Exploring predictive maintenance applications in industry

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ABSTRACT

Purpose - Asset owners and maintainers need to make timely and well-informed maintenance decisions, based on the actual or predicted condition of their physical assets. However, only few companies have succeeded to implement Predictive Maintenance (PdM) effectively. This paper aims to identify why.

Design/Methodology/Approach - A multiple-case study including thirteen cases in various industries in the Netherlands is conducted. This paper examines the choices made in practice to achieve PdM, and possible dependencies between and motivations for these choices.

Findings – An implementation process for predictive maintenance appears to contain four elements: a trigger, data collection, maintenance technique selection and decision making. For each of these elements, several options are available. By identifying the choices made by companies in practice, and mapping these on the proposed elements, logical combinations appear. These combinations provide insight in the PdM implementation process, and may lead to guidance on this topic. Further, while successful companies typically combine various techniques, the mostly applied techniques are still those based on (previous) experiences.

Research implications - This research calls for better methods or procedures to guide the selection and use of suitable types of PdM, directed by the firm’s ambition level and the available data.

Originality/value - While it is important for firms to make suitable choices during implementation, the literature often only focuses on developing additional techniques for PdM. This paper provides new insights in the application and selection of techniques for PdM in practice and helps practitioners reduce the often applied trial-and-error process.

Keywords: maintenance decision making, condition-based maintenance, case studies, prognostics, diagnostics, implementation.

Paper type: Research paper

1. Introduction

1.1. Background

Nowadays, many companies use smart components, such as sensors and microprocessors, to provide feedback about the use, degradation, environment, and location of their physical assets. Effective use of these data helps to head off problems, such as unplanned failures. Collecting these data has become a simple exercise (Lee et al., 2015). But, these data are not useful unless processed in a way they give context and meaning that can be understood by the right personnel (Lee et al., 2015). If that is achieved, predictive maintenance (PdM) becomes feasible.

In this work, predictive maintenance (PdM) is defined according to the European norm EN 13306-2017 as condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item. This implies that maintenance activities (e.g. repairs, replacements) are based on an estimated, measured or calculated assessment of the current and the future state of physical assets. This state or condition assessment can be achieved by applying one of many available methods or analytic techniques, which are called maintenance techniques (MTs) in this paper. These MTs typically use data associated to the asset as input, which can range from condition or loading data provided by sensors, to experience on failure frequencies provided by machine operators.
Although predictive maintenance is often referred to as condition-based maintenance (CBM), predictive maintenance is more than CBM, as it (also) takes prognostic information into account (Shafiee, 2015). Where CBM is based on the (mostly measured) current condition of an asset, PdM is based on an estimate or calculation (i.e. prediction) of the current or future asset condition. This typically provides a longer response time (to a failure), so the MTs enabling PdM assist decision makers to take better-informed maintenance decisions and improve the performance of physical assets.

Examples of commonly applied MTs are experience-based methods like Failure Mode and Effect Analysis (FMEA), data-driven approaches and failure prediction methods based on the physics of failure. With these MTs, insights can be obtained from the collected data that help to determine the remaining useful life (RUL) and the probability a machine works without a failure up to a certain time (Jardine et al., 2006). As will be discussed later, the accuracy and potential of the different MTs varies enormously, but even the simplest MTs (e.g. experience-based, FMEA-type) already provide insights that improve the (predictive) maintenance decision making.

Although many MTs are proposed and described in the academic literature, previous research shows that practitioners find it difficult to apply these techniques for PdM in practice (Tiddens et al., 2015). Also Kerkhof et al. (2016) reported that many companies struggle with implementing PdM. This is confirmed by the case studies performed for the present work: in none of the 13 cases the companies had a predefined structured approach for selecting and implementing the techniques. Moreover, Grubic et al. (2011) show that companies that have applied these techniques experience a gap between the potential and realised benefits. Several reasons can be found for this. Firstly, as also mentioned by other authors (Kerkhof et al., 2016, Garg and Deshmukh, 2006, Veldman et al., 2011), most research within the field of PdM ignores the organisational and managerial facets and only addresses the technical aspects. The latter includes developing accurate sensors, algorithms and models. Secondly, there still is a limited understanding about how PdM can aid further business and service model innovation and what the essential factors are for this (Grubic, 2014). This knowledge might not only be of importance to the asset owner, it is also essential for service providers and OEMs (original equipment manufacturers) when offering performance-based or availability-based contracts.

Thirdly, practitioners experience difficulties in selecting the optimal combination of collected data and maintenance techniques for informed maintenance decision making (Tiddens et al., 2015). This may however become the main factor determining whether a prognostic system is useful and effective (Bo et al., 2010). Many literature reviews of PdM are limited in helping practitioners and industry users select a suitable MT for their specific needs (Sikorska et al., 2011, Dekker et al., 1997, Tiddens et al., 2016). It is this final problem this work focuses on.

1.2. Goal of the study

The aim of this study is to identify the ratio behind the selection of specific MTs (enabling PdM) and other elements required for informed maintenance decision making. The main research question therefore is: “Why have certain MTs been selected and combined with other elements for predictive maintenance decision making in practice, and which of these combinations were successful?” The term successful is not an absolute measure, but refers to whether or not the ambitioned improvement in a specific situation can be achieved. This research leads to the identification of dependencies and factors that can be influenced in that selection process, thus supporting practitioners in identifying and selecting suitable ways for predictive maintenance decision making.

1.3. Research method and outline of the paper

To achieve this goal, it is first important to study possible ways for predictive maintenance decision making from a theoretical point of view. Therefore, we first studied the steps the academic literature describes to use PdM and associated maintenance techniques, resulting in the overview of various elements required for predictive maintenance decision making in Figure 1. To apply this framework and map combinations that have been selected in practice, we conducted a multiple-case study with multiple embedded objects (Yin, 2009), as will be explained in section 3.1. This case study – in which we studied
thirteen cases in various industries in the Netherlands – provides insight on how these maintenance techniques are used. In section 3.3, the results of six of the thirteen case studies are mapped onto the proposed framework of Figure 1. In section 4, we discuss why certain combinations have been selected in the case studies and identify the relative occurrence of different MTs within the case studies. Finally, conclusions, limitations and general reflections will be given in section 5.

2. Implementing MTs: the predictive maintenance framework

The first phase of this study explores the various elements described in academic literature to use MTs for predictive maintenance decision making. Based on that exploration, four elements or basic choices are proposed to support effective decision making based on MTs. Each of the elements contains several options, from which one has to be selected. The proposed framework, shown in Figure 1, guides the user of the MTs in selecting the best option for each of the four elements, that will be present in any PdM implementation process. Since each element contains several options, the possible ways for predictive maintenance decision making (i.e. combination of element options) are numerous, and the selection of a suitable option is challenging. Although these elements could be seen as logical consecutive steps, the order is not fixed and the elements can be considered in a different order (e.g. first selecting the maintenance technique before selecting which data to gather). The four elements, or basic choices to be made, and their options will be discussed in more detail next.

![Figure 1. The four required elements for predictive maintenance decision making, demonstrating the numerous combinations. Based on Jardine et al. (2006), Coble and Hines (2008), and Dibsdale (2015).](chart)

2.1. Element A: Initiation

The first step in the framework is the initiation of the project. The initiation motivates the what, why and how of the maintenance techniques application. The technique can be induced by technology push: a new technology or a new application of that technology is available. Or a certain decision (support)
is desirable: the quest for a technique is born of economic necessity (Dekker, 1996), known as decision pull. Oftentimes, the initiation will be a combination of a technology push and decision pull. This project start-up process coincides with the choice of equipment to be considered (see also Tiddens et al. (2018), Tiddens et al. (2017)), and is closely related to deciding what to monitor and which data to gather (element B), selecting the maintenance technique (element C) and constructing a solid business case to convince stakeholders and investors. The business cases analysis requires to balance the decrease in number and consequences of failures and cost of maintenance with the cost of implementing PdM, as for example shown in Tiddens et al. (2017).

2.2. Element B: Monitoring and data gathering

The second element of predictive maintenance decision making concerns selecting the parameters to monitor and gathering the (available) input data. Data can be gathered from monitoring systems, but also from historical records. These historical records contain event data, reflecting what happened to a piece of machinery, for example failures, overhauls, and repair actions (Jardine et al., 2006). Note that the data collected for the less advanced techniques, such as technical knowledge for the experience-based predictions, can also be used for the more advanced techniques, e.g. model-based predictions, but then needs to be combined with more advanced information (e.g. condition monitoring).

Several types of data gathering and monitoring strategies can be used, which have been clustered in four types in the proposed framework.

1. *Asset history data* can be gathered from technical knowledge, inspections and historical records of e.g. failures or costs;
2. *Usage and process data* entails operational data, e.g. running hours, mileage, or tons produced;
3. *Stressor-data* describes the exerted loads (stressors) on the system. This preferably includes environmental data, e.g. temperature and moisture (Farrar and Lieven, 2007). Load monitoring is the process of collecting loading data on the component itself, e.g. temperature, vibration, humidity, strain or electric current (Tinga, 2010). Process sensors can provide data relating to output characteristics, e.g. pressure, flow, and temperature (Veldman et al., 2011);
4. Data related to signs of imminent failure of the equipment can be collected. *Condition monitoring* is the process of acquiring such information, e.g. vibrations, acoustics or oil quality. (Structural) health monitoring techniques collect data from the measured dynamic response (vibrations) of structures to identify damage and quantify the extent of this damage (Tinga and Loendersloot, 2014). An example of this approach is measuring the vibration response of a steel bridge to wind and traffic loads to detect cracks in the structure.

2.3. Element C: Maintenance techniques

The third element concerns the selection of the suitable MT and conduction of the maintenance analysis. The available data and the required outcome (also depending on the asset, its criticality, and the behaviour and the usage of this asset) determine what MT to select. This requires prior consideration of the amount and quality of the available data and the possibilities for data collection (element B), as well as the ambitioned decision making (element D).

Among reviewers within the prognostic field, little consensus exists what classifications of prognostics are most appropriate (Sikorska et al., 2011). In this paper, two classifications are adopted to encompass the various views in this field: on the type of method and on the type of input. In the first categorization, the model proposed by Coble and Hines (2008) is adopted, which is already extended by Dibsdale (2015) with category V (model based). We further extended this with the least advanced, experience-based route by separating the methods that use historical records (data) and those that only use expert knowledge and the experience of people who use and maintain the equipment. The framework now comprises of five types of MTs:

I. Experience-based predictions of failure times are based on knowledge and previous experience outside (e.g. OEM) or within the company. Sometimes they are supported by little or scattered data. Predictions are based on expert judgement (e.g. facilitated by FMECA techniques). These
methods (subjectively) estimate the life of an average component operating under historically average conditions. Although this traditional type of methods is generally not associated to predictive maintenance, they do enable rough estimates of time to failure. It is therefore believed that these methods, that make experience of operators or technicians explicit, can yield (predictive) maintenance policies that outperform traditional policies, without the requirement for advanced monitoring systems. The only requirement is that the experience of the experts is quantified and used;

II. Reliability Statistics prediction techniques are based on historical (failure) records of comparable equipment without considering component specific (usage) differences. This approach accurately describes population-wide failure probabilities (e.g. MTBF, Weibull distributions). These methods also estimate the life of an average component operating under historically average conditions.

III. Stressor-based predictions are based on historical records supplemented with stressor data, e.g. temperature, humidity or speed, to include environmental and operational variances. The stressor data is typically low-resolution. For example, a limited number (2-3) of temperature / humidity classes is used, or a fleet of assets is divided over a limited number of subsets, e.g. aircraft operating on intercontinental vs. regional flights. This type of MT provides results in terms of expected lifetime of an average system in a specific environment. Predictions are typically based on the extrapolation of a general path derived from build-in-test results or operating history. Sometimes also physical models are used to quantify the effects of stressors (Tinga et al., 2020). This MT type could be considered as an extended version of type II (with additional data), or a simplified version of type V (simplified model). However, after the description of the five types, the comparison of the MTs will reveal that this intermediate type has characteristics that distinguish it from both type II (fleet vs individual) and type V (extrapolated vs. specified conditions), which justifies a separate MT type.

IV. Degradation-based predictions are based on the extrapolation of a general path of a measured degradation parameter to a failure threshold. By applying condition monitoring, i.e. measuring symptoms of incipient failure like rises in temperature or vibration, the system can be diagnosed. The life prediction (for that specific system) is also inferred from the sensor readings, i.e. is always based on a measurement. The prediction starts from the current state of degradation and yields an expected remaining lifetime of a specific system in a specific environment.

V. Model-based predictions give the expected remaining lifetime of a specific system under specified conditions. Their main characteristic is that the degradation is calculated instead of measured. The associated benefit is that the life prediction can be done for any specified condition / environment, instead of only for the presently active environment (as is the case for type IV). Two types of model-based approaches can be followed:
A. Physical model-based: The prognostic parameter is calculated using a physical model of the degradation mechanism, based on either direct sensing (present conditions) or assuming (specified conditions) the loads or usage that govern the critical failure mechanisms of individual components;
B. Data model-based: The prognostic parameter is calculated or inferred using data analytics that use sensed variations of loads, usage data, process data, or condition/health monitoring data as input. The data analytic algorithms aim to derive patterns or relations in the data or try to predict anomalies by comparing with historical data.

To further reveal the differences between these proposed types of maintenance techniques, 2 graphically compares the MTs with respect to six different aspects: (i) are they suitable for a complete fleet of assets or for an individual system? (ii) are the (fleet) average or specific usage differences included in the predictions? (iii) are the average or system specific environmental variances included? (iv) is the prediction based on an extrapolation of a (currently or previously) observed trend or on (any) specified
condition? (v) is the current state of the system considered? (vi) is the prediction based on measurements / sensor data?

<table>
<thead>
<tr>
<th>Maintenance Techn.</th>
<th>(i) technique suitable for</th>
<th>(ii) usage</th>
<th>(iii) environment</th>
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<tbody>
<tr>
<td>I. Experience-based</td>
<td>fleet</td>
<td>individual</td>
<td>average</td>
</tr>
<tr>
<td>II. Reliability Statistics</td>
<td></td>
<td>average</td>
<td>specific</td>
</tr>
<tr>
<td>III. Stressor-based</td>
<td></td>
<td></td>
<td>average</td>
</tr>
<tr>
<td>IV. Degradation-based</td>
<td></td>
<td></td>
<td>specific</td>
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<tr>
<td>V. Model-based</td>
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<table>
<thead>
<tr>
<th></th>
<th>(iv) prediction</th>
<th>(v) current state of degradation</th>
<th>(vi) measurements</th>
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<tbody>
<tr>
<td>I. Experience-based</td>
<td></td>
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<tr>
<td>V. Model-based</td>
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</table>

**Figure 2. Comparison of the five MT types.**

The second categorization classifies the maintenance techniques on the required input. This can be either data-driven, knowledge-based, physical model-based or a combination of the three (Goh et al., 2006, Venkatasubramanian, 2005). In Figure 1, the location of the spot in the triangles (in element C) indicates where each MT is positioned in this categorization. The complete overview of these positions is shown in Figure 3.

Data-driven approaches rely on the assumption that only little changes occur in the statistical characteristics of the data, unless a malfunction occurs in the system (Jianhui et al., 2003). The efficacy of these models depends however severely on the quality and quantity of input data. At the same time, these approaches do not require much system knowledge, which makes them accessible also for non-domain experts. Physical models need an accurate mathematical model (Jianhui et al., 2003), in which the behaviour of a failure mode is quantitatively characterized using physical laws (Sikorska et al., 2011). Physical models are especially useful for predicting system response to not previously encountered loading conditions or new system configurations. Finally, knowledge-based models accumulate experience from subject matter experts to form rules to apply that knowledge (Sikorska et al., 2011). However, such models require a high degree of completeness and exactness to be useful (Biagetti and Sciubba, 2004). Many inputs and outputs can make them rather complex to develop and apply, although this can sometimes be overcome by using systems with fuzzy logic (Sikorska et al., 2011). MT types I (experience-based), V-A (model-based physics) and V-B (model-based data) are
positioned at the extreme corners of the triangle, as they fully rely on one specific type of input. The other three types use combinations of inputs. Type IV (degradation-based) heavily relies on the (condition) monitoring data, but at the same time requires domain / system knowledge and physics to select the monitoring parameters and interpret the measurements.

2.4. Element D: Decision making
The final element focuses on the actual maintenance decision making, such as direct repair or replace decisions or lifetime extension. However, this also includes related aspects like logistic and supply issues (designing the supply chain), planning options (when can systems be used) and inventory options (how many spares, when, where). The quality of this decision making largely depends on the type of information that is available. In this element three options, with different potential for decision making, are given: detection, diagnostics and prognostics. These options are closely related to the selection of the maintenance technique in element C, as not all MT types can provide all three decision input types. Detection and diagnostics are both retrospective. The goal of detection is to signal anomalies in the system. This process is binary by nature, it indicates whether a system is healthy or faulty. Many current systems are equipped with built-in test sensors and diagnostic tests, that are continuously looking for abnormalities in the system. Diagnostics aims to not only find, but also qualify the damage that has occurred (Sikorska et al., 2011). A diagnostic system determines and identifies the cause-and-effect relation, searching for root causes and isolating faults (Lee et al., 2014). A health assessment module in a condition monitoring system works as a diagnostic tool. It generates diagnostic records and suggests possible fault causes. The process of predicting the future state of a system is termed prognostics (Greitzer et al., 2001), and this includes health assessment, detecting incipient failure and predicting the remaining useful life (RUL). For an overview of prognostics, see for example (Lee et al., 2014).

2.5. External and internal limitations
Finally, in addition to the four proposed elements, general limitations to the usage of PdM are created by internal and external laws and regulations. Examples of these are setting norms for the accuracy of the prediction (required type of prescribed techniques) or limiting the possibilities of data gathering (e.g. restrictions on position revealing GPS usage in military applications). These limitations and restrictions will affect the choices that are made in each of the proposed elements.

3. Mapping the use of maintenance techniques in practice to the presented framework
To get a better understanding on the selection and use of MTs in practice, we have conducted a multiple-case study with multiple embedded objects (Yin, 2009) and studied thirteen cases in various industries in the Netherlands. Within our case study, we have encountered all five categories of MTs as described in section 2.3. This section will discuss for six case study examples (one successful application of each maintenance technique and one unsuccessful application) the choices that practitioners have made in each of the four elements in the proposed framework (Figure 1) to implement PdM and apply MTs. Whether a case study is successful depends on whether or not the ambitioned improvement in that specific situation could be achieved. Ambition level is defined as the (PdM) situation in which the company wants to be in the near future. Depending on the present situation, that can be (partly) need-based, but could also be only ‘nice-to-have’. So ‘ambition level’ merely refers to the desired situation in the near future, regardless the motivation for that desire. Note further that the framework is intended for application to a specific asset, system or component, but also that various MTs can be used for different components of that asset. The choices made will be visualized in the mapping in section 3.3. But first, the case-study method will be introduced (3.1) and the six examples of MT applications will be discussed (3.2).

3.1. Design science and case-study
To ensure that the method is tested on a wide variety of assets in various companies, a specific selection of case companies was made based on the coverage of four criteria: the top industries PdM is applied
in; the life cycle of the asset; static vs. moving assets; and the organizational arrangement. Such a structured approach to sampling is important in case study research (Eisenhardt and Graebner, 2007). Grubic et al. (2011) show the typical industries where PdM is applied, namely aerospace, defence, maritime, electronics, power, oil and gas, and energy. We included most of these industries in our selection. The case study now contains cases within these sectors, except for power and oil & gas, but with the addition of process, steel and rail. The systems where PdM is typically applied have an average life cycle of more than ten years, are mechanical or electromechanical, highly complex and installed in large series (Grubic et al., 2011). We therefore studied assets such as vessels, helicopters, aircraft, rolling stock, cranes, wind turbines and a nuclear reactor. Both systems used in a static environment (i.e. cranes) and moving assets (i.e. aircraft) were included. One of the challenges presented by these moving assets is that their maintenance needs can vary dramatically when operated under highly variable operational conditions (Tinga, 2010). This might require the use of different MTs and affect the selection procedure. Finally, the case studies cover a range of maintenance technologies, organizational arrangements, industries, products, and maturity levels. So, they form a good range to evaluate existing knowledge developed in this research field.

Several measures were taken to ensure the reliability and validity of data, since that is the main concern of a case study (Yin, 2009). To guarantee construct validity, multiple informants were interviewed (such as maintenance engineers and managers), multiple documents were studied, and when needed, informants were asked to provide additional information in follow-ups. The interviews were recorded and the transcripts have been analysed. The analysed patterns in the case study were matched with the expected dependent variables (type of data available, prognostic ambition level and the selected MT) to ensure internal validity. To ensure external validity, the framework shown in Figure 1 was used to guarantee replication logic in the multiple-case study. Finally, reliability of the case study was ensured by using a semi-structured case study protocol during the interviews.

3.2. Case-studies on the use of MTs in practice

3.2.1. Case 1: Experience-based MT for steel manufacturing equipment (successful)

A department that provides internal transport of work-in-progress in a steel plant has conducted failure mode, effect and criticality analyses (FMECA) to determine the required maintenance for their vast amount of equipment. The company classified their installations based on the contribution to the core process. Next, it has split these installations into functional blocks of which the criticality is determined. Based on this criticality, the company defined maintenance actions: no actions for non-critical units and preventive replacement close to the predicted (estimated) life time for critical units. Solely based on experience of the maintenance personnel, operators, product quality specialists and maintenance engineers, the (predictive) maintenance concept is developed.

| Required outcome: | Effective preventive (risk-based) maintenance program that helps to prevent severe incidents and minimises downtime. Failure predictions for static assets. |
| Why experience-based – Type I – has been selected: | This technique helps to determine the required maintenance for a vast amount of assets in a relatively short time. Although FMECA sessions are time consuming, creating a maintenance concept for all assets is workable using this technique. Life predictions are estimates based on experience of the people involved. |
| What other possibilities were available? No other options could have been selected. | This case shows a match between the available data and the ambition level of the firm. With the existing data, no other options were possible. |
Achieved decision levels: Detection: -  
Diagnostics: FMECA provided insight in potential failures;  
Prognostics: estimated life time used for maintenance;

3.2.2. **Case 2: Reliability statistics for aircraft tires (successful)**
This commercial aerospace company knows that degradation of the tires of their aircraft is related to the number of take-offs and landings. Using a reliability statistics technique, the number of flights between required tyre changes is calculated. This calculation enables to diagnose the situation: wear of the tyres appears to be related to flights instead of for example flying hours. A prognosis is made with the assumption that this analysis applies to all tyres of this fleet of similar aircraft. This has led to determine an optimal maintenance interval for all tyres of the aircraft.

<table>
<thead>
<tr>
<th>Required outcome</th>
<th>Prediction for a specific component (tyres) of an average system (airplane) under average situations (landings not specified per operational region)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Why reliability statistics – Type II – has been selected</td>
<td>The high amount of available failure data helps to give a good insight in the failure statistics. Using this data set, the exact moment of replacement can be determined.</td>
</tr>
<tr>
<td>What other possibilities were available?</td>
<td>The case shows a match between the ambition level and the available data. Other analyses possible are the experience-based (this would not have led to the ambitioned level) or the inclusion of operational and environmental variances for a stressor-based analysis (for which the data is probably unavailable).</td>
</tr>
</tbody>
</table>
| Achieved decision levels | Detection: -  
Diagnostics: general insight in relevant parameter (# flights);  
Prognostics: calculated average tyre life time used for maintenance; |

3.2.3. **Case 3: Stressor-based MT for a military transportation aircraft structure (successful)**
Traditionally, the maintainer of this military transportation aircraft follows the OEM prescribed maintenance. However, for the airframe, which is critical for the lifetime of the plane, more advanced analyses are required to extend the lifetime. Rudimentary sensors aboard the plane measure the altitude, speed and a global load factor. Recently, more data collection devices have been installed. To meet the newly requested (prolonged) lifetime of the airplanes, the usage and loads (i.e. the stressor) on a specific plane are measured continuously. This way, the consumed lifetime can be balanced throughout the fleet. In addition to collecting this usage and load data, a physical (stressor-based) model is developed in cooperation with the OEM. Based on this analysis, anomalies in the lifetime consumption can be detected and diagnosed and an accurate prediction of the remaining lifetime of each individual plane in the fleet is established. This information is used to take (maintenance) decisions on the (type of) usage of the planes (e.g. avoid high loading situations with certain planes that have little remaining useful life). Further, this information is of crucial importance in the replacement process of the fleet.

<table>
<thead>
<tr>
<th>Required outcome</th>
<th>Prediction of the RUL per plane, based on the actual usage and current state of degradation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Why stressor-based – Type III – has been selected</td>
<td>The department selected the stressor-based route as they have extensive experience with several types of (physical) models that consider different operational environments. Recording these data with the already installed sensors provides worthwhile insights in the degradation of the system. Since large variations in the usage per plane are recognized, a generic prognosis for a general system would give inaccurate results for individual systems.</td>
</tr>
<tr>
<td>What other possibilities were available?</td>
<td>The company could also have employed experience-based techniques, like the MSG-3 methodology it also applies for various other components of the aircraft. Moreover, the department could have opted for an accurate physical</td>
</tr>
<tr>
<td><strong>Type I and V could have been selected.</strong></td>
<td>model for the airframe. However, as insight in degradation of individual planes was not the initial ambition, a stressor-based technique was selected.</td>
</tr>
</tbody>
</table>
| **Achieved decision levels:** | **Detection:** anomalies in service life consumption are detected;  
**Diagnostics:** current status of each aircraft is derived from the stressor data;  
**Prognostics:** remaining useful life for each aircraft is used for flight planning and fleet replacement; |

### 3.2.4. Case 4: Degradation-based MT for rolling stock components (successful)

A company that conducts maintenance, repair and overhaul for rolling stock collects data from various sensors, such as temperature and vibration, installed in the trains. Using Auto Associative Kernel Regression (AAKR), the normal behaviour of the system is constructed. When a monitored system has an imminent failure, the residuals between the model created with AAKR and the measurements become significant. An imminent failure is flagged in the diagnostic system when it exceeds a pre-defined threshold. The timeliness of these early warnings helps the company to schedule preventive maintenance and reduce system downtime and safety incidents.

| **Required outcome:** | Detection of anomalies and prediction of future behaviour per individual train based on the actual usage and behaviour |
| **Why degradation-based – Type IV – has been selected:** | The pre-installed sensors offer the opportunity to use these data for analysis and detection of anomalies. |
| **What other possibilities were available? Type I and II could have been selected.** | The company could have employed experience-based techniques or reliability-statistics. However, as the company ambitioned to monitor their equipment individually and get insight in the varying deterioration per system, a degradation-based technique was preferred. |
| **Achieved decision levels:** | **Detection:** AAKR applied to sensor data detects anomalies in the system;  
**Diagnostics:** some of the anomalies can be related to specific (known) failures, others only yield a detection;  
**Prognostics:** the generation of early warnings allow for preventive actions on the diagnosed systems, but no explicit RUL values are obtained; |

### 3.2.5. Case 5: Physical-model-based MT for a military helicopter structural part (successful)

This maintainer of military helicopters collects health and usage monitoring data. Based on this input, the flown manoeuvres can be determined. A dynamic stress model was developed for a highly critical frame in the fuselage of the helicopter. Since the quality (accuracy and precision) of the prediction has to be high, and many variables influence the degradation of the frame, a physical-model-based analysis, using a physics-of-failure model (fatigue) is used. This model requires input from the installed health and usage monitoring system, strain gauges, and usage data. Analyses are conducted to detect the flown manoeuvres, and diagnose problems with the degradation of this frame. This aids in a prognosis of the remaining life of this part of the airframe. Decisions are taken to reduce the impact of the problem by for example changing the (type of) usage of the helicopter.

| **Required outcome:** | An exact prediction of the RUL of the component based on the actual usage and loads acting on the system. |
| **Why model-based – Type V – has been selected:** | The frame in the fuselage is highly critical. Therefore, an advanced and detailed analysis is required, such as a physical model. This requires detailed knowledge about the failure mechanisms. |
What other possibilities were available? | Due to the varying operational and environmental conditions, the analysis should include these. An experience-based technique or reliability statistics approach would not have included these variances sufficiently. Since the future usage of the helicopter was assessed to vary heavily and the component was identified as being highly critical for the safety and availability of the helicopter, a model-based technique has been selected.

Type I and II could have been selected. | Detection: the MT allows the detection of unacceptable situations (as derived from diagnosis);
Diagnostics: the model and monitoring program allow to assess the state of this component at each moment, and enable acting on that;
Prognostics: the remaining useful life is updated after each flight, and is used for mission and maintenance planning.

Achieved decision levels: | Detection: the MT allows the detection of unacceptable situations (as derived from diagnosis);
Diagnostics: the model and monitoring program allow to assess the state of this component at each moment, and enable acting on that;
Prognostics: the remaining useful life is updated after each flight, and is used for mission and maintenance planning.

3.2.6. Case 6: Reliability statistics for electrical components of a naval vessel (unsuccessful)
This department is responsible for the maintenance of electronic equipment aboard naval vessels. The major challenge for the department is the large number of one-of-a-kind systems. It is therefore difficult to collect representative failure data. Guaranteeing uptime is key since the equipment is critical for the operational effectiveness of the vessels. The traditional maintenance policy adhered by the department is based on recommendations from the original equipment manufacturer (OEM). In the (recent) past, the department tried to shift towards a more fact-based reliability statistics approach. However, inaccurate results were achieved due to unreliable input, incomplete data, and poorly filled recording systems (not all failures recorded). Therefore, the department shifted back towards an experience-based approach, using their internal knowledge base from experts (and OEM). Although the company could develop (probably more accurate) physical or data models, this is currently found too difficult and time consuming for the vast amount of different systems.

Required outcome: | Prediction for specific components under variable situations (i.e. operational regions)

Why reliability statistics – Type II – has been selected: | The available failure data could give insight in the (average) failure behaviour of the components.

Why experience-based – Type I – has been selected: | Expert knowledge is widely available within the department. Using e.g. FMECA, estimates of the lifetime of the components can be made.

What other possibilities were available? | This case shows that the department explored two possibilities: experience-based and reliability statistics analyses. The first approach did, and the second did not match with the available data. Other available options: include stressors (operational environment) in the predictions, employ sensors or build a physical model. However, due to the many different types of equipment, these options were assessed as too costly and time consuming and therefore not feasible.

Achieved decision levels: | Detection: -
Diagnostics: the occurrence of certain failures can be estimated using FMECA and experience
Prognostics: estimated life time (experts, OEM) used for maintenance planning

3.3. Mapping the followed routes of the case study companies
Figure 4 – composed of the same building blocks as Figure 1 – shows the mapping of the choices made in each of the case studies discussed in section 3.2 and visualises these using the coloured areas and lines. To explain the general idea of the figures, we explain as an example the choices made in case 3
The project originated from both the quest to investigate whether the life of the plane can be extended (decision pull) and the technologies available to help measure the actual loads on the plane (technology push). The department decided to collect usage and load monitoring data. In element C, a stressor-based analysis is selected and conducted. Element D shows that applying this technique resulted in a detection of anomalies in the system, a diagnosis and a prognosis of future behaviour. The figure shows that the department uses this technique for maintenance decision making (lifetime extension of the transportation plane).

The advantage of visualising the routes in the proposed MT framework of Figure 1 is that it provides a direct view on the inputs used and results obtained with the various PdM applications. Firstly, the visualisation shows that all four elements are recognized in the six case studies. Further, the figure shows that no detection results are obtained when applying reliability-statistics in case 2 and 6, and for the application of the experience-based prediction in case 1. This is inherent to these types of methods,
which neglect the details of individual systems. Moreover, some form of prognosis seems to be realised in all cases. As this was the objective of all the involved companies, they seem to have succeeded in that. However, the quality of this prognosis is often low, especially for the steel manufacturing, the rolling stock, and the military vessel cases. Therefore, these blocks in the framework are only partly coloured. In case 6, the application of reliability statistics requires high quality historical data and usage data. However, as shown in the visualisation, this was not available (the blocks are only partly coloured), and only limited results could be achieved. This is visualised by the partly coloured blocks diagnosis, prognosis, and maintenance decision making. It can thus be concluded that having the ambition to get a prognosis does not guarantee that it will actually be achieved, although each of the presented MTs is capable of delivering such a prediction (off-course with varying accuracies). Finally, it was already mentioned in the introduction that in none of the 13 cases the companies had a predefined structured approach for selecting and implementing the techniques. This typically resulted in a tedious trial-and-error process, with no guarantee to success. The proposed framework is believed to structure this process and therefore reduce the required time for MT selection.

No combination of choices has been found that could not be mapped onto the framework. However, more or other choices could have been possible for the case companies and no conclusions can be drawn on whether the most efficient and most effective combination was selected in each case. For example, a more advanced MT could have been more successful. In the discussed applications of PdM, the fit between data and type of MT seems to be leading for the success of PdM. In other words, the required data inputs should be available and the data needs to be of sufficient quality. Next to that, also the required outcomes seem to dictate the preferred MT. For example, when operational or environmental variances should be included, the MT must be able to incorporate these differences. This means that in a specific situation, not all choices are available for a successful application.

4. Reflecting on the case-studies: Why the routes were selected
To get a better picture on the types of MTs that are used in practice, we asked the interviewees to estimate the ratio of the various MTs that are used (within their department) for maintenance decision making (see Figure 5). In each of the 13 case studies, a specific asset or system was considered. However, to prevent an overdetailed list, for most of the cases only the industry is mentioned instead of the specific asset. This figure shows that practitioners, within one department, used multiple types of MTs. That confirms our assumptions. Figure 5 also shows that the mostly applied type of MTs is the experience-based approach. This type of MT is highly represented in almost all cases. The more advanced techniques, i.e. stressor-based, degradation-based and mechanism- or model-based only have a relatively small presence in most industries.
Based on the proportion of the most used MT, it seems that four clusters can be discerned (clusters A to D) that provide insight in the specific context of the MT applications.

### A) The three maritime case studies together with the steel manufacturing case form the first cluster.

For the maritime departments, it is often more convenient to apply a time-based maintenance policy than to use more advanced methods. Their static inspection intervals are often prescribed by Class Societies and their vessels are available (in dock) at the predetermined intervals (e.g., every five years). Moreover, often little data on failures and operating history is available to use for advanced analyses. Finally, often a high level of redundancy is present and the level of preventive (compared to corrective) maintenance was high (>90%). For the steel manufacturing case, little (failure) data were collected and the experience-based techniques are widely applied from a historical perspective.

### B) Within cluster B, advanced techniques are only used where necessary. These departments have the historic use of experience-based techniques in common with the departments in cluster A. The departments in cluster B however, have invested in more advanced techniques to improve their predictions. Data collection projects are initiated to improve maintenance decisions for critical or costly systems. For the helicopter and the aircraft, maintenance intervals are currently rather conservative and experience-based analyses are mainly used. The need to cut maintenance costs initiates the development of techniques that are more advanced.

### C) The methods used in cluster C are more advanced for quite different reasons. For the Defence vehicles many data are available. Therefore, reliability statistics analyses are widely used. In the example of the nuclear reactor, the higher the safety risks of unplanned failure for specific subsystems is, the more advanced types of maintenance techniques are used. The closer to the core of the reactor, the more sophisticated, reliable and proven methods are used.

### D) In the final cluster (D), the need to conduct maintenance techniques is very high. The costs to conduct maintenance (either preventive or corrective) are high and the assets are often located remotely (offshore or away from the home base). Next to that, for the wind turbines many data are available.

In conclusion, it seems that the more advanced methods, as for example stressor-based predictions, are especially used in situations where the system degradation varies between the different operational situations. This includes variations in regions (arctic versus beach for defence vehicles), environmental conditions (moisty and hot regions versus dry and cold climate regions for electronics), or usage (flying transits at moderate speed versus manoeuvrability training for aircraft). Within the studied cases, the

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Methods Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Steel manufacturing (90%), Pilotting Vessels (85%), Geotechnical Vessels (80%), Defence Maritime - Mechanical (75%)</td>
</tr>
<tr>
<td>B</td>
<td>Defence Maritime - Electrical (70%), Process industry (70%), Rolling stock (70%), Military helicopter (70%), Military aircraft (60%)</td>
</tr>
<tr>
<td>C</td>
<td>Defence - Vehicles (40%), Nuclear energy (35%)</td>
</tr>
<tr>
<td>D</td>
<td>Commercial aviation (20%), Wind turbines (20%)</td>
</tr>
</tbody>
</table>

![Figure 5. Estimated relative occurrence of various MTs within case companies.](image)
model-based analyses are only applied to the most critical components and therefore more applied to aircraft and helicopters than to vehicles or vessels.

5. Conclusion
Despite the large number of maintenance techniques (MTs) available in the academic literature, practitioners experience multiple difficulties in the application of PdM. One of these is the selection of the appropriate MT to apply in a specific situation. To improve this process, this paper investigated how the choices required for maintenance decision making have been made in practice. We therefore first looked at theoretical elements and choices, providing a framework (Figure 1). Six specific examples (from a total set of 13 cases) of choices that have been made in practice have been mapped on this framework, as shown in Figure 4.

Three conclusions can be drawn from these mappings. First, data dependencies and ambitioned outcomes of analyses appear to primarily govern the selection of MTs, although a business case in many situations also plays a role. Second, both the criticality and the type of asset determine the use of more or less advanced maintenance techniques. Third, the mapping of the choices made in practice demonstrates the usefulness of the proposed MT framework of Figure 1 in analysing the cases in a structured manner.

Further, based on the relative occurrence of MTs in the 13 cases, four different clusters can be distinguished (Figure 5). Mostly applied within firms are the experience-based types of MTs. The more advanced types of MTs are only applied to situations where either a need has arisen to improve a maintenance decision, or where capabilities are available to develop these more advanced MTs. Ultimately, creating a match between the desired level of MTs and decision making and the available capabilities to develop these MTs seems to be critical for successful PdM applications.

6. Limitations and further research
The case studies showed the choices that companies have made in applying PdM. However, more or different choices could have been feasible for the case companies and no conclusions can be drawn on whether the most efficient choice has been made. Therefore, more cases (e.g. from literature or practice) should be mapped to the framework to expand the insights on this topic. Further, research will not only have to focus on observing the choices made, but also on advising firms in the selection of the most suitable choices for their situation. Next to the technical aspects of having an effective and successful implementation of PdM, it is important that the organizational and economical aspects are also included. Therefore, a business case model to evaluate the application of MTs is required, e.g. a generalization of Tiddens et al. (2017). Such a model can help to evaluate the impact of a PdM implementation, by comparing the required investments in monitoring and analysis techniques to the expected benefits. Although the latter are expected to include a higher system availability, reduction of the number of (expensive) unexpected failures and a more efficient maintenance and logistics planning process, quantification of these effects remains challenging.

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