Towards Informed Maintenance Decision Making: Identifying and Mapping Successful Diagnostic and Prognostic Routes

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Abstract

Advanced maintenance techniques (AMTs) are practices that can support informed maintenance decision making by taking the current, but preferably also the future state of physical assets into account. These techniques can be worthwhile to companies when they are well applied.
However, only few companies have effectively applied these techniques and the many available literature reviews fail to help practitioners select the most suitable AMTs for their specific needs. Practitioners often follow a – costly – trial-and-error process in developing more advanced techniques. Next to that, practitioners find it hard to justify development costs and express the added value of AMTs, hindering further advances. Identifying feasible routes helps practitioners to make the step from only knowing the current state of equipment (diagnostics) to also predict the future state of equipment (prognostics).
We therefore conducted five case studies within the Netherlands Ministry of Defence to identify and map the use of advanced maintenance techniques and project these mappings on our earlier proposed framework.
This paper aids the research on the identification and selection of the suitable AMTs by testing a framework to identify and map the use of AMTs. The first mapping results show that practitioners tend to select the type of AMT mainly based on the available (input) data and the type of required outcome. Based on the mapping, a selection framework is proposed which helps identifying the feasible routes towards maintenance decision making. Further research will focus on testing the proposed route selection framework by comparing the findings to industrial settings.

Keywords: Maintenance techniques, mapping, selecting, prognostics, diagnostics

1. Introduction

Smart components, such as sensors and microprocessors, provide feedback to asset owners and manufacturers about the use, degradation, environment and location of physical assets. Real-time logs of various parameters – that describe the current state of distant assets such as airplanes or trains – can be easily transferred to ground stations. Effective use of this data heads off problems, such as unplanned failures, before they occur and thereby helps to improve the performance of physical assets. The thinking company conducts maintenance just-in-time, i.e. Soon enough to prevent critical system failures, but also late enough to not over-maintain assets. Insights obtained from the collected data help companies to make informed maintenance decisions. Short term maintenance decisions focus on typical maintenance questions as when to repair or replace assets or when to alter the mission (change the use). Long-term decisions are related to the life-cycle management of physical assets, such as lifetime extensions.

Collecting real-time data from these physical assets has become a simple exercise when sensors directly measure data or when enterprise manufacturing- and controller systems help to acquire data (Lee, Bagheri, & Kao, 2015). This data, however, is not useful until it is processed in a way it can provide context and meaning that can be understood by the right personnel (Lee et al., 2015). Therefore, meaningful information has to be inferred from this data.
The acquired data can be used to make better-informed maintenance decisions. The core value of maintenance decision making is the determination of the (monetary) values of all options the

decision maker has to make good trade-offs between the available options. Within decisions directly focussed on the actual maintenance, the value of *wait-to-maintain*, the maximum time to be taken before conducting maintenance to prevent severe failures from occurring (Haddad, Sandborn, & Pecht, 2014), is essential. The determination of this value is often difficult for three reasons. Firstly, when dealing with complex systems with interrelating failure modes, human decisions are often not sufficiently reliable or accurate (Sikorska, Hodkiewicz, & Ma, 2011), due to the limited capacity of a human to oversee this complexity. Secondly, multi-component dependencies have to be included in these predictions (Zio, 2009). And finally, system deterioration, and therefore the maintenance needs of complex, moving, assets can vary dramatically when operated under highly variable operational conditions (Tinga, 2010).

Advanced maintenance techniques (AMTs) are practices that can support maintenance decision making by taking the current and future state of physical assets into account. AMTs help to determine the remaining useful life (RUL) and the probability a machine works without a failure up to a certain time (Jardine, Lin, & Banjevic, 2006), and as such assist in determining the value of *wait-to-maintain* and therefore help to determine the value of the options the decision maker has. These techniques hereby help to provide context and meaning to the collected data.

1.1 Problem Statement

Current research shows that practitioners that have applied these techniques experience a gap between the potential and realised benefits (Grubic, Redding, Baines, & Julien, 2011). Besides, previous work conducted by the authors (Tiddens, Braaksma, & Tinga, 2015) shows that practitioners experience difficulties in selecting the optimal routes to informed maintenance decision making.

Many literature reviews of AMTs fail to help practitioners and industry users select a suitable AMT for their specific needs (Dekker, Wildeman, & van der Duyn Schouten, 1997; Sikorska et al., 2011). The struggle with applying these techniques might be reflected by a survey conducted by Grubic et al. (2011), who show that only 11-13 percent of UK-based manufacturers have adopted prognostics and decision-support techniques.

Many scholars in the field have proposed models and algorithms to predict future failures and assess the current state of equipment. However, as also mentioned by other authors (Garg & Deshmukh, 2006; Kerkhof, Akkermans, & Noorderhaven, 2014; Veldman, Klingenberg, & Wortmann, 2011), most research within the field of AMTs excludes the organisational and managerial facets and only addresses the technical aspects such as developing accurate sensors, algorithms, and models. One of the (often neglected) organizational aspects is the selection of the appropriate technique to apply.

1.2 Objective of the Paper

To effectively implement advanced maintenance techniques, various routes from data collection to maintenance decision making can be followed. To come to a closer understanding about how practitioners should select the optimal path for their situation, this paper aims at identifying and mapping the routes that practitioners have taken in a structured way. For the identification of the followed routes, a common framework is required. In previous work conducted by the authors (Tiddens et al., 2015), a framework describing the steps from data collection to maintenance decision making has been presented. Ultimately, successful routes can be mapped on this framework and these routes can be analysed to come to a closer understanding of how the optimal routes should be selected. This mapping of the taken routes can be used to advise practitioners on the route selection process.

1.3 Overview of the Paper

The paper starts with discussing the theoretical routes from data collection to maintenance decision making. After this, the research methodology for the case studies will be discussed in section 3. The fourth section of this paper deals with mapping the routes that are identified in the case studies. These mappings are visualized in section five. The results of the mapping are used in section six to help practitioners select the appropriate route. A brief conclusion and discussion of the main findings ends this paper.

2. Routes Towards Maintenance Decision Making

To support effective decision making, for both maintenance and life cycle management, four consecutive steps have to be taken. The advanced maintenance techniques framework from Tiddens et al. (2015), shown in Figure 1, guides the user of these AMTs through the required steps. The four steps are synthesized from the existing literature and connect the technical parts of the AMTs with the organizational aspects of the implementation process, thus bridging the identified gap between these two disciplines.

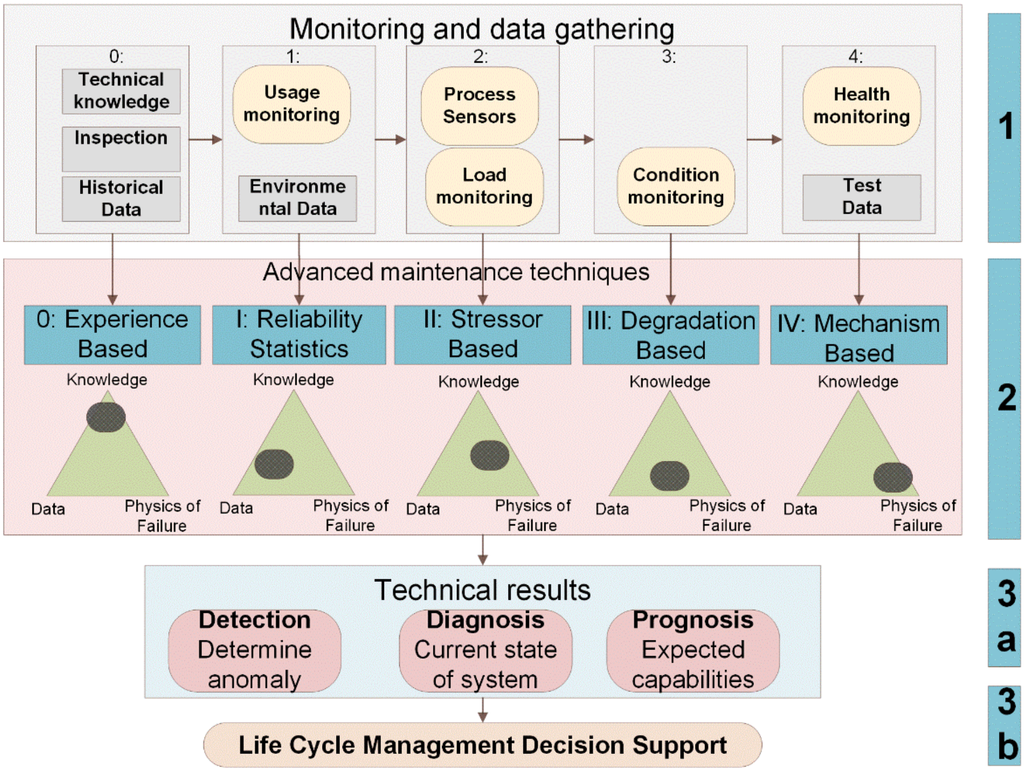

Figure 1. The advanced maintenance techniques framework: routes to maintenance decision making (Tiddens et al., 2015)

2.1 Step 1: Monitoring and data gathering

The first step in the framework is the selection of the parameters to monitor and the gathering of the (available) input data. The data collected for the less mature techniques, such as technical knowledge for the experience-based predictions are also used for the more mature techniques, e.g. mechanism-based predictions. This data can be gathered from either monitoring systems or from historical records. The historical records converge in event data, which reflects what has happened to a piece of machinery, for example failures, overhauls, and repair actions (Jardine et al., 2006). Several types of data gathering and monitoring strategies can be utilized, which are clustered in five types in the proposed framework.

Firstly, historical data can be gathered from technical knowledge, inspections and historical records of failures or costs for instance. Secondly, usage monitoring entails the process of acquiring operational data, e.g. operating hours, mileage, or tons produced. This preferably includes environmental data, consisting of measures of temperature and moisture for instance

(Farrar & Lieven, 2007). Thirdly, data describing the external loads on the system can be collected. Process sensors can be used to acquire data that relates to the operating characteristics of the component, e.g. pressure, flow, and temperature (Veldman et al., 2011). The associated load monitoring is the process of acquiring loading data, e.g. temperature, vibration, humidity, strain or electrical current (Tinga, 2010). Fourthly, data related to signs of imminent failure of the equipment can be collected. Condition monitoring is the process of acquiring signs of imminent failure, e.g. vibrations, acoustics, temperatures or data from oil analysis techniques. Finally, data extracted from the measured system response can be collected with health monitoring techniques to identify the presence of damage and quantify the extent of this damage in a system (Farrar & Lieven, 2007).

2.2 Step 2: Advanced Maintenance Techniques

In the second step, the type of technique is selected and the actual technique is applied. The technique is selected based on the required outcome and the available input. The selection of the AMT therefore requires prior consideration of the available data. However, in a so-called greenfield approach, a situation in which everything is new, the selection of the technique goes hand-in-hand with the selection of the data to collect.

Not only can the types of input data vary, also the quality of the available data is important. Input data can be imprecise or incomplete, especially when actual failure data is missing due to effective failure prevention resulting from conservative preventive maintenance programs. On the other hand, the required outcome depends on the type of asset the technique is conducted for, its criticality, and the type of behaviour and usage of this asset. These aspects can influence the requirements that are set for managing the uncertainties of the prediction. Uncertainties in the technique and uncertainties in the input data lead to uncertainties in the prediction (Bo, Shengkui, Rui, & Pecht, 2010).

In the broad field of maintenance techniques, we can differentiate five types of advanced maintenance techniques. These are:

(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 e.g. Failure Mode, Effect and Criticality Analysis (FMECA) techniques.

(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-based failure probabilities. These models estimate the life of an average component operating under historically average conditions and are based on e.g. Weibull or normal distributions.

(III) Stressor-based predictions are based on historical records supplemented with stressor data, e.g. temperature or humidity, to include environmental and operational variances and give results in terms of expected lifetime of an average system in a specific environment. Predictions are based on the extrapolation of a general path derived from a physical model, built-in test (BIT) results, or operating history.

(IV) Degradation-based predictions are based on the extrapolation of a general path of a prognostic parameter, a degradation measure, to a failure threshold. The prognostic parameter is inferred from sensor readings. The prediction includes the current state of degradation and results in an expected remaining lifetime of a specific system in a specific environment. It also measures symptoms of incipient failure e.g. rises in temperature or vibration.

(V) Mechanism-based predictions are based on direct sensing of the critical failure mechanisms of individual components. This approach gives the expected remaining lifetime of a specific system under specified conditions. The prognostic parameter is calculated using a physical model of the degradation mechanism and this model uses the sensed variation of loads or usage as input.

2.3 Step 3: Decision Making

The final step, step 3, focusses on the actual decision making. Firstly, the technical results from the technique can be used, namely the detection, diagnosis and prognosis. These can be used to optimise – straightforward – maintenance decisions. Secondly, business decisions as discussed in section 2.1 can be improved using the results of the AMTs.
Limitations to the usage of AMTs are created by internal and external laws and regulations e.g. setting norms for the accuracy of the prediction (minimum level of prescribed techniques) or by limiting the possibilities of data gathering (e.g. restrictions on position revealing GPS usage in military applications).

3. Research Methodology

The main aim of our research is theory-building from an exploratory perspective (McCutcheon & Meredith, 1993; Meredith, 1987). This study is exploratory since we have no firm ideas about the exact behaviour and causal relations of the concepts in practice but instead we aim to develop knowledge that can serve as a stepping stone towards such theory building (McCutcheon & Meredith, 1993; Meredith, 1987). For this study it is appropriate to use a multiple-case study (Eisenhardt & Graebner, 2007; Yin, 1989).
Our selected sample consists of five cases in the Netherlands Ministry of Defence (NLMOD). The number of studied cases herewith exceeds the required number of four for multiple-case research (Eisenhardt, 1991). The five cases are all within three branches of the NLMOD: Royal Netherlands Navy (2), Royal Netherlands Army (1) and the Royal Netherlands Air Force (2). The specific case context varies enormously between the three branches of the NLMOD. The maintenance organizations are unrelated and not using the same maintenance practices. However, a computerized maintenance management system (CMMS) that shapes the main IT-infrastructure for the maintenance organization, has been rolled out in recent years throughout the whole NLMOD. We consider the total research as a multiple-case study with multiple embedded objects of analysis (Yin, 1989). The cases within both the navy as well as in the air force can be considered as single-case designs with multiple embedded objects (Yin, 1989). In these cases, the case-context is equal (the navy or the air force).
As it is expected that the selected cases will have followed different routes through the framework (Figure 1), the cases are predicted to provide contrasting results for anticipatable reasons (Yin, 1989). The cases were selected from multiple departments to identify the differences between these departments. The purpose of mapping the prognostic routes is to develop theory – but not to test it – and so theoretical (not random or stratified) sampling is suitable (Eisenhardt & Graebner, 2007).The presented studies cover a range of maintenance technologies, products, and maturity levels. They form a good range of evaluating existing knowledge developed in this research field. Furthermore, also low performing cases were selected since an important theoretical sampling approach, termed "polar types", in which both high and low performing cases are selected, is valuable for observing contrasting patterns in the data more easily (Eisenhardt & Graebner, 2007).
At the five departments, interviews have been conducted with relevant staff including maintenance managers and maintenance or reliability engineers. The interviews were structured using a pre-defined interview protocol. The interview data was structured per case to allow for cross-case analysis. Explanation building is of high importance for this study since one of the aims is to identify *why* practitioners selected a specific AMT. The theoretical framework shown in Figure 1 is used to reflect on theoretical propositions. After two initial case-studies, minor revisions were made to the theoretical framework. Moreover, narrative explanation building is used to identify explanations that are not covered by the theoretical framework. The framework is used to ensure replication logic in the multiple-case study. It provides the conditions when specific routes are both likely or unlikely to be found. Finally, a case study database was created containing careful write-up and recording of interview data.

4. Identifying Prognostic Routes in the Case Studies

At the studied case companies, various types of AMTs have been used for maintenance decision making. To identify the routes from data collection to maintenance decision making that have been taken, five examples from the cases are discussed below to be able to map different routes. *Figure 2* shows that in all studied objects, multiple types of AMTs were used and how the balance of the use of the different types of AMTs differs between the cases.

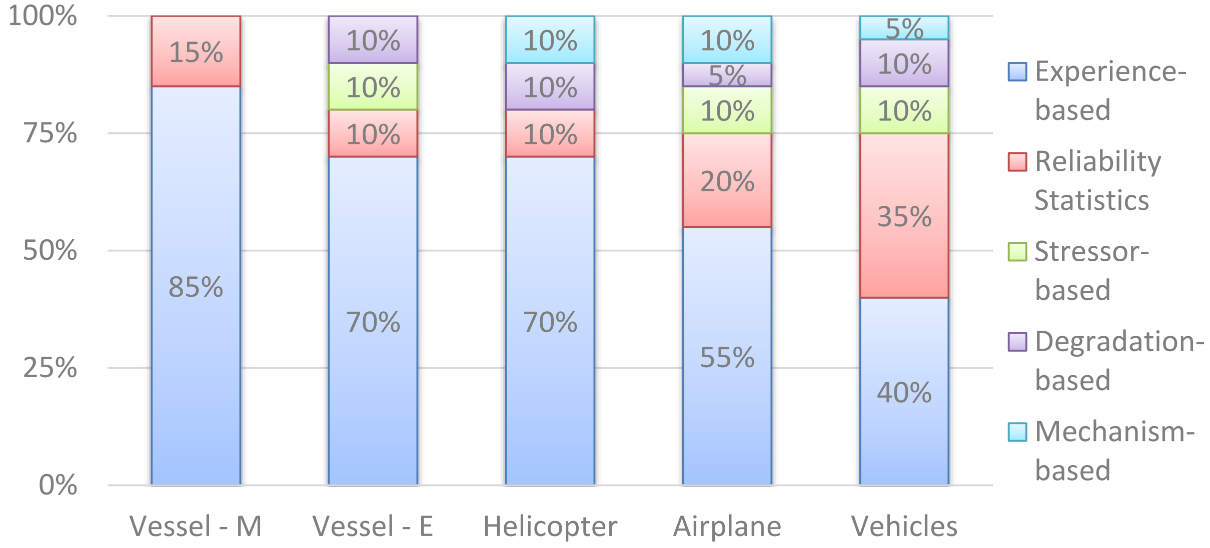

Figure 2. Relative occurrence of AMTs at cases

To give insight in the applied maintenance techniques, we start with narrative explanations of the application of AMTs. Per type of analysis and per branch, an example will be given. In section 5, the routes will be mapped to give a visual overview of the routes taken.

4.1 Case 1: Application of experience-based predictions at a maintainer of electrical components aboard naval vessels

As shown in *Figure 2*, it appears that experience-based techniques are the mostly applied techniques within the studied object. This type of technique is also applied within all the studied departments. This can be attributed to the low complexity and robustness of this type of technique, and the criticality of the systems the analyses are conducted for. The inherent reliability, redundancy or non-criticality of a (sub-)system reduces the need for a complex analysis since failure of such a system will not lead to an immediate risk or threat to the aggregated system (i.e. the vessel).

This department conducts maintenance for all electronical equipment aboard naval vessels. Due to the high differences between naval vessels, few similar systems are available and many one-of-a-kind systems are installed. Collecting accurate and representative failure data is therefore difficult. The systems are often highly critical for the operational effectiveness of the vessels.
Traditionally, maintenance plans are based on advises given by the original equipment manufacturer (OEM). Currently, sessions are organised to bring the expert knowledge of operators, crew, maintenance technicians and subject matter experts together with the reliability data. Using FMECA-like techniques, maintenance decisions can be supported. Triggers to conduct these analyses are signals of recurring problems on one or multiple vessels that are flagged by the crew or outliers detected in the reliability data.
The results of the application of these techniques are the diagnosis of frequently occurring problems, using root cause analyses (RCA), and a prognosis of the expected (remaining) lifetime, based on knowledge from within the company and suppliers.

The experience-based route has been selected since in the (recent) past, the department heavily relied on reliability statistics techniques. These analyses however, provided inaccurate results due to incomplete data, unreliable input and poorly filled systems (not all failures recorded). Therefore, the department has chosen to use more knowledge from within the company to make maintenance decisions. Moreover, since the department conducts maintenance for a vast amount of different systems, it is too difficult and time consuming (at the moment) to develop more accurate physical or data models.

4.2 Case 2: Application of Reliability Statistics at a maintainer of army vehicles

Within all five cases, examples of reliability statistics are found. These analyses are the backbone of the traditional reliability engineer. The analyses can be used, when sufficient reliability data is available, to shed a light on future failure behaviour of (large) series of components or investigate unreliability problems. These analyses are also often used to determine spare-part requirements. Reliability statistics analyses typically require a higher quality level of input data than the experience-based analyses.

This maintainer is responsible for the maintenance of around 10,000 vehicles. This includes combat as well as non-combat vehicles. Application of reliability statistics is possible since many vehicle types are installed in large series. The analyses help in diagnosing problems and making prognoses about failure rates and spare part demands. By collecting data, trends can be extrapolated to give insight in future behaviour and future spare part demands.

The selection of this AMT is based on the available data. Using mean time between failures of the system as provided by the OEM, and data logged in the computerized maintenance management system (CMMS), straightforward analyses can be made to shed a light on future behaviour of the systems. Moreover, many maintenance practices are based on OEM advises and expert opinion. The ambition of the department is to conduct load-based maintenance, where the loads or the usage of the systems determines the required maintenance. Currently, the department is looking into the different data collection systems aboard the vehicles and the possibilities this gives for using more advanced maintenance techniques.

4.3 Case 3: Application of Stressor-based Predictions at a maintainer of a military transport aircraft

Stressor-based predictions are especially useful when the system deterioration varies between the various operational situations the asset is exposed to. This can include operational regions (desert versus beach for a vehicle), environmental conditions (moisty and hot regions versus dry and cold climate regions for electronics) or varying usage (flying transits at moderate speed versus manoeuvrability training for aircraft).

This maintainer conducts maintenance on a small fleet of military transport aircraft. Traditionally, aviation and OEM handbooks prescribe the required maintenance. Since the airframe is (one of) the component(s) that determines the lifetime of the plane, detailed analyses are conducted to investigate whether the lifetime of the total plane can be extended. Rudimentary sensors aboard the plane measure the altitude, speed and a global load factor. Recently, more data collection devices have been installed. To be able to meet the newly requested (prolonged) lifetime of the airplanes, the usage and loads on the plane are measured continuously. This way, the consumed lifetime can be balanced throughout the fleet. By 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. Moreover and most important, an accurate prediction of the remaining lifetime of all individual planes in the fleet is established. This information is used to make (maintenance) decisions about the (type of) usage of the planes (avoid high loading situations with certain planes that have little remaining useful life compared to other aircraft in the fleet) and information about the remaining life of the fleet has become available. The latter is of crucial importance in the replacement process of the fleet.

The stressor-based route has been selected since the department (and its knowledge partners) have extensive experience with several types of physical models. Recording this type of data with the already installed sensors provides worthwhile insights in the degradation of the system. Moreover, since large variations in the usage per plane are recognized, a generic prognosis for a general system or a fleet will result in inaccurate results for individual systems.

4.4 Case 4: Application of Degradation-based Predictions at a maintainer of mechanical systems of naval vessels

Degradation-based predictions offer the opportunity to assess the current state of the equipment and, based on the trending of a prognostic parameter, make estimations of the remaining life. Oil analysis for engines and vibration analysis for bearings are frequently applied analyses that are based on this principle.

This maintenance organization is responsible for the maintenance of all mechanical parts of the vessel, such as the hull and the propulsion system. This maintenance organization has extensive experience and a knowledgeable workforce. Maintenance is conducted for many one-of-a-kind systems, but similarities between equipment can be found (for example: multiple vessels within one class, similar equipment aboard vessels). Traditionally, the maintenance is based on the advises given by the OEM. For new vessels, risk analyses, based on FMECA, are conducted to identify the most critical equipment. For this critical equipment, more detailed analyses are conducted. However, due to the robustness of the design (i.e. built in redundancy), few critical systems are identified. One of the critical systems is the diesel engine: the vessels have either diesel direct or diesel-electric propulsion systems. For these engines, every now and then oil samples are taken. Based on these samples, data about imminent failures and wear of the engines is obtained. Rather straightforward maintenance analyses, using predefined rejection norms, are used based on the measured degradation of the engine. The analyses can result in detection of anomalies in the engines, diagnosis of the exact problems and a prognosis based on a generic trend of the remaining lifetime or the time to the next required maintenance activity.

The type of AMT has been selected based on extensive experience with this – commonly used – technique. Moreover, the OEM advises to use this type of inspections to ensure the state of the engine.

4.5 Case 5: Application of Mechanism-based Predictions at maintainer of a military helicopter

Detailed knowledge about the failure mechanisms of the component, combined with a physical model is required for a mechanism-based analysis. Within the five cases, this type of analysis is only applied to the most critical components and therefore also more applied to aircraft and helicopters than to vehicles or vessels.

This maintainer of military helicopters collects health and usage monitoring data. Based on this input, the flown flight manoeuvres can be determined. For a highly critical frame in the fuselage of the helicopter, a dynamic stress model has been developed. This physics-of-failure model uses input from the installed health and usage monitoring system, strain gauges, and usage data. Analyses are conducted to detect the flown flight 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. Moreover, decisions can be taken to reduce the impact of the problem by for example changing the (type of) usage of the helicopter.

The choice for a physics-of-failure model has been made since many variables influence the degradation of the frame. Moreover, since this is one of the most flight critical parts of the helicopter, the quality (accuracy and precision) of the prediction has to be very high. In cooperation with one of its knowledge partners, the department has therefore chosen to develop a mechanism-based analysis.

5. Mapping the Identified Prognostic Routes in the Case Studies

In section 4, narrative explanations of the taken routes have been given. In this section, the routes are visualized by mapping them on the framework. Figure 3 shows the exact same steps and building blocks as Figure 1, but now the routes are visualized using the coloured lines. To illustrate the figure, we explain the experience-based technique application with the department that conducts maintenance for the mechanical systems of vessels (Vessels-Mechanical). In the figure, this is the red route. As shown, the department starts with collecting historical data. In step 2, an experience-based analysis is applied. Step 3 shows that although the application of this technique does not result in detection results, diagnosis and a small level of prognosis results are achieved. The figure also shows that the department partly uses these techniques for maintenance decision making (step 3b).

The advantage of this visualisation is that it gives a direct overview of what is exactly applied and what is achieved. For example, for the Vessels-Electrical the figure clearly shows that no detection results are achieved with the experience-based techniques.

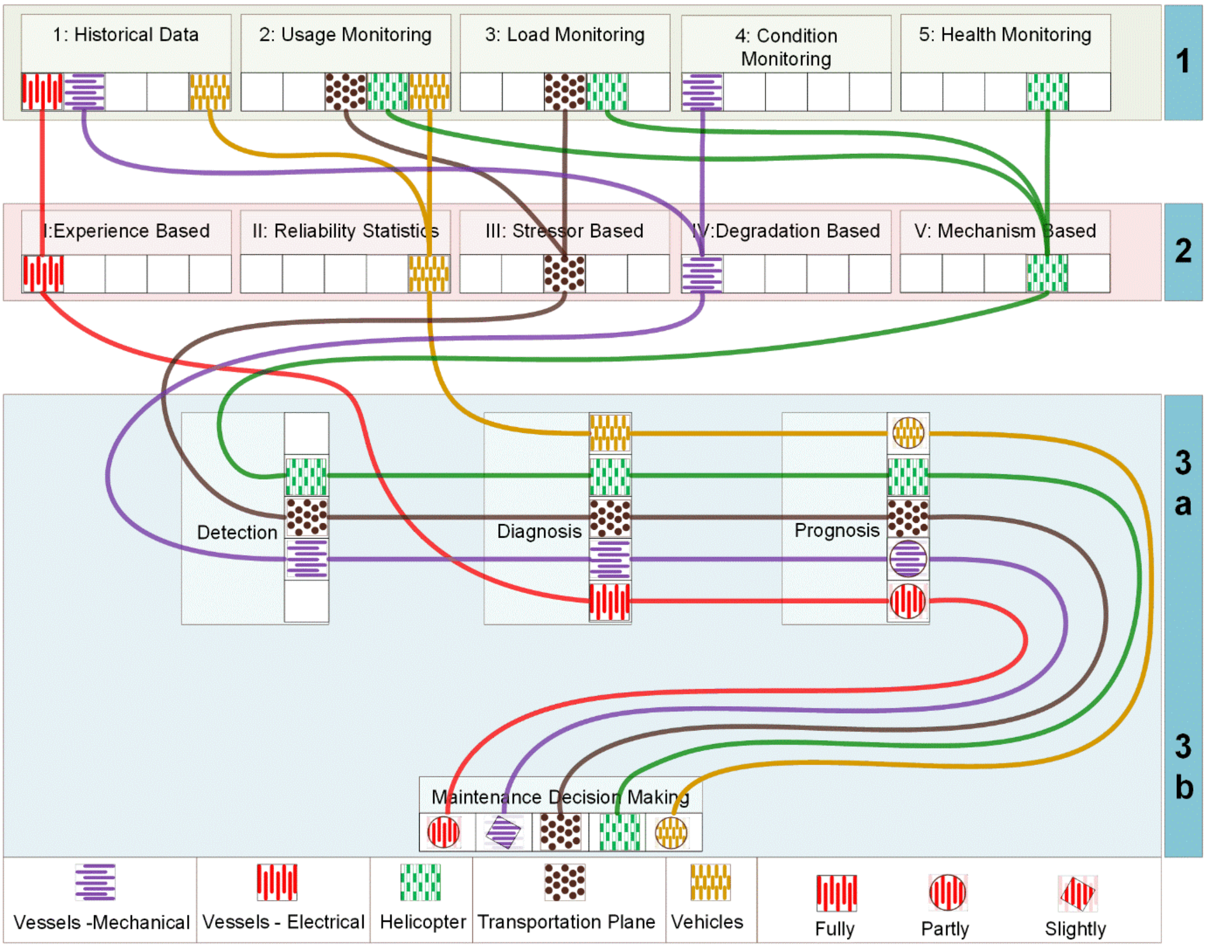

Figure 3. Mapping the prognostic routes

6. Route selection process

The five cases show that the selected routes are chosen based on (i) the available data, and (ii) the required outcome. The former often acts as a barrier to make more accurate predictions. The latter is used as a trigger to develop more accurate techniques. Different techniques result in different (types of) predictions. In Figure 4, the five different AMTs are shown together with the required inputs and outcomes. As seen in the first case, the (low) quality of the input data could result in failure of the (i.e. reliability statistics) analysis. Ensuring the quality of the required input is therefore of critical importance. To enable the selection of the appropriate technique to apply, five types of outcomes of the techniques are proposed. The outcomes are differentiated by four factors: (i) whether it focuses on a general or individual system (from I to II), (ii) whether it considers the (varying) environment (from II to III), (iii) whether the AMT considers the current state of the component (from III to IV), (iv) whether it uses a general trend or a calculation model for a prognosis (from IV to V). The decision scheme in Figure 4 now shows what type of data is required if a certain type of outcome of an AMT is ambitioned.

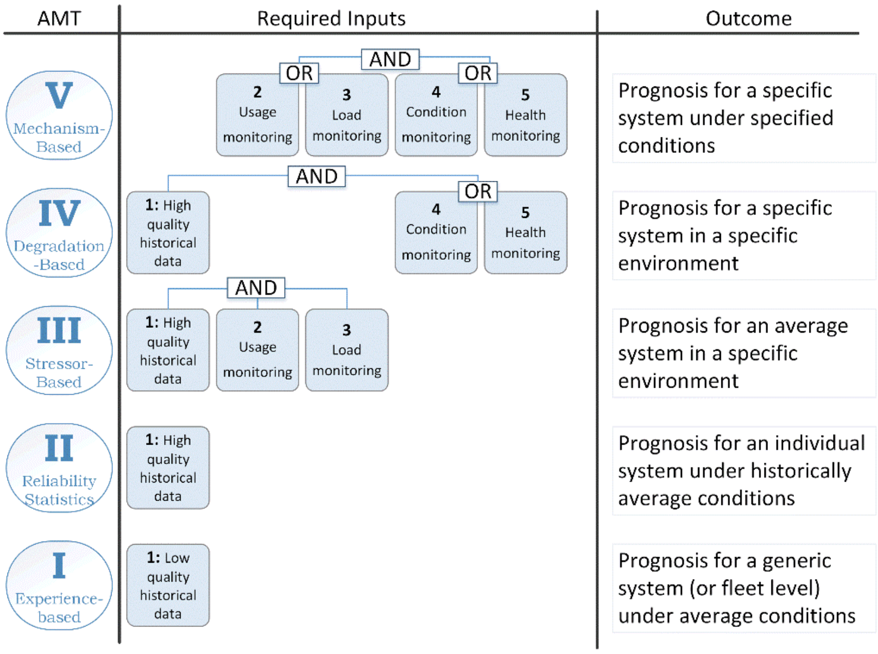

Figure 4. Selecting advanced maintenance techniques

7. Conclusion and Discussion

In this paper, five cases are selected within the NLMOD and five different routes from data gathering to maintenance decision making are discussed and mapped. Mapping the chosen routes gives insight in the steps towards maintenance decision making. This is important since case-studies have shown that it is difficult for practitioners to apply the correct maintenance technique and that determining the correct AMT and selecting the appropriate route is difficult (Tiddens et al., 2015).

The selection of the AMTs in the studied cases seems highly influenced by expert knowledge. Although all departments clearly stated that the analyses are conducted based on the quest to make an informed maintenance decision, the cases show that for low mature techniques (experience-based, reliability statistics), the departments only use the data and knowledge that is available. For the more highly mature techniques (load-based and mechanism-based) the choice seems more substantiated, although again merely based on expert knowledge from within the department or knowledge partners.

The limitations in the availability and quality of input data highly influence the selection of the AMT. It therefore seems that the selection of the applicable AMT is rather straightforward when

only a limited number of options are available, e.g. in case of no data and no monitoring devices. For the naval cases, only knowledge, little reliability data and degradation-based inspections on few components are available. The availability of one of these three types of data is in these cases leading for the selection of the AMT.
In the air force cases, more options are available. Practices in the field of maintenance techniques are (often) better developed (mainly due to regulation standards) and more data is therefore available to support the analyses. However, also in these cases, a large amount of the maintenance is based on experience-based techniques (MSG-3 practices). These analyses however, are often supported with detailed OEM information and the developed experience-based maintenance concepts are therefore often substantiated with more advanced AMTs, which are conducted by the OEM. For few critical components, the maintainer has hired an external agency to develop – mostly – physical and data models. This choice is mainly based on the preferences of experts and the trustworthiness of these analyses, which is crucial for the regulators.
As practitioners indicated in the interviews, for the studied departments, it is very difficult to determine beforehand the relevant methods and parameters when dealing with AMTs that are new to them. To avoid a long and costly implementation process, either external parties are hired to assist in developing the analyses or the analyses are not developed at all.
The recently installed IT structure, which is almost similar for all cases, is (currently) mentioned as a limitation for the application of advanced reliability statistics. On the other hand, the introduction of the CMMS offers for the future. The availability of high-quality data will probably improve in time since the now limited amount of failure and costing data available in the system will grow automatically. For the air force cases (helicopter and airplane) this is less of a problem since the strict aviation regulations prescribe detailed registration of events.
Although only one cases within one – large – company have been studied in this paper, all types of AMTs have been recognized in the five cases. A diverse approach to making informed maintenance decisions is recognized. A plausible reason for this could be found in the maturity and experience of the department in the usage of AMTs. This maturity is highly influenced by the nature of the risk profiles associated with the types of assets and therefore the requirements that are set for the outcomes of the AMTs within the three studied branches: army, navy, and air force.
Since only cases within the NLMOD are selected, further research will focus on conducting case-studies on the application of AMTs in industry to identify different approaches to route selection. Moreover, further research will focus on researching cases where more options for different AMTs are available (e.g. multiple available data sources, different type of equipment, or knowledge of multiple types of AMTs available within a department) since this could bring more detailed insight in the selection process.

8. Acknowledgements

The authors gratefully acknowledge the parties providing funding to this research project. This research is part of the Tools4LCM project, funded by the Netherlands Ministry of Defence and the National Aerospace Laboratory NLR. The research is also part of the MaSeLMA project (Integrated Maintenance and Service Logistics Concepts for Maritime Assets), funded by Dinalog (Dutch Institute for Advanced Logistics). The authors wish to express gratitude to the interviewees of the case-studies for their contributions to this chapter.

9. References

Bo, S., Shengkui, Z., Rui, K., & Pecht, M. (2010, 12-14 Jan. 2010). *Benefits analysis of prognostics in systems.* Paper presented at the Prognostics and Health Management Conference, 2010. PHM '10.

Dekker, R., Wildeman, R., & van der Duyn Schouten, F. (1997). A review of multi-component maintenance models with economic dependence. *Mathematical Methods of Operations Research, 45*(3), 411-435. doi:10.1007/BF01194788
Eisenhardt, K. M. (1991). Better stories and better constructs: The case for rigor and comparative logic. *Academy of Management review*, *16*(3), 620-627.
Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of management journal*, *50*(1), 25-32.
Farrar, C. R., & Lieven, N. A. J. (2007). Damage prognosis: the future of structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *365*(1851), 623-632. doi:10.1098/rsta.2006.1927
Garg, A., & Deshmukh, S. G. (2006). Maintenance management: Literature review and directions. *Journal of Quality in Maintenance Engineering, 12*(3), 205-238. doi:10.1108/13552510610685075
Grubic, T., Redding, L., Baines, T., & Julien, D. (2011). The adoption and use of diagnostic and prognostic technology within UK-based manufacturers. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture, 225*(8), 1457-1470.
Haddad, G., Sandborn, P. A., & Pecht, M. G. (2014). Using maintenance options to maximize the benefits of prognostics for wind farms. *Wind Energy, 17*(5), 775-791. doi:10.1002/we.1610
Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483-1510. doi:http://dx.doi.org/10.1016/j.ymssp.2005.09.012
Kerkhof, R. M. v. d., Akkermans, H. A., & Noorderhaven, N. G. (2014). *Knowledge lost in data: Organizational impediment to condition-based maintenance in the process industry*. Paper presented at the 21st EurOMA Conference, Palermo.
Lee, J., Bagheri, B., & Kao, H.-A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. *Manufacturing Letters, 3*, 18-23.
McCutcheon, D. M., & Meredith, J. R. (1993). Conducting case study research in operations management. *Journal of Operations Management, 11*(3), 239-256.
Meredith, J. R. (1987). Automating the factory: theory versus practice. *International journal of production research*, *25*(10), 1493.
Sikorska, J., Hodkiewicz, M., & Ma, L. (2011). Prognostic modelling options for remaining useful life estimation by industry. *Mechanical Systems and Signal Processing*, *25*(5), 1803-1836.
Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2015). The Adoption of Prognostic Technologies in Maintenance Decision Making: A Multiple Case Study. *Procedia CIRP, 38*, 171-176. doi:http://dx.doi.org/10.1016/j.procir.2015.08.028
Tinga, T. (2010). Application of physical failure models to enable usage and load based maintenance. *Reliability Engineering & System Safety*, *95*(10), 1061-1075. doi:http://dx.doi.org/10.1016/j.ress.2010.04.015
Veldman, J., Klingenberg, W., & Wortmann, H. (2011). Managing condition-based maintenance technology: a multiple case study in the process industry. *Journal of Quality in Maintenance Engineering*, *17*(1), 40-62.
Yin, R. K. (1989). Case Study Research: Design And Methods (Applied Social Research Methods) Author: Robert K. Yin, Publisher: Sage Publicat: Sage Publications, Inc.
Zio, E. (2009). Reliability engineering: Old problems and new challenges. *Reliability Engineering & System Safety*, *94*(2), 125-141. doi:http://dx.doi.org/10.1016/j.ress.2008.06.002