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Predictive maintenance on Dutch civil infrastructure: a structured approach

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Preface

The past couple of months have been all about my thesis, and Predictive Maintenance. During these months I have gained a thorough understanding of the current developments in the field of Predictive Maintenance and the Dutch Vital Transport Infrastructure (VTI). The fact that I worked on my thesis in three different organizations has been both the most challenging aspect of the entire process, as well as the most rewarding. This allowed me to experience the differences between the organizations, such as the different drivers between an asset owner and a maintenance contractor.

Although Predictive Maintenance is still a relatively new concept, I do think that it could enable significant changes in the way maintenance is being organized and executed in the domain of Dutch vital civil infrastructures. This makes it even more interesting to have worked on such an interdisciplinary subject.

This thesis would not have reached its current form without the excellent support from all the supervisors. I would like to thank Hans Moonen, Doina Bucur and Carlos Budde for the academic support and of course all the proof reading. Next I would like to thank Laurens Lapré and William Bats from CGI for the strategic input. Furthermore I would like to give a special thanks to Lex de Warle and Patrick van Beers from Heijmans, and Oscar Enzing from ProRail for facilitating the case studies, and the active support throughout the entire process.

Huibert Alblas
Rotterdam, January 31st 2020

Management Summary

Predictive Maintenance (PdM) is the next step in maintenance regimes which can assist organizations responsible for the upkeep of Vital Transport Infrastructure (VTI) assets with the upcoming challenges due to the increased service requirements, and the decrease in available time and resources for maintaining the assets.

This thesis aims to create a framework on how to approach the implementation of predictive maintenance in an organization around VTI. The implementation framework is derived from [1], and tested on two case studies, one around the degradation of asphalt on Schiphol airport, and the second one around the degradation of rail switches.

In both case studies the importance of complete, and correct health data has been identified. Besides the technical requirements, it has also been identified that the transparency of the resulting predictions is an important factor for the end-user adoption.

The proposed implementation framework is not complete, as became apparent in the case studies, but it does provide a good direction and particularly relevant focus points for the initiation of a predictive maintenance project. Lastly, a revised PdM implementation framework has been defined based on the results from the case studies.

Contents

List of Acronyms

BVP	Best Value Procurement
CBM	Condition Based Maintenance
DBFM	Design & Build & Finance & Maintain
DC	Design & Construct
DSRM	Design science research methodology
EC	Engineering & Construct
GPR	Ground-Penetrating Radar
HI	Health Indicator
HWD	Heavy falling Weight Deflectometer
IoT	Internet of Things
IQ	Information Quality
MTOW	Maximum Take Off Weight
OPC	Output Process Contracts
PBC	Performance-based contracts
PdM	Predictive Maintenance
PM	Preventative Maintenance
ROI	Return On Investment
RUL	Remaining Useful Life
RWS	Rijkswaterstaat
SVM	Support Vector Machine
VTI	Vital Transport Infrastructure

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Chapter 1

Introduction

Vital Transport Infrastructure (VTI) as we know it today consists out of many components that together serve the goal of providing mobility. In this thesis VTI includes the main roads, railways, waterways, ports and airports which play a significant role in the network used for the transportation of people and goods to, from, and within the Netherlands. The implications of the lack of maintenance on these goes further than just a broken section of asphalt or railroad track. As [6] states, poorly maintained roads significantly raise vehicle operating costs, increase accident rates and their associated human and property costs, and aggravate isolation, poverty and poor health in rural communities.

More generally speaking, the main reasons why maintenance is being performed are safety, quality of service, cost reduction, customer experience and since recently environmental sustainability. [7], [8] However, this is becoming more and more challenging as the field of maintenance is under increasing pressure due to the trends of an increase in the expected service level while the available maintenance personnel will decrease the coming years. [9] On the upside, technologies that are capable of streamlining and optimizing the execution of maintenance, by providing a uniform way of data acquisition and future state predictions are breaking out of their respective niches and are slowly becoming mainstream.

Highways, waterways, and deepsea ports play the most significant role for the transportation of goods. Although 73% of the kilometers travelled by people is in a car, and only 10% by train, rail transport is still responsible for roughly 75% of the kilometers travelled by people with public transport. [10]

1.1 Problem statement

Predictive Maintenance (PdM) is an approach which is slowly becoming mainstream, which has the potential to innovate the existing maintenance practises, as well as to tackle the emerging challenges in the field of maintenance. In industrial processes, PdM plays a more significant role. There it also became apparent that the implementation of PdM is not trivial. [11]

Based on these drivers it becomes relevant to investigate a strategy for the implementation of a PdM solution in the VTI domain. This will aim to prevent an initiated PdM project from stranding, by evaluating crucial aspects early on in the project. This creates the research question which will be focused on in this thesis:

Research Question: *How can PdM be implemented in the area of VTI maintenance?*

In order to get and understating of the state of the art of PdM, as well as the current state of the maintenance processes in VTI the following two sub questions are formulated:

1. How is the maintenance landscape around VTI organized?
2. What is the state-of-art of PdM in general and in VTI?

In order to further determine the most relevant approach to be taken for the implementation of PdM in the area of VTI a literature study will aim to answer the third sub question:

3. How to structure a PdM project in VTI?

Thereafter, the identified approach will be validated by applying it to two case studies in the area of VTI. The selection of the case studies was mostly driven by the availability of data. The first case study which has been selected is at ProRail, where the focus is on predicting the breakdown of Railway switches. The second case study is at Heijmans, where the focus is on predicting the lifetime of asphalt on Schiphol airport. This creates the following two sub questions:

4. How to predict the breakdown of railway switches in order to reduce the risks on sudden unavailability and costs?
5. How to predict the development of defects in asphalt on runways and taxiways in order to reduce risks and costs?

Based on the evaluation of the applied framework, as well as on the experiences gained in these case studies a revised framework will be defined. This will mark the ending of this thesis, and potentially the starting point of someone else's work. The final sub question to be answered is:

6. How would a revised design approach look like?

1.2 Methodology

The Design science research methodology (DSRM) framework (Fig. 1.1) will be used as framework for structuring the thesis, as it is a widely accepted method for design science research. [2] The framework provides flexibility by defining multiple research entry points. For this thesis the Object Centered Solution entry point will be used, as the starting point is the objective to introduce PdM in an organization which is involved with the maintenance of VTI.

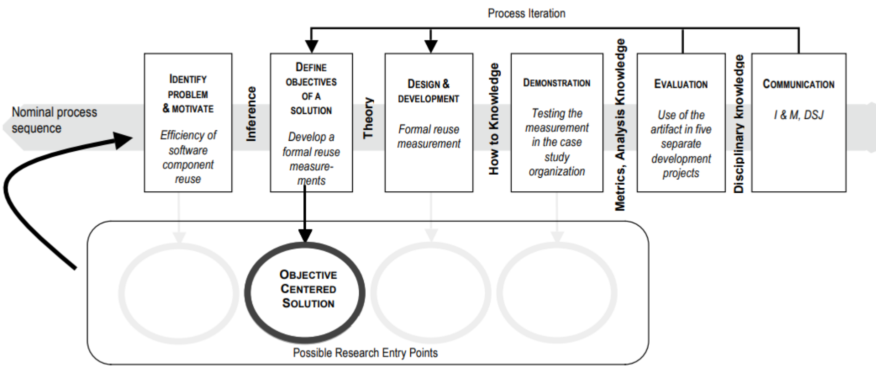


Figure 1.1: Design Science Research Methodology VTI Process Model. [2]

Subquestion one describes the way maintenance is organized in the field of VTI in terms of organizations and their process for the detection and correction of defects. Additionally, the challenges and opportunities emerging in the field of VTI maintenance are covered. The knowledge for answering this question will be sourced from domain experts, and publicly published information.

Subquestion two describes the domain of PdM based on the knowledge available in literature and in public white-papers. Additionally, the status-quo of PdM applications in VTI is covered, which will be discussed based on a literature review. In the DSRM framework subquestion two is part of the problem identification and motivation stage, as it provides insight into the level of adoption of PdM in the field of VTI.

Subquestion three has the goal to setup a general approach to create a PdM application for the field of VTI. Literature research on existing design strategies, and expert knowledge on aspects specific to VTI will be used as basis for the strategy.

Subquestion 4 and 5 capture the demonstration of the artifact defined under subquestion 3. Here the designed strategy will be used to setup a prediction system in the two cases largely based on the already available data. Knowledge used in this stage originates from the domain experts who have knowledge from the domain of the case.

Table 1.1: Mapping research questions to their corresponding chapter

Sub question	**Methodology**	**Covered in**
RQ1	Literature review	Chapter 2
RQ2	Literature review	Chapter 3
RQ3	Literature review	Chapter 4
RQ4	Case design	Chapter 5
RQ5	Case design	Chapter 6
RQ6	Evaluation	Chapter 7

The evaluation phase of the VTI framwork is covered in subquestion 6, where the observed interactions between the artifact and the two contexts are covered. It will be evaluated to what extend the framework was able to support the case studies by evaluating its completeness, relevance, and usability. Additionally two domain experts will evaluate the framework, as well as the execution of the case studies.

Chapter 2

Maintenance in VTI

An overview of the maintenance landscape in the Vital Transport Infrastructure (VTI) domain, together with the challenges present in this field, are presented in this chapter.

In order to determine where and how Predictive Maintenance (PdM) can be applied to improve the predictability of maintenance it is being reviewed how maintenance is organized and managed per domain. Legal contracts which clearly state the roles and responsibility of each party are important in this field due to the large value of the concessions. Therefore the type of contracts used between the contractor and the contract issuing party are being reviewed to determine the roles and responsibilities of both parties. Lastly the party which has the incentive to innovate the maintenance practises is identified, as this defines the context in which PdM methods need to be developed.

Two overarching challenges have been identified to be present in the field of maintenance on VTI that drive the need for improvements on how maintenance is being performed. First of all, more and more pressure is put on these components by the increasing demand, which impacts the overall goal of providing mobility. ProRail expects 2019 to be a record breaking year in terms of the number of kilometers driven over rail, Rijkswaterstaat (RWS) expects the number of kilometers driven over the Dutch road to increase at least until the year 2022, and Schiphol experiences a yearly increase in the number of airplane movements since 2009. [12]–[14] This trend increases the pressure on the correct and efficient execution of maintenance, as the increasing traffic causes the impact of downtime to increase as well. Besides the increasing pressure from the demand side, technically skilled personnel is harder to come by, and on top of that many technically skilled people are retiring the coming years. [9], [15]

The mayor links and points in the networks used to transport goods and people from, to, and within the Netherlands are the Highways, waterways, deepsea ports and airports. For each of these categories an organization managing these assets have been selected. For each organization it is evaluated how the maintenance to their assets is organized. The organizations being covered are: ProRail, RWS, Schiphol, and lastly the Port of Rotterdam. These organization are responsible for the state of the railway network, the highways, the most important airport, and the largest deepsea port respectively.

2.1 ProRail

ProRail is the organization responsible for the railway infrastructure in the Netherlands. ProRail separates maintenance activities into two categories, namely small and large maintenance. Large maintenance is concerned with safeguarding the quality of the infrastructure and managing the life expectancy on the long term. Small maintenance is focused on maintaining the functional state of the infrastructure on a day-to-day basis.

Small maintenance

Small maintenance covers the activities needed to maintain the availability, reliability and safety of the railways. This covers both repetitive activities and incidents. [12] Traditionally, small maintenance was tendered in four regions according to a best-efforts agreement. In the last 10 years, a transition was made from Output Process Contracts (OPC) towards 10 year long Performance-based contracts (PBC), which means that no longer the required efforts are stated, but rather the required achievements. This is shaped by defining a financial incentive for the contractor to keep the safety, availability, and quality of the railroad up to a certain level. The realized effects of this new type of maintenance contracting is a decrease in costs, as well as a decrease of the number of incidents. [16] Additionally, the contractor is motivated to increase the focus on efficiency improvements. Whereas previously, only efficiency improvements in terms of labour and resources where appealing, in order to decrease the costs for the execution of a specific maintenance task. Currently there is also the incentive to increase the effectiveness of the applied maintenance actions, as the quality of the railways as a whole is used as measure for the performance of the contractor, rather than the performance on the execution of the individual maintenance actions. Only in the last year of the 5 or 10 year contract, contractors expect themselves to decrease the amount of maintenance to the bare minimum in order to maximize the profit of the concession. [17] Similar to what has been raised by a contractor of RWS, the relative short duration of the PBC contract opens an opportunity for only some maintenance innovations. Mostly innovations focused on applying the existing practises in more efficient ways are made possible, however implementing innovations on the design of the assets being maintained, based on the experiences gained from maintaining the assets, is too expensive for the duration of the contract. (Personal communication, July 2019)

Even tough the contractors have received more responsibilities, ProRail remains the party who has to guarantee the safety of the railways. However, due to the shift in responsibilities the relation between the parties changed, as the amount of operational cooperation would decrease, and the legal aspect of the relation will increase. [17] identified that ProRail needs to become more aware of the health of its infrastructure in order to guarantee the safety under the PBC, as the contractor now has an incentive to reduce the amount of maintenance. This could jeopardize the safety if not monitored properly. Besides guaranteeing the safety, ProRail also needs a clear insight in the state of the infrastructure in order to maintain the legal relationship with the contractors. ProRail employs inspectors tasked with determining the physical state of the railways, additionally before and after large maintenance projects the state of the railway is inspected by the large maintenance and small maintenance contractors respectively. (Personal communication, July 2019)

Large maintenance

Large maintenance covers changes to the design of the track, and maintenance on objects with a long lifetime, such as the rail. Large maintenance projects are all individually placed on the market with a traditional procurement method, in which all specifications and methods are described in detail. Best-value procurement is used increasingly more, but still only for a limited number of projects. Additionally, contractors who are deemed trustworthy and skilled based on past experiences are more likely to get freedom in the selection of methods used to realize the intended functionality. The application of innovative technologies is possible, but only after they have been certified to guarantee the safety and quality.(Personal communication, July 2019)

Life-cycle costs are not a concern of the contractor, as large maintenance is handled in individual projects, and the methods to be used are defined in the tender. Only when the contractor performs large maintenance in the region in which they are also responsible for the small maintenance, there is an incentive to take future maintenance activities into account.

2.2 Rijkswaterstaat

Traditionally, RWS determined where, when, and how maintenance had to be performed, and it was up to the contractors to execute the works according to the book.

Since recent years, RWS has experimented with the use of Best-value procurement and PBC. Best-value procurement is different from traditional procurement in the sense that only the high level goals and quality characteristics are defined, rather than a more detailed description of the project. In this setting the contractors are expected to be the experts in the field, and have the freedom to use their creativity and innovations to come up with the best possible implementation. This is furthermore encouraged by the ranking scheme, which favours quality over price.

RWS distinguishes 4 types of concessions which are used as basis for construction and maintenance projects: Design & Construct (DC), Engineering & Construct (EC), PBC, and Design & Build & Finance & Maintain (DBFM).

Design & Construct

Design & Construct projects are the most common and allow the contractor to design and build the object based on the functional requirements defined in the contract. In the maintenance field, DC projects are only used for stand alone large maintenance projects. Innovation in this type of project is encouraged, but only within the scope of the design and the execution of the design, long term maintenance innovations and life-cycle costs are out of scope.

Engineering & Construct

Engineering & Construct projects are similar to DC projects, but more simplistic. As the design for the construction of the object, or the procedures for maintaining the object have already been defined. The contractor only needs to determine how to practically execute the specifications. DC contracts are in the maintenance field only used for extremely repetitive maintenance actions, maintenance to object with a low risk profile, or maintenance to objects with a small population. The incentive and possibility for the contractor to innovate maintenance practises is very limited.

Performance

PBC are mostly used for long term maintenance of existing infrastructure, and have a duration of 3-5 years. [18] A PBC defines the quality standards the object has to meet, which makes the contractor the expert on the product and stimulates them to search for the most effective methods to maintain the quality of the object. [19] However, in practise it turns out that a contract duration of 3-5 years is not long enough to make it appealing for the contractor to invest in maintenance innovations that are specific to the region. (Personal communication, June 2019)

Design, Build, Finance, and Maintenance

DBFM contracts are used for large construction projects, in which a consortium is responsible for the design, construction, pre-finance, and maintenance of an object, usually for around 20-30 years. A key difference between a DC and DBFM concession is that with DC a product is being delivered, whereas with the latter a service is being provided. With this concept most of the risks related to the construction and maintenance of the object are the responsibility of the consortium. As it is a service which is being provided, such as the availability of a road, it is also billed as such. This requires the consortium to pre-finance the construction, which would result in a tight control of the risks jeopardizing the successful completion of the project by the financers of the consortium.

Other then with a DC project, a DBFM project encourages to consider the future maintenance costs in the design and construction phases. Additionally, the duration of the contract is long enough to force consortia to try to innovate on the current maintenance practises.(Personal communication, June 2019)However, it is still challenging to implement PdM practises in a BDFM project, as with all new objects, no failure data is known and degradation effects have not yet been observed in real life. None the less, it is possible to make an assumption about the degradation patterns to expect based on past experiences with similar objects, which can be used as basis to include measurement practises already in the design phase of the object.

2.3 Schiphol

Recently Schiphol made a transition from traditional maintenance contracts towards PBC in combination with a best-value procurement method. The contract has a maximum duration of 9 years, which is long enough for the contractors to invest in special materials which require less maintenance. [20] The long term PBC creates an incentive for the contractor to innovate the maintenance processes with the goal to prevent downtime, and to implement innovations in the design of the assets based on the experiences gained with maintaining the assets. The assets to be maintained, such as the asphalt of the runways, has a longer life expectancy than the duration of the maintenance contract. Therefore, the motivation to apply predictive techniques to predict the Remaining Useful Life (RUL) of the entire runway still lays with Schiphol. However, the benefit for the contractor to invest in such a PdM tool is that it can further strengthen their role as maintenance expert, which is highly valued with Best Value Procurement (BVP).

2.4 Port of Rotterdam

The organization Port of Rotterdam is tasked with the maintenance of the Port, such as on the roads, the quaywalls, and the dredging of the port. The Port of Rotterdam is currently in the transition of switching from a traditional RAW procurement method to best-value procurement with a PBC for the maintenance of their roads. [21] A comprehensive overview of the types of contracts used between the Port of Rotterdam and their contractors for maintenance on the other assets could not be determined. Port of Rotterdam has the goal to not only become the port with the best infrastructure, but also with the smartest infrastructure. [22] The creation of an Internet of Things (IoT) platform is one of the ways the Port of Rotterdam aims to reach this goal. Autonomous shipping and PdM are two examples of what should become possible due to the implementation of the IoT platform. [23], [24]

The Port of Rotterdam has already has a PdM program for their quaywalls. Inspection data is fed into an expert system, which uses deterioration models of steel and concrete to predict the future state of the quaywall. The most important question to be answered is if the quaywall will survive the duration of the lease contract with the tenant or not. [25] The implementation of innovative maintenance practises is thus currently done by the Port of Rotterdam itself for assets with a slow degradation process.

2.5 Trends and Challenges

The relations between contractors and owners described in the sections above show trends that are present in the entire sector, as well as remarkable differences. The increasing use of BVP in each organization is an interesting trend, as this is used in cases where the contractors are trusted with fulfilling the expert role in the concession. Another sector wide trend is the use of long term PBC for maintenance to the existing infrastructure. This motivates the contractors to focus on the effectiveness of maintenance actions, rather than just the efficiency with which the maintenance actions are applied. The need for PdM among contractors rises, as they are motivated to perform maintenance in a smarter way.

In short, it can be seen that the incentive for innovating the processes related to small maintenance, with an impact on the short term is placed with the subcontractors. The incentive for innovating the maintenance activities with an impact on the long run, which would be more than 10-20 years, remains at the organizations responsible for the assets. However, the use of BVP gives an opening for contractors to realize maintenance innovations.

Besides commonalities, there are also remarkable differences between the organizations. Whereas all organizations give the market some type of expert role, RWS takes it to a whole different level by introducing infrastructure as a service with DBFM contracts. However, it turned out that the risks involved in these project are too large to be handled by a consortium. Therefore it is expected that DBFM contracts will remain, but in a different form. Another development that stands out is that the Port of Rotterdam is a front runner with implementing new technologies for the use of PdM.

Chapter 3

Predictive Maintenance

The concept of Predictive Maintenance (PdM) will be explained in this section, together with the strong and weak points.

The concept of PdM has been around for a long time, as it started off with visual inspections and predictions based on experience, which evolved towards using sensors and algorithms. [26] Due to these transformations in PdM, the definitions present in literature vary. [27] defines PdM rather broadly as "a philosophy or attitude that, simply stated, uses the actual operating condition of plant equipment and systems to optimize total plant operation." On the contrary, [28] define it rather narrow as "the measurements that detect the onset of a degradation mechanism, thereby allowing causal stressors to be eliminated or controlled prior to any significant deterioration in the component physical state." The definition from [29] seems to be the closest to how PdM is used in practise: "In PdM, data gathered from connected, smart machines and equipment can predict when and where failures could occur, potentially maximizing parts' efficiency and minimizing unnecessary downtime." However, for large implementations of PdM strategies, Mobley's definition stating that it is a 'philosophy or attitude' might be a better fit. As the hardest part of implementing PdM in an organization is getting the 'people-related factors' right. [15] Even though the definitions differ slightly, they agree that having an insight in the condition of the equipment is a crucial part of PdM.

In practical terms, PdM is about predicting the future state of an asset, and using this information to optimize maintenance and other business processes. Prediction about the future state of an asset can be used for a number of applications, depending on the accuracy of the prediction. The most obvious application is to prevent unplanned downtime by servicing the asset before it breaks down. This application can be generalized to optimizing the short term and long term maintenance or inspection planning. Additionally, a predictable long term maintenance planning will also increase the predictability of the associated large investments and the large amount of resources required. However, the use cases can reach further, also the management of spare parts can be optimized. As when it is known that it is unlikely for many assets to break down, less spare parts need to be in stock. This has a positive impact on the amount of capital stuck in spare parts.

[29] names PdM the golden standard for which to aim, but not all maintenance cases are suitable for a PdM strategy. First of all, the object needs to show measurable or derivable deterioration signs long before the actual breakdown will occur, to allow for detecting the signs and preventing the impending failure. Secondly, in order to justify the investments associated with implementing a PdM strategy, the risk appetite for letting the object to fail should be low, as it would be too dangerous or too costly. [30] Due to the advancements in the field of Internet of Things (IoT) and data analysis techniques it becomes a realistic option for more use cases to implement PdM techniques. [31]

3.1 PdM - Technical Implementation

PdM and Condition Based Maintenance (CBM) are almost treated as synonyms in literature, as before the concept of CBM was part of PdM, it was named PdM. [30], [32] Due to the history of the terminology, this sections will be focussed towards CBM rather than PdM. Currently CBM is being defined as a “maintenance strategy that collects and assesses real-time information, and recommends maintenance decisions based on the current condition of the system” [33]

[34], [35], [36] and [3] all provide a subdivision for CBM, which are comparable in content and differ in terms of detail. The categorization presented by [3] is more from a technical point of view, which causes it to be slightly misaligned from the [34] standard. The categorization defined by [34] will be used to structure the next part of this section in which various methods and techniques are reviewed per subsection.

Data acquisition

The data acquisition process is concerned with obtaining data relevant to the condition of the object under study. This is not only constrained to sensor data obtained from the object, but also includes environmental data and log files describing maintenance actions performed on the object.

Generally speaking, the challenges related to the field of data acquisition are mostly the lack of available or easily accessible data, low data quality, and on the other side of the spectrum large amounts of data. [36] Each challenge will be covered briefly in the coming three paragraphs.

A lack of data is an issue in existing systems with limited sensors or sensor data storage, but also in newly implemented systems as there is no available operating data to create predictions from. [37] It can take months or even years of operation before long term degradation signs start to emerge and can be captured. [3] Additionally, if the newly implemented machine is not allowed to fail, and thus repaired before it breaks down, no sensor data can be collected at the time right before the failure. When this censored data is used in a prediction, the results could be too cautious, which might result in objects being serviced long before the components are worn out.

The quality of condition data can be affected negatively by inaccurate input data due to improperly mounted sensors or sensor faults, or by an incomplete representation of the failure mechanisms. [27], [32], [35] Illustratively, low cost sensors tend to 'fail dirty' by which they stop functioning properly, but continue to send out false measurements. [38] Manually entered information, such as maintenance logs, can contain a larger variation of input errors, which makes it harder to clean and therefore more probable to miss certain errors. Data quality errors can partially be corrected or prevented, which is touched upon in the Data Manipulation section. When such faults are not removed a so called 'Garbage in Garbage out' situation is emerging, as the quality of the output information correlates with the quality of the input information. [35]

Large amounts of data is on the one hand presented as an opportunity, which is labeled as Big Data, due to the potential of extracting information previously not possible from smaller datasets, but on the other hand it creates a practical challenge. Limited research has been done into the use of big data for maintenance prognostics. [3] Therefore it is not yet clear how relevant data can be quickly extracted from a wide variety of large data sets.

Sensors are the link between the physical and digital world, and therefore important for PdM. Maintenance predictions are based on information about degradation processes, therefore it is vital for sensors to measure this with sufficient accuracy. This is covered by the emerging field of sensor management, which "aims to optimize a configuration of sensors, with the goal of improving operational availability for a given system". [39]

The initial usages within sensor management were simplistic by being constrained to presenting sensor data directly in a dashboard, however the focus was on enabling maintenance personnel to apply sensors to their own machines to create remote insight which would ease their daily duties. In this way the knowledge a mechanic has about the operational functioning of the machine is translated to a correct and relevant placement of sensors. [39]

Data Manipulation

Data manipulation is concerned with cleaning the raw input data and converting it to a format required for the next stage. For cleaning data, three aspects need to be addressed: Which data errors need to be detected, How can they be detected, and Where can they be detected. The latter refers to a location in the data processing pipeline, the error can be corrected at the source, or after a first analysis or aggregation process. Data cleaning, although it is a large research field, still needs to be performed manually under some conditions. For that reason, [40] proposed a generic technique for cleaning streaming sensor data based on Kalman filter. This work acts on the trend of the increased use of streaming sensor data systems, although [41] still identified the cleaning of distributed sensor streaming data as a challenge as it is hardly known to what extend existing qualitative techniques are applicable to distributed streaming data systems.

State Detection

State detection is commonly being described as: determining the state of a part of the machine by comparing the current sensor data with a baseline. [42] This provides a basic real time insight in the operating condition of the machine relative to its predefined limits. The additional purpose of the State detection stage is to support the diagnosis made in the health assessment stage.

[3] describes the stage differently by naming it Health Indicator (HI), which is not focused on the operating state of a machine, but rather on the degree of degradation of a specific factor. However, the purpose is comparable, as a correct HI is also presumed to ease the health and prognostics assessment stages and to increase the quality of the prognostics assessment. Based on the required independent variables, the available techniques can be divided into: single HI, HI and Time, HI and Health State, multiple HI, and Hybrid approaches. The latter categories are for use cases with a more complex degradation pattern, as these require more information sources to be represented accurately. [3] includes a number of techniques accompanied with a overview of where they have been applied in literature.

Health Assessment

In the Health Assessment stage information regarding the state, historic patterns, or raw sensor data is used to generate a health grade. Additionally, potential or diagnosed failures are also presented. [34]

Techniques for creating a health assessment are mostly model based, data driven, or a combination of the two. [36] A model based health assessment defines the health grade by mapping the objects condition to an analytical model containing the degradation patterns. These models are being constructed based on the physical properties of the object. The benefit of this approach is that it is better suitable for degrading components that only show indirectly observable degradation signs. Although this is the most accurate approach, it is in reality too difficult to create for systems subjected to multiple stochastic degradation processes. [43] Additionally, such a model is specifically designed for one type of object, and can hardly be reused for other objects. [36]

Data driven methods directly use the sensor data to determine the health condition, and thus removes the need for a physics based model as described above. [44] With the model based approach, the knowledge about the degradation patterns was encapsulated in a model by the designer of the model, with a data driven approach this knowledge must originate from historic data containing the relevant degradation patterns. This is the reason why accurate historic information containing all relevant degradation patterns in necessary for the success of this approach. Techniques used for a data driven health assessment originate mostly from the field of pattern recognition, and can be divided in statistical based methods, and learning based methods. [45] provides a comprehensive overview of the techniques used in literature within these two groups.

Hybrid approaches, combining model based and data driven assessments, are claimed to be better than the individual techniques, as the positive aspects of all techniques can be used, and the negative aspects reduced. Additionally the computation complexity can be reduced, and the precision improved. [45]

[3] also provides a different function to the Health Assessment stage. Here a health assessment of an object is presented in the form of two or more health states, such as healthy, degrading, and unhealthy. Components with a complex degradation pattern require three or more stages, as after the initial degradation sign a component can start to display a healthy behaviour again when in fact it is close to failure. (Fig. 3.1) Knowledge about the degradation stage can be used in the health and prognostic assessment stage to allow algorithms to be tailored to a specific stage, which would increase diagnostic and prediction accuracies.

Besides performing a health assessment based on sensor data, it is beneficial to include records describing performed maintenance actions into one analysis. [35] identified and describes suitable techniques for such a combined analysis to be time-dependent proportional hazards model and Hidden Markov Model. Delay-time concept and stochastic process models are also suitable candidates.

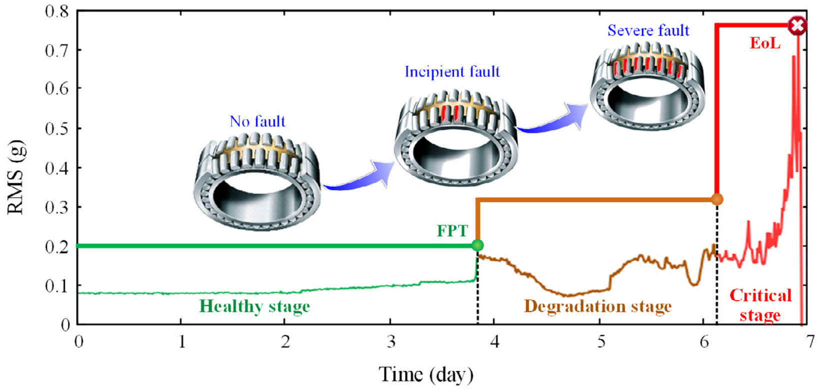


Figure 3.1: Degradation processes with multiple stages. [3]

Prognostics Assessment

[34] provides a clear definition for a prognostic assessment: "Performs agent-specific assessments of a component's or system's future health state with the associated predicted abnormal states and remaining life for a projected operational context."

[35] and [36] describe two concepts being used within prognostics. The most used and most described in literature is estimating the time before a failure occurs based on future anticipated usage, also known as Remaining Useful Life (RUL). The second one is determining the probability that a machine will operate without error for a given amount of time. The latter one is useful for critical objects, such as nuclear plants, to determine if the risk of a critical component failing before the upcoming inspection interval is acceptable.

RUL is commonly used as tool to accurately determine when to service a component preventatively. The techniques used for creating RUL estimations are mostly identical to the techniques used for creating a health assessment. [35]

A number of challenges are still present around RUL. Determining the RUL of a component which is subject to multiple degradation processes is still challenging. Secondly, the effect of fault propagation to other components is difficult to capture and to predict. Lastly, a RUL prediction is based on data containing uncertainties, the challenge is to correctly estimate these uncertainties. As the value of a RUL estimation is low when it is unknown what the uncertainty window is. [3]

Advisory Generation

The results from the health and prognostic assessments can only provide value when used effectively, therefore they have to be relayed to the correct places in the organization. In [34] the Advisory Generation stage is defined as integrating information, such as safety, environmental, operational goals, and financial constraints, with the goal to provide advice to operations, maintenance and capability forecast assessment requests.

The inherent challenge in this stage is to find the right balance between all the seemingly contradicting goals, such as increasing up-time combined with decreasing costs. This balance is defined in the maintenance strategy, which is aligned with the corporate objectives and supported by the mayor stakeholders. [46]

3.2 PdM implementation consideration

In order to realize the proclaimed benefits of a PdM technique, it must be successfully applied to a relevant problem, and align with the organization. This section will list the relevant literature and white papers covering the existing implementation strategies of PdM.

The white papers have been sourced with internet searches, and filtered on content covering implementation frameworks or challenges. This left white papers from [47], [48], and [49].

The implementation strategies from [47] and [48] consider the selection of assets to which PdM can be applied, provide guidance on the type of PdM to apply, and state suggestions on managing the implementation. Whereas [49] describes an incremental approach, where the selected assets should go trough all maturity stages of PdM as defined by [49].

The way in which these frameworks express the alignment of a PdM solution to the organization varies per white paper. [47] includes the technical implementation of a PdM solution in the organization, and suggests a continuous feedback loop to maintain the prediction accuracy. [48] describes stages in which the applicability of PdM for the asset is evaluated, and the feasibility of realizing the expected results is assessed. Additionally, a roadmap for the digital journey is presented, which aids with realizing and implementing digital innovations in general. Lastly, [49] does not explicitly cover organizational alignment.

In literature, PdM is mostly only covered form a technical point of view. Implementation strategies and organizational issues for PdM are seldom mentioned in literature. [50] This leaves a large gap between what is technically being covered in literature and practically being implemented by practitioners. The papers which focus on this gap are [51], [52], and [1].

[51] proposed the use of an Analytic Hierarchy Process for the comparison of alternative predictive techniques in order to identify the most suitable one to be set up in an industrial plant. This process involves defining a number of variables, such

as the costs and the prediction quality of the Predictive technique. The disadvantage of this approach is that these variables are not always known in advance, which makes it difficult to perform the proposed quantitative comparison. The model does include organizational factors in the comparison of the alternatives, such as the current technological maturity of the production facility and criticality of the machinery in reaching the business goals.

[1] identified that practitioners experience multiple challenges in the implementation of PdM even though multiple maintenance techniques are available in literature.

[1] explored the difficulties practitioners face when implementing PdM techniques and proposed a solution set to mitigate these difficulties. This solution set forms a framework to assist practitioners with the selection of the optimal maintenance approach for their situation. The three decision support tools first of all assist practitioners with selecting the most suitable candidates for PdM, secondly practitioners are assisted with the selection of the most optimal PdM approach, and lastly the business value is identified with a hybrid business case approach. Compared to [51], this framework also includes a separation between explorative and exploitative cases, which adapts the tools to the type of information available.

[52] aimed to increase the understanding of contextual barriers that organizations face when implementing CBM. Two of the mayor barriers identified are the lack of knowledge regarding the state of the art maintenance methods, and the use of periodic maintenance budgets which favour reactive solutions over large investments in CBM with returns in the long term. Another challenge is concerned with measuring and proving the benefit of a CBM program, as it is unknown what would have happened otherwise.

Besides barriers and challenges, also a number of enablers have been identified, which each increase the implementation CBM in the process industry. A mayor enabler is the collaboration of asset owners, equipment manufacturers, and maintenance contractors. Therefore, it must be made sure that the interests of these stakeholders are aligned, or can be achieved separately. [53], [54] Secondly, key stakeholders need to be convinced of the potential of CBM and advocate it. And lastly, the knowledge needed to initiate and implement CBM must be made available and retained.

3.3 PdM in VTI

Literature already contains a few cases in which it was attempted to implement Predictive maintenance or CBM in the domain of Vital Transport Infrastructure (VTI). At first the present cases around rail switches and asphalt are being reviewed. Lastly the most noticeable attempts of applying PdM to VTI in general are covered.

[55] attempted to predict rail switch failures in Germany based in a dataset of 29 switches over a time period of 2 years. The literature study performed in this study identified that predicting rail switch failures on electrical current alone is not sufficient. Additional information is required about the temperature, rail switch construction properties, maintenance, age and usage. Detailed reports about historical incidents, which also include the failed parts and causes, has been used as condition information for the prediction. A prediction horizon of 2-3 hours for emergency fault clearance, and a horizon of 3-5 days for scheduled maintenance was identified to be required. Other implementation considerations have not been included in the design process. The results are promising, but given the size of the dataset overfitting could be an issue. Therefore it is unsure how well it will perform on a larger dataset.

[56] attempted to detect rail switch failures due to contaminated slide chair in an experimental setting. A rail switch has been equipped with a large number of load and status monitoring sensors, such as: Current sensor, Voltage sensors, Force sensors, linear rules, and proximity sensors. The predictions made based on the laboratory dataset are promising. However, it must be noted that the factors which increase the difficulty of predicting rail switch failures are not included in this experiment. The dataset has been collected in a short period of time, the influence of temperature is therefore most likely not present in this dataset. Additionally, only one failure mode at a time is present in the experiment. All these factors form a barrier to implementing it in an operational setting.

[57] aimed to predict when tamping of the sub base under a railswitch is needed. Tamping the sub base is required to correct the geometry of the rail track back to the original shape. The predictions are made based on 20 measurements per railswitch over a period of 5 years. Tamping actions are planned 18 months in advance, therefor the prediction horizon is set to 18 months. The vertical displacement of the track is a clear indicator for when tamping is needed, and it turns out to be a reasonable predictor.

Ground-Penetrating Radar (GPR) and Heavy falling Weight Deflectometer (HWD) data are used to calculate the RUL of asphalt. [58] aimed to predict the RUL based on the surface temperature and the thicknesses of asphalt, as an alternative to GPR and HWD. The classification error range being tolerated is 8 years, which seems significant on a lifetime of 40 years.

[59] attempted to estimate the RUL of flexible pavements on airfields with a time-sharing damage accumulation method. Rutting and fatigue cracking are the two failure modes being considered, for which a model proposed by the FAA is being used. [60] The proposed model includes the physical properties of the top and sub layers, moisture, frost, temperature, and the strain induced by the landing gear of

the airplanes. A single case study has been performed, for which the result seems more accurate than the FAARFIELD approach.

The reviewed cases all show a good approach into estimating the RUL of the investigated asset. However, nearly all papers solely limit the scope towards the technical challenges. Additionally it is concluded that the size of the used datasets is limited in all reviewed cases. This makes it difficult to validate the designed methods.

Chapter 4

Implementation stage

The goal of this section is to define a framework which provides support during the first critical stages of a Predictive Maintenance (PdM) project. Surprisingly, the alignment of a PdM solution with the organization is not an extensively covered issue, as became apparent in Section 3.2. Especially in the context of Vital Transport Infrastructure (VTI), literature does not yet present insights into the criticality of the various stages of the implementation process. Therefore it is being attempted to explore the suitability of applying the existing implementation framework from [1] in the context of VTI, as this framework has been based on the challenges experienced with implementing PdM in various domains.

[1] identified a number of challenges which practitioners face when implementing a PdM solution, these are: 'The identification and differentiation of suitable approaches for PdM', 'The gap between a practitioners ambition and the available data and knowledge', and 'Knowing weather the selected maintenance technique will provide benefits'. Other challenges that are present in the process of implementing a PdM solution are the unavailability of a suitable approach for setting up a PdM business case, and the unavailability of a suitable tool for selecting candidates to apply PdM to.

Opposed to the organizational alignment of PdM, the technical implementation is widely covered in literature. Additionally, the advancements made in the field of machine learning and signal processing make this a domain moving at a quick pace. [3] describes a framework for the technical implementation of Condition Based Maintenance (CBM) based on the state of the art methods present in literature, as covered in Section 3.1. Therefore, this framework is selected to support the technical implementation of PdM in these cases.

This section will continue with addressing the framework from [1] by explaining the presented tools designed for assisting practitioners with the herefore mentioned challenges.

4.1 PdM implementation framework

The framework created by [1] identifies five stages as can be seen in Figure 4.1, starting with Initiation, followed by Selecting suitable assets for PdM, Selecting the optimal approach, Investment evaluation, and lastly PdM solution realization. This framework has been slightly changed to better suit the PdM cases in the area of VTI. Each stage of the framework will be covered individually in the sections below.

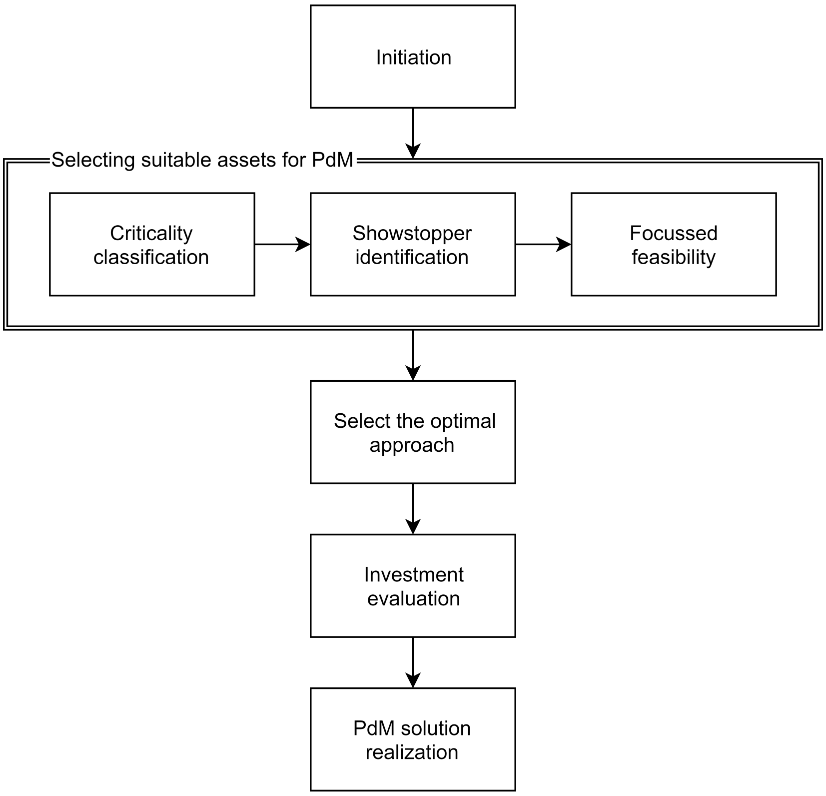


Figure 4.1: Flowchart of the stages in the PdM implementation framework.

4.2 Initiation

At the start of a PdM project it is relevant to define the global goals and intentions for the the project. Two aspects in particular are important to define before continuing with the framework. At first the motivation for initiating the project is to be categorized into either 'Decision Pull' or 'Technology Push'. Starting from a Decision Pull happens in the case where there is an economic necessity to develop a particular PdM technique. A Technology push starting point is used when 'a new technology or new application of that technology is proposed first.' Thereafter a distinction is to be made between an exploitative or explorative project. Exploitative PdM projects use existing well known tools and techniques. Explorative PdM projects use techniques which are state of the art, and not well known (by the organization). The goal of an explorative approach is mainly centered around knowledge building, gaining experiences, and exploring the technical possibilities. On the contrary, the goal of an exploitative approach is centered around solving a specific business issue.

4.3 Select Suitable Candidates for applying PdM to

Due to the large investments associated with PdM implementations, it is not economically feasible to apply PdM to every type of asset. Therefore [1] determined it was relevant to establish a selection framework for determining the assets where PdM can provide the largest benefit in terms of performance and cost of downtime. This assists a practitioner with selecting the best place to start with implementing PdM.

The proposed steps to be taken in this stage are first of all a criticality classification, to determine the importance of the asset for the business goals. Secondly, a showstopper identification is being performed, to test the assets against the most common showstoppers. Lastly a focused feasibility test is performed, where the impact of certain showstoppers is analyzed in further detail.

Criticality classification

The original goal of the criticality classification step is to greatly decrease the number of potential components to apply PdM to, and to only leave the assets with a low frequency of failure and a large impact of failure.

The proposed tool for criticality classification is the four-quadrant framework based on work from [61], [62] and [63]. In this framework each component is mapped based on the number of yearly failures and the average hour of downtime per failure.

However, in the case that a practitioner follows an exploitative approach, it is expected to start from a business need or issue, which is most likely associated with an asset. In such a situation there is no need for a filtering tool such as a criticality matrix.

It is also an option to follow an explorative approach. In that case it is useful to apply a criticality matrix, in order to determine the asset to focus on. However, it is being argued that solely using a ciriticality matrix is not a suitable tool. As the implicit goal of an explorative endeavour is to generate knowledge and experience in a relatively short timespan, and not to directly solve a business issue. In that case the availability of data about the asset is deemed to be more important than the criticality of the asset. As gathering data is generally an expensive operation, and

Table 4.1: Criticality classification factors

Short term	**Long term**
Available data	Knowledge management
Understanding of failure mechanisms	Increasing service level requirements
Organizational alignment complexity	Potential cost & risk reduction
Potential cost & risk reduction	

time intensive for assets with a slow degradation process. Ultimately, high quality data is a key enabler for a successful PdM project.

For these reasons it is being proposed to execute the criticality classification step only in exploitative PdM projects when the asset has not yet explicitly been selected. For explorative projects it is proposed to rate the assets in terms of risk and cost reductions in the short and long term, as outlined in Table 4.1. Under short term factors the potential for 'Quick wins' is investigated by looking at the available data, the level of understanding of the degradation factors, and the organizational alignment complexity. The organization alignment factors are the factors present in the process of converting the predictions to a format usable by the end users. These are described in more detail in Section 4.5 under 'Organizational evaluation'.

Showstopper identification

The showstopper identification stage tests the components, remaining after the Criticality classification step, against common causes for PdM implementations to become infeasible or provide no added value.

The first part of the stage is to determine the ambition level. This helps with identifying the system requirements and with the rating of the potential showstoppers. The ambition levels are divided into: Detection, Diagnosis, or Prognosis. Detection is aim to be used "as safety warning or last resort", Diagnosis is to "determine fault state and short-term (failure) behavior forecast", and Prognosis is for "long-term (failure) behavior prediction".

The second stage is the rating of the potential showstoppers (Tab. 4.2). These have been defined by determining the shortcomings of traditional selection methods. By evaluating these potential showstoppers before committing to a PdM project potential pitfalls can be seen in advance. [1], [64]

The existence of the majority of the organizational showstoppers is supported by [50], who covered these organizational showstoppers by suggesting interventions to prevent these showstoppers from occurring. Additionally, [50] stated the importance of management commitment for making a PdM project a success. Therefore, the list of potential organization showstoppers is extended with this factor.

Table 4.2: Identification of potential showstoppers (PS) for the differentiated application of PdM. [1]

Clustering	
c1	No match with production or mission planning
c2	No match with technical clustering
Technical feasibility	
t1a	Failure cannot be detected with existing technology
t1b	Failure cannot be predicted with existing technology
t2a	Failure cannot be detected with additional research
t2b	Failure cannot be predicted with additional research
Economic feasibility	
e1	Insufficient financial resources
e2	Not enough failures (during lifetime) for positive business case
Organizational feasibility	
o1	No trust in monitoring system
o2	No fit to personnel
o3	No fit to operational task / mission
o4	No fit to relations and policies
o5	No fit to the spare parts
o6	No upper-management commitment

For a number of showstoppers it is difficult for practitioners to foresee the impact of these on the PdM project, and thus to accurately rate these showstoppers. Therefore a showstopper is to be rated with one of the following classifications: ‘Yes’, ‘No’, or ‘Maybe’. The cases where showstoppers are classified with ‘Maybe’ a followup investigation is suggested, which is covered in the next section, named Focused feasibility.

Focused feasibility

The intended function of the focused feasibility stage is to examine the cases for which a technical or economical showstopper has been rated with a ‘Maybe’ in the previous stage. However, the tools [1] proposes for this deepening are identical to the tools presented under the investment evaluation. It is believed that applying these tools twice provides limited added value, therefore it is proposed to skip these tools in the current stage.

4.4 Select Optimal Approach

Selecting the most optimal maintenance approach is more than merely selecting a maintenance policy, but also involves selecting the techniques capable of realizing the policy. The latter is what is currenly not well supported. [1]

The goal of this section is to select the optimal PdM approach for the specific situation of an asset. This is being achieved by following a decision framework as presented in Figure 4.4.

The fist step to go trough when starting from a Decision Pull is to determine the *ambition level*, thereafter the *available data types* are being identified. The next step is to determine the *technologies* capable of achieving the ambition with the available data. Lastly, a *business case* is being created to determine if it is financially viable to realize and operationalize the proposed PdM technology.

When starting from a technology push, the *technology* to employ is solely determined by the *available data*. Thereafter a *business case* is being created, before moving on to the Investment evaluation and Solution development stage.

Ambition level

The ambition level is defined as "the level of detail that is required in the maintenance decision making process." [1] Determining the ambition level is relevant, as that sets the requirements for the quality and type of data necessary to reach the ambition level. The ambition level can be determined by following the flowchart in Figure 4.2 or by answering the following questions: [1]

1. Is predicting the assets lifetime on an individual basis required?
   This determines if assets need to be monitored individually, and if predictions can be made for a fleet of assets.
2. Should variations in usage of the assets be included?
   This determines if usage data is required, otherwise maintenance is done based on time intervals.
3. Should variations in environmental conditions be included?
   This determines if environmental data must be available.
4. Do the future conditions differ from the current or historical conditions?
   If future conditions are not present in the dataset, it is not accurate to make a prediction solely based on historical conditions. One important factor to consider are cyclic environmental effects. If these influence the measurements or the failure probability, it is required to have data captured during at least one full cycle.

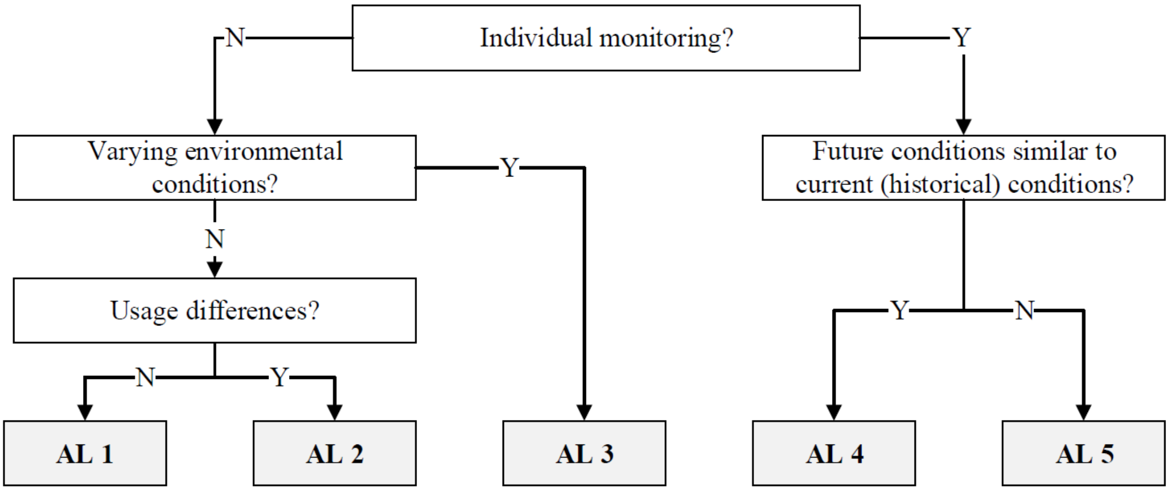


Figure 4.2: Guideline for the selection of the ambition level. [1]

Available data

A higher ambition level, as presented in the previous section, requires a more complex model of the degradation mechanisms of the asset. In order to be able to create such a complex model, data from specific categories needs to be available. By defining these categories, it can be evaluated if the desired ambition level is reachable with the data currently available. For example, ambition level 3 requires at least historical usage and load data as it is required to make a distinction between usage under various conditions. Besides verifying if the set ambition level is reachable, the available data types also indicate which technical methods are applicable. [65]

The four data type categories being defined are:

1. Historical data
2. Usage monitoring
3. Load monitoring
4. Health or condition monitoring

Existing asset data is rarely perfectly indexed per asset, especially in larger organizations this requires an exploration to discover the available data. Additionally the value of the data is also not directly clear, and requires an investigation as well. In order to better target these efforts, it is relevant to index the relevant failure mechanisms with the help of expert knowledge.

Data quality is more often than not an issue in the field of PdM. Therefore the Historical data category in the data type categorization proposed by [1] has been expanded with questions aimed to investigate the Information Quality (IQ). [66] sets out four sources of IQ variance according to which the IQ can be assessed: mapping, changes to the information entity, changes to the underlying entity or condition, and context changes.

Historical data covers besides historical sensor data also historical failure and financial data. The distinction in the quality of historical data is dependant on the collection methods. When it has been collected with detailed monitoring methods it is considered to be of high quality. Manual registrations are considered to be of low quality, due to the human factor. [35] Additionally it is to be critically assessed what the historical data means, as data which is suitable to be used in one context could be too inaccurate in another. [66] Secondly, it is important to know if the characteristics of the asset which is being measured has remained constant during the entire dataset. Furthermore, changes to the measuring methods used to fill the dataset are relevant to determine. Lastly, mapping related inaccuracies are a source of reduced data quality, as different datasets might be updated at different points in times.

Usage monitoring contains the operational data, such as running hours or mileage.

Load monitoring includes loading data, such as temperature or electrical current. For sensor data it is relevant to determine the tools and techniques used to obtain the results in order to understand what the data actually represent. [67]

Health or condition monitoring includes measurements of signs of imminent failures, or alternative ways of measuring the health of the asset. For this data is should be checked for which failure mechanisms validation data is available, and if it is categorized per failure mechanism.

Technology selection

[1] developed a mapping to link the set ambition levels, via the available data types, to groups of maintenance techniques (Fig. 4.2). This mapping aims to easily show a practitioner if the chosen ambition level corresponds with the available data types. Additionally a set of suitable techniques were identified, which would be capable of reaching the selected ambition level with the available data. Where the Technology selection diagram proposed by [1] supports the selection on a high level, [68] covers the selection of a prognostic model on a low level. The latter paper cover the most used algorithms, together with their advantages and disadvantages from a business point of view.

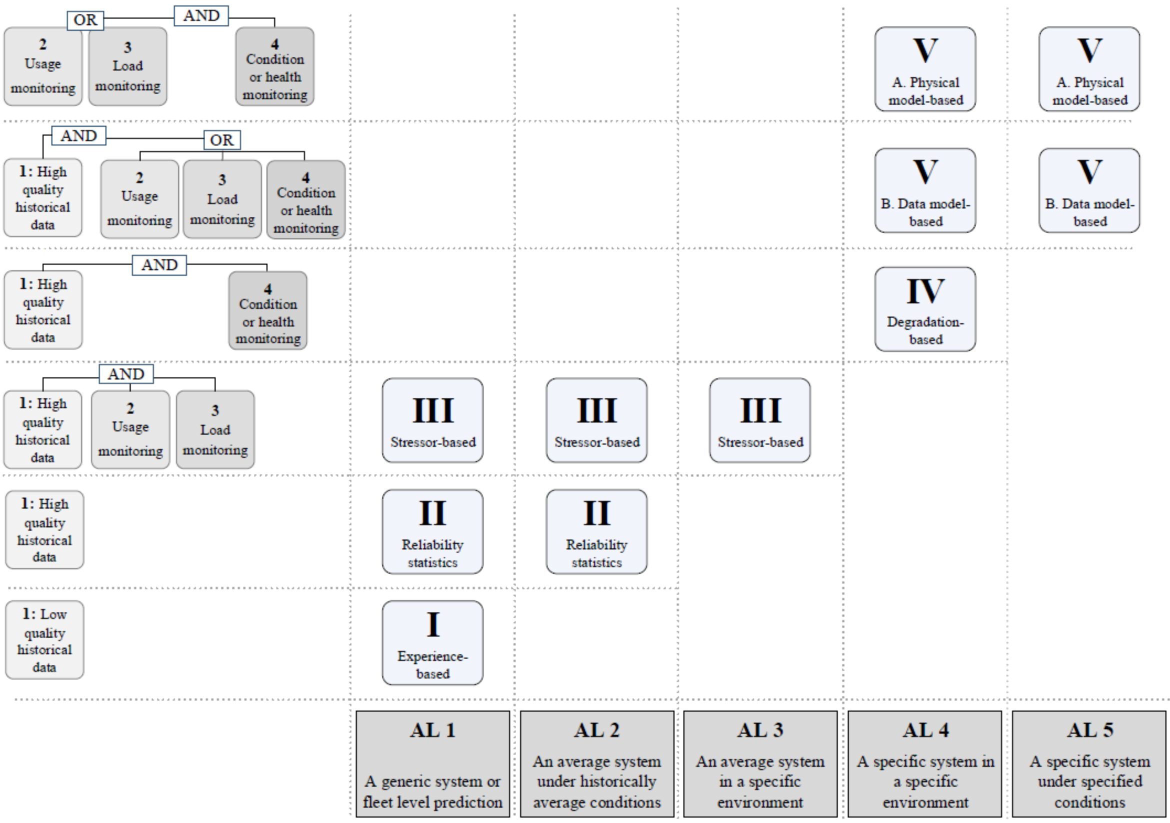


Figure 4.3: Mapping preventive maintenance approaches to the ambition levels and data types. [1]

4.5 Investment Evaluation

The final step in the selection framework shown in Figure. 4.4 is to determine a business case for the project. This section provides the methods and tools to support the creation of a business case by evaluating the feasibility of three crucial aspects: Technical, Organizational, and Financial.

Technical evaluation

The technical evaluation proposed by [1] is performed by elaborating on the feasibility of the seven stages of the OSA-CBM model. Each stage is accompanied with questions which guide the evaluation and can be answered as a starting point.

1. Data acquisition
   - How can the failure mechanism be measured?
   - How can the required data be acquired, back-upped and secured?
2. Data processing
   - How can the signals issued from the sensors be processed to extract

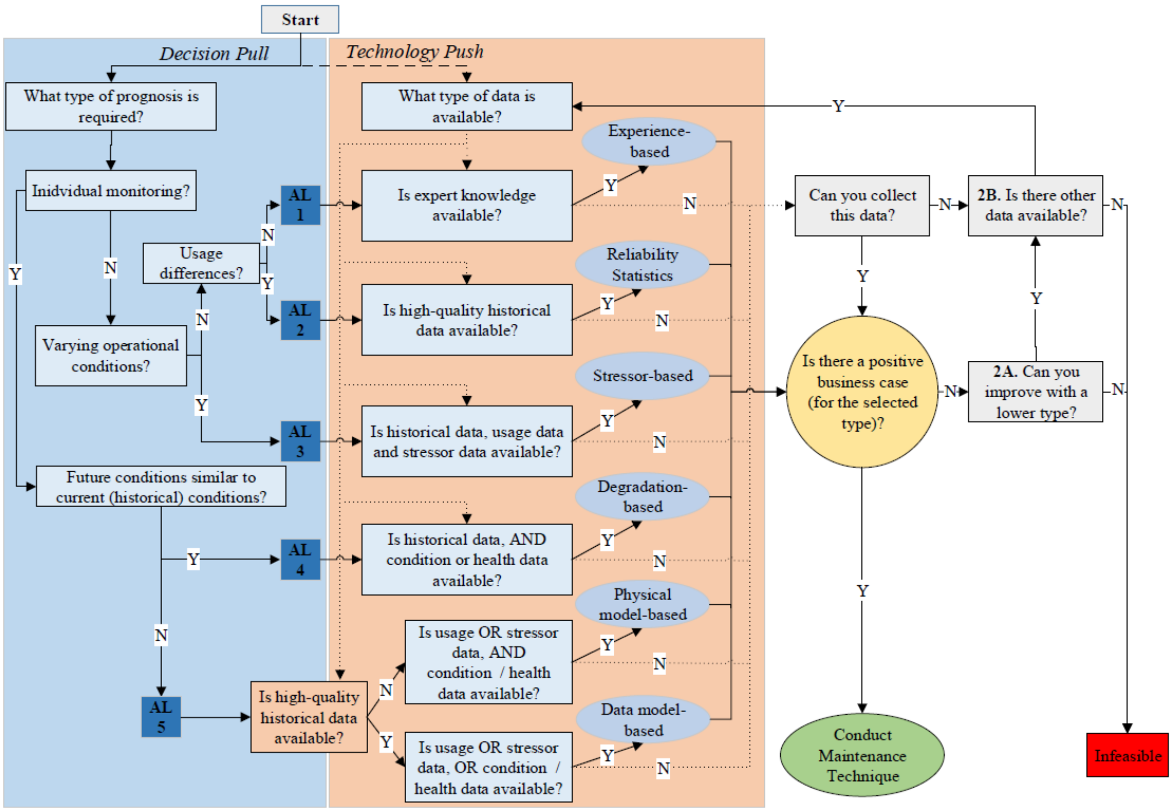


Figure 4.4: Preventive maintenance approach selection framework. [1]

features that suggest the presence of anomalies, and in the long term, represent the state of the monitored system?

3. Detection (condition assessment)
   - How can the real-time data be compared with expected or known values.
   - How can alerts be generated based on criteria of performance, security, etc.?
4. Diagnostics (not required for: 'Detection')
   - How can – based on the detected state – be determined whether the monitored system is degraded?
   - How can insight be provided on influences of interactions with other components, operating and environmental conditions?
5. Prognostics (not required for: 'Detection' and 'Diagnosis')
   - How can the current state of the monitored system be determined?
   - How can the future state of the monitored system be determined and an estimation of the Remaining Useful Life (RUL) be given?
6. Decision analysis
   - How can maintenance/control actions be recommended such that the

system can function until the accomplishment of the mission?

7. Presentation
    - How can the results be presented?

Organizational evaluation

This section covers the expected complexity of the implementation of the PdM solution in the organization from an end-users point of view, as well as from a maintenance process point of view.

Trust in the outcome of a PdM prediction is an important prerequisite for an operator for using the predictions in their work. [1], [65] The trust building process between humans and Artificial Intelligence algorithms can be divided in two stages. At first use, an initial sense of trust is to be build, and after continuous use the sense of trust is to be reenforced. [69] Both stages contain multiple key factors which play a role at building trust with AI applications in general. The most applicable factors for building trust with a PdM solution are:

1. Representation
2. Image and perception
3. Reviews from other users
4. Transparency and explainability
5. Usability and reliability
6. Job replacement

The previously stated factors for the basis for the proposed organization assessment approach. The intention of this approach is twofold. Its first aim is to determine the potential critical factors which might hinder the adoption by the employees due to trust related factors. Secondly, it aims to expose the entry points already present in the organization to which the PdM solution can be linked in order to ease the adoption.

Representation focusses on what the user sees and experiences when interacting with the system. The initial trust building is eased when the format is recognized. Therefore it should be considered to present the PdM results in a format which is familiar to the users.

Image and perception covers the attitude of the user towards PdM systems before any interaction has taken place. An existing positive or negative attitude towards AI or PdM solutions can affect the level of initial trust. [70]

Positive *reviews from other users* increases the level of initial trust. [69], [70] Therefore it is relevant to identify and target the users who identify themselves as early adopters in order to make them spread the message.

Transparency and Explainability focuses on explaining where the predictions of a PdM system are based on, and how they came about. The initial trust is affected when origin of the predictions cannot be substantiated and presented clearly to the user. [65], [69], [71] Additionally, ‘Explainable AI’ is currently an issue receiving substantial attention, as the best performing AI models lack transparency, which makes them unpractical in practice. [72] For this aspect the level of understanding of the users on PdM in general, the fundamental failure mechanisms, and the concept of prediction accuracy can be determined to create an understanding of how transparency and explainabilty can be realised.

Usability and reliability are a factor for creating continuous trust. [69] Insufficient maintenance to the application after its implementation can harm these trust factors. One aspect that needs to be watch for over time is the validity and relevance of the assumptions and expert knowledge which is embedded in the design of the PdM solution. Additionally extra data can be periodically added in order to increase the prediction accuracy. Lastly, the users should have access to an expert familiar with the ins and outs of the PdM system and knowledgeable enough to be able to explain the rationale behind a prediction. With regards to the usability, it should be determined if the results can be delivered to the user via the challenges that are practical to the user.

The fear for *Job replacement* is expected to be a minor issue in the field of VTI, but it does impact the actions of the users when present. [69]

It is expected that PdM will rarely be implemented from scratch in the area of VTI. That implies that there is an existing maintenance process which will be upgraded to a PdM strategy. Based on knowledge from experts from the field the following aspects have been defined to be relevant for the alignment of a PdM solution to the existing maintenance processes.

1. Are there entry points in the current workflow for preventative actions?
2. Do the current policies allow assets to be repaired before they have been reported as broken?
3. Is there an entity in the process who has the responsibility to take preventative measures?

Financial Evaluation

The financial evaluation is a relevant step, as in the area of VTI assets are large in number and in size, which could make the scale-up of the solution expensive. However determining the financial viability of a CBM program is nearly infeasible when it concerns an explorative project. Therefore [1] proposed a Hybrid business case approach (Fig. 4.5) with separate starting points for explorative and exploitative projects. The dashed line in Figure 4.5 is the preferred route for Exploitation type projects, and the Financial evaluation is optional for Exploration type projects.

A non-financial evaluation is used to determine the strategic impact of the PdM approach. For exploitative projects, where only a high level path is known a more innovation management approach can be used. [5] presents a multi-criteria analysis which assess the impact of a PdM strategy on the organization.

A financial evaluation is performed to determine the financial viability of the PdM strategy. A discrete event simulation method in the form of a monte carlo simulation has been implemented by [1]. This method can either be used with historic failure information from a specific asset, or this information can be approximated with expert sessions when historic information is not available. The output of the model are the expected Return On Investment (ROI), life cycle costs, and net present value.

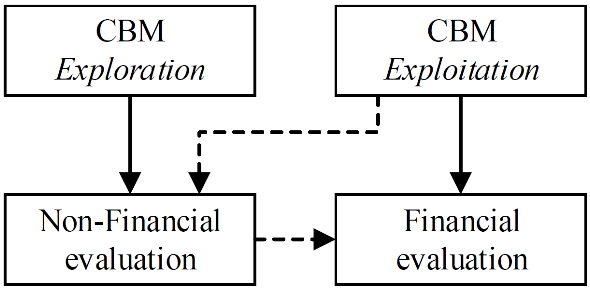


Figure 4.5: Hybrid business case approach. [1]

Chapter 5

Rail Case

5.1 Background

ProRail is the organization responsible for the safety and availability of the railways. However, the maintenance is executed by maintenance contractors with a Performance-based contracts (PBC). By design, the PBC places the motivation to predict incidents with the maintenance contractors. Nevertheless, ProRail still has the desire and the motivation to push improvements which result in higher safety and less operational disturbances. In this light, ProRail is interested in predicting switch failures. ProRail has access to data from all the assets, where the maintenance contractors only have access to the assets located in their maintenance region. Additionally, ProRail has a better Return On Investment (ROI) on developing a prediction algorithm for switch failures, as it is applicable for the switches in all the regions. Therefore ProRail is motivated to support the subcontractors by developing their own prediction algorithm, with the end goal to reduce the impact of switch failures on the availability of the railways.

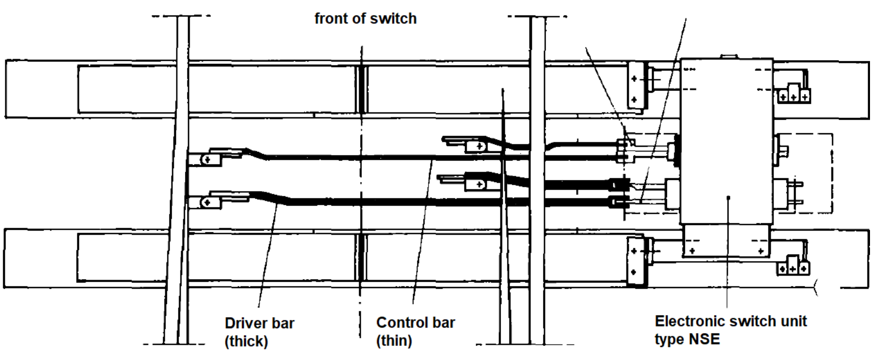


Figure 5.1: Schematic representation of a rail switch with an NSE turnover system. [4] The control bar and driver bar are attached to item 6 and 7 in figure 5.2.

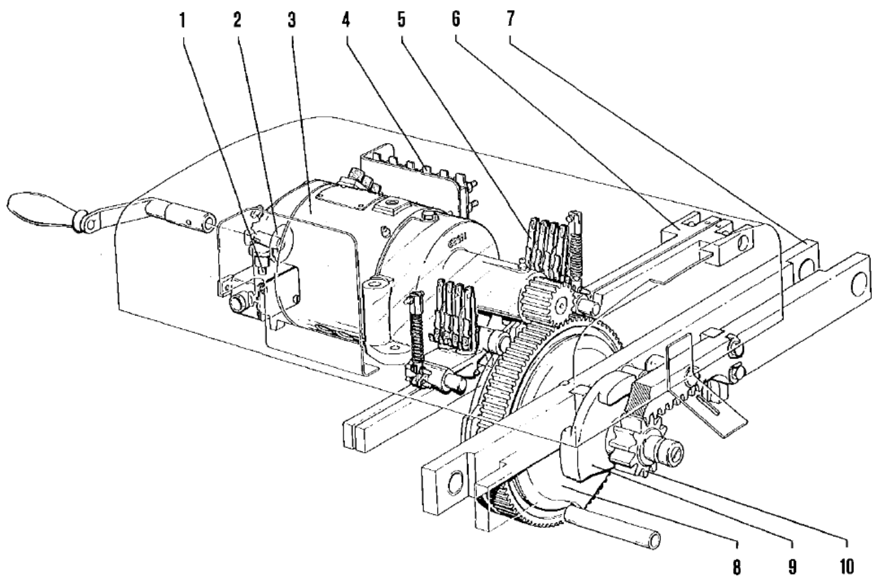


Figure 5.2: Schematic representation of an NSE turnover system. [4] The definitions of the numbered parts are listed in Dutch, followed by their English translation were possible. 1) 'krukkontakt' crank contact, 2) 'krukgat', 3) engine, 4) 'klemmenstrook' clamp strip, 5) 'kontaktbrug' contact bridge 6) 'kontroleschieter', 7) 'bewegingsschieter', 8) 'frictie-eenheid' fritionunit 9) 'grendelstuk' latch, 10) 'kleine tandwiel' small gear.

5.2 Framework

The framework as described in Section 4.1 is filled out based on interviews with three domain experts from ProRail, and complemented with observations from the available data. Once the direction of the project has been defined, the technical approach is determined based on the framework as described in Section 3.1.

Initiation

The project starts from a technology push motivation, as the potential of Predictive Maintenance (PdM) has been recognized. Additionally, ProRail identified themselves as the best party to realised this due to their data position.

Selecting suitable assets

This case has been scoped from the start to rail switches which can no longer turn over. The definition for a malfunctioning switch being used in this project is: switch turnovers which take more than 55 seconds. Such an event results in an alert at the operations center and starts a procedure, which creates a business impact. This focus is already the result from an internal criticality classification process where the unavailability of a rail switch is tackled from multiple angles. The method used to determine the criticality was based on a similar method as proposed by [1], as in essence the risk and impact have been set apart per asset type. The risk was determined by the number of incidents per asset, and the impact by defining the number of impacted trains. From this investigation two focus areas emerged related to rail switch incidents. The first one being the degradation of the railbars, the second one being the degradation of the turnover system. The latter one is the scope which was assigned to this project.

As the scope has already been defined before the beginning of the case, there is no need to perform a criticality classification, as argued in Section 4.3 under 'Criticality classification'. For this reason, the criticality classification method will be used as a checklist, in order to identify any potential issues later on in the process.

Criticality classification

The scope of the project is briefly evaluated to determine the relevance of the project. About 15% of all train delays which are caused by the unplanned unavailability of the infrastructure is due to the unavailability of a rail switch. From all rail switch failures, at least 24% is classified as a failure which is caused by wear and tear, which theoretically could have been detected in advance. However, detecting and interpreting the signs of these failures has long been technically and economically unrealistic. When only considering the incidents related to the turnover system, roughly 950 trains are impacted each year, which is still substantial enough to justify the scope.

Showstopper identification

The first step of the showstopper identification is to determine the ambition level (Sec. 4.3). The ambition level being aimed for at first is 'Diagnosis', and subsequently the focus will be on 'Prognosis'. Currently ProRail is able to detect rail switch failures, but is unable to indicate the section in which the failure is present, or what has caused it.

The second step is to rate the assets based on the showstoppers listed in Table 4.2. Table 5.2 shows the assigned likelihood for each potential showstopper to be a factor in the current case. This table has been filled out based on interviews with three domain experts at ProRail. Additionally, observations made from the available data and processes have been used.

Determining the potential allignment of the format in which the Remaining Useful Life (RUL) prediction is presented with production and technical clustering (c1&c2 in Table 5.2) resulted in new insights for the project. Theoretically, a contractor can service the rail switch every night. This means that the prediction horizon has to

Table 5.1: Criticality classification matrix being used as checklist due to a predefined scope

Short term	**Asset**	**Explanation**
Available data quality	Turnover failures	The current data is of high quality to extract a number of movement related issues, command and control related issues are hard to capture from the available data.
Available failure mechanism knowledge	Turnover failures	There is a basic understanding of the most important failure mechanisms and sources.
Implementation complexity	Turnover failures	The implementation complexity originates from the speed with which the prediction needs to become available, as this impacts the processes which need to be put in place in order to extract the data from the systems, and to communicate the results to the subcontractors. Additionally, the organization is not familiar with maintaining PdM systems.
Largest potential cost & risk reduction	Turnover failures	A reduction of switch failures will result in a better availability of the railways, which will contribute to ProRail reaching the targets as defined in the concession. [73]
Long term	**Asset**	**Explanation**
Knowledge management potential	Turnover failures	ProRail has little to gain from capturing the degradation mechanisms in a model. However, the subcontractors do benefit from knowledge management, as the average skill level from the personnel is decreasing.
Increasing service level requirements	Turnover failures	The occupation of the railways is increasing, a single switch failure will therefore has an impact on more trains and travellers than is currently the case.
Largest potential cost & risk reduction	Turnover failures	Reducing switch failures will remain relevant on the long term. However, at the moment ProRail is purchasing a new switch monitoring system. Even tough the insights gained in this project are relevant when the new system is in place, it is possible that the created model will be obsolete.

be one day in advance at a minimum. But in practise the contractor will always make a cost-benefit estimation to determine if the risk of a switch failure is high enough to justify the costs and impact associated with attempting to repair it right away. Therefore predictions should not only include which rail switch will fail, but also the section or component in which the failure will occur. This will positively influence the costs-benefit estimation, as it will require less man hour to diagnose a potential failure, or to conclude that the prediction is false. The factors influencing if a prediction is actually acted upon are expected to be: time a prediction is preceding a failure, the accuracy of the prediction, the specificity of the prediction. For this reason c1 in Table 5.2 is being rated with 'Maybe'. Furthermore it was discovered that shifting scheduled cyclic maintenance based on the condition of the rail switch is currently not realistic as rail switches are serviced in a cluster. One maintenance contractor stated that it is easier to maintain a rail switch twice than to break up the clusters.

The technical feasibility (t1&t2 in Table 5.2) is not expected to become a show-stopper, as a previous project at ProRail has shown that the data has predictive potential. There are no off the shelf products to predict rail switch failures. One company that provides a rail switch monitoring service still relies on a manual interpretation of the data.

There is no expected lack of financial resources (e1 in Table 5.2), however it could be possible that there are not enough failures to create a positive business case (e2 in Table 5.2). Based on the current information it is unsure if the number of train delays being caused by predictable failures is substantial enough to actually implement and maintain the predictive solution.

Evaluating the organizational showstoppers is slightly complex, as not only ProRail needs to be evaluated, but also the organization of the maintenance contractors to a certain extend. Additionally, ProRail and the maintenance contractors have a complex legal relationship.

A lack of trust in the system by the maintenance contractors is not expected, as under the current PBC contract there is a financial benefit for the contractors to use the predictions. But only after the accuracy of the predictions has been proven. Additionally, the maintenance contractors already receive a basic health report for each rail switch, based on which they can decide to perform Preventative Maintenance (PM). Currently, this report only contains information on railswitches which are generating sporadic errors. It is clear to everyone that these switches are already almost broken. Providing the maintenance contractors with predictions of rail switches that do not yet produce any errors requires a more skilled user to interpret the implications of the prediction. (o1, o2 & o3 in Table 5.2)

The fit between PdM and the operation (o3 in Table 5.2) is not expected to be-

Table 5.2: Showstopper rating. Abbreviation can be found in Table 4.2

Category	c1	c2	t1	t2	e1	e2	o1	o2	o3	o4	o5	Result
turnover	Maybe	No	No	No	No	Maybe	No	No	No	No	No	Maybe

come a showstopper. Maintenance is only expected to be executed during a maintenance window, which is usually during the night. This must be taken into account in the prediction horizon.

The availability of spare parts is not expected to become an issue.(o5 in Table 5.2)

Focused feasibility
Due to the overlap between the methods proposed in the focused feasibility study and the investment evaluation stage it is being proposed to apply the proposed tools solely in the investment evaluation stage. However, in the case that there is a significant number of assets to apply PdM to, it is suggest to use the proposed tools as a quick selection tool.

Selecting the optimal approach

The optimal approach selection stage (Section 4.4) aims to determine the category of tools and techniques which are best suited to reached the desired ambition level with the available data.

Ambition level

The ambition level to be achieved is level 4 (Fig. 4.2), which is defined as “A specific system in a specific environment”, as predictions are to be generated for each individual rail switch, and the future conditions are expected to be similar to the historical conditions present in the dataset.

Available data

- *Usage monitoring data* is available in the form of the number of turnovers a rail switch has made. Additionally, the number of passed trains can be extracted from an existing dataset. This data is available for the past 3 years.

- *Load monitoring data* is available in the form of a 20Hz signal containing the amount of current a rail switch consumes during a turnover. This data is available for the past 3 years.

- *Health data* is available in the form of alerts generated by the automatic train scheduling system when a rail switch failed to turn towards the desired direction. This data is currently available for the past 2 years.
- *Meta data* is available, in which the characteristics of each rail switch are described. It is assumed that the characteristics of the rail switches are constant for the past 3 years.

Technology selection

Based on the ambition level and the available data it can be determined from Figure 4.3 that the Data model based approach is expected to be the best technique to use in this case study.

Investment evaluation

Technical evaluation

1. Data acquisition:

   All factors being considered to include in the model are already being measured and present in a relatively easy accessible format. The current usage data is measured on site with 20Hz. The failures are measured by the automatic train scheduling system (PRL) when a rail switch is not in the desired direction after around 55 seconds after the command has been send. Maintenance logs are not accessible to ProRail.

2. Data processing:

   Previous projects have indicated the possibility of predicting rail switch failures based on the current usage data. In order to be able to compare the failures between different rail switches, each feature can be expressed at the level of deviation from a normal turnover of that particular rail switch.

3. Detection:

   Malfunctioning rail switches are already being detected by measuring the time difference between the send command signal, and the received control signal. The health state is expected to be indicated by the level of deviation the features have from a normal turnover.

4. Diagnostics:

   As the reasons for a switch failure is not clearly labeled, it will be attempted to separate switch failures based on their failure characteristics. Where failure characteristics are defined as the differences between a normal turnover and the turnovers preceding a failed turnover. An example of a failure characteristic could be an increasing current usage in a specific section of the current profile in the turnovers leading up to a failed turnover. In a later stage, domain experts can assign causes to each groep in order to increase the practical relevance of the clusters. This stage assumes that there are multiple failure characteristics that are present in the current usage dataset.

5. Prognostics:

   For each failure group the likelihood of a failure occurring the next few days will be determined.

6. Decision analysis:

   Suggesting a direct intervention is the only practical option, as was identified in a previous stage.

7. Presentation:

   The predictions will be presented per rail switch. Besides the prediction, also the information the prediction is based on is accessible, in order to provide a level of transparency.

Organizational evaluation

In the organizational evaluation the status quo is being evaluated in order to be able to make a solution design that aligns with the current state of the organization. For this the factors listed in section 4.5 are being evaluated, which starts with an evaluation of the trust factors, thereafter the process related factors are covered.
Trust factors evaluation:

1. Representation

   The current dashboards providing insight into the functioning of rail switches (LIM) use a dynamic timeline to present the actions and states. For this reason the initial approach will be to present the predictive results in a comparable format, and in the same systems. Showing the historic signals based on which the prediction is based adds to the transparency of the prediction.

2. Image and perception

   The perception of the current dashboard providing insight into the functioning of rail switches (LIM) is positive.

3. Reviews from other users

   The users of the predictions are the maintenance contractors. It is of limited interest in the current case to identify early adopters and to generate positive reviews from key users.

4. Transparency and explainability

   It is aimed to include transparency by visualizing the development of relevant features over the previous turnovers. Additionally due to the type of potential failures being grouped, a rough cause can be provided.

5. Usability and reliability

   In order to maintain the reliability it is relevant to retrain the model every once in a while with the newly acquired data. Additionally, in order to increase the reliability it is relevant to collect correct and incorrect predictions, however, it is uncertain if this is possible. Additionally it is relevant to determine the effect of the newly added data by reevaluating the previous predictions. This can be used to inform the users of the change in predictions, as this allows them to reevaluate their perception of the usability and reliability of the tool. However, in the exceptional case that all failures are prevented, no new failure data will become available. ProRail is only aware of occurred failures, and not aware of when a railswitch is in a degraded state. Therefore, in the exceptional case that all failures are prevented, no new failure data will become available. This makes that it will become difficult to maintain the accuracy of the model in the long term, assuming an inevitable change of the environment.

6. Job replacement

   At ProRail there is nobody who's task description completely overlaps with the goal of this project. At the side of the maintenance contractors there is a shortage of qualified personnel, additionally the current solution is only expected to increase the number of maintenance actions as not all rail switches will fail if PM is not performed.

Process factors evaluation:

1. Are there entry points in the current workflow for preventative actions?

   There are procedures in place to report preventative maintenance actions to the maintenance contractors. Therefore, it is not expected that mayor process changes are required.

2. Do the current policies allow assets to be repaired before they have been reported as broken?

The current policies do not allow assets to be repaired at any time, as permission to enter the railway track needs to be given to the maintenance contractor by ProRail. As the railway availability is at a premium, ProRail is not generous with allowing the maintenance contractor to enter the rail tracks at any time.

3. Is there an entity in the process who has the responsibility to take preventative measures?

   The entity present in the process who is responsible for the state of the railway tracks is the trace coordinator. Additionally this person is the link between ProRail an the maintenance contractor.

Financial evaluation

This case follows an explorative approach, therefore not a pure financial evaluation but an innovation management evaluation is performed. Table 5.3 compares the current and two of the potential maintenance strategies. The following part aims to substantiate the ratings listed in Table 5.3.

1. Innovation and growth

   Implementing a PdM system is good for innovation and growth because it can act as a backbone to which more data and features can be added in order to make the predictions more accurate. Additionally it is a step in moving the organiztion in the digital direction.

2. Maintenance

   Having PdM will have an impact on the maintenance planning. On the one hand the planning is less ad hoc, due to a reduced number of incidents, on the other hand the number of preventative repair should be more than the number of prevented incidents. As it is unlikely to create a prediction algorithm with zero false positives.

3. Production

   The train traffic will benefit, as it is now possible to replace incidents with PM actions. Opposed to incidents, these can be planned on less inconvenient moments.

4. Customer

   Customers are expected to appreciate the usage of PdM as it has a positive effect on the level of unplanned availability, which will mean that the planning of the customers is impacted less often.

Table 5.3: Balanced score card for the rail case

Perspective	RBM	CBM	PdM
(i) innovation and growth	3	4	5
(ii) maintenance	3	3	3
(iii) production	4	4	4
(iv) customer	3	4	5
(v) society	3	4	5
(vi) financial	2	3	3
Total	**18**	**22**	**25**

5. Society

   The general public will like it if there are less large delays (during busy hours).

6. Financial

   On the long term there is not expected to be a major financial benefit. As the maintenance still needs to be performed, and maybe even more than with the current maintenance strategy. On the short term ProRail will profit from every successful predicted switch failure, while not bearing any direct financial consequences from switch failures which could not be predicted. This is due to the PBC it has with its maintenance contractors.

Technical implementation

Previous attempts

There has been a previous attempt to predict rail switch failures at ProRail, based on the same datasets as are currently available. The approaches were focused on training a dedicated model for each rail switch, based on data which was aggregated per day rather than per turnover. [74] Not all design choices made in the previous project align with the goal of the current project. However, the previously developed methods which are still relevant are included in the current project.

Data description

Rail switches are in an 'error' state when the time between the command and control event is larger than 55 seconds.

The datasets listed in Table 5.4 are available for around 900 rail switches over a period of around 3 years. For the command stage it is known at which point in time a command was send to move the switch towards the left or right position based on

Table 5.4: The available meta data of a rail switch, including a sample value and the range.

Dataset name	Content	-
POSS	The current used during a turnover, measured at 20Hz	
TROTS	Command and control signals of turnovers	
PRL alerts	Alerts generated by the train routing system when a switch is not in the requested position after 55 seconds.	

the TROTS dataset. At the time of this study, this is only available for turnovers which resulted in a failure. During each turnover the current used by the switch engine is measured and available in the POSS dataset. For the control stage it is known at which point in time the control circuit was triggered at the left or right position based on the TROTS dataset. At the time of this study, this is only available for turnovers which resulted in a failure.

Additionally, meta data is available describing the characteristics of the rail switch, as is shown in Table 5.5. The final available dataset contains incident reports, which includes a record for malfunctioning rail switches as reported to the maintenance contractor by ProRail.

Exploratory data analysis

The exploratory data analysis stage provides a detailed description and analysis of the available datasets.

The most common type of current profile can be divided into three distinct regions. The start current peak during which the switch is being brought into motion, the middle section during which the switch is being moved, and the final section. The first and last section have a fixed length of 2 and 1.5 seconds respectively, the middle section is the remaining part. During the previous project a number of features have been defined, as listed in Table 5.6. These are derived for each of the three sections. These features convert the continuous current profile data into discrete values, which reduces the complexity of the remaining processing stages. Figure 5.5 shows a number of features which have relatively little variation.

The distribution of the occurred switch failures over a day provides an interesting insight regarding the quality of the data. Maintenance works usually starts after 23:00, from Figure 5.3 it can be deduced that this results in a large number of errors. These errors do not generate a business impact, and are assumably not predictable.

Table 5.5: The available meta data of a rail switch, including a sample value and the range.

Description	**Sample**	**Range**
Location	[RD coordinates]	
Angle	01:09	01:04,5 - 01:39,1
Manufacturer	[Manufacturer name]	
Switch type	Regular Switch	regular, half-English, English, symmetric, three-way
Purchase date of switch	01.01.2005	
Switch engine type	NSE2 HL	NSE2-x, NSE-x, Ebiswitch, VHO, EHO-x (x are various sub-types)
Switch engine purchase date	01.01.2005	
Non-friction system type	Ekos-rollen	
Switch heater type	GBK.Ztmo.01	
Surface type	Ballast op klei/veen	
Ballast type	Steenslag 31,5/50	
Ballast thickness	$>$ 25 cm	None, $<$ 15 cm, 15-20 cm, $>$ 25 cm
Wisselligger soort	Concrete	Wood, Concrete, Plastic, None
Average tons per day travellers	24.811	0-85.000
Average tons per day goods	85	0-85.000

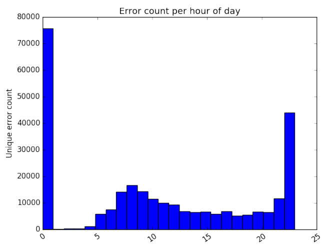


Figure 5.3: The number of errors per hour of day.

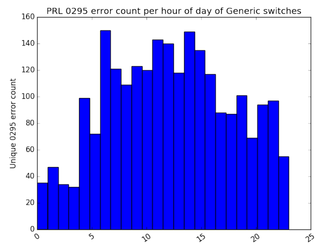


Figure 5.4: The number of 0295 PRL errors for generic switches per hour of day in 2019 between 11-2018 and 07-2019.

After being idle for the entire night, rail switches make their first turnover between 5 AM and 8 AM. This causes a relatively large number of errors due to nightly events, such as debris ending up in the rail switch.

The current method of marking turnovers as failure happens solely by looking at the state of the rail switch. However, this does not include the goal and method with which the rail switch was turned over. For example, during maintenance works rail switches are manually turned over. This causes the turnover to be marked as failed. Additionally, a turnover that fails during a test after the maintenance have been completed, is most likely the cause of improper maintenance and not of general wear and tear. For this reason the context in which the turnover failure occurs is taken into account by only considering turnovers which have been initiated by the automatic train routing system. For this subset of turnovers, turnovers which take longer than 55 seconds are marked as failed. With this method all maintenance related failures are excluded from the dataset, as it is reasonable to assume that no trains are routed over switches on which maintenance is being performed. The result of this method can be seen in figure 5.4, which shows a less skewed distribution per hour of day than figure 5.3.

In order to create a complete overview of the working of a railswitch the following datasets are linked: Failure dataset, TROTS dataset, current usage dataset. (Fig. 5.7) There are 4951 '0295' errors of generic rail switches, however it has been observed that for the majority of the failures the time between failures is smaller than 3 days. It has been visually observed that current profiles of failures on the same rail switch within 5 days after a previous failure are very similar. In order to reduce the bias towards these failures only failures which occur at least 5 days after a previous failure are included in the dataset. This leaves 2211 failures. The current usage is not monitored for all rail switches, this leaves only 244 failures, of which only 166

Table 5.6: The definitions of the features derived for the starting peak section, middle section and final section.

Feature Name	Value type	Description
Maximum	Discrete	The maximum value in the section
Minimum	Discrete	The minimum value in the section
Slope	Discrete	The slope of the trendline in the section
Duration	Discrete	The duration of the section
Mean	Discrete	The mean of all values in the section
Median	Discrete	The median of all values in the section
Standard deviation	Discrete	The standard deviation over all values in the section
Difference	Discrete	The difference between the first and last value of the section
Min Max	Discrete	The difference between the largest and smallest value in the section

Table 5.7: The definitions of the features derived over the entire turnover.

Feature Name	Value type	Description
AUC	Discrete	Area Under Cruve, the integral over time
Return	Boolean	True if the switch started moving back to the original position.
Duration	Discrete	The duration of the turnover

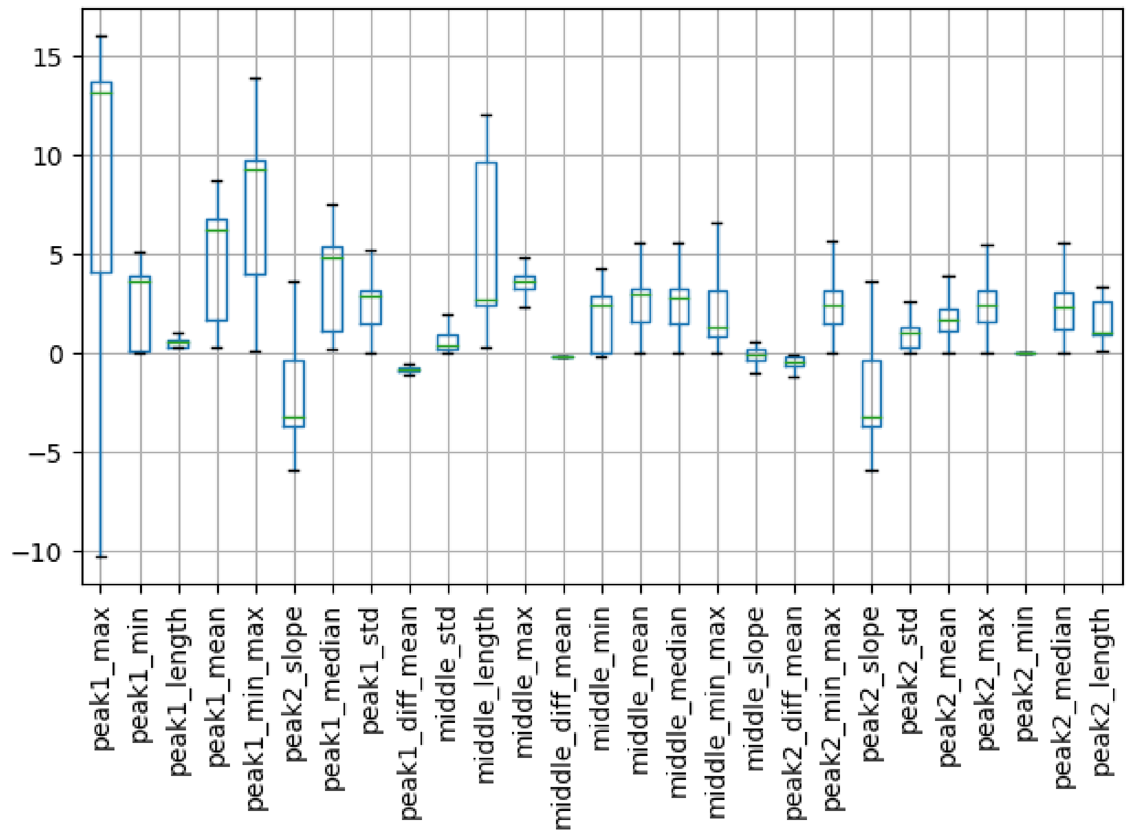


Figure 5.5: Boxplot of the features listed in Table 5.6.

could be reliably connected to a turnover.

Health Indicator construction

The goal of the Health Indicator stage is to define a metric which represents the condition of the rail switch. A low value should indicate that the rail switch is operating in a normal, healthy way. An increasing value indicates that the rail switch starts operating more and more abnormally, which indicates that the condition of the switch is deteriorating.

The data on which the health indicator can be based is a single features, or a combination of various features which have been derived from the current profile data (Tab. 5.6). A sample current profile with the corresponding feature values can be found in the Appendix (Fig. A.1 & Tab. A.1).

A malfunctioning switch can have many causes, some of the cases which have been seen in the maintenance records: 'Cable eaten by rats', 'Stone between the rail bars of the switch', 'latch broken off', 'switch seized due to lack of lubrication'. Based on an expert guess it is being assumed that some of these causes show

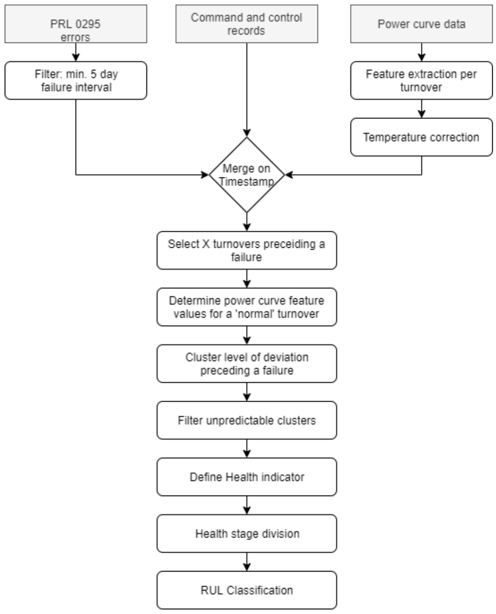


Figure 5.6: Flowchart of the data processing steps.

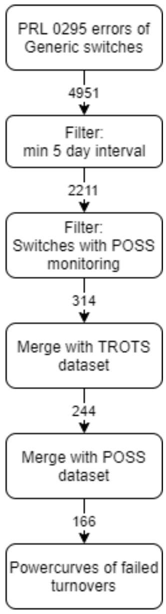


Figure 5.7: The number of items left after the applied filter and merge steps.

symptoms in the electrical-current pattern during the switch moves preceding the fault. Other causes do not show any early symptoms in the current pattern.

The most challenging aspect of this case is the lack of information regarding the cause of a switch failure. Although it is known by domain experts which type of failures are more common than others, it is not known what the cause is of each individual switch failure. Therefore it will be attempted to cluster the symptoms present in the current profile data preceding a failure. The main reason for this is to filter out the switch failures for which the current profile data does not contain any predictive information. Additionally, this makes it possible to focus on one specific failure mechanism, which is expected to reduce the complexity. A health indicator, as explained in Section 3.1, can then be defined for failures in clusters which do not occur suddenly.

A switching action of a rail switch can be divided in three categories: (1) The command stage, in which the command is given to move to either the left or right position. (2) The turnover stage, in which the relay is triggered based on the command and the switch engine moves the switch in the designated direction. (3) The control stage, once the rail switch has turned over, a control circuit is triggered to indicate that the rail switch reached the other side successfully. According to domain experts turnover failures take up around 25% of the failures, command and control failures take up around 25% and 50% respectively.

The method by which the dataset in this case is constructed makes it that no command related failures are present, as only failures for which a current profile is available are selected. By clustering the rail switch failures it is expected that a segregation appears between turnover related failures and control related failures. As according to a domain expert, current profile of a failed turnover look ‘normal’ in the case of a failure in the control circuit. In the case of a turnover related failure the current profile looks abnormal.

Figure 5.10 shows the change in current used per turnover in the turnovers preceding a failure, which is one of the candidates for a health indicator. However, this figure does not show clear signs of a trend in the turnovers preceding the failure. Which can mainly be attributed to the high amount of noise caused by the temperature dependence of the accumulated current used, as well as the duration of the turnover. (Fig. 5.8) The noise can be accounted to the temperature dependence of the friction present during a turnover, as well as the change in electrical resistivity of the copper cables. It has been observed that the amount of temperature dependence differs per railswitch. The features need to be corrected for this temperature dependence in order to be able to compare the change in behaviour before a failure between different rail switches.

The temperature correction is performed by applying a linear fit per railswitch for all turnovers towards the same direction.(Fig. 5.8) Thereafter, all feature values are adjusted to become independent of the temperature.

Unfortunately this method was unable to significantly reduce the noise caused by the temperature dependance. Therefore an alternative approach is being attempted, in which the feature values of subsequent turnovers are subtracted. When a second turnover occurs of the same rail switch within 15 minutes after the first turnover, it is safe to assume that the environmental conditions are very similar for both turnovers. When computing the difference of the current-features between both paired turnovers, causes the environmental effects present in the features to be cancelled out. The downsides of this approach are first of all the need for a sufficient number of turnovers occuring shortly after each other, and secondly it only provides insight into deviations which is only present in turnovers towards a single direction. The first downside is also the main reason why this approach was turned out to be unsuitable to extract a health indicator from.

Defining a clear health indicator with the currently available domain knowledge, data, and used methods does not yield any results. A railswitch turns out to be a complex system, which cannot be captured in a degradation model with the current approach. For that reason it is attempted to take two steps back in the OSA-CMB model by shifting the focus towards detecting the location of a failure in the chain of events that makes up a successful turnover. With the available data it is possible to distinguish three sections: the command stage, the turnover stage, and the control stage. The value of this approach, besides increasing the understanding of the failure mechanisms, is that it will enable the classification of new failed turnovers into one of these groups. This enables the maintenance contractors to more easily diagnose the problem.

The technical definitions for these categories are determined as follow:

- Command stage: Failures for which a sent command to move the switch is not followed up by a measurement of current at the switch. The indicator for this stage is the time it takes
- Turnover stage: Failures which can be observed from the current usage during a turnover
- control stage: Failures which occur after a successful turnover. This will be indicated by the duration between the moment the no more current is used by the rail switch, and the received control signal.

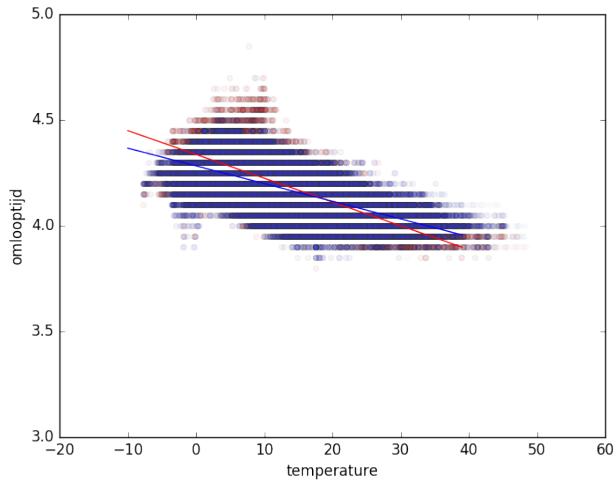


Figure 5.8: Temperature dependence of the turnover time. The distinction between the turnover direction is made in Red and Blue

The current data of each failed turnover is being clustered in order to be able to detect various failure mechanisms. Figure 5.9 shows the current data for each failed turnover, the color represents the result of the clustering step which has been performed with DBSCAN. Three clusters could be formed (blue, black, green), the red turnovers could not be assigned to a cluster. The green turnovers, are normal turnovers. For these turnovers it is expected that they are technically functioning properly, but no control signal was send. This algorithm was chosen as it does not require prior knowledge regarding the number of groups. The parameters for DBSCAN have been empirically determined, by defining a balance between a high level of similarity within the clusters and reducing the number of turnovers which are not be placed in a cluster. Furthermore it is observed that the turnovers from the black group first show a 'normal' current usage, but at the point where a normal turnover would end, the current usage increases in approximately one second to a high stable current usage.

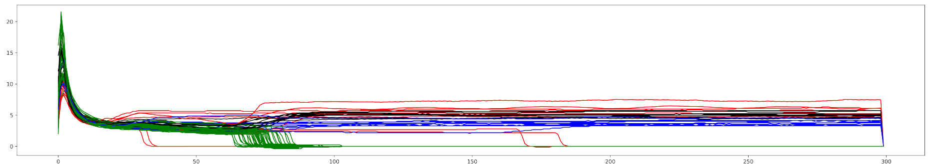


Figure 5.9: Current measurements for failed turnovers of NSE turnover systems. Current is measured in Ampere, the measurements are taken at a rate of 20Hz. Colours represent the clusters, the red turnovers did not fit in any cluster.

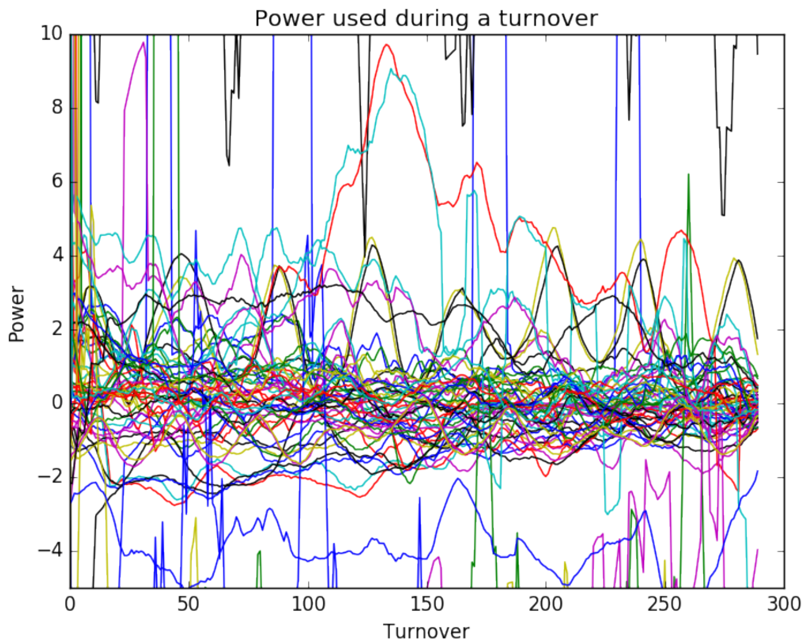


Figure 5.10: Deviation of the current used during a single turnover, compared to turnover 300. Failure occurs at turnover 0. This figure shows a high variance caused by temperature influences, and thus no clear trend towards the failure can be identified.

5.3 Case evaluation

The goal to be reached in this case study was to predict the occurrence of rail switch failures at least one day in advance. A number of interesting insights regarding the applicability of the framework have been gained during the execution of this case study, despite the fact that the initial goal was not reached.

Recommendation

The sensor data originating from dutch rail switches is already very detailed. However, it became apparent that with the current data alone the author was not able to create a predictive model for the failures resulting in train delays. Therefore it is recommended to also gather maintenance information from the subcontractors, as is already legally possible in the latest PBC. This data is expected to increase the value of the already available current data, as these maintenance logs will make it possible to perform more basic statistical analysis. Which will make it more likely to gain results that hold practical relevance. Additionally it is recommended to perform the knowledge generation step, in which relevant the degradation factors are discovered, in an experimental environment, outside of the regular operational environment. In such an experimental environment it is suggested to extensively monitor a rail switch, which can then be used to simulate certain known failure causes. Based on the these results, it will be possible to determine if the existing data originating from the operational rail switches is sufficient to predict the occurrence of the tested failure cause.

Framework evaluation

The framework evaluation is intended to determine the applicability of the framework to the current PdM project in the domain of Vital Transport Infrastructure (VTI). The suitability of the framework will mainly be evaluated based on how well is was able to support the execution of the case. Additionally, the relevance of the final products and insights realised during the technical execution of the case are evaluated with someone from the targeted user group. Thirdly, the entire setup of the framework and the execution of the case is evaluated with two experts who have a long track record in the field of maintenance. The results obtained from the latter two evaluations are used to support the first evaluation. Each stage of the framework will be evaluated based on three factors:

1. Completeness
2. Relevance
3. Practical usability

The first stage encountered in the framework was the *Initiation* stage, in which the scene was set. It has been relevant to execute this stage, but only in retrospect. During this case it was observed that, apart from the ambitious and generic goal of predicting switch failures, there was not a clear objective. After it was determined that in the current state it would be challenging to predict switch failures, it was unclear how the data could still provide value in other ways. Therefore it would have been relevant to identify the potential applications for the predicted, diagnosed or detected failures in advance when starting an explorative technology push project.

The second stage, *Selecting suitable assets*, was performed for a different purpose than originally intended. The scope of the project was already narrowed down to switch turnovers, and no more data was available to further narrow the scope. Therefore this stage was used a checklist in order to identify potential issues. The value gained from the stage was limited, partially due to the lack of clear evaluation criteria. However, it has created awareness regarding the implementation complexity, and confirmed the relevance of the project. The showstopper identification stage did prove its relevance by creating new insights with regards to the clustering of maintenance activities. Additionally, this stage pointed out a lack of attention in the framework towards the relationship between the different organizations involved in the project. During both the expert evaluation, as well as the end-user evaluation this came up as critical factor which was missing from the framework. The usability can be improved upon, mainly by defining clear evaluation criteria which would decrease the level of prior experience required to execute this stage.

The *Selecting the optimal approach* stage provides a clear method to shape the goal to what technically could be achieved. The ambition level is an important step in converting the business goal into a PdM scope. However, the quality of the data was not evaluated properly enough to prevent issues in later stages. Additionally, for classifying the available data, there was no category for meta data. The relevance and usability of this stage both turn out to be positive for this case.

The first step in the *Investment evaluation* is a technical evaluation. The relevant aspect of the technical evaluation appears to be the use of a three step approach, namely detection, followed by diagnosis, and lastly prognosis. Structuring the design in such a way creates a step by step approach, however it still does not guarantee a successful outcome of the project. The result of the organizational evaluation was not entirely relevant, mostly because the end users are the subcontractors who have a financial benefit of using the tool to prevent rail switch failures. However, during the mockup evaluation it became apparent that despite this financial benefit, it is still unsure if the information ends up at the technicians who are working on the rail switches. For that reason it is suggested to include the processes on the side of the maintenance contractor in the evaluation. The evaluation of the business processes is deemed to be relevant, as there are many rules and procedures related to railway maintenance. The financial evaluation did not alter the course of the project, most likely because it is an explorative project, combined with the very broad evaluation criteria.

Mockup evaluation

The end result, for convenience illustrated as a mockup, has been evaluated with a rail switch specialist at ProRail based on the transparency of the information being conveyed. Additionally the expected practical usefullness is being evaluated. The transparency of the mockup was positively received, as it was clear how the displayed information related to the rail switch in the real world. Additionally the relevance of the information was also recognised. But the challenge that was expected to remain was how to communicate the information to the mechanics in the field. This issue is part of a large debate around PBC, as the contract stimulates maintenance contractors to create insights from these datasets themselves. However, this does not reduce the number of failures on the short term.

Lastly, it was noted that a similar classification has already been created in the previous rail switch prediction project. However, this never made it into a production setting. Additionally, there is an ongoing development project where the two datasets that are being used, are merged into one platform. Which indicates that the suggested technical direction is not revolutionar, and has already been identified. However, this case study still supports the direction the project is heading, and identifies that this step is one step closer to PdM.

Chapter 6

Asphalt Case

6.1 Background

Heijmans infra is a company specialised in the design, construction and maintenance of large infrastructure, such as highways and bridges. Heijmans is responsible for the maintenance and construction of all the airside asphalt on Schiphol since 2011. In January 2019 the contract was renewed as a Performance-based contracts (PBC), which gave Heijmans the need to position themselves as an asset manager, rather than a general maintenance contractor. Heijmans desires an increased understanding of the speed at which asphalt degrades under certain measurable conditions in order to be able to start planning maintenance works 3 years in advance, rather than the current 1 year in advance.

6.2 Framework

At first the framework as described in Section 4.1 is filled out based on interviews with 3 domain experts from Heijmans, and observations from the available data. After the goal of the project has been defined, the technical approach is set out based on the framework as described in Section 3.1.

Initiation

This case starts from a decision pull, as there is an economic and strategic necessity to explore the possibilities of Predictive Maintenance (PdM). Additionally, this is an exploitative project. As the goal is to investigate the potential of PdM.

Selecting suitable assets

Criticality classification

The critically classification stage identifies the assets to focus on during the explorative PdM project, by evaluating the factors listed in Table 4.1. The result of this stage can be seen in Table 6.1, which has been filled out based on interviews with the domain experts from Heijmans. The first columns describes the category being evaluated, the second column describes the assets which score best in this category, and the third column lists the argumentation here for. Hereafter the risk matrix which has been used to define the assets for which the largest risk reduction is possible will be elaborated upon.

Based on the results from the critically matrix, the first issue to focus on are the Rafeling and Craquelé damages on the runways, as these categories have the most available data and are relevant to predict on the short term.

The proposed tool for determining the assets with the largest potential of a cost and risk reduction on the short term in the framework from [1] is based on mapping the probability of failure to the impact of a failure.

In the current case it is not realistic to use this measure, as the assumed definition of a failure is when a component causes to halt the operation of the system. However, with damages in asphalt this is less clear cut because of two reasons. First of all, it is still possible to drive over a section of asphalt that is in a bad condition, therefore measuring the impact in downtime of the section of the road is not a good method of measuring impact. Secondly, the asphalt on the airport is generally well maintained, and is being repaired before it becomes unsafe or impossible to drive over.

Therefore, an alternative criticality matrix is being proposed. As substitute measure for the probability of occurrence the total area of a damage type is used, which is set out against the costs required to repair these damages as measure of the impact of a damage. In this measure the direct impact of a bad section of asphalt on the operation is being omitted, however this is reasoned to be permissible as the impact is indirectly included via the size of present damages.

In the proposed method the criticality matrix is being divided into four quadrants in order to separate the less critical assets from the critical assets. [62] When dividing the criticality matrix (Fig. 6.1) into four quadrants, only 'Craquelé' populates the fourth quadrant. Therefor, also 'Rafeling' and 'Langsscheuren' which are present in the lower right quadrant are being considered.

Table 6.1: Criticality classification matrix

Short term	**Asset**	**Explanation**
Available data quality	Rafeling & Craquelé on Runways	For runways more historical usage data is available in the form of the number of Start & Landings per runway. Rafeling & Craquelé are the damage types which are most balanced across the 3 severity categories.
Available failure mechanism knowledge	All damages on Runways	The usage of runways is more consistent and thus easier to conceptually comprehend, therefore there is a better understanding of these failure mechanisms.
Implementation complexity	All damages on Runways & Taxiways	The maintenance processes for maintaining Runways and Taxiways are comparable, as well as the teams.
Largest potential cost & risk reduction	Rafeling, Craquelé & Cracks on Runways	Runways are more business critical than taxiways, and the safety tolerances are significantly tighter on runways. Repairs on the listed damage types make up the largest portion of the repair budget.
Long term	**Asset**	**Explanation**
Knowledge management potential	None	Knowledge management is not considered to be relevant due to the small number of assets being maintained.
Increasing service level requirements	Runways & Taxiways	The freedom to schedule small maintenance on a short term will decrease in the near future, for both the runways and the taxiways.
Largest potential cost & risk reduction	Taxiways	The usage of taxiways is more complex, and maintenance is more challenging to schedule. Most aspahlt on Schiphol is a taxiway, which makes it more attractive from a financial point of view.

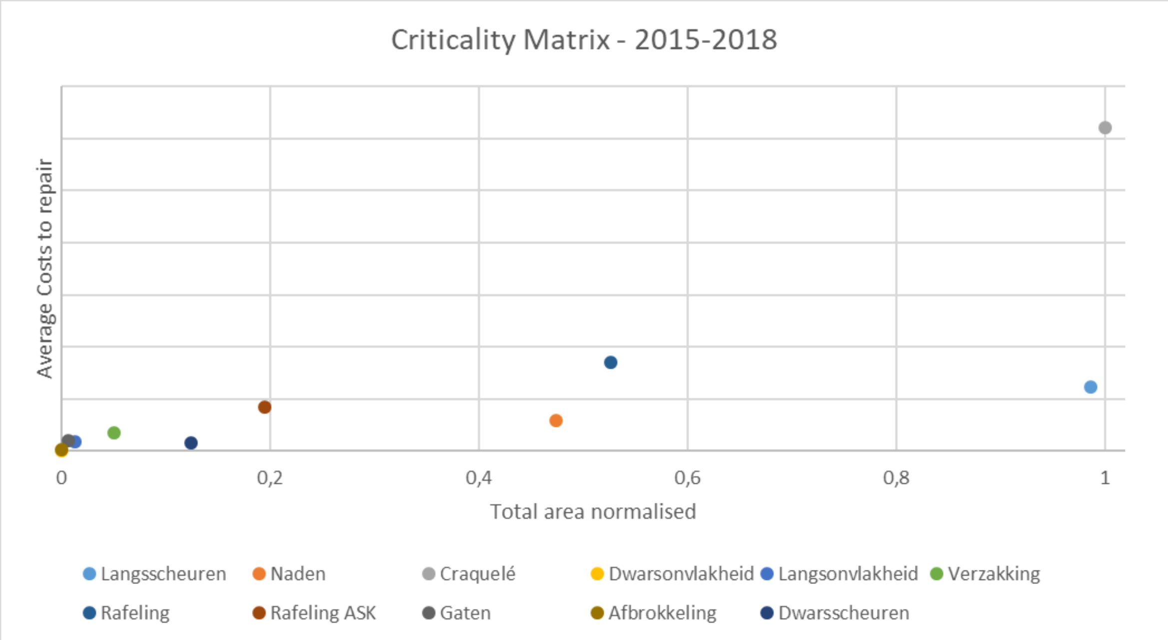


Figure 6.1: Criticality matrix, damage area vs repair costs per damage type. The axis are censored on purpose. Based on data from Heijmans.

Showstopper identification

The first step of the showstopper identification is to determine the ambition level (Sec. 4.3). The ambition level being aimed for is 'Prognosis', as a process for detection and diagnosis is already in place.

The second step is to rate the assets based on the showstoppers listed in Table 4.2. Table 6.2 shows the assigned likelihood for each potential showstopper to be a factor in the current case. This table has been filled out based on interviews with domain and organizational experts at Heijmans. Most failure types and assets have been rated with a similar value, as the underlying processes and datasets are identical across the failure types and assets.

A mismatch with the operational planning is not expected (c1 in Table 6.2), as the predicted degradation will be based on the yearly inspections. Which will make it automatically align with the current yearly maintenance planning routine. However, in the future the maintenance planning has to cover more than one year, which will require a larger prediction horizon of the PdM solution.

The error margins of the degradation models of asphalt which are currently present on the market are too large to be of any practical use, according to Heijmans (t1 in Table 6.2). Additionally, it is unknown whether the currently available data and knowledge is sufficient to predict the degradation with a small enough accuracy that makes it practically usable. However, this will not be a showstopper, as this is one of the goals of this PdM project.

Table 6.2: Rated showstoppers for the asphalt case. Abbreviation can be found in Table 4.2

Category	c1	c2	t1	t2	e1	e2	o1	o2	o3	o4	o5	o6	Result
Langsscheuren	No	No	No	No	No	Maybe	No	No	No	No	No	No	Maybe
Craquelé	No	No	No	No	No	No	No	No	No	No	No	No	No
Rafeling	No	No	No	No	No	No	No	No	No	No	No	No	No
Taxiways	No	No	No	No	No	No	No	No	No	No	No	No	No
Runways	No	No	No	No	No	No	No	No	No	No	No	No	No

There are enough failures present for a positive business case in case the data which is currently available and being collected is sufficient.(e1 in Table 6.2) However, in the case that additional data needs to be gathered this might not be the case anymore, as gathering data is generally and expensive and in the current case a slow process.

The organizational showstoppers are not expected to be a hard showstopper in the current case. It has been identified that both the client as well as the upper management are highly interested and supportive in this PdM project. (o6 in Table 6.2) Additionally, the current maintenance strategy is already almost entirely based on Preventative Maintenance (PM) with a yearly inspection cycle. This requires minor changes to the maintenance processes before the predictive results can be used to base maintenance actions on. (o3&o4 in Table 6.2) The personnel is considered to be experienced and 'IT capable', additionally it is expected that the users will trust the predictions under the condition that the results are transparent.(o1&o2 in Table 6.2)

Focused feasibility

Initially the focused feasibility study has been executed, however the similarities with the investment evaluation stage are too significant for it to serve a purpose. Therefore it is being proposed to apply the proposed tools solely in the investment evaluation stage. However, when there is a significant number of assets to apply PdM to, it is suggest to use the proposed tools as a quick selection tool.

Select the optimal approach

The optimal approach selection stage (Section 4.4) aims to determine the category of tools and techniques which are best suited to reached the desired ambition level with the available data.

Ambition level

The ambition level to be achieved for Rafeling is level 4 (Fig. 4.2), which is defined as "A specific system in a specific environment". It is being assumed that all environmental conditions are roughly consistent for all sections of asphalt. However, this might not be an acceptable assumption for the sections of asphalt close to a de-icing station, as well as locations which have a different priority for clearing the snow. Additionally, crack related damages are not only caused by forces from the surface, but also by tension forces originating from lower layers of asphalt due to aging, and by tension forces originating from the foundation. The latter two are considered to be a change of the environmental condition, as the quality and age of the lower layer of asphalt as well as the foundation is almost unknown.

Available data

- *Usage monitoring data* is available in the form of log records, which include the runway and a timestamp for each arriving and departing airplane.

- *Load monitoring data* is derivable from the transponder dataset, in which the location of each airplane is logged every two seconds. The relevant feature to be derived are the indicated by domain experts.

- *Health data* is available in the form of yearly damage inspections, in which the outline of each damage present on Schiphol is indicated and classified.

- *Meta data* is available in the form the age of the top layer of asphalt.

Technology selection

Based on the ambition level and the available data it can be determined from Figure 4.3 that the Data model based approach is expected to be a suitable technique to use in this case study. Additionally, the available data types and the selected ambition level are not in conflict.

Investment evaluation

The investment evaluation aims to determine if there is a business case before committing to the project. This is done by evaluating the project based on the technological, organizational and financial feasibility.

Technical evaluation

The goal of the technical evaluation is to determine if the degradation mechanisms are predictable in the first place, and secondly if degradation mechanisms are slow enough in order to detect and repair them in time when considering the operations or maintenance cycle.

Technical feasibility:

1. Data acquisition:
   The factors responsible for the degradation of the asphalt are categorised as usage or environmental factors. In the current case, environmental factors are assumed to have a constant impact on the degradation of the asphalt. Additionally, the combination of the asphalt inspections on a yearly basis and the seasonality of the the environmental factors makes it unsuitable to determine the effect of environmental factors on the degradation. The usage factors being considered by the domain experts, mostly relate to the usage actions which exert forces on the asphalt. These are: vehicle weight, wringing, touchdowns, acceleration and deceleration, and vehicles standing still. The usage factors are being extracted from the aircraft GPS positions which will be supplied by Schiphol, and the weight can be derived from the airplane type which is publicly published by the FAA. The health information can be extracted from Heijmans' yearly inspection results.

2. Data processing:
   The processing effort required to convert the aircraft position information into actual usage factors as identified by the domain experts are extensive. As the data is unindexed, unfiltered, and additional transformations need to be designed in order to extract the usage factors from the dataset. All of this needs to be performed on a cluster with big data tools, due to the dimension of the dataset. The usage factors from before 2018 can be derived by creating a general usage profile per airplane type per runway, and combining this template with the number of start and landings per runway per aircraft type from 2012 until 2019. The yearly inspection data only needs minor cleaning.

3. Detection and diagnostics:
   The detection of the health state of the assets is being done manually by outlining and classifying all the visual damages in the yearly inspections. Although the type of damage is being determined, it remains unknown where the cause of the damage originated from.

4. Prognostics
   In the case that there is a strong correlation between certain usage factors

and the development of certain damage types, a prediction will be made by predicting the state of a damage in the coming year based on the relevant usage factors.

5. Decision analysis:
   The decisions to be made based on the predictive results will be done manually as the scope of the current project only looks at asphalt degradation from a specific point of view, and does not take the full picture into account.

6. Presentation:
   The presentation can be made by showing a grid of the runway where for each block the current and future state is visually displayed.

Organizational evaluation

In the organizational evaluation the status quo is being evaluated in order to be able to make a solution design that aligns with the status quo of the organization. This is being determined by evaluating the factors listed in section 4.5, this starts with an evaluation of the trust factors, thereafter the process related factors are covered.
Trust factors evaluation:

1. Representation
   The users are used to working with GIS maps in order to intake information about the state and characteristics of the assets. This is not only being used by the users in the office who prepare the works, but also by the people out in the field who execute the works. Making a visual representation based on the location is therefore more representative than for example a summary with numeric values per runway. Additionally, this representation allows the existing IT infrastructure to be used for distributing the results to the users.

2. Image and perception
   It did became clear that graphs which illustrate certain relations are favoured over maps which show a prediction, however it did not became clear what the existing attitude was towards prediction systems.

3. Reviews from other users
   This factor was not evaluated, as it would both require an assessment of every user from the user group, as well as a working prototype which has to be used during their daily work in order to evaluate the effect.

4. Transparency and explainability
   The initial suggestion is to include the most dominant factors being used to

determine the prediction with the prediction. In this way it is possible for users to 'drill down' on a prediction in order to see where this prediction is based on.

5. Usability and reliability
   Every time a new yearly inspection becomes available the system should be retrained. In order to determine the effect of newly added results on the predictions all previous prediction should be remade in order to determine the classes on which the results differ significantly. Thereafter it is to be evaluated with domain knowledge how the model changed, in order to know the value of the predictions, and in order to inform the users of the changed accuracy in certain cases.

6. Job replacement
   The prototype to be created would replace tasks which are currently not being performed. Additionally the task description of the users are diverse and comprehends more than making predictive assessments.

Process factors evaluation:

1. Are there entry points in the current workflow for preventative actions?
   The current workflow is already almost entirely preventative, the predictions act as an additional source of information for the decision makers. Therefore it is expected that no or minor changes to the process are required before the prediction can be incorporated in the process.

2. Do the current policies allow assets to be repaired before they have been reported as broken?
   The current policy does not allow for incidents, and aims to predict the moment when a damage needs to be replaced three years in advance. Relative to the speed of degradation of a damage there is enough time to repair a damage once it reaches a critical state.

3. Is there an entity in the process who has the responsibility to take preventative measures?
   Heijmans is already responsible to take PM actions.

Financial evaluation

For the financial evaluation the proposed hybrid business case approach is being followed. At first a non-financial evaluation is being made, as this is an explorative project. Thereafter a minor financial evaluation is being performed, in which the expected financial savings are being approximated with the help of an expert.

Table 6.3: Balanced score card method as proposed by [5]

Perspective	PM	CBM manual	CBM models
(i) innovation and growth	2	3	5
(ii) maintenance	3	3	4
(iii) production	2	4	4
(iv) customer	4	4	5
(v) society	4	4	4
(vi) financial	1	3	3
Total	**16**	**21**	**25**

Table 6.3 shows the balanced score card as proposed by [5], in which the impact of PM, Condition Based Maintenance (CBM) performed manually (current situation) and lastly CBM as performed with models and algorithms.

In the category Innovation and growth (i), CBM models has been rated with the maximum number of points due to the potential of transferring the acquired knowledge to the asphalt of motorways. The maintenance perspective (ii) is only awarded one additional point over the current practise, as the benefits are expected to be there, but it is uncertain to what extend. The origin of the benefits is expected to come from clustering maintenance activities. The production cycle (iii) and the experience of the end users (v) is not expected to be impacted by implementing the new type of maintenance strategy as the impact will remain to be low. The direct financial benefits (vi) of the new maintenance strategy are expected to be low for Heijmans, as in the end less maintenance will need to be performed. However, in the future Heijmans will move towards supplying availability of the runway, rather than asphalt maintenance services. Mastering predictive maintenance is important in order to keep the risk level acceptable, and in order to safeguard a profit margin.

Technical implementation

The technical implementation will start with an description of the available data. Thereafter an Exploratory data analysis step will be performed, in which two iterations are made. Next, a number of influence factors are defined base on domain knowledge. After a feature filtering step, a prediction algorithm is trained and validated.

Data description

Regarding the degradation of asphalt, historical condition and historical usage data is available. For each dataset the type of data is being determined where relevant, as explained in Section 4.4, and the contents are briefly explained:

1. Yearly asphalt inspections - Historical condition data
   This contains lines and polygons with the coordinates where damages are located. Each line and polygons is considered to be a single damage. Each damage is accompanied with a severity rating (1-3) and a classification of the damage type. Photographing the runway and taxiways happens at the beginning of the year, and has happened since 2014. For 2019 only half of the inspections are available.

2. Airplane movements - Historical usage & load data
   For every vehicle (airplanes, cars, pushback vehicles, ..) the GPS location is available at a 2 second interval. This data is available since February 2018 up until August 2019, however only for around 85% of this time period.

3. Takeoffs and Landings - Historical usage data
   A log record of every takeoff and landing is available. This contains the runway, airplane identification information, and a timestamp.

4. Airplane characteristics - Load data
   For the most common airplanes the offical Maximum Takeoff Weight (MTW), Maximum Landing Weight (MLW) and the number of wheels is available.

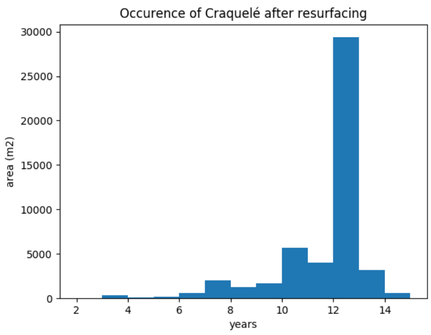
Exploratory data analysis

Figure 6.2 shows the number of years it takes for a damage to form on a new section of asphalt. These figures illustrate that the occurrence of the damages do not follow a normal distribution. This can be attributed to either other degradation factors which are not constant over time, or to the assumption that every section of asphalt on Schiphol degrades according to similar factors.

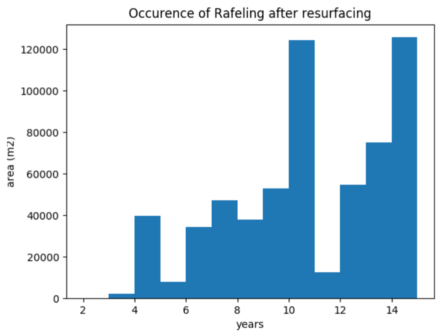
In order to determine which usage related factors to include in the prediction model, domain experts where asked for the factors which they believed to be important. These factors are then calculated based of the airplane locations dataset, and set out against the time it takes for a damage to form. This provides insights in the importance of the factor. Additionally, this creates the opportunity for a new iteration, in which the domain experts can match the results with their practical experiences. This allows them to redefine the potential degradation factors of which they think are important.

Before any of the datasets were explored, a number of factors which impact the degradation of asphalt were defined:

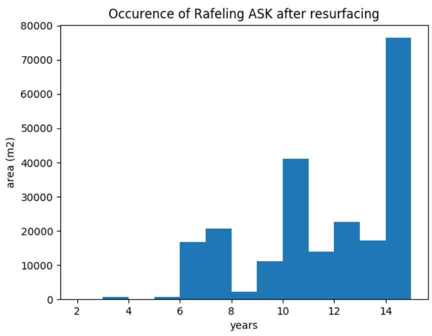
1. UV exposure



(a) Craquelé



(b) Rafeling



(c) Rafeling Anti-Skid

Figure 6.2: The age of the asphalt on locations where a damage emerged. Based on data from both runways and taxiways, additionally the data only covers a few years of the entire degradation cycle of the assets, where each asset is in a different stage of the cycle.

2. Frost

3. Age

4. Forces exerted on the asphalt:

    (a) Combination of vehicle deceleration and weight

    (b) Combination of vehicle speed, weight, and direction change

    (c) The duration a vehicle stands still on the same location

    (d) The initial point of touchdown of a landing airplane

This session provided two types of degradation factors, namely usage related factors, and environmental related factors. The choice has been made to only focus on usage related factors, as it is assumed that environmental related factors remain roughly constant over the years, and affects each section of asphalt in similar amount. This is expected to be permissible, as each section of asphalt is exposed to roughly the same weather conditions. Secondly, the impact of seasonal effects is limited as the data is gathered on a yearly basis. For this reason it is also expected that the influence of environmental related factors is harder to extract from the dataset than usage related factors.

In order to combine the different datasets, Schiphol has been divided into a 5 by 5 meter grid. Where 5m was chosen because it was the smallest grid size which was computationally feasibly. For each grid tile, the following features are calculated:

- Average change in direction of travel
- Average speed
- Average acceleration
- Average Maximum Take Off Weight (MTOW)
- Total number of touchdowns
- Total number of stopped airplanes

The factors listed above, are set out against the number of years it took for a damage of a specific category to form, as illustrated in Figure B.2, B.3 & B.4 which are located in Appendix B.2. The most noticeable insights to be gained from these figures are explained next.

Rafeling ASK damages appear significantly earlier on places where airplanes have their initial point of touchdown. Unfortunately, a limited number damages inside the touchdown zone are present in the dataset. Either because the touchdown zones have been resurfaced around the same time as the data collection process was started (Polderbaan, Zwanenburgbaan, Buitenveldertbaan, Aalsmeerbaan) or because a majority of the damages were already present when the data collection process was started (Kaagbaan). However, when looking at the underlying data, there appears to be a strong correlation. Therefore it is suggested to redo this analysis in 1 to 3 years time. Based on previous experiences it is namely expected that between 2020 and 2022 the first damages will emerge on the recently resurfaced touchdown zones.

The previous statement is also supported by Figure B.3b, which shows the average speed in contrast to the duration for a damage to form. Here it is seen that damages that appear within 8 years, lie primarily in areas where the average airplane speed is high.

Additionally, Figure B.3f shows that the quickly appearing Rafeling ASK damages are present in multiple weight classes, which suggests that an increased airplane weight does not necessarily speed up the forming of Rafeling ASK damages.

Rafeling ASK occurs sooner when located in the touchdown zone, however this is not the case for rafeling damages. For these, only the damages of the oldest category are present in the touchdown zone.(Fig. B.3e) On the contrary, rafeling damages located in areas where a lot of planes stand still, are always of the youngest two classes.(Fig. B.2d) The thirds noticeable insight is that on places where the average airplane weight is large, only damage of the middle class are present. Additionally, on places where the average MTOW is low, fewer rafeling damages are present than on places with a higher average.(Fig. B.2f) Lastly, when the average speed on a rafeling damage is high (60-80 knots) rafeling damages from the oldest category take up a larger portion of the total damages than when the average speed is low (0-20 knots).

Based on the initial data exploration, combined with the renewed insights from the domain experts, the following factors have been selected to use in the prediction model.

- Touchdown count
- Average speed
- Average MTOW
- Stop count
- Average direction change

Table 6.4: The variables used in the model. PV stands for the Prediction Variable, which will be the output. All the other variables are the input variables.

Variable	Description	Value Type
Duration (PV)	Number of year before a damage was detected	Discrete
Speed	The average speed of all airplanes on this location	Continuous
Direction	The average change in direction on this location	Continuous
MTOW	The average MTOW of the passing planes	Discrete
Stops	The number of times an airplane has stopped on this location	Discrete
Touchdowns	The number of time an airplane touched down on this location	Discrete

Remaining Useful Life (RUL) prediction

The Remaining Useful Life (RUL) prediction stage is the stage with the aim to predict the duration until the asset will fail to serve its purpose. However, the data available in this case is censored, because it is unknown when the asphalt will fail, as it is being repaired or replaced before this happens. Therefore it will be attempted to detect the time it takes for a damage to emerge on a new piece of asphalt.

This issue can be defined as a regression problem, as the time it takes for a damage to form is a continuous variable. In order to ease the implementation, only regression algorithms from Scikit-learn library are being considered. From this group Support Vector Machine (SVM) has been selected to use, as it performs well in a wide variety of situations, if correctly applied. [75] The dataset has been normalised before training the SVM.

The SVM algorithm is being tuned by performing a gridsearch over the following variable ranges as suggested by [75]: $C = 2^{-5}, 2^{-3}, ..., 2^{15}; \gamma = 2^{-15}, 2^{-13}, ..., 2^{3}$

The trained model is used estimate the number of years after which damages start to appear based on the section of asphalt is being used. When adding this duration to the year when the asphalt was placed, an estimated 'End of Life' year is determined.(Fig. 6.3)

Algorithm Accuracy

The algorithm is tested by applying an 80/20 split, where 80% is allocated as training data and 20% as testing data. The error rate is determined by computing the R2 value, which has been chosen due to its characteristic of increasing the weight of points with greater absolute error values.

Table 6.5 shows the R^2 results per damage type, in combination with the parameters that resulted in the best R^2 value out of the tested parameter ranges.

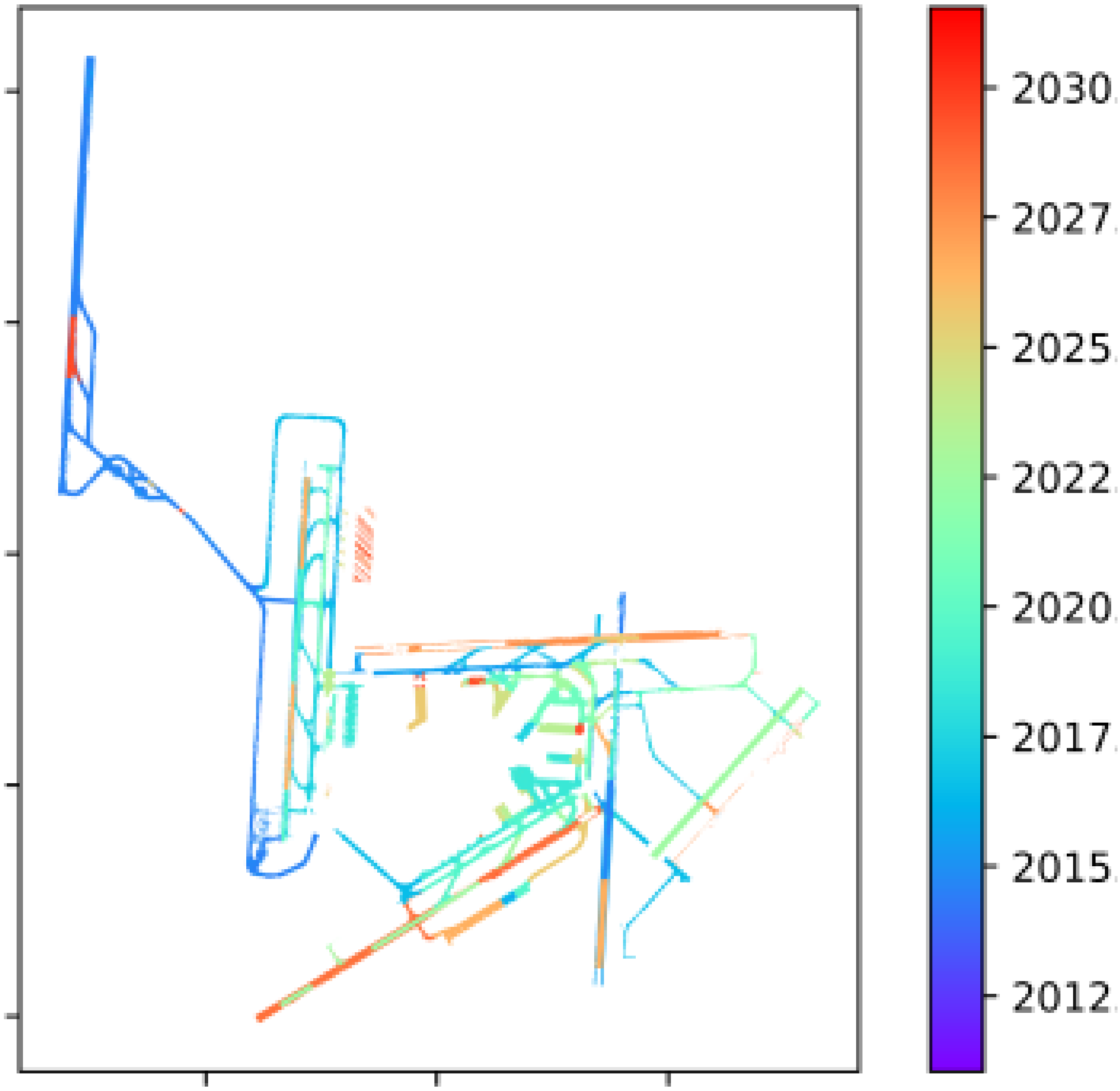


Figure 6.3: The predicted year a craquele damage is expected to appear based on usage data and construction year.

6.3 Case Evaluation

The goal of this case study was to predict the occurrence of asphalt damages one year in advance. Mainly due to lack of inspection data over an entire life cycle of a section of asphalt it was not possible to validate or invalidate the effect of potential degradation factors. Therefore it was also not possible to create a prediction model with a reasonable accuracy. Nevertheless, it was still possible gain insight into the strong and weak aspects of the applied framework. Additionally, the modelling of the expected usage based influence factors was successful, as it expanded the understanding of the stakeholders with regards to the cause of certain asphalt damages

Table 6.5: The parameter and R^2 accuracy values for the three damage categories.

Damage category	C	γ	R^2
Rafeling	2^{-5}	2^{-15}	-0.02
Rafeling ASK	2^{15}	2^{3}	-0.12
Craquelé	2^{15}	2^{3}	-0.19

that were out of scope for this case study.

Recommendation

The current case study has supported Heijmans in moving one step closer towards predicting the occurrence of asphalt damages. The next steps to take in order to reach the ambition will be elaborated upon in this section.

The most important goal to focus on would be to increase the granularity and completeness of the health data, which in this case are the annual asphalt inspections. If the number of inspection per year would increase, it would become possible determine the influence of seasonal factors on the formation of damages in the asphalt. Additionally, it would be beneficial to measure the location and severity of a damage in a more objective manner, rather than a visual classification is happens currently. This alternative and frequent inspection technique could potentially make it possible to detect damages during their early stages, which is before they would be identified as a damage with the existing inspection method. This could make it possible to detect damages 3 years before they enter a critical state, as is in line with the rationale for this project.

The second recommendation is to validate the results obtained regarding the touchdown location. Both based on the results obtained in this case study, as well domain knowledge, it is clear that the touchdown location is an important factor for the formation of damages. Therefore it is expected to be relevant to validate the accuracy of these results.

Finally, it is recommended select a few experimental sections of asphalt were all seemingly relevant variables are monitored extensively at a high interval. The goal of these areas is to provide a detailed insight into how a damage forms, and propagates.

Mockup evaluation

A mockup of the intended final dashboard has been created and tested with three end-users in order to test if the predictive maintenance system is likely to be adopted. The dashboards have a trade off between completeness of the presented data, and complexity. Five mock-ups have been created, each with a different ratio between completeness and complexity. The end-user preferred the dashboard which gave the most insight into the data underlying the prediction model. Another noticeable insight was that the end-user who stood closer the the maintenance operations was more interested in a dashboard with a high granularity, whereas the end-users with a managerial role were more in favor of a simplistic dashboard which would align better with the view of the customer.

Framework evaluation

Each stage of the framework will be evaluated based on three factors:

1. Completeness
2. Relevance
3. Practical usability

Furthermore, the evaluation will be supported by the end-user evaluation, and the expert panel evaluation where possible.

The first stage encountered in the framework was the *Initiation* stage, in which the scene was set. During this stage it was identified that the stakeholders view this as an explorative project, and it was determined that there were higher goals to be reached with PdM. The relevance of this stage appears to be providing the right starting points for the later stages, and during this stage the goal of the project was defined.

The second step in the framework, *Selecting suitable assets*, had to be interpreted in a different way. As the scope was already narrowed towards asphalt, which left no alternative assets to be selected. However, the general goal of the stage, increasing the focus of the project, was still deemed relevant. This stage appears to contribute positively to the feasibility of the project, as this reduced the complexity of the project. Which is a logical step to take when working with a system of which the complexity is unknown at the start.

Originally, the framework from [1] only considered the impact of a failed asset combined with the likelihood for the asset to fail. The extension made to the framework shifted the focus towards selecting the assets for which PdM is the easiest and quickest to implement. This approach aligns with one of the key PdM implementation factors as listed by one of the domain experts from the expert panel, which is that a PdM project needs to be introduced into the organization in small steps.

Of all the factors being evaluated in the criticality matrix, the *Available data quality*, and the *Available failure mechanism knowledge* are experienced to be one of the important factors for the success of a PdM project. During this case the quality of the data was incorrectly assessed, after which the goal of the project had to be redefined. This shows the importance assessing the quality of the data beforehand. The importance of domain knowledge was already identified by [1], and additionally substantiated by van Dongen and Zijm. One major downside of these two categories is the lack of clear criteria to determine the quality of the data or the completeness of the present knowledge regarding failure mechanisms.

The factor *Implementation complexity* did not increase the focus of the project, mostly because of the already narrow scope and the clearly defined goal. Additionally, this factor has a broad scope, which makes it harder to evaluate for relatively inexperienced practitioners.

Lastly, the factors from the 'long term' category were given little importance in the evaluation, due to the this being an explorative project partly focused on increasing the understanding of the failure mechanisms. As the primary business goal is already a long term goal, other potential drivers for the project on the long, as evaluated in the long term category, are unlikely to outweigh the short term factors.

After the criticality classification, the showstopper identification has been performed. From this exercise, no major showstoppers have been identified. In the current case it was experienced that the economical feasibility was rather hard to evaluated, as it is uncertain how much the project will cost. Additionally, assessing 'the number of failures for a positive business case' was hard, as this would depend on a number of factors which were not yet clear. Assessing the Technical feasibly did not add value, as it was already clear form the start of the project that additional research was required in order to predict the formation of damages.

The third stage, *selecting the optimal approach*, gave a good structure and categorized the goal, and the technical approach to take. Almost all items in this stage were experienced to be relevant and practically useful. However, the lack of a data quality assessment before categorizing the available data types ended up being a fatal mistake. This lead to using a technical approach which required condition monitoring data, which was assumed to be present in the form of the damages a varying severity. However, this ended up being too inaccurate, aswell as too little data to move forward with.

The *Investment evaluation* consists out of three parts. The technical evaluation based on the OSA-CBM model contains a relevant 3 step approach consisting out of detection, diagnosis, and lastly prognosis. Again, the practical usability of this stage is to be improved upon, due to the lack of clear evaluation goals.

The organizational evaluation ended up being partially relevant. The factors 'representation', 'Transparency and explainability' appeared to play a significant role in the design process. Whereas the factor 'Reviews from other users', 'Image and perception' and 'Job replacement' did not, and are expected to play more of a role during the actual implementation of the final product, rather than in the design stage. During the end-user evaluation session it was determined that the users related to the operations prefer a tool with a higher level of transparency.

The third and and final part of the investment evaluation stage is the financial evaluation. This stage did not change the course of the project. As the project type is explorative, the non-financial evaluation was used. The evaluation factors in this tool were experience to be vague, and to provide no clear added benefit.

Chapter 7

Evaluation

This evaluation section aims to determine the strong and weak points of the framework as defined in Section 4.1 based on the two case studies. Additionally, the relevance of the applied framework and the execution of the cases has been discussed with two experts around predictive maintenance. These discussions are used to support this evaluation. The items where each stage is evaluated upon are: Completeness, Relevance, and lastly Practical usefulness.

The *initiation stage* only plays a small role in the framework, but still an important role. As this stage sets the objective of the project, and decides if the project starts because of a technology push, or decision pull. This stage appears to be relevant, as a technology push approach would require an additional step, namely finding a use case to create a solution for. The clear evaluation criteria result in an proper practical usability of this stage. This stage could benefit from a stakeholder identification step, as this would make sure that all relevant parties, especially the end users, are involved in the project from the beginning.

The *selecting suitable assets* stage has been an important stage, as it aims to increase the focus, which in turn reduces the complexity of the generally complex Predictive Maintenance (PdM) problems. Additionally, this stage determines the focus of the project based on the data quality and available knowledge about the failure mechanism. During the execution of the cases it has been experienced that data quality, and the understanding of the factors driving the degradation of the object are two of the most important aspects for a PdM project. The criticality classification distinguishes short term, and long term goals. However, based on the two case studies it appears that the long term goals are not relevant to reevaluate for explorative projects, as the rationale for the initiation of the project was already based on these long term goals. The showstopper evaluation has proven its value, as in both cases this step created new insights. The only downside is that the evaluation criteria are very broad and generic, which reduces the practical usability, but increases the general applicability.

The *selecting the suitable technology* stage appears to be the best stage of the framework, as the relevance, usability and completeness are all positively experienced. This stage was also positively received by the domain experts. The relevance of the stage can be expressed in its ability to combine two disciplines, which are on the one hand the potential of the available datasets, and from the business side the level of detail to which the assets can be modelled. The practical usability is good, due to the conciseness of this stage. The one aspect that can be improved upon is in classifying the datasets in the 4 categories. In this step it is unclear when the quality of the data is good enough, or the data is complete enough before it can be categorized.

The *technological evaluation* in the investment evaluation stage provides a clear staged approach, where the detection, diagnostics, and prognostics stage are well received as they provide a structured way to build the domain knowledge and the required datasets for the consecutive stages. One of the domain experts stressed the importance of a staged introduction of PdM in particular, which he identified to be correctly taking into consideration in both case studies. It is being expected that building knowledge on degradation factors is not a sequential, but an iterative process. As an interaction is needed between the data scientist, and the domain expert. This was also stressed by the domain expert. Additionally, the level of understanding only needs to be deepened until the prediction accuracy is good enough for the use case. For this reason stage one to five are better to be executed in an iterative manner. Lastly, the presentation stage is a relevant stage to evaluate due to the complexities present in the implementation phase.

The relevance of the *organizational evaluation* could only be partially evaluated, as the final product in both cases was a mockup of a dashboard. Therefore, the users were unable to test the tool during their daily work. The representation, and transparency factors were evaluated with the mockup, and appeared to be important factors in the perceived usefulness of the tool. One important identified gap in the organizational evaluation is the evaluation of the organization and motivation of the maintenance contractors. As this is the group who actually executes the maintenance actions. It must be noted that more gaps might be identified after the tools have been fully incorporated in the organizations, as the evaluation has been performed based on mockups.

The financial evaluation did not change the direction of the project in both case studies, however it must be noted that only explorative cases has been tested, for which a financial evaluation is less relevant. The lack of influence on the direction of the project appears to originate from the unspecific evaluation criteria, and from the lack of a clear evaluation goal. Additionally, it appears that the real value of this stage is a justification of the use of a PdM approach, which should be determined earlier on in the process with evaluation criteria that are more specific to PdM.

[1] designed the framework originally for the evaluation of already executed PdM projects, and later on suggested how to use it as a design framework. However, during the application of the framework it was noticed that the framework was not initially created as a design framework. First of all because the stages are slightly out of order for a design approach, and secondly the setup of the stages is towards evaluating the designed artifact, rather than evaluation the environment in order to deduce the design requirements.

The selected technical framework, as discussed in Section 3.1, which was intended to be applied to both case studies, did not turn out to be so versatile as initially expected. The framework appears to be only applicable to cases where detailed condition or health monitoring data is available, as the approach is centered around the construction of a health indicator. Therefore, only the ProRail case qualified. However, due to the lack of a result in this case study, it is challenging to accurately evaluate the method.

7.1 Revised Framework

The goal of this thesis was to evaluate the applicability of a framework for the implementation of PdM in the domain of Vital Transport Infrastructure (VTI). Especially during the execution of the case studies it has been experienced how the focus of the framework can be changed for the better. Based on the shortcomings identified in the previous section, together with the observations and experiences gained during the process, a revised framework is being proposed. For the remainder of this thesis, the framework shown in Chapter 4 is referred to as the original framework, and the framework proposed in this chapter will be referred to as the revised framework. The stages which compose the revised framework are as follows:

1. Setting the scope

2. Identify the path to predictive

3. Iterate towards a reliable model

4. Adoption

5. Maintaining the model

Table 7.1: Rating scale: To be improved upon, adequate, good

Stage	Completeness	Relevance	Usability
Initiation	Adequate: The stage is very small, but complete enough to correctly define the goal and approach of the project	Good: It is important to clearly define the cause for the project	Adequate: There are clear evaluation criteria for the distinction between a technology push or decision pull approach, but it is not clear to what detail the goal needs to be defined.
Selecting suitable assets	Adequate: It correctly identifies the assets to focus on, and potential show-stoppers, but it lacks a basic data quality assessment	Good, as it increases focus, and gives a coarse indication in the technical possibilities. The Long term factors appear less relevant to evaluate.	Adequate: This stage contains a number of methods for guidance, but lacks crystal clear evaluation criteria, as well as a logical structure.
Select optimal approach	Good: The provided methods are sufficient to reach this stage's goal, only a data quality evaluation could improve the completeness.	Good: This stage supports the inter-disciplinary process of linking the business goals with the technical opportunities.	Good: The methods provide clear evaluation criteria with the right balance between specificness and Generalisability.
Investment evaluation	To be improved upon: On a high level it is considered to be complete, due to the three stage. On a level for practical use it lacks the structures, especially to effectively perform the financial evaluation.	To be improved upon: The financial evaluation for explorative projects was not found to have an added benefit. The organization evaluation was relevant. The technical evaluation was found to be useful at best.	Adequate: The evaluation criteria are very generic, which makes it challenging to apply correctly.

Setting the scope

The first stage, ‘Setting the scope’, is mainly the combination of the ‘Initiation’ stage and the ‘Select suitable assets’ stage of the original framework, which comes from the small size of the Initiation stage.

The major purpose of this first stage is to narrow the scope of the project, as it has been experienced that PdM project are generally interdisciplinair and complex problems. This makes it worthwhile to tighten the scope as far as is reasonable in order to reduce the complexity. This is especially important when most stakeholders are inexperienced with PdM, and when there is little domain knowledge regarding the degradation mechanisms.

Identify the path to predictive

The second stage, ‘Identify the path to predictive’, is focused on defining the design requirements for the PdM tool.

The requirement process can be structured by considering all the stages of a PdM implementation, as shown in Figure 7.1. This starts with the selection of the ambition level, which combined with the available data can be used to determine the appropriate technical approach based on Figure 4.3

The alignment step covers the embedding of the PdM tool in the current environment. The showstopper evaluation, presented in Section 4.3, and an evaluation of the current maintenance processes are relevant to perform when defining the design requirements.

The adoption stage covers the design requirements which increase the ease with which the PdM tool is adopted by the end-user. One important factor in this stage is the transparency of the predictions, as also listed in the original framework under the organizational evaluation.

The last stage which is to be considered when defining the design requirements is how the model is to be used in the future. The actual factors to be considered are yet unknown, but it is argued that the methods for re-calibration or re-validation of the model are required to be considered for prediction tools that will play an important role in the maintenance process.

Iterate towards a reliable model

The original framework does not contain any directions on how to determine the relevant degradation factors. To a certain extend these can be determined based on domain knowledge, but it has been experienced during the case studies that this is

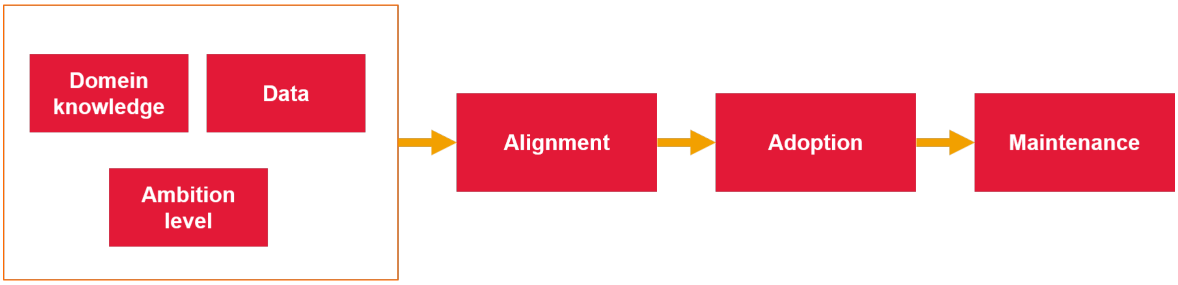


Figure 7.1: PdM development and implementation stages

not sufficient to create a model with a high enough accuracy. Furthermore, it is expected that this stage forms the largest risks for a successful PdM implementation. As in this stage it hopefully becomes apparent which factors need to be measure in an operational setting in order to accurately model the degradation mechanism. Besides the generally slow degradation processes which makes it hard to gather new measurements, it is also difficult to determine a measurement technique which is practical in a operational setting, and can be rolled out cost effectively. The last aspect which makes this a risky stage is the fact that it will always be an interdisciplinary problem, which requires both data scientist and domain experts to work together effectively.

This also highlights the two fundamental components of this stage, namely: Data and Domain knowledge. The domain knowledge is generally captured inside a model during the design phase, and the model is dependant on data as input. The domain knowledge can roughly be sourced from three areas: Peoples experiences, documents or illustrations, and lastly measurement data. In the area of VTI it is most logical to first start with the existing data, supplemented with domain knowledge based on existing literature, and peoples experiences. The latter is generally available as each organization in the VTI domain either has to role to maintain the assets, or to inspect the quality of the maintenance actions performed by other parties. In the case that the available data or domain knowledge is insufficient to determine the degradation factors it is recommended to gather more measurement data from which new insights can be deduced.

In the area of VTI it is relevant to consider gathering more measurement data in an experimental setting where a few assets are monitored extensively. This creates an environment where it becomes possible for the data scientist to prove or disprove the hypotheses stated by the domain expert regarding the degradation mechanisms. Each iteration in this stage is focused on increasing the understanding of the failure mechanisms for both the domain expert, as well as the data scientist. One iteration could be characterised by the delivery of a degradation model, for which potential directions for improvement are formed in a discussion with the domain experts.

Adoption

The adoption stage covers the embedding of the created tool in the organization. An important factor in this process is the adoption by the end users, which is the reason why this stage has been named ‘Adoption’ rather than ‘Implementation’. Other factors are the IT infrastructure required to distribute the information to the end users in a timely manner and an applicable format, the last factor is the alignment with the existing maintenance processes.

Based on the conversations with domain experts and a historical project at ProRail, it became apparent that the end users trust and understanding of the meaning of the prediction is of vital importance for the user to actually use the predictions in their daily work. For that reason, a separate stage in the revised framework is devoted to user adoption. However, it should also be noted that a prediction tool with a high accuracy is always easier to be adopted by a user than one with a medium accuracy. This means that the adoption likelihood is partially determined in the previous stage: ‘Iterate towards a reliable model’.

Maintaining the model

The stage ‘Maintaining the model’ is a new stage which is not present in the original framework. During literature research, and based on the conversations with people from the field it has been noticed that the focus of the discussion is around ‘how to realise predictive maintenance’. However, little is spoken about how to maintain this capability in a constantly changing environment. This is especially relevant in cases where the prediction tool fulfills a vital role in the maintenance process, such as when it is used as a replacement for scheduled maintenance. The underlying problem is that when a prediction model is created based on historical data, it makes it predictions based on how the historical asset interacted with its historical environment. The accuracy of the prediction will be affected in the case that the reality starts to deviate from the model, either because of changes to the properties of the asset, or changes in the environment. This consequentially has an impact on the physical state of the assets, or on the operational goals the asset need to fulfill.

Chapter 8

Closure

8.1 Summary

This thesis started of with the main research question: *How can Predictive Maintenance (PdM) be implemented in the area of VTI maintenance?*

In order to formulate an answer to this question, a number of sub questions have been defined, which will be used as structure for this summary.

1. How is the maintenance landscape around Vital Transport Infrastructure (VTI) organized?

   Chapter 2 describes the existing maintenance landscape around VTI by analysing the type of maintenance contracts used by ProRail, Rijkswaterstaat (RWS), Schiphol, and the Port of Rotterdam. It was identified that there is a sector wide trend of the use of Performance-based contracts (PBC) and Best Value Procurement (BVP).

2. What is the state-of-art of PdM in general and in VTI?

   Chapter 3 covered the state-of-art of predictive maintenance, as well as the use of predictive maintenance in the VTI domain. In this stage it was identified that there are multiple, roughly similar, technical approaches on how to perform predictive maintenance. Additionally, papers and white papers covering the implementation of predictive maintenance from an organizational point of view have been analysed. It turned out that the realisation of a predictive maintenance capability is generally well covered from a technical standpoint, but rather limited from an organizational standpoint.

3. How to structure a PdM project in VTI?

   In chapter 4 an implementation framework for predictive maintenance has been selected from literature, described, and expanded. (Fig. 4.1) The framework constitutes out of 5 stage which are: Initiation, Selecting suitable Candidates, Selecting optimal approach, and lastly the Investment evaluation.

4. How to predict the development of defects in asphalt on runways and taxiways in order to reduce risks and costs?

5. How to predict the breakdown of railway switches in order to reduce the risks on sudden unavailability and costs?

   Chapter 5 and 6 cover the application of the framework, as described in Chapter 4, on two case studies in the VTI domain. In both case studies no predictive model with a reasonable accuracy could be realised, but this did result in the necessary insights to increase the relevance of the framework.

6. How would a revised design approach look like?

   Chapter 7 evaluates the framework on its completeness, relevance, and practical usability. Additionally, a new iteration of the framework is presented, which is based on the results obtained from the case studies.

Lastly, to address the main research question: PdM can currently best be implemented in the area of VTI maintenance by following the original or revised framework, as presented in section 4.1 and 7.1 respectively. Even tough it is to be concluded that the original framework is not complete enough to properly support a PdM implementation, it does contain a number of relevant tools which have resulted in noticeable insights during the case study. Such as in the ProRail case, where the requirements of the PdM implementation were drastically affected due to the performance based maintenance contracts. Besides this, it is also important to critically assess if the available domain knowledge and data are sufficient to reach the goal, and how both of these can be increased if proven insufficient. Lastly, it is important to accurately determine the end-user requirements, as this has an impact on the design decisions in the early stages of the project. The revised framework is expected to better structure a PdM implementation process than the original framework, however this still remains to be validated in a future work.

8.2 Discussion

The framework defined in Section 4.1 has been tested on two cases in order to determine the relevance of the framework for PdM projects in the domain of VTI. The first limitation of this study to highlight is that the framework has only been tested on two cases. Additionally, the two cases are located in two different areas of the VTI domain. In all, this makes it difficult to draw generalised conclusions for the entire domain of VTI. But by determining the applicability in these two cases, it is possible to identify areas for future research, and to suggest which aspects are more important for PdM in the VTI domain than others. These are relevant insights considering the low maturity of the field. A third point for attention is the fact that both case studies are explorative, which makes it that not much can be said about the applicability of the framework in exploitative projects.

The technical framework, as selected in Section 3.1, could not be evaluated. The main reason for this is the fact that the framework has been selected before the stage 'Selecting the suitable technology' was executed. Additionally, the lack of a data quality evaluation step caused that the initial assumption of the applicability of the technical framework to be false. The data quality of the asphalt inspection was too low, which required the use of different technological methods.

During both case studies data quality issues were faced. The framework does not contain specific methods to evaluate the quality of the data. However, it can also be the cause of the desire the get the most out of the dataset, which requires attempts to extract increasingly more from the dataset up until the data quality is not sufficient anymore. The applied framework does consider the availability of various data categories in the technology selection stage, but no quality requirements are defined here. It is expected that the effectiveness of the framework will improve significantly when basic evaluation criteria are defined, as this will reduce the trail and error component needed to locate the edge of what can be achieved with a given dataset.

Creating a reliable prediction model is a difficult endeavour, as has been experienced during the case studies, and observed from other PdM projects. It has also been noticed that the by products of the PdM projects are sometimes already valuable in itself, as they provide new insights to the domain experts, or have the potential to improve the existing processes. For example, the created asphalt usage maps allowed a domain expert at Heijmans to confirm their suspicion regarding the correlation between specific usage characteristics and asphalt damages which are currently not being measured. Additionally, a representative from Schiphol could confirm that a specific runway exit was barely being used. Combined with the general complexity of PdM projects it seems worthwhile to first attempt to create value in the organisation by creating and implementing the by products of a predictive maintenance project, or otherwise called the prerequisites for achieving predictive. This can potentially be achieved by analysing the influence factors stand alone, and sharing these insights with the organization, as has been done in the asphalt case study. The side benefit of this staged approach is that it introduces the data driven way of working step by step, which eases the implementation process as it increases the digital readiness of the organization and the end users.

In essence, a predictive maintenance project aims to capture the physical degradation processes of an asset in order to predict the level of degradation based on forecastable influence factors. This makes the modelling of the physical degradation of the asset the core of a predictive maintenance project. The framework which has been used in both case studies generally requires this to be known in advance, but during the case studies it was discovered that it cannot be assumed that domain experts posses this knowledge in sufficient detail. Therefore more attention should be given to the process of determining the degradation factors of the asset. Additionally, this process is difficult from an organizational standpoint. As it requires both domain knowledge, as well as knowledge of the potential of the available datasets, which makes it an interdisciplinary problem. Especially in the field of VTI the process of determining the degradation factors is important for the timely completion of a PdM project, as assets in the field of VTI generally degrade very slowly. This means that obtaining additional measurements of the degradation of an asset can easily take many years.

8.3 Conclusion

Following the framework inspired on [1] for implementing a PdM project does provide guidance, but is not mature enough to be used as implementation framework in its current state. The main goal of the implementation framework was to provide a structured method to use when initiating a predictive maintenance project. However, as was shown in the case-studies, the goal which was set after the execution of the framework was too ambitious too realise. Thus the framework appears to be unable to capture the essence of a predictive maintenance problem in the VTI domain. In the rail case study, the quality of the data, and the directly available domain knowledge were too low. In the asphalt case it was also the quality of the data which was one of the causes for why no accurate prediction model could be created. Next to that, the framework does not take the relationship between the asset owner, and the maintenance contractor into account. The rail case study identified that not considering these interactions can lead to a product which does not create the expected benefits.

The value created by validating the designed framework inspired on the framework from [1] in the VTI domain is an exploration into how predictive maintenance can best be introduced into the field of VTI, and a revised framework which was created based on the identified challenges.

8.4 Implications & Future work

The theoretical and practical contributions of this thesis are touched upon within this section.

Implications for practise

Recommendations for Heijmans

Due to the tight vertical integration of the organization, the close relationship with the asset owner, as well as the small size of the assets to be maintained, it is expected that there is a limited benefit to be gained from structuring the PdM project according to the revised framework beyond the iterative model creation stage. As the latter stages of the framework are mostly concerned with procedural and end-user alignment.

The 'iterative model creation stage' of the revised framework is expected to be relevant for Heijmans, as it can support the process of creating an understanding of the degradation mechanisms of asphalt. During the case study it became apparent that the granularity of the inspection data is relatively coarse, and cannot be compensated by readily available domain knowledge. In order to gain a clear understanding of the degradation mechanisms it is advised to select an experimental area of asphalt where the state of the asphalt and the environmental variables are measured into great detail. This will provide a detailed representation of the changing state of the asphalt under certain environmental conditions, but more importantly, this will gain an understanding into which factors are to be measured on all assets.

Compared to the duration of the maintenance contract between Heijmans and Schiphol, it takes a long time for asphalt to degrade. For that reason it is recommended to evaluate the possibility to define Health Indicators for each asphalt damage category. This makes it possible to evaluate new degradation factors without needing to wait for damages to appear in the asphalt.

Recommendations for ProRail

The maintenance processes around the assets of ProRail are relatively complex, due to the multiple maintenance contractors with a performance based maintenance contract. The nature of the PBC is to motivate the maintenance contractors to perform maintenance in a smarter way, which includes implementing predictive maintenance practises, based on the data currently provided by ProRail, supplemented with their own measurements, maintenance data, and domain knowledge. However, ProRail is still the asset owner, and is responsible for the sensors and measurements taken on and around the railways. This requires ProRail to make decisions regarding what is being measured. Which is highly relevant for PdM as these datasources are the input for a degradation model of the asset. This makes it relevant for ProRail to identify the degradation mechanisms of the assets themselves. Additionally this allows ProRail to retain the practical knowledge regarding the assets, which could allow them to better inspect the work of the subcontractors. Additionally, the barrier for implementing and applying PdM on the side of the maintenance contractors is reduced by making this knowledge, as well as the required dataset available to all contractors.

Recommendations for CGI

The increasing use of PBC and best-value contracting further increases the need for Predictive maintenance as a risk reduction tool. Additionally the costs and complexities for acquiring and processing data has decreased in the last couple of years, which makes PdM more accessible.

CGI possesses a majority of the competences required for supporting organizations in the field of VTI with creating the capability to perform Predictive Maintenance. The core competence of CGI is to implement complex software solutions, such as the PMP program which is being implemented at ProRail. This solution makes all sensor data being generated around the railways real time available to the maintenance contractors. This shows that CGI already has the technical competences to develop the backbone of a PdM implementation. Combined with their Data science and change management competences, they already have all the skills required for realising PdM solutions.

PdM is currently solely being used for optimising maintenance process. However, it is expected that the PdM tools on the side of the asset owners, compared to the maintenance contractors, will form the basis for more and more operational and financial processes. In this respect, PdM plays a very fundamental role, as it provides the link between the complex and ever changing physical world, and its logical or functional abstraction. Due to the critical role of PdM, as well as the ever changing physical world, it is expected that PdM is an interesting area for CGI to focus on by supporting asset owners with the organizational and technical introduction of PdM.

Implications for academia

The theoretical contributions of the thesis are first and foremost the validation of the framework based on [1] by applying it in two case studies. During the literature research it was identified that there are only a limited number of case studies in this field, and the case studies that are present are generally limited to the technical aspects of predictive maintenance. Secondly, the framework as proposed by [1], where each step was presented in a separate paper and merged later on, has been tested as one complete framework. Which adressed one of the future research suggestions as stated by [1]. This approach tested the completeness of the framework, and it could be concluded that the maturity was not high enough for it to be considered a full implementation framework.

'Predictive Maintenance cannot be implemented, it can only be adopted'

This statement marks the importance of considering the end-users trust in a PdM tool, which appeared to be a major factor for the success of a PdM project. This factor was not directly identified during literature research, which suggests that this is a factor which has not been widely covered within the field of PdM. However, this does raise questions: How to properly capture the prerequisites for an end-user to trust a PdM system? Additionally, how can the designer of a PdM project properly tailor the application towards the end-users needs regarding trust?

Furthermore, it has been identified that the creation of the degradation model relies on both adequate domain knowledge, as well as on sufficient data. In the case that either of these are not present, the goal will need to be redefined or more data or domain knowledge will need to be gathered. These experiences, among others, form the basis for a revised framework as presented in Section 7.1. In future research this revised framework could be used as a starting point, potentially extended with an iterative visualisation stage in order to present the information in a format that is most appropriate for the end-users. Additionally, this revised framework can be made more relevant by deepening it with practical methods and tools which can aid practitioners in the area of VTI to implement PdM in their organization.

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Appendix A

Rail turnovers features

Sample turnover and its feature values, supporting the data exploration section of the ProRail case in Chapter 5.

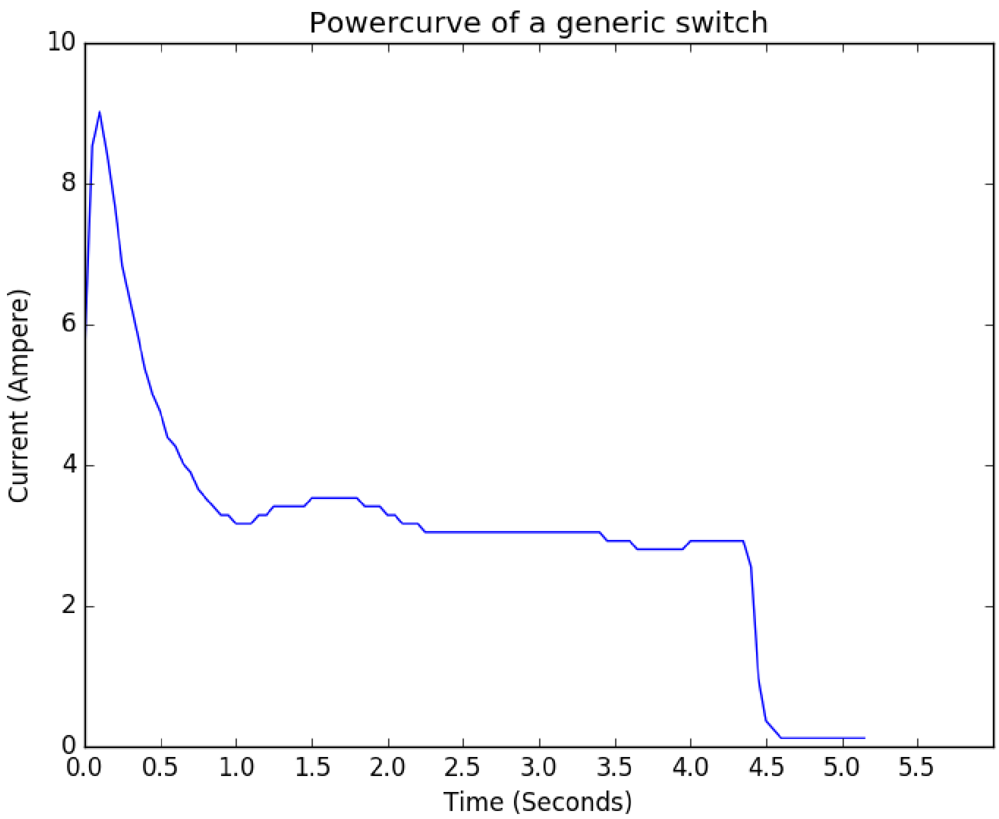


Figure A.1: A sample current profile of a generic switch turnover.

Table A.1: The feature values for the sample current profile in Figure A.1

Feature	**Value**
peak1_max	9.022
peak1_min	5.363
peak1_slope	-12.4571
peak1_length	0.3
peak1_mean	7.07057
peak1_min_max	3.659
peak1_median	6.827
peak1_std	1.35256
peak1_diff_mean	-0.609833
middle_std	1.01548
middle_length	4.45
middle_max	5.363
middle_diff_mean	-0.2605
middle_min	0.12
middle_mean	2.95263
middle_median	3.046
middle_min_max	5.243
middle_slope	-0.589279
peak2_diff_mean	nan
peak2_min_max	0
peak2_slope	0
peak2_std	0
peak2_mean	0.12
peak2_max	0.12
peak2_min	0.12
peak2_median	0.12
peak2_length	0.25
auc	15.3008
terugsturing	0
omlooptijd	5.15

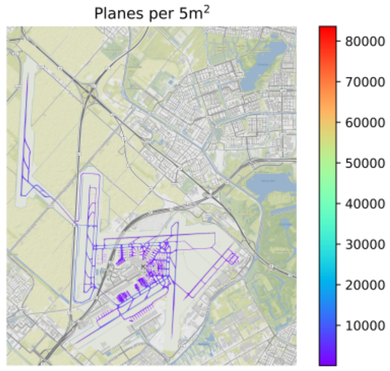
Appendix B

Schiphol asphalt usage and prediction figures

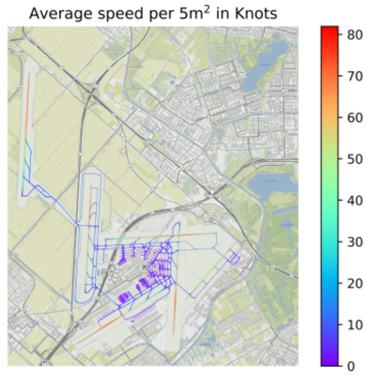
B.1 Usage figures

B.2 Feature dependence figures

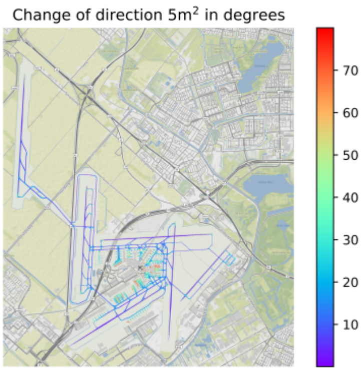
These figures show the dependance between a certain usage factor and the time it takes for a damage to emerge on the asphalt of Schiphol.



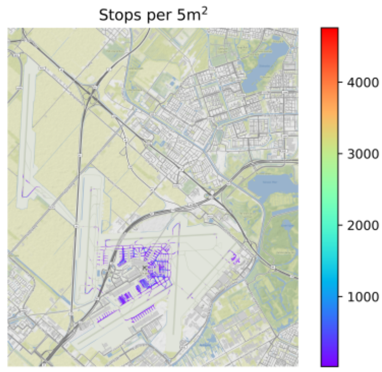
(a) Plane count



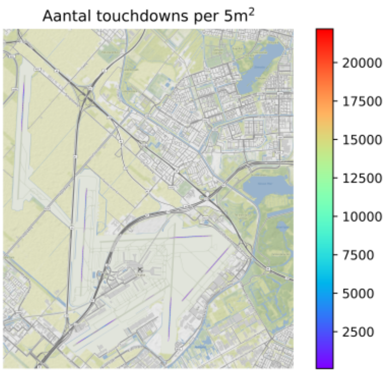
(b) Speed



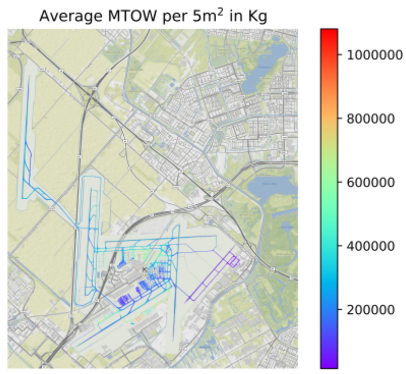
(c) Bearing change



(d) Stop count

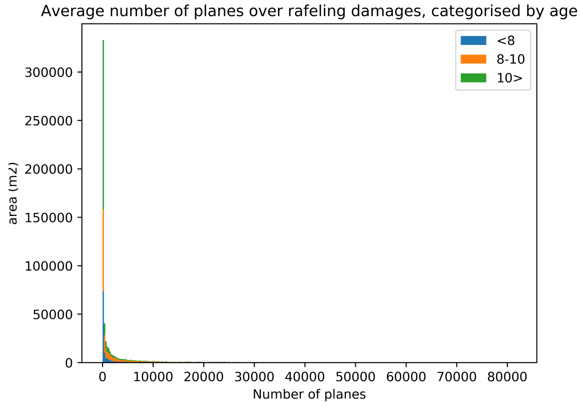


(e) Touchdown count

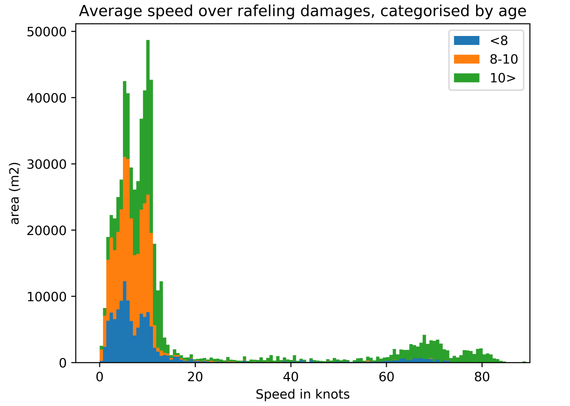


(f) Total MTOW

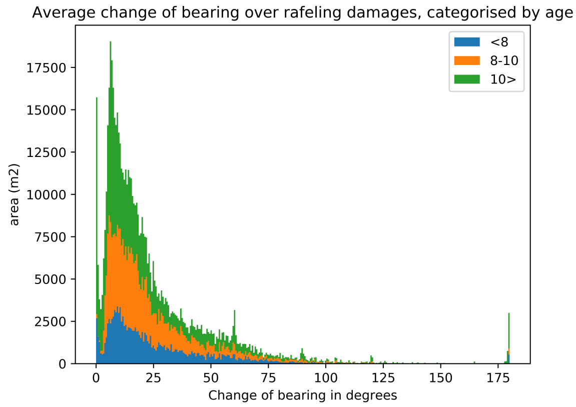
Figure B.1: Insights into the relative usage of the asphalt



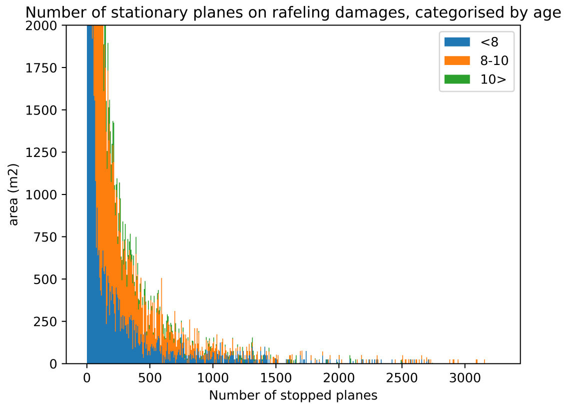
(a) Plane count



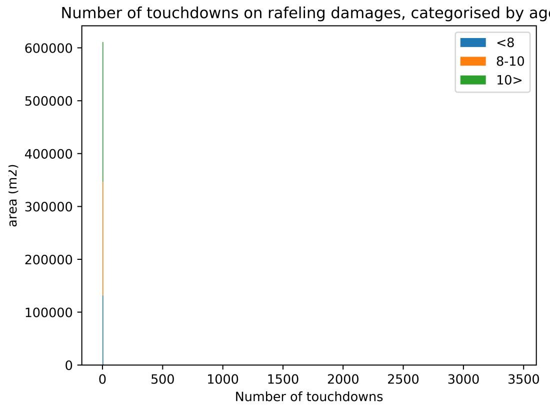
(b) Speed



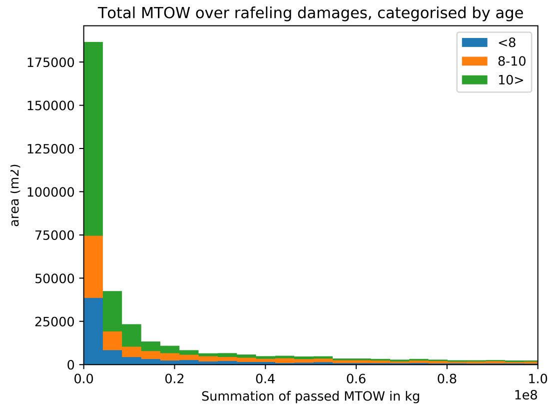
(c) Bearing change



(d) Stop count



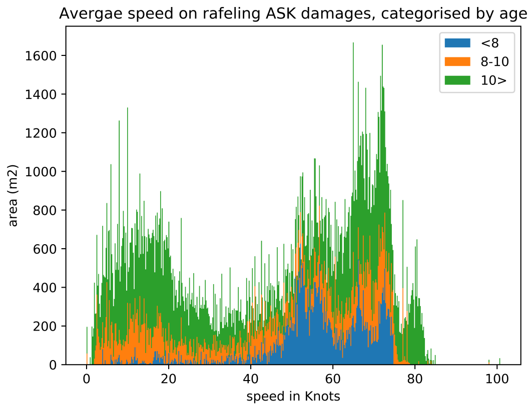
(e) Touchdown count



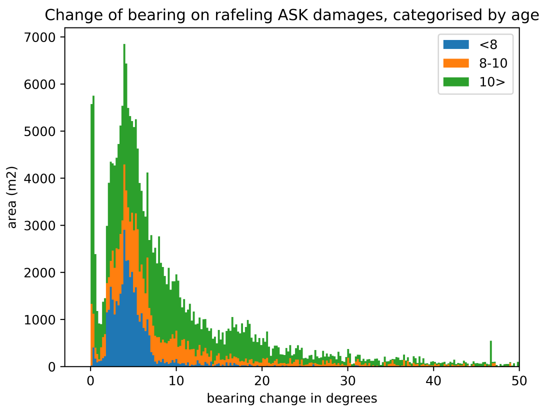
(f) Total MTOW

Figure B.2: Rafeling

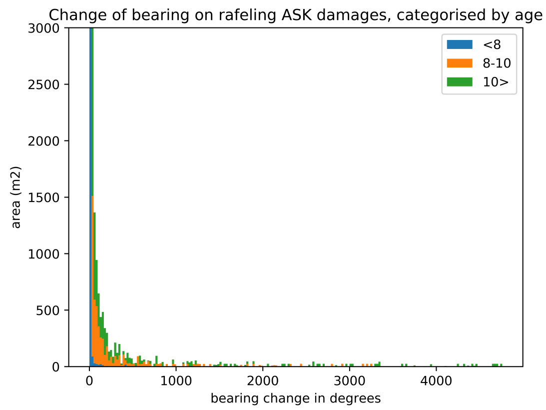
(a) Plane count



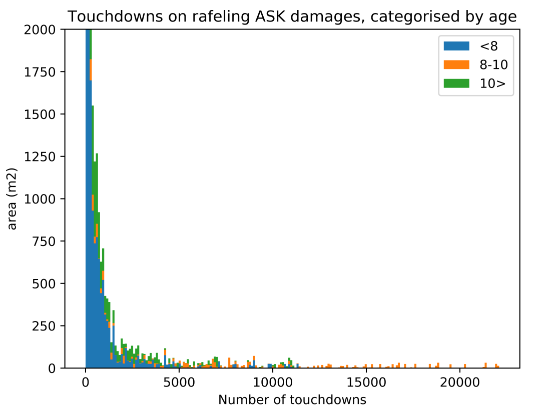
(b) Speed



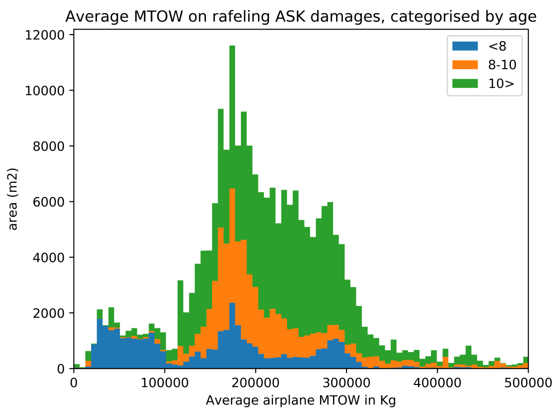
(c) Bearing change



(d) Stop count

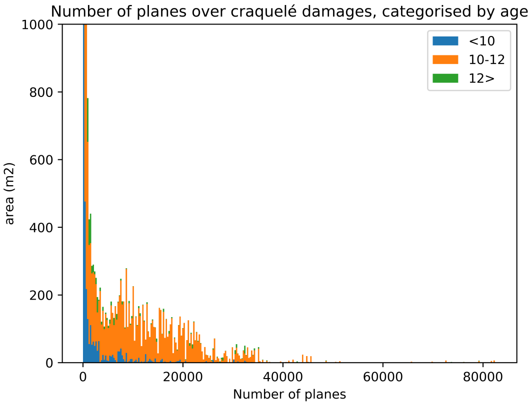


(e) Touchdown count

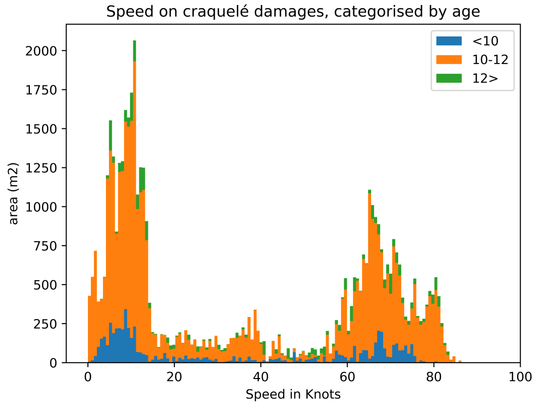


(f) Mean MTOW

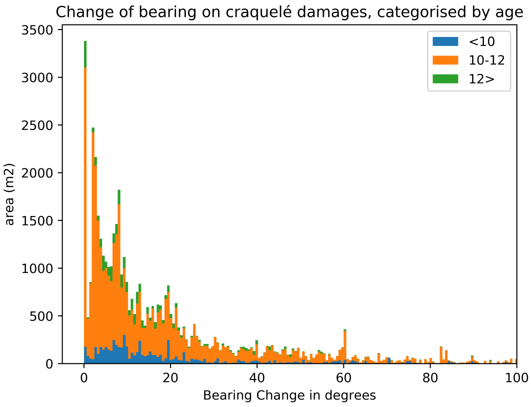
Figure B.3: Rafeling ASK



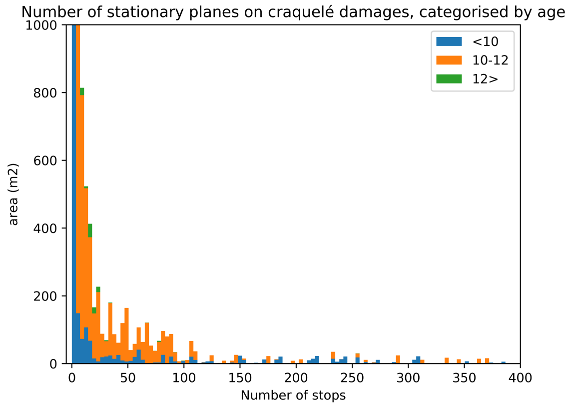
(a) Plane count



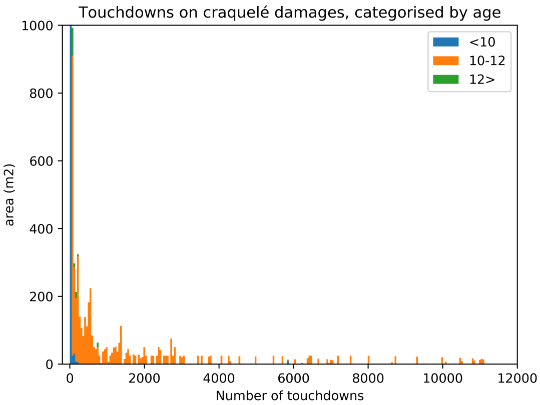
(b) Speed



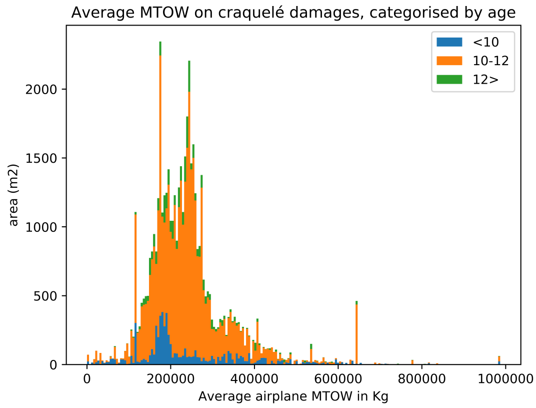
(c) Bearing change



(d) Stop count



(e) Touchdown count



(f) Mean MTOW

Figure B.4: Craquelé