An empirical study on the applicability of train coach temperature readings to reduce the demand peak of HVAC maintenance during heat waves at NS

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Abstract

NS faces the challenge that in the past few years, the number of service requests for heating ventilation and air-conditioning (HVAC) systems exceeds the maintenance capacity during heat waves. As a result, the temperature is undesirably high in some train coaches, which affects passenger comfort. In 2020, a data product providing temperature readings is created to support maintenance decisions. The goal of this study was to generate insights on these train coach temperature readings contribute to reducing the demand peak for maintenance operations for HVACs during heat waves at NS. First, the creation and execution of maintenance tasks is captured in business process models (BPMs). Three different maintenance tasks are identified: corrective work orders, trimonthly preventive maintenance tasks, and the annual maintenance in the spring, which can be executed at three different maintenance locations. Subsequently, the direct and indirect challenges NS faces during heat waves are identified, resulting in four relevant factors that influence these challenges. We show that the average temperature per month and the maximum temperature per day during heat waves are positively related to the number of service requests for HVACs, traction, and low-voltage. Moreover, the analysis on the relation between maintenance operations and temperature deviations at NS gives some unexpected findings. Temperature deviations prior to heat waves contribute to the predictability of temperature deviations during heat waves. However, major HVAC defects are resolved in only 27% of the cases after corrective maintenance tasks at NS. Trimonthly preventive maintenance tasks and the annual maintenance in the spring resolve more temperature deviations, but this study shows that not all temperature deviations are resolved after these three maintenance interventions. This study generates insights on how NS can use temperature readings to reduce the demand peak during heat waves.

Executive Summary

Currently, Nederlandse Spoorwegen (NS) faces the challenge that during heat waves the number of under-performing heating, ventilation and air-conditioning (HVAC) units exceeds the maintenance capacity. As a result, passenger comfort is reduced in two ways. First, less rolling stock (trains) is available for passenger transport, because their HVACs are being maintained. As a result, the passenger delays and corresponding discomfort increase. Second, trains are still allowed to operate, while in parts of the train HVACs are not properly cooling. Consequently, the temperature is undesirably high in the associated train coaches.

NS' current maintenance policy causes difficulties with the demand for HVAC maintenance during heat waves. Malfunctions of HVAC systems are mainly visible at days with high temperatures, because air-conditioning is not required if the ambient temperature is below the desired inside temperature. As a result, the maintenance locations cannot handle the requested corrective maintenance tasks during heat waves, hence insufficient train coaches with working HVACs are available for passengers. In addition, the current system that creates diagnosis codes has limited opportunities to determine cooling malfunctions, and thus to initiate proper HVAC preventive maintenance tasks. Therefore, it is hard to recognize failures and maintain HVAC systems before the temperature rises. The objective of this study is to understand how temperature readings can be used to lower the demand peak during heat waves. We complete the following project assignment:

Generate insights on how NS can use train coach temperature readings to reduce the demand peak for maintenance operations for HVACs during heat waves?

Three research questions are formulated to complete the project assignment:

1. How are maintenance operations for HVAC systems currently planned and executed at NS?
2. What challenges does NS face during heat waves due to under-performing HVAC systems?
3. What is the relation between maintenance operations and temperature deviations in the heat maps at NS?

For this study, nineteen interviews were conducted to answer RQ1 and RQ2, and a data analysis is performed to answer RQ3. In order to answer RQ1, the planning and execution of the current maintenance operations were studied and explained by the use of the constructed business process models (BPMs). These BPMs depict how work orders are created and executed. Information to answer RQ1 was obtained by conducting interviews with NS employees and studying additional NS documentation. For the creation and validation of the BPMs, an iterative approach was used, which means that the results for the BPMs were discussed with employees involved in the maintenance process and adjusted if necessary. The results of RQ1 show that NS' maintenance policy contains preventive and corrective maintenance tasks. Preventive maintenance tasks are executed during trimonthly preventive short cycle maintenance (KCOs) and the annual maintenance in the spring. Corrective maintenance work orders are requested if HVAC failures occur.

The answer to RQ2 provides the direct and indirect challenges NS faces during heat waves. The conducted interviews capture most HVAC-related maintenance challenges during heat waves and the differences between the heat waves in 2019 and 2020. The results of RQ2 show four relevant factors that influence the challenges during heat waves: (i) an increase in the average temperature per month results in an increase in number of service requests for HVACs; (ii) the maximum temperature per day seems positively associated with the number of HVAC-related work orders; (iii) the number of service requests for the traction system and the low-voltage supply system also increase during heat waves, which impacts the maintenance capacity for HVAC-related maintenance tasks; (iv) heat waves usually occur in the summer during the holiday season, resulting in fewer available technicians. Furthermore, the average temperature per month and maximum temperature per day seem to be positively correlated with the number of service requests for HVACs, traction, and low-voltage. However, the number of traction and low-voltage related service requests is low in comparison to the number of HVAC service requests during heat waves.

RQ3 shows the relation between maintenance operations and temperature deviations at NS. The results for RQ3 were obtained by performing a data analysis on the maintenance operations and temperature deviations. As part of the data analysis, we introduced a certainty rating for temperature deviations. The deviations range from 1 to 9, where large numbers indicate larger deviations. The differences between the diagnosis codes with and without temperature deviations visible on the heat map are studied. Moreover, this study shows that temperature deviations with a rating from 1 to 3 are resolved with and without maintenance interventions. Therefore, it can be concluded that temperature deviations with a certainty rating from 1 to 3 indicate small defects or HVACs with insufficient capacity, looking at the fact that these temperature deviations are resolved with and without maintenance interventions. Temperature deviations with a rating from 4 to 9 probably indicate major defects which should be resolved with appropriate maintenance interventions, because this study shows that HVACs are not self-healing systems if the certainty rating of the temperature deviation is above 4. The heat maps can be used to differentiate between the certain (1 to 3) and uncertain (4 to 9) temperature deviations, and the extent of the defect. The demand peak during the heat waves can be reduced by maintaining the under-performing HVACs before the heat wave. Information on the under-performing HVACs can be obtained during semi-heat waves, because 93% of the temperature deviations during semi-heat waves are still present during the subsequent heat wave. These under-performing HVACs should be maintained, which is possible in three ways at NS: (i) service request; (ii) trimonthly KCO; (iii) annual maintenance in the spring. Service requests resolve 27% of the temperature deviations rated with a 4 to 9. In addition, KCO and the annual maintenance in the spring resolve some additional temperature deviations, but not all temperature deviations are resolved after these three maintenance interventions, which is alarming for NS. The annual maintenance in the spring seems most valuable for resolving temperature deviations with a rating from 4 to 9.

Therefore, this study generates insights on how NS can use temperature readings to reduce the demand peak during heat waves. The applicability of these results is large, because the heat maps are already created weekly and shared with employees concerned with maintenance tasks. However, the accessibility should be improved for NS's employees concerned with maintenance operations. Moreover, these results can be generalized to other (train) companies, but only if the HVAC cools an enclosed area served by one HVAC. This study contributes to the literature, since this study discovered a new type of diagnostics, especially applicable to HVAC maintenance.

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It has been a great experience studying at Eindhoven University of Technology and I am proud of the result of this master thesis. I hope you will enjoy reading it.

Nina Rovers
Eindhoven, October 2022

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List of Abbreviations

BPM	Business Process Model
BPMN	Business Process Modeling Notation
CC	Central Computer
FPR	False Positive Rate
GSL	Gespecialiseerde Service Locatie (specialized service location)
HRN	Hoofdrailnet (main rail network)
HVAC	Heating Ventilation and Air Conditioning
KCO	Kort Cyclish Onderhoud (short cycle maintenance)
KNMI	Koninklijk Nederlands Meteorologisch Instituut (royal Netherlands meteorological institute)
KPI	Key Performance Indicator
MBN	Materieel Besturingscentrum NS (material control center NS)
MD	Maintenance Development
NCB	NS Componenten Bedrijf (NS components company)
NS	Nederlandse Spoorwegen (Dutch Railways)
OB	Onderhouds Bedrijf (maintenance company)
PE	Production Engineer
ROC	Receiver Operating Characteristics
ROI	Return on Investment
RTM	Real Time Monitoring
RUL	Remaining Useful Life
SB	Service Bedrijf (service company)
TAE	Technicus ATB en Elektronica (electronics technician)
TMM	Technisch Medewerker Materieel (technical employee equipment)
TPR	True Positive Rate
VBT	Vrijgave Buiten Tolerantie (release beyond tolerance)
VIRM	Verlengd InterRegio Materieel (lengthened interregional rolling stock)
WE	Wagen Einde (coach end)

Chapter 1

Introduction

The introduction provides background information on the problem, company, and research design. In Section 1.1, the research problem is introduced. Section 1.2 and Section 1.3 describe the company and department where this research is conducted, respectively. An explanation on the visual heat maps is provided in Section 1.4. The motivation for this research is addressed in Section 1.5. Section 1.6 covers the research definition, including the problem statement (Section 1.6.1), the project assignment (Section 1.6.2), and the research questions and methodology (Section 1.6.3). The scope of this research is described in Section 1.7. Section 1.8 covers the relevant literature on maintenance policies. Finally, the outline of this thesis is described in Section 1.9.

1.1. General introduction

Currently, Nederlandse Spoorwegen (NS) faces the challenge that during heat waves the number of defect heating, ventilation and air-conditioning (HVAC) units exceeds the maintenance capacity. As a result, passenger comfort reduces in two ways. First, there is less seating capacity available as there are less train coaches operating, because their HVACs are being maintained. The reduced fleet availability during the heat wave in 2019 led to cancellations of entire trains (RTL Nieuws, 2019). As a result, the passenger delays and corresponding discomfort increased. Second, trains are still allowed to operate, while in parts of the train HVACs are not properly working. Consequently, the temperature is undesirably high in the associated train coaches. This research focuses on the above mentioned problem NS faces. In order to overcome this problem, the applicability of temperature readings to reduce the demand peak of HVAC maintenance during heat waves at NS is studied. These measurements indicate which HVACs have potentially failed, based on a higher temperature measurement compared to other train coaches.

1.2. Company description

NS is the largest Dutch passenger railway operator, and is responsible for most passenger rail transport in the Netherlands. There are other train operating companies, but NS holds the current concession for the main rail network (HRN) in the Netherlands. It is a semi-state-owned company of which all shares are owned by the Dutch government. NS is responsible for passenger services on HRN, whereas cargo transportation on HRN is not the responsibility of NS. The rail infrastructure is maintained by another company, called ProRail. NS strives to provide passengers easy, fast, safe, comfortable, and affordable travelling in a sustainable way. NS aims to meet the following requirements for their passengers (NS, 2021):

- Run trains according to schedule
  - Passenger punctuality: arrival time within 5 minutes should be at least 88.9% on HRN (92.6%)
  - Passenger punctuality: arrival time within 15 minutes should be at least 96.7% on HRN (97.7%)
- Ensure sufficient and comfortable equipment
  - Seating opportunity in rush hour should be at least 94.3% on HRN (94.9%)
- Provide good service and information
  - Adequate travel information should be provided at least 75% of the time (84.5%)
- Arrange adequate reception in the event of disruptions

The performed results for 2019 with respect to the above mentioned requirements are presented between brackets. The pre-COVID annual report is used from 2019 to give an overview of NS' operating results not affected by COVID-19 pandemic measures (NS, 2019). On average, 1.3 million passengers were served by NS' rail services every day. The corresponding revenue was equal to €6.661 million in 2019. To provide these rail services, NS employed 20,074 people.

As mentioned above, sustainable mobility is an important aspect for NS. To realize this, a few initiatives have been drawn-up to reduce NS' own emissions and those of their partners in recent years. One of these initiatives concerns reducing the energy consumption every year and to consume energy generated from renewable sources.

The final important key performance indicator (KPI) is that the customer rating should be at least 7.4/10. The customer rating is defined as the opinion of travelers about NS services. In 2019 the customer rating scored 8.9/10.

1.3. Department description

This research is conducted at the Maintenance Development (MD) department of NS. Figure 1.1 shows a selection of NS' organization chart illustrating the position of MD within NS. As displayed in Figure 1.1, MD belongs to the following subsequent departments within NS: Operations, Engineering, Maintenance Management, and Maintenance Development &RAMS. The Engineering department (NS Techniek) belongs to Operations. The Engineering department is responsible for prescribing and controlling equipment in order to meet safety requirements. Maintenance-related topics are covered by the Maintenance Management department.

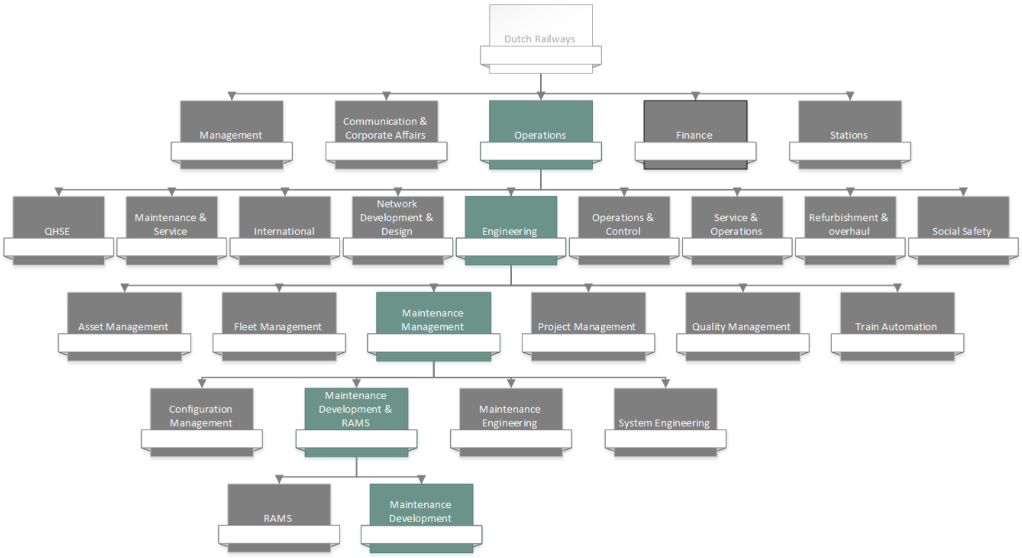


Figure 1.1: Organization chart NS

MD establishes maintenance improvements based on data from data sources within trains. One of these sources is NS' Real Time Monitoring (RTM) application that stores a large amount of technical information from the train. Examples of retrieved data are: the condition of the train, sensor data, and performance counters. RTM is used for live monitoring as well as retrospective analyses by MD.

1.4. Visual heat maps

In 2020, MD created a data product providing weekly reports with temperature heat maps, HVAC diagnosis codes, and service requests for all lengthened inter-regional rolling stock (VIRM) trains to support maintenance decisions using RTM data. VIRM trains are double-decker trains with either four or six train coaches. The VIRM fleet is NS' largest intercity fleet, which consists of 98 train sets with four train coaches and 77 train sets with six train coaches. An example of a heat map can be found in Figure 1.2. The leftmost column indicates the specific train coach designation. Different train coaches have different labels, e.g. if there is an A in the designation, it indicates that there is a first class together with a second class passenger compartment in the train coach, instead of second class only. WE illustrates to which coach end it belongs, and "bov" and "ben" means upper and lower floor, respectively. In the upper figure within Figure 1.2, the deviation from the median coach temperature is shown. The set-point temperature, which is defined as the specified temperature in each train coach, is based on the measured ambient temperature. The daily average temperature for each train coach is displayed in the bottom figure within Figure 1.2. The meaning of each color can be found in the legend at the right of the figure. The column remains grey if sufficient data lacks for that day. Furthermore, the failure diagnosis codes from the central computer (CC) system are given in the first table of Figure 1.2. These diagnosis codes are based on predefined business rules and not on the measured temperatures. It describes the type of error along with the duration and timing of occurrence. Finally, the service requests for performed maintenance actions are displayed at the bottom of Figure 1.2.

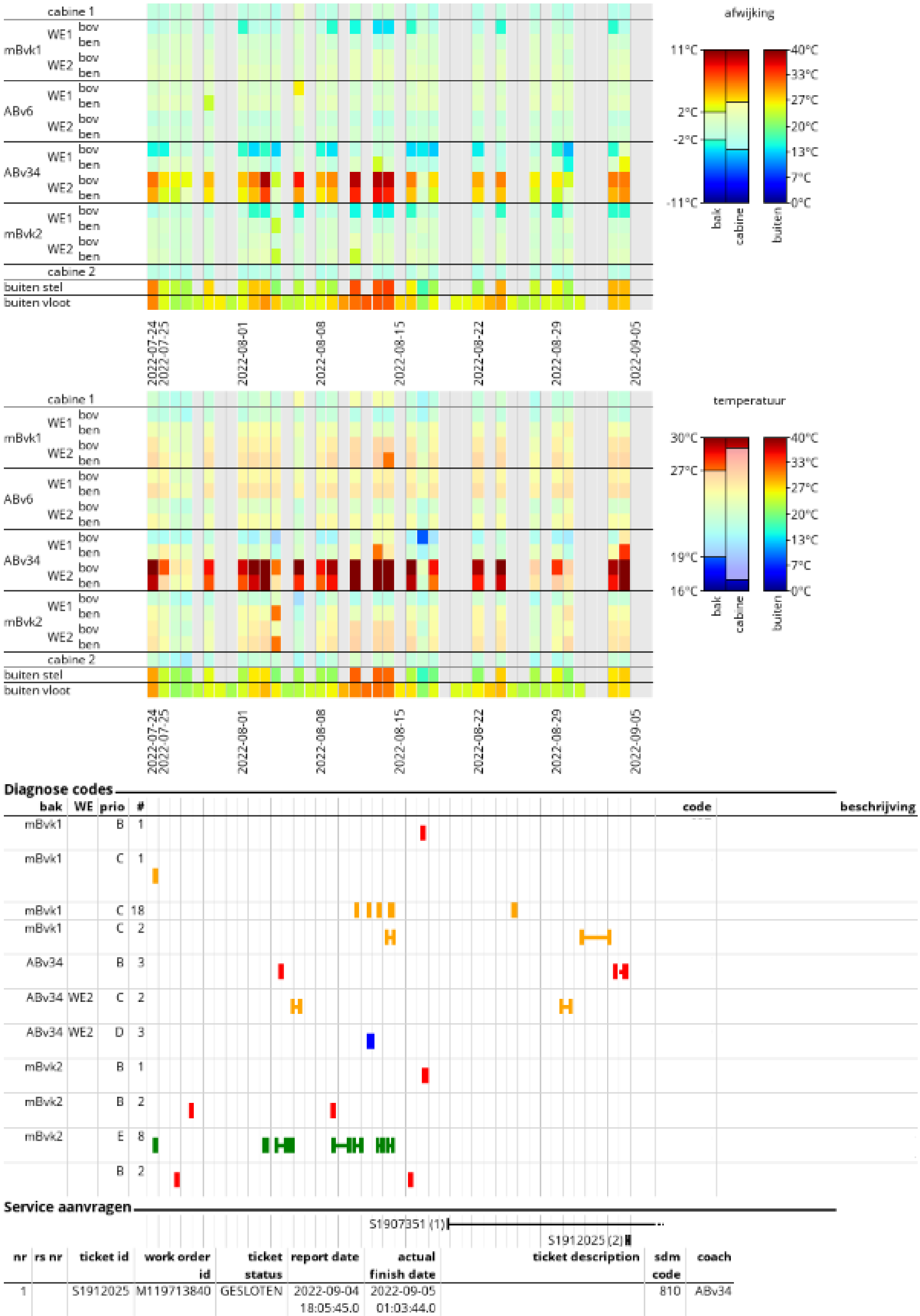


Figure 1.2: Example visual heat map

Figure 1.3 shows the HVAC set-point temperature as a function of the ambient temperature. The horizontal axis displays the ambient temperature, whereas the vertical axis shows the set-point temperatures in °C. The yellow and blue line, referred to as TRwb and TRwo, indicate the specified average temperature for the upper and lower train coach, respectively.

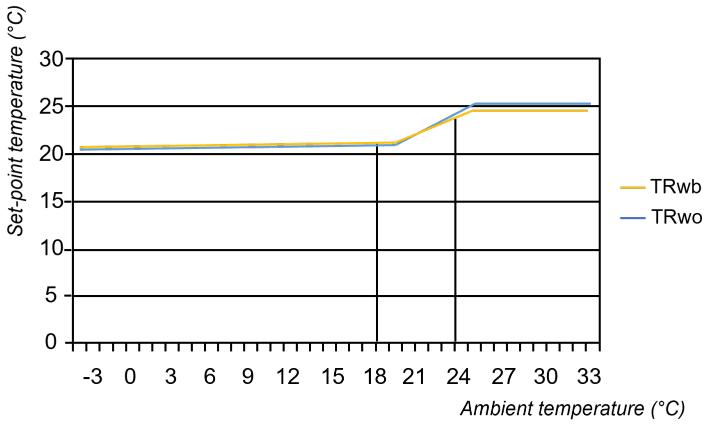


Figure 1.3: Selection set-point temperature based on ambient temperature

In addition to the determination of the set-point temperature, another constraint should be considered. HVAC systems are stated to properly work up to a maximum ambient temperature of 30 °C. This means that the HVAC system has insufficient cooling capacity to drop the coach temperature to 25 °C if the ambient temperature exceeds 30 °C. Therefore, it is good to distinguish two types of functional failures: broken HVACs (unable to cool if it is hot outside), and HVACs that are unable to fully cool the train coach due to insufficient cooling capacity during days with an ambient temperature above 30 °C. Only the first functional failure is independent on the weather, hence maintenance can resolve this. The second functional failure type only affects passenger comfort, and cannot be solved by additional maintenance. Not all HVAC failures are identifiable via heat maps. For instance, if the set-point temperature is equal to or lower than the ambient temperature, then the cooling function is not used. Hence, it is not possible to differentiate between the functioning of the cooling units based on the observed temperature.

1.5. Motivation

The main objective of NS is to ensure comfortable travelling, which is realized by operating sufficient and comfortable trains for passengers, i.e. conform the KPIs mentioned in Section 1.2. This includes running trains on time and arranging a comfortable environment. An important measure of comfort is the temperature in trains. Passengers prefer heated trains in winter and cooled trains in summer. Therefore, regulating the temperature in trains is essential to providing comfort.

A visualization of the temperature in trains is provided in the created heat maps. In some cases, the visual heat maps show reduced cooling, hence failure indications in the deviation chart for multiple consecutive days. Figure 1.2 illustrates an irregular situation for ABv34. From the 24$^{\text{th}}$ of July until the 4$^{\text{th}}$ of September, this train coach shows undesirably high temperatures in the second coach end. However, no maintenance actions are requested for this malfunctioning train coach in the period with undesirably high temperatures. This is a reason for the introduction of the visual heat maps. These heat maps are now supplied to maintenance engineers, but their use is limited in the current maintenance operations.

Especially during heat waves, HVAC systems are underperforming, and multiple heat maps show high deviations for these periods. The maintenance capacity is insufficient to meet the increasing demand of service requests during heat waves. Currently, this peak is inevitable, because the present condition of each HVAC system is not monitored prior to the heat wave. Therefore, as mentioned in Section 1.1, NS has two options: either running trains with underperforming HVAC systems or providing shorter or fewer trains for their passengers.

Moreover, it is challenging to convert HVAC system diagnosis codes from the CC to service requests. On the one hand, this is because some diagnosis codes are generated while there is no apparent function loss of the HVAC. On the other hand, this is because malfunctions of the HVAC can occur without generating a diagnosis code. Therefore, the current system of diagnosis codes has limited predictive power to determine cooling malfunctions.

1.6. Research definition

1.6.1. Problem statement

The current maintenance policy causes difficulties with the demand for HVAC maintenance during heat waves. Malfunctions of HVAC systems are mainly visible at days with high temperatures, because air-conditioning is not required if the ambient temperature is below the desired inside temperature. As a result, the maintenance locations cannot handle the requested corrective maintenance tasks during heat waves, hence insufficient train coaches with working HVACs are available for passengers. In addition, the current system that creates diagnosis codes has limited opportunities to determine cooling malfunctions, and thus to initiate proper HVAC preventive maintenance tasks. Therefore, it is hard to recognize failures and maintain HVAC systems before the temperature rises.

1.6.2. Project assignment

In order to overcome the problem formulated in Section 1.6.1, the goal of this research is to understand how heat maps can be used to lower the demand peak during heat waves. Therefore, the project assignment is:

Generate insights on how NS can use train coach temperature readings to reduce the demand peak for maintenance operations for HVACs during heat waves.

1.6.3. Research questions and methodology

In order to complete the project assignment, the planning and execution of maintenance operations for HVAC systems should be understood, since it is important to understand the current situation before improvements are proposed. The goal of the first research question (RQ1) is to understand which maintenance methods are currently used and how maintenance tasks are executed for HVACs. In addition, the process of requesting HVAC maintenance tasks and the handling process of these work orders should be understood. Therefore, the first research question is stated as follows:

RQ1: How are maintenance operations for HVAC systems currently planned and executed at NS?

In order to answer the first research question, business process models (BPM) are constructed. Business process modeling notation (BPMN) is used to create these processes, since this is a widely-used notation and it is understandable for business users (White, 2004). Information on the current planning and execution of maintenance operations is obtained by interviewing multiple employees from different departments who are engaged in maintenance tasks, such as technicians, reliability experts, and maintenance managers. Semi-structured interviews are used, since key questions help to define the area to be explored, and the interviewer is able to diverge in order to pursue an idea or response in more detail (Gill et al., 2008). Additional information is acquired from internal NS documentation about maintenance operations. A distinction is made between the process to create a work order and the process of executing work orders. In addition, the different types of maintenance (i.e. corrective and preventive) are distinguished. Finally, the constructed BPMs are verified by the interviewees.

With the current planning and execution of maintenance operations, NS has difficulties with the maintenance overload during heat waves for HVAC systems. However, it is important to understand which challenges occur during heat waves and why these result in a problem for NS. Additionally, the parties involved in maintenance for HVACs need to be identified. This leads to the second research question:

RQ2: What challenges does NS face during heat waves due to under-performing HVAC systems?

RQ2 is answered by giving an overview of several maintenance challenges experienced by different NS departments. The previously mentioned interviewees are also asked about their experience with heat waves and the corresponding maintenance challenges. Moreover, the necessity to perform additional maintenance on HVACs prior to heat waves is investigated, i.e. what are reasons to anticipate on the demand peak during heat waves? The impact on the organization is twofold, either direct or indirect. The direct impact involves additional maintenance tasks, and therefore, additional maintenance capacity in terms of qualified employees and materials is required. The indirect impact on HVAC systems refers to other under-performing systems, such as traction, which is the propulsion of the train. As a result, less time for HVAC system maintenance tasks is available.

The answer to RQ2 explains the existing maintenance demand peak during heat waves and the specific problems that occur as a result. The next step is to identify ways to reduce heat wave related problems. Therefore, it is important to understand the relation between maintenance operations and the temperature deviations in the heat maps.

RQ3: What is the relation between maintenance operations and temperature deviations in the heat maps at NS?

To understand the relation between service requests and temperature deviations in the heat maps, the provided data in the heat maps is analysed. Three different situations are distinguished:

1. Service request without a temperature deviation visible on the heat map
2. Service request with a temperature deviation visible on the heat map
3. Temperature deviation visible on the heat map without a service request

The service requests in situation 1 and situation 2 are compared, based on their diagnosis codes to recognize patterns in the data. Moreover, the effectiveness of the maintenance execution in the second situation is tested, i.e. is the temperature deviation resolved after the performed service request? This is compared to situation 3 in which no service requests are performed. Desirably, maintenance operations are performed shortly after a temperature deviation is visible on the heat map, and the temperature deviation is resolved after the performed maintenance task. The temperature deviations are also analysed in two ways. The predictability of temperature deviations before heat waves is analysed, and the relation between temperature deviations in 2020 and 2021. Collectively, these analyses describe the relation between maintenance operations and temperature deviations in the heat maps, and how the heat maps can contribute to reduce the demand peak during heat waves.

1.7. Scope

The goal of this research study is to understand how the heat maps can contribute to reduce the demand peak for maintenance operations for HVACs during heat waves. This research study is based on the data of VIRM-trains, since accurate sensor data is currently only available for this train type. The results for VIRM-trains are generalizable to other train series once sensor data is available. Since the temperature data from the heat maps is mainly related to the air-condition function of the HVAC system, this research study mainly focuses on the AC part of the HVAC system. However, ventilation is required to distribute the cooled air throughout the train coach. Therefore, the ventilation function is included in the scope of this research study.

1.8. Overview of relevant literature

This section summarizes the relevant literature for this study. An extensive version of the literature on this topic is presented in Appendix A. Wu et al. (2006) distinguish four types of maintenance for building systems, such as HVACs:

1. **Test and inspection**: test and inspection are required to meet legislation requirements (e.g. fire alarm systems)
2. **Corrective maintenance**: elimination of the effect of failure
3. **Preventive maintenance** (or scheduled maintenance): maintenance of components is scheduled at specific time intervals to prevent system from failing
4. **Predictive maintenance**: the system is monitored to predict failures and carry out maintenance. The aim of conditioned maintenance is to avoid catastrophic failures.

The following three most relevant maintenance methods for this study will be explained in more detail: corrective maintenance, preventive maintenance, and predictive maintenance (Mobley, 2002). Predictive maintenance tasks are performed based on the condition of the system.

1.8.1. Corrective maintenance

Corrective maintenance, in literature also called run-to-failure maintenance, is the simplest maintenance method. Maintenance is performed when a machine breaks down. In terms of costs, expenses are only incurred if a systems fails to operate. Therefore, corrective maintenance is a reactive maintenance method. If prognostics information on a component is available, corrective maintenance management is the most expensive maintenance method for that component (Tsakatikas et al., 2008). The most significant expenses are high overtime labor costs, high machine downtime, and low production availability. In addition, extensive spare part inventories are required to react adequately to the requested maintenance tasks (Tsakatikas et al., 2008).

1.8.2. Preventive maintenance

The second common maintenance method is called preventive maintenance. Preventive maintenance is a type of planned maintenance, because components are repaired or replaced periodically (Prytz, 2014). Preventive maintenance tasks are usually based on operating hours or elapsed time. The costs of preventive maintenance decrease considerably compared to corrective maintenance for components that are eligible for preventive maintenance, because the repairs are on a scheduled basis (Prytz, 2014). Preventive maintenance should be applied to most HVAC systems that are located in buildings (Kwak et al., 2004). The importance of preventive maintenance programs for HVAC systems is stressed by Suttell (2006): "Think of preventive HVAC maintenance in the same way as the preventive maintenance for your car: If you don't change the oil and replace belts and filters, the engine will lock up and the vehicle won't operate. The same holds true for HVAC systems." For HVAC systems, time-based preventive maintenance is usually applied to non-repairable items with a lifetime distribution. The lifetime can be estimated by calendar time, driven kilometres or consumed fuel (Prytz, 2014).

1.8.3. Predictive maintenance

Lastly, predictive maintenance will be introduced. According to Prytz (2014) and Mobley (2002) predictive maintenance uses a monitoring system or prediction model to determine the machinery condition, predict the likeliness of failure, and minimize the number and corresponding costs of unscheduled outages. This definition will be used in this literature review. A result of predictive maintenance is improved productivity, product quality and overall plant operation.

Actual data and effective tools are used to determine the operating condition of critical components. Based on these results, maintenance activities are scheduled on an as-needed basis. On the one hand, predictive maintenance improves machine availability, hence productivity. On the other hand, it reduces the costs of maintenance and improves the profitability. In order to perform predictive maintenance, real time monitoring features are required instead of average-life statistics. A relevant type of sensor data for this research study mentioned by Jardine et al. (2006) is temperature data from sensors, which is in line with the available sensor data of HVAC systems in trains at NS. Therefore, temperature readings can be promising for predictive maintenance. However, predictive maintenance of HVAC systems based on temperature readings is not performed in other literature studies yet.

Predictive maintenance is the most appropriate strategy for HVAC systems if the components fail accidentally and a good diagnosis system is available (Kwak et al., 2004). The diagnostics and prognostics processes are used for HVAC-related predictive maintenance (Gálvez et al., 2021). Especially, remaining useful life (RUL) predictions precedes the determination of predictive maintenance tasks.

Satta et al. (2017) proposes a dissimilarity-based approach to apply predictive maintenance for HVAC systems. The goal of a predictive approach is to identify anomalous behavior which could indicate a failure. In order to recognise anomalies, a set of homogeneous appliances should be identified. An anomaly is a data point that is not in line with the expected behavior (Chandola et al., 2009). A well-known synonym for anomalies is outliers, which also recognises nonconforming patterns in data sets. Homogeneous appliances are machinery with compatible properties, e.g. all HVAC's in a train. Satta et al. (2017) refers to this as the cohort of appliances.

This cohort of appliances, in Satta et al. (2017) a set of 17 HVAC systems in a hospital, is used to perform predictive maintenance tasks. Mutual dissimilarities between appliances in the cohort can be used to foresee an upcoming failure. A proactive intervention can be used to maintain the anomalous component to avoid interruption after a failure. An important advantage of mutual differences instead of absolute values is that seasonal trends and biases are included in the model. The performance evaluation of the dissimilarity approach is based on the cost of errors related to fault forecasting.

1.8.4. Evaluation failure prediction

The quality of a maintenance policy can be assessed by the costs of two different errors (Susto et al., 2012):

- **Unnecessary maintenance (type I error)**: a maintenance action is performed, because a failure is predicted. However, the system or component would not have been out-of-control if the maintenance task was not performed. So, unnecessary maintenance is performed. The corresponding costs are related to the time spent of mechanics repairing the component, and the costs of replaced spare parts must also be included if the component is replaced.
- **Unprevented out-of-control state (type II error)**: the system has failed, but no maintenance intervention has taken place, because there were no failures predicted. The costs of the out-of-control state, resulting in a reduced production quality, are the corresponding costs for this error.

Often, these errors are called false positives and false negatives (Fielding and Bell, 1997). A false positive, error type I, refers to the situation that a maintenance task has been performed while the system would not have failed. By contrast, a false negative or type II error occurs if the system has failed while no failure was expected. False negatives have more impact on the operation, because of the unplanned maintenance intervention. In addition, the costs for false negatives are usually higher than for false positives. Therefore, extra attention should be given to false negatives. A confusion or error matrix can be used to display the different situations (Visa et al., 2011):

	Predicted negative	**Predicted positive**
Actual negative	a	b
Actual positive	c	d

Table 1.1: Confusion matrix

In Figure A.6 four different situations are distinguished, indicated with a, b, c, and d:

- a: the number or percentage of **true negatives**: no maintenance task has been performed, and no failure has occurred.
- b: the number or percentage of **false positives**: maintenance task has been performed, but no failure would have occurred without maintenance intervention.
- c: the number or percentage of **false negatives**: no maintenance task has been performed, but a failure occurred.
- d: the number or percentage of **true positives**: maintenance task has been performed, and a failure would have occurred without maintenance intervention.

As a result of the confusion matrix, the prediction accuracy and classification error can be calculated by the following formulas (Visa et al., 2011):

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} \tag{1.1}$$

$$\text{Error} = \frac{b+c}{a+b+c+d} \tag{1.2}$$

Accuracy is the most commonly used prediction measure, it measures the number or percentage of correctly classified cases (Fielding and Bell, 1997). Contrary, the error measure is the number or percentage of incorrectly classified cases. This number should be decreased as much as possible.

1.9. Outline thesis

The remainder of this thesis is structured as follows: Chapter 2 describes the current planning and execution of maintenance operations for HVACs at NS. The maintenance challenges NS faces during heat waves are presented in Chapter 3. Subsequently, Chapter 4 outlines the relation between maintenance operations and the heat maps. Finally, Chapter 5 contains the conclusion, recommendations, limitations, and future research.

Chapter 2

Planning and execution of maintenance operations for HVACs

This chapter answers RQ1 by giving an overview of the current planning and execution of maintenance operations for HVACs, to understand the maintenance tasks and departments involved in the process. The interview approach is described in Section 2.1. Section 2.2 provides the current maintenance policy for HVACs at NS. The creation of work orders is described in Section 2.3, after which the execution is presented in Section 2.4. Business process models (BPMs) are constructed, and displayed in Section 2.3 and Section 2.4 to visualize the processes. A conclusion on the findings of this chapter is presented in Section 2.5.

2.1. Interview approach

The information on the current planning and execution of maintenance operations for HVACs is obtained by interviews. This section describes how the interviews are conducted to obtain the required information to construct the BPMs. The list of all interviewees is presented in Appendix B. First, four employees are interviewed to understand the basic maintenance processes and to decide on the selection of interviewees. Subsequently, a list with questions required to answer RQ1 is created based on the obtained information from the orientation interviews. These predetermined questions are assigned to employees with the most knowledge on that topic. As mentioned in Section 1.6.3, semi-structured interviews are used. Therefore, these questions are the basis of the interviews, and follow-up questions were formulated based on the answers of the interviewees. The questions list and corresponding employees are presented in Appendix C. After interviewing these employees, some information to construct the BPMs was still missing. Therefore, additional employees were interviewed to obtain the missing information. These employees were predominantly recommended during the four interviews. Once all required information was obtained, the BPMs on the creation and execution of maintenance operations were constructed. An iterative approach is used, which means that the results for the BPMs are discussed with interviewed employees involved in the maintenance process and adjusted if necessary. Lastly, the final BPMs are checked and approved by employees involved in the maintenance process.

2.2. Current maintenance policy

Before the explanation of the creation and execution of work orders, the current maintenance policy for HVACs is explained. NS uses corrective and preventive maintenance. Corrective maintenance tasks are requested if an unexpected failure occurs. Preventive maintenance for HVACs is distinguished in two types: (i) periodic preventive maintenance is performed four times a year; (ii) once a year this periodic preventive maintenance is extended with annual spring related maintenance. In the remainder of this chapter, some phrases are written in **bold**. These bold phrases refer to a specific point in the BPM figures.

2.3. Creation of work orders for HVACs

This section describes the process of requesting maintenance tasks, and the creation of work orders for HVACs. The corresponding BPM of the creation of work orders for HVACs is displayed in Figure 2.1. The process of creating work orders for HVACs contains corrective (left-hand side) and preventive (right-hand side) maintenance. At NS, preventive maintenance is performed during short cycle maintenance (KCO). Therefore, the term KCO refers to planned preventive maintenance tasks.

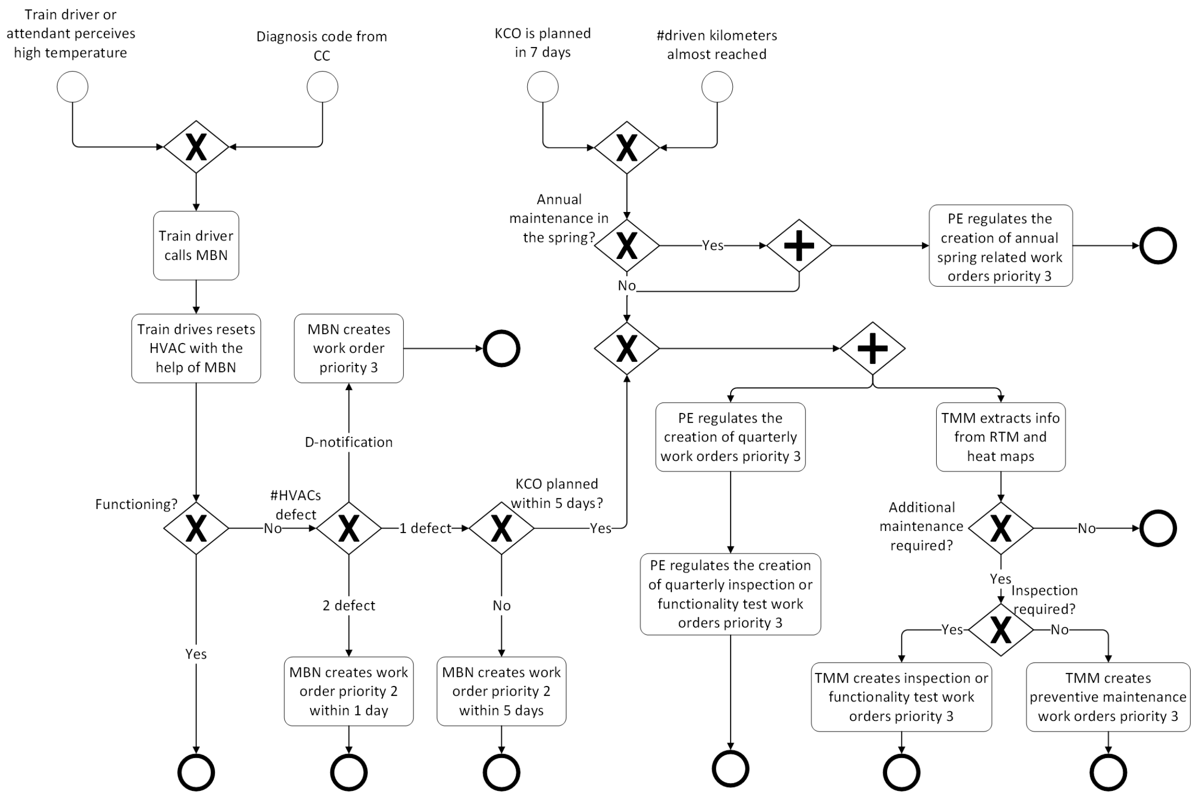


Figure 2.1: BPM of the creation of work orders for HVACs

NS makes a distinction between the priority levels of work orders: priority 1 is safety (defect should be maintained as soon as possible), priority 2 means operational reliability or comfort (defect should be maintained before the predetermined deadline), and for priority 3 a diagnosis code appears, but without functional loss of the system (system will be maintained at the next preventive maintenance moment). Since temperature regulation in the train is a comfort measure, priority 1 never exists for HVAC related work orders, hence priority 1 is excluded from the scope of this study. Work orders with priority 2 contain a predetermined deadline for the maintenance tasks, which is called the Q-procedure (Q-regeling) at NS. Usually, corrective maintenance-related work orders have priority 2, and preventive maintenance work orders belong to priority 3.

There are two possible triggers for corrective maintenance:

1. **Train driver or attendant perceives high temperature**: the train driver or attendant considers the temperature as undesirably high for the passengers in that train coach.
2. **Diagnosis code from CC**: the train driver gets a notification from the active diagnosis code generated by the CC.

If one of these triggers arises, the **train driver calls the material control center NS (MBN)** to continue the process. MBN strives to repair malfunctions in the rolling stock as efficiently as possible in order to maximize availability. MBN, with its dual role as help desk and manager of corrective maintenance, plays a key role in achieving this goal. During the phone call to MBN, the **train driver resets the HVAC with the help of MBN**. This is a standard procedure, whereby the MBN help desk employee goes over the steps of the road map with the train driver to reset the HVAC.

To continue the process, the question arises whether the HVAC is **functioning** or not. If the HVAC is well-functioning (i.e. without any functional loss) again, the process of creating a work order ends. However, if there is still any functional loss, the next step is the determination of the **number of HVACs that is considered as defect within a specific train coach**. In this phase, the number of defects in the corresponding train coach determine the consequent steps:

- **1 defect**: for a train coach with one defect HVAC, the Q-procedure forces the HVAC to be maintained within five days. However, there is a possibility that **KCO is planned within 5 days**. Therefore, there are two possible actions:
  - **KCO is not planned within 5 days**: If the time until the next KCO exceeds five days, **MBN creates a separate work order with priority 2**.
  - **KCO is planned within 5 days**: The work order will be forwarded to the maintenance location, and is included in the creation of work orders during the KCO.
- **2 defect**: if two HVACs are defect in one train coach, the Q-procedure states that **MBN should create a work order with priority 2 that needs to be solved within 1 day**. This implies that the associated train coach with the two defect HVACs should be fixed before its start time in the timetable of the next day.

- **D-notification**: D-notifications are created by the CC, but the functionality of the system is not affected. In other words, a diagnosis code is generated, while there is no functional loss of the system. Therefore, there is no Q-procedure linked to this diagnosis code, and thus the maintenance task can be resolved during the next KCO. As a result, **MBN creates a work order with priority 3**.

As aforementioned, the right-hand side of Figure 2.1 includes KCO-related work orders. KCO can be triggered in two ways:

- **Trimonthly scheduled KCO**: every three months, trains are preventively maintained. Since a few days are required to investigate the necessary maintenance tasks, the trigger for creating work orders is **seven days before the KCO is planned**.
- **Number of driven kilometers almost reached**: very rarely, the train reaches the maximum number of allowed kilometers. In this case, the associated train should also be maintained during a KCO.

Once a year, between the 1st of January and the 1st of May, the KCO is extended with **HVAC-related spring maintenance tasks**. At NS, this is called the spring service (voorjaarsbeurt), which is introduced to give the HVAC a boost before the temperature increases in the summer. If the KCO is planned in these months and it should be extended with the spring-related maintenance tasks, the **production engineer (PE) regulates the creation of the annual spring-related work orders with priority 3**. The PE is responsible for the planning of all KCOs and the corresponding work orders. All annual spring-related work orders are predefined, and the system automatically generates these associated work orders, which the PE regulates. An example of an annual spring-related work order is checking for leaks in the HVAC. The parallel gateway (plus sign) in Figure 2.1 depicts that the annual spring-related work orders are an extension to the regular KCO maintenance tasks and not a replacement of the the KCO maintenance tasks.

For all KCOs, work orders are created in two complementary ways:

- **Automatically generated work orders**: just like the annual spring maintenance tasks, the quarterly preventive maintenance tasks are also predefined and automatically generated. The PE is responsible for creating these work orders, thus **PE regulates the creation of quarterly work orders priority 3** and **PE regulates the creation of quarterly inspection or functionality test work orders priority 3**.
- **Additional work orders**: based on information on the performance of the HVAC in the three months prior to the KCO, additional work can be required during the KCO. **The technical employee equipment (TMM) extracts info from RTM and heat maps** to decide whether **additional maintenance is required**. The TMM is the link between the production floor and the supporting departments, such as the engineering

department of NS' maintenance locations. In addition, the TMM creates sophisticated work descriptions to ensure that the technicians can successfully carry out maintenance work on trains, and they assist technicians if questions arise on the production floor. The data from RTM includes an overview of the diagnosis codes of the CC that were active during the past three months, and the heat maps of the past three months that give an overview of the temperature in the train coaches. An example of an additional maintenance task can be: check cooling function of the HVAC on functioning. In this case the heat maps show higher temperatures in this train coach compared to other train coaches. This is not a clear defect, but the reason for this should be investigated.

If additional work orders are required based on the extracted information, the TMM creates two types of work orders; depending on whether **inspection is required**:

- **Inspection required**: if prior to the maintenance task inspection or a functionality test is required, **the TMM creates inspection or functionality test work orders with priority 3**. This contains inspection or a test to determine the current state of a part of the HVAC, and a decision on the required maintenance for this part.
- **No inspection required**: **the TMM creates preventive maintenance work orders priority 3** if no inspection is required. These are mainly regular tasks, such as replacing filters.

All work orders created by TMM have priority 3, because no Q-procedure applies to preventive maintenance. However, the work orders should be created in the system in advance for the technicians to give an overview of all tasks they have to perform during the KCO.

2.4. Execution of work orders for HVACs

The second part of the current maintenance policy includes the execution of work orders for HVACs, for which two separate figures are created. Figure 2.2 depicts the execution of corrective maintenance work orders, whereas Figure 2.3 illustrates the execution of preventive maintenance work orders.

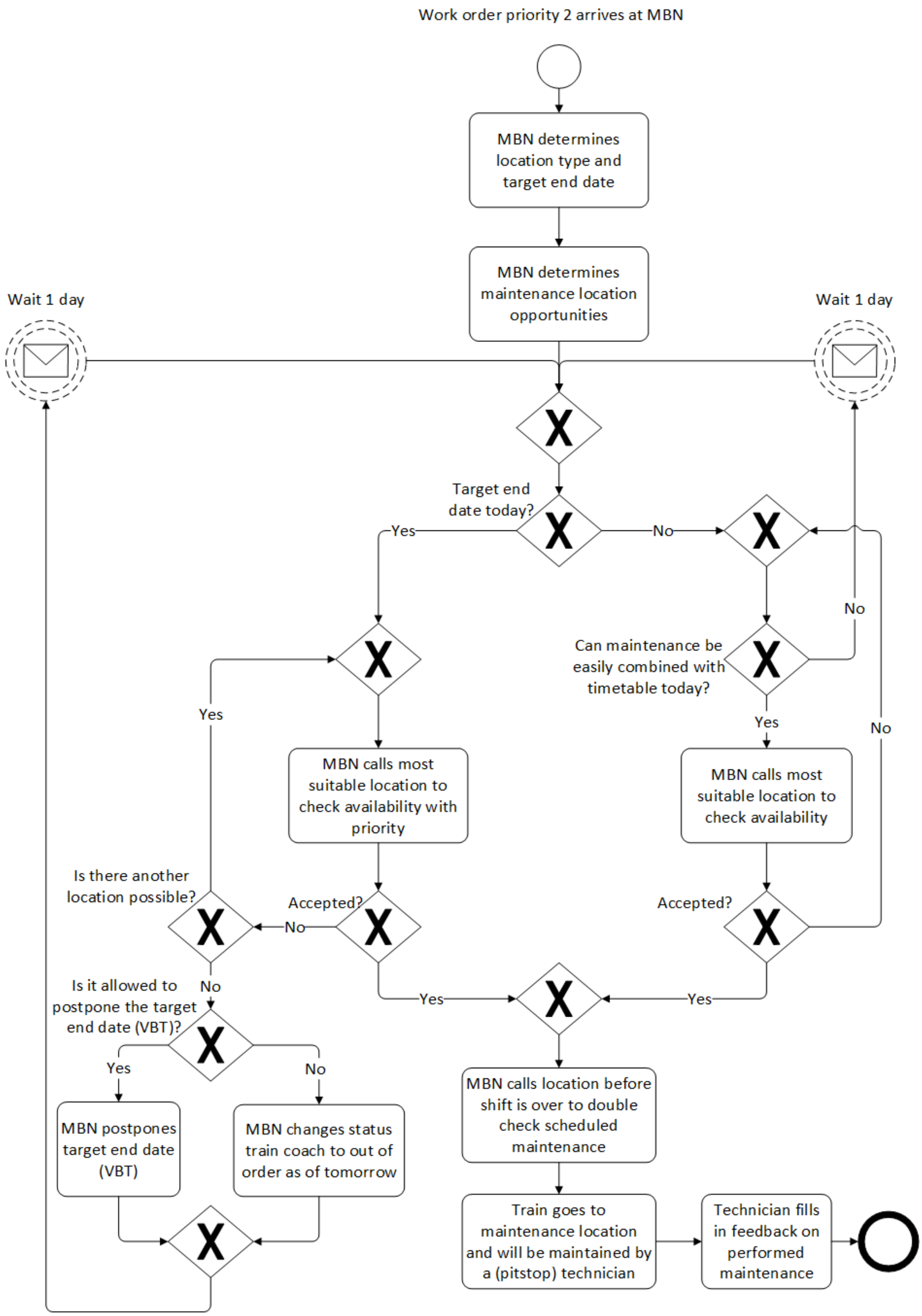


Figure 2.2: BPM of the execution of corrective maintenance work orders for HVACs

2.4.1. Execution of corrective maintenance work orders for HVACs

Figure 2.2 represents the process of executing corrective maintenance work orders. The start of this process is triggered if **a work order with priority 2 arrives at MBN**. Since the work order has priority 2, it is a corrective maintenance work order. To start with, **MBN has to determine the maintenance location type and target end date**. NS makes a distinction between three types of maintenance locations:

- Service company (SB): the first location type is an SB, which has the most sites in the Netherlands. Repairs at SB locations usually have two characteristics: little specific knowledge is required to execute the maintenance task (e.g. cleaning sensors), and these failures can easily be repaired without additional tools (e.g. aerial work platforms). These failures are mainly electronics-related failures that are located inside the train. However, for HVAC-related failures, technicians usually require more knowledge or education and certificates. Therefore, HVAC-related failures are rarely handled at SB locations.
- Specialized service location (GSL): the second location type is a GSL, where technicians are allowed to deal with more complicated electronics failures. GSL technicians usually have more specialized knowledge than SB technicians. GSLs are linked to the different passenger rolling stock types. This study focuses on the VIRM train. For VIRM trains, these GSL sites are located in Roosendaal, Nijmegen, and Alkmaar.
- Maintenance company (OB): the third location type is an OB, of which only four sites exist in the Netherlands: Onnen (location for VIRM trains with 6 train coaches), Maastricht (location for VIRM trains with 4 train coaches), Leidschendam, and Amsterdam. OB technicians are most experienced and certified compared to technicians of the two other maintenance location types. Due to their certificates, some OB technicians are also allowed to work with refrigeration components, instead of electronics failures only. However, not all technicians at OBs have the required certificates to work with refrigeration components. Certified refrigeration and air-conditioning technicians, referred to as climate technicians at NS, are allowed to work with refrigeration technology failures. Refrigeration technology concerns the movement of heat energy to decrease the temperature level.

OBs are responsible for KCO maintenance tasks, whereas GSLs have more unassigned capacity to repair unexpected failures. Therefore, most corrective maintenance work orders for HVACs are allocated to GSLs, since these location have more spare capacity than OB locations. However, if the task requires a technician with specific certificates, in this study a climate technician, the task will be allocated to an OB.

Next to the location type, the target end date is determined based on the associated Q-procedure. Thereafter, **the opportunities for maintenance locations are investigated**. The following example will be used in this section to explain the process: one HVAC system of a VIRM train is defect, and should be maintained at a GSL location. The corresponding Q-procedure states that the target end date is after 5 days. The train in this example only runs from Groningen to Zwolle. In this step of the process, the required maintenance task has three possible maintenance locations: Roosendaal, Nijmegen, and Alkmaar.

The next gateway asks if **the target end day is today**, which has two possible answers:

1. No: in the provided example, the target end date is currently in five days, resulting in the following question: **can maintenance easily be combined with the timetable today?**

    - Since the train in the given example only runs from Groningen to Zwolle, the maintenance tasks cannot be combined with the timetable today. As a result, it is necessary to **wait one day** before continuing the process. This process will be repeated over the next four days, because the train track of the train coach with a defect HVAC has not been changed. After four days, the fifth day has arrived, which corresponds to the target end date. This situation is explained in the second bullet point, where target end date today is yes.
    - If the train track of the corresponding train coach would have been changed to Alkmaar - Breda, the HVAC can easily be maintained in Alkmaar and Roosendaal, which is close to Breda. In this case, **MBN calls the most suitable location to check availability**, which is Alkmaar. Thereafter, the question appears whether the GSL in Alkmaar **accepts the maintenance task**, which results in two possible arcs:
        - GSL Alkmaar **accepts**: the maintenance task will be performed in Alkmaar today
        - GSL Alkmaar **rejects**: in this situation, the question: **can maintenance easily be combined with the timetable today** arises again. In this situation, MBN calls GSL Roosendaal to check availability, resulting in the following possible steps:
            - **Roosendaal accepts**: the maintenance task will be performed in Roosendaal today.
            - **Roosendaal rejects**: this results in the question: **can maintenance easily be combined with the timetable today?** Since there is no location left which can be combined with the timetable today, the repair has to **wait 1 day**, and arrives again at the question **target end date today?** The situation in which the target end date is today is explained in bullet point 2.

2. Yes: the target end date is stated to be today, hence the left arc of the **target end date** gateway is followed. This results in the task that **MBN calls the most suitable location to check availability with priority**. Since the train runs from Groningen to Zwolle, the nearest GSL is located in Nijmegen. Therefore, MBN calls the GSL in Nijmegen to check if they have spare capacity to repair the HVAC today. During the phone call to the GSL, emphasis is put on the priority due to the close target end date. If it is possible, the HVAC should be prioritized over other maintenance tasks to maintain the HVAC before the target end date has passed. The GSL can either **accept or reject** the request:

- **Accept**: the maintenance tasks will be executed in Nijmegen today.
- **Reject**: if the maintenance task is rejected in Nijmegen, the question is if there is **another location possible** to perform this maintenance task, which results in two possibilities:
  - **Other locations available**: in this example, there are two other locations available, namely Alkmaar en Roosendaal. Therefore, Alkmaar will be reached out first, and, depending Alkmaar's availability, Roosendaal second.
  - **No other locations available**: in this situation the target end date is reached, while there is no maintenance capacity available. Postponement can be requested for this task, resulting in the following question: **is it allowed to postpone the target end date?** At NS, this postponement is called release beyond tolerance (VBT). Again, two answers to this question exist:
    - **Postponement is allowed**: MBN decides the length of the allowed postponement and based on this the **target end date will be adjusted**, and the train can continue running until the adjusted target end date.
    - **Postponement is not allowed**: if the postponement is not allowed, the associated train coach is not allowed to run after the target end date. Therefore, **MBN changes the status of this train coach to out of order as of tomorrow**.

  In either situation, the HVAC still needs to be repaired. Therefore, the process of scheduling this maintenance task starts again **the next day**.

Eventually, there will be a location that **accepts** the maintenance task, and the exclusive gateway at the bottom right is reached. After this, **MBN calls the allocated location before the shift is over to double check the scheduled maintenance task**. This is required, because in the meantime something may have happened to the train, train track or maintenance location. Usually, this is just a double check, and nothing changes based on this phone call. Thereafter, **the train goes to the maintenance location and will be maintained by a (pitstop) technician**. At GSLs, the HVAC will be repaired by a technician with sufficient knowledge of HVACs. At OBs, a separate technician is allocated to corrective maintenance tasks, which is called the pitstop technician at NS. To finalize the process, **the (pitstop) technician fills in feedback on performed maintenance**. This feedback contains the analysis of the failure and how the repair is executed.

2.4.2. Execution of preventive maintenance work orders for HVACs

In addition to Section 2.4.1, this section describes the execution of preventive work orders. Figure 2.3 displays the process of executing preventive work orders during KCO. The trigger for this process is that the KCO is planned today, because work orders are expected to be executed today.

First, it should be checked if this KCO is also the **annual maintenance in the spring**. If this is the case, the parallel gateway illustrates that the process continues to the exclusive gateway below as well as the first task at the top right. This task includes that **the climate technician executes annual spring-related work orders with priority 3**. As mentioned in Section 2.3, these work orders were already created a week prior to the KCO date. Thereafter, **the climate technician fills in the feedback on performed maintenance** as explained in the Section 2.4.1.

Contrary to the annual maintenance tasks, the next steps in the process are carried out during every KCO. The quarterly executed tasks contain the following:

1. **Technician executes all active work orders**: all active work orders are executed, which can include work orders with priority 2 or with priority 3. These are predominantly the quarterly work orders with priority 3, or the work orders with priority 3 as a result of a D-notification. To execute the quarterly maintenance tasks you do not need to be certified as a climate technician, hence all technicians who have affinity with, and knowledge on HVACs are allowed to perform these quarterly maintenance tasks. However, it could also be a work order with priority 2 if this failure had occurred at most five days prior to the KCO. Depending on the type of failure, a climate or regular technician is allowed to perform this priority 2 maintenance action. Feedback must also be completed here afterwards, and thus **technician fills in feedback on the performed maintenance tasks**.
2. **Climate technician extracts info from the CC**: the climate-related errors from the CC are extracted and analysed. This CC is located inside the train.
3. **TAE extracts info CC**: the TAE, which is a technician specialized in electronics, extracts the information, such as diagnosis codes, from the CC again. One week before the KCO, the CC is read out by the TMM. However, additional errors may have occurred in the meantime. Therefore, this is a complementary required check of the CC.
4. **Climate technician executes all active inspection and functionality test work orders**: inspection and functionality test work orders are created one week prior to the KCO, and are carried out in this step.

Usually, these four tasks are performed in sequence. But since there is not a specific order required to execute these four tasks, a parallel gateway is used.

As a result of the analyses conducted in bullet point 2, 3, and 4, **additional maintenance tasks can be required**. This results in two possible directions:

- **No**: in this situation, no additional maintenance actions need to be executed.
- **Yes**: there are additional maintenance tasks required, but it should be investigated if there is **time available to perform this task**. This results in two options:
    - **Yes**: if there is time available to execute the required maintenance task, **the climate technician creates a work order**. This step is necessary to store the information about failures that have occurred. Thereafter, the **climate technician performs the maintenance task** and **fills in feedback on the performed maintenance task**.

- **No**: in this case, there is no time available to perform the additional task during the current KCO. The next question that arises, is **whether the defect is blocking for departure**. A defect that is blocking for departure means that the defect affects the functioning of the train.
  - **Defect is not blocking for departure**: the train has a defect, but it still functions properly. This is comparable to a work order based on a D-notification, and therefore, the execution of this work order can be postponed to the next KCO. Another example of this situation is that the functionality depends on the season, e.g. a fully functioning heating is not required in summer. In this case, the maintenance task can also be postponed to the next KCO, since the functionality will not be used the upcoming three months. However, **the climate technician should create a work order priority 3** to report the defect.
  - **Defect is blocking for departure**: the defect has impact on the functioning of the train, hence the defect cannot be postponed to the next KCO. However, depending on the severity of the failure, the train can possibly run a few days before the defect is repaired. Therefore, it should be determined if **it is allowed to postpone the target end date (VBT)**:
    - **Postponement is allowed**: in this case the train can run a few additional days before the defect is fixed. An example of this is a small increase in train coach temperature, which is less pleasant for passengers, but not very uncomfortable. The VBT in this situation can be around ten days, thus that the MBN has some slack to schedule this repair. If the VBT is allowed, **the TMM creates a work order priority 2 based on the VBT deadline**. The target end date on this work order is the same as the VBT deadline.
    - **Postponement is not allowed**: it is not allowed to use this train coach before the failure is repaired. This can for example be if the ventilation is not working, resulting in a too high carbon dioxide level in the associated train coach. **The climate technician creates a work order with priority 2 and changes the status of this train coach to out of order** in this case. A possible remedy is that the remaining, well-functioning train coaches leave the maintenance site, and run without this train coach. However, in some cases the entire train waits until the work order is executed. For example if the defect is in the train driver compartment. **The climate technician performs the maintenance task once time is available**, and **fills in feedback on performed maintenance**

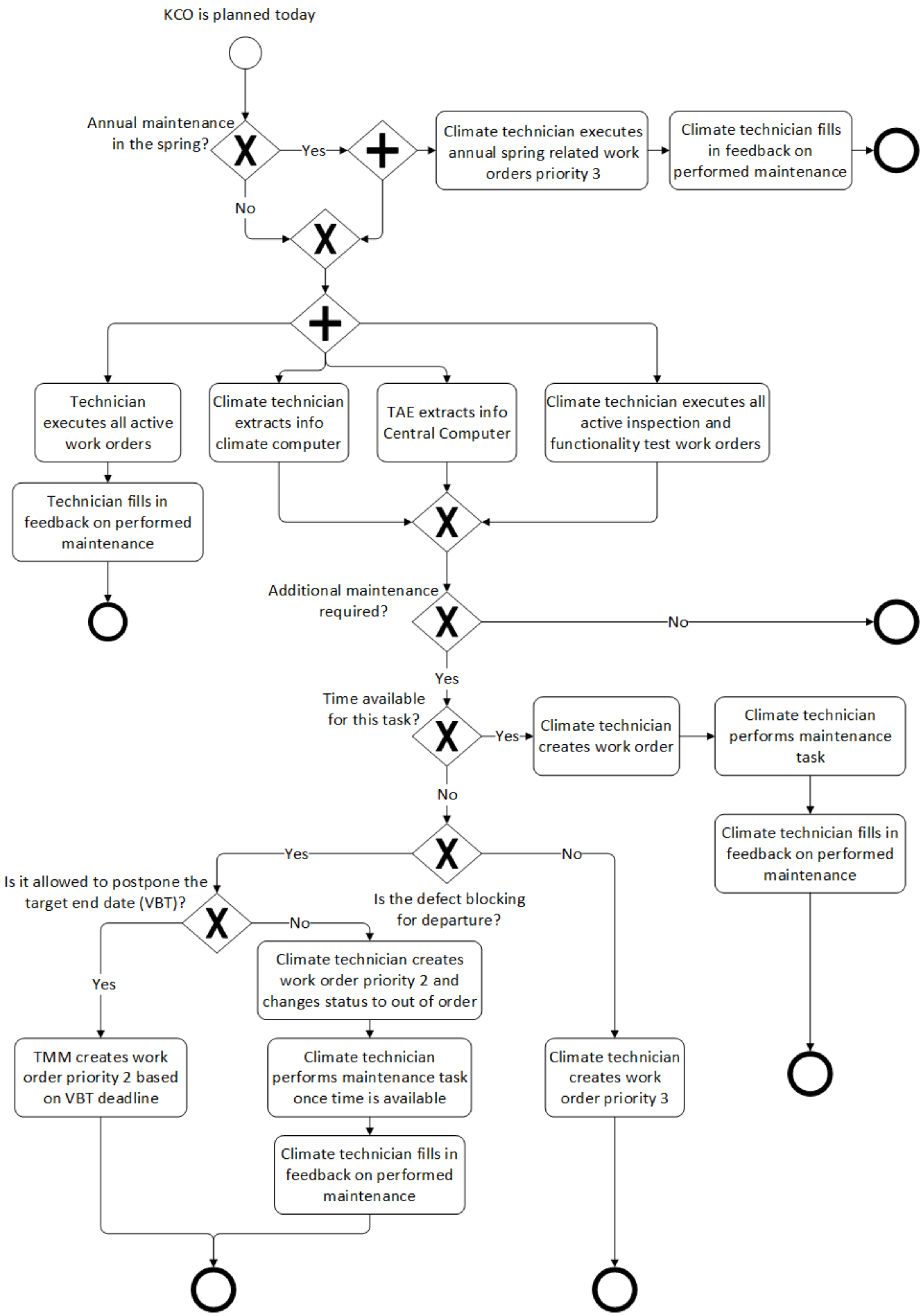


Figure 2.3: BPM of the execution of preventive work orders for HVACs

2.5. Conclusion

In conclusion, NS' maintenance policy for HVACs contains preventive and corrective maintenance tasks that are executed at GSLs or OBs. Preventive maintenance tasks are executed during trimonthly KCOs and the annual maintenance in the spring at OBs. Corrective maintenance work orders are requested if HVAC failures occur, and these work orders are usually executed before the predetermined deadline based on Q-procedures at a GSL or OB.

Chapter 3

Maintenance challenges NS faces during heat waves

This chapter answers RQ2 by giving an overview of the maintenance challenges that NS faces during heat waves. The approach to obtain information to answer RQ2 is provided in Section 3.1. Section 3.2 outlines the direct challenges for the maintenance locations that occur due to HVAC problems, whereas the indirect problems that result in lack of time for HVAC maintenance tasks are presented in Section 3.3. Moreover, the effects of the climate change are addressed in Section 3.4. Finally, a conclusion of the results is provided in Section 3.5

3.1. Data collection

This section describes how information is obtained on the challenges that NS faces during heat waves in order to answer RQ2. The interviewees mentioned in Chapter 2 were also asked about the challenges they experience during heat waves. In addition, the reliability engineer dedicated to VIRM trains is interviewed, since he has much knowledge on this topic. Again, semi-structured interviews were used. The predetermined questions for the reliability engineer and the standard questions for all interviewees are presented in Appendix D. Moreover, additional documentation on the number of service requests is used to calculate the correlation coefficients for this chapter.

3.2. Direct challenges for HVAC maintenance during heat waves

The reliability of the fleet at NS is evaluated based on the number of service requests. All service requests are for corrective maintenance tasks, performed at one of the maintenance locations: SB, GSL, or OB. The number of service requests for VIRM HVACs per month in 2019, 2020, and 2021 are investigated to understand the failure behavior of HVACs over the year. The number of service requests per month is displayed in Figure 3.1. Due to confidentiality, the absolute numbers are omitted from the figure.

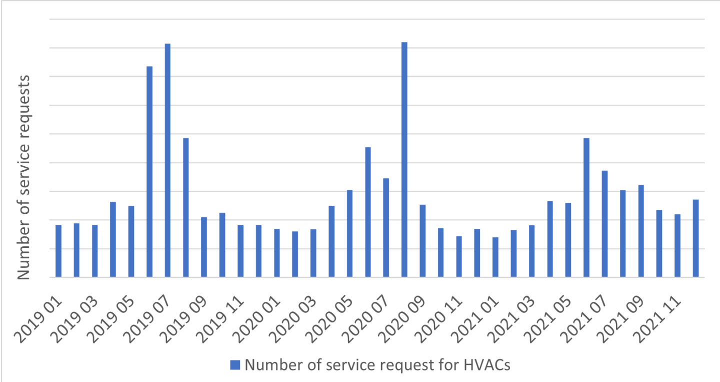


Figure 3.1: Number of service requests for HVACs per month

Figure 3.1 shows a striking peak of service requests in July 2019 and August 2020. The peaks in July 2019 and August 2020 were not a coincidence, because there were heat waves in July 2019 and August 2020 in the Netherlands (KNMI, 2022b). A heat wave as defined by KNMI (2022b) contains at least five consecutive days with a maximum temperature above 25 °C, including at least three three days with a maximum temperature above 30 °C. Maintenance personnel confirmed the maintenance overload in July 2019, and especially in August 2020. The maintenance locations had to deal with more service requests in other summer months as well (e.g. June 2019, August 2019, June 2020, and June 2021). Therefore, it seems that the ambient temperature is positively related to the number of service requests. In order to verify this presumption, the average temperature per month is added to Figure 3.1. The result is displayed in Figure 3.2

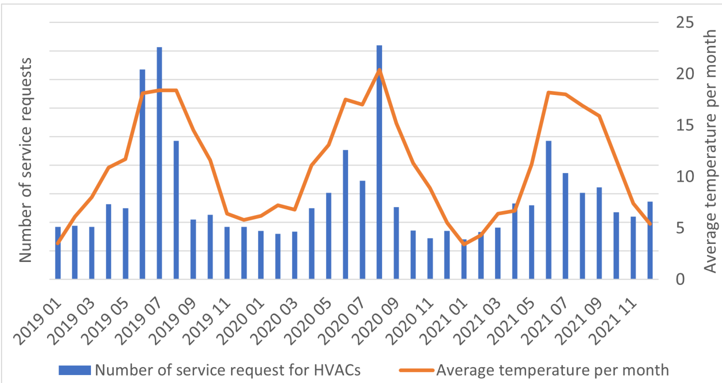


Figure 3.2: Comparison number of service requests and average temperature per month

The orange line in Figure 3.2 shows the average temperature per month (KNMI, 2022c). The y-axis on the right displays the range for the average temperature per month. Based on Figure 3.2 the hypothesis is that the number of service requests is positively correlated with the average temperature. This hypothesis is tested via a calculation of the correlation coefficient. Two common correlation coefficient types are: Spearman's rank correlation coefficient and Pearson's correlation coefficient (Hauke and Kossowski, 2011). Spearman's rank correlation coefficient studies the relation between two variables and can be used for all variables regardless of the distribution of these variables. However, Spearman's rank correlation coefficient is not able to study the linear correlation between variables.

Pearson's correlation coefficient is able to study the linear correlation between variables, but both variables must be mutually independent and normally distributed (Bakdash and Marusich, 2017). Since the average temperature of the next month can be influenced by the average temperature of the previous month, the values for the average temperature per month might be mutually dependent for subsequent months. However, we can assume that the average temperature per month is mutually independent for every other month. This means that Pearson's correlation coefficient should be calculated for all even or odd months to satisfy the requirement of mutually independent variables. Moreover, the normality of variables can be tested by the Kolmogorov-Smirnov test (Razali et al., 2011). The normality for both variables is tested, i.e. number of service requests and average temperature per month. Since the obtained values differ for the even and odd months, both obtained values are used in this analysis. The obtained values for the Kolmogorov-Smirnov test are displayed in Table 3.1

Variable	**Kolmogorov-Smirnov value**
Temperature even months	0.171
Temperature odd months	0.113
Number of service requests even months	0.216
Number of service requests odd months	0.216
Threshold Kolmogorov-Smirnov test	*0.278*

Table 3.1: Values Kolmogorov-Smirnov test

In this case, with a sample size of 18 and alpha equal to 0.05, the critical value is equal to 0.278 (Kanji, 2006). Both the temperature data and the data on the number of service requests can be assumed to be normally distributed for the even and odd months, which follows from the values that are below the threshold of 0.278. Therefore, Pearson's correlation coefficient can be used for this correlation test if all even or odd months are used, but not for all 36 months.

Pearson's correlation coefficient is a statistical measure to find out to what extent two variables are associated. A value between -1 and 1 can be obtained for Pearson's correlation coefficient. A positive correlation coefficient means that there is a general tendency that a higher value of the first variable is associated with a higher value of the second variable. If Pearson's correlation coefficient is below zero, there is a general tendency that a higher value of the first variable is associated with a lower value of the second variable. A correlation coefficient of zero means that the variables are not associated. The strength of the relationship can be evaluated based on the absolute value of Pearson's correlation coefficient. A higher absolute value of Pearson's correlation coefficient means a stronger relationship between the two variables. Pearson's correlation coefficient is usually significant if the p-value is below 0.05. However, the critical p-value needs to be lowered if multiple comparisons are performed simultaneously, also referred to as the Bonferroni correction (Weisstein, 2004). As a result of the Bonferroni correction, the critical p-value is set equal to the previous p-value divided by the number of comparisons, which is two in this case. Therefore, Pearson's correlation coefficient is for this analysis significant if the p-value is below 0.025 (0.05/2). MS Excel is used to obtain the value for Pearson's correlation coefficients and the p-values for even and odd months, and the results are displayed in Table 3.2.

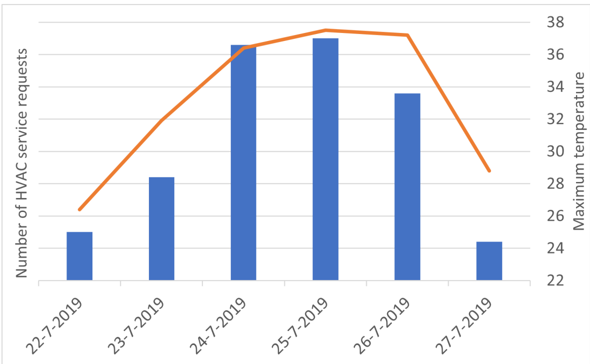
Measure	Value
Pearson's correlation coefficient even months	0.820
p-value Pearson's correlation coefficient even months	$3.05e \cdot 10^{-5}$
Number of service requests odd months	0.707
p-value Pearson's correlation coefficient odd months	0.001

Table 3.2: Values Pearson's correlation coefficient and corresponding p-value

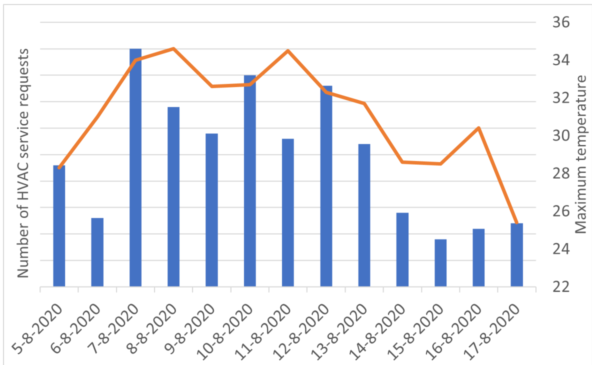
Pearson's correlation coefficients for even and odd months are equal to 0.820 and 0.707, respectively. The corresponding p-values are equal to $3.05e \cdot 10^{-5}$ fore even months, and 0.001 for odd months. These results confirm our hypothesis that the number of HVAC-related service requests is significant positively associated with temperature.

High temperatures usually occur in summer months. Maintenance personnel mentioned that maintenance locations have to deal with less available technicians, because it is holiday season in these summer months. In particular, August 2020 was very challenging at the maintenance locations due to the maintenance overload and decreased maintenance capacity in terms of qualified employees. As a result, the throughput time for maintenance tasks increases.

The relation between temperature and the number of service requests during a heat wave is not visible in Figure 3.2. To understand the importance of the temperature per day, Figure 3.3 is created to zoom in on service requests during the heat waves in July 2019 and August 2020.



(a) July 2019



(b) August 2020

Figure 3.3: Comparison HVAC-related service requests and temperature during heat wave

In Figure 3.3a and Figure 3.3b, the number of service requests per day is displayed by the blue bars. The maximum temperature per day is presented by the orange line (KNMI, 2022a). The Royal Netherlands Meteorological Institute (KNMI) determines heat waves based on the maximum temperature per day. Therefore, these figures use the maximum temperature too. The number of service requests for HVACs and the maximum temperature per day in Figure 3.3 seem to be positively associated. However, Pearson's correlation coefficient cannot be calculated for these relations, because the maximum temperature per day is not independent. Hence, this violates the requirement that all variables are mutually independent. Therefore, the significance of this relation cannot be tested, but we assume that the number of service requests for HVACs is positively associated to the maximum temperature per day based on Figure 3.3.

Interviewees mentioned that service requests in these summer months include broken HVACs, and HVACs that are unable to fully cool the train coach due to insufficient cooling capacity during days with a maximum temperature above 30 °C. However, MBN cannot distinguish these service requests and the corresponding handling process at the maintenance locations. Therefore, maintenance is requested for both broken HVACs and HVACs with insufficient capacity. Heat maps can help to make a distinction between these two types of failures. Deviations that are visible at days with a maximum temperature below 30 °C can indicate broken HVACs, whereas deviations of one or two days at days with a maximum temperature above 30 °C often point to HVACs with insufficient cooling capacity. Structural, long lasting temperature deviations at days with a maximum temperature above 30 °C probably indicate broken HVACs too.

A maximum temperature above 25 °C results in an increase of service requests, but the peaks in Figure 3.3a and Figure 3.3b are usually at days with a maximum temperature above 30 °C. This can partially be explained by the additional service requests due to insufficient capacity of the HVAC. A reliability engineer mentioned that a long period above 30 °C is also very demanding for HVACs, hence the number of broken HVAC increases as well. From July 23, 2019 until July 26, 2019, and August 6, 2020 until August 13, 2020, the maximum temperature exceeds 30 °C. This results in a peak of service requests for these periods. If the temperature drops below 30 °C, the number of service requests immediately decreases as well.

As displayed in Figure 3.3a and Figure 3.3b, NS had to deal with heat waves in July 2019 and August 2020. The heat wave in July 2019 was shorter, but with higher temperatures compared to the heat wave in August 2020. The heat wave in July 2019 contains four days above 30 °C, whereas August 2020 had to deal with eight days above 30 °C. However, three out of these four days in 2019 had a maximum temperature above 35 degrees, and in August 2020 the maximum temperature was 34.6 °C. A few differences between these two heat waves were mentioned by interviewees. The average number of service requests during the four days above 30 °C (including three days above 35 °C) in July 2019 is 80% more than the average during the eight days above 30 °C in August 2020. However, the total number of service requests during the heat wave is higher in August 2020. The high number of service requests in July 2019 was of short duration, which is beneficial for the throughput time. In August 2020, the number of service requests continued to grow, and the cumulative number of service requests became very large. As a result, the throughput time during the heat wave in July 2019 was shorter than in August 2020. The final difference is that there was a delay time between the first day above 30 degrees and the increase in number of service requests in August 2020, whereas the problems started acutely after the first day above 35 °C in July 2019 due to the high temperatures.

MBN employees agreed on the delay time between the temperature increase and increase in number of service requests in August 2020. Additionally, they mentioned that the first days the number of service requests increase, but the peak of service requests is at the end of the day. During the days that follow the peak is becoming earlier in the day. HVACs break down earlier, because the temperature during the night increases. If the HVACs can cool down during the night, the time to failure is higher. In July 2019, the night temperature also increased immediately due to the maximum temperature above 35 °C, resulting in a fast increase in the number of service requests. Contrary, the first nights in August 2020 were cooler, resulting in a higher delay time for the number of service requests.

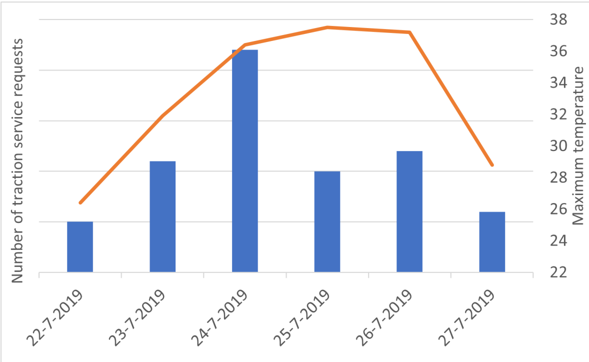
Complex failures need to be examined and repaired at an OB, but, as mentioned in Section 2.4.1, the capacity for corrective maintenance is limited at OBs. Moreover, the OBs are located in Maastricht and Onnen, resulting in a logistical challenge to move trains to an OB, because maintenance at these locations cannot be easily combined with the standard timetable of VIRM trains. Therefore, it is interesting to check whether the HVAC needs to be repaired at an OB or that a GSL has sufficient knowledge to do the repair. If the HVAC has insufficient capacity to cool instead of a defect, it would be better to move this train to a GSL instead of an OB. It is possible that the HVAC has cooled down and the service request has been resolved with limited maintenance (e.g. a reset) or even without maintenance. Moving the corresponding train coach to an OB, while this was not required is very expensive. Therefore, it is beneficial to verify if the failure is still active just before the train moves to an OB. If not, a GSL location has sufficient knowledge to repair the HVAC. As aforementioned, the heat maps can also be used to decide on the maintenance location.

A high number of service requests can result in a reduction of the fleet availability, hence less seating capacity for passengers. To minimize the reduction of fleet availability the Q-procedures are used. As soon as the end-date of the Q-procedures approaches, a VBT can be requested to increase the availability. However, in a warm period with temperatures around 30 °C it is undesirable to postpone the maintenance task, because passengers should travel in train coaches with a malfunctioning HVAC resulting in extremely high temperatures in the corresponding train coaches.

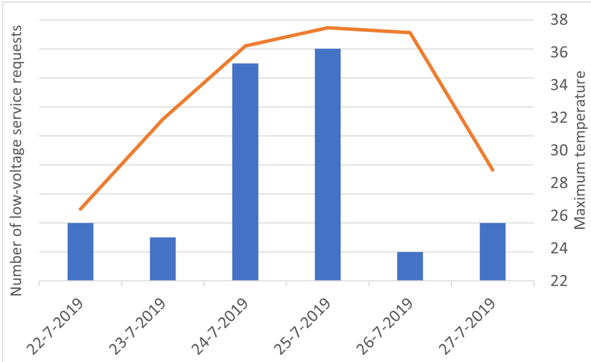
3.3. Indirect challenges for HVAC maintenance during heat waves

In addition to HVAC service requests, NS is faced with an increased number of service requests for other systems during heat waves as well. This results in a lower maintenance capacity for HVAC maintenance tasks due to the increased number of failures of more critical systems related to safety and reliability. Most importantly, traction and the low-voltage supply system have an indirect impact on the challenges for HVACs during heat waves. The traction system is required for the propulsion of the train, hence traction is critical to move the train. Both the traction system and HVAC system are cooled with outside air. If it is warm outside, the cooling systems have to work harder to cool the traction and HVAC systems. As a result, the number of service requests for both systems increase. The low-voltage supply system is required to provide power to electric motors within the train. HVACs require the low-voltage supply system to keep it running. Figure 3.4 is created to compare traction service requests and low-voltage service requests with the maximum temperature per day during heat waves in July 2019 and August 2020, respectively.

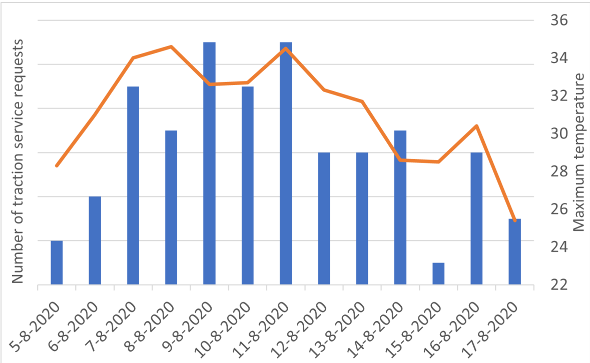
The number of service requests for traction and low-voltage are again displayed by the blue bars, and the temperature by the orange line. Figure 3.4 might imply that the number of service requests for traction and low-voltage is positively associated with the maximum temperature per day. The maximum temperature per day is used in these figures as well, which violates the requirement of mutual independence for this variable. Therefore, Pearson's correlation coefficient cannot be calculated for these relations. We assume based on Figure 3.4 that traction and low-voltage might be associated, but the relation with HVAC service requests and temperature, depicted in Figure 3.3, is more clearly visible.



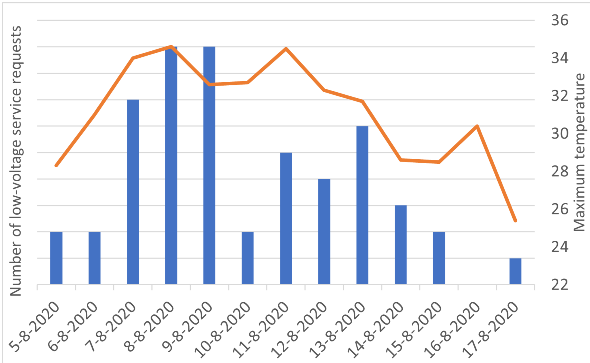
(a) Traction July 2019



(b) Low-voltage July 2019



(c) Traction August 2020

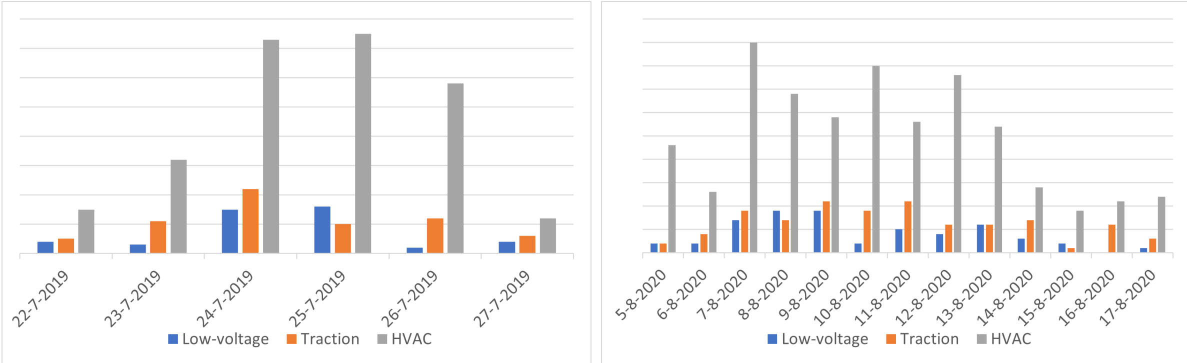


(d) Low-voltage August 2020

Figure 3.4: Comparison traction, and low-voltage service requests with temperature

The reason for a clearer relation with the number of service requests for HVACs can be explained by the total number of service requests for HVACs, compared to traction and low-voltage service requests. Figure 3.5 shows the relative differences between the three types of service requests in July 2019 and August 2020.

As depicted in Figure 3.5, the number of HVAC service requests is considerably more than for traction, and low-voltage. In both July 2019 and August 2020, the number of service requests for HVACs is about 3.5 and 5.5 times as much as for traction and low-voltage service requests, respectively. Since traction and low-voltage service requests are critical systems, it is important to understand how these service requests are prioritized at maintenance locations during heat waves.



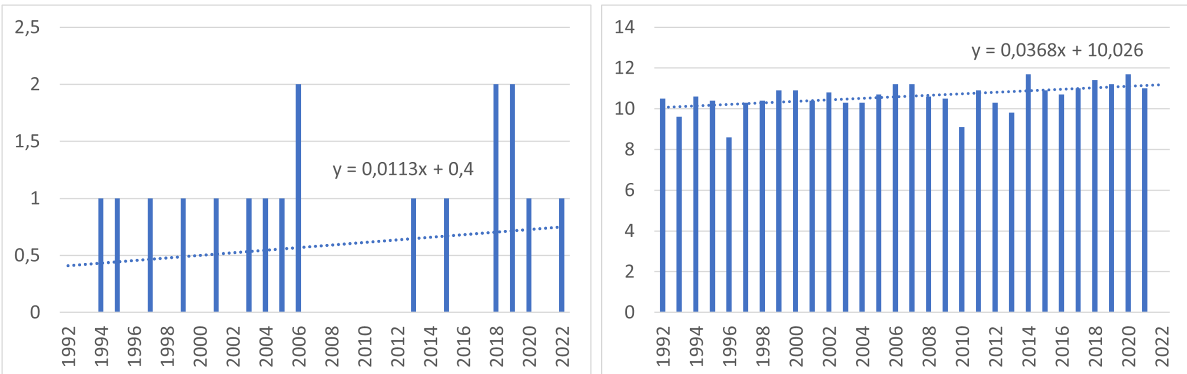
(a) July 2019 (b) August 2020

Figure 3.5: Comparison HVAC, traction, and low-voltage service requests

Service requests for HVACs, traction, and low-voltage prevent train departure if the end-date of the corresponding Q-procedure is approaching. The only possibility to deploy this train is by using a VBT. However, as explained above, this is undesirable during heat waves. Another important aspect is whether the train is able to be used. Trains cannot be deployed without a properly working traction system, and major low-voltage problems prevent train departure as well. In case the HVAC has just been maintained, while the traction system is defect, the train can still not be deployed after finishing the repair of the HVAC system. During heat waves, the main prioritization rule at maintenance locations is to maintain the train coaches with the smallest repair time to reduce the impact of failed train coaches on the fleet availability as much as possible. The next highest priority is assigned to solving traction problems, because failure of traction can lead to stranding of the entire train. However, at a maintenance location it can be decided to prioritize maintaining a simple HVAC failure over a complex traction failure.

3.4. Effects climate change

Finally, the number of heat waves per year and the average temperature per year are presented in Figure 3.6a and Figure 3.6b to evaluate the presence of this problem in the upcoming years. The linear trend line is also added to these figures to illustrate the increase over the years. However, the data is not assessed on its linearity, so the linear trend lines serve as an indication only.



(a) Number of heat waves per year (b) Average temperature per year

Figure 3.6: Effect climate change

It can be concluded from Figure 3.6 that the challenges for NS increase as the number of heat waves and average temperature increases over time due to the climate change. Moreover, the climate change will lead to more extreme weather, leading to potentially more heat waves than if only temperature increases. This expectation is confirmed by KNMI (2021), because the probability of prolonged heat increases as a result of the climate change. Hence, reducing the demand peak for NS becomes even more important the upcoming years.

3.5. Conclusion

Chapter 3 shows four relevant factors that influence the challenges during heat waves: (i) an increase in the average temperature per month results in an increase in number of service requests for HVACs; (ii) the maximum temperature per day seems positively associated with the number of HVAC-related work orders; (iii) the number of service requests for traction and low-voltage requests also increase during heat waves, which impacts the maintenance capacity for HVAC-related maintenance tasks; (iv) heat waves usually occur in the summer during the holiday season, resulting in less available technicians. The maximum temperature per day seems to be positively associated with the number of service requests for HVACs, traction, and low-voltage. However, HVAC-related service requests are most challenging at NS during heat waves, especially at days with a maximum temperature above 30 °C. As long as the systems can cool down during the night, and the demand peak of HVAC maintenance is at the end of the day, the impact on the fleet availability is acceptable for passengers. However, once the maximum temperature per day exceeds 35 °C and the night temperature increases as well, the number of service requests immediately increases even more, which is alarming for the maintenance locations. In order to manage the high number of service requests, maintenance locations should keep the prioritization rules to reduce the impact on the fleet availability as much as possible.

Chapter 4

Relation maintenance operations and temperature deviations

This chapter answers RQ3 via a thorough study of the relation between maintenance operations and temperature deviations on the heat maps. Section 4.1 describes how the data is prepared before the analyses are conducted. The results of the performed analyses are presented in Section 4.2 and Section 4.3. Section 4.2 focuses on the results related to service requests, whereas Section 4.3 is dedicated to temperature deviations. Finally, Section 4.4 provides a conclusion on RQ3.

4.1. Data preparation

Before the relation between maintenance operations and temperature deviations on the heat maps can be investigated, the data should be prepared for the analyses. Chapter 3 illustrates that NS had to deal with a high number of service requests during the heat waves in July 2019 and August 2020. The high number of service requests resulted in a maintenance overload at the maintenance locations. Heat maps and data on maintenance operations are required for this analysis. This combination is available as of 2020, because the heat maps were introduced in 2020. Therefore, the data of August 2020 is used in this analysis. The regular heat maps display the temperature over a period of six weeks. However, for these analyses a longer period is required to understand the relation. To determine the relevant period, box-plots are created that display the expected number of days with a maximum temperature above a certain number of °C, which are presented in Appendix E. These box-plots illustrate that HVAC failures are most likely to occur between April 1, 2020 and October 1, 2020 due to high temperatures. Therefore, the heat maps for a period of six weeks are merged into one heat map of six months for each HVAC. The data in the heat maps of six months are analysed. An example heat map is displayed in Figure 4.1. In total, 220 train coaches are used for the analyses.

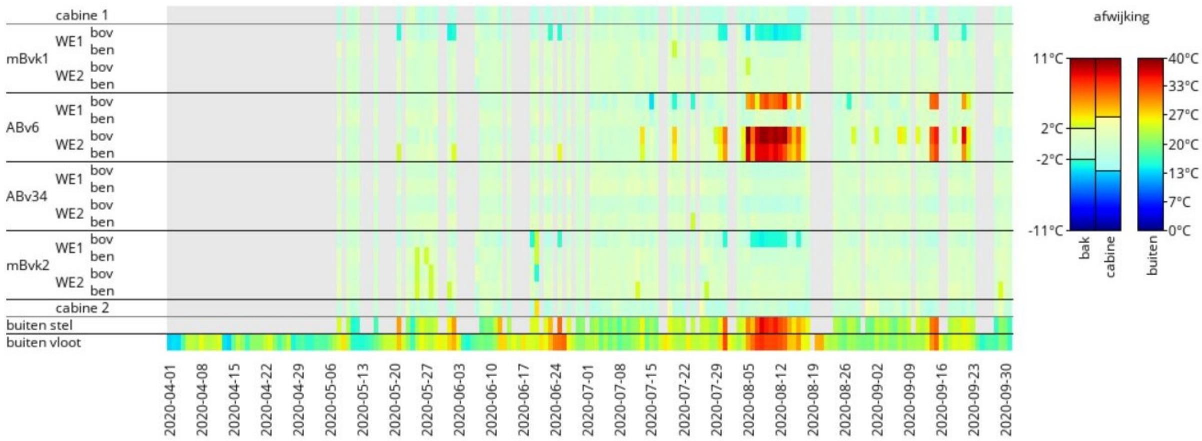
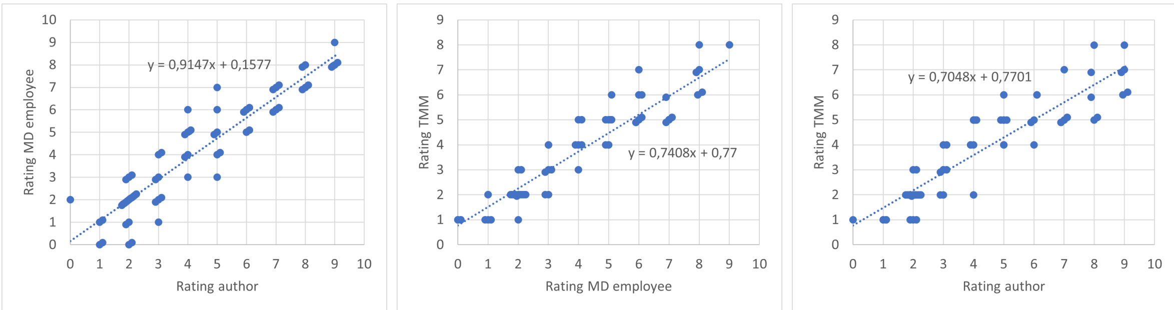


Figure 4.1: Heat map

Next, the temperature deviations are annotated on the heat maps so that they could be compared with the service requests. To determine the deviations, the start and end dates of the temperature deviations were defined. In addition, a rating on a scale of 1-9 was added manually per deviation indicating the certainty of the deviation. A deviation with a 1 means that the deviation is very uncertain, and a deviation with a 9 is very clearly a deviation. We did not define rules, such as a temperature deviation rated with a 5 has a duration of at least four days and a temperature deviations of at least 3 °C, for each potential rating. Therefore, each assessor is provided with freedom to decide on the interpretation of each rating. Several factors impact the determination of the deviations: the person assessing the deviations, the order of the trains within the heat map, rolling stock number recognition, diagnosis codes under the heat maps, and service requests that have taken place during that period. To capture these factors, a few adjustments were made to the heat maps:

- All irrelevant data has been removed from the heat maps. This includes the diagnosis codes and service requests. The remaining document only displays the measured temperatures and temperature deviations. This eliminates the risk of being biased by the service requests and diagnosis codes.
- The rolling stock numbers are obfuscated by random numbers, to avoid rolling stock number recognition. However, after all the heat maps are annotated, the rolling stock number can be traced based on the random number.
- Several documents are created in which the heat maps are ordered randomly, not by train. Every person that annotates the deviations receives a unique order of the heat maps.

The above mentioned adjustments avoid the impact of biases, except for the persons assessing the deviations. An MD employee who developed the heat maps reports and has three year of experiences with VIRM HVAC temperature data and the author of this research assessed the deviations independently. The author of this research is hereafter referred to as the author. In addition, the author annotated the deviations twice on a document with a different order and at a different time of the day. The weighted average of the author's ratings was compiled into a document with the annotations of the MD employee in the created heat map from April 1, 2020 to October 1, 2020 including diagnosis codes and service requests. This document has been shared with a maintenance expert (TMM) working at OB Onnen. The TMM is familiar with the heat maps, and has a lot of knowledge about HVACs. This maintenance expert rated the temperature deviations the MD employee and author annotated on the heat maps. The final assessment of the deviations is based on all three assessments. Three scatter-plots are created to understand the differences in the ratings between all assessors. The ratings are compared, because no rules were defined on the interpretation of the certainty rating. Figure 4.2 illustrates the comparison of all ratings.



(a) MD employee and author (b) MD employee and TMM (c) Author and TMM

Figure 4.2: Rating comparison

First, the ratings are compared based on the linear trend estimation. In Figure 4.2a, Figure 4.2b, and Figure 4.2c, the linear trend estimation is added. This line represents an estimation of a linear trend line across all points in the scatter-plot. The linear trend estimation is usually referred to as y=ax+b, where a is the slope, and b the y-intercept. A slope equal to zero, results in a horizontal linear trend line. The gradient is around 45 degrees if the slope value is around one. However, this does not necessarily mean that the value on the x-axis and y-axis are the same, because this is dependent on the y-intercept. The y-intercept represents the starting point of the linear trend line. First, Figure 4.2a is evaluated based on the slope, and y-intercept. The slope is with a value of 0.9147 close to 1, and the y-intercept of 0.1577 is close to 0. Therefore, it can be concluded from Figure 4.2a that the MD employee and the author rated quite similar. Figure 4.2b and Figure 4.2c have a slope around 0.7, and a y-intercept above zero. Thus, it can be concluded that the TMM rated the temperature deviations with a level of certainty above 3 lower on average. This can be explained by the point of view of the maintenance expert. A higher rating could mean more maintenance interventions, and the maintenance capacity is already fully utilized at maintenance locations. This aspect is now included in the rating.

Second, the correlation coefficient is calculated to compare the ratings. To decide on the type of correlation coefficient, the values for the Kolmogorov-Smirnov test are calculated for the ratings of the MD employee, the author, and the TMM. The values for these three ratings are displayed in Table 4.1

Variable	**Kolmogorov-Smirnov value**
MD employee	0.117
The author	0.133
The TMM	0.167
Threshold Kolmogorov-Smirnov test	*0.166*

Table 4.1: Values Kolmogorov-Smirnov test

In this case, with a sample size of 67 and alpha equal to 0.05, the critical value is 0.166 (Kanji, 2006). According to the Kolmogorov-Smirnov test the data is not normally distributed, since the Kolmogorov-Smirnov value for the TMM exceeds 0.166. Hence, Pearson's correlation cannot be used for this analysis, and Spearman's rank correlation is calculated for these three combinations. To obtain the value for the Spearman's rank correlation coefficient, the values for both variables are ranked and the correlation between these rankings is used to calculate Spearman's rank correlation coefficient. The obtained values for Spearman's rank correlation coefficient and the corresponding p-values are displayed in Table 4.2.

Comparison	**Spearman's rank correlation coefficient**
MD employee & the author	0.93
p-value MD employee & the author	$8.3e \cdot 10^{-30}$
MD employee & the TMM	0.92
p-value MD employee & the TMM	$1.7e \cdot 10^{-11}$
The author & the TMM	0.89
p-value the author & the TMM	$4.7e \cdot 10^{-10}$

Table 4.2: Results Spearman's rank correlation coefficient

The obtained values for Spearman's rank correlation coefficient show that there is a general tendency that a higher value of the first variable is associated with a higher value of the second variable. Moreover, all Spearman's rank correlation coefficients are significant, because the p-values are below the threshold of 0.05. This means that all combinations have a statistically significant positive correlation.

Finally, the preventive maintenance, KCO dates and service requests are annotated on the heat maps. Before the service requests could be added to the heat maps, their relevance should be checked. The service requests are removed if one of the following four statements holds for a service request: (i) insufficient temperature data is available in the corresponding heat maps; (ii) the service request is irrelevant for this research, e.g. heating is defect; (iii) the start and/or end date of the service request is missing. This has been double checked with separate excel files with all service requests; (iv) the train coach designation is missing. KCO dates are added as vertical purple lines, and the service requests in pink boxes. An example heat map with all annotations is shown in Figure 4.3.

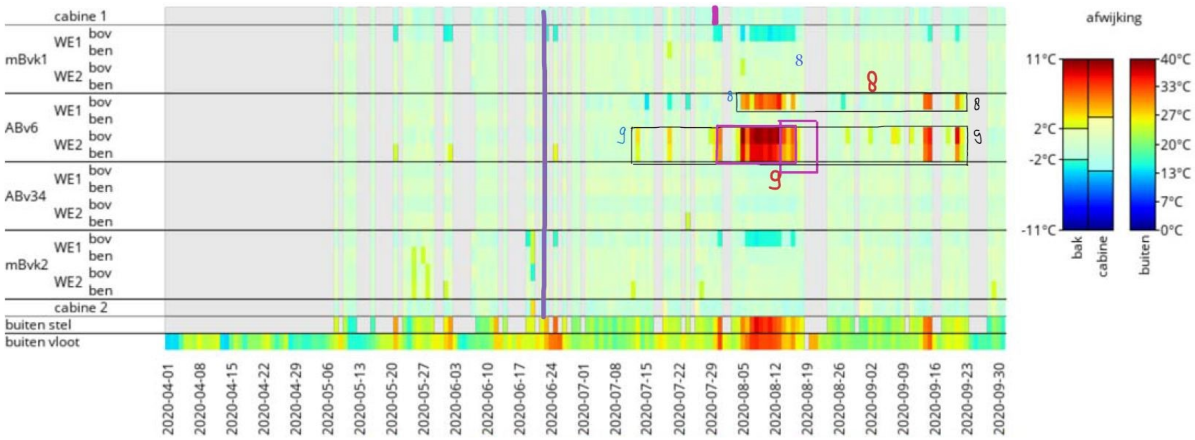


Figure 4.3: Heat map with annotations

The heat maps including the annotations can be used as input for analysis purposes. Section 4.2 and Section 4.3 describe the results of the analysis on the relation between maintenance operations and temperature deviations on the heat map. This approach is elaborated in Section 1.8. A method similar to creating a confusion matrix is used (Visa et al., 2011). However, both information on the maintenance operations and temperature deviations visible on the heat maps are imperfect information sources. Therefore, an information source with the ground truth is missing in this situation. The use of a confusion matrix, and the corresponding measures, e.g. false positives, true positives, false negatives, and true negatives, is not applicable to this problem.

4.2. Results of the service request analysis

The first analysis is related to the service requests. Two situations can be distinguished for service requests:

1. Service requests with a temperature deviation visible on the heat map
2. Service requests without a temperature deviation visible on the heat map

Situation 2 is preferred over situation 1, because passengers are affected by high temperatures in the train in situation 2. As a result, maintenance should be prioritized for service requests in situation 2 to resolve the temperature deviation in the corresponding train coach. In situation 1, passengers are not directly affected by the temperature. However, the service request can be ventilation related, and ventilation is required to avoid a too high carbon dioxide level in the associated train coach. Hence, this service request should be prioritized as well, while the temperature deviation is not directly visible on the heat maps. In total, 132 service requests meet the requirements mentioned in Section 4.1, and therefore these 132 service requests were used for this analysis. The result of this analysis is displayed in Table 4.3

Situation	**Number of service requests**	**Percentage**
1	41	31%
2	91	69%
Total	*132*	*100%*

Table 4.3: Result analysis service requests

4.2.1. Diagnosis codes analysis

Since 69% of the service requests is not associated with temperature deviations, which is an unexpected finding, additional analysis is required to understand this outcome. In this additional analysis, the diagnosis codes of both situations are compared. The results are summarized in Table 4.4. Due to confidentiality, the diagnosis codes are replaced by numbers.

Diagnosis code	#SRs situation 1	#SRs situation 2
1.	9	21
2.	6	13
3.	11	17
4.	1	3
5.	5	1
6.	2	0
7.	1	11
8.	0	12
9.	0	2
10.	0	6
11.	6	5
Total	*41*	*91*

Table 4.4: Comparison diagnosis codes and service requests

In addition to the presented table with absolute values per diagnosis code, a visualization of the diagnosis codes comparison including percentages is constructed and displayed in Figure 4.4

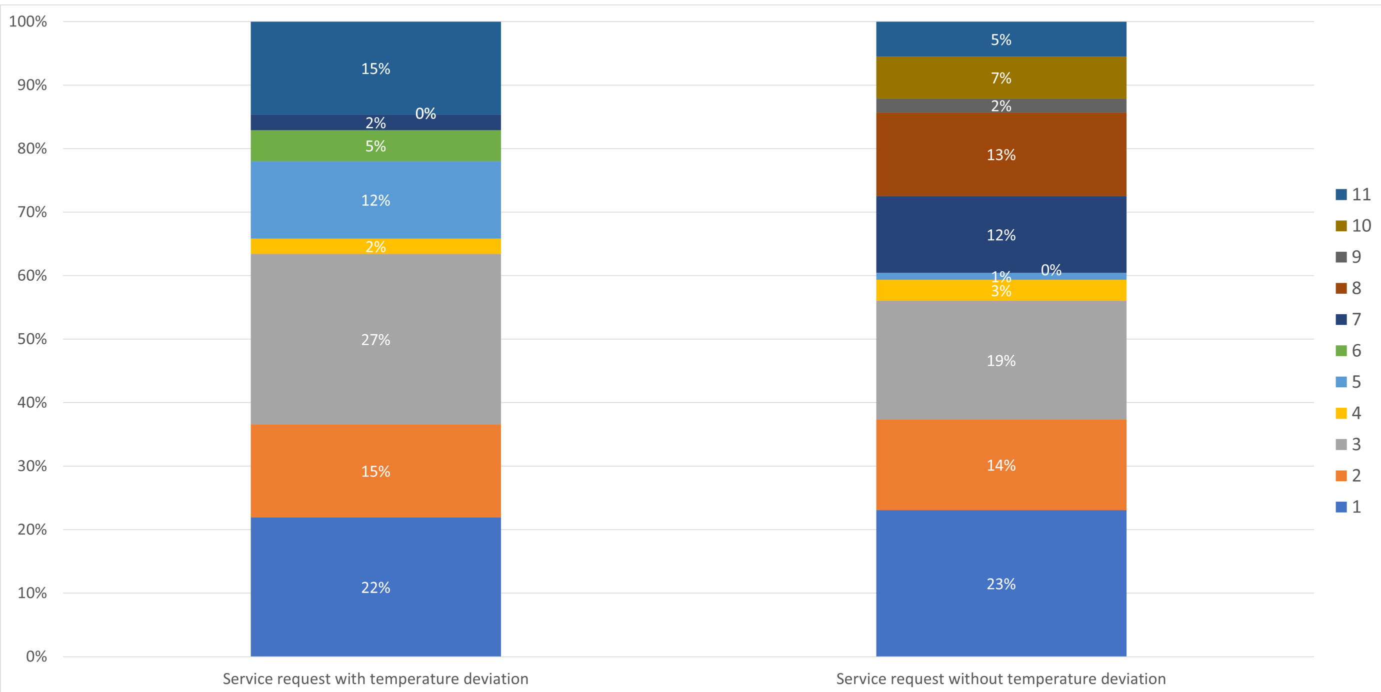


Figure 4.4: Comparison diagnosis codes and service requests

This analysis shows the following. The percentage of diagnosis code 1 and 2 are almost similar in the left and right bar. Both diagnosis codes indicate malfunctioning HVACs, resulting in warmer train coaches. Since these diagnosis codes are present with and without temperature deviation, it means that these diagnosis codes appear on days with high ambient temperatures and ambient temperatures that are equal to or lower than the set-point temperature. The latter justifies the percentages on the right bar of Figure 4.4, because no temperature deviations are visible if the ambient temperature is equal to or lower than the set-point temperature. Moreover, diagnosis code 3 is presented in the left and right bar as well, but relatively more if there is a temperature deviation visible. Diagnosis code 3 means that the self test has failed, which is usually due to the tripped inverter. A high ambient temperature is more demanding for the inverter, resulting in a higher percentage in the left bar of Figure 4.4.

A notable difference is diagnosis code 5, which mainly occurs on days with high ambient temperatures, resulting in temperature deviations in the corresponding train coach. Diagnosis code 7 is not related with high temperatures, thus usually causes no temperature deviations. Lastly, three different ventilation related diagnosis codes (8, 9, and 10) appeared in the right bar only. This can be explained by the fact that the ventilation has an indirect influence on the temperature, but not directly. In addition, ventilation is accompanied by strict Q-procedures, so the corresponding train coach can shortly after this notification not be deployed anymore. Hence, no temperature deviation was visible on the heat map.

4.3. Results of the temperature deviations analysis

Contrary to Section 4.2, this analysis is dedicated to temperature deviations instead of service requests. This analysis is performed to understand the relation from the perspective of temperature deviations. Two situations can be distinguished for temperature deviations:

1. Temperature deviations with at least one service request during or shortly after the temperature deviations
2. Temperature deviations without service request during or shortly after the temperature deviations

In total, 67 temperature deviations were visible on the heat maps in the period April 1, 2020 to October 1, 2020. The results for this analysis is displayed in Table 4.5.

Situation	**Number of temperature deviations**	**Percentage**
1	31	46%
2	36	54%
Total	*67*	*100%*

Table 4.5: Result analysis service requests

Table 4.5 shows that for 54% (36/67) of the temperature deviations no corrective maintenance intervention has been taken place, although there was a clear temperature deviation visible on the heat map. This is undesirable to the company as they aim for high passenger comfort, hence further understanding is required. As explained in Section 4.1, the temperature deviations are rated on a 1-9 scale. The number of temperature deviations per rating is displayed in Figure 4.5 to illustrate the occurrence per rating.

Most temperature deviations are rated with a two, whereas the least common rating with only one case is a temperature deviation rated with a 9. The remaining ratings of the temperature deviations have on average 7 cases.

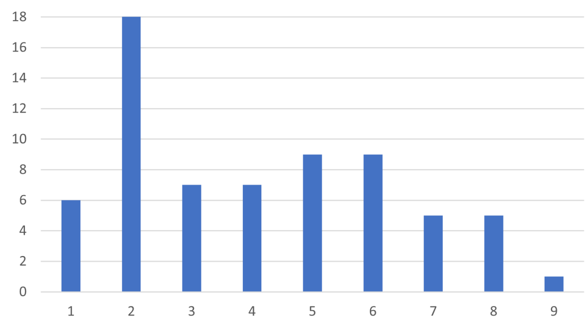


Figure 4.5: Histogram temperature deviation ratings

Three analyses are performed to better understand the relation between temperature deviations and maintenance interventions from the perspective of temperature deviations. Section 4.3.1 explains the effectiveness of service requests with respect to temperature deviations. This analysis evaluates if temperature deviations are resolved with and without corrective maintenance interventions. Thereafter, the predictability of temperature deviations from prior temperature deviations during semi-heat waves is studied in Section 4.3.2. If under-performing HVACs can be maintained before the heat wave, the demand peak during the heat wave will be reduced. Finally, Section 4.3.3 provides the results on the relation between temperature deviations in 2020 and 2021 to assess the effectiveness of the annual maintenance in the spring.

4.3.1. Effectiveness maintenance interventions

This section studies the effectiveness of corrective maintenance interventions, referred to as service requests, in comparison with temperature deviations on the heat maps. The start and end date of the temperature deviations are annotated on the heat maps. In 31 cases one or more maintenance interventions have taken place while a temperature deviation was visible on the heat map. For these 31 temperature deviations, the effectiveness of maintenance interventions is examined based on the presence of the temperature deviation after the service request. The temperature deviation is not resolved if the end date of the temperature deviation is after the end date of the service request, e.g. the temperature deviation rated with a 9 in Figure 4.3 is not resolved after the service requests. The system is viewed as fixed if the temperature deviation is not visible on the heat map anymore after the maintenance intervention.

In total, 52% (16/31) of the temperature deviations has been resolved after the service request(s), 35% (11/31) has not been resolved, and for 13% of the cases the effectiveness is unknown, because the service requests have taken place at the end of 2020. The maintenance's effectiveness of the temperature deviations at the end of 2020 cannot be examined, because the set-point temperature after the maintenance intervention remains equal to or higher than the ambient temperate. Hence the air-conditioning function cannot be tested, and the effectiveness of maintenance interventions is unknown. Additionally, the 36 cases without maintenance intervention are evaluated on whether the temperature deviation is resolved without maintenance intervention. For these temperature deviations the temperature deviation is resolved if the temperature deviation is not visible anymore at days with an ambient temperature higher than the set-point temperature. In 47% (17/36) of the cases the temperature deviation is resolved, 47% (17/36) has not been resolved, and 6% (2/36) is unknown, because it cannot be examined as it occurred at the end of 2020. A visualization of the effectiveness of maintenance interventions in both situation is displayed in Figure 4.6

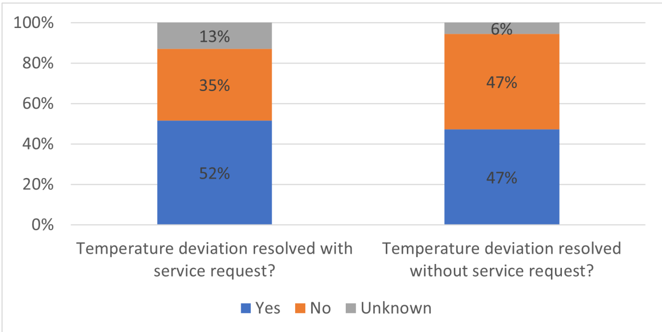
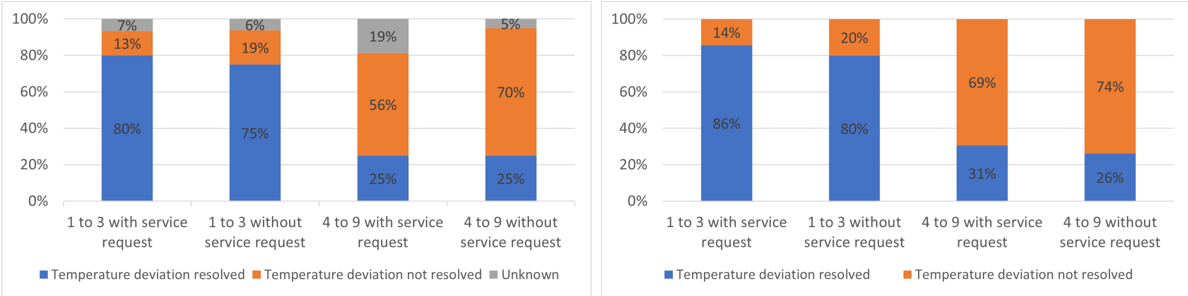


Figure 4.6: Comparison effectiveness of maintenance interventions with and without service request

The percentage of temperature deviations that is resolved is comparable in both situations, which is remarkable, because a higher effectiveness is expected with a service request. To better understand this counter-intuitive finding, the impact of the rating is investigated. The temperature deviations are aggregated, and a distinction is made between the temperature deviations with a rating from 1 to 3, and from 4 to 9. Temperature deviations with a rating from 1 to 3 usually last for one or two days, or the temperature deviation is only 2 °C or 3 °C. If the rating is at least 4, the temperature deviations are structurally visible for a longer duration than one or two days. This aggregation method is motivated and further explained at the end of this section. This threshold is used in the analyses, since this aggregation ensures the most reliable results The results of this analysis are summarized in Table 4.6. A visualization of these results is provided in Figure 4.7

	1 to 3 with service request	**1 to 3 without service request**	**4 to 9 with service request**	**4 to 9 without service request**
Resolved	12	12	4	5
Not resolved	2	3	9	14
Unknown	1	1	3	1
Total	*15*	*16*	*16*	*20*

Table 4.6: Comparison temperature deviations with and without service request per rating range



(a) Resolved, not resolved, unknown (b) Resolved, not resolved (excluded unknown)

Figure 4.7: Comparison temperature deviations with and without service request per rating range

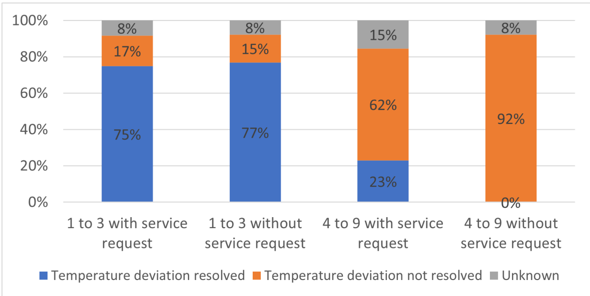
Figure 4.6 shows that more than half of the temperature deviations were resolved after the service request. However, Table 4.6 and Figure 4.7 show that most temperature deviations with a low rating are resolved, whereas temperature deviations with a high rating remain unsolved. Figure 4.7a illustrates the comparison including the cases for which the effectiveness is unknown, whereas these cases are removed in Figure 4.7b. Figure 4.7b is used to evaluate the obtained results, because the comparison between the two situations is more clearly visible in this figure. The results for the maintenance's effectiveness with and without service requests are again comparable. A large difference exists between the results for deviations with a rating of three or lower, and with a rating of four or higher. The obtained result for deviations with a rating from 1 to 3 is promising for NS, because the temperature deviation is resolved in 86% and 80% of the cases for temperature deviations with and without a service request, respectively. However, a service request for these temperature deviations seems unnecessary, because it is also solved without a service request. For temperature deviations with a rating of four or higher, 69% of the temperature deviations was not resolved after the maintenance intervention, and 74% was not solved without maintenance.

The difference between the results of the two aggregations can be logically explained, because deviations with a low rating (especially 1 and 2) are often a deviation of only one day. The temperature deviation can be resolved, because the cooling capacity of the HVAC was insufficient or the sensor measurement was incorrect on that day. Temperature deviations with a rating of four or higher usually last several days instead of only one or two days. These long lasting deviations are often not resolved by the performed maintenance tasks. Another unexpected observation is that 26% of the temperature deviations with a rating of 4 or higher is resolved without a service requests. This leads to the hypothesis that HVACs are self-healing systems. To check if this is true, the temperature deviations in which KCO has taken place are removed, and the same analysis is performed. The results are displayed in Table 4.7, and Figure 4.8

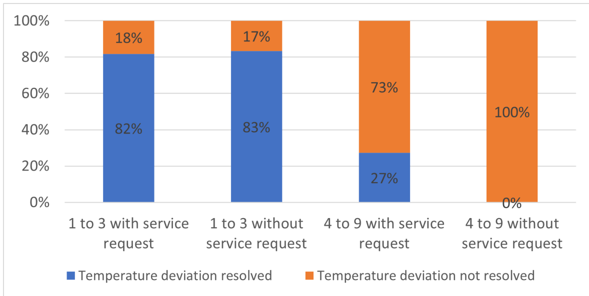
Figure 4.8 illustrates the percentage of temperature deviations that is resolved with only one or more service requests, and temperature deviations that are resolved without maintenance interventions. These results are more reliable to evaluate the maintenance's effectiveness of corrective maintenance tasks, because preventive maintenance tasks are excluded from

	1 to 3 with service request	1 to 3 without service request	4 to 9 with service request	4 to 9 without service request
Resolved	9	10	3	0
Not resolved	2	2	8	12
Unknown	1	1	2	1
Total	*12*	*13*	*13*	*13*

Table 4.7: Comparison temperature deviations with and without service request per rating range without KCO



(a) Resolved, not resolved, unknown



(b) Resolved, not resolved (excluded unknown)

Figure 4.8: Comparison temperature deviations with and without service request per rating range without KCO

this analysis. Figure 4.8b is again used to evaluate the obtained results. The percentages of deviations that were not solved are higher than in Figure 4.7 for all situations, except temperature deviations with a rating from 1 to 3 for which no service request has taken place. This means that part of the temperature deviations are resolved by KCO tasks. However, not all temperature deviations are resolved after these preventive maintenance interventions. This can be concluded from the third row (No) in Table 4.6 and Table 4.7, because the number of temperature deviations that are not resolved is reduced. A thorough analysis based on the temperature deviations including KCO is not possible, because the number of temperature deviations with KCO is equal to three, three, three, and seven temperature deviations for the four situations, i.e. small sample size which cannot be used to obtain reliable results.

Figure 4.8b illustrates that 82% and 83% of the temperature deviations with a rating from 1 to 3 are resolved with and without a service request, respectively. It can be concluded that temperature deviations with a rating from 1 to 3 indicate HVACs that were unable to cool due to insufficient capacity or incorrect sensor measurements instead of defect HVACs. HVACs with insufficient capacity to cool do not need a maintenance intervention to be resolved, whereas defect HVACs need maintenance to be resolved. Temperature deviations with a rating from 4 to 9 are resolved in 27% and 0% of the cases with and without service request, respectively. These percentages are surprisingly low, since only 27% of the temperature deviations are resolved after corrective maintenance interventions. The hypothesis that HVACs are self-healing systems is false in this study, because all temperature deviations with a rating of four or higher remain unsolved.

Maintenance experts were asked why only a quarter of these temperature deviations is resolved. They mentioned that the 73% of unsolved temperature deviations can result from two situations: (i) the service requests is stated as solved, without maintaining the HVAC; (ii) the HVAC is maintained, but the repair did not resolve the defect and corresponding temperature deviation. Furthermore, they mentioned that the technicians often lack sufficient knowledge on HVACs. Usually, technicians only reset the HVAC and state the HVAC defect as resolved after the reset, while the defect is still present after the reset. Maintenance experts mentioned that technicians often have insufficient knowledge to diagnose the defect correctly. Additionally, they mentioned that maintaining HVACs is generally complicated, hence obtaining a high success level will always remain difficult.

In the performed analyses, we decided to make a distinction between temperature deviations with a rating from 1 to 3 an from 4 to 9. This aggregation is based on the patterns that are visible in the heat maps. Temperature deviations for the ratings 1 to 3 and 4 to 9 are non-structural and structural temperature deviations, respectively. To verify the robustness of this distinction, a sensitivity analysis is performed to study the impact of different aggregations. The results for the different aggregations are presented in Appendix F. It can be concluded from Appendix F that the distinction between temperature deviations from 1 to 3, and 4 to 9 is most favorable to draw conclusions.

4.3.2. Predictability of temperature deviations during heat waves from prior deviations

The next analysis concerns the predictability of temperature deviations during heat waves from prior deviations. A possibility to reduce the demand peak during heat waves could be to additionally maintain under-performing HVACs before the heat wave in the summer. For the remainder of this section the following terms are used:

1. Hot day: the maximum temperature exceeds 25 °C
2. Tropical hot day: the maximum temperature exceeds 30 °C
3. Heat wave: At least five consecutive hot days, including at least three tropical hot days
4. Semi-heat wave: At least three consecutive hot days, including at least one tropical hot day

Term 1, 2, and 3 are based on definitions of the KNMI, and we defined term 4 for this analysis. As mentioned in Section 4.3.1, the temperature deviations are only visible if the ambient temperature is higher than the set-point temperature. Temperature deviations are usually visible at hot days, and definitely at tropical hot days. Therefore, the temperature deviations are visible during both semi-heat waves and heat waves. For this analysis, the semi-heat wave in June 2020 and the heat wave in August 2020 are used. An overview of the maximum temperature per day during these periods is displayed in Table 4.8 and Table 4.9, based on KNMI data.

The semi-heat wave in June 2020 lasted for four days, with one tropical hot day at June 26, 2020. In August 2020, NS had to deal with a heat wave with a duration of thirtheen days, including nine tropical hot days. The total number of temperature deviations is equal to 21 and 53 for June 2020 and August 2020, respectively.

Date	**Temperature**
June 23, 2020	26.7 °C
June 24, 2020	29.4 °C
June 25, 2020	29.4 °C
June 26, 2020	30.1 °C

Table 4.8: Temperature semi-heat wave June 2020

Date	**Temperature**
August 5, 2020	28.3 °C
August 6, 2020	31.0 °C
August 7, 2020	34.0 °C
August 8, 2020	34.6 °C
August 9, 2020	32.6 °C
August 10, 2020	32.7 °C
August 11, 2020	34.5 °C
August 12, 2020	32.3 °C
August 13, 2020	31.7 °C
August 14, 2020	28.6 °C
August 15, 2020	28.5 °C
August 16, 2020	30.4 °C
August 17, 2020	25.4 °C

Table 4.9: Temperature heat wave August 2020

The first analysis on the predictability of temperature deviations from prior deviations during semi-heat waves looks back in time from August 2020. For all temperature deviations during the heat wave in August 2020, it is checked if these were already visible during the semi-heat wave in June 2020. In nineteen cases, insufficient temperature data was available in June 2020, displayed as vertical grey lines in the heat maps, to evaluate the predictability of temperature deviations from prior deviations. Thus, this analysis is based on 34 temperature deviations. 41% (14/34) of the temperature deviations were already visible during the semi-heat wave in June 2020, whereas 59% (20/34) of the temperature deviations was not visible in June 2020. An additional analysis is performed on the influence of the rating on this result. Again, a distinction is made between the temperature deviations with a rating from 1 to 3 and 4 to 9. The results per rating (range) for this analysis are displayed in Table 4.10 and Figure 4.9.

Table 4.10 and Figure 4.9 show that temperature deviations with a higher rating are more frequently visible during the semi-heat wave in June 2020, especially temperature deviations with a rating from 6 to 8. This can be explained by the structural behavior of temperature deviations with a higher rating. It is also remarkable that three temperature deviations that are rated with a 2 were already visible in June 2020. Two out of these three cases were structural temperature deviations, but the temperature deviation was very small. The other temperature deviation with a rating 2 was a coincidence that appeared during the semi-heat wave in June 2020 and during the heat wave in August 2020. It looks like two independent temperature deviations in June 2020 and August 2020.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	***Total***
Temperature deviation visible	0	3	0	3	0	3	2	3	*14*
Temperature deviation not visible	3	6	3	3	3	1	0	1	*20*

Table 4.10: Visibility temperature deviation of August 2020 in June 2020 per rating

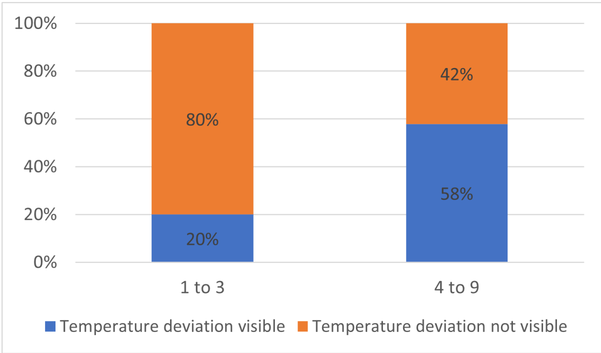


Figure 4.9: Visibility temperature deviation of August 2020 in June 2020 per rating range

Additionally, the other way around is analysed, i.e. if there is a temperature deviation visible during the semi-heat wave in in June 2020, is this still visible during the heat wave in August 2020? Two out of the 21 temperature deviations did not have sufficient data in August 2020 to assess their visibility. The remaining nineteen temperature deviations are evaluated. These results are remarkable, since 84% (16/19) of the temperature deviations during the semi-heat wave in June 2020 are still visible during the heat wave in August 2020. 16% (3/19) of the temperature deviations were not visible during the heat wave in August 2020 anymore. The influence of the rating is again evaluated, and the results are displayed in Table 4.11 and Figure 4.10.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***Total***
Temperature deviation visible	0	3	0	3	2	3	2	3	0	*16*
Temperature deviation not visible	1	0	1	0	0	0	1	0	0	*3*

Table 4.11: Predictability of temperature deviations in August 2020 from prior deviations in June 2020 per rating

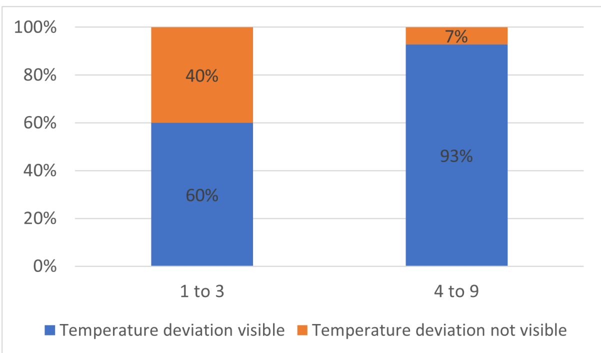


Figure 4.10: Predictability of temperature deviations in August 2020 from prior deviations in June 2020 per rating range

Table 4.11 and Figure 4.10 show that temperature deviations during the semi-heat wave in June 2020 with a rating from 4 to 9 are still visible during the heat wave in August 2020 in 93% of the cases. The temperature deviation with a rating of 7 that is resolved between June 2020 and August 2020 had KCO in the meantime. However, not all temperature deviations are resolved with KCO, because three other temperature deviations with a rating from 4 to 9 had KCO, and these temperature deviations were not resolved. In Figure 4.10, it seems that temperature deviations with a rating from 1 to 3 are also visible during the heat wave in August 2020, because 60% of the temperature deviations during the semi-heat wave in June 2020 were still visible during the heat wave in August 2020. However, the sample size of 5 is insufficient to obtain reliable results. Additionally, the three temperature deviations with a rating of 2 discussed above highly influence this result, while one of these cases was a coincidence and the other two temperature deviations had a small deviation. In contrast, the result for temperature deviations with a rating from 4 to 9 are reliable.

This result highlights a promising way to reduce the demand peak during a heat wave. Under-performing HVACs can be maintained right after a semi-heat wave, or if a heat wave is approaching. However, this does not hold for this situation at NS, since service requests resolve only 27% of the temperature deviations after a service requests. This problem should be addressed before additional maintenance interventions for under-performing HVACs can be included in the maintenance policy.

To evaluate the applicability of these results, the number of semi-heat waves and heat waves in the past 30 years are identified. In the past 30 years, 37 semi-heat waves and 18 heat waves occurred. In 72% (13/18) of the heat waves a semi-heat wave was present prior to the heat wave. The distribution of the number of days between the semi-heat wave and heat wave is illustrated using a box-plot in Figure 4.11. The number of days is calculated from the start date of the semi-heat wave until the start date of the heat wave.

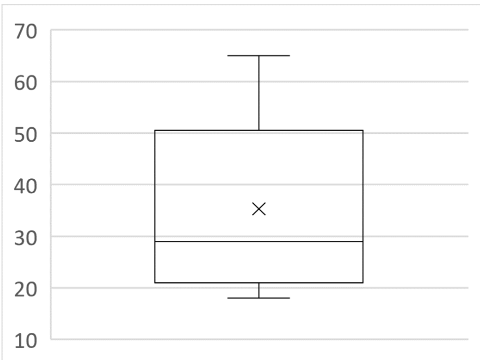


Figure 4.11: Number of days between semi-heat wave and heat wave

The number of days between the semi-heat wave and heat wave is on average 35 days, displayed with the X in the box-plot. 18 days is the minimum, and the maximum number of days between the semi-heat wave and heat wave is equal to 65 days. The median number of days is 29 days. In all situations, sufficient time is left to perform additional maintenance, even with eighteen days. Three days after the start date of the semi-heat wave, sufficient information is available to evaluate which HVACs are under-performing. If the number of days is equal to eighteen, there are still fifteen days left to perform additional maintenance before the start date of the heat wave. A maintenance expert confirmed that one to two weeks is sufficient to perform additional maintenance for these under-performing HVACs.

Moreover, it is analysed how frequently a semi-heat wave is followed by a heat wave. For each year, only the first semi-heat wave is used, because sufficient information is obtained after the first semi-heat wave, so the following ones are not relevant. Furthermore, all semi-heat waves with a start date after August 17 are removed for all years. No heat wave has occurred in September since the heat waves are documented by the KNMI, and at least two weeks before the heat wave are required to perform additional maintenance. It is expensive to perform additional maintenance if the semi-heat wave is not followed by a heat wave. A total of 20 out of 30 years had a semi-heat wave before August 17. 50% (10/20) of these semi-heat waves are followed by a heat wave. It is important to have accurate weather predictions on heat waves to additionally maintain the under-performing HVACs once a heat wave is expected. The accuracy for weather predictions is high for predictions ten days ahead, acceptable for predictions fourteen days ahead, but the accuracy decreases abruptly beyond fifteen days ahead (Lavaysse et al., 2019). Since a semi-heat wave is followed by a heat wave in 50% of the cases and the predictions are acceptable fourteen days ahead, it is better to perform additional maintenance once a heat wave is predicted, instead of right after the end of the semi-heat wave to avoid unnecessary maintenance interventions.

4.3.3. Relation between temperature deviations in 2020 and 2021

Finally, the relation between temperature deviations in 2020 and 2021 is analysed. This analysis is conducted to analyse the potential effectiveness of the annual preventive maintenance tasks in the spring. Section 4.3.1 illustrated that 83% of the temperature deviations with a rating from 1 to 3 is resolved without KCO and service requests. Therefore, the moment in 2020 or 2021 that the temperature deviation is resolved is only identified for all temperature deviations with a rating from 4 to 9. Again, the temperature deviation is resolved if there is no temperature deviation visible after a (semi) heat wave. There are four (semi) heat waves used for this analysis: June 2020, August 2020, September 2020, and June 2021. The KNMI data for September 2020 and June 2021 are displayed in Table 4.12 and Table 4.13, and the temperature data of June 2020 and August 2020 were already presented in Section 4.3.2.

Date	**Temperature**
September 14, 2020	28.5 °C
September 15, 2020	31.4 °C
September 16, 2020	23.5°C

Table 4.12: Temperature semi-heat wave September 2020

Date	**Temperature**
June 16, 2021	28.9 °C
June 17, 2021	30.8 °C
June 18, 2021	29.5 °C

Table 4.13: Temperature heat wave June 2021

September 2020 does not comply with the definition of a semi-heat wave as described in Section 4.3.2, because the maximum temperature at September 16, 2020 is 23.5 °C instead of a maximum temperature above 25 °C. However, it was possible to evaluate the existence of the temperature deviation based on these three days. Hence, an exception is made for September 2020, and it will be used as a semi-heat wave in this analysis.

The total number of temperature deviations with a rating from 4 to 9 is equal to 36 in 2020. One temperature deviation is resolved before the semi-heat wave in June 2020, four temperature deviations are resolved before the heat wave in August 2020, and eleven temperature deviations are resolved before the semi-heat wave in September 2020. As a result, twenty temperature deviations are still visible at the semi-heat wave in September 2020. 65% (13/20) of the remaining temperature deviations is resolved before the semi-heat wave in June 2021, which is high compared to the effectiveness in Section 4.3.1. All thirteen temperature deviations had at least one KCO and the annual maintenance in the spring in the meantime. Eight of these thirteen temperature deviations had a service request in the mean time as well, which means that the temperature deviations might have been resolved by the service request, KCO, or annual maintenance in the spring. Five temperature deviations did not have an additional service request, hence these temperature deviations are resolved due to KCO or the annual maintenance in the spring. It can be concluded that KCO, and especially the annual maintenance in the spring, is more effective than the service requests. However, 35% of the temperature deviations is still visible during the semi-heat wave in June. These train coaches had the annual maintenance intervention in the spring as well. Thus, the annual maintenance in the spring does not solve all temperature deviations.

4.4. Conclusion

Chapter 4 shows the results of the analyses on the relation between maintenance operations and temperature deviations. It can be concluded that temperature deviations with a certainty rating from 1 to 3 indicate small defects or HVACs with insufficient capacity, looking at the fact that these temperature deviations are resolved with and without maintenance interventions. Contrary, temperature deviations with a rating from 4 to 9 probably indicate major defects which should be resolved with appropriate maintenance interventions, because this research study shows that HVACs are not self-healing systems if the certainty rating of the temperature deviation is above 4. The heat maps can be used to differentiate between the certain (1 to 3) and uncertain (4 to 9) temperature deviations, and the extent of the defect. The demand peak during the heat waves can be reduced by maintaining the under-performing HVACs before the heat wave. Information on the under-performing HVACs can be obtained during semi-heat waves, because 93% of the temperature deviations with a rating from 4 to 9 during semi-heat waves are still present during the subsequent heat wave. These under-performing HVACs should be maintained, which is possible in three ways at NS: (i) service request; (ii) trimonthly KCO; (iii) annual maintenance in the spring. Service requests resolve 27% of the temperature deviations rated with a 4 to 9. In addition, KCO and the annual maintenance in the spring resolve some additional temperature deviations, but not all temperature deviations are resolved after these three maintenance interventions, which is alarming for NS. The annual maintenance in the spring seems most valuable for resolving temperature deviations with a rating from 4 to 9.

Chapter 5

Conclusion, Future solution directions, Recommendations & Limitations

The conclusions of this research are presented in Section 5.1. The proposed future solution directions are described in Section 5.2. Section 5.3 outlines the main recommendations to NS. Finally, the limitations and suggestions for future research are addressed in Section 5.4.

5.1. Conclusion

The project assignment of this study was stated as follows: *Generate insights on how NS can use train coach temperature readings to reduce the demand peak for maintenance operations for HVACs during heat waves.* Hereto, three research questions were formulated that enable successfully completing this project assignment. For this research study, nineteen interviews were conducted to answer RQ1 and RQ2, and a data analysis has been performed to answer RQ3.

Chapter 2 shows that NS' maintenance policy contains preventive and corrective maintenance tasks. Preventive maintenance tasks are executed during trimonthly KCOs and the annual maintenance in the spring. Corrective maintenance work orders are requested if HVAC failures occur. Chapter 3 shows four relevant factors that influence the challenges during heat waves: (i) the average temperature per month is positively associated with the number of service requests for HVACs; (ii) the maximum temperature per day seems to be positively associated with the number of HVAC-related work orders during heat waves; (iii) the number of service requests for traction and low-voltage requests also increase during heat waves, which impacts the maintenance capacity for HVAC-related maintenance tasks; (iv) heat waves usually occur in the summer during the holiday season, resulting in less available technicians. Chapter 4 showed that temperature deviations with a certainty rating from 1 to 3 indicate small defects or HVACs with insufficient capacity, looking at the fact that these temperature deviations are resolved with and without maintenance interventions. Contrary, temperature deviations with a rating from 4 to 9 probably indicate major defects which should be resolved with appropriate maintenance interventions, because this research study shows that HVACs are not self-healing systems if the certainty rating of the temperature deviation is above 4. HVACs can be maintained in three ways at NS: (i) service request; (ii) trimonthly KCO; (iii) annual maintenance in the spring. The annual maintenance in the spring seems most valuable for resolving temperature deviations with a rating from 4 to 9.

The obtained results are generalizable, because the results can be applied for other train series at NS, other train companies, and other companies that maintain HVACs (e.g. in buildings). The results can be used for other train series at NS if there are sensors available in the particular train coaches. However, NS' sprinter train series do not have partitions, hence the air can circulate around the entire train. Therefore, the temperature deviation in a train coach is dependent on different HVACs, and it may be more difficult to depict the under-performing HVAC. The same holds for rooms that have multiple HVACs to cool the entire area. Therefore, a requirement to generalize this results might be that it is an enclosed area that is cooled by one HVAC. The generaizability is also dependent on the geographic location and the associated climate. The obtained results are generalizable to countries with a comparable climate as in the Netherlands.

Lastly, the contribution to literature is discussed. To the best of our knowledge, literature on the relation between HVAC maintenance and temperature readings is not available yet. Therefore, this research study is a contribution to the literature, since it shows a maintenance method to reduce the demand peak during heat waves. It is a contribution to the types of diagnostics, as mentioned by Jardine et al. (2006). A type of data mentioned by Jardine et al. (2006) is temperature, and this is a specific case study that proves that temperature readings contribute to the maintenance policy for HVACs. Moreover, it can contribute to research on diagnostics for HVACs. Katipamula and Brambley (2005) reviewed different types of diagnostics for HVAC maintenance, and one example they mention is the measured temperature of a system. Often, the temperature of the system itself is used for diagnostics. In this research study, the temperature readings are indirect measures of the area instead of the system. Therefore, this research study discovered a new type of diagnostics, especially applicable to HVAC maintenance.

5.2. Future solution directions

Based on the performed analyses, insights have been generated on how NS can use the heat maps to reduce the demand peak for maintenance operations for HVACs. This section describes future solution directions for NS based on these generated insights.

Currently, MBN cannot decide on the most suitable maintenance location: GSL or OB based on the work order. Therefore, most work orders for corrective maintenance tasks for HVACs are allocated to GSLs first, and relocated to an OB if refrigeration components should be maintained. However, relocating train coaches from a GSL to an OB is expensive and time consuming. Therefore, it would be beneficial to assess the type of work orders and allocate the corrective maintenance tasks to the most suitable location. The heat maps can be used to allocate the service requests to the most suitable location. If the heat map for the corresponding train coach shows a minor temperature deviation or no temperature deviation, a GSL seems most suitable for the service requests, because it seems to indicate an HVAC with insufficient capacity to fully cool the train coach. Structural, long lasting temperature deviations should be directly allocated to an OB, because this indicates major HVAC defects. Climate technicians at OBs have more certificates and more knowledge on HVAC maintenance, hence the success rate to resolve the temperature deviations is higher than at GSLs. However, GSLs have more unassigned capacity for corrective maintenance tasks, while the maintenance capacity at OBs is already fully utilized. If more work orders are assigned to OBs, the available maintenance capacity at GSL is not being used, while the utilization rate for OBs increases even more. Therefore, one option to consider on the long term is the possibility of certifying some GSL technicians on refrigeration component maintenance to increase the number of work orders that can be handled at GSLs, for example by specializing one GSL in HVACs. As a result, a work order can be allocated to this specialized GSL instead of the fully utilized OB if the heat map for the corresponding train coach shows structural, long lasting temperature deviations. If the heat maps are used to make a distinction between work orders that can be handled at an GSL instead of an OB, the costs for relocating train coaches from a GSL to an OB are expected to reduce.

Moreover, maintenance is always performed when service is requested at MBN, thus for train coaches with and without temperature deviations visible on the heat maps. However, Section 4.3.1 shows that temperature deviations with a rating from 1 to 3 could be resolved without maintenance as well. Furthermore, Section 4.2 shows that 69% of the service requests are performed while there was no temperature deviation visible on the heat map. This study suggests that corrective maintenance tasks seem to be unnecessary for train coaches with temperature deviations rated from 1 to 3 or without temperature deviations visible on the heat maps. In case it was not required, unnecessary maintenance costs were incurred for NS. However, ventilation related corrective maintenance tasks without a temperature deviation must always be performed, because a too high carbon dioxide level is unhealthy for passengers in the corresponding train coach. The heat maps can be used to differentiate between the uncertain (1 to 3) and certain (4 to 9) temperature deviations, and the extent of the defect. As a result, MBN can decide to reject a service request if it is related to the air-conditioning function of the HVAC and no temperature or an uncertain temperature deviation is visible on the heat maps. As described in Section 4.2, 69% (91/132) of the service requests is not associated with temperature deviations. 20 out of these 91 service requests is related to the ventilation function of the HVAC. This means that 54% (71/132) of these service requests is associated with the air-conditioning function of the HVAC and no temperature deviation was visible on the heat maps. If MBN rejects these service requests, the number of service requests can be reduced with around 54%. On the long term, service requests for train coaches with uncertain temperature deviations can be rejected to reduce the number of service requests even more.

The demand peak during heat waves can be reduced by maintaining the under-performing HVACs before the heat wave. Information on the under-performing HVACs can be obtained from the heat maps during semi-heat waves, because 58% of the temperature deviations during heat waves with a certainty rating from 4 to 9 were already present during the preceding heat wave. However, temperature deviations with a rating from 4 to 9 are only resolved in 27%

of the cases with corrective maintenance tasks. This solution involves additional maintenance costs, while the temperature deviation is only resolved in 27% of the cases. Therefore, the success rate should be improved before under-performing HVACs are additionally maintained before the heat wave to avoid unnecessary maintenance costs. Moreover, Section 4.3.2 showed that additional maintenance should be performed once a heat wave is predicted. However, NS is currently not ready to implement this solution, because NS is accustomed to react rather than anticipate on changes. Therefore, the implementation of reacting on semi-heat waves is easier than anticipating on an uncertain heat wave that is approaching. The disadvantage of maintaining under-performing HVACs after a semi-heat wave is that it may involve unnecessary costs, if there is no heat wave after a semi-heat wave. To implement the first situation, in which HVACs are maintained once a heat wave is predicted, it should be investigated what changes in the maintenance process are needed to anticipate on a heat wave. However, the number of under-performing HVACs is expected to reduce considerably if these HVACs are additionally maintained in between the semi-heat wave and heat wave and the success rate of corrective maintenance tasks increases. In case the success rate of corrective maintenance increases to 50% or higher, the number of under-performing HVACs during a heat wave is expected to reduce with 29% (58% $\cdot$ 50%).

5.3. Recommendations

The first recommendation is to share the results with technicians at maintenance locations and discuss possibilities to improve the maintenance operations for HVACs. It is important to make them aware of the results regarding the number of resolved temperature deviations. The reasons for the low number of temperature deviations with a rating from 4 to 9 that are resolved should be identified. If the lack of knowledge is the main reason, managers of maintenance locations can consider additional HVAC courses to improve the success rate. Technicians at GSLs can be educated as well to increase the success rate, for example by specializing one GSL in HVACs. Maintenance experts also mentioned the available time as a restriction for the success rate. Temperature deviations with a rating from 4 to 9 indicate under-performing HVACs. These under-performing HVACs require additional time to be resolved. This additional time can be scheduled for under-performing HVACs with a structural temperature deviation on the heat map, and if a minor or no temperature deviations is visible on the heat map the available time for maintenance tasks should be reduced.

Second, the heat maps should be used structurally in the maintenance operations for HVACs. To increase the accessibility, MBN should attach the corresponding heat map to the service request. Furthermore, MBN can use this heat map to allocate the service request to the most suitable location as explained in Section 5.2. Moreover, the heat map can easily be inspected by the work planner and technician of this service request. The work planner can differentiate between the available time for service requests based on this attached heat map. The technician can use it to understand the relevance of the defect and the type of defect, e.g. a reset for a structural temperature deviations is probably insufficient to resolve the defect. For the long term, an automated system is recommended to attach the corresponding heat map to the service request.

Third, reviewing the criteria for generating diagnosis codes is recommended. As explained in Section 5.2, 54% of the service requests is associated with the air-conditioning function of HVACs, while no temperature deviations were visible on the heat map. If the service request is not associated with a temperature deviation on the heat map, the train driver or attendant probably does not perceive a higher temperature in the corresponding train coach. Therefore, these service requests are most likely triggered by a diagnosis code instead. This is in line with the findings of Budde et al. (2022), in which no strong evidence between diagnosis codes and HVAC failures could be found to predict failures. Hence, studying the relation between diagnosis codes and HVAC failures at NS is recommended, i.e. does this diagnosis code lead to a temperature deviation or degradation of the system? In addition, we suggest to examine the underlying business rules for these diagnosis codes, and adjust the threshold or entire business rule if necessary.

Fourth, a root cause analysis should be conducted to understand why only 27% of the temperature deviations with a rating from 4 to 9 are resolved. Additionally, different methods to maintain HVACs correctively should be considered. Two possible methods are: (i) replace instead of repair HVACs; (ii) execute tasks of the annual maintenance in the spring during each service request. Both methods are discussed with maintenance experts, and they were in favor of the first option. In this situation, the HVAC can be replaced with a spare HVAC, and the defect HVAC can be repaired at the NS components company (NCB) in Berkel-Enschot. This location has more knowledge to repair the HVAC, and the train can be deployed faster. However, HVACs are expensive systems, so it is expensive to have additional spare HVACs in stock. Hence, this possibility should be discussed with many involved parties, such as management of NS, maintenance engineers, and employees working at NCB.

Fifth, under-performing HVAC should be maintained between a semi-heat wave and heat wave. However, the effectiveness of corrective maintenance should be improved before implementing this. As described in Section 4.3.2, temperature deviations with a rating from 4 to 9 during a semi-heat wave are usually still visible during the heat wave. If these under-performing HVACs are maintained prior to the heat wave, and the temperature deviation is resolved due to the maintenance intervention, the demand peak during the heat wave is reduced. The exact moment of maintenance, i.e. after a semi-heat wave or before a heat wave, is dependent on the possibilities at maintenance locations. For the long term, the moment of maintenance is recommended to take place before the heat wave, because the unnecessary costs are lower. This solution is very promising to reducing the demand peak, but only after the maintenance success rate has been improved.

Sixth, a cost analysis is recommended to compare the different suggested solutions based on fleet availability, maintenance costs, passenger comfort, and for example reputation related costs. A possibility to conduct this analysis, is based on multi criteria decision making (Aruldoss et al., 2013). In this method, relevant criteria can be determined, and the importance of the criteria can be defined. The relevant criteria can be expressed in costs, and the optimization can reduce the total costs.

Finally, it is advised to create automated alerts based on measured temperature deviations. This recommendation is likely challenging to implement on the short term, but might be viable as a long term project. The annotations in this research study can be used to validate the model. If the model recognizes a major temperature deviation, an alert arrives at MBN, and MBN can allocate the service request based on this temperature deviations.

5.4. Limitations and future research

The BPMs in Chapter 2 show that the technicians fill in feedback on the repair after the maintenance task is performed, but this feedback is often incomplete. The reason for this is that it is inconvenient to fill it in on the provided iPad in between maintenance tasks. Therefore, technicians usually fill in the feedback on one of the computers after a few maintenance tasks, and this results in feedback as "problem solved". This feedback data could not be used in this research study. Once the feedback data is complete, it would be interesting for future research to analyse the relation between the effectiveness and the performed repair.

The results of Chapter 4 are obtained by analysing the data of 2020. NS had to deal with a heat wave in 2022 as well. It would be interesting to conduct this analysis for 2022 to study the relation between maintenance operations and temperature deviations for different years. The impact of the new structure for the annual maintenance tasks in the spring can be tested with this analysis, because this has changed as of 2022.

Moreover, the analysis is conducted for the VIRM train series, because this is currently the only train series with heat maps at NS. It is suggested to analyze different train series at NS and at other companies, because it would be interesting to verify to what extend the results are directly applicable to other train series.

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Appendices

Appendix A

Literature

For each system, such as HVACs, the right maintenance policy should be identified. Maintenance policy selection aims to determine the most effective maintenance policy for each component, using Figure A.1 (Smit, 2010).

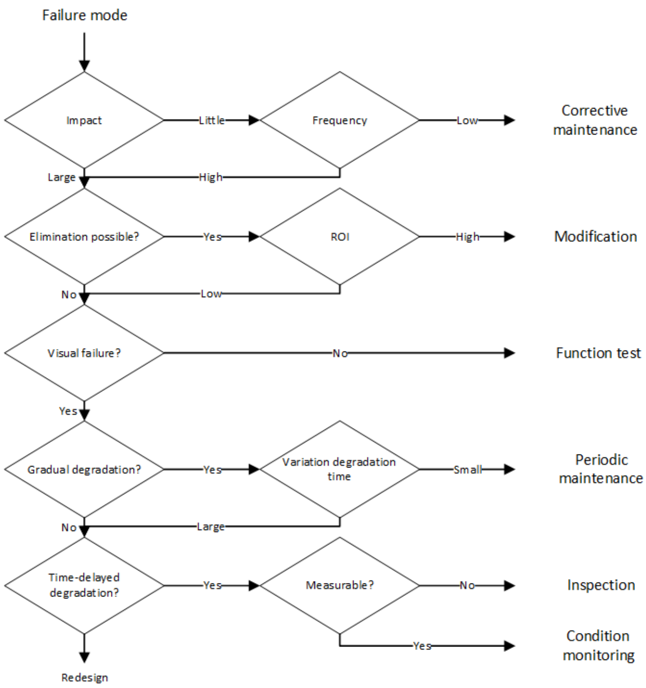

Figure A.1: Decision diagram maintenance policies

Figure A.1 displays the selection of the most effective maintenance policy per component, based on the failure rate, failure impact, degradation visibility, and degradation type. For failure modes with little impact and low frequency, corrective maintenance is applied. For each component that is not eligible for corrective maintenance, the possibility to eliminate the cause of failure is investigated and the corresponding return on investment (ROI) is calculated. If the ROI is above a certain threshold, modification can be applied. Elimination is not beneficial if the ROI is below a certain threshold. In this situation, it is considered whether the symptoms of the failure mode are visual or hidden. For hidden failure modes, a function or availability test should be performed. Whereas for visual failures, it is examined whether the component degrades gradually. In case of gradual degradation, and the variation of the degradation time is small, periodic maintenance is performed. Condition-dependent maintenance is applied to time-delayed degradation types or if there is a large spread of the degradation. If the degradation is measurable, condition monitoring can be used, whereas inspection is used if the degradation is not measurable.

Wu et al. (2006) distinguish four types of maintenance for building systems, such as HVACs:

1. **Test and inspection**: test and inspection are required to meet legislation requirements (e.g. fire alarm systems)
2. **Corrective maintenance**: elimination of the effect of failure
3. **Preventive maintenance** (or scheduled maintenance): maintenance of components is scheduled at specific time intervals to prevent system from failing
4. **Predictive maintenance**: the system is monitored to predict failures and carry out maintenance. The aim of conditioned maintenance is to avoid catastrophic failures.

Figure A.2 displays a different figure to decide upon the type of maintenance to be used, also referred to as maintenance logic tree (Wu et al., 2006).

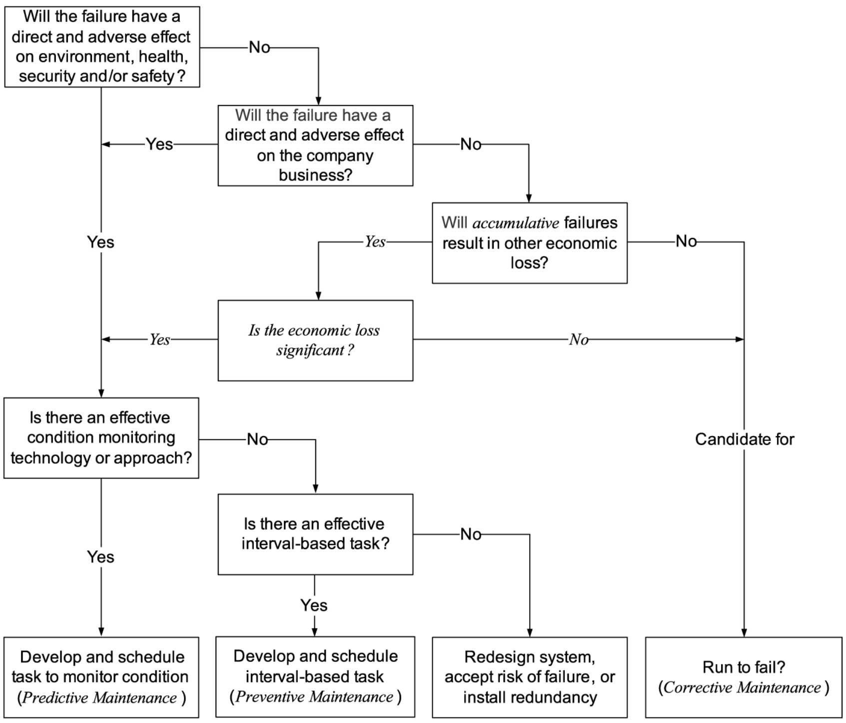

Figure A.2: Maintenance logic tree

The upper four questions in the maintenance logic tree are related to the effect of the failure on various aspects. If the impact is low on all aspects, corrective maintenance must be applied. If the failures have a direct or adverse effect on one of these aspects, the possibility to use condition monitoring is investigated, and predictive maintenance will be performed if this is available. Lastly, a distinction is made between effective interval-based tasks and non-effective interval-based tasks, resulting in preventive maintenance and redesign of the systems, respectively.

The following three most common maintenance methods will be explained in more detail: corrective maintenance, preventive maintenance, and predictive maintenance (Mobley, 2002). Predictive maintenance tasks are performed based on the condition of the system.

A.0.1. Corrective maintenance

Corrective maintenance, in literature also called run-to-failure maintenance, is the simplest maintenance method. Maintenance is performed when a machine breaks down. In terms of costs, expenses are only incurred if a systems fails to operate. Therefore, corrective maintenance is a reactive maintenance method. If prognostics information on a component is available, corrective maintenance management is the most expensive maintenance method for that component (Tsakatikas et al., 2008). The most significant expenses are high overtime labor costs, high machine downtime, and low production availability. In addition, extensive spare part inventories are required to react adequately to the requested maintenance tasks (Tsakatikas et al., 2008).

In addition, failure diagnostics can be difficult for troubleshooting HVAC-related problems (Yang and Ergan, 2016). The increased complexity of modern HVAC systems results in difficulties to diagnose the failing component (Yang and Ergan, 2013). Therefore, applying corrective maintenance can become complicated for HVAC systems. Facility-specific information should be provided to HVAC mechanics in order to maintain the HVAC systems effectively. Yang and Ergan (2013) studied 23 corrective maintenance work orders with expert HVAC mechanics to understand their rationale of handling corrective maintenance work orders. The captured work flow consists of five main stages:

1. **Receive a work order**: a work order with different basic information fields, such as location or symptoms of the problem, is assigned to a HVAC mechanic.
2. **Perform a general check**: in this general check, additional factors (i.e. sensors) can be checked which can cause the problem instead of mechanical faults.
3. **Perform a detailed inspection**: a detailed inspection is performed to understand the problem and check whether it is a mechanical fault. In this state, understanding of the HVAC system is required to do the inspection.
4. **Perform testing**: if the mechanic has located the component that might be failing, a test is performed to check if the component is malfunctioning. It could be that multiple components are tested to identify the failing component.
5. **Deploy remedies**: the final stage involves repairing or replacing the corresponding malfunctioning components.

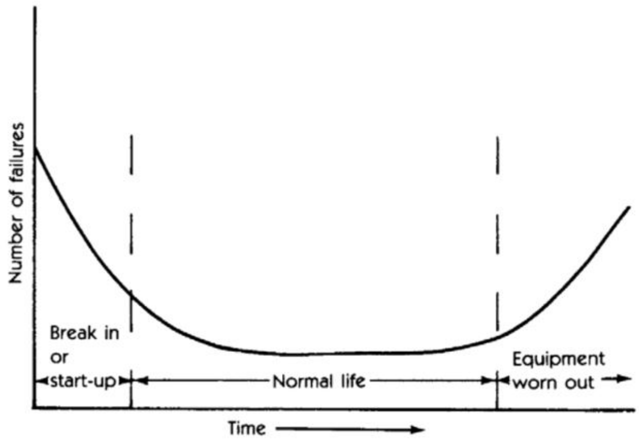

Figure A.3: Bathtub curve preventive maintenance

However, obtaining relevant information to identify the malfunctioning component in step four is challenging. Different types of information are required to identify the problem and deploy the corresponding remedies. Moreover, information requirements change for different work orders, and a systematic way to collect the relevant information lacks in the process. Yang and Ergan (2016) introduces a systematic way to identify malfunctioning components by the use of visualizations, such as color-coding. The required search time for the right documents can decrease by 58% by the use of visualizations.

A.0.2. Preventive maintenance

The second common maintenance method is called preventive maintenance. Preventive maintenance is a type of planned maintenance, because components are repaired or replaced periodically (Prytz, 2014). Preventive maintenance tasks are usually based on operating hours or elapsed time. The statistical life of a machine can be illustrated by a bathtub curve displayed in Figure A.3 (Mobley, 2002).

As Figure A.3 displays, a new machine has a high probability of failure during the start-up phase in the first period of operation due to installation problems or production errors of the component that may occur. In the normal life period, the probability of failure decreases to a constant, and relatively low number for an extended period. In the equipment worn out phase, there is a considerable growth of number of failures based on elapsed time. Preventive maintenance tasks, i.e. machine repairs, are scheduled based on the bathtub curve. However, the implementation in terms of number of repairs can vary between different situations. Limited preventive maintenance tasks can be scheduled, but comprehensive preventive maintenance tasks also exist with large adjustments. The costs of preventive maintenance decrease considerably compared to corrective maintenance for components that are eligible for preventive maintenance, because the repairs are on a scheduled basis (Prytz, 2014).

Preventive maintenance should be applied to most HVAC systems that are located in buildings (Kwak et al., 2004). The importance of preventive maintenance programs for HVAC systems is stressed by Suttell (2006): “Think of preventive HVAC maintenance in the same way as the preventive maintenance for your car: If you don't change the oil and replace belts and filters, the engine will lock up and the vehicle won't operate. The same holds true for HVAC systems." For HVAC systems, time-based preventive maintenance is usually applied to non-repairable items with a lifetime distribution. The lifetime can be estimated by calendar time, driven kilometres or consumed fuel (Prytz, 2014). Preventive maintenance tasks should be scheduled at the moment that the remaining useful life (RUL) based on the lifetime distribution is as little as possible.

A.0.3. Predictive maintenance

Lastly, predictive maintenance will be introduced. Predictive maintenance has different definitions in literature. In several literature studies, predictive maintenance and condition-based maintenance are distinguished as two classes of maintenance policies (Susto et al., 2012). Susto et al. (2012) describes condition-based maintenance as the phenomenon that actions on the process are taken based on the conditions of the equipment, such as degradation. To perform the right condition-based maintenance tasks, continuous monitoring of the machinery health is required. Condition-based maintenance tasks cannot be planned in advance. The definition of predictive maintenance is as follows regarding Susto et al. (2012): predictive maintenance is similar to condition-based maintenance, because maintenance actions should only be performed when necessary based on the health state. However, prediction tools are used, instead of continuous condition monitoring.

Contrary to Susto et al. (2012), most literature studies consider predictive maintenance and condition-based maintenance as the same category. According to Prytz (2014) and Mobley (2002) predictive maintenance uses a monitoring system or prediction model to determine the machinery condition, predict the likeliness of failure, and minimize the number and corresponding costs of unscheduled outages. This definition will be used in this literature review. A result of predictive maintenance is improved productivity, product quality and overall plant operation.

Actual data and effective tools are used to determine the operating condition of critical components. Based on these results, maintenance activities are scheduled on an as-needed basis. On the one hand, predictive maintenance improves machine availability, hence productivity. On the other hand, it reduces the costs of maintenance and improves the profitability. In order to perform predictive maintenance, real time monitoring features are required instead of average-life statistics.

There exist two different approaches for predictive maintenance (Satta et al., 2017): the phenomenological (data driven) approach and the model-based approach. In the phenomenological approach, detection of imminent failures is based on anomalous behavior compared to normal behavior in historical data. The latter approach uses a model of the appliance to compare the actual behavior with the simulated behavior to detect outliers.

Predictive maintenance is the most appropriate strategy for HVAC systems if the components fail accidentally (Kwak et al., 2004). The diagnostics and prognostics processes are used for HVAC-related predictive maintenance (Gálvez et al., 2021). Especially, RUL predictions precedes the determination of predictive maintenance tasks. The process of condition-based maintenance, applicable to HVAC related predictive maintenance, consists of four steps, displayed in Figure A.4 (Gálvez et al., 2021).

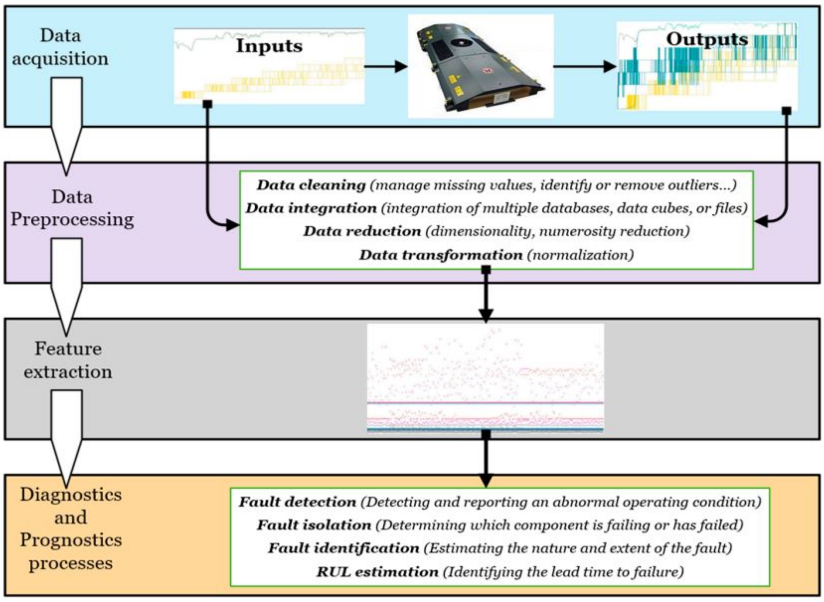

Figure A.4: Steps condition-based maintenance

First, data is acquired by sensors in the system. Data acquisition is followed by data processing, in which the data is prepared for the feature extraction process. The feature extraction process transforms data in an assessment on the condition of the equipment. Lastly, diagnostics and prognostics result in the RUL estimation, and eventually the corresponding predictive maintenance tasks can be defined.

The condition-based maintenance concept explained by Jardine et al. (2006) is comparable to the above mentioned process. However, Jardine et al. (2006) divides the creation of a condition-based maintenance concept in three steps:

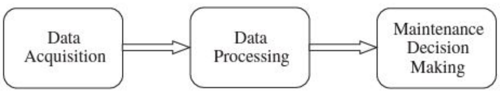

Figure A.5: Three steps of condition-based maintenance

The first step, data acquisition, is required to collect data containing the system's health. A relevant type of sensor data for this research study mentioned by Jardine et al. (2006) is temperature data from sensors, which is in line with the available sensor data of HVAC systems in trains at NS. Therefore, temperature readings can be promising for predictive maintenance. However, predictive maintenance of HVAC systems based on temperature readings is not performed in other literature studies yet. The second step, data processing, is required to understand and interpret the data obtained in the data acquisition phase. This phase starts with cleaning of the data, which could be removing errors caused by sensor faults. Lastly, decisions should be made regarding the most efficient maintenance policy. Jardine et al. (2006) stresses the importance of diagnostics and prognostics in condition-based maintenance as well.

Satta et al. (2017) proposes a dissimilarity-based approach to apply predictive maintenance for HVAC systems. The goal of a predictive approach is to identify anomalous behavior which could indicate a failure. In order to recognise anomalies, a set of homogeneous appliances should be identified. An anomaly is a data point that is not in line with the expected behavior (Chandola et al., 2009). A well-known synonym for anomalies is outliers, which also recognises nonconforming patterns in data sets. Homogeneous appliances are machinery with compatible properties, e.g. all HVAC's in a train. Satta et al. (2017) refers to this as the cohort of appliances.

This cohort of appliances, in Satta et al. (2017) a set of 17 HVAC systems in a hospital, is used to perform predictive maintenance tasks. Mutual dissimilarities between appliances in the cohort can be used to foresee an upcoming failure. A proactive intervention can be used to maintain the anomalous component to avoid interruption after a failure. A machine learning approach is used to analyse the dissimilarities within the cohort. The machine learning model to recognise failures is trained with faults in historical data. An important advantage of mutual differences instead of absolute values is that seasonal trends and biases are included in the model. Satta et al. (2017) uses a phenomenological approach in their proposed model, because machine learning techniques have shown many success cases in recent years. The performance evaluation of the dissimilarity approach is based on the cost of errors related to fault forecasting.

A.0.3.1. Evaluation failure prediction

The quality of a maintenance policy can be assessed by the costs of two different errors (Susto et al., 2012):

- **Unnecessary maintenance (type I error)**: a maintenance action is performed, because a failure is predicted. However, the system or component would not have been out-of-control if the maintenance task was not performed. So, unnecessary maintenance is performed. The corresponding costs are related to the time spent of mechanics repairing the component, and the costs of replaced spare parts must also be included if the component is replaced.
- **Unprevented out-of-control state (type II error)**: the system has failed, but no maintenance intervention has taken place, because there were no failures predicted. The costs of the out-of-control state, resulting in a reduced production quality, are the corresponding costs for this error.

Often, these errors are called false positives and false negatives (Fielding and Bell, 1997). A false positive, error type I, refers to the situation that a maintenance task has been performed while the system would not have failed. By contrast, a false negative or type II error occurs if the system has failed while no failure was expected. False negatives have more impact on the operation, because of the unplanned maintenance intervention. In addition, the costs for false negatives are usually higher than for false positives. Therefore, extra attention should be given to false negatives. A confusion or error matrix can be used to display the different situations (Visa et al., 2011):

	Predicted Negative	Predicted Positive
Actual Negative	a	b
Actual Positive	c	d

Figure A.6: Confusion matrix

In Figure A.6 four different situations are distinguished, indicated with a, b, c, and d:

- a: the number or percentage of **true negatives**: no maintenance task has been performed, and no failure has occurred.
- b: the number or percentage of **false positives**: maintenance task has been performed, but no failure would have occurred without maintenance intervention.
- c: the number or percentage of **false negatives**: no maintenance task has been performed, but a failure occurred.
- d: the number or percentage of **true positives**: maintenance task has been performed, and a failure would have occurred without maintenance intervention.

As a result of the confusion matrix, the prediction accuracy and classification error can be calculated by the following formulas (Visa et al., 2011):

$$\text{Accuracy} = \frac{a+d}{a+b+c+d} \tag{A.1}$$

$$\text{Error} = \frac{b+c}{a+b+c+d} \tag{A.2}$$

Accuracy is the most commonly used prediction measure, it measures the number or percentage of correctly classified cases (Fielding and Bell, 1997). Contrary, the error measure is the number or percentage of incorrectly classified cases. This number should be decreased as much as possible.

Two additional parameters to assess a maintenance policy for HVAC systems are (Gluck et al., 2017):

- **Prediction look-ahead length**: The look-ahead time is the time it takes to change the temperature in a room to a certain temperature, which is described as the optimal temperature. If the look-ahead prediction is too short, the room temperature cannot be appropriately cooled in the desired time. On the other hand, energy is wasted if the look-ahead length is too long, because the room temperature is optimal too early. In terms of

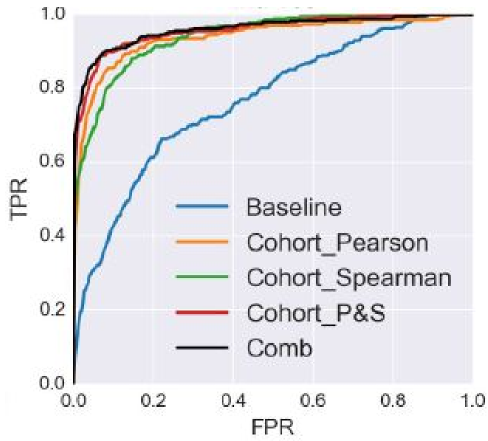

Figure A.7: ROC curve

trains, a too long look-ahead length means that a train coach is at optimal temperature before passengers are in the train.

- **Temperature setback settings**: the minimum and maximum temperature measures within an indoor area before the HVAC turns on. These settings can be tweaked to change the number of required maintenance interventions. However, unoccupied train coaches should have different temperature bounds, to avoid energy waste.

For the above mentioned parameters, it is usually a consideration between the impact on energy consumption and the comfort of passengers.

The performance evaluation for HVAC-related predictive maintenance used by Satta et al. (2017) is a receiver operating characteristics (ROC) curve. By the use of this curve, a trade-off can be made between false positives and false negatives, based on the set threshold value. In the case of HVAC systems, a higher temperate deviation threshold will result in less maintenance tasks, hence less false positives and more false negatives. If a lower temperature threshold is set, the number of false positives increase, and false negatives decrease. An example of a ROC curve is displayed in Figure A.7.

The false positive rate (FPR) is displayed on the x-axis, and the true positive rate (TPR) on the y-axis. The obtained percentages in the confusion matrix can be used to construct this graph. A line localized close to the left upper corner performs best. A different method to evaluate the performance is to compute the Area Under the ROC Curve (AUC). Satta et al. (2017) found that the dissimilarity-based cohort approach performed best for HVAC systems. This means that anomalous behavior can be detected easier by mutual dissimilarities instead of each appliance in isolation. However, a combination of different features outperformed the individual approaches.

Appendix B

Interviewees

Function interviewee	Number of interviews
System Engineer	1
System Engineer	1
Reliability Engineer	3
Reliability Engineer	1
Maintenance Engineer	1
Maintenance Engineer	1
Production Engineer	1
TMM	4
Climate technician	1
Engineering Manager GSL	1
GSL technician	1
Fleet analyst MBN	2
Process Manager MBN	1

Appendix C

Interview Questions RQ1

C.1. Production engineer

- How do you schedule preventive maintenance?
- How do you receive notifications for corrective maintenance?
- How do you schedule requests for corrective maintenance?
- What are the main dilemmas/bottlenecks in scheduling work?
- How is the available time determined?
- What happens if the maintenance turns out not to fit within the prescribed time?
- What happens if the maintenance cannot be scheduled within the time of the Q-procedure?
- To what extent is there room to perform additional maintenance operations?
- How is it determined which technician is needed for the maintenance task?
- How is the required material for maintenance determined?

C.2. TMM

- What does maintenance for HVACs entail?
- Where on the train does most maintenance take place (on the roof or on the train)?
- How is it determined which materials are required for maintenance?
- What tests are performed when maintaining HVACs?
- How are diagnosis codes used in maintenance operations?
- How are the heat maps used in maintenance operations?
- How is feedback given on maintained HVACs, i.e. how is determined if the maintenance task was successful?

C.3. Climate technician

1. What do you pay attention to when checking an HVAC?
2. How do you know what tasks to perform?
3. How do you perform preventive maintenance operations for the HVAC?
4. How do you perform corrective maintenance operations for the HVAC?
5. How do you use the heat maps when maintaining the HVAC?
6. How do you use the diagnosis codes when performing preventive maintenance for HVACs?
7. How do you use the diagnosis codes when performing corrective maintenance for HVACs?
8. Does the prescribed maintenance often fit into the prescribed time?
9. To what extent is time available for additional maintenance tasks?
10. To what extent do you notice a difference in the amount of work during heat waves?

C.4. Fleet analyst MBN

- How are work orders triggered?
- How are the work orders for corrective maintenance scheduled?
- How do you get from work order to the performed maintenance operation?
- How is the maintenance location determined (SB/GSL/OB)?
- How are Q procedures determined?

Appendix D

Interview Questions RQ2

D.1. Standard questions RQ2

- What challenges do you experience in terms of maintenance for HVACs during heat waves?
- What challenges do you experience for other systems during heat waves?
- What problems do you encounter in terms of maintenance on HVACs?
- What do you think could be improved for maintenance operations of HVACs?

D.2. Reliability engineer

- How does NS evaluate the reliability in general? And for HVAcs?
- How does NS evaluate the availability in general? And for HVAcs?
- What is your experience with the reliability of HVACs?
- What do you experience during heat waves due to failing HVACs?
- How does NS prioritize maintenance tasks for HVACs and other systems such as traction that also require more attention during heat waves?

Appendix E

Boxplots temperature expectation

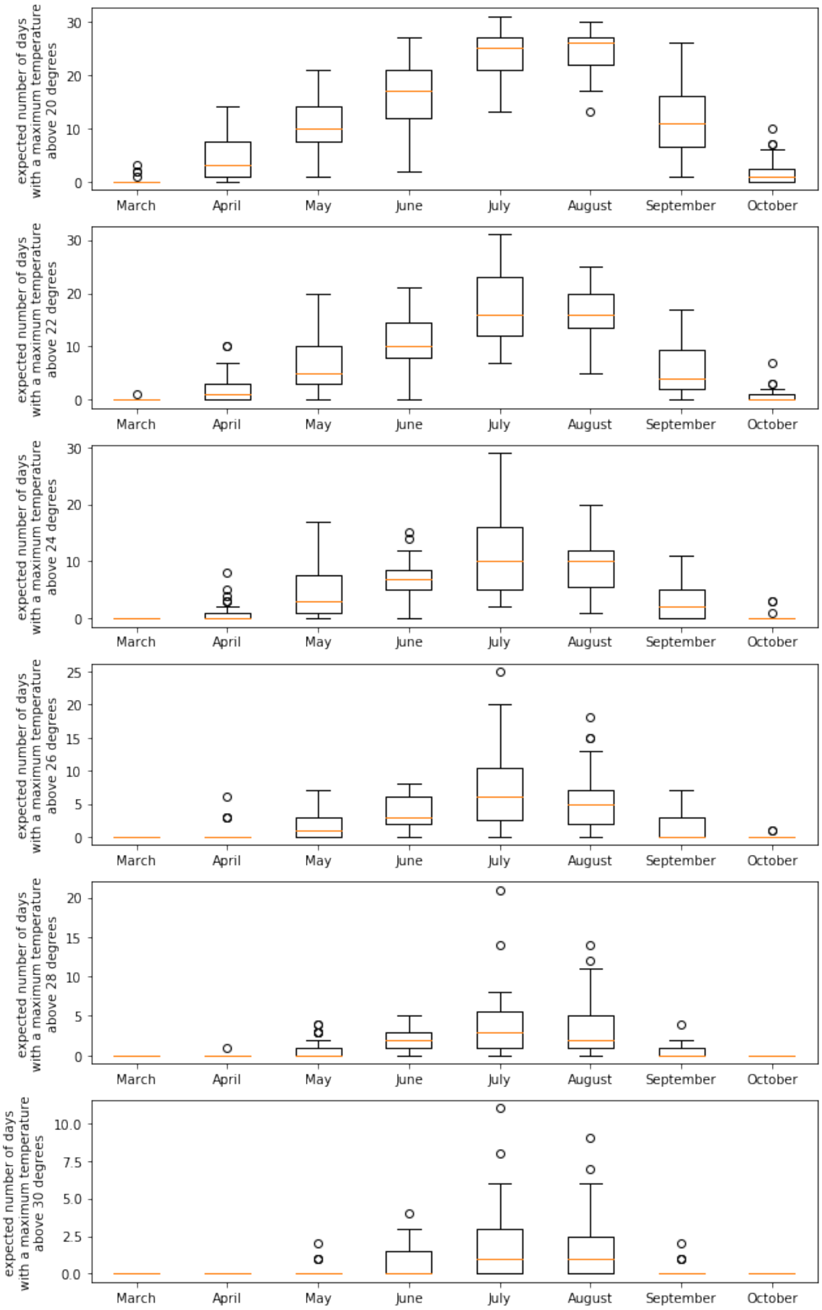

Figure A.1: Box-plots temperature expectation

Appendix F

Figures sensitivity analysis

The conclusions for the effectiveness are drawn based on the blue part of the bars for temperature deviations with a rating from 1 to 3, and on the orange part of the bars for temperature deviations with a rating from 4 to 9. A higher percentage for the corresponding part of the bar results in a higher reliability of the conclusions, because a result that is true for 80% of the cases is more reliable than if it is true in 50% of the cases. Therefore, the different aggregations are tested based on the deviation from the percentage in the used aggregation, referred to as best aggregation. Four different aggregations are tested: 1 to 2 and 3 to 9, 1 to 3 and 4 to 9, 1 to 4 and 5 to 9, and 1 to 5 and 6 to 9. The deviation from the used aggregation is displayed in white. An increase in the percentage improves the reliability of the drawn conclusions, whereas a decrease reduces the reliability of the drawn conclusions. The four used situations are tested: temperature deviations with a service requesting including KCO; temperature deviations without service request including KCO; temperature deviations with a service and without KCO; and temperature deviations without service request and without KCO. For all four situations, the used aggregation has the highest percentages for the combination of the blue and orange part of the bar.

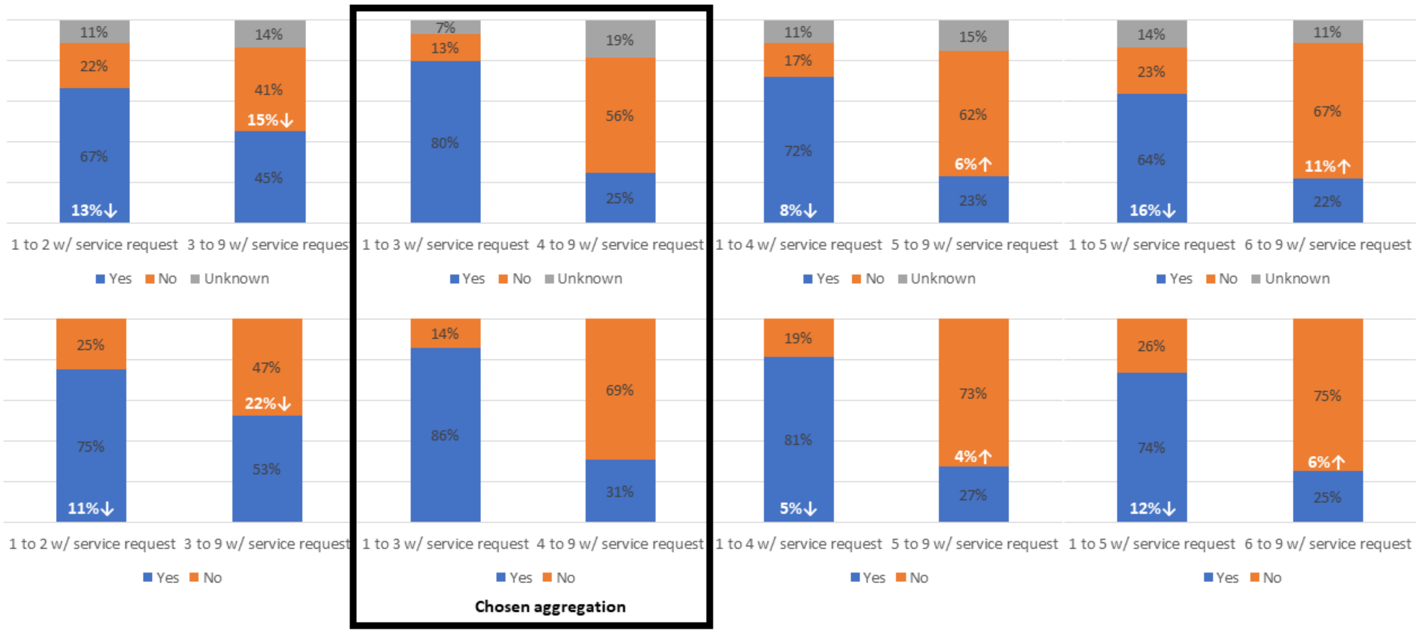

Figure A.1: Temperature deviation resolved with service request?

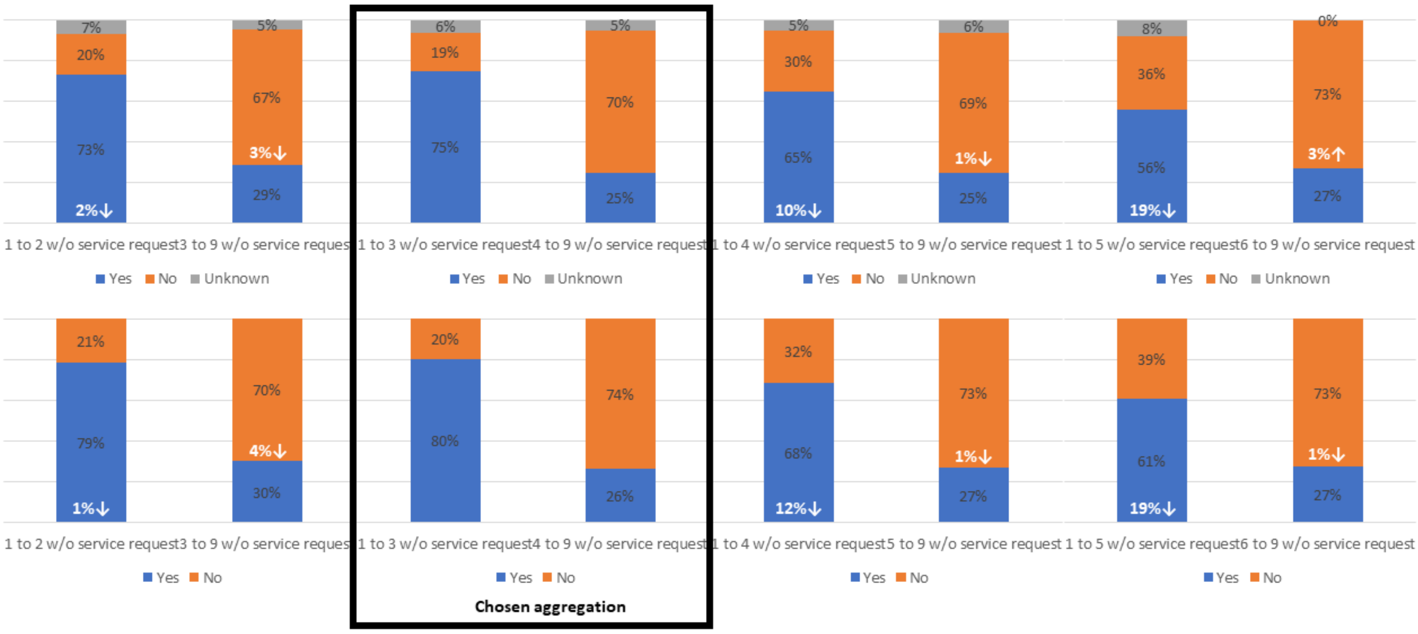

Figure A.2: Temperature deviation resolved without service request?

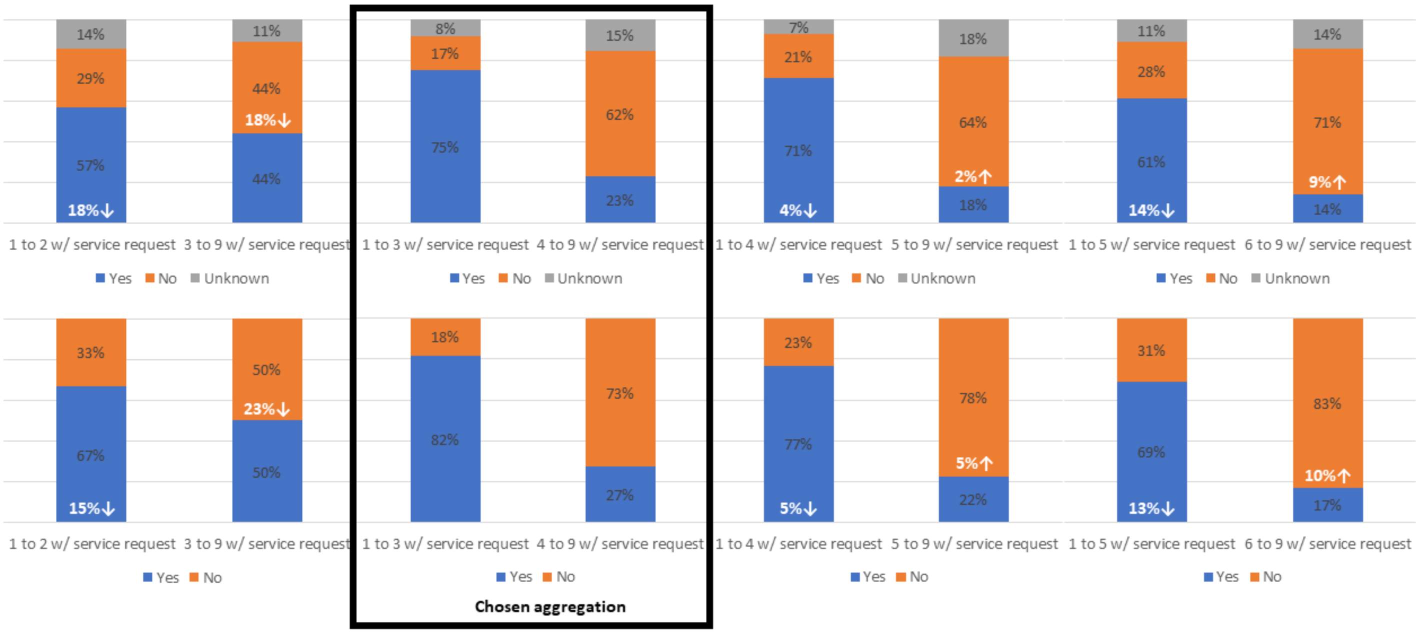

Figure A.3: Temperature deviation resolved with service request and without KCO?

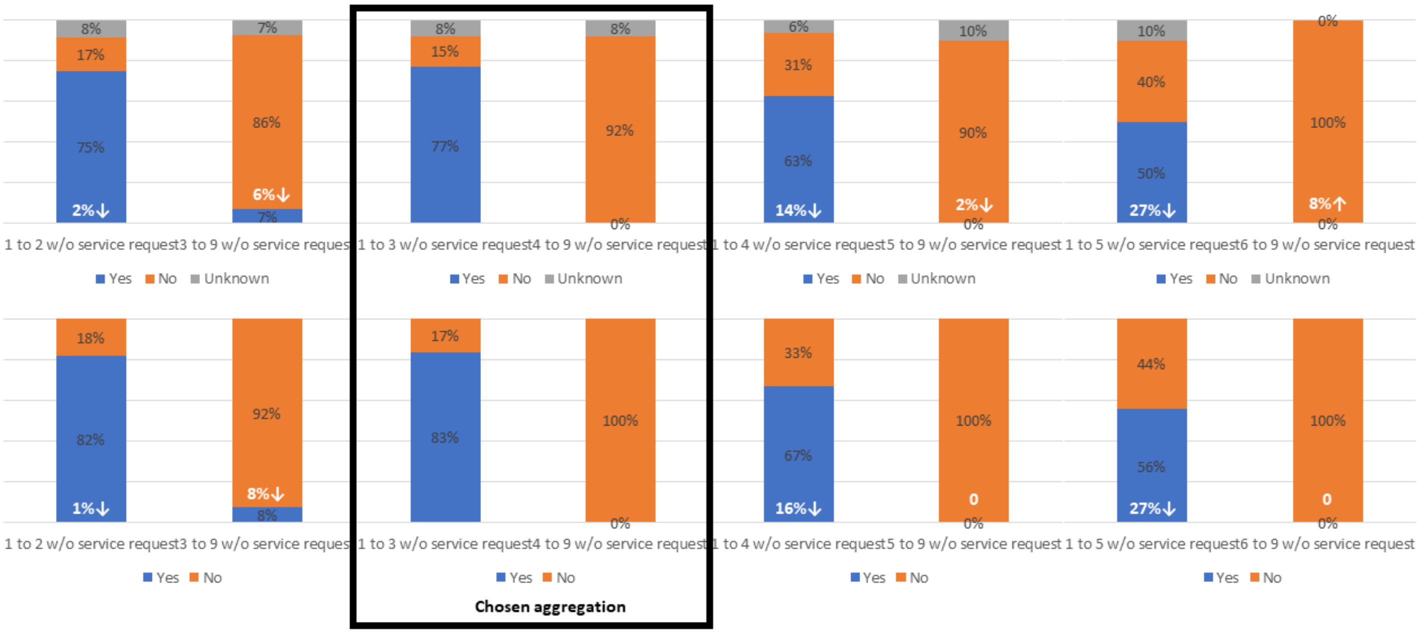

Figure A.4: Temperature deviation resolved without service request and KCO?