operations will not be modeled in the model, however it is assumed that a certain amount of rolling stock O has to be available in operation every day k.
Based on the PM thresholds of NS and the state of the art, it is defined that rolling stock requires PM before running $D = 45,000$ km or every $E = 108$ days. Since premature maintenance is undesired by NS, PM is not allowed to be planned before running at least $D_{LB} = 42,800$ [km] (94% out of D). In order to reach this mileage threshold, it is defined that if a rolling stock runs passenger operation a certain day, it runs the *Mission Profile* defined by the NS as $P = 475$ [km] a day. When a rolling stock is approaching either of these thresholds, whatever is reached first, it is going to the maintenance depot out of operation for PM. After PM, the rolling stock is readily available and able to run another D km within E days.

The way rolling stock is modeled to run operation, results into a certain feasibility region for PM, as they are constrained to the time in operation and cumulative mileage since last PM. This feasibility region is showed in figure 4.1. The green dotted lines illustrate how the constraints in the model ensure that PM is performed at the right time and that it is bounded. This graph shows that when the rolling stock is constantly in operation, the lower bound mileage threshold D_{LB} will be reached in $k = 91$ days, mileage threshold D in $k = 94$ days. Simultaneously, the grey feasible region in the figure demonstrates that there is room for flexibility in the model to plan rolling stock for PM.

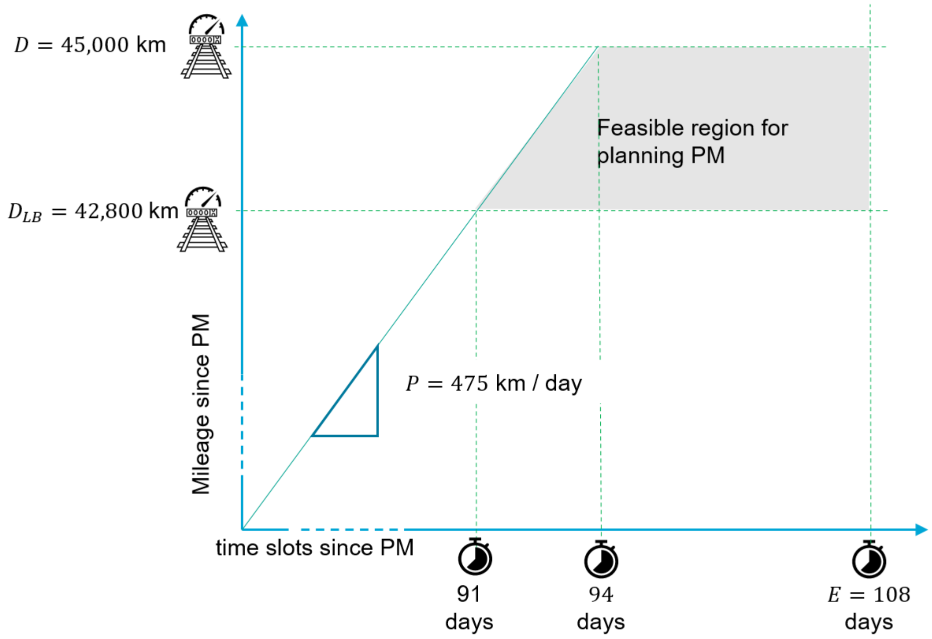


Figure 4.1: Graph showing the feasible region for planning PM of the maintenance planning model

Objective function The state of the art of rolling stock PM planning optimization methods offers only a handful of objective functions. The objective function is the quantification for the maintenance planning decision-making. The resulting maintenance planning of the optimization model is strongly dependent on how the objective function is formulated. So the performance of the planning can be justified based on the objective function value. The objectives found in literature are to minimize:

- Unavailability
- Shunting through the railway network to the maintenance depot
- Mileage losses
- Maintenance costs

The optimization model will not optimize the availability of rolling stock for operation, so it will not be integrated in the objective function, because the availability of rolling stock for passenger operations at NS is not a direct concern of the maintenance planner.

Earlier is assumed that shunting is out of the scope of this study. Therefore, this will not be integrated in the objective. However, the shunting costs from the railway network to the maintenance depot are standardized and taken into account. Shunting costs are incurred when the rolling stock goes to the depot for either CM, PM of CBM, so this will be integrated in the objective function.

At NS, the mileage loss is an important KPI for the PM planning. The rule of thumb is to outrun at least 94% out of 45,000 km before performing PM. Therefore, the goal is to perform PM when a maximum possible mileage is reached within the mileage threshold. If the rolling stock is maintained before running 45,000 km, the maintenance operator introduces additional costs. This argument is in line with the state of the art, where it is common to minimize the mileage losses. Previous chapter, the costs per mileage loss is specified, so the mileage losses can be expressed as *mileage costs*. Mileage costs will therefore be integrated in the objective function.

Maintenance costs for PM, CM and CBM are defined in the previous chapter. These costs will be accounted for in the objective function if one of these maintenance will be planned.
Overall, all possible maintenance decisions can be related to costs, therefore, the objective function will

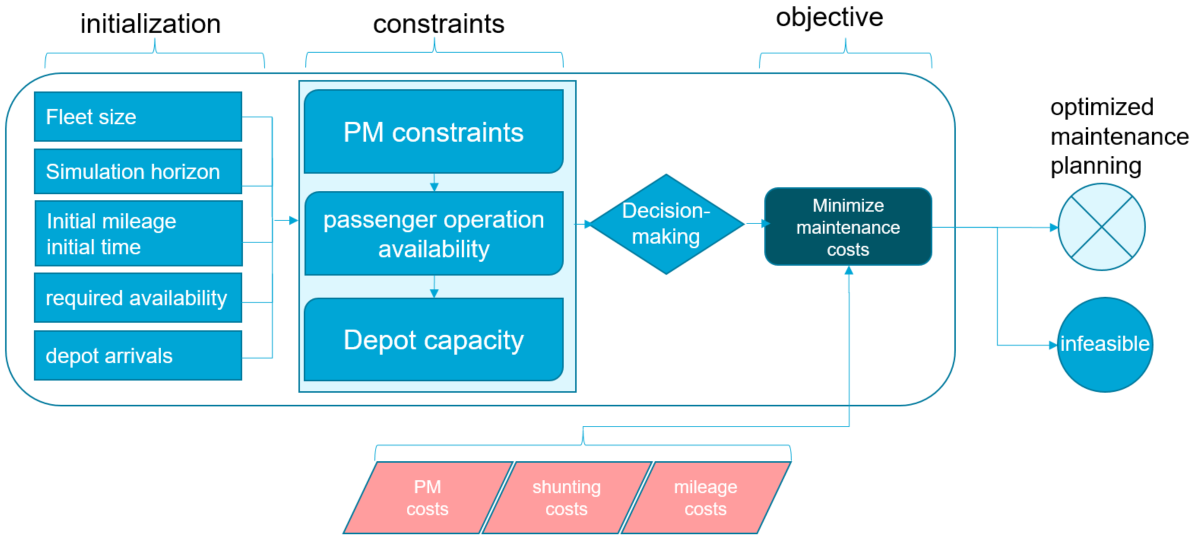


Figure 4.2: Structure how approach 1 optimizes the PM planning

be formulated as a *cost function* that sums up all maintenance related costs that are described above, based on the decisions in the model. If the costs are minimized, it can thus be argued that the planning is optimized.
As a result, the outcome of the model presents the optimal planning that describes when a certain rolling stock should be withdrawn out of operation to the depot for maintenance under the given conditions. The conditions the planning optimization model is formulated as constraint functions which are fed by parameter values. These conditions are formulated in such a way that they represent the actual conditions of the maintenance practice of NS and that these "design parameters" can be used for general rolling stock maintenance planning optimizations.

4.3. Approach 1: Mathematical model for the rolling stock PM planning optimization

This section, approach 1 will be elaborated, which is a rolling stock PM planning optimization model based on the way of practice of NS. Constraints, parameters, decision-variables and the objective function are chosen according to the former discussed models in the state of the art.

The structure of approach 1 is illustrated in figure 4.2. The figure illustrates how parameter sets are used for the initialization of the problem formulation which are subsequently used for formulating the constraints. While respecting the formulated constraints, the model performs the PM decision-making and when a rolling stock runs passenger operations. When a the decision-making expressed in decision-variables results into a minimum costs, an optimized maintenance planning is conducted. If this cannot be found because of an ill defined initialization or when the constraints are not bounded, no solution can be found and the solution is "infeasible".

The mathematical MILP model that is used for establishing the optimized rolling stock PM planning is described in the following sub-sections.

4.3.1. Notations

Indices are used to specify the element of an array. For example, which rolling stock number from the fleet.
Parameters that are used a priori for the model are listed and based on the case of NS.
Indices:

u	Denotes the rolling stock number
k	Denotes the day number

Sets:

$U = 21$	[-], size of the rolling stock fleet
K	[days], set of days in the planning

Parameters:

$D = 45,000$	[km], mileage threshold for PM
$D_{LB} = 42,800$	[km], mileage threshold lower bound for PM is 94% of D
$P = 475$	[km], operating mileage per rolling stock per rolling stock per day (mission profile)
$d_u(0) = \{0, ...D_{LB} - P\}$	[km], initial rolling stock mileage integer values, ascending with an evenly distributed interval
$E = 108$	[days], time threshold for PM
$e_u(0) = \frac{D_u(0)}{D} \cdot E$	[days], initial cumulative time of every rolling stock is set in ratio according to ascending mileage
$N = 3$	[days], duration of PM routine, based on the standard PM routine
O	[-], amount of rolling stock required in operation of the fleet size, however this may be iterated
$A = 1$	[-], amount of rolling stock that can go to the depot in A_{days}, this may be iterated
$A_{days} = 3$	[days], amount of days that the amount of A can arrive in
C_{PM}	[euro], costs of PM per day
$C_{mileage}$	[euro], costs per mileage loss
$C_{shunting}$	[euro], costs per two-way shunting to the depot

Numerical parameters:

$M = 100,000$	Very large number (big M)
$S = 10^{-4}$	Very small number

Parameter values justification Most of the parameter values are directly based on the data of NS. Because computational limit or for simplification, some values are not like the actual situation at NS and need to be estimated. The assumed values choices will be elaborated below:

- Fleet size U:
  The fleet size have been downsized due to to 21 rolling stock computational reasons. Therefore, the required amount of rolling stock in operation is $O_{percentage}$% of the fleet denoted by an amount of O [-] rolling stock.
- Initialization of mileage $d_u(0)$ and cumulative time $e_u(0)$in operation:
  The rolling stock are at $k = 0$ initialized in such a way that the mileage is constantly increasing over the fleet $d_u(0) \in \{0, ..., D_{LB}\}, \forall u \in U$, while $d_u(0)$ is a multiplication of the mission profile P. The initial cumulative time $e_u(0) \in \{0, ..., 101\}, \forall u \in U$ for the fleet is set linearly increasing to the initial mileage.
  As a result, the model is guaranteed to start with a feasible solution without immediately requiring PM for the first rolling stock nearest to D_{LB}. The complete list of initial values can be found in table 4.1.

- PM routine duration N:
  The model is discretized in days unlike at the NS depot, where maintenance is planned per shift of 8 hours. It is assumed that the maintenance that the PM routine takes 3 days. This is illustrated in figure 4.3.

- Maintenance arrival frequency A and A_{days}:
  In literature, the depot capacity is often constrained by amount of rolling stock to be maintained per day as in Lai et al. (2015), Li et al. (2016), and Lin and Zhao (2021). While Lin et al. (2019) restricts the capacity of the depot like NS to not more than 3 rolling stock arriving per day for maintenance. Ma et al. (2016) and Méchain et al. (2020) restrict the capacity by the amount of spare parts and mechanics available. How the capacity of the NS maintenance depot is constrained is defined in the previous chapter, which is according to the arrivals, constrained by 9 rolling stock per 2 days. However, the model is scaled down to a fleet size of 21 rolling stock instead of 190, which is 9 times as small. So it can be logically scaled down to 1 per 2 days. Still, the the optimization model resulted in too optimistic results because there was too much room for planning maintenance, while through interviews with the NS, this appeared to be quite strict. Therefore it is formulated to accept a maximum of one rolling stock arrivals during three days, so $A = 1$ and $A_{days} = 3$.

rolling stock	$d_u(0)$ [km]	$e_u(0)$ [days]	rolling stock	$d_u(0)$ [km]	$e_u(0)$ [days]
1	0	0	12	23275	56
2	1900	5	13	25175	60
3	4275	10	14	27550	66
4	6175	15	15	29450	71
5	8550	21	16	31825	76
6	10450	25	17	33725	81
7	12825	31	18	36100	87
8	14725	35	19	38000	91
9	17100	41	20	40375	97
10	19000	46	21	42275	101
11	20900	50			

Table 4.1: Default mileage and cumulative time initialization for 21 rolling stock

4.3.2. Decision-variables

Decision-variables represent the decisions of the model. Hence, the outcome of the model is the mileage and time since the latest PM routine of every rolling stock. Binary variables are introduced that indicate whether the rolling stock is running passenger operations or is undergoing PM.

$\forall k \in K,\ \forall u \in U,$	$d_u(k)$	cumulative mileage of rolling stock u at time k integer variable with lower bound 0
$\forall k \in K,\ \forall u \in U,$	$e_u(k)$	cumulative time of rolling stock u at time k integer variable with lower bound 0
$\forall k \in K,\ \forall u \in U,$	$x_u(k)$	$\begin{cases} 1, & \text{if rolling stock } u \text{ is not in operation at } k \\ 0, & \text{otherwise} \end{cases}$
$\forall k \in K,\ \forall u \in U,$	$y_u(k)$	$\begin{cases} 1, & \text{if rolling stock } u \text{ undergoes PM at time } k \\ 0, & \text{otherwise} \end{cases}$
$\forall k \in K,\ \forall u \in U,$	$w_u(k)$	$\begin{cases} 1, & \text{if rolling stock } u \text{ arrives at depot and starts PM at } k \\ 0, & \text{otherwise} \end{cases}$

4.3.3. Objective function for optimizing PM planning

The objective function is a cost function that should be minimized in the model. The objective function can be formulated in equation 4.1 containing costs that considered by the model.

$$\text{minimize } \underbrace{C_{mileage} \sum_{k \in K} \sum_{u \in U} D y_u(k) - d_u(k-1) y_u(k)}_{1}$$
$$+ \underbrace{C_{PM} \sum_{k \in K} \sum_{u \in U} w_u(k)}_{2} + \underbrace{C_{shunting} \sum_{k \in K} \sum_{u \in U} w_u(k)}_{3} \tag{4.1}$$

1. Mileage costs
   Upper bound mileage threshold parameter D is subtracted by the decision-variable $d_u(k-1)$ at one day before it is in the depot for maintenance when $y_u(k) = 1$. This function is results into a outcome of 0, except for a day when one of the rolling stock in the model arrives for maintenance.
2. PM routine costs
   Decision-variable $w_u(k) = 1$ only when one of the rolling stock in the model arrives for maintenance. By taking the PM routine costs in product with the decision-variable, the costs are counted when it is righteous.
3. Shunting costs
   Decision-variable $w_u(k) = 1$ only when one of the rolling stock in the model arrives for maintenance. So similarly to the PM routines costs, this variable is taken in product with the shunting costs.

4.3.4. Constraints

The constraints bound the model and force to find a solution while respecting the constraint equations.

Cumulative constraints for the time and mileage decision-variables

- **Accumulated mileage** The accumulated mileage is formulated as the mileage of the previous day plus the mission profile if the rolling stock is in operation, so if $x-u(k) = 0$. This formulation is inspired from the study of Lin and Zhao (2021).

$$d_u(k) = (1 - y_u(k))) \cdot (d_u(k-1) + (1 - x_u(k)) \cdot P), \qquad \forall k \in K, \forall u \in U \tag{4.2}$$

- **Accumulated Time** The calculation for accumulative time is comparable to constraint 4.2. The operating time is still accumulating while the rolling stock is not deployed for passenger operation, so if $x-u(k) = 1$. This explains the difference with constraint 4.2. Despite not being in use, this shows that the rolling stock is still ”aging”.

$$e_u(k) = (1 - y_u(k)) \cdot (e_u(k-1) + 1), \qquad \forall k \in K, \forall u \in U \tag{4.3}$$

Time and mileage thresholds for PM

- **Mileage threshold** The accumulated mileage of every rolling stock should not exceed the formulated maximum mileage threshold. The threshold of NS before performing PM is 45,000 km .

$$d_u(k) \leq D, \qquad \forall k \in K, \forall u \in U \tag{4.4}$$

- **Time threshold** The accumulated time of every rolling stock should not exceed the formulated maximum time threshold. The threshold of NS before performing PM is 108 days. It is not possible to reach this amount of days when the rolling stock is operation everyday and running the mission profile of 475 [km] until the rolling stock is going into to the depot for PM.

$$\frac{45,000}{475} \simeq 95 \; days \tag{4.5}$$

This implies that the rolling stock could $108 - 95 = 13$ days not be used for operation while the mileage threshold of 45,000 is still reached.

$$e_u(k) \leq E, \qquad \forall k \in K, \forall u \in U \tag{4.6}$$

- **No PM before lower bound mileage threshold** Since performing PM earlier than the maximum mileage threshold is considered as a loss, rolling stock can only go to the depot after running for at least the mileage value of the lower bound mileage threshold. The constraint is formulated in such a way that the mileage $d_u(k)$ value should be larger than the lower bound mileage threshold D_{LB} at the time that the rolling stock is going to undergo maintenance and the constraint is satisfied. When the rolling stock will undergo maintenance: $y_u(k) - y_u(k-1) = 1 - 0$ resulting into a positive 1. If the rolling stock is going into operation, this results into -1 and if the rolling stock is undergoing maintenance or in operation this equal 0. As integer decision-variable $d_u(k)$ is always positive and greater than 0, the constraint is still satisfied.

$$d_u(k) \geq D_{LB} \cdot (y_u(k) - y_u(k-1)), \qquad \forall k \in K, \forall u \in U \tag{4.7}$$

Operational constraints

- **Rolling stock in operation** Based on the 'bakkenstand', the train operator needs to deploy $O_{percentage}$% of the SNG fleet into operation. Therefore, the constrained is formulated to maintain at least $O_{percentage}$% of the fleet available for operation (see confidential annex B B.2). This implies that a maximum of $100 - O_{percentage}$% is either undergoing maintenance activities or is standby. Since it is not the objective to minimize unavailability of the rolling stock in the optimization problem, it was chosen to keep the availability constant throughout the model, similarly to the models of Lai et al. (2015), Li et al. (2016), and Lin and Zhao (2021). So constraint 4.8 is formulated that the every day, exactly $O_{percentage}$% of the fleet is deployed for operation. As a result, no more rolling stock than required are in operation.

$$O = U - \sum_{u \in U} x_u(k), \qquad \forall k \in K \tag{4.8}$$

- Rolling stock can only be maintained when not in operation. This constraint is satisfied only if decision-variable $y_u(k) = 1$ if $x_u(k) = 1$.

$$y_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{4.9}$$

Preventive Maintenance routine constraints

- **PM routine** The PM routine is modeled by the following constraints. If the rolling stock starts the PM routine, it stays for maintenance for 3 days, the sum of decision-variable $y_u(k)$ should be at least have the value of 1 for 3 days in a row, defined by constraint 4.10. Constraint 4.11 defines that the rolling stock is not longer in PM than 3 days.

$$\sum_{k \in K}^{k+N} y_u(k) \geq N(y_u(k) - y_u(k-1)), \qquad \forall k \in K, \forall u \in U \tag{4.10}$$

$$\sum_{k \in K}^{k+N+1} y_u(k) \leq N, \qquad \forall k \in K, \forall u \in U \tag{4.11}$$

- **Maintenance depot capacity for PM** At NS, the capacity for rolling stock at the maintenance depot is defined by the amount of arrivals per day. The arrival decision-variable is defined in constraint 4.12 and 4.13. Because of these constraints, decision-variable $w_u(k)$ has the value 1 only if a rolling stock starts undergoing PM.

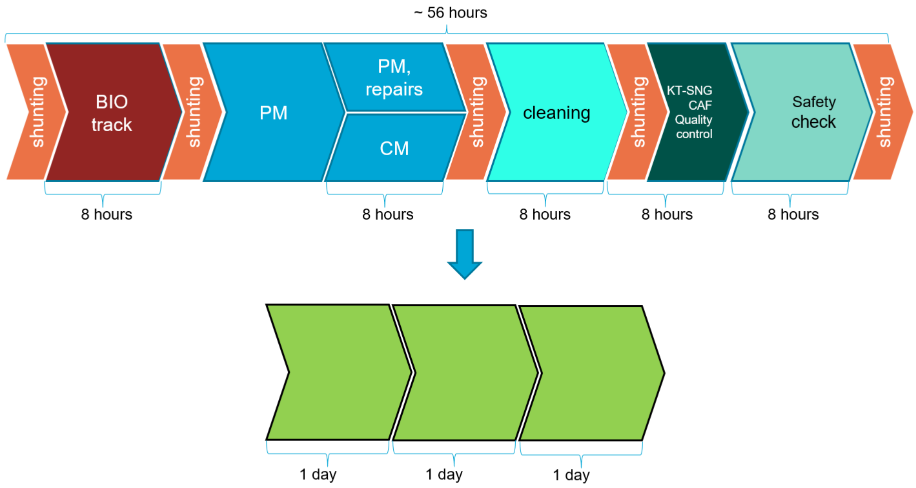


Figure 4.3: Preventive Maintenance standard routine and simplified routine

The depot capacity is constrained by the amount of arrivals per a certain amount of days. Constraint 4.14 is therefore defined to sum up the amount of arrivals over $A_{days} = 3$ days. This constraint is satisfied when the summation is less or equal to $A = 1$ arrival.

$$w_u(k) \geq y_u(k) - y_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{4.12}$$

$$w_u(k) \leq d_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{4.13}$$

$$\sum_{u \in U}^{k+A_{days}} w_u(k) \leq A, \qquad \forall k \in K \tag{4.14}$$

4.3.5. Linearization and numerical issues

The mathematical model is coded in Python and the objective is minimized with the Gurobi solver algorithm that uses by default branch and bound as solution approach, but an initial solution is often found through heuristics as solution approach. In order to perform the computation faster and make the problem less complex, the mathematical model is linearized. Numerical issues that arise if the mathematical model is solved in a numerical algorithm such as Gurobi. How to cope with these issues is addressed in this section.

Numerical issues Since a MILP model is formulated, it integrates a mix of integer variables and binary variables. Therefore, the numerical solver might encounter numerical issues. In order to avoid these issues, small numbers are introduced in certain equations. Binary numbers are in code estimated numbers. As a result, 0 can be for example 10^{-8} and 1 can be $1 + 10^{-6}$. This has consequences for constraints as equation 4.15.

$$y_u(k) \leq x_u(k) \tag{4.15}$$

$$1 + 10^{-6} \nleq 1 \tag{4.16}$$

It is assumed that the binary decision-variables can only be 0 or 1. Therefore, the constraint will be satisfied if $y_u(k) = 1$ and $x_u(k) = 1$ since their values are equal. However, for example when $y_u(k) = 1 + 10^{-6}$ and $x_u(k) = 1$, due to numerical issues, the constraint is not satisfied as can be seen in equation 4.16, although it should be algebraically satisfied. By introducing a small number $S = 0.001$ to the constraint, this numerical issue can be avoided. The constraint can be programmed as the following:

$$y_u(k) \leq x_u(k) + S \tag{4.17}$$

$$1 + 10^{-6} \leq 1 + 0.001 \tag{4.18}$$

This solution is introduced for similar problems in constraints. Since this is a numerical problem, this will not be included in the mathematical model.

Linearization of the objective function The objective function of the maintenance planning models calculates the KPI 'mileage loss'.

$$\text{minimize} \sum_{k \in K} \sum_{u \in U} D y_u(k) - d_u(k-1) y_u(k) \tag{4.19}$$

This calculation can be classified as nonlinear because two decision-variables are in product ($d_u(k-1)y_u(k)$). The mileage loss is calculated by multiplying the integer decision-variable mileage of the rolling stock at the day right before undergoing PM with the binary decision-variable that defines when the rolling stock undergoes PM. This product is subsequently subtracted by the mileage threshold D. This nonlinearity in the objective function results in computational complexities. However, this can be linearized by introducing an auxiliary integer decision-variable $v_u(k)$, see equation 4.20 and 4.21.

mileage of rolling stock u before undergoing PM at time k, integer variable with lower bound 0: $v_u(k), \quad \forall k \in K, \forall u \in U$ (4.20)

$$v_u(k) = d_u(k-1) y_u(k), \quad \forall k \in K, \forall u \in U \tag{4.21}$$

Lin and Zhao (2021) encountered the same issue for the same formulation of the objective function for their rolling stock PM planning optimization model. They have proposed a pragmatic linearization technique, which can be used for the objective formulation of this study.

$$M(y_u(k) - 1) + d_u(k-1) \leq v_u(k) \leq d_u(k-1), \quad \forall k \in K, \forall u \in U \tag{4.22}$$

$$v_u(k) \leq M y_u(k), \quad \forall k \in K, \forall u \in U \tag{4.23}$$

Note that in these equations, the big M method (Hillier and Lieberman, 2015) is used, which is a large number. By implementing these constraints, it forces auxiliary variable $v_u(k)$ to take the value of $d_u(k-1)$ when $y_u(k)$ equals to one. When $y_u(k)$ take the value of zero, equation 4.23 forces $v_u(k)$ to be zero as well. Hence, $v_u(k)$ can be used in the objective function and it becomes linear as can be seen in function 4.24. For the numerical computation, equation 4.24 is used to replace segment 1 from the objective function 4.1.

$$\text{minimize} \sum_{k \in K} \sum_{u \in U} D y_u(k) - v_u(k), \quad \forall k \in K, \forall u \in U \tag{4.24}$$

4.4. Approach 2: rolling stock maintenance planning optimization integrating CM and CBM

With approach 1, a rolling stock PM planning optimization model is established that may be used by NS as planning tool. However, approach 1 does not integrate CM or CBM. A second approach to optimize the rolling stock maintenance planning is therefore formulated: "approach 2". Approach 2 is formulated building on approach 1, but contains additions that concern the integration of CM and CBM. The addition of this approach is that *disruptive* CM and CBM will be included in the existing PM planning. When discussing disruptions, this refers to instances of CM or CBM.

CM will be modeled as one particular moment in the planning when CM should take place. These instances are initialized a priori and CM is determined to be performed at a certain time at a specific rolling stock taking 2 days time. The rolling stock is thus unavailable for 2 days when CM is performed. CBM is assumed to be a maintenance routine also taking 2 days time similar to CM, but CBM is based on the prognosis that a rolling stock system will fail within a given amount of time, the RUL. It is assumed that planning optimization integrates either CM or CBM, not both. Furthermore, it was earlier described how CBM creates an opportunity to save costs if PM and CBM are combined. So for this approach it can be enabled to the model to perform CBM and PM adjacent to another to save shunting costs. The outcome of approach 2 consists therefore of three results, one with CM, one result with

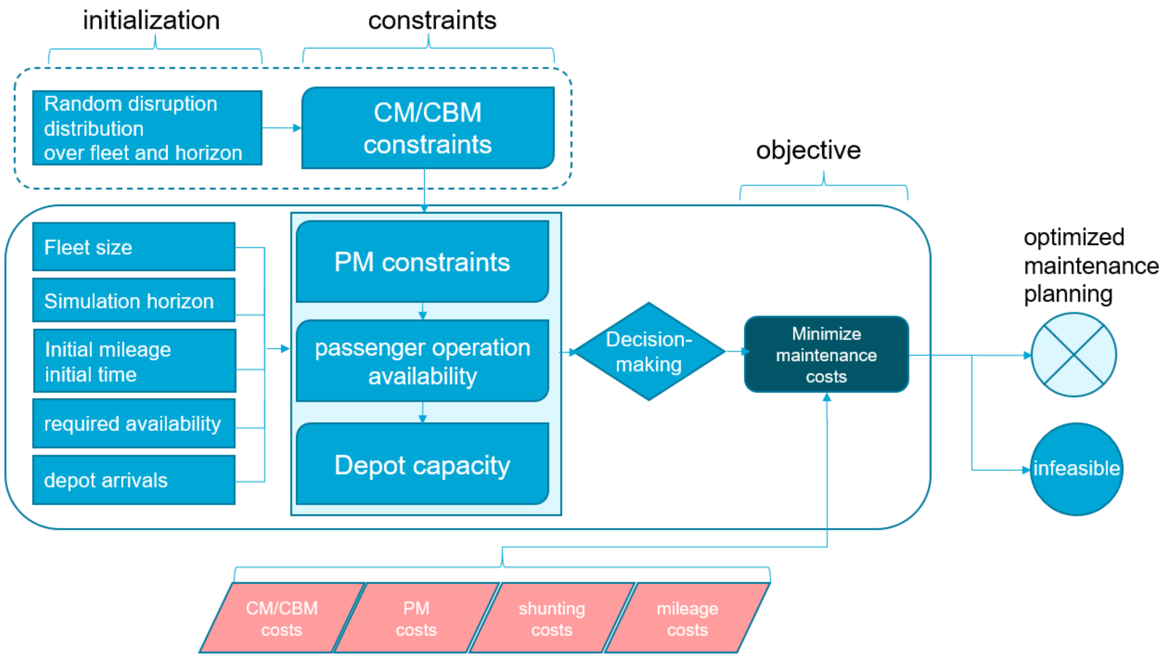


Figure 4.4: Structure how approach 2 optimizes the maintenance planning

CBM and a result where CBM may be combined with PM.
How approach 2 is structured, is shown in the diagram in figure 4.4. This figure shows that it is similar to approach 1, but it contains the addition of the initialization of random times of CM or CBM that are used for the formulated constraints that concern CM and CBM. The instances when CM or CBM take place are randomized and therefore artificial, because the timing for CM or CBM is not based on actual historical failure data. CBM will be modeled as a time period in the planning wherein CBM should take place. CBM is thus more flexible planning wise in comparison to CM because CBM is not determined to be realized at a particular day.

In literature, the actual degradation of the rolling stock is modeled, which determines the RUL (Bougacha et al., 2022; Rokhforoz and Fink, 2021; Wang et al., 2022). The time in the planning when a fault detection takes place is in these studies related to the rolling stock usage. However, for this approach, the degradation of the rolling stock is not modeled and the timing of fault detection is thus independent on the usage of the rolling stock for passenger operations. A simplified approach for CBM is thus established in this study so that only the feasibility of planning CBM in the PM planning will be studied regardless of any degradation. The prognostic information including the RUL is thus artificially integrated in the model. It is assumed that at a random time in the planning a failure will occur. The RUL determines how far ahead of time this failure is predicted to take place. For instance, if a fault is detected with a RUL of 14 days, the failure is predicted 14 days in advance.

The objective of this approach is to evaluate the maintenance planning decision-making for a case where disruptions are caused by unforeseen CM in comparison with a case where disruptions are predicted with prognostics, so with CBM. It is anticipated that the model can make more effective decisions when a failure is predicted by prognostics, because the planning up to when the failure is predicted to occurs can still be rearranged. These decisions would result into less mileage costs and less PM routines overall. On the contrary, when a failure occurs unexpected and CM is determined to be performed immediately, the planning can only be rearranged as the failure already happened.

For this approach, more decision-variables, parameters and objectives will be added to the formulated problem of approach 1. The same notations will be used as approach 1.

4.4.1. Parameter values

Additional costs of CM and CBM are defined, based on the costs of NS. The duration of the routine for CM and CBM is assumed to take 2 days. It is assumed that there is no maintenance depot capacity restriction for CM or CBM. Because the RUL of the prognostics is considered to be constant in duration, each failure is predicted an identical amount of time in advance. Based on the NS maintenance depot capacity, there is a dedicated track free for this type of maintenance and it is assumed to be free at any time.

$T_{CM} = 2$	[days], amount of days needed for a Corrective repair
$T_{CBM} = 2$	[days], amount of days needed for a Condition based repair is 94% of D
C_{CM}	[euro], costs for a Corrective repair
C_{CBM}	[euro], costs for a Condition based repair
Q	[-], amount of CM in the decision horizon
R	[-], amount of CBM in the decision horizon
R_{CBM}	[days], amount of days wherein CBM can be planned as if the rolling stock has a RUL
$W_u(k)$	[-], defines when in the decision horizon for rolling stock u at time k CM occurs, with the amount of CM defined by Q according to a randomized definition
$V_u(k)$	[-], defines when in the decision horizon for rolling stock u at time k CBM occurs, with the amount of CBM defined by R according to a randomized definition

Random instances of CM and CBM The initialization of when CM will take place in the decision horizon is defined a priori by parameter value $W_u(k)$. As earlier mentioned, the timing of CM or CBM will be unrelated to the usage of rollings stock or any degradation. The timing of the disruptions will therefore be modeled as random. Parameter $W_u(k)$ is a matrix full of zeros structured in a way that there are Q instances of ones in random places in the matrix. The size of matrix $W_u(k)$ is $u \times k$, so that it indicates which rolling stock u fails at what time k. The randomization is performed according to the following steps and figures 4.5 and 4.6:

1. An amount of Q ones are randomly distributed over the rolling stock, so over column $W_u(0)$. Every rolling stock can only get one 1 per row.

2. Subsequently, the ones at $k = 0$ will be randomly distributed over the row per rolling stock u, so that at a random point in time is determined that rolling stock u will get CM.

Parameter matrix $V_u(k)$ is constructed in a similar manner, but then according to parameter R instead of Q. However, $V_u(k)$ defines the moment for CBM not as an instance in time, but as a period in time, because it is assumed that CBM will be performed according to the RUL, which is a period of time until failure. Therefore, for constructing $V_u(k)$, the random ones of $W_u(k)$ are repeated adjacent to another R_{CBM} times so that a chain of ones is constructed in matrix $V_u(k)$. The length of this chain of ones represents the RUL of the asset as can be seen in figure 4.6.

$$\begin{bmatrix}0 & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & 0\end{bmatrix} \rightarrow \text{randomize}\updownarrow\begin{bmatrix}1&0&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\1&0&0&0&0\\0&0&0&0&0\end{bmatrix} \rightarrow \overset{\xleftrightarrow{\text{randomize}}}{\begin{bmatrix}0&1&0&0&0\\0&0&0&0&0\\0&0&0&0&0\\0&0&1&0&0\\0&0&0&0&0\end{bmatrix}}$$

Figure 4.5: Construction of $W_u(k)$ according to steps, simplified example for $U = 5$ and $K = 5$

$$\begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \xrightarrow{\text{make chain of ones}} \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Figure 4.6: Construction of $V_u(k)$ according to steps, simplified example for $U = 5$, $K = 5$ and $R_{CBM} = 3$

4.4.2. Decision-variables

Additional decision-variables are introduced to formulate the decisions of CM and CBM. Decision-variables represent the arrival at the depot and the days that the rolling stock undergoes CM or CBM.

$$\forall k \in K,\ \forall u \in U, \quad z_u(k) \quad \begin{cases} 1, & \text{if rolling stock } u \text{ undergoes CM at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad m_u(k) \quad \begin{cases} 1, & \text{if rolling stock } u \text{ undergoes CBM at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad q_u(k) \quad \begin{cases} 1, & \text{if rolling stock } u \text{ arrives at depot and starts CM or CBM at } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad r_u(k) \quad \begin{cases} 1, & \text{if rolling stock } u \text{ combines CBM adjacent to PM at the depot at } k \\ 0, & \text{otherwise} \end{cases}$$

4.4.3. Objective function for optimizing the PM planning while disrupted by CM or CBM

The objective function is similar to the linearized objective cost function of the PM planning model. However, a few costs are added. Segment 1 of 4.25 is the linearized formulation of the computation of the mileage costs.
Segment 3 and 4 contain the costs when either CBM or CM is performed in the planning.
Segment 5 now also contains the arrival of CM or CBM, so that the shunting costs are also incurred.

$$\begin{aligned} \text{minimize } & \underbrace{C_{mileage} \sum_{k \in K} \sum_{u \in U} Dy_u(k) - v_u(k)}_{1} + \underbrace{C_{PM} \sum_{k \in K} \sum_{u \in U} w_u}_{2} + \underbrace{C_{CM} \sum_{k \in K} \sum_{u \in U} q_u}_{3} \\ & + \underbrace{C_{CBM} \sum_{k \in K} \sum_{u \in U} q_u(k)}_{4} + \underbrace{C_{shunting} \sum_{k \in K} \sum_{u \in U} w_u(k) + q_u(k)}_{5} \end{aligned} \tag{4.25}$$

As earlier described, CBM can be combined with PM, saving shunting costs. Hence, decision-variable $r_u(k)$ will be subtracted from the amount of arrivals, resulting in equation 4.26. If the model integrates CBM in the PM planning and also PM and CBM can be combined, the segment of equation 4.26 replaces segment 5 of the objective function so that shunting costs are subtracted.

$$C_{shunting} \sum_{k \in K} \sum_{u \in U} w_u(k) + q_u(k) - r_u(k) \tag{4.26}$$

4.4.4. Constraints

All constraints from the initial model formulation are preserved. The additions are listed below.
Constraint 4.27 and 4.29 define that PM and CM or CBM cannot be performed at the same time.
Constraint 4.28 and 4.30 define that for CM and CBM the rolling stock has to be out of operation.

$$z_u(k) + y_u(k) \leq 1, \qquad \forall k \in K, \forall u \in U \tag{4.27}$$

$$z_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{4.28}$$

$$m_u(k) + y_u(k) \leq 1, \qquad \forall k \in K, \forall u \in U \tag{4.29}$$

$$m_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{4.30}$$

Constraint 4.31 defines at which time CM is determined to take place for which rolling stock, therefore, the equal sign is used. Constraint 4.32 defines that CBM has to take place within the predefined time period. The model can decide at which instance within that time period it would plan CBM, but not outside of this time period, hence why the less or equal sign is used.
Since planning CBM is more complex to formulate because of its flexible ability to plan, two extra constraints are added. Constraint 4.33 defines that over every period of R_{CBM} days long, the amount of CBM divided by the duration of CBM, has to be greater or equal to the amount of ones in matrix $V_u(k)$ during the same time period. And by adding constraint 4.34, CBM is always planned the defined duration within the predefined time period.
The arrival day of CM and CBM is monitored by decision-variable $q_u(k)$ that will be 1 only if the rolling stock arrives at the depot for CM of CBM. Since CBM and CM will never be combined, the same notation of decision-variable can be used.

$$z_u(k) = W_u(k) \qquad \forall k \in K, \forall u \in U \tag{4.31}$$

$$m_u(k) \leq V_u(k) \qquad \forall k \in K, \forall u \in U \tag{4.32}$$

$$\sum_{k \in K}^{k+R_{CBM}} \frac{V_u(k)}{R_{CBM}} \geq \sum_{k \in K}^{k+R_{CBM}} \frac{m_u(k)}{T_{CBM}} \qquad \forall k \in K, \forall u \in U \tag{4.33}$$

$$\sum_{k \in K}^{k+R_{CBM}} m_u(k) \leq T_{CBM} \qquad \forall k \in K, \forall u \in U \tag{4.34}$$

$$q_u(k) \leq z_u(k) - z_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{4.35}$$

$$q_u(k) \leq m_u(k) - m_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{4.36}$$

Finally, if CBM will be combined in one maintenance routine with PM another constraint should be added defining the possibilities. This is formulated in constraint 4.37. When binary decision-variables $m_u(k)$ and $y_u(k)$ are adjacent to another, the sum over two days equals 2. When the model decides to make $r_u(k) = 1$, so combining CBM and PM, this constraint is only satisfied when $m_u(k)$ and $y_u(k)$ have the value of 1 adjacent to another. This is only possible when firstly CBM is performed and subsequently PM.

$$2 \cdot r_u(k) \leq m_u(k-1) + y_u(k), \qquad \forall k \in K, \forall u \in U \tag{4.37}$$

4.5. Approach 3: rolling stock maintenance planning optimization integrating CM and CBM with rolling horizon framework

In previous sections, maintenance planning optimization approaches 1 and 2 are formulated. It will be explained why both approaches are inadequate for evaluating the impact of integrating CBM in rolling stock PM planning in comparison to CM, which is why ”approach 3” is introduced.

With approach 1 and 2, the rolling stock maintenance planning is established in once over the decision horizon defined by parameter K. The *simulation-horizon* is defined to be the amount of days that is ultimately optimized by the rolling stock maintenance planning optimization model. Since for approach 1 and 2 the total planning is optimized in once, the decision horizon K equals the simulation-horizon. This suggests that for approach 2, the model is aware of all disruptions a priori defined by parameter matrices $W_u(t)$ and $V_u(t)$ from the start of the decision horizon ($k = 0$) to its ending ($k = K$). So, the model can take into consideration any disruptions once the CBM or CM moments are initialized in the model and it will consequently optimize around these moments in the planning from the start of the decision horizon, because the moments of failure are known by the model a priori. This is not satisfactory for analyzing the impact of CBM on the decision-making, because realistically, the maintenance planner cannot predict all failures over the complete decision horizon. The maintenance planner, can only realistically account for failures as they happen in real-time or account within the RUL when they are predicted by a prognostic model.

Because of this problem, an optimization method is formulated according to a rolling horizon framework where the optimization model cannot predict all failures over the complete simulation-horizon. So with this method, a situation is simulated where the maintenance planning is made per week and rearranged in real-time. Approach 3 will be formulated building on approach 1 and 2, therefore, a similar mathematical model will be used. The methodology of this approach is illustrated in figure 4.7, which is similar to approach 2. However it becomes clear that the optimization process functions in a loop where new optimizations are updated with new information. So, the total planning is split up in smaller decision horizons than the simulation-horizon, which are optimized individually and chronologically with the rolling horizon framework. The smaller plannings however, are initialized with the former planning, hence why figure 4.7 resembles a feedback loop. Also, the CM/CBM constraints are only taken into consideration when a failure happens of a fault is detected.

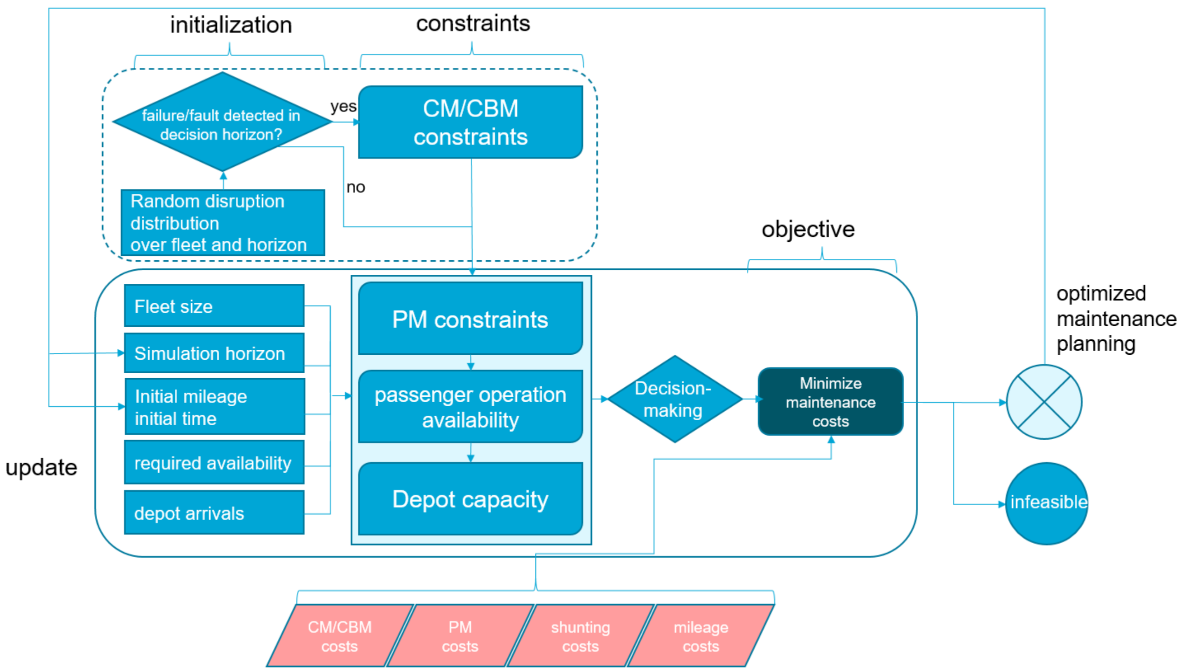


Figure 4.7: Structure how approach 2 optimizes the maintenance planning

4.5.1. Justification of using a rolling horizon framework

The state of the art of rolling stock PM planning includes one study that considered a rolling horizon in order to cope with unexpected failures and rearrange the planning to this (Lai et al., 2015). The state of the art of rolling stock maintenance that integrates prognostics also includes a study that used a rolling horizon principle in order to plan according to the degradation of RS components (Bougacha et al., 2022). These studies used a MILP model as is formulated for the rolling stock PM planning optimization. Therefore, this rolling horizon principle will be used for maintenance decision-making integrating prognostics since it is able to rearrange the planning when disruptive events happen during the execution of the optimization of the planning. A rolling horizon simulates a scenario in which the maintenance planner makes a planning per week, while considering recent failures or failures that are predicted in the near future.

4.5.2. Applying a rolling horizon framework to the maintenance planning optimization

A rolling horizon method that is used for approach 3 is illustrated in figure 4.8. The rolling stock maintenance planning will be executed over a period of K [days] in total, which is defined as the simulation-horizon. The figure illustrates how the rolling stock maintenance planning increases in length on the x-axis as the value of j increases on the y-axis. Instead of a single optimization, multiple optimizations indicated by j will be performed for solving the complete maintenance planning. So, every number j indicates that a new optimization has been taken place. This implies that the total maintenance planning optimization is established step-wise, by shifting the planning 7 [days] forward every optimization, while implementing the first 7 [days], *implementation-horizon* I. The implementation-horizon I is defined to be the initialized time-period for the following planning, maintenance decisions cannot be changed in this implementation horizon. The decision-making from implementation-horizon I is what is in the feedback loop in figure 4.7. The darker colors in figure 4.8 represent the final planning, while the light colors can still be changed the following optimization when new information is received. This indicates that every optimization j, there is a limited time horizon that the optimization considers denoted by W, the *decision horizon*. Constraints of the rolling stock maintenance planning optimization are only considered in this decision horizon W. The same MILP model formulation of approach 1 and 2 is used for every single optimization for approach 3. But instead of optimizing the maintenance planning once over the simulation-horizon of K, a smaller decision horizon W is considered every optimization.

Formulating CM as unexpected and CBM as predicted The model may be deceived if constraints governing CM and CBM are not considered until they can be predicted. This can be established by modifying the decision horizon in which the constraints are taken into account for in the optimization model. As a consequence, it can be modeled that CM is not foreseen until it immediately should be performed and CBM can be foreseen, but only when a failure is predicted. decision horizon length W, defines in a rolling horizon framework how much time in advance an event can be foreseen by the optimization model. However, CM should be modeled as unforeseen and CBM can only be predicted when a fault is detected, so decision horizon W is not satisfactory for simulating this. Therefore, new decision horizons, that are referred to as *prediction-horizon* should be introduced:

- Only if a failure actually occurs, so 1 day in advance, the optimization model can recognize the disruption, making it unexpected and only little room to plan CM in the planning.
  Prediction-horizon F will be considered for CM (equation 4.47).

- Meanwhile if CBM is implemented, a failure can be foreseen R_{CBM} days in the future, representing the RUL, so the prediction-horizon should be the length of R_{CBM} days. Consequently, the optimization model can take an upcoming disruption into account, so there is still time to rearrange and make the planning more efficient by minimizing the costs.
  Prediction-horizon G will be considered for CBM (equation 4.48).

In this manner, CM and CBM may be distinguished from one another as CM will not be considered at all in advance. Also CBM can only be recognized by the model only when a failure prediction is assumed. This is shown in figure 4.8, where it is shown that prediction-horizon G is 14 days after implementation-horizon I, indicating that CBM can be considered by the model 14 days in advance.
prediction-horizon F is shown to be only 1 day after implementation-horizon I, indicating that CM can be considered by the model 1 days in advance. Actually, prediction-horizon F is 8 days in the figure, but since 7 days out of the 8 days of F fall within the implementation-horizon, these decisions cannot be changed. Therefore, CM can only be foreseen 1 day in advance, and the same rule applies for CBM.

4.5.3. Notations

The overview of decision horizons, sets and indices are listed as follows. It should be noted that the implementation-horizon and prediction-horizon fall within the simulation-horizon K and are dependent on the optimization number indicated by j. However, the length of the horizons remains constant.

Indices

i	Denotes the day in the implementation-horizon	(4.38)
j	Denotes the optimization number in the rolling horizon	(4.39)
k	Denotes the day in the simulation-horizon	(4.40)
f	Denotes the day in the prediction-horizon for CM	(4.41)
g	Denotes the day in the prediction-horizon for CBM	(4.42)
w	Denotes the day in the decision horizon	(4.43)

Sets As is earlier described, some sets are dependent on the optimization number j. This phenomenon occurs because every optimization, the horizon shifts 7 days in the future. This implies that in figure 4.8, horizons W, F, G and I are starting at $k = j \cdot 7 = 2 \cdot 7 = 14$ for optimization number $j = 2$, while as illustrated for $j = 3$, the horizons start at $k = j \cdot 7 = 3 \cdot 7 = 21$.

$I = \{j \cdot 7, ..., (j \cdot 7) + 7\}$	**Implementation-horizon** of 7 [days]	(4.44)
J	[-], Set of optimizations that equals the amount of weeks of the total rolling horizon optimization K	(4.45)
K	**Simulation-horizon** in [days] which is the total amount of days in the complete planning	(4.46)
$F = \{j \cdot 7, ..., (j \cdot 7) + 8\}$	**Prediction-horizon** in [days] in which CM is considered	(4.47)
$G = \{j \cdot 7, ..., (j \cdot 7) + R_{CBM}\}$	**Prediction-horizon** in [days] indicated by R_{CBM} in which CBM can be predicted	(4.48)
W	**decision horizon** in [days], the period that is considered every individual optimization of the rolling horizon	(4.49)

4.5.4. Assumptions and modifications in comparison to approach 1 and 2

To enable approach 3 to function, a few assumptions and modifications are made in comparison to approach 1 and 2:

- It is assumed that with using a rolling horizon framework, the rolling stock maintenance planning is implemented per week and shifts every finished optimization one week in time. This implementation week is symbolized by I with a length of 7 [days], see equation 4.44. At NS, the planning is made per week and executed accordingly, so this method is in line the way of practice.
- The first implementation-horizon I for $j = 0$ is obtained from the first week of a feasible solution from the approach 1 that is solved for 21 rolling stock over a decision horizon of 32 weeks time without CM or CBM. So the model with rolling horizon is initialized with a historical verified optimal solution excluding CM or CBM.
- The objective function 4.25 from approach 2 is preserved and the identical minimization is used for approach 3 every optimization in the rolling horizon framework.
- The majority of constraint formulations from approach 1 and 2 remain preserved, because they remain valid in the simulation-horizon K. Only constraints related to CBM and CM will be modified for approach 3.
- New decision horizons are introduced, these are dependent on the number of the optimization of the rolling horizon j and listed above.
- Every optimization j is computed over decision horizon W.
- The constraints that deal with CM are valid in prediction-horizon F defined in 4.47 and for CBM in prediction-horizon G defined in 4.48. The horizon definitions correspond with figure 4.8.
- Similar to approach 2, three different results can be achieved with approach 3: One with CM, one result with CBM and a result where CBM may be combined with PM.

4.5.5. Constraints

Because the optimization method for approach 3 differs from that of approach 2, a few constraints must be modified to be valid for approach 3. This is primarily due to the newly introduced decision- and prediction-horizons, which indicate at which day or time period a particular constraint is valid.

The artificial method of how the RUL in for CBM is initialized in parameter matrix $V_u(k)$ and how failures

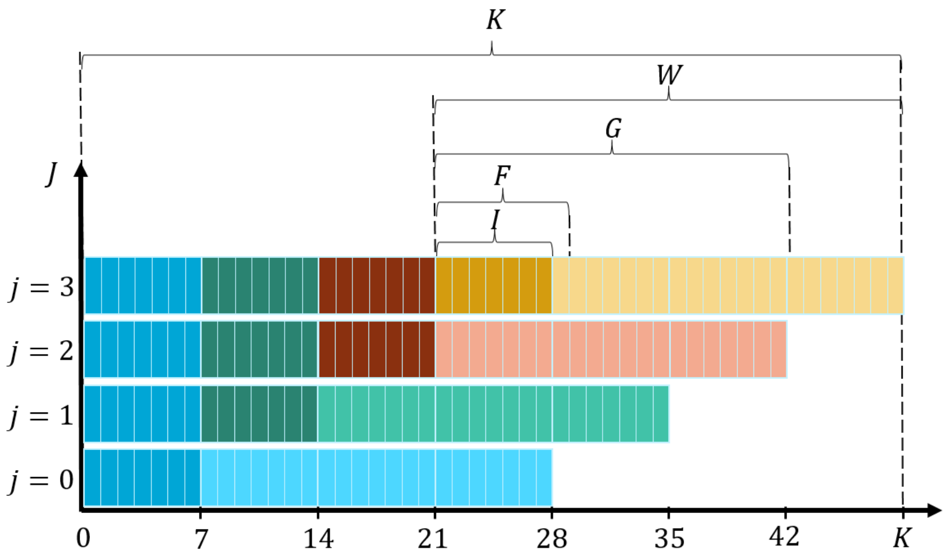


Figure 4.8: Rolling horizon framework principle example with $J = 4$, implementation-horizon $I = 7$ days, simulation-horizon $K = 47$ days, decision horizon $W = 28$ days, CM prediction-horizon $F = 8$ days, CBM prediction-horizon $G = 21$ days

are initialized in order to perform CM with parameter matrix $W_u(k)$ remain preserved for approach 3.

The prediction-horizon F for CM is formulated in such a way that per optimization in, CM cannot be foreseen. The mathematical model is formulated to plan CM according to the random matrix $W_u(k)$, but when the constraints considering CM are now formulated as below:

$$z_u(f) = W_u(f) \qquad \forall f \in F, \forall u \in U \tag{4.50}$$

$$q_u(f) \leq z_u(f) - z_u(f-1), \qquad \forall f \in F, \forall u \in U \tag{4.51}$$

Since the constraints are only valid in prediction-horizon F, they cannot be considered in the whole decision horizon W. Consequently, CM is unforeseen until it appears right after the implementation horizon in the decision horizon and the unpredictableness of CM is simulated.

The CBM constraints are modified similarly to the modifications of the constraints for CM. The CBM constraints are valid for the prediction-horizon G. The prediction-horizon of G depends on the how far ahead a failure is predicted, so on parameter value R_{CBM}. The formulation of the constraints are similar to approach 2 and will therefore not be further elaborated.

$$m_u(g) \leq V_u(g) \qquad \forall g \in G, \forall u \in U \tag{4.52}$$

$$\sum_{g \in G}^{g+R_{CBM}} \frac{V_u(g)}{R_{CBM}} \geq \sum_{g \in G}^{g+R_{CBM}} \frac{m_u(g)}{T_{CBM}} \qquad \forall g \in G, \forall u \in U \tag{4.53}$$

$$\sum_{g \in G}^{g+R_{CBM}} m_u(g) \leq T_{CBM} \qquad \forall g \in G, \forall u \in U \tag{4.54}$$

$$q_u(g) \leq m_u(g) - m_u(g-1), \qquad \forall g \in G, \forall u \in U \tag{4.55}$$

As earlier stated, approach 3 can achieve three different results:

- A rolling stock maintenance planning optimization integrating CM.
- A rolling stock maintenance planning optimization integrating CBM.
- A rolling stock maintenance planning optimization integrating CBM and additionally, CBM can possibly be combined with PM in one routine.

Examples of these results are plotted in eventplots that are enclosed in appendix C for each type of result.

4.6. Verification analysis

In order to prove the correctness of the established optimization model, a verification analysis should be conducted. The goal of the verification is to check whether the outcome of the programmed model is correctly executed. So with a certain initialization, a specific outcome can be expected. When the results of the model meet the expected outcome, the verification check is satisfied.
A validation cannot be performed, because this would mean that real world available data should be used in order to compare it with the results of the artificial model. This cannot be performed in the scope of this study and the analysis consists therefore solely of a verification.

Firstly, the optimization performed by the Gurobi solver in the Python environment should be verified. However, this is difficult to verify because Gurobi is an integrated solver algorithm. But since Gurobi is a professional solver algorithm, it should be assumed that no errors are made during the optimization. Secondly, the mathematical models should be verified by running its translation in programming language. Since there is a large understanding of the model, it can be expected how changing parameter values impacts the deterministic optimization solution. Therefore, logical relations between the input parameters and decision-variables as output of the model can be listed. Accordingly, these logical relations can be checked by running the model with the changed input parameters. When the outcome of the verification tests match the deterministic expectations, the test has passed. These runs are verification tests. This helps identifying errors in the model and bottlenecks of the model.

Cumulative time verification check For all models, the maximum time threshold is set to $E = 108$ days. When a rolling stock starts operation after PM, its cumulative time and mileage is getting reset to zero. The mission profile is set to 475 [km] per day. Accordingly, when the rolling stock is only in operation, it will reach the mileage threshold within $\frac{45{,}000}{475} = 94.7$ days, so the maximum amount of days the rolling stock can be in operation is then 94 days if the optimal mileage has been reached. While assuming that the rolling stock runs the maximum possible mileage, the rolling stock can be in rest ($x_u(k) = 1$) for a maximum of $108 - 94 = 14$ days between maintenance routines. This phenomenon can also be seen in figure 4.1, when from 94 up to $E = 108$ the mileage threshold be reached.

Minimal mileage losses verification The mileage losses are considered optimal when losses are 350 [km] before going to the depot for PM. The mileage threshold can be reached in 94.7 [days] of running, but the model is discretized in [days]. So in order to comply with the mileage threshold constraint 4.4, every rolling stock can only run $94 \cdot 475 = 44,650$ [km]. The minimal remaining mileage loss is therefore always $45,000 - 44,650 = 350$ [km].
Consequently, the total mileage losses over an optimization is therefore always a multiplication of 350 [km] with the amount of PM routines in the decision horizon. It is therefore reasonable to initialize the mileages of all rolling stock with a multiplication of the mission profile of $P = 475$ [km] which is shown in table 4.1. This makes it easier to verify whether the optimal solution is found. When the mileage losses per rolling stock before performing PM equal 350 [km], it can be concluded that the model found the optimal solution.

Finite horizon effect verification After solving approach 1 with Gurobi, it is observed in the outcome when the upcoming PM routine can be potentially planned after the decision horizon, that the rolling stock will not be deployed for passenger operation. These effects can be explained by so-called "horizon effects" (Berliner, 1973). Since the optimization has a finite horizon defined by parameter K, only within the decision horizon, the objective function will be optimized. This phenomenon has two consequences for approach 1.

- After the decision horizon, too many rolling stock require immediate maintenance that cannot be feasibly distributed because of the maintenance depot capacity constraints.
- The lower bound mileage threshold D_{LB} is impossible to reach for a few rolling stock if the optimization would continue after the decision horizon K resulting into an infeasible solution.

rolling stock u [-]	$e_u(k=K)$ [day]	$d_u(k=K)$ [km]	mileage where $D_{max} \leq D_{LB}$ [km]
10	97	13775	37525
11	102	1710	42750
12	107	16150	36100

Table 4.2: Model 1 optimization resulting decision variables at the end of the decision horizon with model parameters $U = 21$, O (confidential annex B section B.2), $K = 223, A = 1, A_{days} = 3$

Since PM will be postponed until after the decision horizon, this could result into a peak in rolling stock requiring immediate PM, because mileage threshold D and time threshold E are almost reached. Since the depot capacity does not allow this, a consecutive optimization initialized with the decision-variable values at time $k = K$ results into an infeasible solution.

The second consequence is proved in table 4.2. For rolling stock number 10, 11 and 12, at time $k = K$, so at the end of the decision horizon, the decision-variable values $e_u(k = K)$ and $d_u(k = K)$ are called after optimizing the PM planning with approach 1 over 32 weeks (also in figure 4.9). Decision-variable value $e_u(k = K)$ in the table shows how the rolling stock are nearing the time-threshold $E = 108$ while the cumulative mileage $d_u(k = K)$ is still below the lower bound mileage threshold $D_{LB} = 42,800$. The third column is calculated with equation 4.56, where the remaining days until time-threshold E is taken in product with the mission profile P and accordingly added up to the mileage monitored at the end of the decision horizon. If this calculated value is below the lower bound threshold, this implies that if the PM planning would continue after the decision horizon, this results into a infeasible solution because it will become impossible to satisfy constraint 4.7. For this experiment, in the given configuration this occurred only for three rolling stock 9 to 11.

$$D_{max} = d_u(k = K) + P\,(E - e_u(k = K)) \tag{4.56}$$

Lin and Zhao (2021) also observed this issue and stated that the workload of maintenance cannot be balanced adequately as a consequence. Their decision horizon consists of 7 days with a fleet of 30 rolling stock, wherein two rolling stock were not deployed at all within the decision horizon. They did not overcome this problem.

It can be observed from the PM planning results that the deployment decision-making between PM routines is dependent on the upcoming PM routine. Consequently, all deployment decision-making since the last PM routine in the decision horizon per rolling stock does unrealistically not consider upcoming PM routines. This can be seen in figure 4.9 where after the last PM routine, many rolling stock are unrealistically not in operation. This phenomenon is highlighted in the red square, because after the last PM routine, rolling stock $u = 12$ is 31 days out of operation. It has been verified in the previous paragraph and in table 4.2 that the rolling stock can only be out of operations for 14 days maximum while still reaching the lower bound mileage threshold, so 31 days out of operation is an unrealistic outcome.

A possible solution to overcome this horizon effect is therefore to disregard all maintenance decisions after the last PM routine per rolling stock. From this can be concluded that to make sure that the decision-making post last PM in the planning is disregarded, $E = 108$ [days] should be cut off the established maintenance planning. Hence, the red line in figure 4.9 is drawn to illustrate the end point for valid analyses, in this case at $k = K - E$ so $k = 224 - 108 = 116$. Consequently, every planning decision horizon should be larger than $E = 108$ days in order to retrieve reliable decision-making from the optimization models.

Finite horizon effects cannot be observed in approach 3. Because of the rolling horizon principle, the horizon becomes ”infinite”. However, when the rolling horizon optimization stops, planning after the last implementation-horizon should be disregarded. This complies with the previous statement, because the decision horizon $W < E$ and should therefore be disregarded.

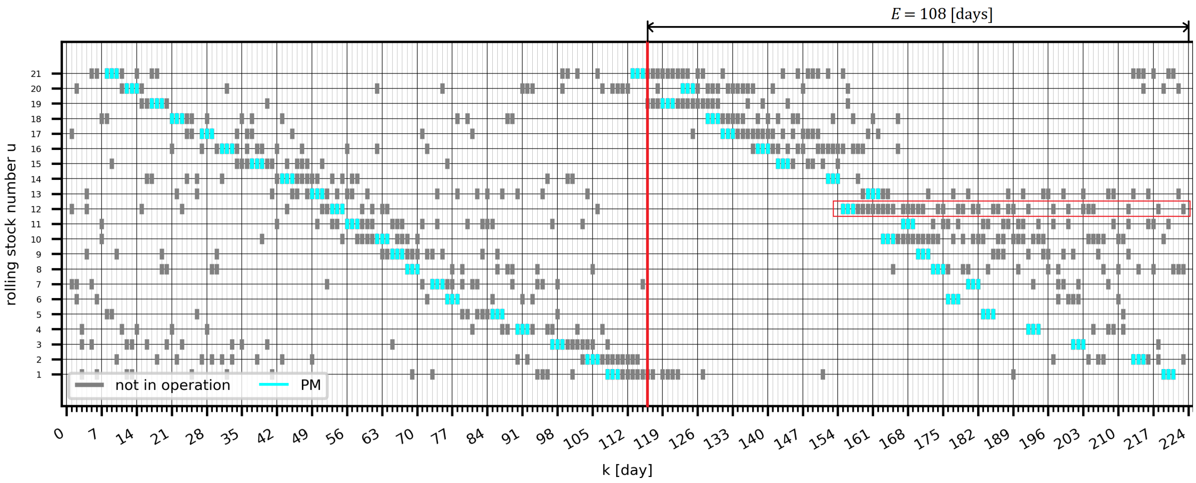


Figure 4.9: PM planning with approach 1 showing horizon effects after the last PM routine of rolling stock $u = 21$ and therefore disregarded

4.6.1. Constraint verification of approach 1

Verification checks are listed below. Since approach 2 and 3 are building on approach 1, it can be assumed that these checks also account for approach 2 and 3.

- The amount of rolling stock in operation at all times is formulated in constraint 4.8. With a verification check in figure 4.10 it, Parameter O is set to 1 rolling stock out of the $U = 4$. It can be seen that every time k, exactly 1 rolling stock is in operation, by leaving a blank.

- Constraint 4.10 and 4.11 bound the PM duration to be exactly N days. However, decision-variable $y_u(k)$ is indexed this case out of simulation-horizon K because PM can be scheduled at the end of the decision horizon $k = K$. In order to satisfy the constraint, PM still should take N days, but this this is after the decision horizon, because $K + N \notin K$. This is inspired by the rolling stock maintenance planning in the model of Lin and Zhao (2021), where the same issue is identified and solved. This is modeled for continuity of the model, so it may occur that only 1 or 2 days of PM are modeled in the decision horizon.
  A verification of this constraint is defined:
  Four rolling stock from which 1 is available are initialized as table 4.3. A decision horizon is set to $K = 7$ days. As can be seen in figure 4.10, rolling stock number 1 only has 2 days in PM (at $k = 6$ and $k = 7$) in the modeled decision horizon. The results show that this is always the case, and therefore it is satisfied.

rolling stock number u	$d_u(0)$	$e_u(0)$
1	43700	104
2	44175	105
3	44650	106
4	0	0

Table 4.3: PM routine verification initialization.

- Constraint 4.14 defines that the depot does not accept more than A arriving rolling stock over A_{days} days. While assuming that the initial mileages are a multiplication of the mission profile and the accumulated time and mileage is initially equally distributed over the fleet (table 4.1), it can be verified that in case there are 21 rolling stock, the arrival rate cannot be less than a frequency of 1 per 5 days. The solution becomes infeasible when the arrival rate is set to a frequency 1 rolling stock to be maintained per 6 days. Because that rate would result in needing $6 \cdot 21 = 126$ days for maintaining 21 rolling stock. Since the upper bound time threshold is $E = 108$ days < 126 days, the solution will become infeasible. Table 4.4 shows how this is proved for a fleet size of

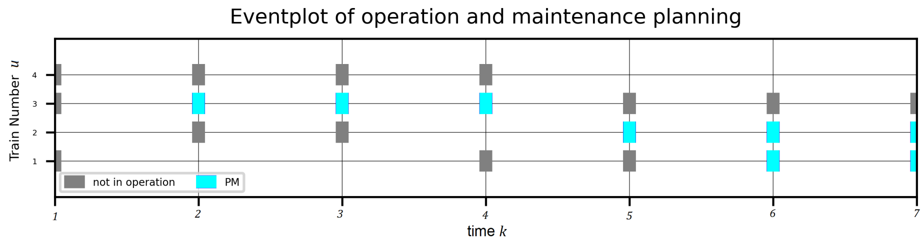


Figure 4.10: PM routine verification test.
Performed in model 1 for 1 week with Mileage loss = 1050 [km].
Relevant parameters: $O = 1$ in operation, $K = 7$, $U = 4$ depot capacity: $A = 1$ arrival per $A_{days} = 1$ day.

21 rolling stock by iterating parameter A_{days}. Additionally, this can be further checked by higher number of rolling stock as long as it is in line with the following equation:

$$\frac{Amount\ of\ days\ accepting\ arrivals}{Amount\ of\ RS\ arrivals} \cdot RS\ fleet < 108 \tag{4.57}$$

$$\frac{A_{days}}{A} \cdot U < E \tag{4.58}$$

If it does not satisfy the equation, the model becomes infeasible.

- Constraint 4.8 forces the rolling stock to be always out of operation when PM is performed, this is always the case, otherwise the constraint cannot be satisfied. Therefore, it is considered to comply at all times. Figure 4.10 shows that while performing PM, the rolling stock is considered to be not in operation.
- Because of constraint 4.10 and 4.11 that forces the model to perform maintenance 3 days, maintenance cannot be performed a different duration, this is checked to be always satisfied. However, the constraint holds for longer than the decision horizon, making it possible to plan maintenance after the decision horizon. The PM after the decision horizon is not considered in the cost objective function since it only minimizes the cost over the decision horizon. Consequently, 2 days before the decision horizon, PM may only takes 2 days, because it continues after the horizon, similarly to 1 day before the decision horizon, PM only takes 1 day within the decision horizon. This can be checked if the cumulative time rolling stock in a decision horizon of 1 week is initialized with 103 days, so it should be maintained within 6 days, resulting in only 1 day of PM in the decision horizon. Figure 4.10 demonstrates this.

amount of arriving rolling stock A:	per amount of days A_{days}:	solution result:
1	2	optimal
1	3	optimal
1	4	optimal
1	5	optimal
1	6	infeasible

Table 4.4: Verification of the depot capacity constraint, for this test, the terms in which rolling stock can arrive is iterated resulting into infeasibility when the terms are equal or larger than 6 days

4.6.2. Verification of approach 2 and 3

The mathematical model of approach 1 is built upon in approaches 2 and 3. It can thus be concluded that approaches 2 and 3 pass the verification criteria of approach 1 as well. Still, the additions of approach 2 and 3 need to be verified. This is done by means of:

- Verify the foreseeability of approach 2 and 3.
- Verify the foreseeability difference between CM and CBM with the difference in decision-making.

Foreseeability verification The premise that approach 2 can predict all initiated disruptions has to be verified. With approach 3, the formulated different decision horizons W, F and G define how far in the future events are considered for establishing the current week planning. This can be referred to as the "foreseeability".

The claim that with approach 3 cannot foresee disruptive events in the future has to be verified as well. An experiment will be set up in order to investigate the difference in foreseeability of approach 2 and 3. When this experiment is conducted with approach 2 and no mileage losses are made, this proves that approach 2 can foresee failures in the model and it becomes unsatisfactory to use for further analyses on disruptions.

For this experiment the approach is initialized with the following:

- Approach 2 is initialized with the mileage and time as defined in table 4.1.
- Approach 2 optimizes over a decision horizon of $K = 35 + E$ days, so that horizon effects are excluded and the first 35 days / 5 weeks can be used for trustworthy analysis.
- The first implementation-horizon I of approach 3 is initialized with the first 7 days of a optimization of approach 1 over 32 weeks that is also initialized according to table 4.1. Thus, there are no horizon effects.
- 1 disruption for rolling stock number $u = 18$ on day $k = 21$ for $T_{CM} = 1$ day is determined to occur with matrix $W_u(k)$, so $W_{18}(21) = 1$.
- Approach 3 performs $J = 5$ optimizations in the simulation, so including implementation-horizon, 5 weeks are optimized.

Figure 4.11 a and b show the outcome of the experiment. The CM disruptions are shown to be at the exact same timing and for the same rolling stock number in both optimizations. PM for rolling stock number 18 is in both approaches performed on the day after that the cumulative time decision-variable had the value of $e_{18}(21) = 107$. PM had to be performed immediately for that reason on day $k = 22$. However, a difference can be observed in the operational planning of rolling stock number 18 before the PM routine. In approach 2, the rolling stock was out of operation twice, while in approach 3, is was out of operation three times. So approach 2 optimized this in order avoid mileage losses. While this is not decided for approach 3, because the optimization could not foresee the disruption, the rolling stock had to be corrective maintained, hence the rolling stock did not run enough mileages in operation for minimal mileage losses.
The cumulative mileage losses are shown in figure 4.11, where it is illustrated that when PM is performed, the total mileage loss accumulates. Figure 4.12 shows as a result that in approach 3 more mileage losses are made at $k = 22$ for approach 3 with CM, while in approach 2, CM, minimal mileage losses of 350 [km] were made only.

From this can be concluded that approach 2 foresees disruptions and thus acts on this while this are realistically unforeseen events. Approach 2 is therefore unsatisfactory to further conduct experiments on in regards to analyze the impact on the decision-making of the rolling stock maintenance planning.

Decision-making difference between CM and CBM verification A second verification is performed on approach 3. This verification check will prove the difference in decision-making between CM and CBM for approach 3. A comparison is made between the same results from figure 4.12b and c.

A disruption in the form of failure can be initialized in the optimization model using approach 3. When this disruption is responsible for mileage losses because CM has to be performed, this can be compared to a situation where instead of a failure, a fault is detected and the asset has to perform CBM within the given RUL. Figure 4.12 shows that more than 350 [km] as mileage losses are made at $k = 22$ for approach 3 with CM. The same disruption as defined in $W_u(k)$ is initialized for approach with CBM, so $V_{18}(21) = 1$. The initialization of approach 3 with CBM is identical to the approach 3 with CM.

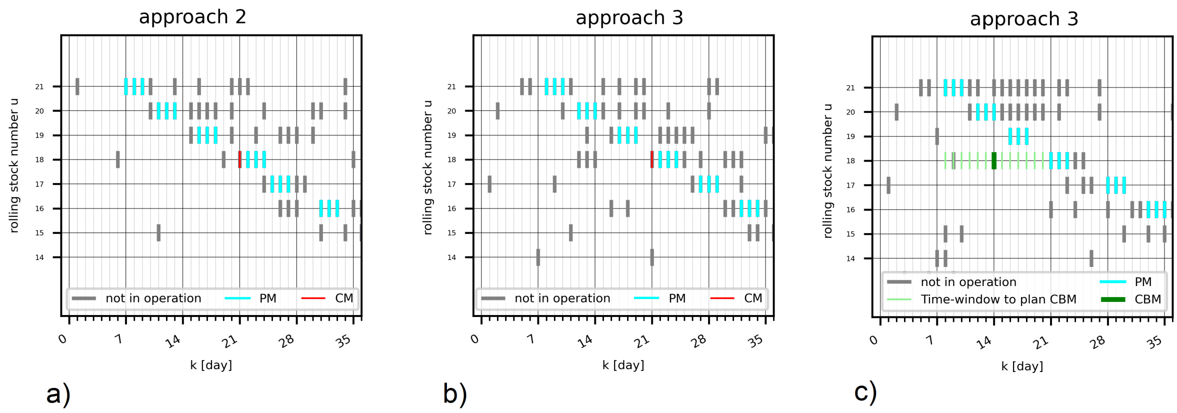


Figure 4.11: Verification of approach 2 with CM (a), versus approach 3 with CM (b), versus approach 3 with CBM (c)
$W_{18}(21) = 1$ and $V_{18}(21) = 1$
Optimization for $U = 21$, O (confidential annex B section B.2), $A = 1$, $A_{days} = 3$ [days], $R_{CBM} = 14$ [days]

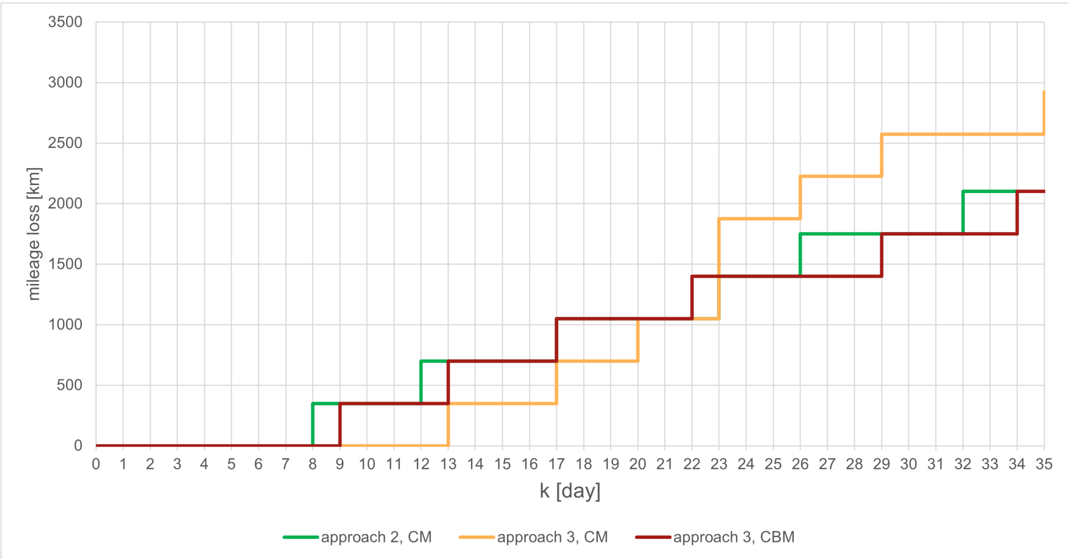


Figure 4.12: Cumulative mileage loss of approach 2 CM versus approach 3 CM versus approach 3 CBM
Optimization for $U = 21$, O (confidential annex B section B.2), $A = 1$, $A_{days} = 3$

The result of this experiment is shown in figure 4.11b and c and in figure 4.12. 4.11 b and c are identical the first 7 days, showing that they are initialized the same. Because of the flexibility of CBM, no mileage losses are made, it can be proved that CBM has a positive effect on the maintenance decision-making.

Verification of combining CBM with PM routine Decision-variable $r_u(k)$ creates the possibility with constraint 4.37 to combine CBM with PM. Note that this constraint only holds for the combination of PM after CBM, not the other way. This is reasonable, since CBM is detected first and should be maintained, while PM should be maintained within the given constraints.

As earlier discussed in the state of practice, the combination of CBM with PM is an opportunity. But a trade-off should be made between the mileage costs due to early PM with avoiding double shunting costs. Mileage costs are defined to be $C_{mileage}$ [euro] and shunting costs $C_{shunting}$ [euro]. So if the total amount of mileage costs are less than $C_{shunting}$ [euro] and it suits better in the maintenance planning, it becomes tempting for the optimization problem to combine the two maintenance routines. Therefore, the mileage losses should be less than 3125 [km] (see calculation in confidential annex B section B.4) to be still profitable. However, it is still desired to run at least 94% of the upper bound mileage threshold D, so constraint 4.7 still holds. It can therefore be verified that if the cumulative mileage of D_{LB} is reached, it becomes feasible for for constraint 4.37 to combine CBM with PM and save costs in the maintenance planning.

4.7. Concluding Remarks

By describing how the mathematical model is formulated with the decision-variables, constraints, parameters and objective function that considers the explained mileage costs, research question 3 has been well addressed.

3. *How to formulate an optimization problem for rolling stock maintenance planning considering the mileage costs and what are the associated decision-variables and constraints?*

The elements of the mathematical model are formulated using similar models from the state of the art. Passenger operations are not considered in the study which are often integrated with rolling stock maintenance planning optimization state of the art. Instead, the mathematical model is formulated to have a specified amount rolling stock available for operation that cannot be maintained as a consequence. The mathematical constraints are designed in such a way that the model resembles the maintenance planning method at the maintenance depot of NS. The objective function of the models is therefore formulated to minimize the mileage losses and PM routines. It is explained how approach 1 results into a rolling stock PM planning optimization that is in accordance with the state of the art and the state of practice. So a PM planning decision-making optimization tool is developed for NS that establishes the PM planning while making a minimum amount of mileage losses as possible.

The numerical problems that are encountered during the establishment of approach 1 are described and the methods on how to resolve these issues is explained. Solving these problems led to a linear model that can be solved in python by the Gurobi solver algorithm.

The optimization approaches 1 and 2 are further verified with verification checks showing for example that for approach 1 and 2 only the maintenance planning up to day $k = K - E$ can be used as realistic planning due to the described horizon effect.

Research question 4 is also addressed in this chapter by formulating approach 3 that establishes the rolling stock maintenance planning using the rolling horizon framework.

4. *How to design a rolling stock Preventive Maintenance planning algorithm for integrating Corrective Maintenance or Condition Based Maintenance?*

Approach 2 conducts a single optimization considering all of the initialized disruptions over the decision horizon a priori, but the approach is unable to process updates and other disruption in the planning. With approach 2, an unrealistic outcome is generated, because the optimization is able to take upcoming failures into account. Hence, approach 2 is not satisfactory for evaluating the impact of disruptions on the maintenance planning decision-making.
The state of the art showed how to overcome this problem by using a rolling horizon as framework. A rolling horizon framework can be used in order to simulate rearrangements in the planning as a result of newly appearing disruptions. Ultimately, approach 3 is satisfactory for analyzing how planning maintenance based on prognostics impact the decision-making for rolling stock maintenance which will be performed in the next chapter.

5
Sensitivity and Results

In this chapter, the performance of the formulated maintenance optimization approach 1, 2 and 3 and will be evaluated. The approaches have been be verified.
The actual fleet of SNG at NS consists of 190 available rolling stock. This large fleet number results into very long computational times and the current computer on which the optimization runs does not have sufficient numerical capacity. The computational time increases as the amount of rolling stock increases, because it enlarges the size of the optimization problem, similar to the decision horizon. Due to these computational limitations, the fleet size has been down-scaled to 21 rolling stock in order to evaluate the performance of the optimization approaches in this chapter.

Research question 5 will be addressed in this chapter by comparing and evaluating the outcome of the rolling stock Preventive Maintenance planning algorithm considering the integration of CM or CBM according to Key Performance Indicators.

5. *How to evaluate the performance of the rolling stock Preventive Maintenance planning algorithm considering the integration of Corrective Maintenance or Condition Based Maintenance?*

This research question will be answered by evaluating the performance of approach 3. Approach 3 can achieve 3 different results that should be compared:

- The rolling stock maintenance planning optimization integrating CM.
- The rolling stock maintenance planning optimization integrating CBM.
- The rolling stock maintenance planning optimization integrating CBM and additionally CBM can possibly be combined with PM in one routine.

Comparisons between results can be used to assess performance and justify the impact of CM and CBM on the rolling stock maintenance planning. This includes also the cost effectiveness of combining CBM with PM in the rolling stock maintenance planning.

Ultimately the main research question will be answered:

What is the impact of integrating Condition Based Maintenance in the Preventive Maintenance planning decision-making?

5.1. Key Performance Indicators of the maintenance planning optimization

To quantify the performance of an optimization approach, multiple Key Performance Indicators (KPI's) are generally used in the state of the art and the state of practice. An KPI is a quantitative value that reflects the performance of an approach. KPI's can thus be used to evaluate and compare the performance of different approaches. The following KPI's based on the state of the art and state of practice will be used for the analysis in an order from highest priority to low:

1. **Mileage losses**: The mileage losses are calculated in the objective function. The equation that isolates this KPI is formulated in equation 5.1. This KPI is found in the state of the art and NS uses the mileage losses as KPI as well. The optimization is increasingly less optimal the more mileage losses are incurred and therefore is this KPI from the highest priority. Since it is assumed for modeling purposes that every rolling stock runs constantly 475 [km] per day when in operation ($x_u(k) = 0$) and the mileage threshold is $D = 45,000$ [km], the optimal mileage losses is nonzero. $\frac{45,000}{475} = 94.7$ is not a round number and therefore the maximum amount of days that a rolling stock can be in operation before PM is 94. Consequently, the mileage losses are $45,000 - 94 \cdot 475 = 350$ [km] per rolling stock as minimal value. The optimal value of mileage losses in the decision horizon is therefore the a multiplication of PM routines with 350 [km].

$$\sum_{k \in K} \sum_{u \in U} D y_u(k) - d_u(k-1) y_u(k) \tag{5.1}$$

2. **Feasibility**: When the optimization is initialized with parameters values that cannot be bounded by the formulated constraints, it is impossible to find a feasible solution. In the case of the maintenance planning, the infeasibility can be coupled to the problem formulation. When the maintenance depot is too full and a rolling stock should be maintained for example. Or when a disruption takes place and not enough rolling stock can be available as a consequence.
Therefore, a maintenance planning approach that puts out a feasible solution is thus better in decision-making than a planning that results into a infeasible solution. A feasible solution will be considered as a success. An infeasible solution is a cumulative result of poor decision-making in the past or due to unfortunate disruptions.

   This KPI cannot be found in other studies or in practice. However, it became evident that this KPI directly shows the difference in quality of decision-making, since poor decisions result into infeasible solutions. As a result, this KPI is considered to be important.

3. **Combinations of CBM with PM**: As discussed, CBM can be planned in advance. When the RUL is overlapping the nearest PM routine in the planning, this can be used as an opportunity in the to combine CBM with PM, saving shunting costs. Since this is highly desired, the amount of combinations are used as KPI. The higher the number of combinations the better. However, this might be at the expense of the mileage costs.

4. **Maintenance costs**: The maintenance costs can be obtained directly from the objective function 4.1. This KPI indicates the total performance and is optimal when the mileage losses are minimal and the time between PM routines is maximal. This KPI indicates to overall outcome, but does not necessarily specify how the optimization is performing, therefore, other KPI's have more priority.

5. **Total amount of PM routines in the decision horizon**:
The total amount of PM routines in the decision horizon can indicate the efficiency of the PM planning. This KPI is related to the decision horizon length, because when a time of $E = 108$ days has passed, every rolling stock had PM once. When the decision horizon length is a multiplication of E, the least amount of PM routines can be calculated, by performing the same multiplication number times the total rolling stock, this is defined to be the least amount and thus optimal. When this has not been reached, it can be concluded that the outcome of the optimization is sub optimal. Doganay and Bohlin (2010) approached this KPI by calculating the time between PM routines and integrating this in the objective function. However, this is not done for the approaches is this study hence, the amount of PM is used as KPI.
This KPI can be calculated by summing decision-variable $w_u(k)$ that has the value 1 when a rolling stock arrives at the depot for PM. Note that only PM is counted in the domain that does not include horizon effects as is explained in previous chapter with the verification. The domain $k \in \{0, ..., K - E\}$ is therefore used for performance evaluation.

$$\sum_{k \in \{0,...,K-E\}} \sum_{u \in U} w_u(k) \tag{5.2}$$

Since the rolling stock maintenance planning is only optimized over a relatively small fleet in comparison to practice and the planning for approach 3 will only be computed for 133 [days], the value of this KPI is relatively small. The number of PM routines grow over longer periods and larger fleets so that variations of this KPI become less significant as a result. It is therefore expected that this KPI is a better indicator for larger fleets and longer periods, hence for this analysis, the KPI is not highly prioritized.

6. **Computational time**: The computational time to the optimal solution is considered to be an KPI of the optimization approaches. This KPI indicates complexity of the problem and the complexity of resolving a problem because of disruptions in the planning for example. Since the computational time is not considered to highly contribute to the qualility of the solution, this KPI has the lowest priority.

5.2. Sensitivity analysis

For a broader understanding of the optimization, performing a sensitivity analysis helps identifying computational relations of the approaches. The sensitivity analysis is performed by iterating input parameters and accordingly checking the optimization results. It is expected that certain input parameters have an effect on the computational optimization and outcome of the approaches. This has to do with the computational capacity and algorithm version, thus the available computer with processor (Intel(R) Core(TM) i7-6700HQ CPU with 2.60GHz), computed at Gurobi Version 10.0 and Python 3.8. The effect of the iterations can be measured with the outcome. These analyses will be performed separately with every approach. The differences of the outcome will be ultimately compared between the three approaches. Analyses and comparisons will be made based on KPI's that are previously defined in section 5.1.

decision horizon It is expected that the computational time increases significantly every time when the decision horizon is increased. It is expected that less PM has to be planned when the decision horizon is shorter than the time threshold. This will result into shorter computational times.

Optimality Gap The Gurobi solver optimizes the formulated program to the best solution. The optimality gap is defined by Gurobi as: $gap = \frac{|z_P - z_D|}{z_P}$, where z_P is the primal objective upper bound for minimization problems and z_D the lower bound for minimization problems. The quality of the solution usually depends on the optimality gap, indicated in a percentage. The closer the gap to zero, the better the solution is. It is desired to obtain a optimality gap of 0%. However, this usually is expensive because it costs a lot of computational time. A feasible solution with a slightly larger optimality gap is in some cases already satisfactory, because it can be verified that there is no better solution. This may also depend on the objective function formulation and how the solution is bounded. Méchain et al. (2020) described for the rolling stock maintenance planning how the computational time impacts the optimality gap. It was concluded that the longer the computational time, the better the solution, but this relation is not linear. The optimality gap decreases minimally over the long run and it is therefore not worth the extra computational time.

decision horizon length The decision horizon length ultimately determines how many PM routines are performed since this is time dependent. The longer the decision horizon is, the more PM are decided to be planned. Since all decision-variables are related to the decision horizon length, the model size exponentially grows as the decision horizon increases. It is therefore expected to have a large impact on the computational time.

5.2.1. Sensitivity analysis approach 1

With approach 1, only costs are minimized that are made by not sufficiently utilizing the mileages that a rolling stock may run before going to the depot for Preventive Maintenance. So the final objective cost value of approach 1 is only influenced by the mileage losses and the amount of PM routines in the decision horizon. It can be verified what the optimal minimum costs are depending on the decision horizon and amount of rolling stock. However, while the optimal costs are achieved, the optimality gap is not yet closed to 0%. Therefore, for this sensitivity analysis, the influence of the optimization gap on

the maintenance decision-making while the minimal costs are achieved will be analyzed.
Also the influence of the decision horizon length will be analyzed.

Optimality Gap For the approach 1, from the objective function and knowing how much maintenance should minimally take place in the decision horizon for a fleet size of 21 rolling stock and the costs according to this, the optimal solution may be calculated as can be seen in the dotted line in figure 5.1. This optimal solution was already found while the optimality gap was still 6.71%, as can be seen in figure 5.1. It can be noticed that the objective costs is therefore steady at 208,659.36 [euro]. From this can be concluded that the optimality gap does not necessarily relate to the best solution. This can also be proved because while the verified solution is found, the Gurobi solver still runs while the optimality gap decreases (as figure 5.1 shows a decreasing optimatilty gap at time 698 [s] to 796 [s]), but the best solution of 208,659.36 [euro] is already found at 538 [s]. This phenomenon can be seen in figure 5.1. This implies that the gap should not be necessarily closed to 0% in order to compute performance evaluation results for the optimization approached. A stopping criteria for approach 1 is defined as the following: The optimality gap is either less than 1% or the algorithm did not find a better solution in 1800 [s] time.

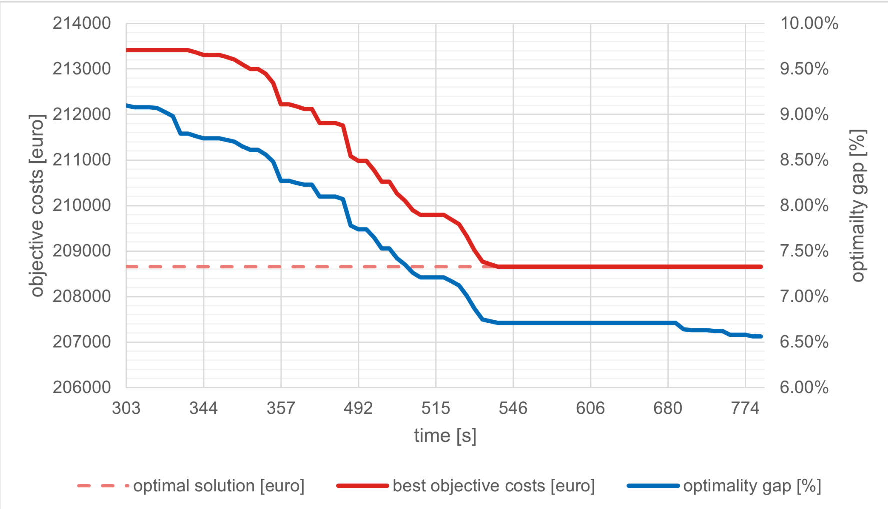


Figure 5.1: Optimization computation approach 1 PM planning 224 [days], 21 rolling stock.
The graph shows the maintenance costs (red) and optimal costs from on the left y-axis (costs are multiplied with factor Y see confidential annex B section B.1) and the optimality gap (blue) on the right y-axis

decision horizon length iteration The decision horizon length is iterated from 16 up to 40 weeks with increments of 4 weeks. The Gurobi solver is used to solve the MILP problem, but for quicker computation, the Gurobi solver parameter "NoRelHeurTime" is adjusted (Gurobi Optimization, 2022). With this parameter, the computation of the optimization starts with 300 [s] of heuristic solving. This is a robust method that finds feasible solutions quickly of the MILP problem. The found solutions are often far from optimized, but the they are used by the algorithm as starting point of the optimization after 300 [s].
The stopping criteria for the optimization is preserved from the previous analysis: The optimality gap is either less than 1% or the algorithm did not find a better solution in 1800 [s] time. This method is used consistently through the iteration of the decision horizon.

The for all approaches, the optimization is initialized with 21 rolling stock according to table 4.1. After 16 weeks (112 days), the maximum time threshold $E = 108$ days for PM just passed, so every rolling stock went to the depot for PM at least once. The decision horizon has to be at least 16 weeks in order to avoid horizon effects, therefore the iteration is selected to begin at $K = 112$ [days]. Figure 5.2 shows that the computational time up to a decision horizon of 32 weeks is relatively quick, being within 45 minutes (2500 [s]). From that point every rolling stock had its second PM routine in the decision

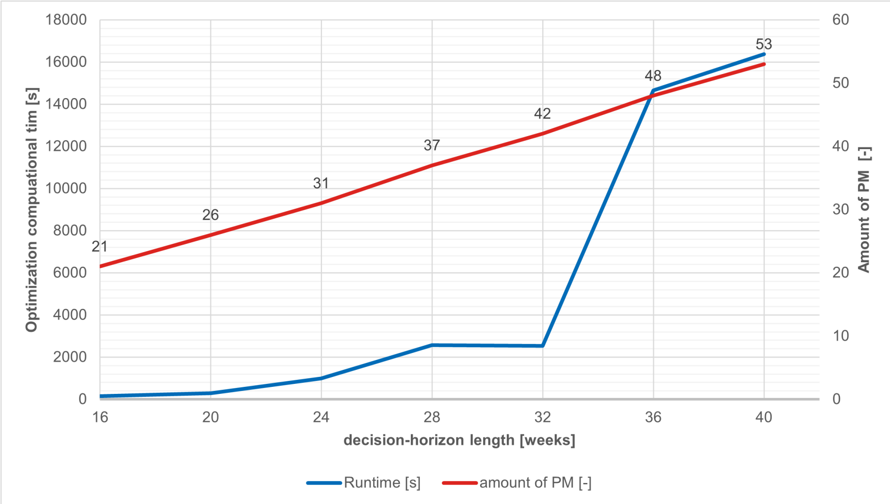


Figure 5.2: Illustration how the decision horizon length influences the computational time (left y-axis) and how the amount of PM (right y-axis) increases linearly with the decision horizon for a fleet of 21 rolling stock

horizon. Once a few rolling stock in the planning must go for their third PM routine, the computational time spikes to almost 4 hours for a decision horizon of 36 weeks and even longer for 40 weeks. It has to be noted that the mileage loss KPI is optimal with every iteration. The linear increase in the decision horizon coincides with a linear rise of PM routines. From this can be concluded that the computational time increases significantly once the decision horizon is longer than 32 weeks and some rolling stock are planned for their third PM routine in the decision horizon.

5.2.2. Sensitivity analysis approach 2

From approach 1, the optimal solution can be retrieved. With the verification of approach 1 and its optimal solution, the minimal objective costs can be calculated for approach 2 as well. Because for approach 2, the only addition is that CM or CBM is included in the planning, resulting into extra shunting costs and CM or CBM costs. These costs can then be added to the minimal solution of approach 1. When this value is programmed as parameter in the Gurobi solver environment as ”Best objective”, the solver automatically stops, regardless of the optimality gap. Consequently the optimal solution can be found and if this cannot be reached, it can be concluded that CM disrupts the planning in such a way that the optimal solution cannot be achieved.
The influence of the increasing number of CM over a constant decision horizon is iterated in order to analyze the impact of CM on the maintenance planning optimization computational time.

However, it can be concluded that the increasing number of CM and CBM over the decision horizon has no logical effect on the computational time. Because no observable relation in computation is observed, this is excluded from this study.

5.2.3. Sensitivity analysis approach 3

Approach 3 performs the same optimization method as for approach 1 and 2. Hence, the sensitivity for approach 1 and 2 also applies to approach 3. However, for approach 3, the rolling horizon framework is added, so horizon effects are excluded in this approach. Therefore, the conclusion from the verification check on approach 1 and 2 concerning horizon effects do not apply to approach 3. As a result, the decision horizon W in approach 3 may be shorter than the PM time threshold E

The decision horizon length have according to the study of Bougacha et al. (2022) an enormous impact on the decision-making and also on the computational time. In order to comprehend how the decision horizon W impacts the output, this parameter will be iterated for the sensitivity analysis.

The decision horizon is iterated from 2 to 16 weeks as can be seen in table 5.1. For this iteration, no disruptions are initialized in the model, only a PM planning is conducted during these optimization.

It can be concluded that from a decision horizon of $W = 13$, the rolling horizon optimization is stable and results into a feasible and optimal solution. Similarly to approach 1 and according to the sensitivity analysis considering the computational time as a result of the decision horizon length, approach 3 takes also longer to solve as decision horizon length increases. It is therefore desired to solve the problem with a decision horizon length as small as possible. Considering these two factors, is has been decided that a decision horizon of $W = 14$ will be used for further performance evaluations of approach 3.

decision horizon W [weeks]	infeasible after j [weeks]
2	2
3	6
4	21
5	20
6	18
7	> 32
8	22
9	> 32
10	> 32
11	7
12	14
13	> 32
14	**> 32**
15	> 32
16	> 32

Table 5.1: decision horizon W iteration for approach 3 with rolling horizon over j optimizations in the simulation horizon without CM or CBM
The decision horizon length of 14 weeks is chosen as demonstrated in bold

5.3. Results of the rolling stock maintenance planning optimization approaches

In section 5.1, the KPI's were defined from which the performance of the rolling stock maintenance planning optimizations can be evaluated and quantified. This section, the performance of the formulated verified approaches will be compared and evaluated on their decision-making. Ultimately, these conclusions can be used for the discussion that describes the impact on the integration of CBM on the PM planning.

5.3.1. Rolling stock availability for operation in approach 1

From the "bakkenstand" of NS, it is assumed that the availability of rolling stock should be $O_{percentage}$% so a parameter value for availability of O for a fleet of $U = 21$ rolling stock is considered (see confidential annex B section B.2). However, the "bakkenstand" is an average percentage over a whole week. More availability is required in peak hours or peak days as more passengers should be transported. Moreover, because of Covid19 for instance, less rolling stock were required because less people needed transportation services (Hildebrand, 2022). Therefore, it is analyzed how the required availability of rolling stock influences the decision-making for PM.

For this analysis, the amount of rolling stock in operation is analyzed with approach 1 by iterating parameter O with $U = 21$ rolling stock in total. The decision horizon is set to $K = 224$, however, because of the horizon effect, only the planning up to $k = 224 - E$ is analyzed. The outcome of the analysis is expressed in total mileage losses and total amount of PM in the decision horizon.

Parameter O is iterated from 15 up to 20 rolling stock in operation. For a value of $O = 16$ and lower, the optimal mileage loss (350 [km] per PM routine) cannot be achieved. In these optimizations, too few rolling stock had the chance of running operation and accumulating mileages as can be seen in table 5.2. Therefore the mileage threshold has not been reached when the time threshold is nearly reached. Consequently, the maximum mileage threshold is below 45,000 [km] resulting into higher mileage losses overall because all rolling stock will be maintained prematurely.
With optimization with $O < 16$, the problem becomes infeasible because the rolling stock runs too little

mileage in order to even reach the lower bound mileage threshold before reaching the time threshold. Figure 5.3 illustrates the cumulative mileage losses over time with the parameter values of O that can be iterated. As earlier described, the minimal mileage loss is 350 [km]. Consequently steps in the figure are steps of 350 [km] accumulating every time a rolling stock undergoes PM. However, the steps for the simulation where $O = 16$, the steps are larger than 350 [km], indicating that the mileage losses are made.

The cumulative mileage and the quantity of PM increases when an optimization is conducted with parameter $O = 20$ as opposed to $O_{percentage}$ by default. A few rolling stock are thus unable to cover enough kilometers when only 1 out of every 21 assets of rolling stock can be unavailable. A concession is made in the optimization by deciding to let 5 rolling stock perform early PM in order realise PM with minimal mileage losses for the remaining rolling stock (at k =3, 50, 53, 76 and 99). This can be explained by the fact that rolling stock run too much mileage and require PM more frequently, hence why 23 rolling stock are maintained in only 116 days. With too many rolling stock requiring maintenance, the depot capacity restricts rolling stock from running the optimal mileage can be concluded. Practically, two conclusions can be made from the sensitivity of the parameter O:

- As less rolling stock are required for operation than the "bakkenstand", the deployment of rolling stock becomes less. This results into less running mileages before reaching the time threshold for PM resulting into mileage losses.
- When more rolling stock are required for passenger operation than the "bakkenstand", the mileage threshold is reached earlier in time resulting into more PM routines in total. Due to the more PM routines in total, the maintenance depot workload becomes higher.

Finally, the conclusion can be made that for a required availability of $O_{percentage}$%, an optimal solution can be found, so no more than 350 [km] in mileage losses are made every PM routine. This proves that the model is capable of optimizing the rolling stock PM planning.

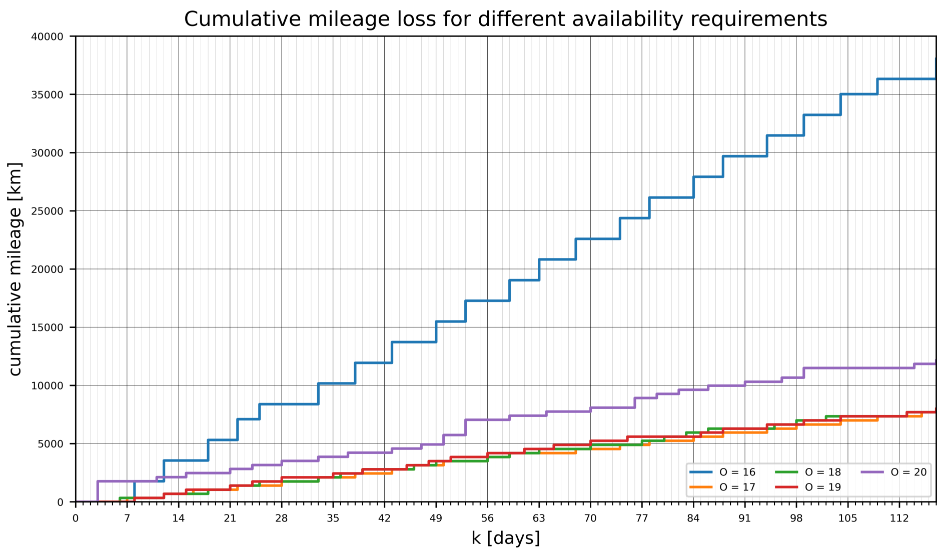


Figure 5.3: Iteration of availability parameter O resulting in different cumulative mileage losses over the decision horizon. Optimization run with $U = 21$, $A = 1$, $A_{days} = 3$ optimization over $K = 224$ values retrieved from the domain $K - E$

availability O [-]	PM in horizon [-]	accumulative mileage loss [km]
16	22	36325
17	22	7700
18	22	7700
19	22	7700
20	23	11850

Table 5.2: Iteration of availability parameter O.
Optimization run with $U = 21$, optimization over $K = 224$ values retrieved from the domain $K - E$
The lower, the better

5.3.2. Performance of approach 3 comparing CM with CBM

The optimization approaches are very capable of minimizing the costs of the maintenance planning with a minimal amount of mileage losses, which has been shown by the evaluation of approach 1.
CM and CBM are disruptive factors in the maintenance planning. However it can not always be observed based on the KPI's that CM and CBM disrupt the planning. So CM and CBM are sometimes not disruptive enough to the planning to have an effect on additional maintenance costs. There may however occur some instances of CM in the planning that result into sub-optimality indicated by the increased mileage costs due to premature PM.

Because of a failure in a rolling stock, it has to go to the maintenance depot for CM and it becomes unavailable. Due to this unavailability, the rolling stock cannot run operation for a certain amount of time. In the meantime, the cumulative time is increasing, nearing the time threshold for PM. So since the rolling stock is unable to run enough distance before the time threshold, mileage losses are made. This has been identified in the verification of approach 3 with CM in the previous chapter.

To measure the impact of disruptive CM and CBM on the PM planning, instances of CM and CBM will be initialized in random matrix $W_u(k)$ and $V_u(k)$. Approach 3 will be used for this analysis since it has been verified that CM is unforeseen in the planning and CBM is foreseen in the RUL. The matrices $W_u(k)$ and $V_u(k)$ will be initialized in such a way that disruptions always occur at the first day of the week ($k = 0, k = 7, k = 14$ and so on), because the implementation horizon I is one week or 7 days. In this way, the unexpectedness of CM is perfectly simulated, because with the rolling horizon, the disruption appears in the disruption horizon F right after the last implemented day. Therefore, there is no way for the optimization to prepare for this disruption.

The instances in random matrix $W_u(k)$ and $V_u(k)$ will be chosen as follows:

- No more than 1 disruption per rolling stock over the simulation horizon.
- Amount of disruptions (R for CBM and Q for CM) are iterated from 4 to 12 with increments of 1: $\{4, 5, 6, 7, 8, 9, 10, 11, 12\}$.
- The disruptions will be randomly distributed over the simulation horizon from $k = 21$ to $k = 98$ with increments of 7 days: $\{21, 28, 35, 42, 49, 56, 63, 70, 77, 84, 91, 98\}$.
- No more than 3 disruptions per day, otherwise, not enough rolling stock can be available for passenger operations due to parameter O.
- The RUL length of $R_{CBM} = 14$ [days] is chosen for the comparison of CBM with CM.
- 20 different randomization configurations (random seeds) are used in order to exclude coincidences of successes.
- A planning will be established with approach 3 for $J = 19$ weeks so 133 days. This differs from the results of approach 1, because no horizon effects can take place.

Disruptions resulting into losses It has been shown in the PM planning from approach 1 that in the time between PM routines, the rolling stock does not always have to be available for operations. It became apparent that in 108 days, the rolling stock could be 13 days out of operation. So when a rolling stock becomes unavailable due to a failure or a fault detection that requires maintenance, the planning can resolve this by substituting another rolling stock for the unavailable one. And if a rolling stock becomes unavailable for a longer period of time, the optimization approach resolves this by deploying this rolling stock after CM or CBM as much as possible in order to minimize the mileage losses.

The sensitivity of the time of CM and CBM (parameters T_{CM} and T_{CBM}) on the maintenance planning is therefore analyzed for 1 day and 2 days. The same method for increasing disruptions is used as previous section. However, the percentages shown for $T_{CM} = 1$ and $T_{CBM} = 1$ are only the result out of 5 random configurations, while the other percentages are a result out of 20. Also the iteration of amount of disruptions increases with increments of 2.

Table 5.3 shows the outcome of this analysis. When the table shows that 100% of the times no mileage losses are made, this means that over a planning over 133 it did not occur that the planning became disrupted by the CM or CBM and no mileage losses are made. From the table can be concluded that the duration of CM or CBM of one day have no disruptive effect on the planning and never result to mileage losses. Alternatively, if CM or CBM takes 2 days, it has an effect on the mileage losses. The disruptive effect is relatively small, since still for 44% of the configurations, the minimum amount of mileage losses can be reached for $T_{CM} = 2$. Still a difference between CBM and CM can clearly be identified, because with CBM the percentage of optimal mileage losses is consistently higher than with CM.

From this analysis can be concluded that the optimization is very capable of optimizing the PM planning despite a number of disruptions of CM or CBM and mileage losses do not have to be made necessarily. However, it can be shown that a disruption due to CM more likely results into mileage losses. Since the analysis demonstrated that duration of 2 days for CM and CBM is disruptive, this duration is chosen to be used for further evaluations.

	CBM	[%]	CM	[%]
amount of disruptions [-]	$T_{CBM} = 1$	$T_{CBM} = 2$	$T_{BM} = 1$	$T_{CM} = 2$
4	100	87.5	100	66.7
6	100	75	100	44.4
8	100	80	100	55.6
10	100	80	100	75
12	100	50	100	0

Table 5.3: Percentage of solutions resulting into minimal mileage losses, iterated for 1 day and 2 days duration of CM or CBM The higher, the better

Performance of the maintenance planning optimization comparing the integration of CM with CBM while increasing disruptions The results of 9 iterations over 20 random configurations are presented by showing the KPI's in graphs. This means that for CM and CBM each, $20 \cdot 9 = 180$ optimizations are performed.

The first graph 5.4 shows the comparison in percentage of infeasible solutions between CM and CBM. What can be seen from the figure is that in any optimization with disruptions, for either CM and CBM, a certain amount of cases become infeasible. No logical relation of infeasible solutions can be noticed for CBM, because for 4 to 6 disruptions, 45% of all optimizations become infeasible and with 9 disruptions, only 15% is infeasible. It can be stated that the percentage of infeasible solutions is stable throughout the iteration and on average 42.2%.

On the contrary, there can be a significant increase in infeasible solutions observed for CM, the more disruptions take place in the simulation horizon. From an amount of 9 CM in the simulation horizon, the amount of infeasible solutions steadily increases with respect to the amount of CM up to a percentage of 85%, while for the same amount of disruptions only 35% of the optimizations integrating CBM came

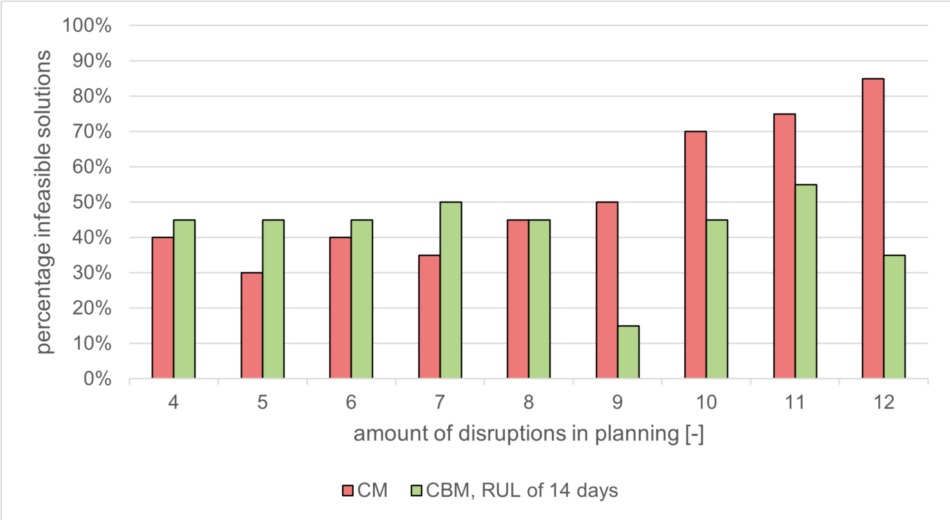


Figure 5.4: Percentage of infeasible solutions out of 20 random configurations, a comparison between CM and CBM with increasing amount of disruptions

out as infeasible. However, for the disruptions amounts 4 to 7, more CBM infeasible solutions came out the optimizations, on average 41.2% against 36.3% for CM.
For a low amount of disruptions in the planning, CM came out 5% better in optimization performance in comparison to CBM. However, in total, 27 more solutions are found with a planning with CBM than for CM. Moreover, there is no sign of a trend in infeasible solutions for CBM whilst there is for CM.

Graph 5.5a and 5.5b are whiskers plots. These whiskers plots show the performance of the feasible solutions that integrate CM or CBM indicated by the mileage losses. The average mileage loss over the complete rolling stock maintenance planning is selected from every feasible solution and categorized per amount of disruptions. The data is plotted in a whiskers plot that demonstrates that 50% of all of the solutions are in the box, showing the spread of data and the median (middle stripe in the box). The ”x” indicate the average and the ”dots” indicate the outliers of the data set. The standard deviation is demonstrated by the bars when this is outside of the box.

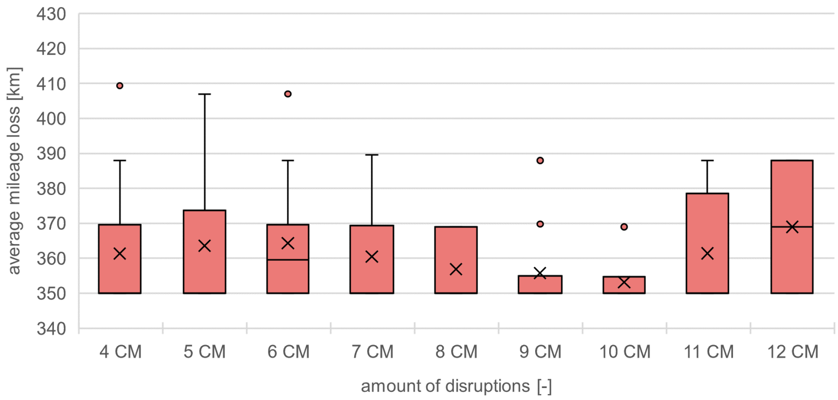
Firstly, it can be noticed that in figure 5.5b, for 4 to 10 disruptions, there is no box. This implies that the median, the first and second quartile of data lies within the same point of 350 [km]. This means that the majority of feasible solutions integrating CBM into the maintenance planning make no mileage losses on average. When 11 and 12 disruptions take place in the planning, the spread of mileage losses becomes higher, so more mileage losses are made on average when more disruptions take place.

Alternatively, the whiskers plot 5.5a for CM solutions show that the spread of average mileage losses is higher in comparison to CBM, since the standard deviation reaches higher and the median is at a higher number of mileage losses. This implies that mileage losses are made more often in an optimization integrating CM in comparison to an approach with CBM. So the performance of the maintenance planning optimization integrating is lower when CM is considered.

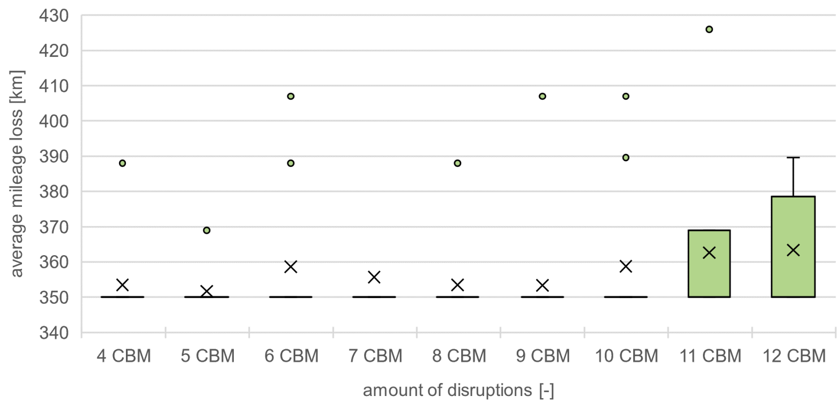
It can be observed that the mean average of the data sets per box is sometimes higher for CBM than for CM (with 10 and 11 disruptions). This can be explained by the outliers that can be found in graph 5.5b, resulting into a significant increase of the mean average. This leads to the conclusion that, while the performance of a maintenance planning integrating CBM is overall more successful than CM, mileage losses are very large with CBM on average when they actually occur.

This evaluation quantifies that a rolling stock maintenance planning integrating CBM is better to plan, based on the 27 more feasible solutions out of the 180 optimizations. Besides, a trend is observed for the maintenance planning optimization integrating CM, that ’the more disruptions take place, the higher the chance is that no solutions can be found’.

The evaluation based on the whiskers plots quantifies that CBM is more than halve of the times able to establish a rolling stock maintenance planning without inducting more than optimal amount of mileage losses. Meanwhile the spread of overage mileage losses for a planning considering CM is higher. This implies that it frequently occurs that mileage losses are made when a disruption in the planning is unexpected.



(a) CM



(b) CBM, RUL of 14 days

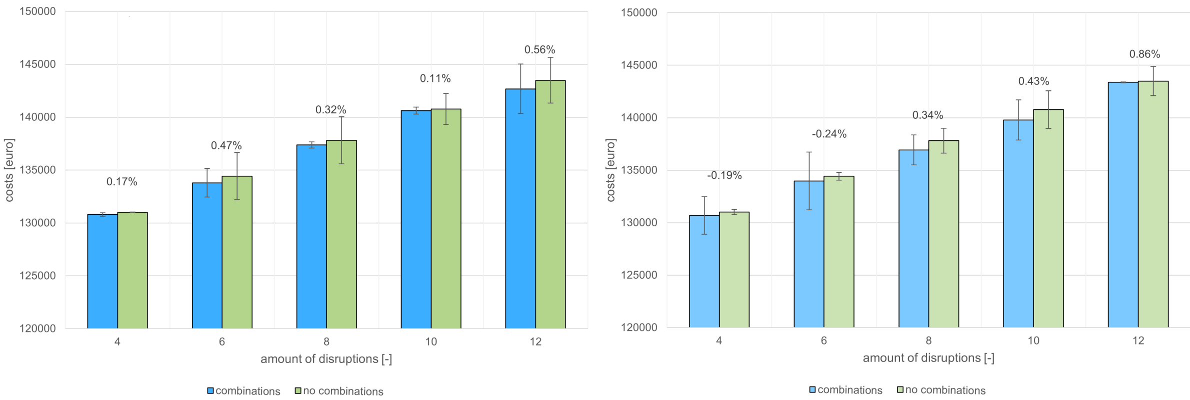
Figure 5.5: Whiskers plot of the average mileage losses (y-axis) that are made by by the feasible solutions that successfully integrated CM (a) and CBM (b), categorized by the amount of disruptions occurring in the planning (x-axis).
Dots demonstrate outliers of the data set, "x" indicates the mean average mileage loss and the bars indicate the standard deviation.

5.3.3. Performance of approach 3 with opportunity to combine CBM with PM

Approach 3 provides the opportunity to combine CBM with the PM routine. Since with CBM, the time to failure of the rolling stock is indicated with the RUL. When this occurrence is close to an upcoming PM routine, the two maintenance routines can be combined. A "combination" refers to the combination of CBM with PM in one maintenance routine. An example of how this is combined is illustrated in appendix C in figure C.3 If this combination is feasible to plan, it reduces shunting costs, because the rolling stock only has to go to the depot once. The maintenance costs are directly related to the amount of combinations of CBM with PM, since every combination saves $C_{shunting}$ [euro] in shunting costs. However, the costs also depend on the extra mileage losses that are made. As is verified, combining CBM with PM is a trade-off between mileage losses and shunting costs.

A case will be initialized with approach 3 similarly as the previous two cases where disruptions are randomly initialized in disruption matrix $V_u(k)$. The same method is used for the following evaluation where the opportunity is given that a combination of CBM with PM can take place. This is realized with decision variable $r_u(k)$. For this performance evaluation:

- 20 random configurations for $V_u(k)$ are used with the same conditions as previous case.
- The RUL indicated by parameter R_{CBM} is iterated from 7 to 21 with increments of 7, so $\{7, 14, 21\}$ [days].
- The amount of disruptions R is increasing over the iterations is performed with increments of 2, so: $\{4, 6, 8, 10, 12\}$.



(a) CBM, RUL of 14 days

(b) CBM, RUL of 21 days

Figure 5.6: Comparison of the average maintenance costs (multiplied with cost factor Y from confidential annex B section B.1) of approach 3 for CBM with a RUL of 14 days (a) compared to CBM with a RUL of 21 days (b), where in blue, combinations are possible, in green without combinations of CBM with PM.
The costs savings are expressed in percentages and the error bars demonstrate the standard deviation of the maintenance costs.

The performance of approach 3 with combinations can be evaluated with the KPI that expresses the amount of combinations of CBM with PM. The results are expressed in table 5.4 that shows the average number of combinations that are made in the planning for a RUL of 7, 14 and 21 days in relation to the amount of disruptions in the planning.
It can be seen in table 5.4 that the longer the RUL, the more combinations are made. This is expected, because the longer the RUL, the higher the chance in overlap with the upcoming PM routine. Additionally, the more disruptions that take place, the higher the chance that there is an overlap between the RUL and the upcoming PM routine.

Approach 3 with possible combinations is compared to approach 3 where no combinations are permitted. The comparison is made with the average maintenance costs as KPI. This costs comparison is presented in figure 5.6a and b. The average maintenance costs are provided in these figures as a result of combinations in relation to the amount of disruptions by CBM in the optimization for an RUL of 14 days and 21 days.
Graph 5.6a illustrates by the comparison that the mean average maintenance costs are very close, but overall, the percentages show positive costs savings if combinations are possible in the planning. Alternatively, graph 5.6b illustrates that for 4 and 6 disruptions, the maintenance costs are on average not less than approach 3 without combinations. This is logical, because less cost savings can be made to lower the amount of disruptions as is concluded from table 5.4. However, the standard deviations show with the lower bar that the maintenance costs are generally lower than for approach 3 without combinations.
Overall, for an RUL of 14 days over disruptions from 4 to 12, an average cost savings of 0.32% is made. The graph of figure 5.6b shows the relations that the more disruptions take place, the higher percentage in costs are saved. For an RUL of 21 days over disruptions from 8 to 12 resulted to an

average cost saving of 0.54%, which is more cost efficient than CBM with an RUL of 14 days.

From this can be concluded that 'the more disruptions take place and the longer the RUL, the higher the chance is of combinations of CBM with PM'. It is shown by the maintenance costs comparison that these combinations generally result into cost savings. The highest cost savings of 0.86% is achieved with the longest RUL of 21 days and for the most disruptions, which are 12, as shown in figure 5.6b. So more combinations have a positive impact on the performance of the rolling stock maintenance planning decision-making.

		RUL length [days]		
		7	14	21
amount of CBM [-]	4	0.5	0.7	1
	6	0.7	0.9	1.4
	8	1.1	1.4	1.7
	10	1.1	1.9	2.1
	12	1.1	2.5	2.8

Table 5.4: Average number of combinations CBM and PM over 20 random configurations iterated over increasing amount of disruptions and RUL length

5.4. Concluding remarks on the rolling stock maintenance planning optimization results

The goal of this chapter is to evaluate the performance of the rolling stock maintenance planning optimization approaches. KPI's are therefore defined in order to quantitatively evaluate the performance. Sensitivity analyses showed how the formulated approaches are solved by the Gurobi optimization solver algorithm. By iterating the decision horizon for approach 1, the effect on the *computational time* is analyzed.
For approach 3, the decision horizon and its impact on the *feasibility* are evaluated so that further outcomes may be produced while still employing the same decision horizon.

Results from approach 1 showed how the availability impacts the efficiency of maintenance decision-making. This is shown by the increasing *amount of PM* in the planning and the mileage loss when less or more than rolling stock are available for operation than needed. This confirms the dependencies between passenger operations and maintenance decision-making. Moreover, the results of approach 1 showed that with governing the default "bakkenstand" of $C_{percentage}\%$, the amount of mileage losses are minimal. As results, approach 1 may be used as an optimization tool to plan PM.

Research question 5 is answered in this chapter by evaluating the performance of approach 3 integrating either CM, CBM or CBM with combinations according to the KPI's.

5. *How to evaluate the performance of the rolling stock Preventive Maintenance planning algorithm considering the integration of Corrective Maintenance or Condition Based Maintenance?*

Comparisons are made between the optimization approach 3 integrating CM and CBM. CBM and CM demonstrated to be disruptive to the PM planning when the duration is 2 days. This value is therefore employed for further evaluations.
The performance is further evaluated by making comparisons in feasibility. This demonstrates a trend that the more CM disrupts planning, the more infeasible solutions occur up to 85% in total. While when the planning is disrupted by CBM, the percentage of infeasible solutions remain stable with an average of 42.2% of infeasible solutions and 27 more feasible solutions in total.
Moreover, whisker plots demonstrate the comparison in the average mileage loss spread of data between CM and CBM. The majority of cases with CBM, the mileage loss remained minimal, while for a planning integrating CM as disruptive factor, mileage losses are made more frequently.

CBM creates the opportunity to combine the routine with PM so double shunting operations can be avoided, saving shunting costs. Consequently, earlier PM is performed, so the combination of CBM with PM results in more mileage costs. However, it is demonstrated by the average maintenance costs comparison that combining CBM with PM generally leads to average cost savings, which are on average 0.32% for an RUL of 14 days, which proves the cost efficiency of combinations of CBM with PM. By counting the amount of combinations of CBM with PM, the following relation is observed: the more disruptions take place, the higher the chance of combinations and the longer the RUL, the more combinations can be made. This may also hold up for costs savings as a higher percentage of costs is saved when a higher amount of disruptions take place with a longer RUL, because the highest costs saving of 0.86% is found for an RUL of 21 days with 12 disruptions.

The main research question can be answered with the results of the approaches of the rolling stock maintenance planning optimization that are provided in this Chapter:

What is the impact of integrating Condition Based Maintenance in the preventive maintenance planning decision-making?

It can be concluded from the comparisons of approach 3 resulting to the 3 different results (CM, CBM and CBM with combinations) that CBM impacts the decision-making positively by creating flexibility in planning resulting into more feasible solutions. Moreover, less mileage costs are made because of better decision-making in comparison to a situation where failures cannot be predicted and result into CM as is proved in the whiskers plots. This demonstrates that more than 50% of the time that CBM is integrated in the rolling stock PM planning, no more than the minimal mileage losses of 350 [km] per PM routine are made. Combining CBM with PM saves maintenance costs and has therefore a positive effect on the rolling stock Preventive Maintenance decision-making.

However, the approach for optimizing the rolling stock maintenance planning has its limitations and is solved under the assumptions that are formulated in chapter 4. This will be further discussed in the next chapter where the main conclusion will be provided.

6 Conclusions and Recommendations

This study addresses the main research question:

What is the impact of integrating Condition Based Maintenance in the Preventive Maintenance planning decision-making?

This question is approached by formulating a deterministic MILP mathematical model that represents the maintenance decision-making process of NS, which can be optimized using a Gurobi solver algorithm. It has been verified that with approach 3, the rolling horizon framework is perfectly able to approach the maintenance planning problem because of its ability to rearrange in response to (predicted) disruptions. Using a rolling horizon provides the opportunity to distinct CM from CBM in its foreseeability, so that fair comparisons could be made.
The final model presents an integral simplified version of the NS rolling stock maintenance planning case. For the formulation of this model, assumptions and concessions are made to be able to model the case. As a consequence, the results of the model may therefore deviate from reality, but the concept can still be of practical use.

Nevertheless, conclusions can be drawn from the model. As a result, the impact of CBM instead of CM on the PM planning can be described. This will be presented as key findings.

Moreover, general recommendations are proposed on the integration of CBM with the rolling stock PM planning. These reasoned recommendations ultimately answer research question 6.

6. *What suggestions could be made to NS for improving the maintenance planning based on the results of the rolling stock maintenance planning algorithm?*

Finally, limitations will be described and recommendations for future research and a proposal to NS will be described that conclude the study.

6.1. Key findings

A rolling stock PM planning optimization model is established with approach 1 based on the SNG fleet of NS that minimizes the mileage losses and optimizes the utilization efficiency of the rolling stock. A rolling stock PM planning optimization model is established that integrates disruptions in the form of CM and CBM with approach 3. Approach 3 can be used as planning tool for rolling stock maintenance optimization that accounts for unexpected events. Based on the results of approach 1 and approach 3 in the previous Chapter, the following outcome can be interpreted:

1. The utilization efficiency of rolling stock maintenance planning depends on the required amount of rolling stock that should remain available for passenger operations.

2. CBM is less disruptive to the PM planning than CM, resulting into better decision-making and less mileage costs.

3. CBM can be combined with PM if the RUL overlaps with the upcoming PM routine, saving maintenance costs because of less shunting operations.

The first finding is based on the sensitivity analysis of approach 1 on the required availability of rolling stock for passenger operations. If less rolling stock is required for operation, the deployment of rolling stock is less. This results into less running mileages before reaching the time threshold for PM resulting into mileage losses. Alternatively, when more rolling stock is required for passenger operation than allowed, the mileage threshold is reached earlier in time resulting into more PM routines in total resulting into higher maintenance costs.

The second finding can be justified, because knowing that the rolling stock is going to fail within the RUL, gives time to plan the optimal moment for maintenance in the planning. Planning maintenance in this way has no direct impact on the availability of the rolling stock, because the asset may continue to operate passenger operations meanwhile it is going to be planned for an optimal moment for maintenance. CM is determined to be performed immediately when a failure occurs, if the optimization could not deal with this, this resulted into infeasible solutions. The amount of infeasible solutions quantifies that 27 out of 180 more feasible solutions are found with CBM, so CM is more disruptive to be planning. Furthermore, results showed that if the planning is disrupted by CM, there is a high chance that this results into mileage losses. CBM is less disruptive to the planning, because while the planning is disrupted by CBM, still more than halve of the times, no mileage losses where made in the planning.
It has also been shown that the disruptive effect on the PM planning depends on the duration of CM or CBM. When CM only takes one day, the disruptive effects on the planning are minimal as is shown by the results. NS aims to perform CM in one day, so maybe the actual difference in impact on the planning is less high than the outcome of the model. However, it is expected that since CBM is based on a diagnosed fault, the throughput time of CBM is less than CM. Maintenance activities can be prepared and arranged at the depot while the rolling stock is still in operation. This aspect implies that CM is even more disruptive than CBM.

The third finding can be explained by the results of approach 3 that enables the possibility to combine PM with CBM. Assuming that prognostics give plenty of time to plan the maintenance, the decision-making optimization model might also check if PM is planned for the rolling stock in the near future. If so, this gives an opportunity to combine the two maintenance operations at the depot. Combining PM with CBM is making a trade-off between logistic shunting costs and mileage costs. If it is more convenient in the planning to perform PM prematurely so that it can be combined with CBM, it is worth the extra mileage costs, since shunting costs are saved. The longer the RUL length, the higher the chance is to overlap with the following PM. And more CBM result into more combinations of CBM and PM. Therefore, the longer the RUL of the prognostic models, the more cost efficient the integration of CBM into the PM planning can be. This is suggested by the results that indicate when a prognosis is made 21 days in advance and 12 disruptions occur in the simulation horizon, on average, 0.86% of the total maintenance costs are saved.

As previously stated, with CBM, maintenance mechanics can be informed ahead in time which maintenance activities should be performed based on the prognosis. This saves inspection costs, time and the best specialized mechanics can be deployed for the specific activity. CBM is also maintained while the predicted failure is still in its infant state, whilst with CM, the rolling stock already has failed. It is therefore expected that CM leads to more repairs and higher costs than CBM. However, the effect of these assumptions on the planning is not further modeled.

6.2. Recommendations

In this section, the limitations from the study will be addressed. Following from the limitations of the approach, recommendations are formulated, that may be reasoned with the literature that is reviewed in this study.

6.2.1. Limitations and recommendations for rolling stock maintenance planning optimization approach

- In reality the SNG fleet exists of 190 rolling stock from which $O_{percentage}$ should be available for passenger operation according to the ”bakkenstand”. This cannot be modeled with the current optimization methods because it results computational delays.
- The ”bakkenstand” is variable depending on the time of the day and the day of the week, due to peak hours and peak days. In the approaches, it is assumed that it is a constant. The maintenance decision-making can be more realistic if the variable rolling stock availability requirements are integrated in the maintenance planning model. Lin et al. (2019) integrated the seasonal availability requirements of rolling stock in the model in order to approach this, so this methodology can be used for future research.
- Seasonal maintenance can be considered as well, since during the winters more failures are expected and the maintenance planning of NS acts on these predictions.
- From interviews with the production engineer of NS, it became apparent that more rolling stock is maintained during weekends because more rolling stock can be unavailable. The capacity of the maintenance depot varies throughout the week and should be taken into consideration for a future rolling stock maintenance planning optimization approach.
- In the model, the maintenance planning is discretized per day, while in practice at NS, maintenance shifts endure 8 hours, so three shifts per day. This approach is able to plan maintenance in more detail, but because of computational complexities it was simplified to a day discretization. Future research may consider this.
- Disruptions in the form of CBM and CM are modeled as random instances for experiments. There is historical data failure data available over the whole fleet. So if the whole fleet is considered for a future approach, historical data can be used in order to validate the decision-making and making more valid comparisons between CM and CBM. In reality less disruptions take place and this should be validated with historical data.
- Furthermore, the mileage losses of the SNG rolling stock fleet is also available, so if the whole fleet is considered, the optimizations approach can be validated with the actual mileage loss historical data.
- Another aspect that should be analyzed is the capacity of the depot for CM and CBM. The arrival of a rolling stock for CM or CBM is in the model not constrained to any maintenance depot capacity limitations. It is reasonable that more arrivals for CBM results in more workload for the depot. In a situation where solely maintenance is decided based on prognostics, this is recommended to thoroughly analyze and compare it to the current situation with PM.

Comparisons with models found in literature It is evident that multiple rolling stock maintenance planning MILP optimizations are performed in literature. It is helpful to check similarities between the formulated model and the models in literature, because this will verify the results of the model. When the formulated model of this thesis report can be initialized with the input parameters retrieved from literature, the results can be compared. It should be kept in mind that the decision-variables, constraints and objective is formulated differently from the literature. Equal results are not anticipated, but inferences may be derived from the findings comparison and it can be argued why discrepancies between the models can be observed.
Studies that provide input parameters and results are listed below.

- Bougacha et al. (2022)
- Herr, Nicod, Varnier, Zerhouni, Cherif, et al. (2017)
- Li et al. (2016)
- Lin and Zhao (2021)
- Lai et al. (2015)

Infeasible solution or penalized solution The formulated approaches are designed to plan PM when this is determined due to the mileage or threshold, a failure, or a predicted failure. When optimizing this under the given conditions, a solution can only be found when this bounded by the constraints. Otherwise, the model responds by stating that it is impossible to find a feasible solution. So the model formulation is limited by this aspect.
However, in literature, a few optimization approaches can be found where the planning of rolling stock maintenance is less strict (Bougacha et al., 2022; Lai et al., 2015; Li et al., 2016; Lin et al., 2019; Sriskandarajah et al., 1998). When it is too difficult to find a feasible solution with the ”normal” constraints, a secondary option appears for the optimization model. This secondary option is formulated as a failed rolling stock that cannot be available and not maintained because it is infeasible to plan. Consequently, the model penalizes the decision for letting the rolling stock fail, because there is no depot capacity. Since this penalty is incorporated into the objective function, the model tries to prevent this undesirable event from occurring. This improves the model flexibility and problem solvability (Lin et al., 2019), because instead giving a model call-back of ”infeasible”, the objective costs increase significantly due to the penalization while still a feasible solution can be found.
It is recommended to apply this in future work, because as a result of the method, more feasible solutions can be achieved from the optimization approaches.

Uncertainties of CBM because of incorrect prognostic information It is assumed that the RUL from a fault detection in the formulated model is perfectly accurate. Realistically, since actual CBM is conducted according to prognostic information that predicts a failure, it is not 100% certain if the rolling stock is actually going to fail. The prognosis might be false positive and the rolling stock is going to the maintenance depot for CBM purposeless. When considering CM, the rolling stock fails and shunting to the maintenance depot and is guaranteed useful. Alternatively, CBM might lead to a false negative, so CM can still occur despite that the health of the rolling stock condition is monitored and potential failures can be predicted. A statement can be made that more routines for CBM can be expected than CM, because CBM contains false positive fault detection and for CM, the rolling stock is always failed. More CBM routines brings more shunting costs. This distinction is not considered in the study and the trade-off between CBM and CM can be reconsidered if the uncertainty of the prognostic model is taken into account.
Furthermore, it is assumed that the RUL is expressed in time units, not in usage. The planning optimization becomes more complex when the degradation evolution of a rolling stock is related to usage, so there is a limited usage of the rolling stock until failure. It is recommended to take these aspects in consideration for future research.

Mileage losses because of early CBM When CBM is performed immediately after the fault detection, similar to PM, mileage losses are made, because the rolling stock could have been in operation for longer due to the RUL. Performing early CBM can therefore be considered as a loss. PM is related to the upcoming PM routine, because the time between two routines should not be longer than 108 days, so performing PM early has cumulative effects on the next PM routine. However, unlike PM, performing CBM early has no cumulative effects on the planning, because CBM is unrelated to the next maintenance routine. Penalizing mileage losses for early CBM is therefore not as important as mileage losses for PM. A situation where all maintenance is based on prognostic data and no PM are performed in the strategy, mileage losses because of CBM becomes a more important factor in efficient decision-making. When the prognosis to failure is expressed in months as time units, early maintenance becomes a bigger loss than in a situation where the prognosis to failure is expressed in days as time units. From this can be concluded that it is dependent on RUL length of the prognostics, whether it is valuable to take the mileage losses before CBM into account.

6.2.2. Proposal to NS for improving the integration of CBM in the rolling stock PM planning

As stated earlier, the results of this study are based on 21 rolling stock instead of for a fleet size of 190. However, the performance of the optimization approaches can be translated to practice.
The maintenance planner at NS knows in advance, based on the prognostics, how many rolling stock require more complex repairs at the maintenance depot. As a result, maintenance can be planned

when this is most convenient with the resources at the maintenance depot. Shunting to the maintenance depot is relatively expensive and can be logistically complex. The opportunity to combine CBM with PM is proven to be cost efficient by the model if a failure can be predicted far in advance. It is therefore recommended to develop prognostic models to predict failures far in advance, most ideally 108 days as the time threshold, because the longer the RUL of the prognostic models, the more efficient the integration of CBM into the PM planning can be.

The findings of the approach integrating CBM in the PM planning showed that, despite a significant number of disruptions occurring in the simulation horizon, that the majority of times PM is performed with minimal mileage loss. This implies that with the integration of CBM in the PM planning of NS, even if there is an increase of disruptions, because this can be foreseen, it is still feasible to plan.

The current maintenance strategy at NS is constrained by the PM activities that should be performed periodically and distance-based. Given that the future rolling stock has multiple prognostic models to ensure that a rolling stock does not fail, the amount of PM operations may be reduced. As a result, the throughput time of PM routines can be reduced as well. Or the time threshold for PM of 108 days may be extended, because the condition monitoring ensures that the rolling stock does not fail. It can be expected that a certain optimum can be found for the cost efficiency between a shorter PM throughput and that a larger amount of maintenance activities that is determined by prognostic models, resulting in CBM. The feasibility of this strategy can be further analyzed and compared with the current maintenance strategy.

6.3. Conclusion

In this study, 3 approaches of the rolling stock planning optimization are formulated based on the state of the art and practice in order to come to approach 3 that is satisfactory for evaluating the impact of the integration of CBM on the rolling stock PM planning. The optimization approaches can be used as tool for planning rolling stock maintenance and minimizing the mileage losses.
The main research question is answered:

What is the impact of integrating Condition Based Maintenance in the Preventive Maintenance planning decision-making?

With the formulated model that has been evaluated on it its performance based on the defined KPI's, it has been shown that CBM enhances the maintenance planning decision-making by being more flexible planning wise in comparison to unexpected CM. This is concluded from the comparison in infeasible solutions between a PM planning that integrates CBM with a PM planning that integrates CM. Also, the maintenance costs are less with the integration of CBM, because less shunting costs are made. It can be concluded that CBM creates the opportunities to combine the maintenance with PM that saves shunting costs.

By providing a proposal based on the results of the optimization approaches, research question 6 is answered.

6. *What suggestions could be made to NS for improving the maintenance planning based on the results of the rolling stock maintenance planning algorithm?*

It is recommended to first extend the optimization approach to a fleet size of 190, make the required amount of rolling stock in operation variable based on actual requirements and to approach the depot capacity more precisely. When this is validated, it is expected that the optimization model will more closely match reality. Thereafter, it is recommended to further research how uncertainties of prognostic information influence how to cope with CBM. Nevertheless, it is expected that the integration of CBM in the PM planning benefits NS when prognostic models can predict a failure far in advance so that maintenance can be prepared and possibly combined with PM.

It can be concluded that this study provides insight into how CBM benefits the rolling stock maintenance planning and how prognostic models and CBM development can be directed in the future.

A

Research Paper

Integration of Condition Based Maintenance in the Preventive Maintenance Planning of Rolling Stock

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Abstract

Planning rolling stock maintenance based on prognostic data (Condition Based Maintenance, CBM) is a trend since the ideal timing for maintenance before failure can be planned. With the use of prognostics, a failure can be predicted so Corrective Maintenance (CM) can be avoided. Traditional rolling stock decision-making for Preventive Maintenance (PM) is based on the time and/or mileage since last PM routine at the maintenance depot. A sufficient amount of literature is available that considers rolling stock PM planning optimization methods. Planning rolling stock maintenance is constrained by the required availability for passenger operations, the conditions for PM and the maintenance depot capacity. However, the integration of CBM with the rolling stock PM planning has not been researched. CM also needs to be performed and is considered a disruptive element in the maintenance planning. It is expected that integrating CBM in the rolling stock PM planning is less disruptive than CM. This study investigates how CBM impacts the rolling stock PM planning by formulating a deterministic MILP that uses a rolling horizon framework that minimizes the maintenance costs. An approach that optimizes the rolling stock PM planning while being disrupted by unexpected failures that lead to CM is compared with an approach that integrates CBM that is disrupted by predicted failures that can be planned in advance. The outcome of the model demonstrates that CBM is less disruptive to the maintenance planning than CM, because the time to failure gives the model flexibility to find the ideal moment to perform CBM. Conclusions and recommendations of this study can be used for implementing CBM approaches for rolling stock.

1 Introduction

Maintenance is performed on rolling stock in order to ensure reliable and safe passenger transportation without failures during operation (Zhong et al., 2019). Currently, decision-making for rolling stock maintenance planning and activities is based on standardized frameworks such as Failure Modes Effects and Criticality Analysis (FMECA) that determines the Preventive Maintenance (PM) frequency and activities of rolling stock while ensuring reliability (de Vos and van Dongen, 2015). Rolling stock requires PM after running a specified mileage and/or after a specified time period since its previous Preventive Maintenance routine (Wagenaar et al., 2017). Rolling stock PM is usually performed at a maintenance depot, so the rolling stock has to be scheduled out of operation in order to shunt (moving a railway vehicle) to the depot for PM. *Shunting* to the maintenance depot brings costs, because a train driver, energy and a railway path should be arranged. A rolling stock maintenance planning should thus be established in order make efficient decision-making for maintenance while complying with the required availability of rolling stock for passenger operations.

The efficiency of the rolling stock PM planning can be quantified by the *mileage losses*. The usage of a rolling stock is related to the mileage (Lai et al., 2015), hence why PM has to be performed every time that a rolling stock ran a certain mileage. This is considered to be the maximum usage that the rolling stock can safely run according to experts ensuring a minimum amount of failures. If a rolling stock undergoes PM when the mileage since previous PM is less than the allowed mileage threshold, this remaining mileage is considered as a loss. The mileage loss can be expressed into costs, the *mileage costs*, which are desired to be minimal. This KPI is considered in the state of practice and the state of the art (Lai et al., 2015; Li et al., 2016; Lin and Zhao, 2021; Méchain et al., 2020).

Planning rolling stock maintenance does not only concern PM, but also Corrective Maintenance (CM). CM has to be performed if a rolling stock has (unexpectedly) failed and is not able to perform the required function anymore (*Maintenance - Maintenance terminology*, 2019). CM also needs to be performed at the maintenance depot, so shunting (logistic) operations to the depot have to be organized and the rolling stock becomes unavailable for passenger operation. Unexpected CM is a disruptive element in the maintenance planning, because the maintenance planning is optimized in accordance with the rolling stock PM requirements while an acceptable number of rolling stock should remain available for passenger operation. CM is therefore problematic and can be at the expense of the rolling stock availability.

However, recently with the use of sensors, microprocessors and an online network that can be used for *condition monitoring*, the health state of a component or sub-system can be retrieved in real-time by detecting faults based on monitoring data (Brahimi et al., 2020). Subsequently, maintenance decision-making can be based on the actual health condition of the asset (Nappi et al., 2020). This is arguably more efficient since unlike PM, maintenance activities can be suggested when they are certainly required. In addition to obtaining the current health state with the use of online condition monitoring, also the degradation evolution of the system can be approximated and CM can be avoided.

When an anomaly is detected with the use of condition monitoring, the health of the system has started degrading. This detected anomaly can be isolated and diagnosed, this is defined to be a *fault*. From the moment in time that a fault is detected, the component or system will further degrade until failure. The estimated time between the point in time of fault detection until the time of failure, is defined as the Remaining Useful Life (RUL). The length of the RUL in time units is established by a prognostic model. Planning rolling stock maintenance according to this prognosis to failure is referred to as Condition-Based Maintenance (CBM). The maintenance planner can act and rearrange the current maintenance planning in response to a failure prognosis. CBM is thus anticipated to mitigate the disruption of the maintenance planning in comparison to CM.

In this paper, the focus is to investigate the latter hypothesis. Dutch railway operator *NS* (Nationale Spoorwegen) and railway consultancy company *Ricardo Rail* is involved in this study because of a mutual interest in researching the enhancement of CBM to maintenance planning decision-making. The fleet of the newest light-train rolling stock type of NS "Sprinter Nieuwe Generatie" (SNG) and its maintenance requirements is used as case study in order to determine whether CBM is complementary to the current maintenance strategy.

The maintenance planning decision-making process will be approached by formulating a MILP mathematical model that can be solved with the Gurobi optimization solver algorithm. The outcome of the model is an optimized rolling stock maintenance planning for the SNG fleet considering the maintenance depot capacity, required availability and the PM conditions. The proposed model uses a *rolling horizon* framework, which implies that it is able to rearrange the planning based on disruptive events as CM and it can act and optimize in response to predicted failures (CBM).

A sufficient amount of research is performed on optimizing the rolling stock maintenance planning based on PM conditions and passenger operations e.g. Lai et al. (2015) and Lin and Zhao (2021) in which the objective is to minimize the mileage

losses and overall maintenance costs with a MILP optimization model that is solved with a solver algorithm. The challenge is often in these studies to comply with passenger operations while performing efficient PM. Other challenges found in these works are to minimize shunting through the network to the maintenance depot (Lai et al., 2015; Méchain et al., 2020; Mira et al., 2020).
Alternatively, a few studies can be found that integrate a prognostic model of the health of rolling stock into the maintenance planning e.g. Bougacha et al. (2022) and Herr, Nicod, Varnier, Zerhouni, and Dersin (2017). The objective in these studies is to exploit the degradation of the rolling stock and maintain the asset right before failure in order to perform efficient maintenance. However, these studies do not consider if planning maintenance based on the actual degradation actually enhances the maintenance planning or study the feasibility of proceeding CBM in combination with PM.

2 Motivation and structure

Rolling stock maintenance operators have expressed interest to optimize maintenance operations by using condition monitoring and prognostics for decision-making of rolling stock maintenance. However, it is unknown whether the integration of this CBM with the PM planning that is time- and/or mileage-based is complementary.

This paper is organized as follows. The state of the art of maintenance optimization methods is described in the "related works" section 3. Also methods that integrate prognostic models for rolling stock maintenance decision-making will be considered. The rolling stock maintenance planning case at NS will be described accordingly, presenting the maintenance conditions and practice of NS in section 4. The model approach formulation for the maintenance planning optimization will be presented in section 5. Results of different cases of the approach are presented and compared, followed by concluding remarks and recommendations in section 6 and 7.

3 Related works

In the state of the art for optimizing rolling stock maintenance planning that integrates prognostic models for decision-making, planning methods can be found that are able to rearrange the planning based on unexpected disruptions. These prognostic models are presented in the form of a component degradation evolution and when the component is about to fail, maintenance is planned in order to prevent a failure (Herr, Nicod, Varnier, Zerhouni, Cherif, et al., 2017; Herr, Nicod, Varnier, Zerhouni, and Dersin, 2017). This indicates that a certain foreseeability of a failure has to be simulated in such models in order to verify if maintenance planning based on prognostics can be performed. This predicted failure can be considered as a "disruption" since it disrupts the original maintenance planning. Therefore, the *rolling horizon* framework is often proposed (Bougacha et al., 2022; Lai et al., 2015). Within this framework, an optimization model optimizes the maintenance planning given the information within a limited decision horizon that can be foreseen at that moment. When time has passed and the planning has been executed, the decision horizon shifts further in time and a new optimization starts with new information that can be seen in the new decision horizon. This method is used in comparable (maintenance) planning problems, such as railway or aircraft maintenance (Consilvio et al., 2020; de Pater et al., 2021). Or for acting on disruptive events in the timetable planning for passenger trains (Nielsen et al., 2012). From this can be concluded that this framework is frequently used in literature to model time plannings while unexpected events may happen and rearrangements are required.

4 Rolling stock maintenance planning, NS case

The rolling stock maintenance planning strategy at NS will be considered for this study. At NS, short cycle PM implies that a fleet of 190 rolling stock require maintenance activities based on the individual components of the multi-component asset. The components require PM that is time-based and distance-based. The smallest time interval for PM per component is 108 days and distance interval is 45,000 [km]. Every 108 [days] or 45,000 [km] in operation a standardized cluster of maintenance activities is performed per rolling stock at the depot of NS (see figure 1). This cluster is assembled while making use of economic, structural and stochastic dependencies for efficient maintenance (Ghamlouch and Grall, 2018). As a result, every rolling stock PM routine takes 3 days.

The decision-making for maintenance is constrained by the depot capacity. Since the workload needs to be balanced at the maintenance depot and because the maintenance tracks are limited, no more than 9 rolling stock may arrive in 2 days.

Simultaneously, an adequate amount of rolling stock should remain available for passenger operations. The maintenance planning at NS is very dense and there is little room for flexibility.

CM is also performed at the maintenance depot of NS at a designated track for CM. A failure can not be predicted and happens unforeseen and is therefore a disruptive factor to the planning. It is a challenge for the maintenance planner to plan CM. On the other hand, if a rolling stock fails, another rolling stock should remain available for passenger operations instead.

CBM that can be planned according to online prognostics from a prognostic model is not yet implemented at NS. So for an ideal future strategy, it is assumed that CM is excluded if the rolling stock is condition monitored, so instead of CM, a failure is predicted. This provides two opportunities:

- The maintenance planner should utilize the RUL to determine the ideal time for maintenance that will cause minimum disruptions.
- When PM has to be performed in the near future and a failure is predicted simultaneously, the CBM can be combined with PM, saving shunting costs because the rolling stock only has to go to the depot once. This will be referred to as a "combination of CBM with PM".

Prognostics give insight to the maintenance operator which component or sub-system is going to fail. The maintenance activities can be prepared before the rolling stock arrives at the maintenance depot, because the failure is already diagnosed online.

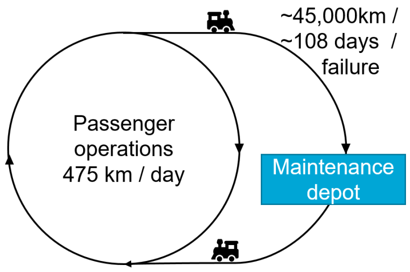


Figure 1: Short cycle maintenance or going to the depot due to a (predicted) failure

While assuming that the RUL gives the maintenance planner flexibility for planning the maintenance, it becomes reasonable to see this as an opportunity to combine PM with CBM. When PM has to be performed in the near future and a failure is predicted simultaneously, the two maintenance activities can be combined, saving shunting costs because of this economic dependence. Consequently, a trade-off can be made. Either separating PM and CBM, requiring the rolling stock to visit the depot twice with minimal mileage loss. Or combining PM and CBM by scheduling earlier PM, which results in mileage losses but saves costs because the rolling stock only needs to visit the depot once. It is expected that the more combinations of CBM with PM can be made, the more efficient the PM planning will become.

5 Rolling stock maintenance planning optimization approach with rolling horizon

In this section, the rolling stock maintenance optimization problem will be formulated as a deterministic MILP model. The goal of this optimization approach is to evaluate the performance of the rolling stock PM planning optimization integrating CM in comparison to an approach that integrates CBM. So three types of planning may be established by the optimization model:

- A rolling stock PM planning optimization integrating CM as a result of unexpected failures.
- A rolling stock PM planning optimization integrating CBM as a result of predicted failures.
- A rolling stock PM planning optimization integrating CBM as a result of predicted failures. Additionally, CBM can possibly be combined with PM in one routine.

The maintenance planning will be optimized using a rolling horizon framework that is shown in figure 2. It will be explained how this method helps distinguishing a rolling stock PM planning integrating CM from a PM planning integrating CBM.

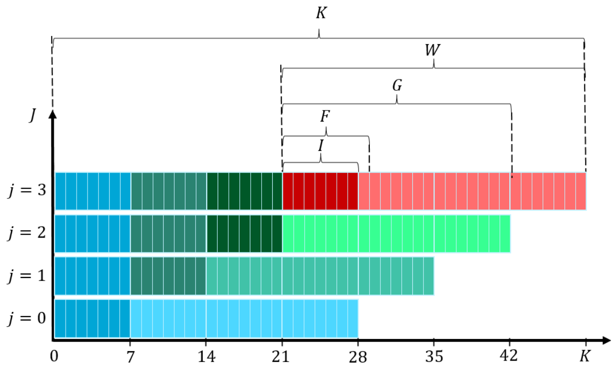


Figure 2: Rolling horizon principle example with $J = 4$ as number of optimizations in the simulation horizon of $K = 47$ days, implementation horizon of $I = 7$ days, decision horizon of $W = 28$ days, 8 day prediction horizon for CM F, prognosis prediction horizon G of 21 days

The model accounts for planning rolling stock PM while being constrained by depot capacity, passenger operation availability, conditions for performing PM and disruptive CM or CBM in response to a failure or a predicted failure. A **simulation horizon** (denoted by K in figure 2 as the light colored segments) indicates the time period over which the total planning will be established. However, the model optimizes over the smaller **decision horizon** (denoted by W in figure 2). So, the total planning is split up in smaller decision horizons than the simulation-horizon, which are optimized individually and arranged chronologically with the rolling horizon framework. The first optimized 7 days from the decision horizon is already implemented and cannot be changed, the **implementation horizon** (denoted by I and the dark colored segments in figure 2). After implementation, the decision horizon shifts 7 days forward and starts a new optimization as can be seen by a new color in figure 2 (denoted by j) initialized with the maintenance decisions of the former implementation horizon.

Formulating CM as unexpected and CBM as predicted Using this rolling horizon framework helps distinguishing the PM planning integrating CM from a PM planning that integrates CBM. Since CM is performed according to an unexpected failure, this should not be considered in decision horizon W, otherwise the failure could be foreseen by the model. Simultaneously, CBM is performed according to a predicted failure, so this should also not be considered in the decision horizon. Therefore, **prediction horizons** F for CM and G for CBM are introduced that are smaller than decision horizon W as can be seen in figure 2. Prediction horizon F is 8 days, but 7 out of the 8 days lie within the darker colored implementation horizon I that cannot be changed. Consequently, the model may only foresee a failure 1 day in advance, making a failure unexpected and determined to perform CM at that day. The same rules apply to prediction horizon G for CBM, but alternatively, a failure can actually be foreseen in advance, so G is larger than F. In the case illustrated in figure 2, a failure can be foreseen 14 days in advance. As a result, the optimization model can consider this predicted failure and rearrange the planning accordingly, while for an unexpected failure, the planning cannot be rearranged because it occurs unexpected. Additionally, the optimization model has the freedom to pick the ideal day in the planning within the period to failure to perform CBM. Planning CBM is thus more flexible.

A rolling stock maintenance planning optimization problem will be formulated. The outcome of this optimization will be a rolling stock PM planning for a fleet size of 21 rolling stock over 133 days. The planning is disrupted by failures, so that CM and CBM have to be performed also. Failures that lead to either to CM or CBM will be referred to as "disruptions". The following assumptions are made for the formulation:

- Time units in the planning are discretized per [day].
- The limiting factor of the capacity of the depot is assumed to be the a maximum amount of arrivals over a certain amount of days.
- The fleet size has been downsized due to 21 rolling stock computational reasons. Therefore, the required amount of rolling stock in operation is O of $U = 21$ and the depot capacity has been downsized to 1 arrival per 3 days according to the same ratio.
- Maintenance is performed perfectly.
- The time is still accumulating when the rolling stock is not in operation, so when the rolling stock is standby.
- It is assumed that every rolling stock in operations builds up the same amount of cumulative mileage ("mission profile") while in operation per day which is 475 [km].
- The amount of O rolling stock should be in operation at all times
- The duration of a PM routine takes 3 days time based on the method from NS.
- Performing CM or CBM takes 2 days time.
- The rolling stock is not allowed to undergo PM if the rolling stock has been running less than 94% of the mileage threshold. This implies that rolling stock has to run at least 94% out of 45,000 [km], which is 42,800 [km].

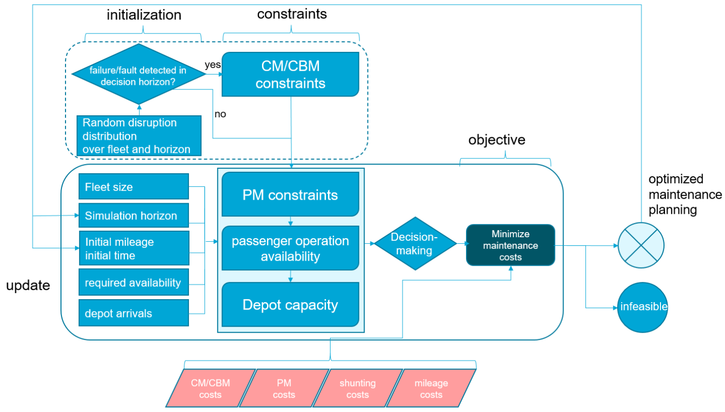


Figure 3: structure of the maintenance planning optimization approach as feedback loop due to the rolling horizon framework

- Disruptive CM or CBM is initialized randomly distributed over the planning and can only occur once per rolling stock in the simulation horizon.
- A prognosis is modeled artificially as a time to failure and CBM should be maintained within that given time period. This time period is considered as always correct and no unexpected failure may happen due to uncertainties of the prognosis.
- The moments when disruptions take place in the planning are randomly initialized artificially, not based on historical data.
- The following costs for rolling stock maintenance estimated based on the data from NS are considered:
  Shunting costs
  PM costs
  CM costs
  CBM costs

Optimization approach The objective of the optimization model is to minimize the costs associated with rolling stock maintenance.
The methodology of the optimization approach is illustrated in figure 3. The figure demonstrates that the model is initialized by parameters, which are then

used for the constraints. With the constraints, the rolling stock maintenance planning is bounded and decisions can be made. The CM/CBM constraints are only taken into consideration when a failure happens or a fault is detected (according to the prediction horizon). The rolling stock maintenance planning decision-making is subsequently optimized over the decision horizon by minimizing the associated maintenance costs. The model initially aims to perform PM only when the maximum mileage threshold has been reached, so that the mileage costs are minimal. However, simultaneously, CM or CBM must be performed and the model optimizes also by finding the best moment for performing CBM. If this is done successfully, an optimized planning is established. If this cannot be found because of an ill defined initialization, when the constraints are not bounded, or failures leading to CM or CBM are too disruptive to the planning, no solution can be found and the outcome of the optimization approach is "infeasible". Due to the rolling horizon framework, the optimized outcome is used for updating the initialization for the next optimization which explains why figure 3 is structured as a feedback loop.

In the optimized planning, the rolling stock has five possible states: assigned for PM $y_u(k)$, assigned for CM $z_u(k)$, assigned for CBM $m_u(k)$, not in operation $x_u(k)$ or in operation. These will be indicated by binary decision-variables. Two integer decision-variables are the cumulative mileage $d_u(k)$ and the cumulative time $e_u(k)$ that indicate the time and mileage per rolling stock since the last PM routine. Auxiliary integer decision-variable $v_u(k)$ is introduced in order to linearize the objective function and indicates the mileage at the time that a rolling stock arrives at the depot for performing PM. Decision-variable $r_u(k)$ indicates whether CBM can be combined with PM. Other auxiliary binary decision-variables $w_u(k)$ and $q_u(k)$ indicate the decision when a rolling stock arrives at the maintenance depot for PM, CM or CBM.
The notations of the mathematical model, including the indices, sets, and parameters and decision-variables are listed in the following sections.

5.1 Indices

u	Denotes the rolling stock number
i	Denotes the day in the implementation-horizon
j	Denotes the optimization number in the rolling horizon
k	Denotes the day in the simulation-horizon
f	Denotes the day in the prediction-horizon for CM
g	Denotes the day in the prediction-horizon for CBM
w	Denotes the day in the decision horizon

5.2 Sets

$U = 21$	[-], Set of rolling stock fleet
$K = 133$	[days], Set of days in simulation horizon
$W = 98$	[days], Set of days in decision horizon
$I = 7$	[days], Set of days in implementation horizon
$J = 19$	[-], Set of optimizations that are performed to establish the total simulation horizon K
$F = 8$	[days], Set of days in prediction horizon for CM
G	[days], Set of days in prediction horizon for CBM based on the RUL in time days

5.3 Coefficients and parameters

$D = 45,000$	[km], mileage threshold for PM
$D_{LB} = 42,800$	[km], mileage threshold lower bound for PM
$P = 475$	[km], operating mileage per per rolling stock per day (mission profile)
$d_u(0) = \{0, ...D_{LB} - P\}$	[km], initial rolling stock mileage integer values
$E = 108$	[days], time threshold for PM
$e_u(0) = \frac{D_u(0)}{D} \cdot E$	[days], initial cumulative time of every rolling stock is set in ratio according to mileage
$N = 3$	[days], duration of PM routine,
O	[-], amount of rolling stock required in operation of the fleet size

$A = 1$	[-], amount of rolling stock that can go to the depot in A_{days}
$A_{days} = 3$	[days], amount of days that the amount of A can arrive in
C_{PM}	[euro], costs of PM per day
C_{CM}	[euro], costs for CM
C_{CBM}	[euro], costs for CBM
$C_{mileage}$	[euro], costs per mileage loss
$C_{shunting}$	[euro], shunting costs to depot
$T_{CM} = 2$	[days], amount of days needed for CM
$T_{CBM} = 2$	[days], amount of days needed for CBM
Q	[-], amount of CM in the simulation horizon
R	[-], amount of CBM in the simulation horizon
R_{CBM}	[days], RUL length
$W_u(k)$	[-], defines when in the simulation horizon for rolling stock u at time k CM occurs, with the amount of CM defined by Q according to a randomized definition
$V_u(k)$	[-], defines when in the simulation horizon for rolling stock u at time k CBM occurs, with the amount of CBM defined by R according to a randomized definition
M	[-], Big M, denotes a very large number

5.4 Decision-variables

$\forall k \in K,\ \forall u \in U,$	$d_u(k)$	integer variable with lower bound 0 cumulative mileage of rolling stock u at time k
$\forall k \in K,\ \forall u \in U,$	$e_u(k)$	integer variable with lower bound 0 cumulative time of rolling stock u at time k
$\forall k \in K,\ \forall u \in U,$	$v_u(k)$	integer variable with lower bound 0 cumulative mileage of rolling stock u at time k when it enters the depot for PM

$$\forall k \in K,\ \forall u \in U, \quad x_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ is not in operation at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad y_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ undergoes PM at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad w_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ arrives at depot and starts PM at } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad z_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ undergoes CM at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad m_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ undergoes CBM at time } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad q_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ arrives at depot and starts CM or CBM at } k \\ 0, & \text{otherwise} \end{cases}$$

$$\forall k \in K,\ \forall u \in U, \quad r_u(k) \begin{cases} 1, & \text{if rolling stock } u \text{ combines CBM adjacent to PM at the depot at } k \\ 0, & \text{otherwise} \end{cases}$$

5.5 Objective function

$$\begin{aligned} \text{minimize } & \underbrace{C_{mileage} \sum_{k\in K} \sum_{u\in U} Dy_u(k) - v_u(k)}_{1} \\ & + \underbrace{C_{PM} \sum_{k\in K} \sum_{u\in U} w_u}_{2} \\ & + \underbrace{C_{CM} \sum_{k\in K} \sum_{u\in U} q_u}_{3} \\ & + \underbrace{C_{CBM} \sum_{k\in K} \sum_{u\in U} q_u(k)}_{4} \\ & + \underbrace{C_{shunting} \sum_{k\in K} \sum_{u\in U} w_u(k) + q_u(k)}_{5} \end{aligned} \tag{1}$$

$$C_{shunting} \sum_{k\in K} \sum_{u\in U} w_u(k) + q_u(k) - r_u(k) \tag{2}$$

The linear objective function 1 is formulated to minimize the costs associated with maintenance while CM or CBM are integrated in the rolling stock PM planning. Segment 1 of the objective function in equation 1 is the formulation of the mileage losses at the moment that a rolling stock arrives at the depot for PM. Segment 3 and 4 contain the costs when either CBM or CM is performed in the planning. Segment 5 contains the arrival of PM and CM or CBM, so that the shunting costs to the depot are also incurred. If the model integrates CBM in the PM planning and also PM and CBM can be combined, the segment of equation 2 replaces segment 5 of the objective function so that shunting costs are subtracted.

5.6 Constraints

The accumulated mileage is formulated in linearized constraints 3 and 4 as the mileage of the previous day plus the mission profile if the rolling stock is in operation. The linearization is performed with the big M method (Hillier and Lieberman, 2015). For the accumulated time constraint 5 and 6 is formulated in a similar manner. The time is still accumulating while the rolling stock is not deployed for passenger operation.

$$d_u(k) = (d_u(k-1) + (1 - x_u(k)) \cdot P) + M \cdot y_u(k), \quad \forall k \in K, \forall u \in U \tag{3}$$

$$d_u(k) \leq M \cdot (1 - y_u(k)), \qquad \forall k \in K, \forall u \in U \tag{4}$$

$$e_u(k) = (e_u(k-1) + 1 + M \cdot y_u(k), \quad \forall k \in K, \forall u \in U \tag{5}$$

$$e_u(k) \leq M \cdot (1 - y_u(k)), \qquad \forall k \in K, \forall u \in U \tag{6}$$

Constraint 7 and 8 linearly define the auxiliary decision-variable $v_u(k)$ that is used to define the mileage when a rolling stock enters the depot for PM and otherwise this variable is always zero. The constraints are linearized using the big M method.

$$v_u(k) \leq M y_u(k), \qquad \forall k \in K, \forall u \in U \tag{7}$$

$$M(y_u(k) - 1) + d_u(k-1) \leq v_u(k) \leq d_u(k-1), \quad \forall k \in K, \forall u \in U \tag{8}$$

Constraint 9 and 10 prevents the rolling stock from exceeding the mileage and time thresholds. Constraint 11 bounds rolling stock to only perform PM when the lower bound mileage threshold is reached.

$$d_u(k) \leq D, \qquad \forall k \in K, \forall u \in U \tag{9}$$

$$e_u(k) \leq E, \qquad \forall k \in K, \forall u \in U \tag{10}$$

$$d_u(k) \geq D_{LB} \cdot (y_u(k) - y_u(k-1)), \qquad \forall k \in K, \forall u \in U \tag{11}$$

Constraint 12 is formulated to ensure that every day exactly an amount of O rolling stock of the fleet is deployed for operation. As a result, no more rolling stock than required are in operation. Constraint 13, 14 and 15 define the rolling stock state if it is in operation or not and that PM, CM and CBM cannot be performed while performing passenger operations. CBM or CM cannot be performed simultaneously with PM as defined in constraint 16 and 17.

$$O = U - \sum_{u \in U} x_u(k), \qquad \forall k \in K \tag{12}$$

$$y_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{13}$$

$$z_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{14}$$

$$m_u(k) \leq x_u(k), \qquad \forall k \in K, \forall u \in U \tag{15}$$

$$z_u(k) + y_u(k) \leq 1, \qquad \forall k \in K, \forall u \in U \tag{16}$$

$$m_u(k) + y_u(k) \leq 1, \qquad \forall k \in K, \forall u \in U \tag{17}$$

Performing PM is modeled by the following constraints. PM is performed at the depot and always for 3 days exactly as is defined by constraint 18 and 19.

$$\sum_{k \in K}^{k+N} y_u(k) \geq N(y_u(k) - y_u(k-1)), \qquad \forall k \in K, \forall u \in U \tag{18}$$

$$\sum_{k \in K}^{k+N+1} y_u(k) \leq N, \qquad \forall k \in K, \forall u \in U \tag{19}$$

The capacity for rolling stock at the depot is defined by the amount of arrivals per day. The arrival decision-variable is defined in constraints 20 and 21. The depot capacity is constrained by the amount of arrivals per a certain amount of days. Constraint 22 is therefore formulated to sum up the amount of arrivals over A_{days} days, which is satisfied when the summation is less or equal to $A = 1$ arrival.

$$w_u(k) \geq y_u(k) - y_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{20}$$

$$w_u(k) \leq d_u(k-1), \qquad \forall k \in K, \forall u \in U \tag{21}$$

$$\sum_{u \in U}^{k+A_{days}} w_u(k) \leq A, \qquad \forall k \in K \tag{22}$$

The maintenance states of performing CM or CBM are defined by constraints 23 to 28. These constraints are only considered in the prediction horizons F and G using indices f and g related to the foreseeability of failures. Hence the difference formulation compared to previously defined constraints. Constraint 23 defines at which time CM is determined to take place

for which rolling stock, therefore, the equal sign is used, this is performed according to parameter value $W_u(k)$. Constraint 25 defines that CBM has to take place within the predefined time period indicated by the RUL of parameter $V_u(k)$. The model can decide at which instance in that time period it would plan CBM, but not outside of this time period, hence why the less or equal sign is used.
Since planning CBM is more complex to formulate because of its flexible ability to plan, two extra constraints are added. Constraint 26 defines that over every period of R_{CBM} days long (the RUL), the amount of CBM divided by the duration of CBM, has to be greater or equal to the amount of ones in matrix $V_u(k)$ during the same time period. And by adding constraint 27, CBM is always planned before failure.
Finally, the arrival day of CM and CBM is indicated by decision-variable $q_u(k)$ that will be 1 only if the rolling stock arrives at the depot for CM or CBM as constraint 24 indicates for CM and constraint 28 for CBM. Since CBM and CM will never be integrated in the same approach, the same notation of decision-variable can be used.

$$z_u(f) = W_u(f) \quad \forall f \in F, \forall u \in U \tag{23}$$

$$q_u(f) \leq z_u(f) - z_u(f-1), \quad \forall f \in F, \forall u \in U \tag{24}$$

$$m_u(g) \leq V_u(g) \quad \forall g \in G, \forall u \in U \tag{25}$$

$$\sum_{g \in G}^{g+R_{CBM}} \frac{V_u(g)}{R_{CBM}} \leq \sum_{g \in G}^{g+R_{CBM}} \frac{m_u(g)}{T_{CBM}} \quad \forall g \in G, \forall u \in U \tag{26}$$

$$\sum_{g \in G}^{g+R_{CBM}} m_u(g) \leq T_{CBM} \quad \forall g \in G, \forall u \in U \tag{27}$$

$$q_u(g) \leq m_u(g) - m_u(g-1), \quad \forall g \in G, \forall u \in U \tag{28}$$

Finally, if CBM will be combined with PM when binary decision-variables $m_u(k)$ and $y_u(k)$ are adjacent according to, constraint 29. This is only possible when firstly CBM is performed and subsequently PM.

$$2 \cdot r_u(k) \leq m_u(k-1) + y_u(k), \qquad \forall g \in G, \forall u \in U \tag{29}$$

6 Results

The optimization problem is solved with the Gurobi solver algorithm. The formulated model will be evaluated on its performance, especially the decision-making of the rolling stock PM planning optimization integrating CM in comparison to an approach that integrates CBM. Comparisons between results can be used to assess performance and justify the impact of CM and CBM on the rolling stock maintenance planning. This includes also the cost effectiveness of the possibility to combine CBM with PM in the rolling stock maintenance planning.
To quantify the performance of the optimization approach, multiple KPI's are generally used in the state of the art and the state of practice. An KPI is a quantitative value that reflects the performance of an approach. The following KPI's are defined in order to evaluate and compare the performance of different approaches prioritized from high to low according to the state of the art, practice and experience:

1. Mileage losses
2. Amount of infeasible optimization solutions
3. Amount of combinations of CBM with PM
4. Maintenance costs

The **mileage losses** can be calculated from the first segment of the objective function from equation 1. Since it is assumed that every rolling stock runs constantly 475 [km] per day when in operation and the mileage threshold is $D = 45,000$ [km], the optimal mileage losses is nonzero. $\frac{45,000}{475} = 94.7$ is not a round number and therefore the maximum amount of days that a rolling stock can be in operation before PM is 94. Consequently, the mileage losses are $45,000 - 94 \cdot 475 = 350$ [km] per rolling stock as minimal value. The optimization is increasingly less optimal the more mileage losses are incurred and therefore is this is considered the most important KPI.
Infeasibility is characterized as when the optimization initialized with parameters values cannot be bounded by the formulated constraints and a solutions is found by the solver algorithm. A maintenance planning approach that puts out a feasible solution is better in decision-making than a planning that resolves into an infeasible solution. Based on experience, an infeasible solution is a cumulative result of poor decision-making in the past or unfortunate disruptions. The performance of the optimization approach is therefore quantified by this KPI.
When the RUL is overlapping the nearest PM routine in the planning, this can be used as an opportunity to combine CBM with PM, saving shunting costs. Since this is highly desired, the amount of combinations are

used as KPI, the higher the **amount of combinations of CBM with PM**, the better. However, this might be at the expense of the mileage costs. The amount of combinations of CBM with PM can be retrieved by summing up decision-variable $r_u(k)$.
The **maintenance costs** can be obtained directly from the objective function equation 1. This KPI indicates to overall outcome, but does not necessarily specify how the optimization is performing, therefore, other KPI's have more priority to characterize this.

6.1 Performance of the PM planning optimization while disrupted by CM or CBM

CM and CBM are disruptive factors in the maintenance planning. Because of a failure, a rolling stock has to go to the maintenance depot for CM and it becomes unavailable. Due to this unavailability, the rolling stock cannot run operation for a certain amount of time. In the meantime, the cumulative time is increasing, nearing the time threshold for PM. So since the rolling stock is unable to run enough distance before the time threshold, mileage losses are made.
To evaluate the performance of the maintenance planning optimization while being disrupted by CM and CBM, instances of CM and CBM will be initialized in random matrix $W_u(k)$ and $V_u(k)$. The matrices $W_u(k)$ and $V_u(k)$ will be filled with instances in such a way that ensures disruptions always occur at the first day of the week ($k = 0, k = 7, k = 14$ and so on), because the implementation horizon I is one week or 7 days. In this way, the unexpectedness of CM is perfectly simulated, because with the rolling horizon, the disruption appears in the disruption horizon F right after the last implemented day. The instances in random matrix $W_u(k)$ and $V_u(k)$ will be chosen as follows:

- No more than 1 disruption per rolling stock in the simulation horizon.;
- Amount of disruptions (R for CBM and Q for CM) are iterated from 4 to 12 with increments of 1: $\{4, 5, 6, 7, 8, 9, 10, 11, 12\}$, or for other comparisons with increments of 2.
- The disruptions will be randomly distributed from $k = 21$ to $k = 98$ with increments of 7 days: $\{21, 28, 35, 42, 49, 56, 63, 70, 77, 84, 91, 98\}$.
- No more than 3 disruptions per day, otherwise, not enough rolling stock can be available for passenger operations due to parameter O.
- The RUL length of $R_{CBM} = 14$ [days] is chosen to enable the comparison of CBM with CM.
  The RUL length of $R_{CBM} = 14$ and 21 [days] is chosen for comparing the integrating of CBM in the PM with possible combinations of CBM with PM.
- 20 different randomization configurations for CM and CBM are used in order to exclude coincidences of successes. The results in data of the different outcomes can be processed in order to analyze the impact of disruptions on the decision-making.
- A planning will be established for $J = 19$ optimizations, so a simulation horizon of $K = 133$ days.

Amount of infeasible solutions The first graph 4 shows the comparison in percentage of infeasible solutions between CM and CBM. What can be seen from the figure is that in any optimization with disruptions, for either CM and CBM, a certain amount of cases become infeasible. No logical relation of infeasible solutions can be noticed for CBM, because for 4 to 6 disruptions, 45% of all optimizations become infeasible and with 9 disruptions, only 15% is infeasible. It can be stated that the percentage of infeasible solutions is stable throughout the iteration and on average 42.2%.

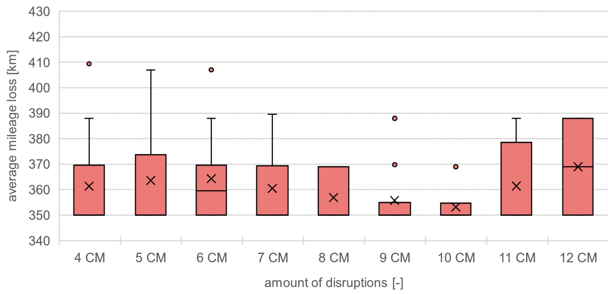
On the contrary, the more disruptions take place in the simulation horizon, significantly more infeasible solutions are observed for CM. From an amount of 9 CM in the simulation horizon, the amount of infeasible solutions steadily increases with respect to the amount of CM up to a percentage of 85%, while for the same amount of disruptions only 35% of the optimizations integrating CBM came out as

infeasible. However, for the disruptions amounts 4 to 7, more CBM infeasible solutions came out the optimizations, on average 41.2% against 36.3% for CM.
For a low amount of disruptions in the planning, CM came out 5% better in optimization performance in comparison to CBM. However, in total, 27 more solutions out of 180 are found with a planning with CBM than for CM. Moreover, there is no sign of a trend in infeasible solutions for CBM whilst there is for CM.

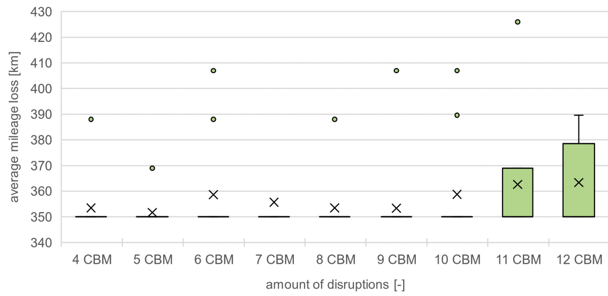
Figure 4: Percentage of infeasible solutions out of 20 random configurations, a comparison between CM and CBM with increasing amount of disruptions

Average mileage losses per rolling stock maintenance planning Graph 5a and 5b are whiskers plots. These whiskers plots show the performance of the feasible solutions that integrate CM or CBM indicated by the mileage losses. The average mileage loss over the complete rolling stock maintenance planning is selected from every feasible solution and categorized per amount of disruptions. The data plot demonstrates that 50% of all of the solutions are in the box, showing the spread of data and the median (middle stripe in the box). The standard deviation is demonstrated by the bars when this is outside of the box.

First of all, it can be noticed that in figure 5b, for 4 to 10 disruptions, there is no box. This implies that the median, the first and second quartile of data lies within the same point of 350 [km], which is proven to be the minimal amount of mileage loss. This means that the majority of feasible solutions integrating CBM into the maintenance planning make no mileage losses on average. When 11 and 12 disruptions take place in the planning, the spread of mileage losses becomes higher, so more mileage losses are made on average when more disruptions take place.



(a) CM



(b) CBM, RUL of 14 days

Figure 5: Whiskers plot of the average mileage losses (y-axis) that are made by by the feasible solutions that successfully integrated CM (a) and CBM (b), categorized by the amount of disruptions occurring in the planning (x-axis).
Dots demonstrate outliers of the data set, "x" indicates the mean average mileage loss and the bars indicate the standard deviation.

6.2 Performance of the PM planning optimization with the opportunity to combine CBM with PM

The opportunity is provided by the optimization approach by replacing segment 5 from the objective function 1 with equation 2 to combine CBM with the PM routine. The time to failure of the rolling stock is indicated with the RUL. When this occurrence is close to an upcoming PM routine, the two maintenance routines can be combined. If this combination is feasible to plan, it reduces shunting costs, because the rolling stock only has to go to the depot once. The maintenance costs are directly related to the amount of combinations of CBM with PM, since every combination saves $C_{shunting}$ [euro] in shunting costs. However, the costs also depend on the extra mileage losses that are made. Combining CBM with PM is therefore a trade-off between mileage losses and shunting costs.

A case will be initialized with disruptions similarly as the previous section. Disruption matrix $V_u(k)$ randomly distributes time of failures over the fleet size and simulation horizon. For evaluating the performance of the rolling stock PM planning optimization that integrates CBM that can be combined with PM, the following assumptions are made:

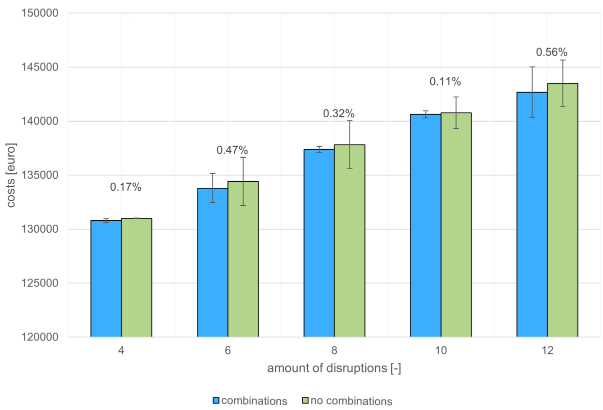
- 20 random configurations for $V_u(k)$ are used with the same conditions as previous experiment.
- The RUL R_{CBM} is iterated from 7, 14 to 21 with increments of 7, so $\{7, 14, 21\}$ [days].
- The amount of disruptions R is increasing over the iterations $\{4, 6, 8, 10, 12\}$.

The performance is evaluated with the KPI that expresses the amount of combinations of CBM with PM. The results are expressed in table 1 that shows the average number of combinations that are made in the planning for a RUL of 7, 14 and 21 days in relation to the amount of disruptions in the planning. It can be seen in table 1 that the longer the RUL, the more combinations are made. This is expected, because the longer the RUL, the higher the chance in overlap with the upcoming PM routine. Additionally, the more disruptions that take place, the higher the chance that there is an overlap between the RUL and the upcoming PM routine.

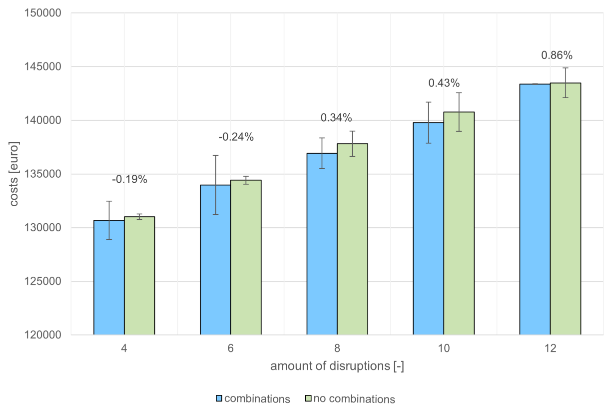
The comparisons are made with an approach that enables combinations versus an approach that does not. This costs comparison using the maintenance costs as KPI is presented in figure 6a and 6b. The average maintenance costs are provided in these figures as a result of combinations in relation to the amount of disruptions by CBM in the optimization for an RUL of 14 days and 21 days.
Graph 6a illustrates by the comparison that the mean average maintenance costs are very close, but overall, the percentages show positive costs savings if combinations are possible in the planning. Alternatively, graph 6b illustrates that for 4 and 6 disruptions, the maintenance costs are on average not less than an approach without combinations. This is logical, because less combinations of CBM with PM can be made with a lower amount of disruptions as is concluded from table 1, so also less cost savings. However, the standard deviations show with the lower bar that the maintenance costs of the maintenance planning that enables combinations are generally lower than for the approach without combinations.
Overall, for an RUL of 14 days over disruptions from 4 to 12, an average cost savings of 0.32% is made. The graph of figure 6b shows the relations that the more disruptions take place, the higher percentage in costs are saved. For an RUL of 21 days over disruptions from 8 to 12, an average cost savings of 0.54% is made, which is more cost efficient than with an RUL of 14 days.

7 Conclusion and Recommendations

A deterministic MILP mathematical model that represents the maintenance decision-making process



(a) CBM, RUL of 14 days



(b) CBM, RUL of 21 days

Figure 6: Comparison of the average (fictional) maintenance costs (multiplied with cost factor Y see confidential annex B) where in blue, combinations are possible, in green without combinations of CBM with PM.
The costs savings are expressed in percentages and the error bars demonstrate the standard deviation of the maintenance costs.

amount of CBM [-]	RUL length [days] 7	14	21
4	0.5	0.7	1
6	0.7	0.9	1.4
8	1.1	1.4	1.7
10	1.1	1.9	2.1
12	1.1	2.5	2.8

Table 1: Average number of combinations CBM and PM over 20 random configurations iterated over an increasing amount of disruptions and RUL lengths

of NS, which can be optimized using a Gurobi solver algorithm, is formulated in this study. The rolling horizon framework is perfectly able to approach the maintenance planning problem because of its ability to rearrange in response to (predicted) disruptions. This frameworks provides the opportunity to distinct CM from CBM in its foreseeability, so fair comparisons could be made.
The model presents an integral simplified version of the NS rolling stock maintenance planning case.

For the formulation of this model, assumptions and concessions were made to model the case. As a consequence, the results of the model may therefore deviate from reality. Nevertheless, conclusions can be drawn from the model, under the assumptions and conditions that are made earlier in this study.
Overall, it can be concluded from the results of the formulated optimization problem that CBM impacts the decision-making positively by creating flexibility in planning resulting in more feasible solutions. Besides, a trend is observed for the maintenance planning optimization integrating CM, that the more disruptions take place, the higher the chance is that no solutions can be found. The evaluation quantifies that a rolling stock PM planning integrating CBM is better to plan based on the 27 more feasible solutions out of the 180 optimizations. Under the condition that disruptions take 2 days and 4 to 12 disruptions take place randomly distributed over 21 rolling stock over 12 weeks. Moreover, the evaluation based on the whiskers plots qualifies that CBM is more than halve of the times able to establish a rolling stock maintenance planning without inducting more

than optimal amount of mileage losses. Meanwhile the spread of overage mileage losses for a planning considering CM is higher. This implies that it more frequently occurs that mileage losses are made when a disruption in the planning is unexpected.

CBM creates the opportunity to combine the routine with PM so double shunting operations can be avoided, saving shunting costs. It is shown by the maintenance costs comparison that these combinations generally result into cost savings to maximum of 0.86% on average for an RUL of 21 days. So more combinations have a positive impact on the performance of the rolling stock maintenance planning decision-making. The more disruptions take place, the higher the chance of combinations and the longer the RUL, the more combinations can be made.

In reality the fleet exists of 190 rolling stock from which a certain amount should be available for passenger operation. This cannot be modeled with the current optimization method, because it results in computational complexities, so the optimization approach is limited. The required availability for passenger operations is actually variable depending on the time of the day and the day of the week, due to peak hours and peak days. The maintenance decision-making can be more realistic if the variable rolling stock availability requirements are integrated in the maintenance planning model.

Disruptions in the form of CBM and CM are modeled as random artificial instances, it is recommended to initialize this with historical failure data to further validate the model with the maintenance costs and mileage losses of NS.

Another aspect that should be analyzed, is the capacity of the depot for CM and CBM. The arrival of a rolling stock for CM or CBM is not constrained to any maintenance depot capacity limitations. It is reasonable that more arrivals for CBM results into more workload for the depot. In a situation where solely maintenance is decided based on prognostics, this is recommended to thoroughly analyze and compare it to the current situation with PM.

It is assumed that the RUL from a fault detection in the formulated model is perfectly accurate. Realistically, since actual CBM is conducted according to prognostic information that predicts a failure, it is not 100% certain if the rolling stock is actually going to fail. The prognosis might be false positive and the rolling stock is going to the maintenance depot for CBM purposeless. With CM, the rolling stock fails and shunting to the maintenance depot and is always necessary. Alternatively, CBM might lead to a false negative, so CM can still occur despite the health of the rolling stock condition that is monitored and potential failures can be predicted. It is recommended to take these aspects in consideration for future research.

Since according to the results, the integration of CBM to the PM planning is beneficial, it is recommended to perform more research on the integration of CBM in the rolling stock maintenance planning. Planning maintenance according to prognostic information has no direct impact on the availability of the rolling stock because the asset may continue to operate passenger operations, while it is going to be planned for an optimal moment for maintenance. Since CBM can be planned ahead of time, it can be researched how this is beneficial to maintenance strategies.

It is shown that combining CBM with PM in one routine is cost efficient. It is therefore recommended to develop prognostic models to predict failures far in advance, because the longer the RUL of the prognostic models, the more efficient the integration of CBM into the PM planning can be.

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C

Eventplots of Approach 3

Examples of eventplots of approach 3 are presented, illustrating the difference in planning. The eventplots demonstrate the timeline (x-axis) over the simulation-horizon for every rolling stock (y-axis). The block of the color in the eventplot indicate the state of the rolling stock. When there is no color, the rolling stock is in operation and runs 475 [km] that given day.

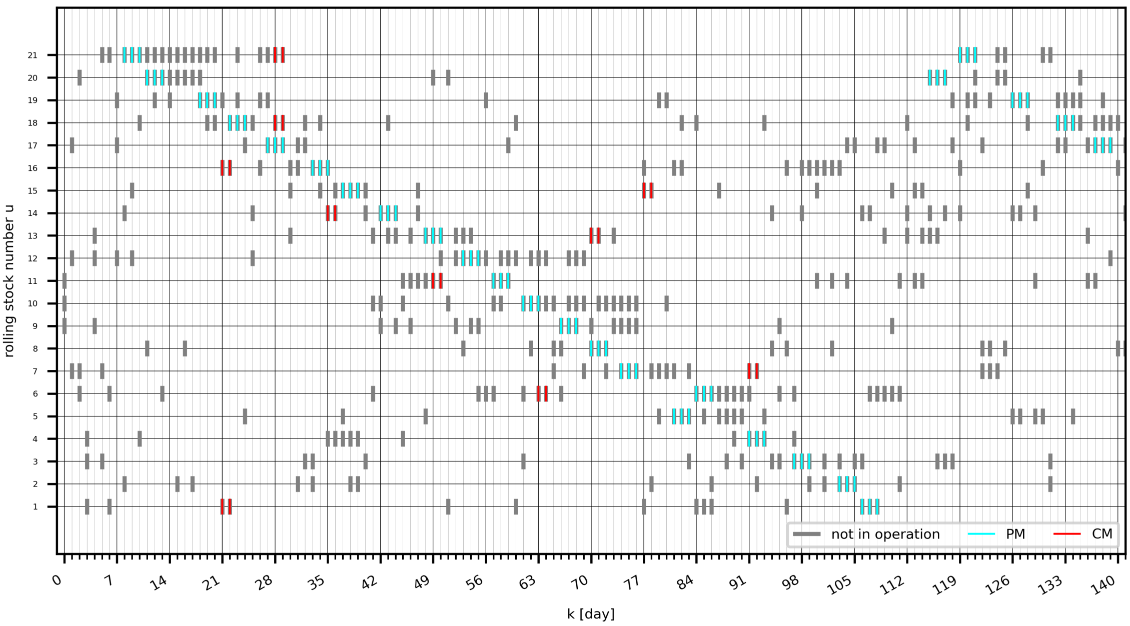

Figure C.1: Eventplot of approach 3 for $Q = 10$ CM, random configuration 5

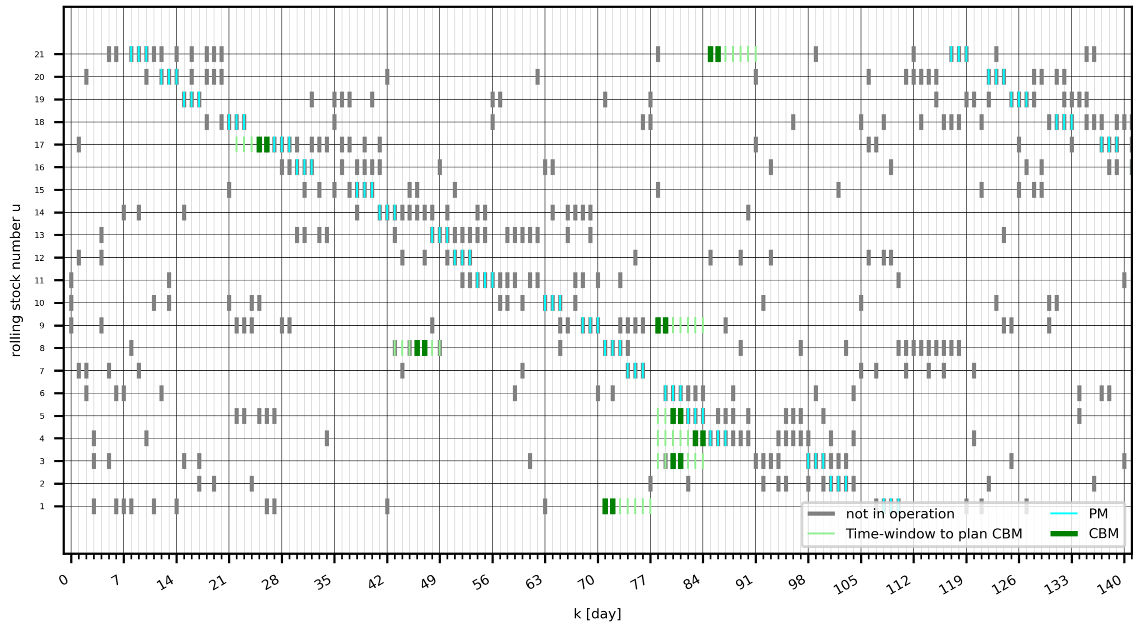

Figure C.3: Eventplot of approach 3 for $R = 8$ CBM and $R_{CBM} = 7$ including CBM+PM combinations as can be seen, random configuration 9

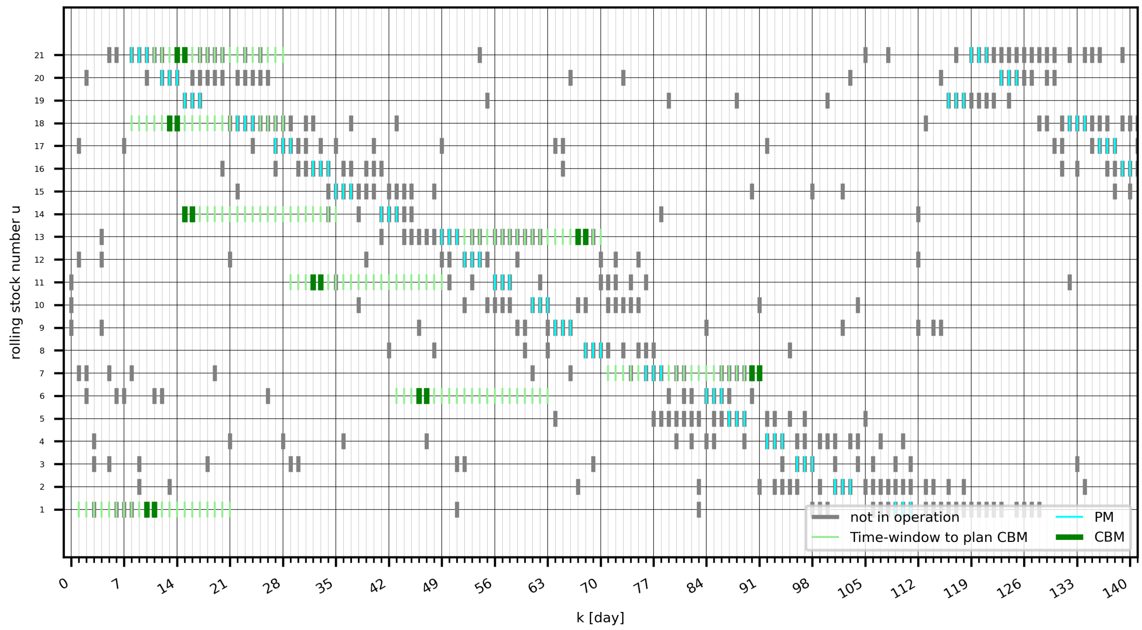

Figure C.2: Eventplot of approach 3 for $R = 8$ CBM and $R_{CBM} = 21$, random configuration 5

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