# Setting sail towards predictive maintenance

## Developing tools to conquer difficulties in the implementation of maintenance analytics

Wieger Tiddens

# Setting sail towards predictive maintenance

DEVELOPING TOOLS TO CONQUER DIFFICULTIES IN THE IMPLEMENTATION OF MAINTENANCE ANALYTICS

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# SETTING SAIL TOWARDS PREDICTIVE MAINTENANCE

## DEVELOPING TOOLS TO CONQUER DIFFICULTIES IN THE IMPLEMENTATION OF MAINTENANCE ANALYTICS

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# Summary

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Executives in asset-intensive industries often regard unexpected failures of their physical assets as the primary operational risk to their business. Unexpected downtime can be disruptive in complex manufacturing supply chains and imposes high costs due to forgone productivity. Competitive pressure therefore forces companies to use the reliability and dependability of their equipment as a competitive weapon.

To increase this reliability and dependability of assets, maintenance actions such as repairs or replacements, machine updates (consider changes in production speed), planned overhauls and corrective actions are conducted. These actions affect the flexibility, throughput time, and quality at the operations and logistics level of a firm. It is therefore important to plan maintenance actions before a failure occurs, i.e. not too late. But also not too early. Since the costs of maintenance and support can account for 60 – 75% of the total lifecycle costs of a manufacturing system, maintenance actions should only be conducted when required.

However, most current maintenance programs still rely on previous experiences and expert knowledge and do not consider (or reconsider) the actual condition of the asset. Traditional preventive maintenance programs often prescribe maintenance actions based on calendar time or running hours (or mileage as for a car). A drawback of this is that maintenance is often conducted far before the end of the part's service life. A theoretical optimum, but practically not always feasible, is therefore to conduct maintenance only based on the actual condition of the asset. This requires collecting (real-time) data on the condition of the asset, using for example sensors and microprocessors. Such an approach has in many situations proven to be more successful in preventing unexpected failures and reducing the total costs of maintenance compared with other maintenance approaches.

Predictive maintenance (PdM) is a preventive maintenance approach that uses these types of techniques or analytics to inform (the owner, service provider or operator) about the current, and preferably also the future state of their physical assets. For this, PdM employs analytics, methods and techniques that use asset data, such as condition and loading data or experience, to detect or predict changes in the physical condition of equipment.

The use of these analytics for PdM contributes to a wider shift towards Industry 4.0 by integrating PdM with production, logistics and services in the current industrial practices. Besides, as an example, in a study about the use of business analytics, recent studies found that top-performing firms put analytics to use in the widest possible range of decisions and cite effective analytics as a competitive differentiator. The use of PdM is also stimulated by servitization. Servitization aims to better understand the needs of customers and build unique, loyal customer relationships. Benefits of higher availability and reliability can be shared with or marketed to the customer, it thereby becomes more interesting to invest in the use of PdM.

Although predictive maintenance offers various benefits to asset owners, OEMs and service providers, the adoption of PdM in practice seems to lag behind the theoretical understanding of its use. Practitioners experience a gap between the potential and realized benefits. The latter may be due to an inadequate understanding of how firms can achieve these benefits and the means that are required to translate those benefits into tangible value propositions. Research showed that practitioners see 'a lack of understanding in how analytics can help to improve their business' and 'a lack of management bandwidth' as the top two barriers in achieving the competitive advantage the use of analytics can offer their company. It has been suggested that many of these issues are overlooked by the academic literature as most research within the field of PdM seems to exclude the organizational and managerial facets and only addresses the technical aspects (such as developing accurate sensors).

The current study therefore aims to further develop our understanding on the use and adoption of predictive maintenance and, based on these observations, develop tools to better support the practical application of predictive maintenance. This research is guided by the following research question: *How can the practical application of predictive maintenance better be supported?*

To be able to answer this question, a multiple-case study is conducted including fourteen cases from various industries in the Netherlands. The focus in this multiple-case study lays on both the technical and organizational application process of PdM. The results of this multiple-case study reveal three main difficulties in the application of PdM that structure the remainder of this thesis. These show that practitioners need guidance in:
1. Selecting the most suitable techniques for PdM;
2. Identifying the most suitable candidates for PdM;
3. Evaluating the added value of PdM.

To assist in selecting the suitable techniques for PdM (difficulty #1), a framework for the selection of the optimal preventive maintenance approach is proposed. The selection framework is developed in a four-step design science process. After exploring typical difficulties in the selection of predictive maintenance techniques, a set of initial solutions is proposed for these identified problems. Among these are a classification of the various maintenance approaches into five types, a guideline to select the appropriate ambition level for the maintenance process and a classification of the available data types.

The initial solutions are then integrated into a framework that assists practitioners in selecting the optimal maintenance approach. Finally, the proposed framework is successfully tested and demonstrated using four case studies.

Identifying the most suitable candidates (that is systems, components) is critical for the successful implementation of PdM (difficulty #2). This is to assess where PdM would provide the greatest benefit in performance and costs of downtime. The second identified difficulty shows that practitioners mainly use straightforward methods such as a top ten list of performance killers or cost drivers to select the candidates for PdM. However, these methods do not always lead to the most suitable candidates for PdM. The main reason is that these methods mainly focus on critical components without considering the clustering of maintenance, and the technical, economic, and organizational feasibility.

A three-stage funnel-based selection method to improve this selection process is therefore proposed. The first step of the funnel helps to significantly reduce the number of suitable systems or components by a traditional filtering on failure frequency and impact on the firm. In the second and third step, a more in-depth analysis on the remaining candidates is conducted. These steps help to filter potential showstoppers and study the technical and economic feasibility of developing a specific PdM approach for the selected candidates. Finally, the proposed method is successfully demonstrated using two distinct cases: a vessel propulsion system and a canal lock.



The final identified difficulty (#3) indicates that even technically successful companies tend to have difficulties in showing their business value. This suggests that PdM is sometimes not applied in the most efficient way and sometimes an alternative strategy should be followed. Moreover, although developing business cases is key for evaluating project success, the costs and benefits of PdM implementations are often not explicitly defined and evaluated.

A hybrid business case approach to help managers evaluate and justify implementing PdM is ttherefore proposed. Depending on the innovativeness (for the organization) of the applied technique, the business case should have a different goal orientation and be composed of different support elements. The proposed hybrid business case approach is demonstrated in an in-depth single case study that focuses on developing engine condition trend monitoring for a military transport aircraft. The case study explores differences in applying innovative maintenance techniques (exploration) or applying well-known techniques (exploitation). Using a combination of non-financial (strategic multi-criteria analysis) and financial elements (using Monte Carlo simulation), the investment in PdM are compared with both fixed-interval preventive maintenance and corrective maintenance.

This research set out by studying difficulties in the implementation of PdM. This dissertation reveals that almost all organizations who applied PdM successfully have followed a costly trial and error process, partly due to the complexity and the absence of effective theoretical guidance. This study highlights the importance of the organizational aspects of PdM implementations, since it seems that these are often overlooked by the academic literature.

To conquer the three main difficulties that were identified in the multiple case study, three decision support tools have been developed. The – combination of the – three proposed methods aim to assist(s) practitioners in the implementation of PdM.

# Samenvatting



Leidinggevenden werkzaam in kapitaalintensieve industrieën beschouwen onverwachte storingen van fysieke kapitaalgoederen, ook wel fysieke assets genoemd, vaak als een primair risico voor hun bedrijf. De onverwachte stilstandstijd die uit die storingen voortkomt, kan ontwrichtend zijn in complexe toeleveringsketens. Het brengt daarnaast hoge kosten met zich mee vanwege de afgenomen productiviteit. Concurrentiedruk dwingt bedrijven daarom om de betrouwbaarheid van hun assets als een concurrentiewapen te gebruiken.

Om deze betrouwbaarheid van fysieke kapitaalgoederen te vergroten, worden onderhoudsacties zoals reparaties of vervangingen, machine-updates (denk bijvoorbeeld aan veranderingen in productiesnelheid), geplande revisies en correctieve acties uitgevoerd. Deze acties hebben invloed op de flexibiliteit, doorlooptijd en kwaliteit van het bedrijf haar operationele en logistieke niveau. Het is belangrijk om onderhoudsacties te plannen voordat een storing optreedt, dat wil zeggen niet te laat. Maar ook niet te vroeg. Omdat de kosten van onderhoud tot wel 60 - 75% van de totale levenscycluskosten van een productiesysteem kunnen uitmaken, is het gewenst dat onderhoudsacties alleen worden uitgevoerd als dat daadwerkelijk nodig is.

De meeste onderhoudsprogramma's zijn echter nog steeds gebaseerd op historische ervaringen en expertkennis en houden geen rekening met de actuele conditie van systemen (bijvoorbeeld een dieselmotor). Traditionele preventieve onderhoudsprogramma's schrijven vaak onderhoudsacties voor op basis van kalendertijd of draaiuren (of kilometrage zoals voor een auto). Een nadeel hiervan is dat onderhoud vaak ver vóór het einde van de levensduur van het onderdeel wordt uitgevoerd. Een theoretisch optimum, maar praktisch niet altijd haalbaar, is daarom om onderhoud alleen uit te voeren op basis van de werkelijke conditie van de asset. Dit vereist het verzamelen van (real-time) gegevens over de conditie van de asset, met behulp van bijvoorbeeld sensoren en microprocessoren.

Een dergelijke aanpak heeft in veel situaties bewezen succesvoller te zijn in het voorkomen van onverwachte storingen en het verminderen van de totale onderhoudskosten, in vergelijking met andere onderhoudsbenaderingen. Voorspellend onderhoud (in het Engels: Predictive Maintenance, hier afgekort tot PdM) is een set van activiteiten die de eigenaar, fabrikant, dienstverlener of gebruiker informeren over de huidige en bij voorkeur ook de toekomstige status van hun fysieke asset. PdM maakt hiervoor gebruik van analyse-instrumenten (analytics), methoden en technieken. Deze gebruiken asset data, zoals data over de conditie en belasting, of ervaring, om veranderingen in de fysieke conditie van assets te detecteren, diagnosticeren en te voorspellen.

Het gebruik van deze analyse-instrumenten voor PdM draagt bij aan een bredere verschuiving naar Industrie 4.0 (in Nederland ook vaak Smart Industry genoemd) door PdM te integreren met productie, logistiek en de diensten die een bedrijf aanbiedt. Recente onderzoeken naar het gebruik van bedrijfsanalyses bijvoorbeeld, laten zien dat de best presterende bedrijven analyse-instrumenten gebruiken voor een zo breed mogelijk scala van beslissingen. Deze bedrijven beschouwen het effectief kunnen gebruiken van deze analyse-instrumenten dan ook als een onderscheidende competitieve factor.

Het gebruik van PdM wordt ook gestimuleerd door servitisation: het aanbieden van een klantgerichte combinatie van goederen en diensten. Servitisation heeft tot doel het beter begrijpen van de klantvraag en het opbouwen van unieke, loyale lange-termijn klantrelaties. Daarnaast kunnen behaalde voordelen zoals hogere beschikbaarheid en betrouwbaarheid met de klant worden gedeeld. Het wordt daardoor interessanter voor de leverancier om te investeren in het gebruik van PdM.

Hoewel voorspellend onderhoud verschillende voordelen biedt aan de eigenaren van assets, OEM's (original equipment manufacturer, de fabrikant) en dienstverleners, lijkt de invoering van PdM in de praktijk achter te blijven bij het theoretische begrip van het gebruik ervan. Gebruikers ervaren een kloof tussen de potentiële en gerealiseerde voordelen. Dit laatste kan te wijten zijn aan onvoldoende inzicht in de manier waarop bedrijven deze voordelen kunnen behalen en de middelen die nodig zijn om deze voordelen om te zetten in tastbare waarde proposities. Onderzoek laat zien dat gebruikers "een gebrek aan inzicht in de manier waarop analyse-instrumenten kunnen bijdragen aan het verbeteren van hun bedrijf" en "een gebrek aan managementbandbreedte" zien als de twee belangrijkste obstakels bij het behalen van het concurrentievoordeel dat het effectief gebruik van analyse-instrumenten hun bedrijf kan bieden. Er wordt gesuggereerd dat veel van deze kwesties over het hoofd worden gezien in de academische literatuur, omdat de meeste onderzoeken op het gebied van PdM de organisatorische- en managementfacetten lijken uit te sluiten en alleen betrekking hebben op de technische aspecten (zoals het ontwikkelen van nauwkeurige sensoren of algoritmes).

Dit promotieonderzoek heeft daarom tot doel het begrip van het gebruik van en de acceptatie van PdM verder te ontwikkelen. Om vervolgens op basis van deze observaties instrumenten te ontwikkelen om de praktische toepassing van voorspellend onderhoud beter te ondersteunen.

Dit onderzoek wordt gestuurd met de volgende onderzoeksvraag: Hoe kan de praktische toepassing van voorspellend onderhoud beter worden ondersteund?

Om deze onderzoeksvraag te kunnen beantwoorden, is een meervoudige casestudy uitgevoerd, met daarin veertien casussen uit verschillende industrieën in Nederland. De focus in deze studie ligt zowel op het technische als het organisatorische toepassingsproces van PdM. De resultaten van dit onderzoek laten drie belangrijke problemen zien die gebruikers van PdM in de praktijk ervaren. Deze drie problemen zullen ook het vervolg van dit proefschrift structureren. Het blijkt dat bedrijven en organisaties ondersteuning nodig hebben bij het:

1. Selecteren van de meest geschikte technieken voor PdM;
2. Identificeren van de meest geschikte kandidaten voor PdM;
3. Evalueren van de toegevoegde waarde van PdM.

Om te helpen bij het selecteren van de geschikte technieken voor PdM (probleem #1), wordt een raamwerk voor de selectie van de optimale preventieve onderhoudsbenadering voorgesteld. Het model is ontwikkeld in een vier-staps design science-proces (ontwerpend onderzoek). Na het verkennen van de meest voorkomende problemen in de praktijk bij de selectie van voorspellende onderhoudstechnieken (stap 1), wordt een reeks initiële oplossingen voorgesteld voor deze geïdentificeerde problemen (stap 2). Hiertoe behoren een classificatie van de verschillende onderhoudsbenaderingen in vijf types, een richtlijn om het juiste ambitieniveau voor het onderhoudsproces te selecteren en een classificatie van de beschikbare datatypen.

De initiële oplossingen worden vervolgens geïntegreerd in een beslissingsondersteuningsmodel dat gebruikers helpt bij het selecteren van de optimale onderhoudsaanpak (stap 3). Ten slotte is het voorgestelde raamwerk met succes getest en gedemonstreerd met behulp van vier casussen (stap 4).

S

Het identificeren van de meest geschikte systemen of componenten voor PdM is doorslaggevend voor de succesvolle implementatie hiervan (probleem #2). Deze identificatie is nodig om te beoordelen waar PdM het grootste voordeel kan bieden in de bijdrage aan bedrijfsprestaties en het reduceren van de kosten van stilstandstijd. In de praktijk worden hiervoor overwegend eenvoudige methoden gebruiken. Om de meest geschikte systemen of componenten voor PdM te selecteren, wordt bijvoorbeeld gebruik gemaakt van een top tien lijst van prestatiekillers of kostendrijvers of Pareto-analyses.

Deze methoden leiden echter niet altijd tot de selectie van de meest geschikte systemen of componenten voor PdM. De belangrijkste reden is dat deze methoden vooral gericht zijn op het identificeren van kritieke componenten zonder rekening te houden met de clustering van onderhoud en de technische-, economische- en organisatorische haalbaarheid.

Een drie-traps trechtervormige selectiemethode om dit selectieproces te verbeteren wordt daarom voorgesteld. De eerste stap van de trechter helpt het aantal opties aanzienlijk te reduceren door een traditionele filtering op faalfrequentie en impact op het bedrijf (bijvoorbeeld kosten van stilstandstijd). In de tweede en derde stap wordt een meer diepgaande analyse van de resterende componenten uitgevoerd. Deze stappen helpen om mogelijke showstoppers (redenen waarom een PdM aanpak uiteindelijk geen waarde oplevert) te filteren, zoals onderhoudsclustering voortkomend uit plannings- of technische overwegingen. Vervolgens wordt een diepgaande analyse uitgevoerd op de technische- en economische haalbaarheid van het ontwikkelen van een specifieke PdM-aanpak voor de geselecteerde componenten. De voorgestelde methode wordt met succes gedemonstreerd met behulp van twee verschillende casussen: een scheepsaandrijving en een sluizencomplex.

Het derde geïdentificeerde probleem (# 3) geeft aan dat zelfs technisch succesvolle bedrijven vaak moeite hebben om de bedrijfswaarde van PdM aan te tonen. Hoewel het ontwikkelen van businesscases belangrijk is voor het evalueren van projectsuccessen, worden de kosten en baten van PdM-implementaties vaak niet expliciet gedefinieerd en geëvalueerd. Dit suggereert dat PdM soms niet op de meest efficiënte manier wordt toegepast en dat er soms een alternatieve strategie moet worden gevolgd. Daarom wordt een hybride business case-aanpak voorgesteld om te helpen bij het evalueren en motiveren van de implementatie van PdM.

Hieruit kan geconcludeerd worden dat afhankelijk van de innovativiteit (voor de organisatie) van de toegepaste techniek, de businesscase een andere doeloriëntatie moet hebben en verschillende ondersteunende elementen dient te bevatten.

De voorgestelde hybride business case-aanpak wordt toegepast in een casestudy die zich richt op het ontwikkelen van trendmonitoring van motorcondities voor een militair transportvliegtuig. De casestudy laat verschillen zien in het toepassen van innovatieve onderhoudstechnieken (exploratie) en het toepassen van bekende technieken (exploitatie). De voorgestelde aanpak bestaat uit een combinatie van niet-financiële, een strategische multi-criteria analyse en financiële elementen, met behulp van Monte Carlo-simulatie. Hiermee wordt de investering in PdM met zowel vast-interval preventief onderhoud als correctief onderhoud vergeleken.

Concluderend, dit proefschrift laat zien dat bijna alle organisaties die PdM met succes hebben toegepast een kostbaar proces van vallen en opstaan hebben gevolgd, deels vanwege de complexiteit en deels vanwege de afwezigheid van effectieve theoretische ondersteuning. Daarbij benadrukt deze studie het belang van de organisatieaspecten van PdM-implementaties aangezien het lijkt alsof deze vaak over het hoofd worden gezien in de academische literatuur.

Dit promotieonderzoek begon met het bestuderen van problemen die in de praktijk voorkomen bij de implementatie van PdM. Om de drie belangrijkste problemen die in de meervoudige casestudy werden geïdentificeerd te overwinnen, zijn drie beslissingsondersteunende hulpmiddelen ontwikkeld. De combinatie van deze drie voorgestelde methoden helpt gebruikers bij de implementatie van PdM.

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# Chapter 1

# Introduction

## 1.1. Maintenance as a competitive weapon

Executives in asset-intensive industries regard unexpected failures of their physical assets as one of the primary operational risks to their business (LaRiviere et al. 2016). Unexpected downtime can be disruptive in complex manufacturing supply chains and imposes high costs due to forgone productivity (LaRiviere et al. 2016). In addition, competitive pressure forces companies to use the reliability and dependability of their equipment as a competitive weapon (Simões, Gomes, and Yasin 2016).

To increase the reliability and dependability of assets, maintenance actions such as repairs or replacements, machine updates (consider, for example, changes in production speed), planned overhauls and corrective actions are conducted. These actions affect the flexibility, throughput time, and quality at the operations and logistics level of a firm (Waeyenbergh and Pintelon 2002). It is therefore important to plan maintenance actions before a failure occurs, i.e. not too late, but from an efficiency perspective, also not too early.

However, most current maintenance programmes still rely on previous experiences and expert knowledge and do not consider, or reconsider, the actual condition of the asset (Van Noortwijk 2009; Singpurwalla 1995; Zio et al. 2012). Traditional preventive maintenance programmes often prescribe maintenance actions based on calendar time, running hours, or mileage as in cars, for instance. A drawback of these programmes is that maintenance is often conducted far before the end of the part's service life (Tinga 2010). A theoretical optimum, which is practically not always feasible, is therefore to conduct maintenance only based on the actual condition of the asset. This requires collecting and processing (real-time) data on the condition of the asset, using e.g. sensors and micro-processors. Such an approach has, in many situations, proven to be more successful in preventing unexpected failures and reducing the total costs of maintenance than other maintenance approaches (Jardine, Lin, and Banjevic 2006; Veldman, Klingenberg, and Wortmann 2011).

## 1.2. Predictive maintenance

The term predictive maintenance (PdM) refers to a maintenance policy that triggers maintenance activities by predictions of failures. To obtain accurate predictions, PdM is typically based on a set of activities that inform (the owner, service provider or operator) about the current, and preferably also the future state of their physical assets. For this, PdM employs analytics, methods and techniques (denoted as maintenance analytics, MAs, or synonymous: maintenance techniques, MTs) that use asset data, such as condition and loading data or experience, to detect or predict changes in the physical condition of equipment (signs of failure). Thus, the term PdM covers a set of maintenance policies (pointed out by the dashed region in Figure 1) that are based on the condition of the asset. These condition-based policies can be subdivided in policies that use the measured condition of the asset and policies that use the calculated condition of the asset. Traditionally, the measured policies are regarded as condition-based maintenance (CBM) and the calculated as truly predictive maintenance. In this work however, all condition-based policies are regarded as predictive maintenance. This is first to create clarity since a wide variety of definitions for PdM tend to be used in both practice as in the academic literature. Second, it thereby also recognizes the large variety in types of analytics that are used for PdM.

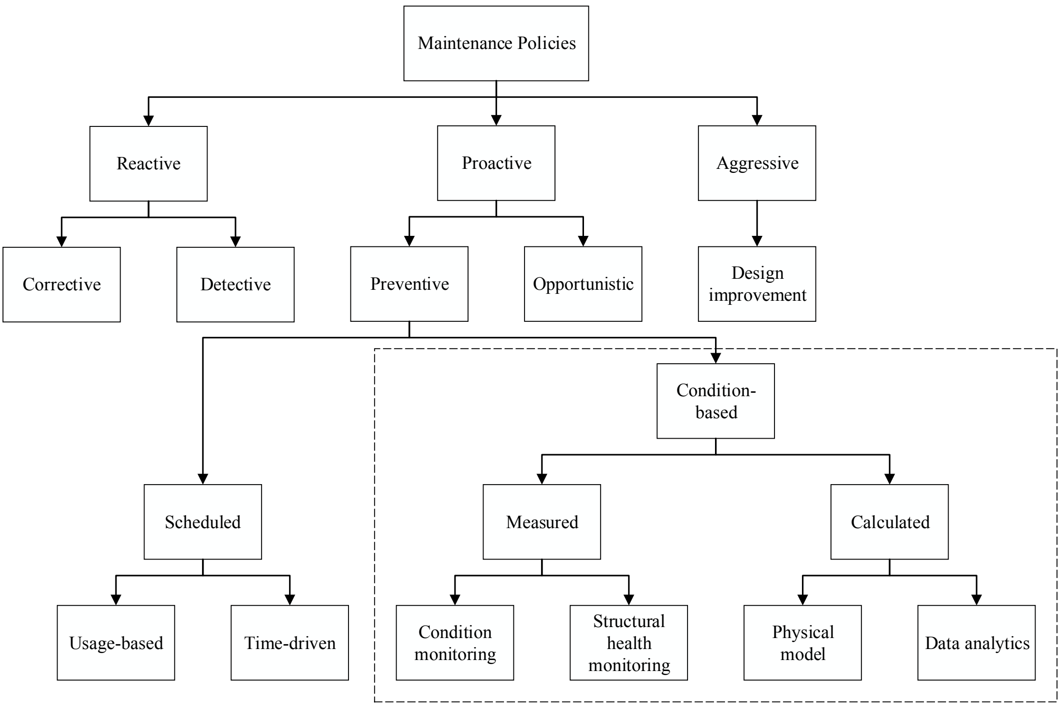


*Figure 1. The predictive maintenance policies (dashed region) within the maintenance landscape (explained in chapter 5).*

## 1.3. Context of the research

### 1.3.1. The fourth industrial revolution as a catalyst for the development of predictive maintenance

Although becoming popular in recent years, the analytical techniques used for PdM, are not new. For example, a machine-tool manufacturer used remote monitoring techniques already in 1975 to reduce the high traveling costs in the service department (Küssel et al. 2000).

The digitization of manufacturing however, acts as a catalyst for the development of PdM. Smart, connected machines reshape the operations of manufacturing plants where machines can increasingly be linked together in systems (Porter and Heppelmann 2015). This wider shift towards Smart Industry, also denoted as Industrie 4.0 (Germany) or Smart Manufacturing (United States), revolutionizes the maintenance domain. The name Industry 4.0 recognizes the existence of three previous industrial revolutions and suggests that its impact in transforming the world we live in, will be comparable to these previous revolutions (see Figure 2). Historians however, sometimes rather speak of evolutions than revolutions since these 'revolutions' took several decades rather than just a few years for their full effect to be felt (Kagermann 2015).

The fourth industrial revolution enables manufacturing individual and customizable products at the same cost as mass production (Wang 2016). Industry 4.0 thereby enables intelligent and flexible production control using IT-based intercommunicating and interacting machines, products, services, equipment, and tools (Wang 2016). The transformative technologies that manage the interconnected systems between physical assets and computational capabilities are termed Cyber-Physical Systems (Baheti and Gill 2011).

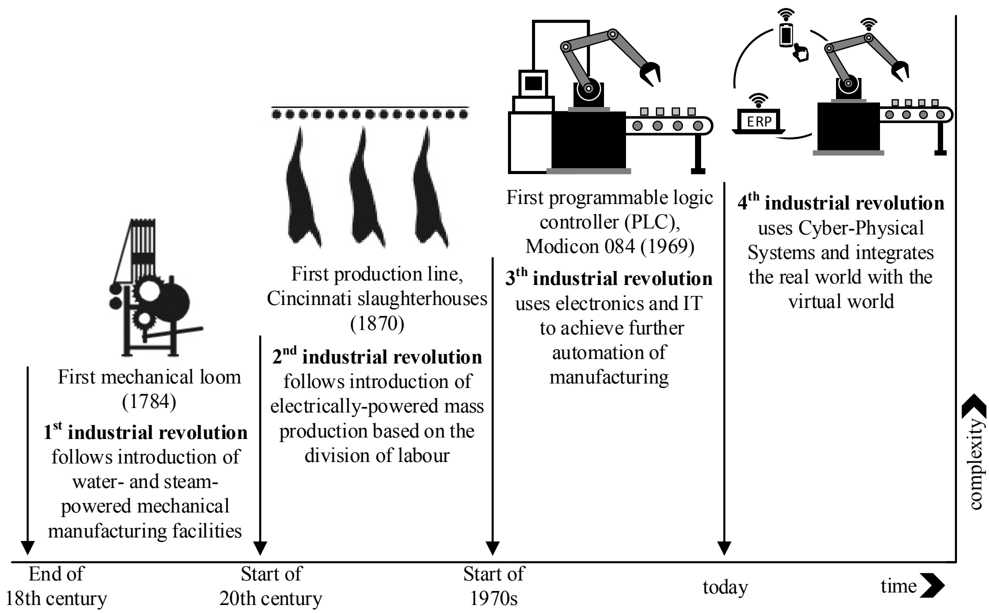


*Figure 2. Four Industrial Revolutions, adapted from: Kagermann et al. (2013).*

These are seen as a major component of Industry 4.0, next to the Internet of Things, Big Data and Data Mining, and the Internet of Services (Wang 2016).
Porter and Heppelmann (2015) describe four capabilities delivered by smart, connected products that reshape the competitive landscape: (i) by monitoring and reporting on themselves and their environment, new data and insights are created; (ii) with remote control through embedded or cloud software, users have unprecedented ability to tailor product function and personalize interactions; (iii) optimization of product operation, capacity utilization, and predictive maintenance is enabled by analytics and algorithms; and (iv) autonomous operation, self-coordination and self-diagnosis is allowed by access to monitoring data, remote control and optimization algorithms.

Three of these four capabilities (monitor, optimize and self-diagnose) enhance the development of PdM. Also, the advances in information technology make it less complicated to gather and analyze data (Lee, Bagheri, and Kao 2015) and these have thereby improved the ease-of-use of the analytics for PdM. Hence, collecting maintenance related data has become easier by using sensors, micro-processors and computerized maintenance management systems. Also the usefulness of the analytics has improved by the emergence of smart algorithms and intelligent machines that can help to perform a predict-and-prevent practice instead of a fail-and-fix operation (Lee, Ghaffari, and Elmeligy 2011) and integrating PdM with production, logistics and services in the current industrial practices (Lee, Bagheri, and Kao 2015). The use of analytics does not strictly have to be limited to the maintenance domain. In a study about the use of business analytics, LaValle et al. (2010) found that top-performing firms put their analytics to use in the widest possible range of decisions and these firms mention effective analytics as a competitive differentiator.

The use of PdM is also stimulated by servitization (Vandermerwe and Rada 1988; Kastalli and Van Looy 2013). Knowledge on the actual condition of assets can help service providers and original equipment manufacturers (OEMs) in offering services that are directly coupled to their product (Baines and Lightfoot 2014) , e.g. providing maintenance or guaranteeing availability. Creating such a long-term relationship can help to better understand the needs of customers and build unique, loyal customer relationships (Tukker 2004). Moreover, servitization provides routes for companies to move up the value chain and exploit higher value business activities (Baines et al. 2009).

Benefits of higher availability and reliability can be shared with the customer, manufacturers can offer through-life support for their products, and the product's performance can be guaranteed over the life time or contract period. Roy et al. (2013) note that within the aerospace and defence sectors, more than 55% of the revenue is coming from these through-life engineering services nowadays. This makes it increasingly interesting for firms to invest in the use of PdM.

## 1.3.2. Research and development by close cooperation between science and practice

### National level

Various (inter-)national initiatives are set up to help companies adopt the principles of the fourth industrial revolution. In the Netherlands, the goal of the action agenda for Smart Industry – 'Smart Industry – Dutch Industry fit for the future' – is "to accelerate the digitization of industry in order to enhance its competiveness, which is crucial for future welfare and well-being in the Netherlands" (Smart Industry 2014, p. 25). Within this action agenda which provides directions for the Dutch research agenda, the use of predictive maintenance is highlighted as one of the prevailing Smart Industry themes.

Also the branch organizations for smart maintenance in the Netherlands, World Class Maintenance (WCM) and the NVDO (the Dutch association for effective maintenance, in Dutch: *Nederlandse Vereniging voor Doelmatig Onderhoud)* list (the techniques for) predictive maintenance as belonging to today's most important innovations in the field of maintenance.

In developing a maintenance innovation agenda, WCM conducted a Delphi study on maintenance innovation priorities amongst maintenance practitioners in the Netherlands (Akkermans et al. 2016). This report highlights a top-14 of the most important maintenance innovations, according to practitioners. Four of these 14 innovations are closely related to predictive maintenance (including their position on the ranking): big-data analysis (1), use of smart sensors (2), condition and risk based maintenance strategies (4), interfacing between asset management and IT systems (7) and degradation models (8).

The NVDO developed a maintenance compass that identifies the top 10 maintenance trends for 2017 and 2018. The use of predictive maintenance relates to six of these: ageing asset bases (3); need for ICT systems (4); attention for operational excellence (5); dealing with large amounts of data (6); need for outsourcing (7); and, focus on technology and innovation (10).

Following the Smart Industry action agenda, several predictive maintenance field labs have been initiated by WCM on a national level. The objective of these field labs is to create practical environments where companies and knowledge institutions can develop, test and implement solutions for smart industry issues in a targeted manner[1].

### Project level

Besides these initiatives on a national level, also within specific organizations projects have been initiated to explore the opportunities created by digitization.

This is the setting of the current work, which has been initiated within the Netherlands Ministry of Defence. The project 'quantitative tools for life cycle management' (Tools4LCM) set out to develop quantitative tools to improve the life cycle management process, both in general and specifically within the Ministry of Defence. Researchers from the Netherlands Defence Academy (NLDA) and the Netherlands Aerospace center NLR aim

1 These field labs are set up in various industries: the process industry (CAMPIONE), infrastructure (CAMINO), manufacturing (CAPELLA) and the maritime industry (SMASH).

to develop methods that provide insight in the maintenance performance of assets from the Air Force, Army and Navy.

By using data from different sources, such as failure, maintenance, logistic, usage, condition, and financial data, the maintenance performance (i.e. realized availability) and costs are quantified. This data also helps to provide insight in the reasons for e.g. changes in the maintenance demand (work orders), fleet availability or maintenance budget realization (Andela et al. 2015a, 2015b). These initial results stimulate the development of predictive tools, as these can provide insight in (among others) future fleet availability, maintenance costs and work orders.

Next to that, this work is also linked to the Integrated Maintenance and Service Logistics Concepts for Maritime Assets (MaSeLMA) project. This project, funded by the Dutch Institute for Advanced Logistics (Dinalog), is composed of a group of asset owners, service providers, original equipment manufacturers, and knowledge institutes. The project focuses on developing innovative concepts to improve the predictability of maintenance and service logistics demand. Furthermore, it aims to develop smart concepts for service logistics optimization, supply chain coordination and cooperation. The development and implementation of predictive maintenance techniques plays a pivotal role in this project since these models form the input for the service logistics models.

## 1.4. Problem statement

The variety of initiated projects to develop predictive maintenance techniques and assist practitioners in developing predictive maintenance illustrates its perceived potential within practice. However, the adoption of PdM in practice seems to lag behind the theoretical understanding of its use. Moreover, practitioners seem to experience a gap between the potential and realized benefits (Grubic et al. 2011). This may be due to an inadequate understanding of how firms can achieve these benefits and the means that are required to translate those benefits into tangible value propositions (Grubic et al. 2011). LaValle et al. (2010) showed that practitioners see ‘a lack of understanding in how analytics can help to improve their business’ and ‘a lack of management bandwidth’ as the top two barriers in achieving the competitive advantage that the use of analytics can offer their company. It has been suggested that many of these issues are overlooked by the academic literature (Kerkhof, Akkermans, and Noorderhaven 2016; Garg and Deshmukh 2006; Veldman, Klingenberg, and Wortmann 2011) as most research within the field of PdM seems to exclude the organizational and managerial facets and only addresses the technical aspects (such as developing accurate sensors).

The current study therefore aims to further develop our understanding on the use and adoption of predictive maintenance and, based on these observations, develop tools to better support the practical application of predictive maintenance. This research is guided by the following research question:

**Research Question:**

***HOW CAN THE PRACTICAL APPLICATION OF PREDICTIVE MAINTENANCE BETTER BE SUPPORTED?***

## 1.5. Research approach

To achieve the research aim, first the actual use of predictive maintenance within practice is studied. Then, based on the identified difficulties, tools will be developed to conquer these difficulties. This research thereby follows the basic idea of design science, which does not just evaluate (management) practices but also contributes by developing new ideas and practices (Holmström, Ketokivi, and Hameri 2009). Typically, two components of design science can be recognized: (i) an exploratory component to study the problem in practice, and (ii) a design and evaluation component to develop designs that address the problem (Van Aken, Chandrasekaran, and Halman 2016).



For the *problem exploration*, a multiple-case study within various asset intensive industries is conducted to answer the following research question: *How is predictive maintenance used in practice and what are the main difficulties?* The aim of this multiple-case study is to develop knowledge that can serve as a stepping stone towards theory building (Meredith 1987; McCutcheon and Meredith 1993).

Therefore some of the main assumptions and descriptions identified from the literature on the application and use of PdM are postulated. The case studies are used to confront and reflect on these postulates. Not all the possible issues in using PdM are included, but this study focuses on the three main steps (asset data acquisition, maintenance analytics, and maintenance decision making) in a typical PdM application process, as defined by Jardine, Lin, and Banjevic (2006).

This study hereby aims to offer theoretical insights by identifying to what extent these assumptions in the literature correspond to the current practice. The results of this multiple-case study reveal three main difficulties that practitioners experience in the application of PdM. Three solutions to these difficulties structure the remainder of this thesis:

1. Selecting the most suitable techniques for predictive maintenance
2. Identifying the most suitable candidates for predictive maintenance
3. Evaluating the added value of predictive maintenance

The *solution development* ambitions to improve the current situation by solving the three identified problems. The artifacts that will be designed are however not the sole outcome. The design and its evaluation also lead to an understanding of the mechanisms that deliver the outcome of the artifacts (Van Aken, Chandrasekaran, and Halman 2016).

Van Aken (2004) argues that the rigor-relevance dilemma should be considered in developing such practical tools. These tools can either be scientifically proven but then too reductionistic and hence too broad or too trivial to be of much practical relevance, or relevant to practice, but lacking sufficient rigorous justification (Van Aken 2004, p. 221). The designed artefacts are therefore not specific solutions to a particular problem in a unique context, but a generic solution to a set of similar problems.

Hence, the designs are demonstrated in different application domains to establish the effectiveness of the solution in different (but similar) contexts without losing its basic effectiveness (Van Aken, Chandrasekaran, and Halman 2016). In this solution evaluation, the outcomes of testing allows for further improvement of the proposed designs (hence the iterative loops in Table 2). This makes design science an iterative process (Peffers et al. 2007) and allows to assess the generalizability of the artefact.

## 1.5.1. Case studies

Within the design-science approach used in this dissertation, the use of case-studies forms another important methodological instrument employed. Case-studies are used to explore the problem in practice and to demonstrate the proposed solutions. This section discusses the use of case studies within this thesis in a general sense. The specific (case-study) methodology will be discussed in the methodology sections within the specific chapters.

| **Research phase** | **Problem exploration** | | | **Solution development and evaluation** | | |
|---|---|---|---|---|---|---|
| Chapter | 2 | 3 | | 4 | 5 | 6 |
| Basic design type | Multiple-case | Multiple-case | Multiple-case | Multiple-case | Multiple-case | Single-case |
| Mode | Theory generation | Theory generation | Theory generation | Theory testing | Theory testing | Theory testing |
| Phenomenon of interest | Use of PdM in practice | Pathways of MT applications | Frequency of MT occurrence | Selection of appropriate MT | Selection of components for PdM | Business case for PdM |
| Used Cases* | GEO | | GEO | | GEO | |
| | DEF1 | DEF1 | DEF1 | | | |
| | DEF2 | DEF2 | DEF2 | DEF2 | | DEF2** |
| | DEF3 | | DEF3 | | | |
| | DEF4 | DEF4 | DEF4 | DEF4 | | |
| | DEF5 | | DEF5 | | | |
| | PRO | | PRO | | | |
| | WIND | | WIND | | | |
| | RAIL | RAIL | RAIL | RAIL | | |
| | MAR | | MAR | | | |
| | STEEL | STEEL | STEEL | | | |
| | AERO | AERO | AERO | | | |
| | NUC | | NUC | NUC | | |
| | SEM | | *** | | | |
| | | | | | RWS | |

*Table 1. Summarizing the use of case studies within the dissertation. * the case descriptions are given in the individual chapters. ** additional data was used for this chapter. *** case excluded because insufficient data was available.*

### Case study design and case selection

To unravel the use of PdM in practice, the *problem exploration* phase, aims at studying various distinct cases in practice. The studied cases emphasize the rich, real-world context in which the phenomena (the use of PdM in this study) occur (Eisenhardt and Graebner 2007). The basic design type (Yin 2013) is a multiple-case study.

A multiple-case study is selected because these typically provide a stronger foundation for theory building than single-case studies (Yin 2009), typically yielding more robust, generalizable, and testable theory (Eisenhardt and Graebner 2007). Multiple cases also enable comparisons that clarify whether an emergent finding is simply particular to a single case or consistently replicated across several cases (Eisenhardt 1991).

Ketokivi and Choi (2014) defined three ‘modes’ of conducting case study research. For these three types they show the input of the empirical context (EC) and the general theory (GT), both ranked as either low, medium, or high: (i) theory generation (low GT, high EC);

(ii) theory testing (high GT, low EC); and (iii) theory elaboration (medium GT, medium EC). Table 1 shows the mode of the various case studies.

Central to building theory from case studies is replication logic (Eisenhardt 1991). Since the purpose of the first phase of the research is to develop theory, theoretical sampling is appropriate (Eisenhardt and Graebner 2007). The multiple-case study presented covers a range of maintenance technologies, organisational arrangements, industries, products, and maturity levels. Section 2.3 discusses the exact case selection and introduces the case companies. Table 1 shows which cases are used in the various chapters. Since this research was funded by the Netherlands Ministry of Defence, an opportunity arose to investigate multiple cases at the same organisation (the Netherlands Ministry of Defence, denoted as DEF in Table 1).



Only in chapter 6 (the business case for PdM), a single case study was chosen as a basic design type to evaluate the developed decision support tool. This case was chosen, using theoretical sampling, because it offered an opportunity for unusual research access to studying (and working together in) the development of a predictive maintenance technique for aircraft engines and gave at the same time insight in the associated costs aspects.

# 1.6. Outline

Following the research approach, the outline of the research is set out below. The thesis is structured around the three problems (visualized in Table 2) that were identified in the problem exploration (Chapter 2). These show that practitioners need guidance in:

1 selecting the most suitable techniques for predictive maintenance

2 identifying the most suitable candidates for predictive maintenance

3 evaluating the added value of predictive maintenance

| # | Description | Phase | |
|---|---|---|---|
| | | **Problem exploration** | **Solution development and evaluation** |
| **1** | introduction | | |
| **2** | case studies on the application and use of predictive maintenance in practice | 1 2 3 | |
| **3** | identifying the pathways that are followed in the application of predictive maintenance | 1 | |
| **4** | the development of a method to select the optimal preventive maintenance approach | | 1 |
| **5** | the development of a method to identify suitable candidates for predictive maintenance | | 2 |
| **6** | the development of a method to evaluate and justify the investment in predictive maintenance | | 3 |
| **7** | discussion & conclusion | | 1 2 3 |

*Table 2. Structure of the research showing the relation between the three defined problems, the research phases and the chapters. Note the iteration loops in the development of the three solutions that conquer the identified difficulties.*

**Chapter 2** starts with the problem exploration to identify the main difficulties that firms encounter in the application of PdM. Therefore, a multiple-case study is conducted including fourteen cases from various industries in the Netherlands. The focus in this multiple-case study lays on both the technical and organizational application process of PdM. Four postulates are therefore tested on Jardine's (2006) generic PdM application process. The resulting three main difficulties (introduced before) will structure the remainder of this thesis (see also Table 2).

**Chapter 3** therefore aims at identifying the pathways that are followed in the application of PdM (first identified problem). This reveals that an incorrect match between a firm's ambition level, the available data and the selected pathway seems to cause a trial-and-error-process in PdM applications. Moreover, while successful companies typically combine various routes, the most applied techniques are still those based on (previous) experiences.

This chapter calls for better methods or procedures that guide the selection and use of suitable types of PdM, directed by the firm's ambition level and the available data.



**Chapter 4** therefore proposes, based on the criteria set out in Chapter 3, a framework for the selection of the optimal preventive maintenance approach. The selection framework is developed in a four-step design science process. After exploring typical difficulties, a set of initial solutions is proposed for these identified problems. Amongst these are a classification of the various maintenance approaches into five types, a guideline to select the appropriate ambition level for the maintenance process and a classification of the available data types. These solutions are the main contribution of this chapter, together with the proposed mapping of the maintenance approaches onto the ambition levels and data types.

The initial solutions are then integrated into a framework that assists practitioners in selecting the optimal maintenance approach. Finally, the proposed framework is successfully tested and demonstrated using four case studies.

**Chapter 5**, proposes a three-stage funnel-based selection method to identify the most suitable candidates (i.e. systems, components) for PdM (the second identified problem). This is to assess where PdM would provide the greatest benefit in performance and costs of downtime. The second identified difficulty shows that practitioners predominantly use straightforward methods such as a top ten list of performance killers or cost drivers to select the candidates for PdM. However, these methods do not always lead to the most suitable candidates for PdM. The main reason is that these methods mainly focus on critical components without considering the clustering of maintenance, and the technical, economic, and organizational feasibility.

The first step of the proposed funnel helps to significantly reduce the number of suitable systems or components by a traditional filtering on failure frequency and impact on the firm. In the second and third step, a more in-depth analysis on the remaining candidates is conducted. These steps help to filter potential showstoppers and study the technical and economic feasibility of developing a specific PdM approach for the selected candidates. Finally, the proposed method is successfully demonstrated using two distinct cases: a vessel propulsion system and a canal lock.

**Chapter 6** proposes a hybrid business case approach to help managers evaluate and justify implementing PdM. The third identified problem (guidance is needed in evaluating the added value of PdM) indicates that even technically successful companies tend to have difficulties in showing their business value. This suggests that PdM is sometimes not applied in the most efficient way and sometimes an alternative strategy should be followed. Moreover, although developing business cases is key for evaluating project success, the costs and benefits of PdM implementations are often not explicitly defined and evaluated

Depending on the innovativeness (for the organization) of the applied technique, the business case should have a different goal orientation and be composed of different support elements. The proposed hybrid business case approach is used in an in-depth single case study that focusses on developing engine condition trend monitoring for a military transport aircraft. The case study explores differences in applying innovative maintenance techniques (exploration) or applying well-known techniques (exploitation). Using a combination of non-financial (strategic multi-criteria analysis) and financial elements (using Monte Carlo simulation), the investment in PdM are compared with both fixed-interval preventive maintenance and corrective maintenance.

**Chapter 7** finally starts by showing how the three proposed decision support tools can be integrated in the implementation process of PdM and discusses the implications of the proposed methods that help improve the application of PdM in practice. Finally, this chapter gives main conclusions, limitations and directions for further research.

## 1.7. List of publications

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2018). *Selecting suitable candidates for predictive maintenance*. International Journal of Prognostics and Health Management, 9 (1).

Tiddens, W.W., Braaksma, A.J.J., & Tinga, T. (2017). *Towards Informed Maintenance Decision Making: Guiding the Application of Advanced Maintenance Analyses.* In Optimum Decision Making in Asset Management (pp. 288-309). IGI Global.

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2017). *The business case for condition-based maintenance: a hybrid (non-) financial approach.* Safety & Reliability - Theory and Applications: ESREL 2017. Cepin, M. & Bris, R. (eds.). Taylor & Francis.

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2016). *Towards informed maintenance decision making: Identifying and mapping successful diagnostic and prognostic routes.* Paper presented at the 19th International Working Seminar on Production Economics, Innsbruck, Austria.

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.

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). Case study on the application of predictive maintenance in asset intensive industries. Submitted.

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). Framework for the selection of the optimal preventive maintenance approach. Submitted.

Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). *Exploring predictive maintenance applications in industry.* Submitted.

# CHAPTER 2

2

# Case study on the application of predictive maintenance in asset intensive industries[2]

## 2.1. Introduction

This chapter aims to further develop our understanding on the use and adoption of predictive maintenance (PdM) in practice. We therefore studied fourteen cases at ten companies within various industries in the Netherlands. Within the cases we tried to gather information on the specific circumstances that hindered or advanced the application of PdM. In the current multiple case study, we therefore postulated four main assumptions made in the literature about the application and use of PdM. These postulates summarize some of the main assumptions and descriptions identified from the literature. We confront and reflect on these postulates with the case studies. We did not include all the possible issues in using PdM, but focused on the three main steps (asset data acquisition, maintenance analytics, and maintenance decision making) in a typical PdM application process (see Figure 3), as defined by Jardine, Lin, and Banjevic (2006). This chapter aims to offer theoretical insights by identifying to what extent these assumptions in the literature on the use of PdM correspond to the current practice. Such an in-depth evaluation on the use of these techniques in practice is also suggested by Benedettini et al. (2009).

This chapter is structured as follows: Section 2.2 discusses the four postulates that summarize the main assumptions and descriptions discussed in the academic literature. In Section 2.3, the case companies are introduced and the research methodology is discussed. Section 2.4 describes the results of the postulates. Finally, concluding remarks and directions for further research will be given in Section 2.5.

2 This chapter is based on: Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). Case study on the application of predictive maintenance in asset intensive industries. Submitted.

## 2.2. Predictive Maintenance: the Postulates

In the application of PdM, typically three process steps have to be followed: data acquisition, data processing, and maintenance decision making (Jardine, Lin, and Banjevic 2006). In the following subsections, we will present four postulates, which in our opinion describe the 'common sense' missing from scientific literature regarding the application of PdM.

To cover the main issues of, and assumptions that are made in the use of PdM we studied the three main disciplines that have contributed to the (technical) development of PdM in recent years. Traditionally, many maintenance programmes rely on previous experiences and expert knowledge (Van Noortwijk 2009; Singpurwalla 1995; Zio et al. 2012). However, the fields of condition-based maintenance (CBM), prognostics and health management (PHM), and structural health monitoring (SHM) have contributed to the development of PdM concepts in which the exact moment to conduct maintenance is based on the actual condition of the assets. Condition-based maintenance (CBM) is widely applied in industry. It uses condition monitoring techniques such as vibration monitoring and oil analyses to determine the asset's current condition. Based on this condition, maintenance actions are recommended. Prognostics and health management (PHM) is rooted in in military industry and is geared more towards managing the health of the asset (Tinga and Loendersloot 2014). Structural health monitoring (SHM) has its origin in the non-destructive inspection of structures and is widely applied to aerospace and infrastructure such as bridges (Tinga and Loendersloot 2014; Farrar and Lieven 2007).

Since we have included all these three fields in our study, we have extended the three process steps of Jardine, Lin, and Banjevic (2006), who only studied CBM, to: asset data acquisition, maintenance analytics (the data processing), and maintenance decision making. Figure 3 shows how the four postulates are positioned relative to the input of the data acquisition and the three main process steps. In the next subsections, each of these process steps will be discussed and the associated postulates will be presented.

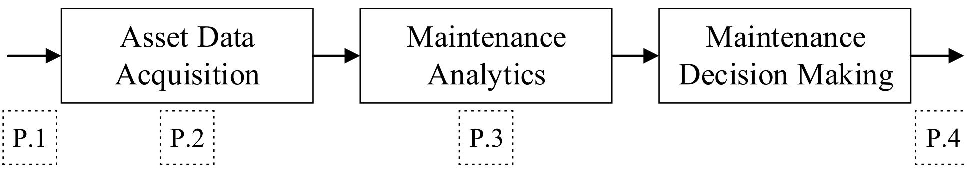


*Figure 3: The three main process steps in the application of predictive maintenance based on Jardine, Lin, and Banjevic (2006) and the positioning of the four postulates.*

### 2.2.1. Asset data acquisition

The first step focuses on collecting and storing useful data (Jardine, Lin, and Banjevic 2006). Event-data describes what happened to the asset, e.g. failures, repairs or overhauls. This data can be collected from historical logs and maintenance or cost records. Monitoring data consists of measurements related to the state of health of the asset.
Although the value of the collected data is only materialized when it can be incorporated in the decision making step, in a typical business analytics application, 80 per cent of the time and effort and 50 per cent of the unexpected project costs are typically associated with data

collection (Watson and Wixom 2007). This means that realising a slight improvement in this first process step could have a large impact on the use and value of PdM.

Advances in information technology and sensor technology have radically reshaped how maintenance practitioners can collect their asset data. Where previously operators had to manually inspect their assets and keep track of the asset's condition using paper trails, assets can nowadays be monitored remotely and in real-time using sensors and microcontrollers. This can bring an end to manual data entry, which is often mentioned as one of the main reasons for erroneous event data (e.g. failure or inspections) in enterprise resource planning (ERP) systems (Davies and Greenough 2000).

Although difficulties can exist in using the data collected by the many available sensors, advances in sensor technology and digitisation have dramatically reduced these issues ensuring useful input for PdM. We therefore put forward the following postulate.

**Postulate 1: The available asset data is useful for predictive maintenance**



As a variety of sensors has become available, many parameters (such as vibration or temperature) of the asset can be monitored. However, merely connecting sensors to a machine will not give users the insights that are needed to make better maintenance decisions (Lee et al. 2013). Moreover, only looking at the data without knowing the underlying failure mechanisms can result in incorrect decisions (e.g. failures caused by wear out and by operator errors) (Dekker 1996). To be able to monitor relevant parameters, a proper selection of the sensors needed to achieve this requires knowledge about the failure mechanisms of the asset and the governing loads (Tinga and Loendersloot 2014)

Considering the fact that a proper selection of the parameters to monitor is necessary to ensure that the right data is collected, we therefore postulate:

**Postulate 2: The selection of monitored parameters is well-motivated**

### 2.2.2. Maintenance analytics

The maintenance analytics step consists of cleaning and processing the collected data to produce meaningful information. Cleaning of the collected data improves the data quality for further analysis as parts of the collected data can be incorrect, incomplete, inaccurate, or irrelevant. After modifying, replacing or deleting these parts, the data is suitable for processing.

In this day and age, a wide variety of analytics is available to practitioners. Many of these, however, are equipment or application specific. The traditional methods that rely on expert knowledge and previous experiences are usually more generic and therefore often applied in industry.

Regarding the common availability of analytics and the fact that no type of analytics is effective in every situation, we expect that firms make a motivated choice for the type of analytics to apply. We therefore postulate:

**Postulate 3: The selection of the type of predictive maintenance is well-motivated**

### 2.2.3. Maintenance Decision Making

The actions taken in the previous steps are combined in the decision-making process. The analytics for maintenance decision making typically yield technical results, such as a detection of anomalies, a diagnosis of the system and a prognosis of the remaining capabilities. These technical results are input for the planning of maintenance, the introduction of midlife updates, or the extension of the life of the asset.

Benefits (that should result from the improved maintenance decision making supported by PdM) that are often associated with implementing PdM are: improving performance and availability of products, cost reduction, gaining insight into customers' needs and getting feedback for R&D that enables learning and knowledge creation (Grubic 2014). Additionally, for original equipment manufacturers (OEMs), it promises to reduce the total cost of ownership, deliver increased availability, and to reduce risk to their customers (Grubic et al. 2011). The introduction of the many types of PdM in the scientific literature suggests that companies can benefit from these. We therefore postulate:

**Postulate 4: The use of predictive maintenance techniques benefit the firm**

## 2.3. Case study method and case company introduction

To test the postulates against current industrial practice, we have conducted a multiple case study within various industries in the Netherlands. This study is exploratory since we have no concrete ideas about the exact behaviour of the concepts and causal relationships of the concepts in practice. Instead, we aim to develop knowledge that can serve as a stepping stone towards theory building (Meredith 1987; McCutcheon and Meredith 1993). The followed methodology is also used by Meredith (1987), Veldman, Klingenberg, and Wortmann (2011), and Braaksma, Klingenberg, and Veldman (2013).

We have conducted fourteen semi-structured interviews, these in-depth interviews lasted between 2 and 3 hours. These were conducted at the case companies with relevant staff including maintenance and reliability engineers, staff from maintenance development departments, and maintenance managers. Before conducting the interviews, we familiarised ourselves with the firm's current practices by studying the firm's website and online presentations, conducting introductory interviews, and if possible, attending presentations given by the company at seminars, conferences or project meetings about their use of PdM.

The in-depth interviews were recorded and the interviewer created extensive transcripts of each recording. The data from the in-depth interviews was structured per company and per postulate to allow cross-case analysis. To permit triangulation and allow internal validity (Yin 2009), multiple data sources were used. We draw our conclusions from the in-depth interviews, the review of additional documents and online media, the presentations attended, working with six case companies on research projects, and conducting follow-up interviews where needed. Table 4 provides an overview of the sources that were used per case.

To mitigate bias, we combined retrospective and real-time cases. Retrospective cases rely on interviews and archival data that increase the number and depth of cases efficiently (Leonard-Barton 1990). In contrast, real-time cases employ longitudinal data collection from interviews and, often, observations. This combination of retrospective and real-time cases helps to mitigate against retrospective sense making and impression management (Leonard-Barton 1990). Table 3 provides an overview of the case study tactics that were followed to ensure the reliability and validity of the case studies (Yin 2009). Multiple-case studies typically provide a stronger foundation for theory building than single-case studies (Yin 2009), typically yielding more robust, generalizable, and testable theory (Eisenhardt and Graebner 2007). Multiple cases also enable comparisons that clarify whether an emergent finding is simply particular to a single case or consistently replicated across several cases (Eisenhardt 1991).

| Test | Followed Case study tactic |
|---|---|
| Construct validity | • A chain of evidence has been established by making write-ups of interview recordings and analyzing and re-using these write-ups for the current chapter.<br>• Key informants were asked to review the main conclusions of the draft case study report. |
| Internal validity | • Explanation building was of great importance for this study since one of its aims is to identify whether the current literature matches the current practice of applying PdM.<br>• Rival explanations were addressed to identify various viewpoints on the postulates.<br>• To permit triangulation, various sources are used per case, see Table 4 for an overview. |
| External validity | • The theoretical framework proposed in Tiddens, Braaksma, and Tinga (2015) is used to ensure replication logic in the multiple-case study. It provides both conditions for when specific applications of PdM are likely or unlikely to be found. |
| Reliability | • A semi-structured case study protocol was used during the interviews.<br>• A case study database was created, consisting of transcripts and recordings of interview data. |

*Table 3. Followed case study tactics to ensure case-study reliability and validity, following Yin (2009).*



### 2.3.1. Sample selection

The multiple-case study presented, covers a range of maintenance technologies, organisational arrangements, industries, products, and maturity levels. The study therefore contains a suitable range of cases for evaluating existing knowledge developed in this research field. Furthermore, 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 and Graebner 2007). Therefore, less advanced cases, such as firms that did not apply advanced types of PdM, were also included in our research. A specific selection of case companies was made based on the four criteria set out below, thus complying with the structured approach to sampling as suggested by Eisenhardt and Graebner (2007).

Firstly, the selected companies should be in the defence, aerospace, maritime, electronics, power industry, oil and gas, or energy industry sectors, as most users of PdM can be found in these sectors where governmental agencies play important roles (Grubic et al. 2011). Secondly, the selected assets should have a long lifecycle, be mechanical or electromechanical in nature and be highly complex, as Grubic et al. (2011) found that these are the main systems that these technologies are applied to. Thirdly, companies should have enough resources and opportunities to develop maintenance techniques (Carnero 2006). Therefore, only companies with a minimum of 50 employees are selected. Fourthly, the selected companies should consider maintenance a key priority. This was measured by interviewing personnel before the case study or previously communicated in explicit statements made by the company.

To avoid double dipping, a selection of unrelated cases was made. An opportunity arose to investigate multiple cases at the same organisation (DEF, case 2, 3, 4 and 5). This provided the opportunity to shed light on different practices within the same organisation and possibly identify department-specific practices.

### 2.3.2. Case company descriptions

Fourteen cases within ten case companies have been studied. Below, we will briefly introduce the ten case companies, a summary of their main characteristics is given in Table 4. Because of confidentiality issues, we refer to the companies by their *code in chapter* (see Table 4).

*GEO* monitors the seas and collects engineering and earth data. GEO is developing the use of PdM.

*DEF* provides disaster relief and ensures safety from the air, sea and land all over the world. For this case study, we visited three different departments. Respecting applying PdM, these departments operate independently. The first department, case 2 and 3 are from different sections within this department, has already applied several PdM applications effectively. A large part of their asset fleet is equipped with, sometimes rudimentary, sensory systems. The second department, case 3 and 4 are from different sections within this department, is learning about the importance of PdM and is developing practices and techniques to embed these in maintenance decision making. The third department: case 5, is developing its competence in the application of PdM.

*PRO* is a maintenance providing company, and co-owner, of chemical plants in the process industry. Real-time performance data of all assets is available and failure data of many years is stored in a structured manner.

*WIND* is a research company that advises asset owners on strategic, policy and maintenance matters in the field of new energy sources. A large part of the equipment the company focuses on is equipped with sensory systems, which are used for PdM.

*RAIL* is a department of a large transportation company for which it conducts maintenance, repair and overhaul activities of rolling stock. A large part of the studied asset fleet is equipped with sensory systems which are used in a real-time diagnostic system. The department is developing and embedding PdM.

*MAR* provides transportation for people from and to vessels. The organisation contributes to the efficient and safe handling of shipping traffic. The company is learning about the importance of maintenance techniques.

*STEEL* is a manufacturer of steel products. The studied department is responsible for the transportation of product flow, both liquid and solid goods, through the production plant. The firm is aware of the importance of using more advanced analytics and develops these for specific critical components.

*AERO* provides air transportation for passengers, mainly to European destinations. The company is learning about the importance of PdM and developing their practices during operation. Some sensory systems have been installed aboard.

*NUC* is an owner of nuclear facilities that are used to produce isotopes and other nuclear products. The company has extensive experience in the application of PdM for their most critical equipment.

*SEM* is an original equipment manufacturer (OEM) of machinery that is used in the back-end production of semiconductor products. The company is developing analytics to guarantee uptime of the machines they produce.

| Case | Code in chapter | Data collection tactic * | Industry | Type of assets | Asset owner | # Plants or assets | Total asset value (€) |
|---|---|---|---|---|---|---|---|
| **1** | GEO | a, b, d, e | Geomatics | Vessels | Yes | > 50 | > 200m |
| **2** | DEF1 | a, b | Defense | Helicopters | Yes | > 15 | > 200m |
| **3** | DEF2 | a, b | Defense | Transport planes | Yes | < 5 | > 100m |
| **4** | DEF3 | a, b, e | Defense | Platform systems of vessels | Yes | > 25 | > 4bn |
| **5** | DEF4 | a, b | Defense | Electronic systems of vessels | Yes | > 25 | > 4bn |
| **6** | DEF5 | a, b, e | Defense | Vehicles | Yes | > 10,000 | > 2bn |
| **7** | PRO | a, b, d | Process | Chemical plants | Partly | >20 | > 3bn |
| **8** | WIND | a, d | Consultancy | Wind Turbines | No | N/A | N/A |
| **9** | RAIL | a, c, d, e | Rail Transport | Rolling Stock | Yes | > 3000 | > 5bn |
| **10** | MAR | a, b, d, e | Maritime | Vessels | Yes | > 30 | > 100m |
| **11** | STEEL | a, c, d | Steel Manufacturing | Cranes | Yes | > 15 | > 70m |
| **12** | AERO | a, c | Aerospace | Aircraft | Yes | > 25 | > 500m |
| **13** | NUC | a, d | Energy | Nuclear reactor | Yes | 1 | 600m |
| **14** | SEM | a, c, d | Semiconductor | Production machinery | No, OEM | N/A | N/A |

*Table 4. Summary of the cases and data collection tactics. * a) in-depth interviews, b) involvement in research project, c) additional information in follow-ups and preparatory interviews, d) additional documents, brochures and presentations, and online media including companies' official website, e) presentations provided by the company.*

## 2.4. Results

In this section we will present the empirical findings of our case studies on the use of PdM in practice.

### 2.4.1. Asset data acquisition

**Postulate 1: The available asset data is useful for predictive maintenance**

The case studies create a varied picture of the usefulness of the data for PdM, which is the input in the application process. The usefulness of the data seems to be related to the way in which the data is collected. The case studies firstly show that these days, it is easy to measure and store data. The trend is that a lot of data is collected, as the maintenance manager of DEF1 illustrates:

> *"These days we tend to measure everything. And to put it bluntly, that is because measuring helicopter data is not that complicated anymore. Everything the sensors measure is on data busses. It is just inexpensive to collect the data on those. It is much harder to decide what to do with the data."*

Several assets are equipped with on-board measurement systems. As data storage has become inexpensive, DEF2 for example, is currently storing more data than they can analyse at the moment. They expect to be able to use the collected data for analytics in the near future. In some of the cases, data collected by sensors is streamed, sometimes in real-time, to central data warehouses (DEF1, DEF2, RAIL, WIND, PRO). PRO, for example, is able to view the performance of their equipment in near real-time on mobile devices. In the case of NUC, however, data is not collected via remote monitoring, but by manually logging the usage. To improve the quality and quantity of existing data, NUC invested in gathering additional historical data, which is highlighted by their Asset Manager:

> *"Recently, we executed a large project, which was to go through all [paper] logbooks of the last fifty years and collect all relevant data for the whole reactor vessel programme. The data of the last ten years is now easily accessible."*

However, collecting more data does not seem to guarantee that more useful data becomes available, it only raises the probability that useful data is collected. Companies mainly seem to struggle with the quality of the collected data. This quality is in some cases stimulated by regulatory agencies as for example in the aerospace industry (AERO, DEF1, DEF2). RAIL and MAR have to prove to authorities that they are operating their assets safely. For that reason, MAR is conducting Failure Mode and Effect Analyses (FMEA) to determine and provide motivation for the required maintenance. RAIL stores failure data to substantiate changes in their maintenance intervals.

Besides difficulties in the data quality, as the generic determinant for the usefulness of the data, the case studies showed eight specific difficulties in using the data, as is summarized in Table 5.

| Identified difficulties that hinder using asset data for predictive maintenance | |
|---|---|
| (i) | *difficult to access data*, e.g. data in legacy systems and data stored in unstructured data formats, i.e. word-processor documents (GEO, DEF3, DEF4, DEF5, MAR, STEEL). |
| (ii) | *incompleteness of data*, e.g. data which is not or incorrectly entered in the data collection system. The maintenance engineer of RAIL gives a clear example of this: *"If the data tells you that twenty compressors are replaced, it doesn't always tell you if that was for one train or for the whole fleet"*. |
| (iii) | *fractured data*, e.g. the maintainers of STEEL and DEF3 store much of their maintenance data on local desktops which are not centrally accessible. |
| (iv) | *infrequent data storage*, e.g. the manager of DEF5 noted that the mileage of vehicles is only registered during maintenance, while more frequent registration is required for analytics. |
| (v) | *unusable process data*, data that is originally collected to control the production process or the product quality, does not always prove to be valuable for PdM (SEM). |
| (vi) | *restrictive permission rights* which prevent companies from being able to retrieve data from the system e.g. the research manager of WIND stated that owners of wind turbines often do not have access to the technical construction data of the turbine. DEF5 is not able to access the data on the CAN-busses of their vehicles. |
| (vii) | *surveillance issues*, firms are afraid that information about their operation or process will leak to competitors (DEF1-5 and SEM). |
| (viii) | *practical problems in managing the available data,* such as gaining access to the central database where all (monitoring) data is stored. |

*Table 5. Identified difficulties in using asset data for PdM.*

In summary, although collecting maintenance related data has become easier, for instance by using sensors and computerised maintenance management systems, the data is not always useful for PdM. This is especially true for the more advanced types of maintenance analytics that require more data of a higher quality. Although the quality of data is stimulated in some sectors or contexts by e.g. regulatory agencies, firms still struggle with issues such as poor data quality, legacy technology, and data which is not intended for PdM. As more data has become available and the value of this data has increased due to applicability in analytics, digitisation has also introduced new challenges. Firms now have to deal with restrictive permission rights, surveillance issues and more practical problems such as how to store data when centrally accessible data warehouses are not (yet) available to the company.

As such, we can conclude that we have only found **limited support** for this postulate.

**Postulate 2: The selection of monitored parameters is well-motivated**

In selecting relevant parameters to monitor, we observe that all firms have at least one or several assets which are equipped with (rudimentary) pre-installed sensors. In several cases (DEF1, DEF2, DEF5, PRO, RAIL, WIND, AERO, SEM), the vast majority of this data is also collected and stored. The advances in information technology and sensor developments increasingly allow companies to follow a trial-and-error approach in the selection of the parameters to monitor as the costs of measuring and storing data have decreased in recent years. This is reflected by the case studies which show that the aforementioned companies are measuring more than they can currently use for PdM.

Oftentimes, this data collection then happens without a concrete aim, but merely based on the assumption that the collected data can be beneficial for PdM (in the future). This is illustrated by the lifecycle manager of DEF5:

> *"We get a truck with a CAN [Controller Area Network] bus and see what we can do with that. I'm advocating for a big-data-like approach. We just look at what we can do with what is being measured, instead of looking at what kind of sensors are needed and then apply those. That is because the costs of the latter approach are set to spiral."*

This supply-driven approach in selecting the parameters to monitor does not seem properly substantiated. Oftentimes, more data is collected than is used for analytics, which clearly indicates some data is not useful for PdM. This is illustrated by the maintenance engineer of RAIL:

> *"Our supplier pre-installed a temperature sensor on a location which is not that relevant to us. It is however very expensive to relocate this sensor for the whole fleet of assets. We therefore sometimes just have to deal with what we have."*

However, as the cases of RAIL and DEF5 show, practitioners seem apprehensive about the costs of installing many sensors spiralling steeply. Therefore an approach that is often followed is to start with the available data and improve the data collection strategy by following a demand-driven approach, in addition to the pre-installed sensors or when no sensors are pre-installed, for specific cases (GEO, DEF1, DEF2, DEF3, DEF4, MAR, RAIL, STEEL, PRO, NUC).

In their selection of the required sensors, we observe that companies are oftentimes supported by external parties such as consultancy firms or researchers to determine what exactly has to be monitored. For a good selection of sensors, knowledge about the failure mechanisms of the assets is required. Only then, can sensors (partially) fulfil the human task of identifying abnormalities, since *"people hear, smell, and see all the abnormalities. Sensors can only measure very specific parameters"* [manager maintenance RAIL].

Not only do companies experience difficulties in establishing which parameters to monitor, they also experience these in selecting appropriate equipment to monitor. The case studies show that limited resources and budgets force practitioners to limit the number of components they can apply PdM to. In order to select these components, practitioners apply rather straightforward selection methods. Various methods are mentioned: the criticality of assets expressed in for example A, B, C ratings (DEF3, DEF4, STEEL, PRO), top-10 lists of maintenance costs and availability killers (DEF2, DEF5), the impact on the deployment of the asset (MAR), the impact on safety (NUC, AERO, DEF1), or a differentiation between disposable assets, revision assets and assets that are safety-critical or expensive (RAIL).

However, the cases also show that maintenance activities are often clustered based on high-level production planning (i.e. STEEL), mission planning (i.e. DEF 1-5) or the most convenient moment to conduct maintenance, as in for example wind turbines or GEO's ships that do not operate close to their home port. This restricts asset owners' ability to shift maintenance intervals. Optimising the maintenance interval for only one of these clustered components will therefore not provide any benefit.

In summary, several of the studied cases aim to collect a large amount of data without deciding beforehand exactly which data has to be collected. This is also partially the goal of several big-data-approaches: discovering unknown relations. However, such a big-data-like approach assumes that no knowledge is required in the data acquisition stage and that in a later stage the collected data can always be transformed into information and knowledge about the behaviour of the system. However, this is not always true. Issues such as setting the correct sampling rate, monitoring the correct parameters, such as temperature or vibration, and assessing the underlying failure mechanism play a vital role in determining what data should be collected. Moreover, data is sometimes collected for components for which PdM may not be the most suitable approach.

In conclusion, we, therefore, **reject** this postulate.

## 2.4.2. Maintenance analytics



**Postulate 3: The selection of the type of predictive maintenance technique is well-motivated**

The cases reveal that especially the amount and quality of the available data seem to guide the use of specific analytic techniques. The case studies show that this limits the selection since some data is only appropriate for specific techniques. Furthermore, many practitioners stress that the combination of domain knowledge and data is important in order to guarantee that sensible conclusions can be drawn. For example, RAIL couple domain experts to data scientists for this reason. Also, when the quality and quantity of data is insufficient, firms often fall back on traditional practices, such as relying on expert knowledge. In the case of DEF4, insufficient and sometimes incorrect data was available, which meant incorrect conclusions were drawn from the adopted reliability statistics methods. For this reason, they reverted back to their experience-based analyses.

Safety seems to drive (e.g. AERO, NUC, and DEF1) the necessity to apply advanced types of maintenance analytics. For some sectors (e.g. GEO, DEF1, MAR, RAIL) regulatory agencies oblige firms to apply specific types of maintenance analytics. However, as is the case with internal motivations, this does not seem to ensure that the most suitable techniques are applied.

The case studies further reveal that the available data not only dictates the choice for the type of analytics that can be applied, it also seems to determine the types of results that are feasible. This means that for some types of equipment, additional data has to be collected to be able to make a good prognosis of the remaining useful life. Because of insufficient data, not all types of failures can be predicted, as explained by WIND's asset manager:

> *"If there is no loading data, then fatigue is hard to determine. In that case you have to speculate using a different approach. However, this makes the prognostic route a rather unlikely choice."*

The cases thus show that practitioners do not always apply structured methods to selecting analytics. Aside from the reasons mentioned above, specific types of analytics are selected because they are accepted within the industry (DEF1, MAR), always applied within the firm (GEO, DEF3, DEF4, DEF5, PRO, RAIL, STEEL, SEM) or based on experiences and insights from individual engineers (DEF2, AERO, NUC, WIND). Changing the type of analytics is often not a technical problem, but merely an organisational problem as the maintenance engineer of PRO explains:

> *"Technology is not our main problem. We have many techniques that we can apply. However, getting it done and changing the [maintenance] processes within the organisation is often the problem. "*

The application and selection of the appropriate type of analytics seems to be a process of trial-and-error for many firms. It is not an unambiguous path, iteration loops are therefore required. Especially the use of the experience-based types of analytics has often been established over a long period of time (e.g. GEO, MAR, STEEL). Also, firms seem to select methods that are commonplace in the firm or industry, such as Reliability Centered Maintenance in the aviation industry. In the past, practitioners mainly relied on these traditional techniques. The case studies show that these experience-based approaches are still the most applied types of analytics. Nowadays, various algorithms and methods are accessible to practitioners. Therefore, firms try to work with OEMs, external experts and researchers to implement these types of analytics, which are often new to the firm.

We have found that organisational factors in particular play a role in the selection of the type of analytics. For example, the trustworthiness of the analytics requires attention for a more streamlined introduction of PdM. People are sometimes not easily convinced by methods that are new to them (DEF1) and these methods are therefore occasionally distrusted (GEO). The technical match, such as the availability of accurate sensors and monitoring systems, which is assumed to be the prime selection reason in the relevant literature, only seems to be a hygiene factor. In hindsight, the selection of the analytics applied often seemed to be a logical choice. However, it appears that the experience gained from selecting and implementing a specific approach only helps companies with the specific application. They are typically not able to generalize this process, and thus often repeat exactly the same procedure, although analytics may not be the best approach for the new applications (GEO, DEF3, DEF4, MAR, STEEL). Similarly, firms experience difficulties in new applications of PdM, since structured selection methods once more seem to be lacking. This highlights the need for knowledge management within the maintenance function, since the selection and application of, especially the more advanced types of, analytics appears to be a knowledge intensive effort.

In conclusion, we **reject** this postulate.

### 2.4.3. Maintenance Decision Making

**Postulate 4: The use of predictive maintenance benefits the firm**

The case studies show that PdM is predominantly used for straightforward maintenance decisions such as determining the maintenance interval. SEM's system engineer explains how the monitoring of plungers in their machines led to concrete results:

> *"The starting point was a certain number of cycles for a plunger and then we had to do something and this approach didn't work. In some cases, there was no problem at all and in other cases the number of cycles could not be reached. So, this [using PdM benefits the firm] is absolutely true for the things we monitor."*

But PdM also helps to gain insight into the required maintenance. RAIL, where most maintenance actions are inspections, sees the highest potential for PdM in: "*knowing what is* *wrong with our equipment before it comes into the workshop".* Moreover, PdM is used to guarantee safety (NUC), convince regulatory agencies (MAR, RAIL, DEF1) or to advise users to change the use of their assets (DEF2).

However, converting the technical results of PdM, such as an estimation of the remaining useful life into valuable business results, for example a reduction in maintenance costs, has proven difficult for the companies studied. To be able to demonstrate the added value to the business, practitioners aim to construct business cases. However, especially in the application of the more advanced types of analytics, or those the firm is inexperienced with, expressing and quantifying the (monetary) benefits to the firm seems difficult. As many factors play a role (e.g. the current maintenance programs and the possibilities of changing maintenance intervals), the extracted value is context specific. Practitioners lack accepted methods or procedures to clearly justify investments in PdM. Therefore, only ballpark estimates of the improvement potential of PdM are made. Also, the expected benefits are often not immediate, thus the payback time is long. Monitoring systems are therefore hard to sell as the manager of WIND explains:

> *"We want to convince asset owners to invest in monitoring systems to help to make lifetime extension decisions. However, these are too distant in time. Payback periods of 3 to 4 years have to be achieved but these lifetime extensions will only pay for themselves after, say, 20 years."*

2

The cases also show that analytics can only be applied to a limited variety of equipment, such as a specific wind turbine gearbox. The use of PdM becomes more beneficial when development costs can be spread over multiple assets, as can be done for fleets of assets. Moreover, to reduce the number of sensors required, fleet managers try to adopt smart solutions as the asset manager of WIND explains:

> *"One of the things we try to apply is the fleet leader concept, which we adapted from the aerospace industry. The central question is: can you extrapolate the loads of two turbines to all the turbines in a wind park in such a way that you can make correct decisions? We demonstrated that this can work for wind parks, when making certain assumptions which require models."*

Practitioners often only look for the benefits of PdM in extending the maintenance interval or changing the type of use. However, the cases of DEF5 and GEO show that benefits achieved with analytics also include changing the operating behaviour, as the asset manager of DEF5 explains:

> *"The highest profit in my business case is caused by changes in the driving behaviour. That has nothing to do with analytics. If you know that I am monitoring you, you will not mistreat the car. Because you'll know that you will get into an argument with me."*

In summary, although analytics can benefit the firm, we have encountered several difficulties that prevented companies from reaching their PdM's full potential. This is in addition to the eight identified reasons stated in the first postulate related to the usefulness of data. Table 6 gives an overview of the major difficulties.

We can conclude that for firms which technically succeeded in applying PdM, the use of PdM in general benefits the firm. However, it seems that the full potential of these techniques has not yet been reached and the added (business) value cannot always be demonstrated. This suggests not only that PdM is sometimes not applied in the most efficient way, it also suggests that from an individual asset perspective, PdM is not always the better strategy to follow.

Therefore, we have, only found **limited support** for this postulate.

| | **Identified difficulties hindering that the full potential of PdM is achieved** |
|---|---|
| (i) | *limited quality of analytics*. PdM is in some cases not (yet) advanced enough to extend maintenance intervals (DEF1, STEEL, DEF3, MAR). This is explained by the maintenance manager of DEF1: *"With our health and usage monitoring systems we are not yet able to translate the measurements of pressure, temperature or altitudes into signs of incipient failure like crack size, or use these for failure predictions."* |
| (ii) | *limited experience with the PdM system*. Firms are unsure whether the system can provide valid results as the engineer of RAIL explains: *"I even think that you aren't able to draw conclusions when the equipment is new. Well, you can make statements, but you don't know if it is true."* |
| (iii) | *system not designed for maintenance decisions.* The monitoring system is not always intended to advise on maintenance decisions, as the maintenance manager of DEF1 explains: *"The alerts triggered by the diagnostic system are sufficient to guarantee the safety of the crew. The system is, however, not really effective to aid maintenance decision making yet."* |
| (iv) | *limited trust in analytics.* Interrelated with the first three reasons is the level of trust in the PdM system. When the system is not trusted, the advised actions are not followed up on. An example is given by DEF3's manager of engineering: *"When we detect that an engine is not vibrating to the extreme, we will conduct maintenance anyway. Although the analysis could be a reason to postpone the maintenance, we are not at that point yet."* |
| (v) | *insufficient knowledge to conduct the analysis*, e.g. DEF4's only specialist who was able to analyse certain impulse measurements left the company. |
| (vi) | *unable to shift maintenance activities in planning.*<br>*a)* The cases of DEF3, DEF4 and STEEL demonstrated that the firm's high-level planning prevented the company from shifting large maintenance activities. This high-level (production) planning only has predefined blocks in which maintenance can take place.<br>*b)* *regulations that prevent companies from changing their maintenance intervals.* MAR, for example, has to substantiate their maintenance activities using failure mode and effect analyses. However, should they want to deviate from these maintenance schedules, they have to convince Class-society (the maritime regulation agency) that their operation remains safe using detailed analyses. |
| (vii) | *no improvements made in the PdM system during the lifetime.* As the cases of MAR, GEO, and STEEL show, attempts to improve the maintenance concepts are often one-time activities. |

| | |
|---|---|
| (viii) | *no investment in PdM during acquisition phase of assets.* Systems that enable PdM (such as a monitoring system) are often not purchased during the acquisition of a new asset (GEO, DEF3). This prevents data on the whole lifetime of the asset from being collected. The maintenance engineer of GEO explains that operations rather prefers other or extra functionalities. *"That [a PdM system] is one of the first things that is crossed off the list, because it costs money and our customers [the operational division] prefer extra functionality."* |
| (ix) | *inadequate selection of the equipment to which PdM is applied.* As indicated in postulate 3, the selection methods for the suitable components, such astop-10 lists of availability killers, to apply PdM to do not consider the actual improvement potential as they do not take into account the technical, economic and organizational feasibility. |

*Table 6. Identified difficulties that prevented companies from reaching PdM's full potential.*



## 2.5. Concluding remarks

This research sought to establish to what extent the assumptions made in the literature on the use of PdM match the current practice. For this reason, we postulated four main assumptions on the use of PdM. We followed the three main steps in a typical maintenance program that uses these techniques: asset data acquisition, maintenance analytics and maintenance decision making (based on Jardine, Lin, and Banjevic 2006). To test the postulates against industrial practice, we studied fourteen cases within various industries in the Netherlands.

The results of the testing of the postulates, summarised in Table 7, demonstrated that two postulates were rejected and for two postulates, only limited support was found. We can thus conclude that although the main theoretical steps of PdM are followed, the assumptions underlying these steps are seldom fully realized in practice. Research does not provide sufficient support for how these steps should be followed and seems to overlook important organizational issues which should be addressed before and during the application of PdM.

| Step | Postulate | Statement | Result |
|---|---|---|---|
| 1 | 1 | The available asset data is useful for PdM | Limited support |
| | 2 | The selection of monitored parameters is well-motivated | Rejected |
| 2 | 3 | The selection of the type of PdM is well-motivated | Rejected |
| 3 | 4 | The use of predictive maintenance benefits the firm | Limited support |

*Table 7. Summary of postulate analysis results.*

We can also conclude that practitioners are in many cases not (yet) able to successfully implement PdM nor do they sufficiently grasp its business potential to make investments in PdM worthwhile. Analytics are predominantly used for straightforward maintenance planning decisions. Notable exceptions are using analytics to change driving behaviour (DEF5) or to change the use of the asset (DEF2, GEO). Thus, the maintenance function should seek more collaborative relationships with e.g. quality management (early detection of process deviations), the service department (using analytics and remote monitoring for servitization), or the financial department (by using analytics to better determine the asset's remaining useful life and aiming for lifetime extensions).

As also stated in several other papers (Kerkhof, Akkermans, and Noorderhaven 2016; Garg and Deshmukh 2006; Veldman, Klingenberg, and Wortmann 2011), many scholars in the field only seem to focus on the technical aspects of PdM. However, this study demonstrates that managerial difficulties such as implementing analytics and justifying the investments are just as important and more research should focus on these difficulties.

### 2.5.1. Outlook

This study reveals that almost all organizations that have applied PdM successfully followed a costly trial-and-error process, partly due to the complexity, and the absence of effective theoretical guidance. The study contributes to the literature by providing an overview of the difficulties that firms experience in the applications of PdM and by explicitly identifying the gaps between the literature and how it is applied in practice. In terms of future research, we believe that the following issues associated with guiding the practical implementation of PdM are unaddressed and further study is needed: (1) methods that advise practitioners in the selection of components suitable for PdM, as an addition to their, commonly applied, experience-based methods; (2) methods that assist companies in determining which parameters need to be monitored and which types of analytics are best suited to the firm for their specific application; (3) how firms can better benefit from PdM and (4) how they can innovate their existing business models. Hence, further research on the (financial) evaluation of PdM is required; (5) finally, better justification of choices made in the scientific literature could aid practitioners in selecting suitable maintenance approaches.

2

# CHAPTER 3

# Exploring predictive maintenance applications in industry[3]



## 3.1. Introduction

### 3.1.1. Background

Thinking 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, Bagheri, and Kao 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, Bagheri, and Kao 2015).

Predictive maintenance (PdM) is hereby defined as a maintenance policy based on methods and analytic techniques (the maintenance techniques, MTs) that use asset data, such as condition or loading data or experience, to inform about the current, and preferably also the future state of physical assets. Although predictive maintenance is often referred to as condition-based maintenance (CBM), predictive maintenance goes further than CBM by also taking prognostic information into account (Shafiee 2015). The MTs that enable PdM can thus help decision makers to take better-informed maintenance decisions and improve the performance of physical assets.

PdM helps to conduct maintenance not too early (leading to unnecessary costs and downtime) and also not too late (leading to unplanned downtime and failure costs). Examples of commonly applied MTs are experience-based methods like Failure Mode and Effect

[3] This chapter is based on: Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). Exploring predictive maintenance applications in industry. Submitted.

Analysis (FMEA), data-driven approaches and failure prediction methods based on the physics of failure. With these MTs, the current and preferably also the future state of assets is assessed. Insights obtained from the collected data help to determine the remaining useful life (RUL) and the probability a machine works without a failure up to a certain time (Jardine, Lin, and Banjevic 2006). Although many MTs are described in the academic literature, previous research shows that practitioners find it difficult to apply these techniques for PdM in practice (Tiddens, Braaksma, and Tinga 2015). Grubic et al. (2011) show that companies that have applied these techniques experience a gap between the potential and realized benefits. Several reasons can be found for this.

Firstly, as also mentioned by other authors (Kerkhof, Akkermans, and Noorderhaven 2016; Garg and Deshmukh 2006; Veldman, Klingenberg, and Wortmann 2011), most research within the field of PdM excludes the organizational 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 routes (the combination of the collected data and maintenance techniques) to informed maintenance decision making (Tiddens, Braaksma, and Tinga 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, Hodkiewicz, and Ma 2011; Dekker, Wildeman, and van der Duyn Schouten 1997; Tiddens, Braaksma, and Tinga 2016). It is this final problem this chapter focuses on.

### 3.1.2. Goal of the study

The aim of this chapter is to identify the ratio behind the selection of the MTs (enabling PdM) and of pathways towards informed maintenance decision making. The main research question therefore is: *"Why have certain MTs and pathways towards informed maintenance decision making been selected in practice?"* This leads to the identification of dependencies and factors that can be influenced in the pathway selection, thus supporting practitioners in identifying and selecting suitable pathways to maintenance decision making.

### 3.1.3. Research method and outline of the chapter

To achieve this goal, it is first important to study possible pathways towards 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 routes towards maintenance decision making in *Figure 4*.

To validate this framework and map routes that have been taken in practice, we conducted a multiple-case study with multiple embedded objects (Yin 2009), as will be explained in Section *3.3.1.* 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 *3.4*, the results of six of the thirteen case studies are used to map the pathways that are taken on the proposed framework of *Figure 4*. In Section *3.5,* we discuss why routes have been selected in the case studies and identify the relative occurrence of different MTs within the case studies. Next, using the technology acceptance model (TAM) of Davis (1989) we aim to provide understanding in the underlying reasons for the implementation and acceptance of PdM within firms. Finally, conclusions, limitations and general reflections will be given in Section *3.6*.

# 3.2. The maintenance techniques framework

The first phase of this study aims to explore the steps the academic literature describes to use MTs for maintenance decision making. Therefore, based on different views, four consecutive steps are proposed to support effective decision making based on MTs. The proposed framework, shown in Figure 4, guides the user of these MTs through the required four consecutive steps.



## 3.2.1. Step 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 proposed. Or a decision (support) is desirable: the quest for a technique is born of economic necessity (Dekker 1996), known as decision pull. This process coincides with the choice of equipment to which to apply the techniques and constructing a solid business case to convince stakeholders and investors.

## 3.2.2. Step B: Monitoring and data gathering

After the initiation, selecting the parameters to monitor and gathering the (available) input data follows. The data collected for the less advanced techniques, such as technical knowledge for the experience-based predictions, are also used for the more advanced techniques, e.g. model-based predictions. 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, Lin, and Banjevic 2006).

Several types of data gathering and monitoring strategies can be used, which we clustered in five types in the proposed framework. First, asset history data can be gathered from technical knowledge, inspections and historical records of e.g. failures or costs. Second, collecting usage and process data entails the process of acquiring operational data, e.g. running hours, mileage, or tons produced. Third, stressor-data describes the exerted loads (stressors) on the system. This preferably includes environmental data, comprising measures of temperature and moisture for instance (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, Klingenberg, and Wortmann 2011).

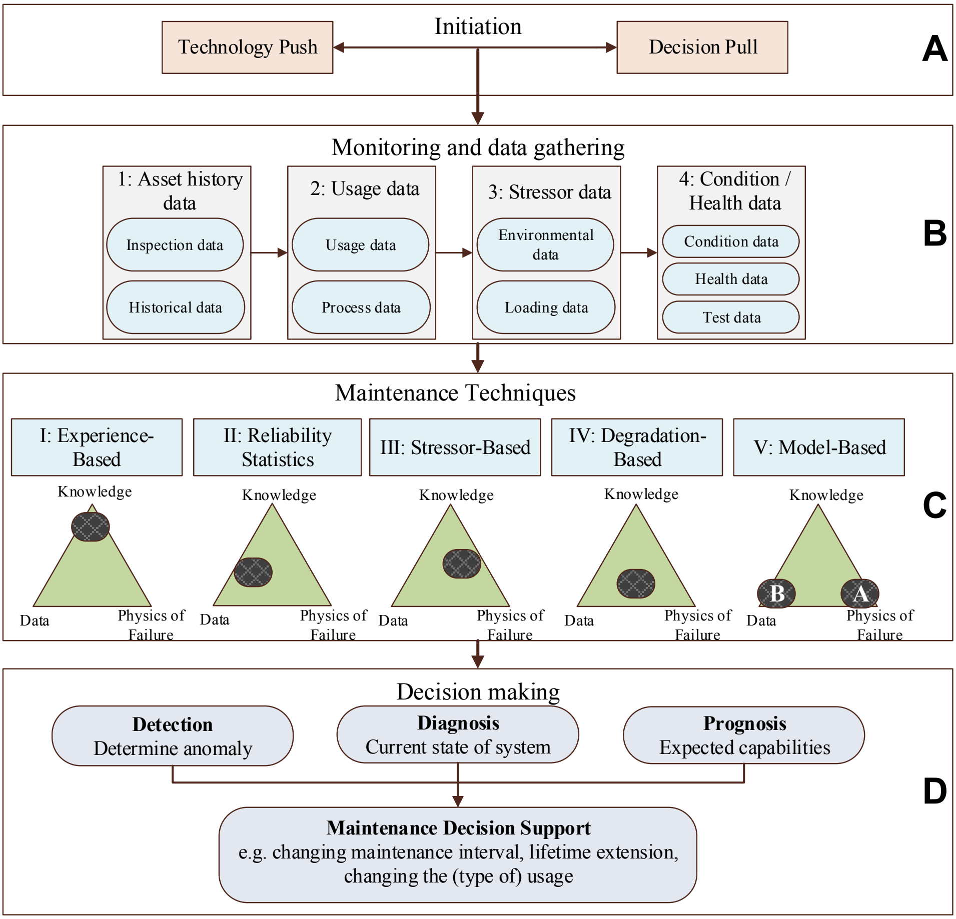


*Figure 4. Overview of maintenance techniques: steps and options to maintenance decision making, based on Jardine, Lin, and Banjevic (2006), Coble and Hines (2008), and Dibsdale (2015).*

Fourthly, 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 data from oil techniques. (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.

### 3.2.3. Step C: Maintenance techniques

The third step aims at selecting the applicable MT and conduct the maintenance analysis. The available data and the required outcome (depending on the asset, its criticality, and the behavior 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 (Step B: Monitoring and data gathering).

Among reviewers within the prognostic field, little consensus exists what classifications of prognostics are most appropriate (Sikorska, Hodkiewicz, and Ma 2011). In this chapter, we adopt two classifications to encompass the various views in this field. In the first categorization, we adapt the model proposed by Coble and Hines (2008), which is already extended by Dibsdale (2015) with category V (model based). We slightly extend this with the least advanced, experience-based route by considering the difference between 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 estimate the life of an average component operating under historically average conditions.

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. These methods also estimate the life of an average component operating under historically average conditions and are based on e.g. Weibull distributions.

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 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, build-in-test 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. By measuring symptoms of incipient failure, e.g. rises in temperature or vibration, the system can be diagnosed. The prognostic parameter is also inferred from sensor readings, i.e. is always based on a measurement. The prediction starts from the current state of degradation and results in 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. 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 direct sensing of 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 uses sensed variations of loads, usage data, process data, or condition/health monitoring data as input. The algorithms aim to derive patterns or relations in the data or try to predict anomalies by comparing with historical data.

The second categorization classifies the maintenance techniques on the input data: data-driven, knowledge-based, physical model-based or a combination of the three (Goh et al. 2006; Venkatasubramanian 2005). In Figure 4, the spot in the triangles (in layer C) indicates where each MT is positioned in this categorization.

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 on the quality and quantity of input data.

Physical models need an accurate mathematical model (Jianhui et al. 2003). The behavior of a failure mode is quantitatively characterized using physical laws (Sikorska, Hodkiewicz, and Ma 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, Hodkiewicz, and Ma 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, Hodkiewicz, and Ma 2011).

### 3.2.4. Step D: Decision making

The final step focusses on the actual decision making. These decisions mainly focus on maintenance decisions, such as direct repair or replace decisions or lifetime extension. However, they also include 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 decision making in this final step is based on the results from the maintenance technique, being (combinations of) detection, diagnosis and prognosis.

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, which are continuously looking for abnormalities in the system.

Diagnostics aims to not only find, but also qualify the damage that has occurred (Sikorska, Hodkiewicz, and Ma 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 proposes possible fault causes. Diagnostic systems are critical to the cost-effectiveness and safety of many systems.

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).

Finally, limitations to the usage of PdM are created by internal and external laws and regulations e.g. setting norms for the accuracy of the prediction (required type of prescribed techniques) or by limiting the possibilities of data gathering (e.g. restrictions on position revealing GPS usage in military applications).

# 3.3. Mapping the use of MTs in practice to the presented framework

To test the proposed framework (Figure 4) and to get a better understanding on the 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 3.2.3. This section will discuss for six case study examples (one successful application of each maintenance technique and one unsuccessful application) the routes that practitioners have taken to apply MTs. The routes (from initiation to maintenance decision making, Figure 4), will be visualized in the mapping in Section 3.4. But first, the case-study method will be introduced (3.3.1.) and the six examples of MT applications will be discussed (3.3.2).

## 3.3.1. Case-study method

To ensure that the method is tested on a wide variety of companies and assets, 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, defense, 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 analyzed. The analyzed 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 theoretical framework shown in Figure 4 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.

### 3.3.2. Case-studies on the use of MTs in practice

#### *Case 1: Experience-based in the steel manufacturing industry (successful)*

The department that provides internal transport of work-in-progress in a steel plant has conducted failure mode, effect and criticality analyzes (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 (i.e. no actions for non-critical units). Solely based on experience of the maintenance personnel, operators, product quality specialists and maintenance engineers, the maintenance concept is developed.

| | |
|---|---|
| Required outcome: | Effective preventive (risk-based) maintenance program that helps to prevent severe incidents and minimizes 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. |
| 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 identified. |

#### *Case 2: Reliability statistics within the aerospace industry (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 tire changes is calculated. This calculation has given input for the diagnosis of the situation, wear of the tires is related to flights instead of for example flying hours. A prognosis is made with the assumption that this analysis applies to all tires of this fleet of similar aircraft. This has led to determine an optimal maintenance interval for all tires of the aircraft.

| | |
|---|---|
| Required outcome: | Prediction for a specific component (tires) of a generic system (airplane) under generic situations (landings not specified per operational region) |
| Why *reliability statistics – Type II –* has been selected: | 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. |
| What other possibilities were available? *Type I and III could have been selected.* | The case shows a match between the ambition level and the available data. Other analyzes 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). |

*Case 3: Stressor-based MT for a military transportation aircraft (successful)*
Traditionally, this maintainer follows the prescribed maintenance from the OEM handbooks of the military transportation aircraft. However, for the airframe, which is a component that determines the lifetime of the plane, more advanced analyzes 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 on the 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 all individual planes 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). The information on the remaining life of individual aircraft is of crucial importance in fleet's replacement process.



| | |
|---|---|
| Required outcome: | Prediction of the RUL per plane, based on the actual usage and current state of degradation |
| Why *stressor-based – Type III* – has been selected: | 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. |
| What other possibilities were available?<br><br>*Type I and V could have been selected.* | 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 model for the airframe. However, as insight in degradation of individual planes was not the initial ambition, a stressor-based technique was selected. |

*Case 4: Degradation-based MT for rolling stock (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 behavior 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 behavior per individual train based on the actual usage and behavior |

| | |
|---|---|
| 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. |

### *Case 5: Physical-model-based MT for a military helicopter (successful)*

This maintainer of military helicopters collects health and usage monitoring data. Based on this input, the flown flight maneuvers 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 is used. This model requires input from the installed health and usage monitoring system, strain gauges, and usage data. Analyzes are conducted to detect the flown maneuvers, 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? *Type I and II could have been selected.* | 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. |

### *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. 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 failure behavior 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?<br><br>*Type III could have been selected.* | This case shows that the department explored two possibilities: experience-based and statistics-based analyzes. 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. |



## 3.4. Mapping the followed routes of the case study companies

Figure 5 – composed of the same building blocks as Figure 4 – shows the mapping of the routes, followed in the case studies discussed in Section 3.3.2 and visualizes these using the colored lines. To explain the figures, we explain the route taken in case 3 (military aircraft, brown line). 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 starts with collecting usage and load monitoring data. In step C, a stressor-based analysis is conducted. Step D shows that applying this technique resulted in a detection of anomalies in the system, a diagnosis and a prognosis of future behavior. The figure shows that the department uses this technique for maintenance decision making (lifetime extension of the transportation plane).

The mapping of the followed routes confirms the proposed MT framework of *Figure 4*. The advantage of visualizing the routes is that it provides a direct view on the inputs used and results obtained with the various PdM applications. Firstly, the visualization shows that all building blocks are recognized in the case studies. Next, in the initiation (step A) the figure shows that three out of the six projects are started by both technology push and decision pull, for these cases the ability and need to do prognostics come together. 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, the step from diagnosis to prognosis seems to be made in all cases. 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 colored. In case 6, the application of reliability statistics requires high quality historical data and usage data.

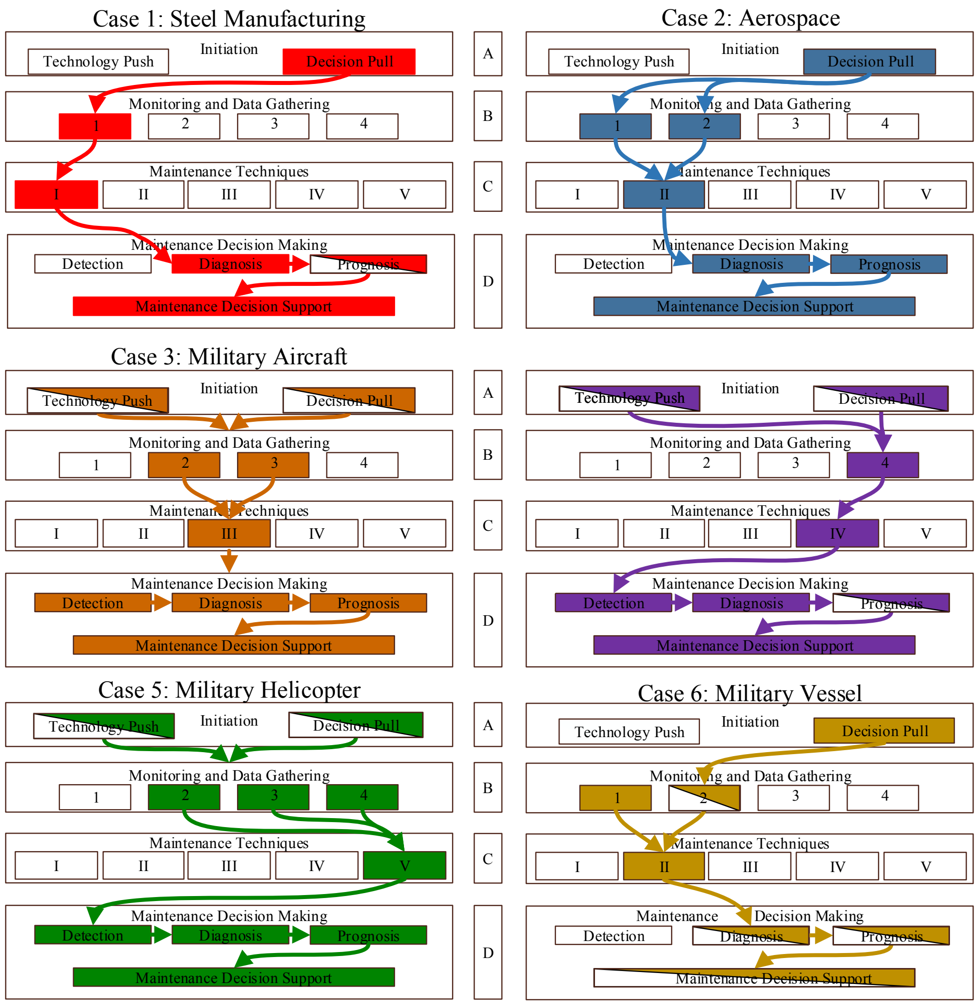


*Figure 5. Mapping the six cases to the framework of Figure 4.*

However, as shown in the visualization, this was not available (the blocks are only partly colored), and only limited results could be achieved. This is visualized by the partly colored blocks *diagnosis, prognosis,* and *maintenance decision making.*

We did not identify routes that cannot be mapped onto the framework. However, more routes could have been possible for the case companies and no conclusions can be drawn on whether the most efficient and most effective route 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 routes are available for a successful application.

## 3.5. 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 6*). This shows that practitioners, within one department, used multiple types of MTs. That confirms our assumptions. *Figure 6* 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.

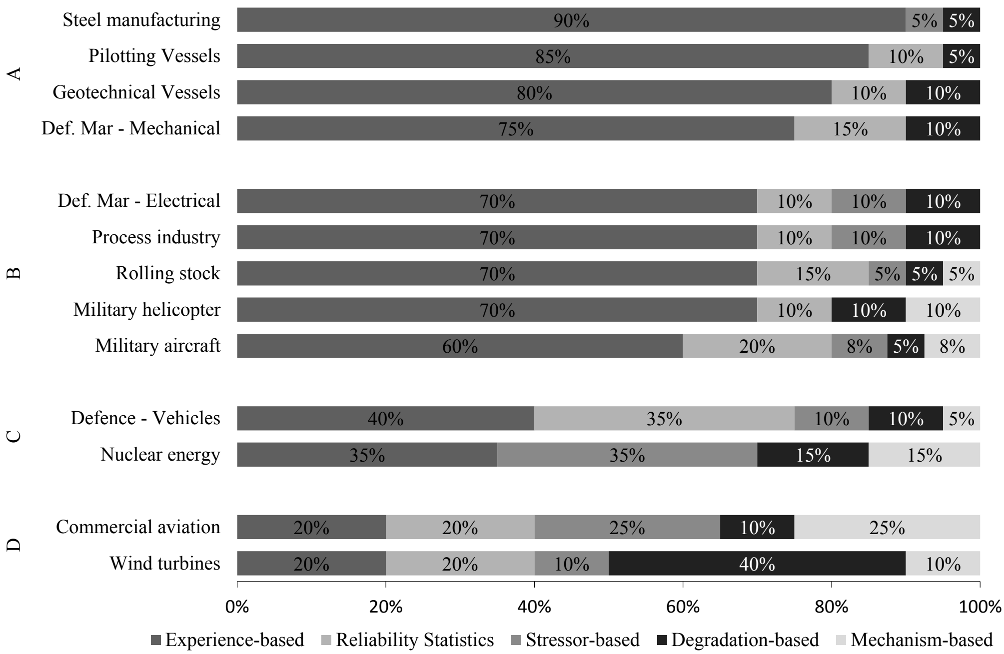


*Figure 6. Estimated relative occurrence of various MTs within case companies.*

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 analyzes. 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 analyzes 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 analyzes 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 maneuverability training for aircraft). Within the studied cases, the model-based analyzes are only applied to the most critical components and therefore more applied to aircraft and helicopters than to vehicles or vessels.

The cases also show that the development of PdM is initiated by either the ease of using the available data or a perceived need to know the exact moment of failure. This can be explained by the technology acceptance model (TAM) of Davis (1989). The TAM describes that the perceived usefulness and the perceived ease-of-use of new technology determine its acceptance. Summarizing from the cases, the factors listed in Table 8 seem to determine the perceived ease-of-use and usefulness of MTs to firms.

The TAM concept can now be coupled to initiating the development of PdM within firms (i.e. decision pull versus technology push, see also *Figure 4*). From the decision pull perspective, firms start by finding (more) systems for which applying PdM would be useful, and thereby improve the perceived usefulness of PdM. By starting to improve the usefulness before the ease-of-use (decision pull), the need for starting a PdM trajectory is clearly communicated. This is in line with the multi-step process proposed by Kotter (1995), which helps firms to overcome organizational issues in an implementation process. This process has to be driven by high-quality leadership and should create power and motivation to overwhelm reactionaries. It therefore focusses on establishing a sense of urgency, which can be achieved by clearly communicating the usefulness of PdM. Difficulties that can be encountered with this process are that the firm's capabilities are not up to par with the desired level of application of advanced types of PdM, as shown in *Figure 7*. In that case firms should focus on developing knowledge, IT capabilities and use external skills to successfully develop PdM. This can be achieved by cooperating with OEMs and suppliers.

| Perceived ease-of-use | Perceived usefulness |
|---|---|
| - Availability of data (failures, operating history) | - High safety effects of failures |
| - History of application of advanced types of MTs | - Highly varying deterioration between operations |
| - High level of cooperation with OEM/experts | - High need to cut costs or improve availability |
| - Internal/external knowledge on MTs | - High criticality of assets and operation |
| - Regulatory agencies permitting new techniques | - Possibility to postpone maintenance activities |
| - Low variety of equipment | - Remoteness of equipment location |
| - High level of IT system integration | - Low redundancy levels |

*Table 8. Factors in case study improving perceived ease-of-use and perceived usefulness of MTs.*



In the technology push perspective, firms start by increasing the perceived ease-of-use. This is achieved by investing in automatic data gathering systems, installing sensors, collecting larger amounts of data, investing in data processing and the skills of employees. In some cases this is obtained by acquiring new assets which are equipped with more sensors and can easily be connected to remote monitoring stations or by adopting innovative technologies offered by other companies. Only after this process, the firms try to find suitable applications, i.e. components of which the remaining life can be predicted.

Starting to improve the ease-of-use, can help to overcome infant mortalities in the PdM application process. However, it can be difficult to find the right applications that help to create sufficient usefulness of the techniques. When this leads to insufficient business cases, management can decide to focus their resources for example on new product development instead of the development of PdM. Therefore, short-term wins have to be created by starting up small projects which are visible within the company (Kotter 1995). This helps to convince people that PdM offers additional benefits compared to conventionally used methods.

Another option for firms to approach these development strategies could be to decouple the two routes. Not all techniques have to be developed within the organization, but firms can follow a ‘technology watch’ strategy. The trick in such a strategy is “to identify the right technologies at the right time and make the most cost-effective investments possible” (Dhillon 2009). Typically, a technology investment agenda can help firms to identify the technologies in which to invest versus those that get little financial attention. Dhillon (2009) argues that “management must find the technologies likely to yield the most growth and profitability, not the coolest write-up in a technical trade publication”. This means that the decision-pull perspective within the firm should determine which technologies to look for in the market and the technology-push perspective role could be picked up by parties that are specialized in blue sky research projects, e.g. universities, research institutes or technology start-ups.

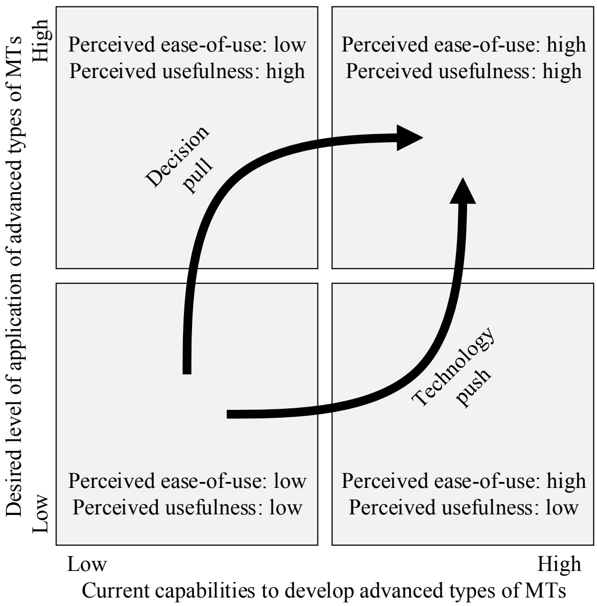


*Figure 7. Developing advanced types of MTs from a technology push perspective versus a decision pull perspective. The decision pull perspective requires focus on the perceived ease-of-use, whereas the technology push perspective requires emphasis on the perceived usefulness.*

# 3.6. 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 chapter investigated how routes to maintenance decision making have been selected in practice. We therefore first looked at theoretical routes, providing a framework (Figure 4) with possible routes. Six specific routes (from a total set of 13 cases) that have been taken in practice have been mapped on this framework, as shown in Figure 5.

Three conclusions can be drawn from these mappings. First, data dependencies and ambitioned outcomes of analyzes appear to govern the selection of MTs. Second, both the criticality and the type of asset determine the use of more or less advanced maintenance techniques. Third, the mapping of the followed routes confirms the correctness of the proposed MT framework of Figure 4 by showing that all routes could be mapped onto the framework.

Further, based on the relative occurrence of MTs in the 13 cases, four different clusters can be distinguished (Figure 6). 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. Thereby, the decision pull versus technology push perspective seems an important discriminator for the route selection. As many firms' maintenance budgets are under pressure, sufficient opportunities to improve maintenance decisions are often available. However, one can question whether that always leads to the most optimal route for a firm's situation.

Finally it is discussed how starting from a technology push perspective leads to other start-up difficulties (creating perceived usefulness) than starting from a decision pull perspective (creating perceived ease-of-use). As the combination of perceived ease-of-use and the perceived usefulness eventually leads to technology acceptance, it is important for firms to define the required outcome of the MTs and the required and available capabilities at forehand. Creating a match between the desired level of applications of advanced types of MTs and the available capabilities to develop these MTs seems to be critical for successful PdM applications.

## 3.7. Limitations and further research



The case studies show the routes that companies have taken in applying PdM. However, more routes could have been feasible for the case companies and no conclusions can be drawn on whether the most efficient route has been selected. Therefore, more cases (e.g. from literature or practice) should be mapped to further validate the framework.

Further research will not only focus on observing the followed route, but on advising firms in the selection of the most suitable route 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. Such a model can help to evaluate the impact of a PdM implementation and thereby improve the perceived usefulness of the techniques.

# CHAPTER 4

# Framework for the selection of the optimal preventive maintenance approach[4]

4

## 4.1. Introduction

### 4.1.1. Background

In the last decades, maintenance has evolved from merely reacting to failures, via preventive replacements at fixed intervals or based on visual inspections, towards automated methods that continuously inform about the asset's future state (Hashemian and Bean 2011). Many different maintenance policies are available now, ranging from the traditional corrective maintenance to more advanced policies like condition-based or predictive maintenance. Moreover, many methods and techniques for monitoring and inspecting assets, analysing data or predicting remaining useful life have been developed. Therefore, selecting the optimal approach for maintaining a specific asset has become quite a challenge for the asset owner.

The first step in this process is the maintenance *policy* selection, i.e. determining which maintenance policy is most suitable in a specific situation. This challenge has been addressed by many authors in the past, well-known strategies such as Reliability Centered Maintenance (RCM) and Total Productive Maintenance (TPM), but also more specific methods such as the analytical hierarchy process (AHP), are available to support asset owners in making this choice. Moreover, Waeyenbergh and Pintelon (2002) have proposed a decision tree for selecting the most suitable maintenance policy regarding both technical and economic implications. This method aids in the selection of various maintenance policies for

[4] This chapter is based on: Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (n.d.). Framework for the selection of the optimal preventive maintenance approach. Submitted

components, as the preventive maintenance approach for a complex system such as a train is often a combination of several policies (e.g. a combination of usage-based and corrective maintenance). All of these concepts mainly advise either a reactive or a proactive (or preventive) maintenance policy, and depending on the method, make more detailed subdivisions in each branch (e.g. condition-based as a specific proactive policy). As modern systems are in most cases critical to operations, proactive maintenance policies have become common practice.

However, merely selecting a policy is not sufficient. Once the maintenance policy has been selected, the next challenge is to determine how this policy must be executed. If, for example, a preventive maintenance *policy* has been selected, how can the optimal moment of replacement be determined? The number of methods and techniques to assist in this process is enormous, but at the same time much less support for these lower-level decisions is available in scientific literature, despite the fact that this step is crucial for practitioners.

The methods and techniques that typically assist in determining the critical parts in a system, estimate the mean time between failures (MTBF), assess the system condition or predict the remaining useful life (RUL). In addition, since real-time logging of various parameters, sensors and microprocessors is feasible nowadays, this type of (big) data can provide feedback about the degradation, use, environment, and location of assets. Effective use of this data helps to anticipate problems, such as unplanned failures. Collecting this data has become a simple exercise (Lee, Bagheri, and Kao 2015). However, this data is not useful unless it is processed in such a way that it provides context and meaning that can be understood by the appropriate personnel (Lee, Bagheri, and Kao 2015). All of these methods can thus help decision makers to make better-informed maintenance decisions and improve the performance of their physical assets. This can be achieved by not conducting maintenance prematurely, which would lead to unnecessary costs and downtime, nor too late, which would lead to unplanned downtime and failure costs, or even change the usage of the system (e.g. load reduction).

It can therefore be concluded that selecting the optimal maintenance *approach* involves more than just maintenance policy selection, but also includes a selection of the most suitable methods or techniques to operationalize the policy. The latter methods and techniques will be denoted Maintenance Techniques (MTs) in this chapter. It is mainly the selection of these MTs that is not well-supported yet, as also can be concluded from earlier work conducted by the authors (Tiddens, Braaksma, and Tinga 2015), demonstrating that practitioners find it difficult to select and effectively apply these techniques in practice. Additionally, a study by Grubic et al. (2011) showed that companies experience a gap between the potential and realised benefits of advanced maintenance methods and techniques. This challenge has in recent years become emergent by choosing between a data analytics approach or a physical model. Note that this challenge is specifically acute when a preventive maintenance policy has been selected. For a reactive (corrective) policy the operationalization is rather trivial. This work will therefore focus on selecting the most suitable preventive maintenance approach.

## 4.1.2. Objective and contribution

The objective of this chapter is to help practitioners in selecting the optimal preventive maintenance approach for their situation, by proposing a framework that provides support in these decisions. The proposed method extends existing methods as it focuses on executing the maintenance *policy,* and the way maintenance decisions are made. The method therefore does not take into account aspects already covered by existing methods, such as the maintenance *policy* selection (Figure *8*) and the *optimization* of maintenance policies or *organization* of maintenance processes (e.g. clustering of maintenance activities). Thus, given that a specific preventive maintenance *policy* has been selected, the method proposed here advises which MT should be used to determine when a maintenance task must be performed.

The scientific contributions of this chapter lie primarily in the classification and analysis underlying the proposed decision support framework:

- detailed analysis and classification of the whole range of preventive maintenance approaches, assessing the strengths / weaknesses and requirements / limitations;
- classification of the various ambition levels in preventive maintenance and the available data types;
- linking of approaches, ambition level and data types.

This structured analysis provides valuable insights for researchers, enabling them to develop new methods that can more easily be applied in practice.



## 4.1.3. Research method and outline of the chapter

The design of a method to conveniently select the proper preventive maintenance approach is guided by the design science methodology (Holmström, Ketokivi, and Hameri 2009). The aim of this method is "tackling ill-structured problems in a systematic manner" (Holmström, Ketokivi, and Hameri 2009, 67) and allows for both explaining and predicting a phenomenon of interest and shaping this phenomenon by designing novel solutions (Simon 2000). Using the design principles from Hevner et al. (2004) and Peffers et al. (2007), this research involves all four defined design stages: *problem exploration*, *initial solution design, solution development* and *solution evaluation*.

For the first stage of this research: *problem exploration,* we previously reported on the difficulties that companies experience in maintenance decision making and the steps the academic literature describes to use methods and techniques for maintenance decisions (Tiddens, Braaksma, and Tinga 2015; Tiddens, Braaksma, and Tinga 2017). This multiple case study – in which we studied thirteen cases in various industries in the Netherlands – provides insight on how maintenance techniques are used in practice. In Section 4.2, the main findings of this study will be discussed and the identified problems will be defined as input for the second stage of this research in Section 4.3: the initial solution design. In this second stage, initial solutions will be proposed for the identified (sub) problems in the case studies. These initial solutions will be brought together in Section 4.4 in the third stage: the design of the solution. In this section, we propose a selection framework that provides decision support to practitioners in selecting the appropriate preventive maintenance approach for their situation. In the final stage of this research, the solution evaluation, the design will be evaluated. Therefore, Chapter 4.5 presents multiple case studies to demonstrate and evaluate the proposed framework. Finally, conclusions, limitations, and general reflections will be given in Section 4.6 and 4.7.

## 4.2. Problem exploration

As was discussed before, in addition to selecting the proper maintenance policy, maintenance techniques should support practitioners in maintenance decision making by providing information about the current, and preferably also the future (predicted), performance of assets. However, practitioners experience several difficulties in the selection of the most suitable maintenance technique to apply. In this section, we will introduce and discuss the three main difficulties that affect the selection and application of the most suitable maintenance technique, as obtained from the case studies.

### 4.2.1. Difficulties in identifying and selecting approaches for preventive maintenance

As was mentioned in the introduction, a maintenance approach consists of selecting a proper maintenance policy, as well as the maintenance techniques (MT) for operationalizing this policy. Although many methods for maintenance policy selection are available in literature, for example, multi-criteria decision making (MCDM) (Shafiee 2015), the analytical hierarchy process (AHP) (Goossens and Basten 2015), or reliability centered maintenance (RCM) (Moubray 1997), however, methods to select the required MTs are non-existent. Moreover, the separation between policy selection and MT selection is not always completely clear. This is shown in Figure 8, providing an overview of the most common maintenance policies.

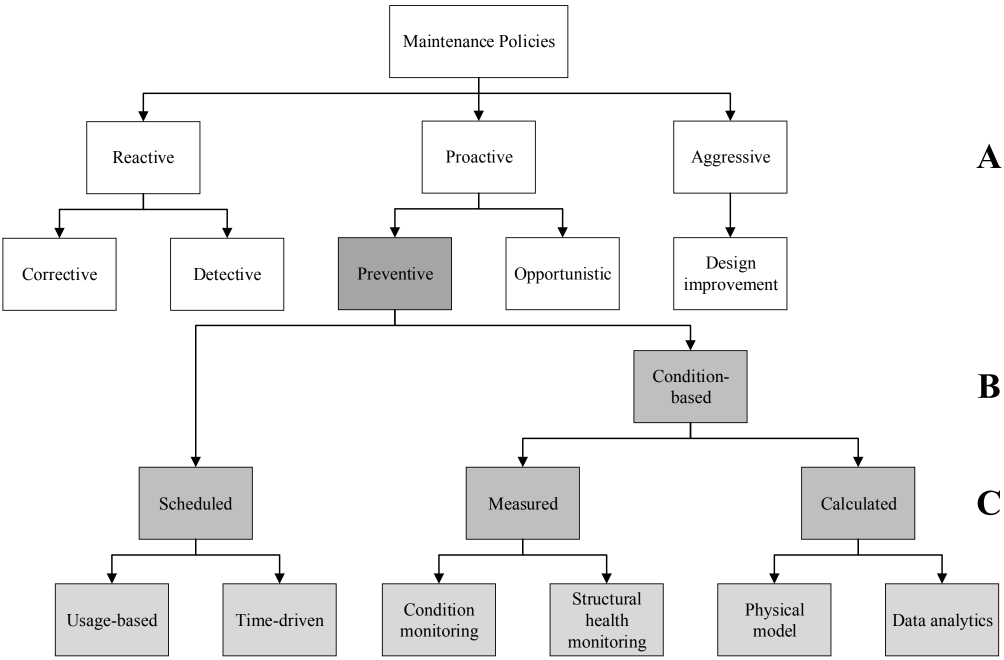


*Figure 8. Overview of maintenance policies.*

At the highest level (A), a division is made between reactive, proactive and aggressive policies. The preventive maintenance branch is then subdivided into various policies at levels B and C, where they start to interact with the maintenance techniques (e.g. condition monitoring, prognostic methods). The commonly used policy selection methods, such as RCM, support the selection at level A, and in most cases also at level B. For the selection at level B, various methods are available in the literature that incorporate specific factors, for example, practical factors to consider in comparing condition-based to time-based maintenance as shown in de Jonge, Teunter, and Tinga (2017), or by comparing the performance of these methods in terms of e.g. life cycle costs, as shown in Kim, Ahn, and Yeo (2016).

Although these methods help to incorporate various factors in the selection of maintenance policies, the detailed selection at level C is not supported by these methods, as that is typically the level where an MT must be selected.

Many maintenance techniques are discussed in the literature (Sikorska, Hodkiewicz, and Ma 2011; Dekker, Wildeman, and van der Duyn Schouten 1997; Tiddens, Braaksma, and Tinga 2016), but support in selecting a suitable MT for a specific need is lacking. This issue might be reflected in a survey conducted by Grubic et al. (2011), who demonstrated that only 11-13 percent of UK-based manufacturers have adopted prognostics and decision-support techniques. An earlier study demonstrated that practitioners often follow a costly trial-and-error process in developing more advanced techniques, caused by a lack of methods or procedures that guide the use of available MTs (Tiddens, Braaksma, and Tinga 2015).

It is important that the selected combination of policy and MT suits, amongst others, the company's expertise, current situation, maintenance organization, assets, and the use of their assets. Especially when practitioners are dealing with approaches that are new to them, there are many possible pathways towards better-informed maintenance decision making, but they find it difficult to determine the relevant methods and parameters to select. In other words, practitioners find it difficult to (*i*) identify and (*ii*) distinguish between the suitable paths. To avoid a long and costly trial-and-error process, either external parties are hired or the techniques are not developed at all.

**Identified problem 1:** Practitioners find it difficult to identify and differentiate suitable approaches for preventive maintenance.

### 4.2.2. There is often no proper fit between the ambition level and the available data

To manage their physical assets, practitioners often use fixed maintenance intervals prescribed by the original equipment manufacturers (OEM). In addition to that, previous experiences and historical data are input for stochastic or statistical techniques of failure prediction (Van Noortwijk 2009; Singpurwalla 1995; Zio et al. 2012). Although these traditional methods are widely used, they are limited in effectively predicting future behaviour and reliability of individual systems, especially when the behaviour or use of the system is variable. When the company has the ambition to incorporate these variabilities in operational conditions in the maintenance approach, it is important that this requirement (i.e. the specific purpose for which the model can be used) is defined explicitly to ensure the selection of a suitable MT (Nguyen, Fouladirad, and Grall 2018).

Moreover, such an ambition level sets requirements for the data to be used as input for the analyses, as the data completeness and quality significantly affects the outcomes (Sandborn and Wilkinson 2007). The input data these models rely on can be imprecise or incomplete, especially when actual failure data is missing due to bad registration or effective failure prevention. In the case studies, it was observed that the more advanced companies tend to have more structured and accessible data. Especially the less mature companies seem to experience difficulties with scattered data, e.g. it is stored in multiple systems, local desktops, and data which is difficult to access, e.g. it is stored in legacy systems, data stored in text format (i.e. word or pdf), or incomplete data. Note that additionally, the knowledge level of the people involved can be considered part of the data quality, as experience and expert insight is often used in maintenance decision making.

In previous work (Tiddens, Braaksma, and Tinga 2016) we demonstrated that the fit between data and the (strived for) type of analysis seems to be leading for the success of the MT. This means that when the company's assets are used in varying operational and environmental conditions, a technique has to be selected that considers these variabilities. However, this means that data about these operational and environmental conditions should be available. As this data is not always initially available, not all routes are possible for a successful application without additional data gathering.

**Identified problem 2:** There is often a gap between the ambition level and the initially available data and knowledge.

### 4.2.3. The justification to select a specific maintenance approach is not clear

The final problem identified is the financial justification for the implementation of the maintenance technique. As *problem 2* shows, there is not always the right fit between the ambition level and the available data. To solve this, a company can either reduce its ambition level or collect the right data. The latter is often associated with substantial investment costs. Therefore, although it often seems to be difficult to (financially) justify these investment costs, a positive business case is important for the successful implementation of the selected maintenance technique.

The benefit of MTs to the asset performance can often (primarily) be found in helping to reduce the number of unplanned failures while not conducting too many repairs or replacements (as in a fixed-interval preventive maintenance policy). When, for example, a health monitoring system detects an anomaly, it will create a prognostic identification and estimate the remaining useful life (RUL), allowing the user to take a preventive action before the system fails (Haddad, Sandborn, and Pecht 2014). Such a maintenance technique creates timely knowledge about failures and improves the flexibility in managing the asset. The challenge is to express this benefit in financial terms, to enable a comparison to the required investment costs, or to find another (non-financial) way to weigh costs and benefits. It was observed that many companies do not make such an assessment before starting the development of an advanced maintenance approach.

**Identified problem 3:** It is often unclear whether the selected MT will provide benefits.

## 4.3. Initial solution design for a method to select the appropriate preventive maintenance approach

To overcome the problems identified above, this section introduces a set of initial solutions. The main goal of these initial solutions is to support the development of the final framework, as proposed in section 4, to help practitioners select the appropriate maintenance approach. However, the separate initial solutions also constitute the second main contribution of this chapter, which is the structuring and classification of maintenance policies, methods and techniques, as well as the definition of ambition levels and data types. The results will not only assist in designing the decision framework, but also benefit other researchers in the field.

### 4.3.1. Initial solution 1: Differentiate between the various available preventive maintenance approaches

To be able to select a preventive maintenance approach, the various combinations of maintenance policies and MTs that are described in the literature have to be differentiated between and classified first (problem 1). However, among reviewers within the diagnosis and prognostics field, little consensus exists as to which classifications of methods are most appropriate (Sikorska, Hodkiewicz, and Ma 2011). In this thesis, therefore, a broad classification is adopted to encompass the various views in this field. In this categorization, the model proposed by Coble and Hines (2008), which has already been extended by Dibsdale (2015) with category V (model-based), is adapted. This is slightly extended (Tiddens, Braaksma, and Tinga 2015) with the least advanced, experience-based approach by considering the difference between methods that employ historical records (data) and those that only employ expert knowledge and the experience of people who use and maintain the equipment (Moubray 1997). We have found that this category is the most used type of maintenance technique in practice. The framework is now comprised of five types of preventive maintenance approaches:

I. Experience-based predictions of failure times are based on knowledge and previous experience outside of (e.g. OEM) or within the company. Sometimes they are supported by limited or scattered data. Predictions are based on expert judgement (e.g. facilitated by FMECA techniques). These methods estimate the life of an average component operating under historically average conditions.

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. These methods also 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, humidity or speed, to include environmental and operational variabilities 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, build-in-test 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 determine a failure threshold. By

4

measuring symptoms of incipient failure, e.g. rises in temperature or vibration, the system can be diagnosed. The prognostic parameter is also inferred from sensor readings, i.e. is always based on *measurements*. The prediction starts from the current state of degradation and results in 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. 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 direct sensing of 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 uses sensed variations of loads, usage data, process data, or condition/health monitoring data as input. The algorithms aim to derive patterns or relations in the data or try to detect anomalies by comparing to historical data.

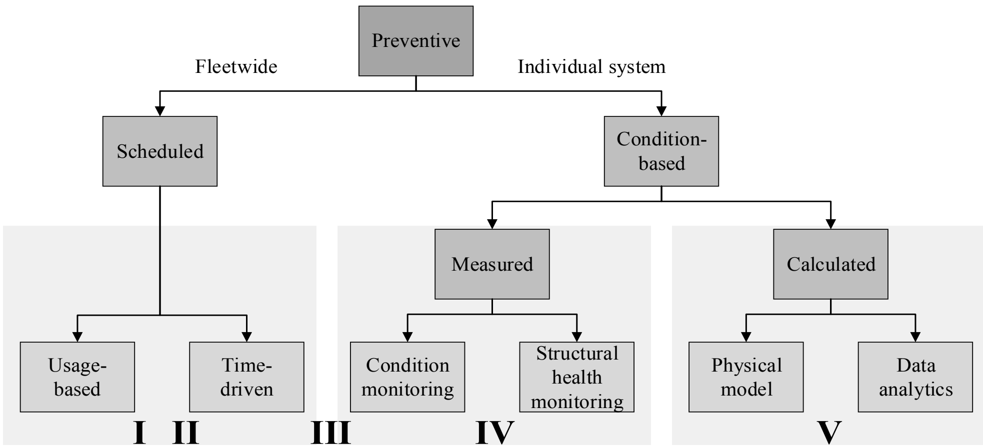


*Figure 9. Relation between preventive maintenance policies and proposed types of MTs.*

These five approaches all combine specific maintenance policies with certain methods and techniques. To clarify the link between policies and the proposed approaches, Figure 9 schematically shows their relations. Note that in a bottom-up reasoning approach a certain preventive maintenance approach can only be combined with one specific policy: e.g. following the model-based approach (V) automatically means that a condition-based policy is adopted. However, the other way around, selecting a condition-based maintenance policy (e.g. using some policy selection method) still leaves several options for the complete maintenance approach (III, IV and V). The present chapter especially focuses on this final step.

An important aspect in differentiating the various approaches is how precisely the lifetime of a system can be predicted. The lower maturity methods of experience-based (I) and reliability statistics (II) cannot predict the lifetime of an individual system or take into account a specific operating condition, they only provide fleetwide and long-time averages, e.g. an MTBF value. This branch is therefore referred to as 'fleetwide' in Figure 9. The more advanced approaches III, IV and V are based on condition-based policies, which do differentiate between individual systems or operating contexts. However, a model-based approach (V) can also predict the lifetime for not previously encountered situations, while the degradation-based approach (IV) can only rely on extrapolating the current trend.

### 4.3.2. Initial solution 2A: Define the ambition level

The second identified problem was the commonly observed mismatch between the ambition level of the company and the initially available data. Therefore, both a definition of the ambition levels (this subsection) and the data types (section 3.3) is required. The ambition level is defined as the level of detail that is required in the maintenance decision making process. Therefore, it is important to consider the four aspects set out below.

1. Is predicting the assets life time on an individual basis required?
    - If this is not required, only a generic prediction can be made for a fleet or group of assets;
    - If individual predictions are required, this also means that monitoring of individual assets is required.
2. Should variations in usage of the assets be included?
    - If not included, maintenance will be based on calendar time;
    - Typical variations in usage to be included are operating hours, driven kilometres, start/stops;
    - If these variations are to be included, they must also be monitored or registered during operation;
3. Should variations in environmental conditions be included?
    - If not included, maintenance will be based on average conditions;
    - Operating the system at elevated temperatures, high humidity, etc. could lead to accelerated degradation;
    - If these variations are to be included, they must also be monitored or registered during operation;
4. Do the future conditions differ from the current or historical conditions?
    - If there is no difference, an extrapolation of a general trend can be made;
    - Otherwise, these expected variabilities have to be included in the prediction using a model.

Based on these four aspects, five different ambition levels (AL) can be defined, as shown in *Table 9*. The decision scheme in *Figure 10* then provides a guideline for selecting the appropriate ambition level.

| Type | Level of detail in maintenance decision making |
|---|---|
| AL 1 | Insight into future behaviour of the asset or fleet considering static conditions |
| AL 2 | Insight into future behaviour of the asset or fleet considering differences in usage |
| AL 3 | Insight into future behaviour of the asset or fleet considering differences in usage and environmental conditions |
| AL 4 | Insight into real-time deterioration of the individual asset and extrapolation to the future under constant conditions |
| AL 5 | Insight into real-time deterioration of the individual asset and extrapolation to the future under largely varying conditions |

*Table 9. Types of prognostic ambition levels.*

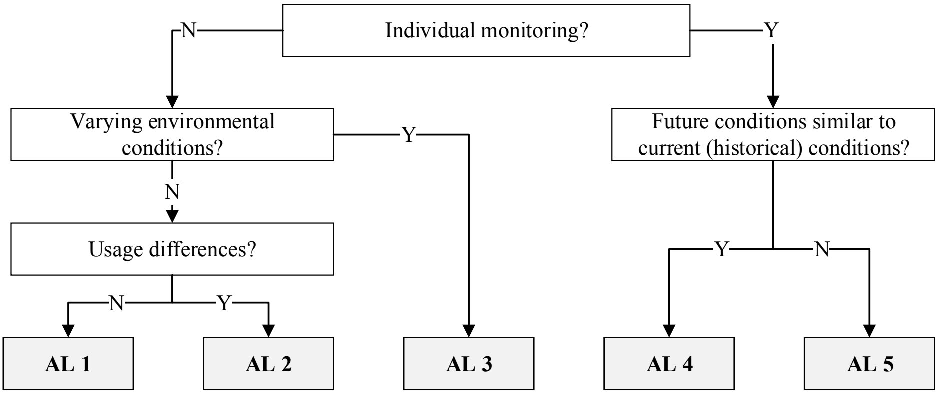


*Figure 10. Guideline for the selection of the ambition level.*

### 4.3.3. Initial solution 2B: Defining data types

The next step, that also follows from problem 2 (gap between ambition level and initially available data), is defining the various data types used in maintenance. *Table 10* shows four types of data that are required for the five maintenance approaches as defined in Section 4.3.1.

| Type of data: | Description: |
|---|---|
| Historical data: | This data can be gathered from technical knowledge, inspection, and historical records of, for instance, failures or costs. We can differentiate between high and low quality historical data. High quality data includes information on historical usage, loads (including environmental stressors) or condition/health per group of systems (fraction of fleet, i.e. a specific unit or type). This information is collected by manual registration, e.g. logbooks or databases, instead of detailed monitoring. |
| Usage monitoring: | The process of acquiring operational data, e.g. running hours, mileage, or tons produced and/or process control data (e.g. Supervisory Control and Data Acquisition: SCADA). This preferably includes environmental data, consisting of, for instance, measurements of temperature and moisture (Farrar and Lieven 2007). |
| Load monitoring: | The process of acquiring loading data, e.g. temperature, vibration, humidity, strain or electrical current (Tinga 2010). |
| Health or condition monitoring: | The process of acquiring signs of imminent failure, e.g. vibrations, acoustics, temperatures, or data from oil analyses (all denoted *condition monitoring*) or data extracted from the measured (dynamic) system response to identify the presence and magnitude of damage in a system (Farrar and Lieven 2007), denoted as *structural health monitoring*. |

*Table 10. Description of data types*

# 4.3.4. Initial solution 2C: Mapping data inputs and ambition levels to the five maintenance approaches

The final step in solving problem 2 is to map the various ambition levels to the required data types and link them to the preventive maintenance approaches. This will quickly reveal whether the chosen ambition level matches the available data. Selecting the appropriate preventive maintenance approach is then proposed as a trade-off between the available input and the ambition level. On the one hand, the ambition level determines the techniques that should be applied. On the other hand, the available data puts limitations on the applicable techniques.

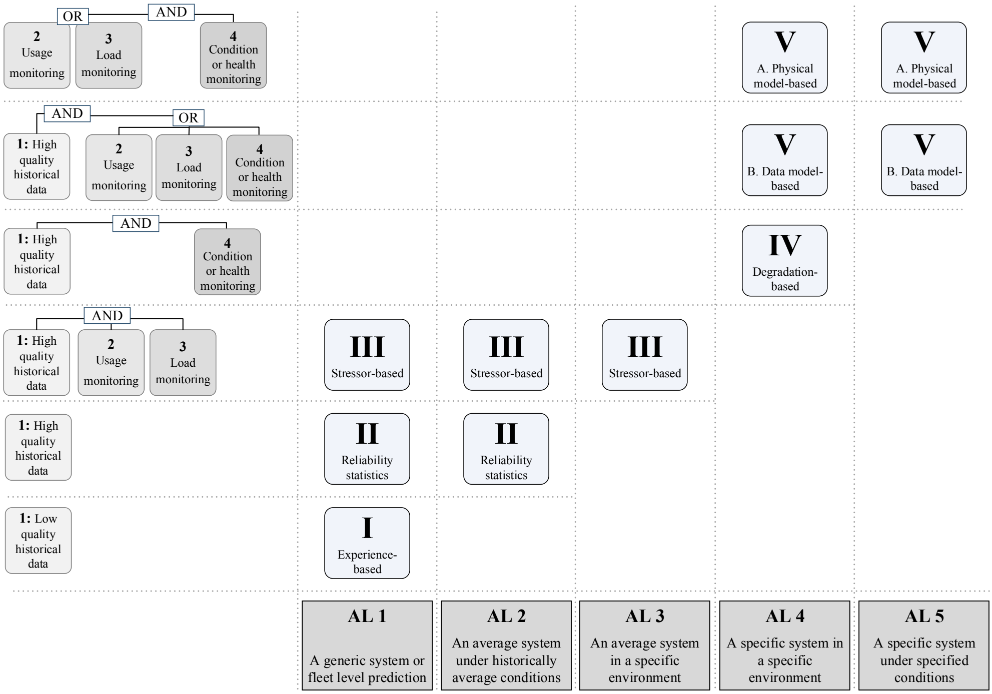


*Figure 11.Mapping preventive maintenance approaches to the ambition levels and data types*

Figure 11 shows the relation between the ambition levels, the available preventive maintenance approaches, and the required data types. The figure shows that with some maintenance approaches, several types of ambition levels can be achieved (i.e. reliability statistics for AL 1 & AL 2). At the same time, the figure shows which data is required for each approach. For example, required inputs for 'analysis IV' are high-quality historic data (1), and condition- or health-monitoring data (4). Required inputs for 'analysis V sub A using a 'physics of failure model' are usage or load monitoring data (2 or 3) and condition- or health-monitoring data (4). Only when these high-level data sources are available, an AL 4 prognosis is feasible. Note that the differences between 'V sub A' and 'V sub B' are the data requirements. A data model requires high quality historical data to train the algorithm. If this data is not available, the only other option is to use a physical model.

Thus, the figure shows that there is no one-to-one relationship between the ambition levels and MTs. Reasoning from either the available data perspective or from the ambition level perspective, (in most cases) several MTs are feasible. However, the combination of available data and the ambition level gives unambiguous and unique advice: the preferable MT.

### 4.3.5. Initial solution 3: Business case

The third identified problem is that it is difficult for the firm to prove the added value of the implemented maintenance approach. However, it is well-established that developing a business case is key to project success (Fortune and White 2006), and it has been observed that often a costly trial-and-error approach is followed in the implementation of CBM (Tiddens, Braaksma, and Tinga 2015). Moreover, for almost 30% of industrial equipment CBM does not provide any benefits (Hashemian and Bean 2011). Therefore, it is important to evaluate the investment in CBM in a structured way before the MT is actually selected.

For techniques that are familiar to the company, or proven within the field, a clear business case can often be defined as reliable estimates of the costs and benefits can be made. However, when more innovative techniques are developed, estimating the costs and benefits is difficult. Such a case often requires the costly collection of extra data for which sensors have to be acquired and installed. Moreover, the time before achieving the benefits is longer and therefore the benefits are more uncertain.

In other work (Tiddens et al. 2017), see chapter 6 of this dissertation, we have developed a hybrid method to construct the business case for condition-based maintenance. This method demonstrates that a justification should be composed of both a non-financial and a financial analysis. In case of innovative techniques, with their highly uncertain costs and benefits, a business case should be composed of non-financial elements. When the costs and benefits can be reliably estimated, a financial evaluation should be added to this business case. In the present chapter, this existing method will be adopted, and developing or enhancing the business case is outside the scope of this chapter, but will be dealt with in Chapter 6.

## 4.4. Designing a method to select the appropriate maintenance technique

To offer decision-support for practitioners, a preventive maintenance approach selection framework is proposed in this section. This framework is based on the five initial solutions that have been presented in Section 4.3.

The proposed framework is shown in *Figure 12* as a decision tree. The choice for a specific maintenance approach can be made via two starting points. Either *decision pull*, based on the demand to achieve a certain ambition level as is depicted in *Figure 10* (initial solution 2A), or *technology push*, based on available and (possibly) worthwhile data as shown in *Table 10* (initial solution 2B).

Ideally, the selection starts via the *decision pull* starting point. This gives the company the opportunity to select the optimal maintenance technique (i.e. a selection that is not directly limited by the available data). After the ambition level has been determined, the company checks whether there is a match with the available data, as follows from initial solution 2B. The mapping in *Figure 11* (initial solution 2C) is then used to suggest one of the five types of maintenance approaches.

When there is a match between the available data and the ambition level, the framework will directly indicate the associated maintenance approach. The only thing remaining then is that a business case should be made (initial solution 3). When a positive business case can be made to invest in the maintenance approach for this asset, the selected approach can be conducted.

However, in practice there will quite often be a mismatch between the ambition level and the available data. The framework will then guide the user to a suitable combination. When the required data for the selected ambition level is not available, the first check is to investigate whether it is possible to start collecting this data. If so, the business case should be checked again. If not, other data might be available. This leads to the process restarting, but this time from a technology push starting point.

When starting from the *technology push* starting point, the available data is leading in the choice of the maintenance approach. Therefore, the first step after selection, and getting advice for the associated maintenance approach, is to examine whether a positive business case can be made to continue with this approach. If the business case check results in a negative advice to continue, it should be evaluated whether improvements can be made with a lower or different type of data and associated ambition level.

Note that starting from the technology push starting point, led by the available data, is a common approach in many companies. However, it is somewhat dangerous since the definition of the ambition level is neglected. This could lead to a positive business case for the selected data type and maintenance approach, but the company could discover at some stage that this approach does not perform as expected. Explicitly defining the ambition level

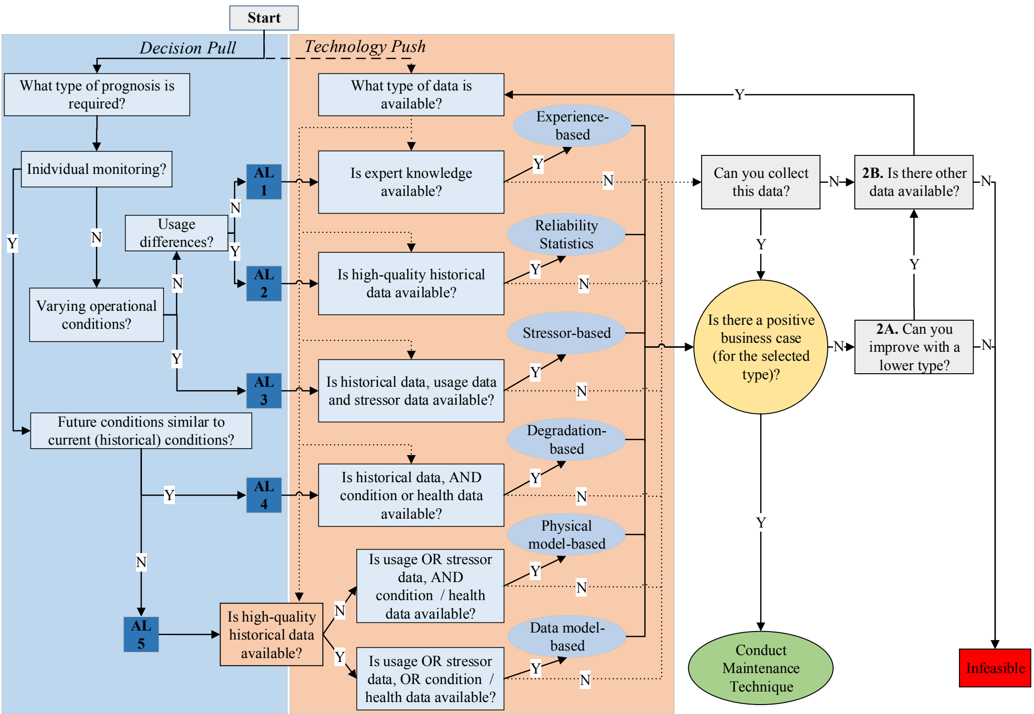


*Figure 12. Proposed preventive maintenance approach selection framework*

beforehand and incorporating that in the selection process, as is done in the framework, could prevent such a situation.

## 4.5. A multiple-case study to evaluate the selection of maintenance techniques

To test and demonstrate the proposed preventive maintenance approach selection framework, four case studies have been conducted. In these case studies, the logic proposed in *Figure 12* will be applied to the cases. Thus, the output of the case studies is the selection of the most suitable MT for the discussed case. But firstly, the case study method will be introduced. After that, the four cases will be discussed.

### 4.5.1. Case study method

To be able to test all elements in our proposed framework, a specific case selection was applied based on the four criteria set out below. Such a structured approach to sampling is important in case study research (Eisenhardt and Graebner 2007). In our case study we firstly focussed on the typical industries where MTs are applied (aerospace, defence, marine, electronics, power, oil and gas, and energy (Grubic et al. 2011)). Secondly, systems were selected where MTs are applied most frequently. These have an average lifecycle of more than ten years, are mechanical or electromechanical, highly complex or installed in large series (Grubic et al. 2011). Thirdly, both systems used in a static environment (i.e. nuclear reactor) and moving assets (i.e. vessel) were included. One of the challenges presented by these moving assets is that the maintenance needs of these assets can vary dramatically when operated under highly variable environmental conditions (Tinga 2010). This might require the use of different MTs and therefore influence the selection procedure. Finally, one case with a technology push starting point and three cases with a decision pull starting point were selected to illustrate both routes.

Several measures were taken to ensure the reliability and validity of the 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. These 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. Finally, reliability of the case study was ensured by using a semi-structured case study protocol during the interviews.

### 4.5.2. Case 1: Electrical components of a naval vessel

*Case description:* This department maintains all electronic equipment aboard naval vessels. Due to the large 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 critical for the operational effectiveness of the vessels. The maintainer therefore tries to prevent unplanned downtime of its assets. Traditionally, maintenance plans are based on advice given by the original equipment manufacturer (OEM).

*Challenge:* The department recently executed a trial-and-error process in selecting the optimal maintenance technique for their situation. In the (recent) past, the department relied on reliability statistics techniques. These analyses however, provided inaccurate results due to incomplete data, unreliable input and poorly filled in recording systems (not all failures recorded). The department has therefore chosen to fall back on using more knowledge from within the company to make maintenance decisions. Since the department conducts maintenance for a large number of different systems, it is too difficult and time consuming, at the moment, to develop more accurate physical or data models. Using the procedure proposed in *Figure 12*, we will demonstrate in the analysis below that the trial-and-error process could have been accelerated considerably.

| **Step in framework** | **Result & explanation** |
|---|---|
| Starting point | **Decision pull** - ambition to optimize maintenance intervals |
| Ambition level | - Assets used in highly variable situations<br>- Company wants to take environmental and operational variabilities into account (e.g. temperature, saline conditions)<br>- Average degradation level of components can be estimated based on usage and environmental conditions (thus: no individual monitoring)<br>→ **Ambition level 3** |
| Type of data available | - Expert knowledge<br>- Low-quality historical data<br>  - amount of failure data limited (low failure frequency, small number of systems)<br>  - incomplete data, unreliable input and poorly filled in recording systems |
| Match ambition level and available data? | **No** - AL3 also requires data on the operational environment (stressors) |
| Can you collect this data? | **Possible** - to install sensors and collect more environmental data by hand |
| Positive business case? | **No** - too costly and time consuming due to variety of equipment types |
| Improve with a lower type? | **Yes -** experience-based techniques will also improve the current maintenance plans |
| Other data available? | **Yes** - expert-knowledge is available |
| Positive business case? | **Yes** - no major investments required (knowledge is available, organizing FMECA studies for critical equipment is expected to improve the maintenance program) |
| Conduct MT | **Advice**: apply an experience-based maintenance technique. Technique will not satisfy original ambition level, but with available data and expertise it is expected to contribute to the maintenance program. |

*Conclusion:* This structured way of comparing the ambition (decision pull) to conduct an AL 3 approach with the data availability, i.e. expert knowledge and low-quality historical data, reveals a clear mismatch. The framework explains why the attempt to use reliability statistics has failed: no sufficient *high-quality historical data* is available. Subsequently, the framework guides the user to alternative approaches. Firstly, it is checked whether the data required for the ambitioned type of approach can be collected. This appeared to be infeasible (no positive business case) at the moment. A suggested reduction of the ambition level to AL1, based on only expert knowledge, appeared to make the *experience-based* type of maintenance approach feasible. This is also the approach that is successfully applied currently. The trial-and-error process the company went through could thus have been accelerated considerably by using the procedure proposed in *Figure 12*.

## 4.5.3. Case 2: Nuclear Reactor

*Case description:* This department conducts maintenance on the equipment of a nuclear facility. Due to the strict regulations within this sector, detailed analyses are conducted for critical equipment. Also, a high level of redundancy is present to guarantee safety in case of equipment or process failures. Due to the high amount of redundancy, little similar equipment is available. This reduces the applicability of reliability statistics approaches. A high level of knowledge and historical data on the usage and loading of the reactor is available. In process logs, every activity in the reactor has been logged. However, since modifications on the reactor have taken place over the years, not all data is equally useful for maintenance analyses.

*Challenge:* The company wants to check whether the present preventive maintenance approach is appropriate.

| Step in framework | Result & explanation |
|---|---|
| Starting point | **Decision Pull** - ambition to understand deterioration of reactor core (also required by safety regulations) |
| Ambition level | - Monitor individual system<br>- Include changes in future usage of reactor (e.g. different end products)<br>→ **Ambition level 5** |
| Type of data available | - Expert knowledge<br>- High-quality historical data<br>- Loading data and usage data<br>- Condition and health data |
| Match ambition level and available data? | **Yes -** AL 5 requires data on the usage or loads and data on the condition or health, which are available |
| Positive business case? | **Yes** – Possible impacts on safety create enough urgency for a maintenance approach giving insight in future conditions of the reactor |
| Conduct MT | **Advise**: apply a model-based approach, by using a physical model<br>This approach satisfies the originally set ambition level |

*Conclusion:* For this nuclear reactor case there is a clear match between the ambition level and the data available. The framework correctly advises a model-based approach, which is also the approach followed currently by the company.

### 4.5.4. Case 3: Engine condition trend monitoring for a military transport aircraft

*Case description:* This department maintains military transport aircraft. For the engines, a fixed-interval preventive maintenance policy has been applied successfully in the past. Recently the Engine Condition Trend Monitoring (ECTM) technique has become available. ECTM is the process of using measured characteristics (i.e. compressor speeds, inter-turbine temperature and fuel flow) during specified flight conditions (i.e. altitude, airspeed, outside air temperatures) and comparing these to predicted values to provide confirmation of engine gas path efficiency and predict maintenance needs based on this data (Guimarães 2015).
*Challenge:* To reduce the maintenance costs, the department is investigating whether it is both economically and technically feasible to apply a condition-based maintenance approach using ECTM.

| Step in framework | Result & explanation |
|---|---|
| Starting point | **Decision Pull** - aim to reduce maintenance costs by conducting condition-based maintenance |
| Type of data available | - Expert knowledge is widely available within the department<br>- Usage and load data (sensors on aircraft measure altitude, airspeed, outside air temperatures and inter-turbine temperature) |
| Ambition level | - Monitoring of individual engines<br>- Operated in varying environmental conditions<br>- Future conditions assumed to be similar (might be different, not included yet)<br>→ **Ambition level 4** |
| Match ambition level and available data? | **Yes** - AL 4 requires condition monitoring data (available)<br>Data required for physical model-based approach (AL5) is also available |
| Positive business case? | **Yes** - financial justification conducted (Tiddens et al. 2017) (total lifecycle costs of ECTM lower than corrective maintenance or fixed-interval preventive maintenance) |
| Conduct MT | **Advice**: apply a degradation-based maintenance approach<br>Organization will further develop ECTM, set ambition level is satisfied |

*Conclusion:* For this aviation case there is a match between the ambition level and the data available through the new technology (ECTM). The framework confirms that this degradation-based maintenance approach is the appropriate approach for this company.

### 4.5.5. Case 4: Predicting rolling stock maintenance

*Case description:* This department conducts maintenance for rolling stock. Within their trains, many pre-installed sensors are available that provide data on parameters such as temperature and vibration. A large amount of expert knowledge is available within the department. This knowledge is used for the current experience-based maintenance program.

*Challenge:* The department is trying to use the available data to optimize their preventive maintenance and reduce system downtime and prevent safety incidents.

| **Step in framework** | **Result & explanation** |
|---|---|
| Starting point | **Technology Push** – ambition to use available data to enable prognostics |
| Ambition level | - Detection of anomalies and prediction of future behaviour per individual train<br>- Take into account actual usage<br>- Future conditions similar to current / historical conditions (trains operated similarly and in same environment)<br>→ **Ambition level 4** |
| Type of data available | - Expert knowledge<br>- High quality historical data (inspection, costing and failure data)<br>- Usage data of trains<br>- Condition monitoring data |
| Match ambition level and available data? | **Yes** – AL4 requires condition monitoring data and high quality historical data (available) |
| Positive business case? | **Yes** - only minor investments required to check usability of data, high potential gain (expected extension of many maintenance intervals, reduced costs) |
| Conduct MT | **Advice**: apply a degradation-based maintenance approach. This will satisfy the set ambition level |

*Conclusion:* Applying the framework from a technology push (large amount of data available) perspective for this rolling stock case confirms that the available data allows for the increased ambition of the company. The company is now working on implementing this approach.

## 4.6. Conclusion

Although this is not recognized in a large part of the academic literature, practitioners still experience difficulties in the selection and application of preventive maintenance approaches. This is especially true for selecting the more advanced approaches (for the company) associated with condition-based maintenance policies. To aid practitioners in the selection of the appropriate preventive maintenance approach for their situation, a selection framework has been proposed. Its development was guided by the design science research methodology consisting of four steps: problem exploration, initial solution development, solution development, and solution evaluation.

In the problem exploration section, the difficulties companies experience in maintenance decision making have been explored. Practitioners often follow a costly trial-and-error process in developing maintenance techniques, as guidance in the selection of a maintenance approach is lacking. The following three main underlying problems appeared: *(i)* it is difficult to distinguish between the available approaches; *(ii)* there is often a mismatch between the ambition level and the required data; and *(iii)* it is difficult to show the added value of a certain maintenance approach.

Subsequently, five initial solutions have been developed that solve the three identified problems. Firstly, the various preventive maintenance approaches have been classified into five types, ranging from the rather traditional experience-based approach to an advanced model-based approach. Secondly, the required performance of the maintenance approach has been made explicit in five ambition levels, clearly specifying the level of detail of the strived for maintenance decisions. Thirdly, the data requirements for each of the maintenance approaches have been identified and have been mapped with the ambition levels and maintenance approaches. Finally, a previously presented method to construct the business case for maintenance approaches has been discussed.

Following on this the initial solutions are integrated into a framework that uses the identified dependencies and ambition levels to steer the selection of the appropriate preventive maintenance approach. The initial solutions are the core, and also the main contribution, of this chapter, as they are not only used for the proposed framework, but also structure the field of preventive maintenance approaches. Moreover, the link to well-defined ambition levels and data types will assist other researchers in making further developments in this field.

Four case studies are used to test and demonstrate the proposed framework. The case studies demonstrated that the proposed selection framework helps to select the correct ambition level and the maintenance approach to achieve that. Furthermore, the framework provides insight into the required data. When this data is not available, the maintenance approach will provide insufficient results, as can be seen in the first case study: electrical components of a naval vessel. Thus, the proposed framework can help practitioners reduce the costly trial-and-error-process in applying a preventive maintenance approach.

Typically, the maintenance program of a complex asset (e.g. a train) is a combination of various maintenance *policies* (e.g. a time-driven policy, and a condition-based policy). The proposed method will be capable of assisting the MT selection not only at the component or subsystem level, but also at this (complex) system level, provided that the level is well defined and there are not too many different policies at the considered level.

The case studies demonstrate the use of the proposed method on a variety of levels: the component level (case 1: electrical components of a naval vessel), the system level (case 2: nuclear reactor, and case 3: engines of military aircraft) and finally, the fleet level (case 4: rolling stock).

## 4.7. Limitations and further research

The case studies show how the proposed framework can be used to advise practitioners in the selection of the appropriate maintenance approach. In further research, more cases, from literature and practice, will be conducted to further validate the proposed decision support framework.

# CHAPTER 5

# Selecting Suitable Candidates for Predictive Maintenance[5]

5

## 5.1. Introduction

Preventing unexpected failures from occurring is important for many complex systems such as production systems, medical equipment and high-tech products. Executives in such asset-intensive industries often regard unexpected failures of their physical assets as the primary operational risk to their business (LaRiviere et al. 2016). Such unexpected downtime can be disruptive in complex manufacturing supply chains and imposes high costs due to forgone productivity (LaRiviere et al. 2016). Competitive pressure therefore forces companies to use the reliability and dependability of their equipment as a competitive weapon (Simões, Gomes, and Yasin 2016).

Typically, a lot of preventive maintenance is conducted to avoid negative impacts (such as safety hazards, production losses, logistic costs, or high repair costs) caused by failures. Ideally, predictive maintenance strategies are employed to provide insight in the future state of assets. Predictive maintenance (PdM) techniques inform the asset owner or operator about the current and preferably also future state of their assets. PdM thereby helps to reduce unexpected failures, improve the reliability and dependability of equipment and prevent unnecessary replacement of components. Next to that, system level monitoring can be used to get control and system performance data.

Predictive maintenance is enabled by PHM (prognostics and health management) technologies in response to the indicated deteriorated condition, performance or the remaining useful life (RUL) of a component or system (Lei and Sandborn 2016). Although predictive maintenance is often referred to as CBM (condition-based maintenance),

[5] This chapter is based on: Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2018). Selecting suitable candidates for predictive maintenance. *International Journal of Prognostics and Health Management*, *9*(1).

predictive maintenance goes further than CBM by also taking prognostic information into account (Shafiee 2015; Tinga and Loendersloot 2014).

Predictive maintenance is enabled by PHM (prognostics and health management) technologies in response to the indicated deteriorated condition, performance or the remaining useful life (RUL) of a component or system (Lei and Sandborn 2016). Although predictive maintenance is often referred to as CBM (condition-based maintenance), predictive maintenance goes further than CBM by also taking prognostic information into account (Shafiee 2015; Tinga and Loendersloot 2014).

Typically, two motivations for implementing PdM can be discerned. Either (1) industrial practitioners look for the best maintenance approach (also termed: maintenance policy selection) for their high-impact components and systems, and PdM appears to be the most suitable approach. Or (2) opportunities arise that make the application of PdM feasible, for example by digitization of assets (an example of this will be shown in Section 5.5.2: the canal lock case).

By having the desire to implement a PdM approach, by either of these two motivations, the first step is to consider whether PdM is indeed the most suitable approach (for candidates from the first perspective) or to identify the most suitable candidates (i.e. systems or components) for PdM (for candidates following the second perspective) (Lee et al. 2014).

The purpose of selecting the most suitable candidates for PdM is to assess where PdM would provide the greatest benefit in terms of performance and/or cost of downtime (Lee et al. 2014). Since many maintenance techniques that enable PdM are costly to develop, it would not be cost-efficient to apply them on all equipment (Bengtsson and Jackson 2004). That is to say, almost 30% of industrial equipment does not benefit from applying techniques (i.e. condition monitoring) that enable CBM (or similarly PdM / PHM) (Hashemian and Bean 2011). It is therefore often stated that CBM should only be applied where it is suitable, not as an overall policy (Moubray 1997). It is therefore critical to select the suitable candidates for a PdM application to achieve the optimal benefits (Brahimi et al. 2016).

Therefore, in this chapter, a method is developed to identify and select suitable candidates for predictive maintenance. A design science method (Holmström, Ketokivi, and Hameri 2009) is followed in developing the selection method. First, Section 5.2 gives an overview of current methods. After this, Section 5.3 covers the *problem exploration* (step 1). The problem exploration serves as design criteria for the *initial solutions* (step 2), which are proposed in the literature review and in the reflection of existing methods. The *solution is designed* (step 3) in Section 5.4 to identify suitable candidates from the plethora of components that are typically available in complex systems. The *solution is demonstrated* (step 4) in Section 5.5 in two distinct cases: a propulsion system of a ship and a canal lock. Finally, concluding remarks will be given in Section 5.6.

# 5.2. Review of current methods

The literature describes various well-known and accepted methods to select suitable candidates for PdM. In this section, we will first discuss various methods that have been proposed to identify or select critical components. In Section 5.3, we will discuss the shortcomings of current methods and how the discussed methods can contribute to an improved approach to select the suitable candidates for PdM.

### 5.2.1. Methods based on risk assessment and dependability of components

An often applied approach is to define critical components as a component whose failure leads to unavailability of the whole system, and/or a component which has a high failure rate (Gouriveau, Medjaher, and Zerhouni 2016).

A first alternative for this is to define the critical components of a system by conducting a dependability analysis (Brahimi et al. 2016). A dependability analysis brings components to light whose failures have the highest impact on the availability, reliability, maintainability, safety, and integrity of the system (Avizienis et al. 2004). Qualitative dependability analyzes use expert judgment to evaluate potential failures to evaluate risk, using for example a Failure Mode Effects (and Criticality) Analysis (FMEA and FMECA) (Brahimi et al. 2016) or a Fault Tree Analysis (FTA). Quantitative dependability analyzes use statistical methods and can be deterministic or probabilistic. These methods are used to estimate measures such as the mean time to failure (MTTF), mean time between failures (MTBF), or failure rates to evaluate a system's reliability (Brahimi et al. 2016).

A quantitative approach that follows this logic is to select the top 10 cost drivers or availability killers for a PdM policy, as done in for example the degrader analysis of Banks et al. (2008). This approach has similarities with an often applied Pareto analysis based on maintenance costs, failures, downtime, or safety.

The reliability-centered maintenance (RCM) method (Moubray 1997) uses systematic logic to rank the criticality of failure modes and provides guidelines for selecting the applicable maintenance task (Tsang 1995). RCM is normally performed at the system level since the criticality of failures at the component level can only be judged on the basis of its impact on delivering the required system functions  (Tsang 1995).

An example of such a dependability analysis that uses RCM logic is the Most Important Systems (MIS) and Most Critical Components (MCC) analysis of Waeyenbergh and Pintelon (2002). Their analysis first focuses on selecting the so called most important systems by regarding the impact of its breakdown on safety, environment, production, repair costs, and secondary damages. This includes bearing in mind the system's ease of repair and the ease of failure detection. Next to that, in the MIS analysis it is considered whether the system is a bottleneck, redundant, or complex. The second step, the MCC analysis, helps to determine the most critical components within the selected system (the MIS). This is done with a simplified FMECA, which is according to the authors "rather 'quick and dirty', but […] very easy to use". In this simplified analysis, the same consequences are considered as is done in the MIS analysis. RCM cannot only be used to select the most critical components, based on for example their risk priority number (RPN), but also advises on the most suitable maintenance task.

Dehghanian et al. (2012) proposed a fuzzy-AHP (analytical hierarchy process) method to identify critical components in a RCM program. They prioritize components based on: (i) the number of failures, (ii) the number of component failures, (iii) repair duration, (iv) component investment costs, and (v) component repair and maintenance costs.

Lee et al. (2009) argue that identifying the critical components on which the PdM approach should be performed is the first key step by deciding which components' degradation has significant impact to the system's performance or costs a lot when the downtime happens. They propose to use a four-quadrant chart which quickly distinguishes between components based on their failure rate (low vs high) and their associated downtime (low vs high). Lee et al. (2014) argue that predictive maintenance should only be applied on those components that have a critical impact on the firm (i.e. high downtime) and a low failure rate. Note that components with a high failure rate and high associated downtime should be designed out.

Labib (2004) proposed a similar idea that helps to determine the suitable maintenance policy for components based on a trade-off between the frequency of failure and the downtime. In their approach, a condition-based concept is only applied to those components that have a low frequency of failure but a high associated downtime. This is comparable to the approach of Lee et al. (2009).

## 5.2.2. Maintenance policy selection methods

Maintenance policy selection methods do not directly help to select the most suitable candidate for predictive maintenance. However, as was also mentioned in the introduction, the starting point for many companies is to find a suitable policy for their high-impact components and systems. When PdM is selected to be most appropriate, a check on the suitability of the candidates might prove valuable. Moreover, reviewing these policy selection methods may provide valuable insights into when to select PdM for a (component in the) system as it provides rules or criteria for when to apply predictive maintenance strategies.

Different goals and criteria can be taken into account in the selection of the most suitable maintenance policy. A maintenance policy can be defined as a rule or set of rules that describe the triggering mechanism, such as time, usage or an expression of deterioration, for the different maintenance actions (repair, replace, monitor, shutdown) (Pintelon and Van Puyvelde 2006). To take these various criteria and goals into account, multi-criteria decision making (MCDM) methods can be used for maintenance policy selection (MPS). The MCDM approach is typically suitable in contexts where the goals and criteria are difficult to express in monetary terms and are therefore difficult to quantify. For MPS, these criteria include the investment required for implementation, safety aspects, environmental issues, failure costs, reliability of the strategy, and manpower utilization of the facility (Shafiee 2015).

Shafiee (2015) reviewed the use of MCDM methods for MPS. MPS, which is by other authors sometimes also termed maintenance strategy selection (MSS), helps practitioners in selecting between policies such as corrective maintenance (CM), preventive maintenance (PM), opportunity-based maintenance or predictive maintenance. Goossens and Basten (2015) proposed a maintenance policy selection method for naval ships based on a multi-criteria decision making (MCDM) method that helps to select between failure-based maintenance, time or use-based maintenance, and condition-based maintenance. In their method they consider whether the maintenance policy fits the: (i) crew's size and education level, (ii) available knowledge in the company, (iii) mission profile, (iv) internal and external relations of the company, and finally (vi) influences on performing maintenance tasks.

## 5.3. Problem exploration: shortcomings of existing methods

Based on practical experience and literature, the problem exploration in this subsection will point out several factors that cause that traditional selection methods not always lead to the best selection of components.

### 5.3.1. Underestimating time consuming process

Even though a PdM policy might be the preferable strategy for an asset, not all components within that asset might be suitable for PdM. FMECA analyzes can be used to identify suitable components. However, FMECAs can become very extensive and time-consuming when they are conducted down to the component level for a complex system.

Tinga et al. (2017) for example, showed that a complex asset like a ship typically can be decomposed in up to 60 installations. In case of a naval vessel, the installations within the propulsion section can be formulated on the level of a gearbox, thruster or diesel engine. But these installations again contain numerous components, e.g. main bearing, connecting rod, cylinders and pistons for the diesel engine.

Approaches such as streamlined FMECA or simplified FMECA (as used in the approach of Waeyenbergh and Pintelon (2002)) can help to reduce this complexity by first focusing on the criticality of the installation / subsystem. However, these approaches do not guarantee that all critical components have been identified (Tinga et al. 2017). Therefore, methods like a recursive combination of FTA and FMEA have been proposed (Peeters, Basten, and Tinga 2018). In this method, FMEA is used to assess the criticality of system level failure modes that are identified in a FTA. For the selected (critical) failure modes, a function level FTA is conducted followed by another FMEA. Since applying traditional methods can lead to a time consuming process, it would be useful to find ways that can reduce the required effort.



### 5.3.2. Ignoring clustering of maintenance activities

Only being a critical component does not make a component a suitable component for PdM. Using prognostic methods to extend the component's lifetime is only useful when the failure prediction actually enables reducing or extending the maintenance intervals. Interval reductions typically mean that failures that otherwise would have occurred can be prevented, thereby leading to an increase in the system availability. Interval extensions lead to cost reductions (conducting less preventive maintenance) and thereby also higher availability of the asset (as it is not in maintenance).

Maintenance activities however, are often clustered based on a production (i.e. opportunistic maintenance planning in a production plant) or mission (i.e. docking intervals for a ship) planning. Such a planning dictates when maintenance activities can be conducted and thereby restrict shifting maintenance activities, unless these can be extended to the next planned opportunity. In these cases, preventive (opportunity-based) maintenance is sometimes more convenient than more advanced methods.

Clustering of maintenance activities can also be caused by technical restrictions. Take the example of gearbox maintenance. Extending the maintenance interval of a gearwheel in a gearbox would make little sense if all other parts in the gearbox have to be maintained anyway (unless it concerns a very expensive component). The benefits of extending maintenance of the gearwheel can only be achieved when all maintenance activities for the gearbox can be extended. Finally, a single maintenance activity can also contribute to preventing multiple failure modes from occurring. This means that it might be possible to extend a maintenance activity by monitoring a specific failure mode, but that another failure mode can become dominant when this maintenance activity is extended.

### 5.3.3. No consideration of technical feasibility

Although an imminent failure might be beneficial to monitor, it is not always possible to predict or detect the anomaly before a failure occurs. Besides, prognostics can never be 100% sure to predict failures and faults (Jardine, Lin, and Banjevic 2006). Moreover analyzing data sets without knowing the underlying failure mechanisms can lead to incorrect results. This means that a root cause analysis is essential in achieving an effective maintenance policy. The technical feasibility goes hand in hand with the knowledge level within the company. Understanding of the degradation mechanism is often required to predict or detect the failure. Either internal or access to external knowledge sources is required to gain this understanding. When this is not available, the PdM approach cannot be implemented successfully. Next to this, considering the technical feasibility of PdM is important for: (i) failures due to human error (which can typically not be predicted or monitored); and (ii) failures of which the faulty condition cannot be detected early enough (early warning), in comparison to the maintenance opportunity (suppose a large part aboard a ship). The latter can cause that the prognostic model is ineffective. Finally, firms should consider whether a prognostic model is already available or that additional research has to be conducted.

### 5.3.4. No consideration of economic feasibility

Although costs are often mentioned as a criterion for maintenance policy selection, there are more reasons that can hinder the full potential of PdM. The four quadrant chart of Lee et al. (2009) and the selection method of Labib (2004) consider a trade-off between the failure frequency and an failure effect criterion such as downtime, costs or safety. However, these methods do not consider a lower boundary for the failure frequency or an upper boundary for the failure effect. The four quadrant method of Lee et al. (2009) was therefore first improved by Tiddens, Braaksma, and Tinga (2017) who introduced upper boundaries for the failure effect and upper boundaries for the failure frequencies; both to advise redesign as the consequences of these types of failures can disrupt firms. After that, Tinga et al. (2017) introduced lower boundaries for the failure frequency to guarantee the economic justification for PdM policies; the investment in PdM is not recovered when there are not ‘enough’ failures or these are not experienced within the realistic (economic) lifetime of the asset.

Next, the business case for predictive maintenance could be negative because: (i) introducing PdM is more costly than preventive or corrective maintenance; (ii) there is a low probability of unnecessary replacements (high confidence that failure will occur as predicted in preventive policy); (iii) probability of correct prediction of time to failure is not important as part will be replaced anyhow before each mission.

### 5.3.5. No consideration of organizational feasibility

Even though PdM might be economically and technically feasible, it should also fit the organization. Issues such as a lack of system and domain knowledge, a lack of trust in monitoring systems and the organization not being ready to implement PdM can hinder the adoption of PdM. Jonsson and Westergren (2004) clearly expressed the opinion of one employee towards the adoption of PdM: “What will break first – the motor or the remote [monitoring] system?”. Jonsson and Westergren (2004) argue that firms should work hard on showing the added value of the system or on integrating it with a larger monitoring system to overcome this barrier.

### 5.3.6. No focus on desired use and outcome of predictive maintenance approach

The reviewed methodologies pay little attention to the different possible outcomes of the selected predictive maintenance approach. In the literature, three types of end results of a prognostic approach are often distinguished: detection, diagnosis, and prognosis (Jardine, Lin, and Banjevic 2006). The inputs from a condition monitoring (CM) system can be used for CBM, but also (in a simplified manner) to only detect anomalies (detection). These differences in outcomes should be included in the selection of suitable candidates as this difference leads to another view on the discussed limitations of existing methods.

For example, considering the clustering of maintenance activities (as discussed in 5.3.2) is not important for detecting anomalies (for example preventing safety incidents) while it is important for extending maintenance actions (the goal of prognosis). Although PdM/PHM and CBM are sometimes used interchangeable, they lead to different end results. CBM is a dynamic maintenance policy based on performance and/or condition monitoring. CBM thereby aims to detect anomalies in the operation of industrial machinery: the discovery of changes in their characteristics prefigures a future failure in the short term (Gouriveau, Medjaher, and Zerhouni 2016). Where CBM is mainly diagnostic, PHM (used for PdM) includes prognostic capabilities (Tinga and Loendersloot 2014). We therefore consider CBM as diagnosis and PdM / PHM as prognosis. Detection (using e.g. CM) is typically used to recognize imminent failures before the system fails and can therefore be seen as a safety warning.

### 5.3.7. Factors to consider

The factors discussed before in this section serve as design criteria for the final solution development that should help to reduce time consumption of the process (following Section 5.3.1). These factors have been added to the already known factors to create the list shown in Table 11, now containing all factors that can hinder the usage of predictive maintenance. The overview of Goossens and Basten (2015) was used as starting point, and this list was extended with the factors discussed in Sections 5.3.1 to 5.3.6 (marked with ‘*’).

| Factors hindering the use of predictive maintenance | |
|---|---|
| **Clustering** | |
| | No consideration of production/mission clustering * |
| | No consideration of technical clustering * |
| **Technical feasibility** | |
| | Other failure modes become critical * |
| | Failure cannot be predicted due to human errors * |
| | Failure cannot be detected with existing technology * |
| | Failure cannot be detected even with additional research * |
| | Failure cannot be predicted with existing technology * |
| | Failure cannot be predicted even with additional research * |
| **Economic feasibility** | |
| | Insufficient financial resources available * |
| | Not enough failures (during life time) * |
| **Organizational feasibility** | |
| | No trust in monitoring system |
| | No fit to crew (size and education level) |
| | No fit to existing knowledge levels |
| | No fit to the operational task (maintenance location) |
| | No fit to mission (equipment age, location and profile) |
| | Not compliant with existing policies and prescriptions |
| | No fit to (external) relations (outsourcing) |
| | No fit to the spare parts (commonality, availability) |

*Table 11. Factors that hinder the use of predictive maintenance (new factors are marked with '*').*

## 5.4. Solution development: Proposed solution for identification of suitable candidates for PdM

### 5.4.1. Proposed method

The proposed methodology (visualized in Figure 13) consists of three stages: the criticality classification, the identification of showstoppers, and a focused feasibility study. The proposed method works as a funnel, the first stage aims to reduce the number of potential candidates significantly to reduce the required efforts in the two following stages. Each of the three stages will be elaborated in the following subsections, and demonstration of the proposed method in two real cases then follows in Section 5.5.

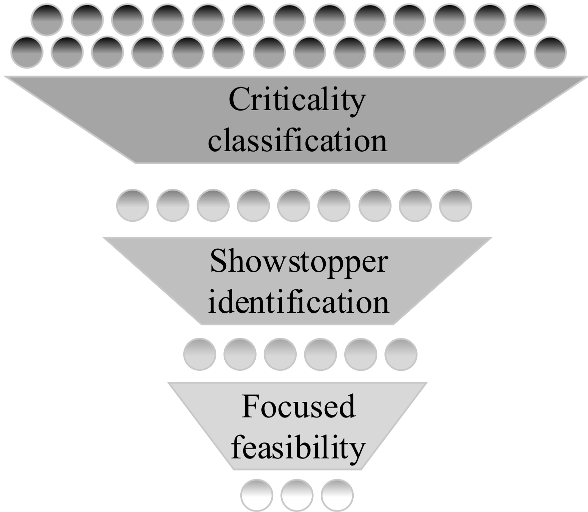


*Figure 13. Proposed funnel approach for the identification of suitable candidates for PdM.*

5

## 5.4.2. Criticality classification

The initial criticality classification acts as a filter to significantly reduce the number of possible candidates from a plethora of components. The four quadrant chart based on the work of Labib (2004), Lee et al. (2009) and Tinga et al. (2017) helps to bring focus to only the most promising candidates, namely those with a low frequency of failure and a high associated failure consequence (e.g. failure, costs or downtime). The improved focus established by the introduction of a lower limit (in addition to the upper limit) on the failure frequency helps to only select those candidates that fail often enough for a positive business case.

## 5.4.3. Identifying showstoppers related to the desired outcome

Showstoppers are factors that can make the prognostic approach infeasible or providing no added value. In Section 5.3 several factors were identified that hinder the use of PdM / PHM. These are clustered in the potential showstoppers (PS) listed in Table 12.

Firstly, following Section 5.3.6, a differentiation is made between three ambition levels, the desired results of prognosis: *Detection*: used as safety warning or last resort; *Diagnosis*: determine fault state and short-term (failure) behavior forecast; and *Prognosis*: long-term (failure) behavior prediction. Determining the desired outcome by differentiating between detection, diagnosis, and prognosis helps to firstly describe the requirements of the prognostic system and secondly explore the possibilities and impossibilities by recognizing the potential showstoppers. Next, when considering technical feasibility, a choice has to be made whether additional research may be conducted or only existing technologies can be applied.

Per approach, it is then determined whether the potential showstopper is present in the situation under analysis, which then prevents that approach to be successful. For practitioners, it will however not always be trivial whether a factor will be a showstopper. Three possible outcomes can therefore be chosen: *Yes* (it is a showstopper), *No* (it is not a showstopper), or *Maybe* (it might be a showstopper). In the final stage of the procedure, the focused feasibility study (section 5.4.4), these *Maybe*'s will be looked at in more detail. When no other showstoppers have already made the desired approach infeasible, the *Maybe* has to be transformed in a decisive *Yes* or *No* in this final stage.

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

*Table 12. Identification of potential showstoppers (PS) for the differentiated application of PdM.*

The potential showstoppers (listed in Table 12) can be operationalized in the following manner:

- **c1: Mission clustering:** can a possible PdM activity be conducted during or in-between missions? If not, can the predicted maintenance activity be planned with a minimum of the duration of one operational period in advance (i.e. this requires a prognostic distance of at least one mission duration)?
- **c2: Technical clustering:** does the predicted failure mode drive the package of clustered maintenance activities (i.e. does it drive the maintenance interval)? If not, can it be skipped one interval? Note: this also requires considering whether all relevant failure modes of the component are listed.
- **t1 / t2: Detecting/predicting with existing/additional research:** is it viable to build a model that is able to detect/predict the failure mode/mechanism with existing/additional research?
- **e1: Sufficient financial resources:** are sufficient resources available to cover the investment costs?

- **e2: Enough failures during life time:** will sufficient failures occur (and thus be prevented under a predictive maintenance policy) to recover the investment costs? Note: the lower limit line in the four quadrant chart also helps to cover this PS.
- **o1: Trust in monitoring system:** will the developed monitoring system be trusted by maintenance personnel and operators?
- **o2: Fit to personnel:** is sufficient knowledge, qualifications and experience with maintenance available within the company? Is there sufficient willingness to adopt PdM?
- **o3: Operational task and mission:** does the predictive maintenance fit with performing the operational mission?
- **o4: Relations and policies:** does the predictive maintenance fit with the internal and external relations of the company?
- **o5: Spare parts:** does the predictive maintenance policy fit with the type, commonality and availability of spares?

Table 12 shows that each of the 11 factors can act as a showstopper for the two most ambitious (*Diagnosis* and *Prognosis*) levels, but only six of them could affect the lower level *Detection*. Showstoppers that are identified on the aspects *"organizational feasibility"* and *"clustering"* can result in a (temporary) stop on developing the desired PdM approach. Therefore, analysis is required to see how these showstoppers can be mitigated. For the clustering, it should be examined how the candidate can be removed from the maintenance (either mission or technical) cluster or whether the interval of the other maintenance activities within the cluster can be coupled to the selected candidate.

For the organizational feasibility, the identified showstoppers point at factors that have to be addressed before PdM can be successfully implemented. Bengtsson (2008) provides a checklist with organizational factors to take into consideration when implementing PdM. Bengtsson argues that when a positive business case can be made for the implementation, small scale pilot projects and gradual implementation can help to overcome these barriers.

The showstoppers on the aspects *"technical feasibility"* and *"economic feasibility"* can also result in a (temporary) stop on developing the desired PdM. However, for these factors the answer is not always a clear *Yes* or *No*, so these will be addressed in the third and final stage, the focused feasibility study.

## 5.4.4. Focused feasibility study

In the final stage of the method, the feasibility of developing a prognostic model is further examined for those candidates where a '*Maybe*' has been selected for one or several of the showstoppers (and no definite showstoppers were identified). This means that these factors will be studied in more detail.

The **economic feasibility study** focuses on whether developing the prognostic model is beneficial to the firm, from a strategic point of view. This is because not all industrial equipment benefits from the application of prognostic techniques. It is difficult to assess the financial impact with a high accuracy at the start of the project, but it is important to discuss and brainstorm on the possible gains in comparison to the possible investment costs (Bengtsson 2008). As proposed by Tiddens et al. (2017), first a distinction should therefore be made between *explorations* and *exploitations* of PdM / PHM.

*Exploitations* regard applying well-known (to the firm) technologies. For these, a detailed financial modelling can be executed, using for example the method proposed by Tiddens et al. (2017). This method helps to determine whether developing PdM for the candidate system leads to a financial justification. In these cases, it is often quite clear whether the use of PdM is beneficial to the firm and the showstopper identification can be conducted with limited uncertainties.

*Explorations* are those developments in which the frontiers of what is known (within the firm) are pushed. For *explorations*, a detailed cost benefit analysis cannot be made since the costs and benefits are highly uncertain. Then, a maintenance balanced scorecard approach can be used. An example of this approach, proposed by Alsyouf (2006), is shown in Table 19. A multi-criteria decision making approach could in this situation be used to compare PdM with fixed-interval preventive maintenance (PM) and corrective maintenance (CM) (or any other maintenance policy) at a strategic level. Although PdM was – technology wise – possibly already selected as the preferable maintenance approach for the candidate system, the highest total score (22) for PdM in Table 13 confirms that in this case developing PdM is of strategic interest to the firm.

| Perspective | CM | PM | PdM |
|---|---|---|---|
| (i) innovation and growth | 1 | 2 | 4 |
| (ii) maintenance | 2 | 3 | 3 |
| (iii) production | 1 | 3 | 3 |
| (iv) customer | 1 | 4 | 5 |
| (v) society | 1 | 3 | 4 |
| (vi) financial | 2 | 3 | 3 |
| **Total** | **8** | **18** | **22** |

*Table 13. Example multi-criteria analysis to assess the (positive) impact of PdM (1 = low, 5 = high).*

The technical feasibility study focuses on whether it is possible for the firm to develop and implement the desired prognostic approach. The technical feasibility goes deeper than the showstopper identification. Determining the feasibility is not always trivial, since for innovative PdM approaches, a successful outcome can be quite uncertain. In the technical feasibility study, focus should be paid to the seven functional levels that are used in the OSA-CBM (Open System Architecture for CBM) (Lebold, Reichard, and Boylan 2003). The level of detail of this technical feasibility study should be determined per case. In case of a highly uncertain and costly PdM implementation a complete proof-of-concept might be required, whereas in case of a low cost and low risk application, only briefly discussing the questions would be sufficient. Following the requirements defined by Gouriveau, Medjaher, and Zerhouni (2016), based on the original OSA-CBM, the following questions guide the assessment of the technical feasibility:

1. **Data acquisition:** How can the failure mechanism be measured? How can the required data be acquired, back-upped and secured?
2. **Data processing:** How can the signals issued from the sensors be processed to extract features that suggest the presence of anomalies, and in the long term, represent the state of the monitored system?

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

# 5.5. Solution demonstration

## 5.5.1. Selecting suitable candidates for PdM for a ship's propulsion system



MAR is a maritime company that monitors the seas and collects engineering and earth data. For its vessels, MAR wants to introduce PdM and has therefore joined the MaSeLMA (maintenance and service logistics for maritime assets) research project. In this project (in which the authors are also involved), MAR cooperates with other maritime companies to develop a PdM approach for the diesel-direct propulsion system of a series of their vessels. The first step for MAR therefore is determining the most suitable candidates for PdM within the propulsion system. As multiple companies are involved in this project, the final selection is based on the result of the identification of suitable components at multiple companies. For clarity, this case study only discusses the selection of suitable candidates at MAR.

### 5.5.1.1. Criticality classification

A streamlined FMECA has been conducted to determine the most critical failure modes within the diesel-direct propulsion system of MAR. These FMECAs were conducted using experts at MAR and external experts from the supplier of the diesel engines. The identified failures are plotted in the four quadrant chart, see Figure 14. The four quadrants represent the following maintenance advice: Q1 (upper right, including the cut-off regions of Q2 and Q4): fix unreliability during design; Q2 (upper left): fix failures with spare parts; Q3 (lower left): regular (OEM prescribed) maintenance; and Q4 (lower right): predictive maintenance. The dotted line indicates the lower limit for Q4, failures with a lower failure frequency are expected to lead to a negative business case. Eleven failures (Table 14) are identified in the Q4 area. These failures cause a downtime longer than 24 hours and have a failure occurrence of more than once every 30 years (the minimum economic lifetime of the vessel). The upper limit on the failure frequency for Q4 is set at one failure every three years.

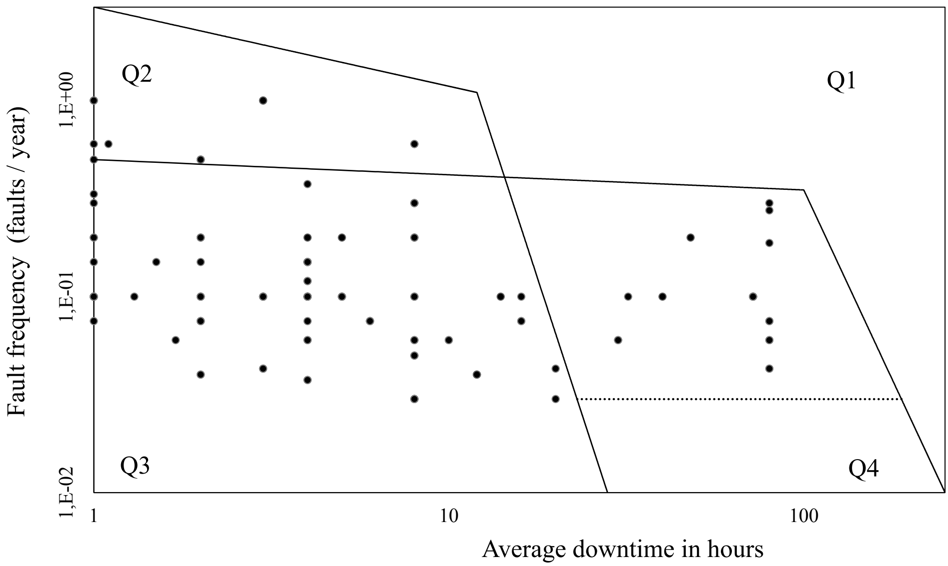


*Figure 14. Four quadrant method, showing failures for MAR's vessel propulsion system.*

| ID | Description of event / failure mode |
|---|---|
| 1 | Diesel engine – bearing shells worn |
| 2 | Diesel engine – connecting rod bearing shell worn |
| 3 | Diesel engine – pistons (+ springs) seized / fouled due to liner wear |
| 4 | Diesel engine – valve mechanism – valve broken due to fatigue / overload / wear |
| 5 | Diesel engine – gear wheel train worn |
| 6 | Diesel engine – air cooler waterside fouled |
| 7 | Gearbox – gearwheels teeth worn / broken due to wear / overload |
| 8 | Gearbox – thrust bearing worn |
| 9 | Thruster – coupling slipped due to wear |
| 10 | Thruster – frequency converter failed |
| 11 | Thruster - encoder failure due to software error |

*Table 14. Identified candidates using the four quadrant chart method*

### 5.5.1.2. Identifying showstoppers related to the desired outcome

MAR has the desire to do prognostics, so the associated potential showstoppers are analyzed (*t1a* and *t2a* are not applicable for prognostics). MAR operates its vessels all over the world. Consequently, their maintenance opportunities are limited. The current fixed-interval preventive maintenance policy prescribes many clustered maintenance activities (*c2*). The larger maintenance activities are scheduled during docking periods. The mission schedule allows for small maintenance activities during operations and bad weather periods (*o3*). However, at those moments limited tools and specialisms are available thus not all maintenance activities can be conducted (*c1*).

Next, the different crews aboard the vessels are to be trained in the use of prognostic systems (*o2*). Moreover, high reliability is demanded in the industry and trust in the monitoring systems has to be gained in time (*o1*). Finally, limited funds are available to invest in monitoring systems. Therefore, the cost effectivity of the investments in PdM is key for MAR (*e1, e2*). Table 15 shows the complete overview of identified showstoppers for the candidates remaining from the first step (the four quadrant chart).

| **ID** | **c1** | **c2** | **t1b** | **t2b** | **e1** | **e2** | **o1** | **o2** | **o3** | **o4** | **o5** | **Result** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | N | Y | M | N | N | N | N | N | N | N | N | Y |
| 2 | N | Y | M | N | N | N | N | N | N | N | N | Y |
| 3 | N | Y | M | N | N | N | N | N | N | N | N | Y |
| 4 | N | N | M | N | N | N | N | N | N | N | N | M |
| 5 | N | M | N | N | N | N | N | N | N | N | N | M |
| 6 | N | M | N | N | N | N | N | N | N | N | N | M |
| 7 | N | N | N | N | N | N | N | N | N | N | N | N |
| 8 | N | N | M | N | N | N | N | N | N | N | N | M |
| 9 | N | N | N | N | N | N | N | N | N | N | N | N |
| 10 | N | N | M | N | N | N | N | N | N | N | N | M |
| 11 | N | N | Y | M | N | N | Y | N | N | N | N | Y |

*Table 15. Identification of showstoppers for the 11 candidates (ID) at MAR. Y= yes, N = no, M = maybe.*



### 5.5.1.3. Focused feasibility study

The showstopper identification shows that the candidates with ID: 4, 5, 6, 8, 10 are 'Maybe' suitable for PdM. The technical feasibility will therefore be studied in more detail in this section, focusing on the valve mechanism (ID: 4). Studying the economic feasibility in detail is not necessary as developing and applying a PdM approach is expected to result in financial savings. The technical feasibility of developing PdM for the valve mechanism has been studied by Duplex (2017), the results are presented here along the seven levels of the OSA-CBM structure.

**1. Data acquisition:** based on the work conducted by Lewis et al. (2004), a physical model has been developed. This model accounts for impact (when the valve closes) and abrasion (sliding of valve and seat under combustion pressure). The former is estimated by an empirical relation used in erosion studies, and the latter by Archard's wear law. These are then summed to make a final wear prediction. Key input parameters for the model are thermodynamic working characteristics of the engine, material properties, and engine operational scenarios. The required data will be collected from engine operational parameters, simulations, experiments and empirical values from literature. The operational profile will be estimated in discussions with ship managers. If the results are promising then a data acquisition system will be installed to record actual operational hours and load conditions.

**2. Data processing:** based on the estimated or logged operational profile, a wear rate can be determined using the developed physical model.

**3. / 4. Detection and Diagnostics:** The model output will be compared with manufacturer instructions for rejection criteria. The actual wear profile of valves can be determined for a given or logged set of operational scenarios.
**5. Prognostics:** Based on the estimated future operational scenario, the model calculates a remaining useful life (RUL).
**6. / 7. Decision analysis and Presentation:** The decision support tool will be customized to determine actual wear and remaining life of valves. Subsequently, a set of working scenarios can be simulated in this tool to estimate an approximate maintenance interval or assist in mission planning.

### 5.5.1.4. Discussion on MAR case

The showstopper identification proves to be of high value for the MAR case. Initially, the cylinder liners (ID: 3) were selected in the MaSeLMA project. This selection was made by conducting the FMECA analyzes and applying the four quadrant chart only. During the project it however turned out that the developed physical model, that helped to prolong maintenance intervals, could not be used to its optimum. As the maintenance activities of the complete diesel engine are clustered into a use-based preventive maintenance policy, only conducting maintenance for the liners would not be efficient. The showstopper identification, as used in the proposed method, clearly points at this issue (*c2*). By using the proposed method, the clustering of maintenance activities could have been identified in advance as a showstopper.

Further, one of the factors affecting the failure: diesel engine bearing shells worn (ID: 1) is fouling of lubrication oil. Periodic oil sample analysis is already ongoing at MAR. However, considering the mission clustering (*c1*) requires checking whether the prognostic distance of these analyzes is large enough. Oil samples cannot be analyzed aboard all vessels. These samples are therefore send to a lab. However, when the vessel is operating in a remote location, the period between taking the sample and receiving the analysis result can be too long to take timely measures (i.e. change the oil). Nevertheless, other CM techniques (e.g. vibration monitoring) could still provide a way to timely predict a bearing failure, so *c1* is not considered to be a showstopper for ID: 1.

## 5.5.2. Selecting suitable candidates for PdM in a canal lock

Rijkswaterstaat (RWS) is, on behalf of the Dutch ministry of infrastructure, responsible for the design, construction, management and maintenance of the main infrastructure facilities (such as highways and waterways) in the Netherlands. In this context, RWS, is responsible for numerous canal locks and pumping stations in waterways. The studied complex consists of a lock gate and a water pumping station (Figure 15). The two main functions of this complex are: controlling the water level in the waterway, and providing passage of shipping. The complex should therefore be able to pump water (increase upstream level), drain water (decrease upstream level), and stop the water. The moveable miter gates of the canal lock allow for the passage of shipping.

*Figure 15. The canal lock (left hand side) and the water pumping station, source: RWS.*

5

RWS is currently investing in data extraction technologies that can enable PdM for the studied complex in the eastern part of the Netherlands. In this project, real time data on the operation and performance of the whole complex will become available remotely. Having the opportunity to remotely monitor the performance of e.g. the pumps in the pumping station could enable PdM. However, as many data from various installations will become available, the first question of RWS is: *For which components should a predictive policy be developed first?*

#### 5.5.2.1. Criticality classification

For the first stage filtering process, existing data from a fault tree analysis (FTA) is used as input for the four quadrant chart. These FTA's were conducted by an external bureau using expert knowledge. The 175 identified events were plotted in the four quadrant chart, see Figure 16. The FTA identified 84 basic events that lead to downtime less than 24 hours (48%), 4 events leading to downtime between a day and a week (2%), 44 events leading to downtime between a week and a month (25%) and 43 events leading to downtime longer than one month (25%).

After identification of the failure modes that can be plotted in the four quadrant chart, it is important to set the boundaries for the quadrants and to set a lower level for the failure frequency, as is suggested by Tinga et al. (2017). The lower limit was set at a failure frequency of one failure every billion hours, the upper level at one failure per million hours. The lower boundary for the associated downtime was set at 24 hours (1 day).

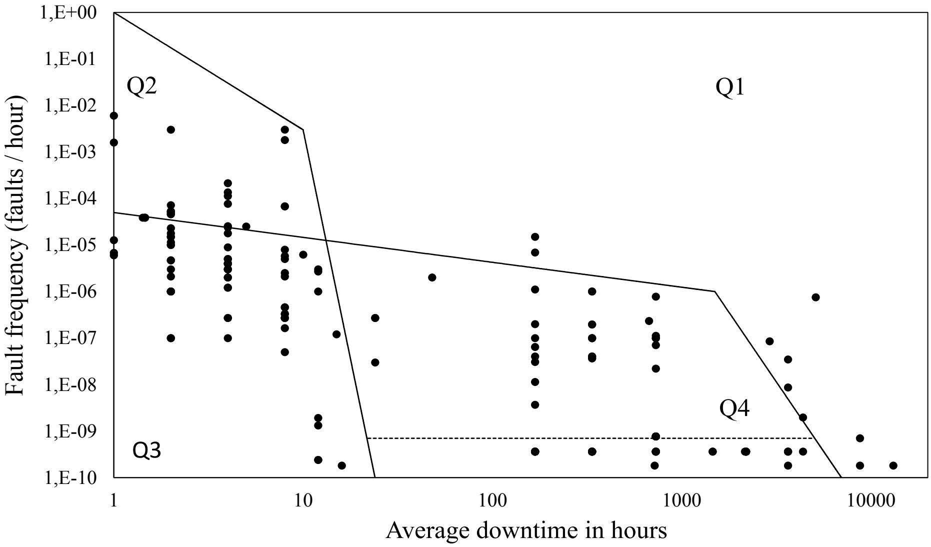


*Figure 16. Four quadrant chart for the canal lock. The Q4 area indicates the failures that are suitable for PdM.*

Table 16 shows the events that were identified by applying the four quadrant chart method. 29 failures potentially interesting for PdM were identified, as they were located in Q4 of the graph. For clarity reasons, this list was cleaned up and reduced to 14 failures.

For example, similar failures for different gearboxes were grouped and also natural events influencing various installations were clustered (i.e. lightning strike for the control building and lightning strike for the tower were clustered into "lightning strike").

| **ID** | **Description of event** |
|---|---|
| 1 | Lightning strike |
| 2 | Fire |
| 3 | Ship collision |
| 4 | Gate closed too early |
| 5 | Drive hydro motor lock failure |
| 6 | Cylinder levelling slider front lock failure |
| 7 | Reduction gearbox failure |
| 8 | Control panel pump system failure |
| 9 | Return valve does not open |
| 10 | Butterfly valve (electric drive) failure |
| 11 | Hoist and electromotor protective gate failure |
| 12 | Pump failure |
| 13 | Fiber network ring connection breaks |
| 14 | E-motor failure |

*Table 16. Identified candidates using the four quadrant chart method.*

### 5.5.2.2. Filtering showstoppers related to the desired outcome

The desired level of RWS is to be able to reduce unplanned downtime by looking at current and short-term future behavior, thus: Diagnosis. The focus of this project is to use the data that is available using the new data extraction technologies that RWS has invested in. Therefore, extra data collection is not desirable and mainly data on e-motors and pumps will become available (*t1a, t2a*). Clustering of maintenance tasks (*c1, c2*) does not give any restrictions here.

The results of the showstopper identification show that for 8 of the 14 candidates one or more showstoppers are identified, in 4 cases (where the total result is M), a more detailed feasibility study has to be conducted, and for 2 cases no showstoppers are identified at all. Oftentimes, a 'Maybe' is given for the categories *o1* (trust in the monitoring system) and *o2* (fit to personnel). RWS is convinced that PdM has many benefits that can be gained on the long-term, but on the short-term, hick-ups can occur within the organization. Trust in the monitoring systems should be gained over time, since there is no wide spread previous experience within the organization. Next, in recent years a lot of RWS's maintenance has been outsourced. It is therefore important to consider whether sufficient domain knowledge (*02: fit to personnel)* is still present. RWS's goal is to build this up by investing in the conduction of failure analyzes and implementing PdM. To succeed in the development of PdM for the canal lock, sufficient domain knowledge will be gained by cooperating with knowledge institutes and partners. Therefore, also RWS's relations and policies will be challenged by adopting PdM (*o4*). As this is labelled an 'innovation project', no insurmountable problems are foreseen. Sufficient resources (both human and financial – *e1, e2*) are available to solve difficulties that might occur.



| **ID** | **c1** | **c2** | **t1a** | **t2a** | **e1** | **e2** | **o1** | **o2** | **o3** | **o4** | **o5** | **Result** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | N | N | Y | Y | Y | Y | Y | Y | N | N | Y | Y |
| 2 | N | N | Y | Y | Y | Y | Y | Y | N | N | Y | Y |
| 3 | N | N | Y | Y | Y | Y | Y | Y | N | N | Y | Y |
| 4 | N | N | Y | Y | Y | Y | Y | Y | N | N | Y | Y |
| 5 | N | N | N | N | N | N | N | N | N | N | N | N |
| 6 | N | N | M | N | N | N | M | M | N | N | N | M |
| 7 | N | N | M | N | M | N | M | M | N | N | N | M |
| 8 | N | N | Y | N | M | N | M | M | N | N | Y | Y |
| 9 | N | N | Y | N | M | N | M | M | N | N | N | Y |
| 10 | N | N | Y | N | M | N | M | M | N | N | N | Y |
| 11 | N | N | N | N | N | N | M | M | N | N | N | M |
| 12 | N | N | N | N | N | N | N | N | N | N | N | M |
| 13 | N | N | Y | N | N | N | Y | M | N | N | Y | Y |
| 14 | N | N | N | N | N | N | N | N | N | N | N | N |

*Table 17. Identification of showstoppers for the canal lock. Y= yes, N = no, M = maybe.*

### 5.5.2.3. Focused feasibility study

The reduction gearbox (ID: 7) is one of the four failures selected as a potentially interesting candidate for PdM for which a more detailed feasibility study has to be conducted. The economic feasibility of developing PdM for the gearbox is assessed using the maintenance balanced scorecard approach, for which the results are shown in Table 18:

(i) **innovation and growth**: an innovative maintenance policy will be developed that helps developing competences, skills and knowledge within RWS. The impact is therefore rated considerably higher (value 5 in Table 18) compared to the traditional corrective maintenance (CM) and preventive maintenance (PM).

(ii) **maintenance**: The PdM introduction can reduce the non-utilized remaining life of the gearbox while complying with safety regulations and standard. However, it is not as easily plannable as fixed-interval PM activities. PdM can also decrease the work load of the maintenance organization by increasing the time between overhauls. PM and PdM are therefore scored equally. UM scores low because it can create high variances in the maintenance organization's work load and unplanned failures can occur.

(iii) **production**: PM and PdM can be scored equally as they both assure reliable operation and thereby guarantee the operational effectiveness of the lock.

(iv) **customer**: PdM might improve the availability of the lock. PdM is therefore rated slightly higher than PM, which also ensures reliable operation of the lock (the main concern of the customers).

(v) **society**: RWS serves the interests of society. Therefore, a reduction in the operating costs and improvements in the lock's availability are of interest to the society.

(vi) **financial perspective:** PdM can help to prevent costs associated with unplanned failures and damages and helps to prevent spoiling remaining useful life by only conducting maintenance when required. A downside of the introduction of PdM is the capital investment that is required for the development.

| Perspective | CM | PM | PdM |
|---|---|---|---|
| (i) innovation and growth | 1 | 2 | 5 |
| (ii) maintenance | 1 | 4 | 4 |
| (iii) production | 1 | 3 | 4 |
| (iv) customer | 1 | 3 | 4 |
| (v) society | 1 | 3 | 4 |
| (vi) financial | 1 | 3 | 4 |
| **Total** | **6** | **18** | **25** |

*Table 18. Results of the economic feasibility study for the gearbox.*

The technical feasibility of developing PdM is assessed using the seven levels of the OSA-CBM structure:

**1. Data acquisition:** A SCADA system is available for automatic collection of sensor data (i.e. oil level, oil fouling, temperatures and motor current) and event data. The newly available data extraction technologies ensure secure data connection and back-up possibilities. The raw SCADA data is coded and send to a data center in real-time. Via this connection, asset managers are able to process the data.

**2. Data processing:** The project initiated by RWS focuses on developing models to process this data. Praveenkumar, Saimurugan, and Ramachandran (2017) recently showed the potential of using motor current signal for gearbox fault detection.

**3. / 4. Detection and Diagnosis:** Kar and Mohanty (2006) showed how motor current signal analysis can be used for gearbox fault detection. Based on the principles explained in this work, alerts can be generated based on the gearbox performance and a short-term failure prediction can be developed.

**5. Prognosis:** not required for the set ambition level.

**6. / 7. Decision analysis and Presentation:** via the data center, the results from the data processing can be converted to information. Dashboards and status reports are to be developed to present anomalies in behavior of the gearbox to asset managers.

In conclusion, developing a PdM approach for the gearbox seems feasible from both a strategic (financial) as a technical point of view.

#### 5.5.2.4. Discussion on RWS case

Filtering showstoppers for the canal lock was helpful. After applying the four quadrant chart method, many natural events (such as lightning strikes) and external events (such as a transport accident) came up as possibly suitable candidates for PdM. Although it might be straightforward to not develop PdM for these candidates, during the session it was indicated that normally the non-technical factors that could be potential showstoppers, could easily have been ignored. The main value for RWS was therefore having a structured way of assessing the applicability of PdM per candidate. Also the feasibility study provides, at an early stage, a clear indication of how PdM can be developed using currently available technology. It points at academic literature that shows that achieving the set ambition 'Diagnosis' with the existing sensors is indeed possible.



## 5.6. Conclusion

This chapter aimed to propose a method to select the suitable components for PdM / PHM within an asset. It can be concluded that the proposed three stage approach can be widely applied for suitable candidate selection, as was demonstrated by the canal lock (RWS) and naval vessel propulsion system (MAR) cases. Applying the four quadrant chart as a first filter has shown to reduce the time effort as it significantly reduces the number of potential candidates with up to 90% for MAR and 84% for RWS. The second stage, i.e. identifying showstoppers proves to be an important contribution of this chapter. In both cases, several showstoppers have been identified that are easily overlooked by traditional methods (as the cylinder liner example in the MAR case clearly showed). Thus, simply applying PdM / PHM on the top cost drivers or performance killers will in many cases not lead to optimal results (i.e. reducing downtime or maintenance costs by applying PdM). Besides, the value of the proposed method is not only in generating a list of suitable candidates for PdM, but also in providing a structured and traceable way to determine these candidates. By identifying potential showstoppers in advance and conducting a structured feasibility study, the often observed trial-and-error approach in developing PdM in practice can be prevented.

The cases also show that the group of persons applying the proposed method affect the results, since especially the showstopper identification and the feasibility study are fairly subjective. This is however not problematic by itself: although attention is required to create reproducible results, the goal of the method is to assess showstoppers and the feasibility within the company. It is nevertheless advised to use a multidisciplinary team which is well suited to estimate the feasibility within the firm. This feasibility is determined by e.g. the knowledge level of employees, maturity of the firm, previous experiences with PdM and experience in applying the proposed selection method.

Finally, the proposed method has only be tested in situations where a clear project aiming at developing PdM was initiated. This might also explain why only a limited number of organizational showstoppers have been identified; the companies were ready to start with implementing PdM. Besides, the proposed list of showstoppers might not be complete for any application, but can easily be extended with additional factors when necessary. Further research should therefore focus on testing the proposed method in standard maintenance improvement programs in practice.

5

# CHAPTER 6

# The business case for predictive maintenance: a hybrid (non-) financial approach[6]



## 6.1. Introduction

Maintenance techniques such as condition monitoring, enable the application of maintenance policies like condition-based maintenance (CBM). CBM is widely applied in industry, within other domains, for example the military, a comparable strategy is used: Prognostics and Health Management (PHM).

CBM uses condition monitoring techniques such as vibration monitoring and oil analysis to determine the asset's current condition. Based on this condition, maintenance actions can be recommended. Moreover, maintenance decision making is supported by taking the current, but preferably also the future state of capital assets into account. The goal of these types of maintenance strategies is to help asset owners, original equipment manufacturers (OEMs) and service providers to increase equipment availability and decrease maintenance costs of their assets.

However, although developing business cases is key for evaluating project success (Fortune and White 2006), the – monetary – costs and benefits of CBM implementations are often not explicitly defined and evaluated in practice (Tiddens, Braaksma, and Tinga 2015).

Moreover, the uncertainty of these costs and benefits depends on the type and innovativeness of the applied technique while in practice the different techniques are often considered as being similar. As also case studies conducted by the authors show, only few

[6] This chapter is based on: Tiddens, W. W., Braaksma, A. J. J., & Tinga, T. (2017). The business case for condition-based maintenance: a hybrid (non-) financial approach. Safety & Reliability - Theory and Applications: ESREL 2017. Cepin, M. & Bris, R. (eds.). Taylor & Francis

practitioners have effectively applied maintenance techniques. Moreover, not all industrial equipment benefits from these techniques; almost 30% of industrial equipment does not benefit from CBM (Hashemian and Bean 2011). Therefore, it is important to evaluate the investment in CBM in advance. Often, the full potential of CBM techniques is not achieved and a costly trial-and-error approach is followed in the implementation of CBM (Tiddens, Braaksma, and Tinga 2015). Finally, uncertainties in costs and benefits of developing innovative CBM approaches stress the need for solid business cases.

Current methods for making the business case for CBM often require many input parameters, which are regarded as 'knowns', and they focus on the exact calculation of financial parameters. However, in practice this data is unavailable or very difficult to acquire. Moreover, the benefits of CBM implementations are difficult to quantify (Bo et al. 2010). In determining these benefits, many factors play a role: the current maintenance plan, safety boundaries, the logistics support system and the technical features of the prognostic technique (Bo et al. 2010). But also the prognostic technique's quality and accuracy, its development costs and the asset's failure distribution. Finally, intangible benefits (e.g. safety improvements or reputation) play a role, but are hard to quantify.

### 6.1.1. Research method and outline of the chapter

This chapter presents a hybrid business case approach to help managers evaluate and justify a planned development of CBM. The design science methodology (Holmström, Ketokivi, and Hameri 2009) has been used to guide the design of this investment evaluation. Therefore, first, related research and findings from case studies conducted by the authors provide the design criteria. Next, the initial design is elaborated on and evaluated using the single-case study (cf. Ketokivi and Choi 2014). We conclude that depending on the uncertainty of the applied technique, the hybrid business case should have a different goal orientation and different support elements. Therefore, we propose a method to evaluate the investment in CBM in Section 6.3 based on the identified design principles and criteria from Section 6.2. In Section 6.4, we apply the proposed method to a case study at the Royal Netherlands Air Force. Finally, conclusions are given in Section 6.5.

## 6.2. Evaluating the investment in CBM: A review of methods

To be able to understand how the business case for CBM should be constructed, we start with reviewing the current literature on methods for investment evaluations. First, we will evaluate the type of models available. And after that, we will discuss financial and non-financial models to specifically evaluate investments in CBM.

### 6.2.1. Methods for investment evaluation

Renkema and Berghout (1997) reviewed various methods to evaluate investments in information systems (IS). Also within the IS domain, it is difficult to formally justify investments, because reliable estimates of costs and benefits are not always available (Remenyi and Sherwood-Smith 2012). In their review, Renkema and Berghout (1997) distinguish four approaches:

($i$) the financial approach: these methods focus on the incoming and outgoing cash flow as a result of the investment, e.g. return on investment (ROI).

($ii$) the multi-criteria approach: these methods score the different alternatives on several pre-set criteria. These can be financial as well as non-financial consequences.

($iii$) the ratio approach: this approach evaluates the ratio of the investment costs against for example the total turnover. These are not necessarily only financial figures, it can for example also relate to the number of employees.

($iv$) the portfolio approach: this approach considers a specific product mix. In the project portfolio the combination of projects or investments are plotted against several evaluation criteria. In the portfolio approach of Bedell (1984), a trade-off has to be found between importance and quality of the project. Three questions that are raised in this method (reformulated to the application of CBM evaluations): ($i$) should the organization invest in CBM methods?; ($ii$) in which activities should the organization invest?; ($iii$) which techniques for CBM should be developed?

Business cases can be constructed on macro, meso and micro levels (Remenyi and Sherwood-Smith 2012). A macro model employs a general concept on a high level. It contextualizes the problem or opportunity and presents a conceptual picture of a suggested solution. A macro approach can be followed when there is little specific (i.e. failure) data to assess the effects of the CBM approach. When more data is available, the business case can be constructed on a deeper level. A meso level model adds more detail. It expresses generalities of the dimensions of the problem and proposed solution on an intermediate level. A micro level model helps to understand the detailed impact of the proposed solution. Remenyi and Sherwood-Smith (2012) note that although all models are simplifications of the reality by nature, the simpler the model, the more meaningful they may be.



## 6.2.2. Financial metrics applied to CBM justification

Traditional investment evaluation criteria can be applied to evaluate investments in CBM. Metrics such as the Return on Investment (ROI) and Net Present Value (NPV) focus on projecting the (future) costs and benefits of a CBM policy. The return on investment metric can be calculated as the return minus the investment, divided by the total investment. Feldman, Jazouli, and Sandborn (2009) show the simplest formulation (Equation 1) of the return on investment applied to the evaluation of prognostic techniques. They compare the costs of CBM ($C_{CBM}$) to the costs of unscheduled maintenance ($C_{UM}$). $C_{UM}$ and $C_{CBM}$ are lifecycle costs. $C_{CBM}$ includes all investments in CBM ($I_{CBM}$), all the changes to the life-cycle costs, and the costs of the undetected failures. $I_{CBM}$ consists of the costs of the required infrastructure added to the recurring and non-recurring costs.

$$ROI = \frac{C_{UM} - (C_{CBM} - I_{CBM})}{I_{CBM}} - 1 \qquad (1)$$

The Net Present Value is an important capital budgeting model that considers discounted cash flows; the metric considers the present value of both benefits and costs ($i$ is the discount rate). Equation 2 shows the calculation of the NPV (Myers 1984). Regular NPV calculations focus on a certain return ($R_t$), an incoming monetary flow (as for example in the ROI method). However, in the case of CBM, the 'benefits' can only be found in cost savings resulting from cost reductions (less repairs and replacements) and cost avoidances (avoiding failures).

Therefore, in the case of a CBM implementation, $R_t$ should be seen as the cost avoidance (or conversely an increase in costs) that is achieved at time $t$. This is the difference in the yearly lifecycle costs of an unscheduled maintenance (UM) or preventive maintenance (PM) approach compared to a CBM approach. $C$ is the cost of the project at $t = 0$.

$$NPV(i, N) = \sum_{t=0}^{N} \left( \frac{R_t}{(1+i)^t} \right) - C \tag{2}$$

## 6.2.3. Financial approaches to assess the investment in CBM

A number of methods to evaluate the financial investments in prognostic techniques are discussed in the academic literature.

In the field of maintenance optimization, extensive work has been conducted to determine the optimal balance between the costs and benefits of maintenance (for an overview see: Dekker 1996). The state of the art in simulation based optimization has been reviewed by Alrabghi and Tiwari (2015). These simulation based approaches have a large potential and growing interest amongst researchers in optimizing maintenance systems (Sharma, Yadava, and Deshmukh 2011). Using these approaches, a business case for CBM could be constructed. However, these approaches often require many input variables which make them hard to apply in practice. Reliability data can be sparsely available and censored, therefore, additional information from expert judgement is important (Marquez, Neil, and Fenton 2007).

Sandborn and Wilkinson (2007) present a discrete event simulation model that results in a methodology to establish a business case for PHM. Therefore, they determine the optimal prognostic distance and safety margin (i.e. how far into the future can a failure be predicted) for various PHM approaches. Short prognostic distances increase the probability of missing failures, while long prognostic distances may be costly to achieve. High safety margins result in throwing away remaining useful life. In their model, Sandborn and Wilkinson (2007) include single and multiple socket systems where the line replaceable units (LRU's) that make up a system can be subject to different PHM approaches (or no PHM structure at all). Using Monte Carlo simulations, they compare unscheduled and fixed-interval maintenance policies with the PHM approaches.

## 6.2.4. Non-financial approaches to assess the investment in CBM

A financial evaluation of an investment in CBM looks only at the impact on the internal processes of the maintenance function. However, managers want a balanced presentation of both financial and operational measures (Kaplan and Norton 2005, , p.172). Moreover, an evaluation that only considers financial criteria might fail to account for the impact on functions external to the maintenance function such as production, logistics, customers, employees and organizational goals (Kumar et al. 2013). Finally, a purely financial evaluation neglects the skills and competencies that companies are trying to master (Kaplan and Norton 2005). Such a balanced evaluation can be made with the balanced scorecard.

Alsyouf (2006) presents an extended balanced scorecard which can be applied to maintenance. Alsyouf (2006) demonstrates with cause and effect relationships how maintenance can contribute to the firm's overall success. Therefore, he describes six perspectives. These are (influencing one another from bottom to top): (*i*) innovation and growth; (*ii*) maintenance; (*iii*) production; (*iv*) customer; (*v*) society; and (*vi*) financial.

In conclusion, the non-financial approaches are useful in finding out whether a CBM approach is of strategic interest to the company. These however lack a detailed financial calculation that incorporates the uncertainty of developing CBM. The discussed financial approaches incorporate uncertainty and are helpful in creating a detailed business case. However, sufficient data is not always available for such an evaluation, specifically for innovative approaches.

A combination that includes the specific uncertainties associated with introducing CBM and the strategic considerations of the firm is missing.

## 6.3. Proposed approach to evaluate the investment in CBM

Following the design science methodology (Holmström, Ketokivi, and Hameri 2009), after discussing literature on (non-) financial evaluation methods, the next step is to formulate the design principles for the initial design of the business case approach.

### *First design principle*: *exploring or exploiting*

Tidd and Bessant (2009) argue that organizations should organize and manage various innovation types differently. *Exploitation* of an innovation happens when adaptive and incremental development takes place. *Exploration* happens when new territory is explored and the frontiers of what is known are pushed.

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The application of CBM sometimes seems to be treated as incremental, as several techniques for CBM, like vibration or oil analysis, can be considered to be proven technology. However, as also shown in Tiddens, Braaksma, and Tinga (2015), a trial-and-error process is often followed in the implementation of CBM. As many contextual factors such as the maturity of the organization, existing knowledge and experience within a company play a role, CBM implementations should often be treated as local innovations. This means that where a proven technique (e.g. vibration monitoring) can be an *exploitation* of CBM for firm *A*, firm *B* that is not experienced in applying this technique might have to approach this as an *exploration* of CBM. Therefore, the approach to justify and evaluate the investment should also depend on the context in which a technology such as CBM is applied, rather than solely considering the degree of newness of a technology.

### *Second design principle: hybrid-approach*

Many of the reviewed justification methods (section 6.2) follow the financial approach (cf. Renkema and Berghout 1997) and can be characterized as micro-models (cf. Remenyi and Sherwood-Smith 2012). The reviewed non-financial approaches take a more strategic (macro) non-financial approach. However, these models exclude uncertainties of the inputs. For example, Monte Carlo analyzes can help to include these to give a better picture of the sensitivity of the business case result.

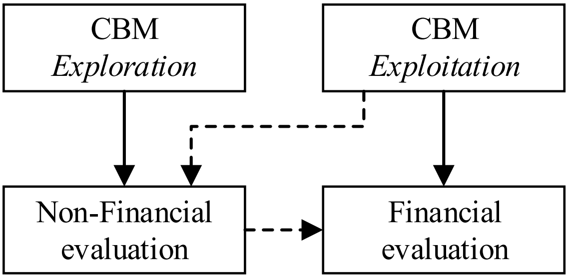


*Figure 17. Proposed hybrid business case approach. Following the dashed lines is recommended but optional.*

We therefore argue that a hybrid approach, consisting of a financial and non-financial evaluation should be followed in the evaluation of CBM investments. Depending on the uncertainty and innovativeness (for the specific firm), the business case should have a different goal orientation and different support elements. As Renkema and Berghout (1997) noted, four approaches can be followed (financial, multi-criteria, portfolio, and ratio approach). Myers (1984) argues that discounted cash flow methods (i.e. NPV) can be safely applied to cash cows (relative safe businesses / investments). However, these methods are less helpful in valuing investments that have substantial growth opportunities and in assessing strategic value (Myers 1984, , p.135).

### *Third design principle: flexible goal orientation*

The hybrid approach should offer the possibility to switch between a strategic non-financial assessment on a macro level or a detailed financial modelling on a micro level as suggested by (Remenyi and Sherwood-Smith 2012). This means that for *exploitation* of CBM techniques, the goal orientation is to evaluate the financial contribution to the firm. Therefore, a detailed financial evaluation on a micro level using the Monte Carlo approach of Sandborn and Wilkinson (2007) can be made. The business case can then be supported with traditional financial elements (i.e. ROI, NPV).

For *exploration* cases, the goal orientation should be to assess the strategic impacts of the CBM approach on the firm on a high (macro) level. The business case can then be supported with non-financial methods such as a multi-criteria analysis using the extended balanced scorecard of Alsyouf (2006). Also a portfolio approach could be applied in this situation. By using the considerations of Bedell (1984), it can be evaluated whether the organizations should introduce CBM and what activities and techniques should be employed.

Note that in practical cases often a combination of *exploitation* and *exploration* is found. Although some proven technologies may be adopted, the overall CBM strategy and implementation is typically an exploratory process for any company. That once more motivates why a hybrid approach is required.

The proposed hybrid approach (Figure 17) starts with analyzing whether the CBM introduction can be categorized as merely *exploration* or *exploitation*. This directs the goal orientation of the business case.

For *exploration* cases, a non-financial evaluation has to be made. Where possible (i.e. this can only be done if sufficient information on the CBM approach is available), this evaluation has to be complemented (dotted line) with a financial evaluation to assess whether it is expected that the CBM introduction can reduce costs.

For *exploitation* cases, it is optional (dotted line) to start with a non-financial evaluation to assess whether, strategically, it is beneficial to invest in CBM techniques. After this, a financial evaluation should be conducted to assess the financial consequences.

## 6.3.1. Exploration of CBM: Non-financial evaluation

As was mentioned before, the exploration part of CBM implementations must be tackled with a high level non-financial approach to assess the strategic impacts. Depending on the objectives and ambition of the firm, several routes can be followed.

First, when the firm is orienting on investing in methods to improve their maintenance process, a ratio approach can be used to dedicate a certain percentage of the maintenance budget to the development of techniques that enable CBM.

Second, if the firm is orienting on different types of techniques to develop, a portfolio approach can be adopted. Then, the firm can decide to invest primarily in *exploitations* for example, but also investigate the opportunities of *explorations*.

For the latter, a straightforward financial business case is often not possible because the uncertainty of development is high. Financial approaches encourage short-termism while innovations (*explorations*) are typically long term. Therefore, it can be difficult to estimate the benefits. In that case, a more 'innovation management' approach should be followed to assess the impact of the introduction of the CBM technique to the firm. Therefore, a multi-criteria approach can be followed. In this multi-criteria analysis, the factors of the extended balance scorecard of Alsyouf (2006) can be used to assess whether CBM contributes to the firm's success.

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## 6.3.2. Exploitation of CBM: Financial evaluation

As strategic analyzes are also subject to random error (Myers 1984), the proposed hybrid approach includes an evaluation of the monetary cost benefits using discrete event simulation. Therefore, an Excel-based Monte Carlo simulation model has been developed using the logic presented by Sandborn and Wilkinson (2007). With this model, failures can be sampled during a given lifecycle of the asset. A comparison of the lifecycle costs, average number of failures and replacements is made between CBM, fixed-interval preventive maintenance and unscheduled maintenance. Both current as calculated (optimal) PM intervals can be selected for comparison.

As smart managers do not accept positive (or negative) NPVs unless they can explain them (Myers 1984, , p.130), the model was simplified by reducing the number of required inputs. Moreover, as data can be censored and sparse (Marquez, Neil, and Fenton 2007), the inputs can be obtained from only expert sessions.

The model consists of three modules, being an input, processing, and output module. The input module consists of parameters concerning failure distributions, the prognostic distance, and economic parameters such as (non-) recurring costs. The processing module calculates the outputs using equation 1 and 2. The discrete event simulation works as follows: every simulation trial equals one lifecycle of the fleet of assets. For UM: a simulated failure means asset failure. For PM: for every simulated failure it is checked whether the simulated failure occurs before or after the PM action. In the former case, the asset fails. For the latter, only a PM action takes place at the predefined interval. For CBM: the simulated failure is compared to a sample from the PHM distribution. This distribution shows the probability that the PHM technique 'sees the failure coming' (for further reading, see: Sandborn and Wilkinson 2007). If the sample of the PHM distribution is smaller than the sample from the failure distribution: a PM action takes place. Otherwise, this leads to an asset failure.

Finally, the output module provides an overview of the economic impact by displaying life cycle costs, net present value, and return on investment.

## 6.4. Evaluating the investment in CBM for the engines of the C130 Hercules of the Royal Netherlands Air Force: A case study

An in-depth single case study (Yin 2013) at the Royal Netherlands Airforce is conducted to evaluate the application of the business case approach. The Royal Netherlands Air Force (RNLAF) wants to explore the possibilities of conducting more condition-based maintenance activities. This originates from declining budgets and the perception that the current fixed-interval maintenance policy is too conservative. This is supported by evidence from an ally, having flown many more hours before a failure occurred.

However, as the engines are critical for safe operation of the aircraft, there is a need to substantiate an extension of the overhaul interval. Next to that, safe operation after a potential extension also has to be proven towards the military aviation authorities (MLA). Therefore, together with the Netherlands Aerospace center (NLR), the RNLAF has started a pilot project to investigate both the technical and economic feasibility of a CBM program for the engines of the C130 Hercules fleet.

The C130 Hercules (in service since 1994) is an aircraft primarily used for transportation purposes. The whole fleet consists of four aircraft, each driven by four T-56 turboprop engines. To account for long overhaul periods, a number of spare engines are permanently on stock. Currently, the RNLAF applies a fixed-interval planned maintenance policy, based on flight hours. Due to confidentiality, exact numbers cannot be provided. However, it can be noted that the overhaul interval is conservative due to safety regulations and the high costs of failures.

### 6.4.1. Engine Condition Trend Monitoring

During normal operation, turboprop engines can produce rated power for extended periods of time. Under specific flight conditions, engine operating parameters such as compressor speeds, inter-turbine temperature and fuel flow for individual engines are predictable (Guimarães 2015). Hereby, deterioration of gas path components can be detected at an early stage by comparing the actual (measured) parameters to a calculated baseline.

Engine Condition Trend Monitoring (ECTM) is the process of using these measured characteristics during specified flight conditions (i.e. altitude, airspeed, outside air temperatures) and comparing these to predicted values to provide confirmation of engine gas path efficiency and predict maintenance needs based on this data (Guimarães 2015).

## 6.4.2. Non-financial evaluation of ECTM

Although ECTM is an established approach to monitor the performance of Hercules engines (Glenny 1982), application of such technologies and approaches is new for the C130 fleet of the RNLAF. Moreover, due to the varying military flight profiles, measuring the specified flight conditions for ECTM is more difficult than in civil settings. In military settings, the flight profiles are more dynamic (i.e. more flight level variance, low level flight operations, maneuvers, etc.). Therefore, as the uncertainty of implementing ECTM is high, the new setting requires a more 'innovation management' approach.

To assess the strategic impacts of the introduction of the CBM approach using ECTM at the RNLAF, we conducted a multi-criteria analysis using the six perspectives of Alsyouf (2006), see Table 19. Below we will elaborate on the contribution of the three compared maintenance strategies to the overall success of the RNLAF.

| Perspective | UM | PM | CBM |
|---|---|---|---|
| (i) innovation and growth | 1 | 2 | 4 |
| (ii) maintenance | 1 | 3 | 3 |
| (iii) production | 1 | 3 | 3 |
| (iv) customer | 1 | 4 | 5 |
| (v) society | 1 | 4 | 5 |
| (vi) financial | 1 | 3 | 3 |
| **Total** | **6** | **19** | **23** |

*Table 19. Results of the multi-criteria analysis to assess the (positive) impact of UM, PM and CBM on the non-financial perspectives (1 = low, 5 = high).*

6

**(*i*) innovation and growth:** An – for the RNLAF – innovative maintenance policy (ECTM) can be implemented. Improvement of the maintenance organization is important to increase effectiveness and decrease costs, which is necessary due to budget cuts. By investing in relevant and promising maintenance techniques, competences and skills both within as outside (i.e. a research center as the NLR) can be developed. This can help to improve the effectiveness of the maintenance organization. The impact of this development is therefore rated considerably higher (value 4 in Table 1) than the traditional UM and PM.
**(*ii*) maintenance:** The CBM introduction can help to reduce the non-utilized remaining life of the engines while complying with safety regulations and standard. However, it is not as easily plannable as fixed-interval PM activities, which can be problematic due to the long repair times of the engines. However, CBM can decrease the load on the maintenance organization by increasing the time between overhauls. We therefore scored PM and CBM equally. UM scores low because it can create high variances in the maintenance organization's work load and many unplanned failures can occur.
**(*iii)* the production perspective** looks at how the overall operational effectiveness of the RNLAF can be maximized. For the operational units that use the aircraft, safe and reliable operation of the aircraft is key. Therefore, PM and CBM can be scored equally as they both assure reliable operation. Although a longer mean time between overhauls, possible with a CBM approach might improve the availability, we scored PM and CBM equally.
**(*iv)* customer:** The RNLAF services the government of the Netherlands and their allies. In this respect, improvements in the effectiveness and lower costs are important. We therefore scored the CBM approach higher.

**(*v*) society:** The defense organization serves the interests of society. Therefore, a reduction in the operating costs and improvements in the operational availability are of interest to the society. Note: in this case customer and society are more or less the same.
**(*vi*) finally, on the financial perspective**, ECTM can help to prevent costs associated with unplanned failures and damages and helps to prevent spoiling remaining useful life by only conducting maintenance when required. A downside of the introduction of ECTM is the substantial capital investment that is required for the development.

The non-financial evaluation has helped to get insight in the contribution that CBM can have to the RNLAF. The highest total score of CBM in the multi-criteria analysis shows that for the RNLAF, it is interesting to conduct a financial evaluation of the introduction of ECTM. As the criticality of the engines and the associated maintenance costs are high, CBM is favorable on a number of perspectives.

Recent budget cuts on the defense department stress the need for innovations that have potential to decrease costs. In other environments, stable fixed-interval policies might be preferable when for example maintenance activities are clustered or factory stops are planned in advance. Further, the introduction of ECTM requires a substantial capital investment, which makes it (from a financial perspective) not directly favorable over PM. It is therefore interesting to conduct a more detailed financial evaluation that regards the uncertainties and financial effects of an ECTM introduction.

### 6.4.3. Financial evaluation of ECTM

The implementation of an ECTM program requires the acquisition of in-flight data, the development of mathematical models to normalize and compare the in-flight data to predicted values, data analysis for the detection of anomalies, alert management and computer hardware and software (Guimarães 2015). Thus, significant investment costs and recurring costs are associated with an ECTM program. We used the precursor to failure monitoring approach of Sandborn and Wilkinson (2007) in our Monte Carlo Simulation model to determine the outcomes of implementing ECTM. Interviews were held with a technical officer maintenance of the RNLAF and a R&D researcher of the NLR who investigates the technical feasibility of the ECTM program. The case interviews show that it is difficult to estimate the numerical values of the business case, such as the quality and accuracy of the prognostic model, the development costs and the failure distribution of the asset. Because the fixed-interval policy for the engines is conservative, little data is available on the time to failure of the engines. Therefore, we used triangular distributions to estimate the component time to failures. Using triangular distributions is easier compared to more complex distributions (Marquez, Neil, and Fenton 2007). Next to that, as the engines are halfway their lifetime, the current hours will be considered in the analysis (i.e. the hour counter does not start at 0). Because of confidentiality, we use fictive numbers (Table 20).

The results of the analysis (Table 21) show that the lifecycle costs of the CBM approach are favorable compared to the UM and PM approaches, see also Figure 18. Due to the long time to failure (~11 years), the costs of the UM approach only increase after a couple of years. Due to the high number of simulations (1000) and considering the current hours of the engines, the discrete events (i.e. failures, overhauls) are less visible in Figure 18.
A sensitivity study was conducted to determine the effects of uncertainties in the model. Figure 19 shows the probability distribution of the ROI of the CBM approach compared to

the preventive maintenance policy. Also, we (quite conservatively) added twice the standard deviation (~€2M) to the CBM lifecycle costs and subtracted twice the standard deviation (~€2.5M) from the PM lifecycle costs. Third, several Monte Carlo simulations with different inputs were conducted to identify influences of errors in the input parameters on the ROI of the CBM approach.

Finally, the model was used to determine the minimum requirements for the prognostic system. These were determined by investigating what the minimum quality (expressed in the distribution width) and prognostic distance should be to obtain a positive ROI.

Together with the developers of the ECTM system, it was discussed whether it is feasible to develop a system that fulfils at least these minimum requirements. In this fictive case, a reduction of the prognostic distance by 50% and an increase in the distribution width of 50% still gives a positive ROI. Developing such a CBM system is assumed to be feasible.

| **Parameter** | **Input value** | |
|---|---|---|
| Time to failure: | 8000 hours; min 5000; max 10,000 | |
| Operational hours: | 700 hours per year | |
| Sustainment life: | 15 year | |
| Preventive interval: | 6500 hours | |
| CBM non-recurring: | €1,000,000 | |
| CBM recurring: | €100,000 per year | |
| Prognostic distance: | 20 hours (distribution width: 50 h) | |
| | **Corrective** | **Preventive** |
| Value out of service: | €14,000 / h | €2500 / h |
| Overhaul costs: | €2,000,000 | €1,000,000 |
| Time to repair: | 300 days | 300 days |
| Time to replace: | 1 day | 1 day |

*Table 20. Fictive inputs for example analysis.*



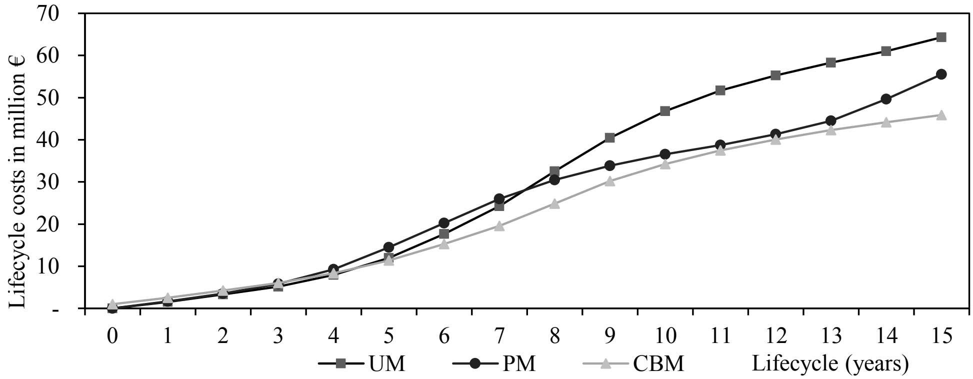


*Figure 18. Comparison of lifecycle costs for three different maintenance policies. The Monte Carlo simulation shows that, over a sustainment life of 15 years, a CBM approach for the fleet of engines can be favored over unscheduled maintenance (UM) and fixed-interval preventive maintenance (PM) (1000 simulations).*

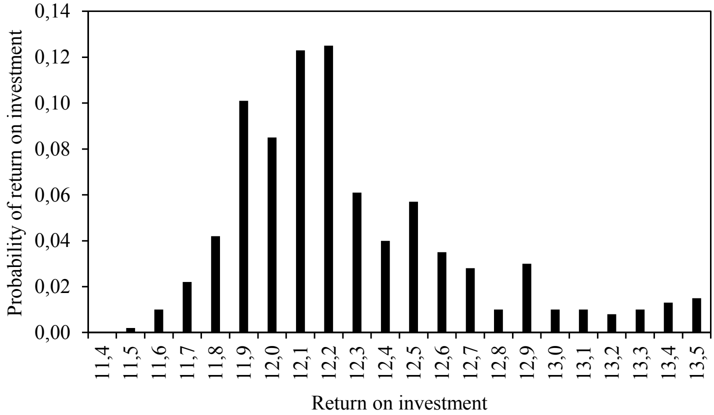


*Figure 19. Sensitivity plot showing the probability of the ROI of the CBM investment compared to a PM approach.*

| **Results: CBM compared to** | **UM** | **PM** |
|---|---|---|
| Return on investment | 21 | 12 |
| Net present value | € 14M | € 8M |
| Lifecycle cost avoidance | 33% | 22% |
| Preventive removals | N/A | - 22% |
| Corrective removals | - 99% | - 93% |

*Table 21. Results of the financial evaluation.*

## 6.5. Conclusion

In this chapter a hybrid approach to construct a business case for CBM has been proposed based on the identified design principles in Section 6.3.

We argue that a strategic non-financial assessment should be combined with a detailed financial modelling on a micro level. For *exploitation* of CBM techniques (applying well-known techniques), the goal orientation is to evaluate the financial contribution. Therefore, a detailed evaluation can be made, supported with traditional financial elements (i.e. ROI, NPV). For *exploration* cases (applying innovative techniques), the goal orientation is to assess the strategic (non-financial) impacts of the CBM approach on the firm. The business case can be supported with non-financial methods as a multi-criteria analysis.

The case study at the RNLAF highlights the applicability of a hybrid approach when a known technique is applied in a new context and when available data is limited. The non-financial evaluation shows that the CBM approach can increase the effectiveness of the maintenance organization while reducing costs, which is a necessity after budget cuts. It can thereby contribute to maintaining the operational availability, which has priority to the RNLAF.

The financial evaluation contributes to the non-financial evaluation by showing that although substantial capital investments are required, the CBM approach is financially favorable in the long run.

The results presented in this chapter are limited as we did not include all possible effects of the CBM approach. Therefore, further research should focus on testing the proposed approach in more cases in different industrial settings.

6

# CHAPTER 7

# Discussion & Conclusion

*This chapter aims to answer the main research question of this thesis: "How can the practical application of predictive maintenance better be supported?" To do so, 7.1 introduces how the proposed decision-support tools help in setting sail towards predictive maintenance. After this, the main conclusions will be summarized in 7.2 and Section 7.3 will present how the three proposed tools in this thesis can be used sequentially to conquer difficulties in the use of predictive maintenance. Finally, some overall concluding remarks will be given in 7.4. Detailed conclusions, discussions and directions for further research have also been given within the context of the individual chapters in this thesis.*



## 7.1. Setting sail towards Predictive Maintenance

This thesis has concentrated on researching the practical application – especially to existing asset bases – of predictive maintenance in industry. The focus in this lies mainly on supporting practitioners in embarking on their journey towards predictive maintenance (PdM). The presented research on (successful) pathways towards the desired destination helps to better guide this voyage, as in ancient days, where old log books and sea maps were consulted before embarking.

The sail setting aims at putting the sails in position to catch the wind, or analogously, choosing suitable paths towards predictive maintenance. As this thesis has shown, not all paths are equally suitable in every situation and developing predictive maintenance is not even beneficially in every situation. Further, firms that have their processes in place are better able to achieve their desired destination. Thereby their trial-and-error process in implementing PdM can be reduced, but not completely avoided. This makes the sail setting process important in deciding what (not) to do and how to do this. As such, the tools developed in this thesis help companies in steering the application of predictive maintenance.

However, even having the tools to embark on this journey, it still requires the knowledge and capabilities to actually sail (develop PdM), although not every voyage is equally difficult. Therefore, as also posed in Chapter 6, *explorations* of PdM should be distinguished from *exploitations* of PdM. This means that one's ambition level (as should be defined before selecting the type of maintenance analytics, see Chapter 4) relative to the firm's current capabilities determines the difficulty level. Moreover, previous experiences in developing PdM will help in future PdM applications. Finally, as history has shown, embarking on a specific journey that leads to an unexpected destination is not always problematic, it could lead to beautiful discoveries. This is also recognized in the pathway selection for PdM developments: Chapter 2 and 3 show that the followed (and sometimes successful) pathways are often unconsciously chosen and lacking ratio. However, in the long run, continuously choosing these illogical pathways might not be efficient. And finally, applying advanced types of PdM is not always the most optimal (and suitable) approach (Chapter 5).

## 7.2. Summarizing the concluding remarks

To answer the main research question, first the difficulties that practitioners experience in the application of predictive maintenance were explored in Chapter 2. This exploratory part of the research was guided by the following question: *"How is predictive maintenance used in practice and what are the main difficulties?"*

Therefore, four postulates on a generally accepted PdM application process description (Jardine, Lin, and Banjevic 2006) were tested. The four postulates reveal not only that there is a gap between theory and practice on the use of PdM, they also highlight several difficulties practitioners experience in applying PdM.

This exploration shows that decision support is required on the three main problems that were identified in the multiple-case study. The main conclusions of this dissertation will therefore be discussed in more detail based on these three themes (selecting the suitable maintenance approach, identifying suitable candidates and evaluating the investment in PdM).

### 7.2.1. Selecting the suitable type of PdM (Ch. 3,4)

Even successful practitioners often seem to follow a costly trial-and-error process in developing maintenance techniques, as guidance in the selection of a maintenance approach is lacking. Three main underlying problems appeared: (i) it is difficult to distinguish between the available approaches; (ii) there is often a mismatch between the ambition level and the required data; and (iii) it is difficult to show the added value of a certain maintenance approach.

Firms seem to start with what is available: either a quest to improve a maintenance decision or available capabilities to develop PdM. As many firms' maintenance budgets are under pressure, sufficient opportunities to improve maintenance decisions are often available. However, from a theoretical point of view, one can question whether that always leads to the most optimal route for a firm's situation.

In applying PdM, firms use multiple types of maintenance analytics. But mostly applied are the experience-based types of Maintenance Techniques (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. Thereby, the decision pull versus technology push perspective seems an important discriminator for the route selection. From a decision pull perspective, both the criticality and the type of asset determine the use of more advanced maintenance techniques. From a technology push perspective, the availability of information technology, sensors and high quality data stimulates the use of the more advanced types of analytics.

Starting from a technology push perspective seems to lead to different start-up difficulties than starting from a decision pull perspective. As the combination of perceived ease-of-use and the perceived usefulness eventually leads to technology acceptance (this does however not necessarily lead to a positive business case), it is important for firms to define the required outcome of the MTs and the required and available capabilities at forehand. In selecting the optimal PdM approach, it is thus key to select the required ambition level and map the available data.

The proposed approach to select the optimal predictive maintenance approach (Chapter 4) therefore starts with identifying the ambition level and mapping the available data. Hence, first, five types of preventive maintenance approaches are distinguished. Next, ambition levels are defined to help identifying the right approach and a guideline to select the most suitable ambition level is given. Based on these, decision-support is provided to select the optimal approach. Four case studies successfully demonstrate the proposed approach.

### 7.2.2. Identification of suitable candidates for PdM (Ch. 5)

The problem exploration phase of this research shows that limited resources and budgets force practitioners to limit the number of components they can apply PdM to. To select these components, practitioners apply rather straightforward selection methods, such as: the criticality of assets expressed in for example A, B, C ratings, top-10s of maintenance costs and availability killers, the impact on the deployment of the asset, and the impact on safety. However, the cases also show that maintenance activities are often clustered based on a high-level production planning, a mission planning or the most convenient moment to conduct maintenance. Thereby, showstoppers regarding the feasibility of PdM are excluded in the identification of the suitable candidates for PdM.



The method proposed in Chapter 5 helps to identify suitable candidates. This three-stage funnel-based approach has been demonstrated in two distinct cases: a canal lock (RWS) and a naval vessel propulsion system (MAR). Applying the four quadrant chart as a first filter has shown to reduce the time effort as it significantly reduces the number of potential candidates with up to 90% for MAR and 84% for RWS. The second stage, i.e. identifying showstoppers proves to be an important contribution of this method. In both cases, several showstoppers have been identified that are easily overlooked by traditional methods. Thus, simply applying PdM on the top cost drivers or performance killers will in many cases not lead to optimal results (i.e. reducing downtime or maintenance costs by applying PdM). Besides, the value of the proposed method is not only in generating a list of suitable candidates for PdM, but also in providing a structured and traceable way to determine these candidates.

### 7.2.3. Evaluating the added value of PdM (Ch. 6)

Converting the technically successful results of PdM (i.e. an estimation of the remaining life) into valuable business results (i.e. a reduction in maintenance costs) has proven difficult for the studied companies. To be able to demonstrate the added value to the business, practitioners aim to construct business cases. However, especially in the application of the more advanced types of analytics (or those the firm is inexperienced in), expressing and quantifying the (monetary) benefits to the firm seems difficult. As many factors play a role (e.g. the current maintenance program and the possibilities to change maintenance intervals), the extracted value is context specific. Practitioners lack accepted methods or procedures to clearly justify investments in PdM. Therefore, only ballpark estimates on the improvement potential of PdM are made. Also, the expected benefits are often distant in time, thus the payback time is long.

Chapter 6 therefore proposes a hybrid approach to construct a business case for PdM. This chapter argues that a strategic non-financial assessment should ideally be combined with a more detailed financial modelling. For exploitation of PdM techniques (applying well-known techniques), the goal orientation is to evaluate the financial contribution. Therefore, a detailed evaluation can be made, supported with traditional financial elements (i.e. ROI, NPV). For exploration cases (applying innovative techniques), the goal orientation is to assess the strategic (non-financial) impacts of the PdM approach on the firm. The business case can be supported with non-financial methods such as a multi-criteria analysis.

The case study at the Royal Netherlands Air Force (RNLAF) highlights the applicability of a hybrid approach when a known technique is applied in a new context and when available data is limited. The non-financial evaluation shows that the PdM approach can increase the effectiveness of the maintenance organization while reducing costs, which is a necessity after budget cuts. It can thereby contribute to maintaining the operational availability, which has priority to the RNLAF. The financial evaluation contributes to the non-financial evaluation by showing that although substantial capital investments are required, the PdM approach is financially favorable in the long run.

Moreover, companies can decide to invest in PdM developments to start a learning trajectory. Although investing in PdM for one specific application might be financially unfavorable on the short term, by investing in relevant and promising maintenance techniques, competences and skills can be developed. This can help to improve the effectiveness of the maintenance organization and therefore be – financially – favorable on the long term. This way of appreciating the PdM development is captured in the *innovation and growth* perspective of the non-financial evaluation.

# 7.3. Conquering difficulties in the application of predictive maintenance

The three proposed solutions are presented as individual and separate answers to the problems that were identified in the problem exploration phase of this research. However, a vast amount of overlap and cohesion exists between the proposed methods. This section will present how the proposed tools can be used sequentially, prior to the final step: developing the predictive maintenance approach. Figure 20 visualizes the relation between the proposed solutions.

Chapter 3 presented a framework (Figure 4) that shows the pathways towards maintenance decision making. This framework consists of the four steps (project initiation, data gathering, maintenance analytics, and maintenance decision making) that are typically taken in the application of PdM. Within this rather descriptive process, choices have to be made. Specifically these choices are formalized in the proposed frameworks.

First, in the project initiation, suitable candidates for PdM are identified and selected. This selection is either done based on a need to apply prognostics (decision pull) or an opportunity to use available sensors or data (technology push). However, for both scenarios it remains important to evaluate, using the method proposed in Chapter 5, whether PdM is a feasible policy for a certain component. Here, the showstopper identification plays a pivotal role.

The second and third step in the descriptive framework of Chapter 3 are data gathering and maintenance analytics. Therefore, first the optimal approach should be selected. Chapter 4 introduced a method that helps to select the optimal preventive maintenance approach, based on a mapping of the available data and the ambition level. Finally, the proposed PdM application should be evaluated using three perspectives: technical, organizational, and financial. The financial perspective has been discussed extensively in Chapter 6 (the business case for PdM). Evaluating the technical and organizational aspects has been discussed in Chapter 5 (selecting suitable components for PdM).

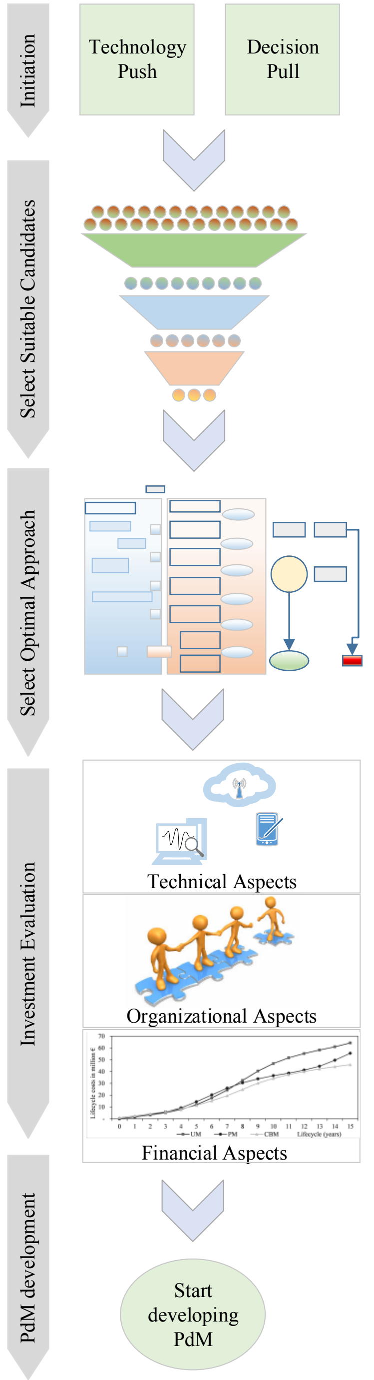


*Figure 20. Combining the proposed steps.*

## 7.4. Final remarks and outlook

The digitization of manufacturing is gradually transforming the maintenance function from analogue and paper based towards digital and sensor based. This offers on the one hand many opportunities for e.g. predictive maintenance, but on the other hand, it requires many new skills. Partly, this digitization helps to improve registrations of failures, asset condition and usage by making the registration less dependent on human input. However, expert knowledge and knowledge management remain key: more specialists are required for collecting and analyzing specific data.

The large potential offered by PdM, as has been shown in this thesis, should urge practitioners to improve their data collection strategies. Chapter 2 has shown that the unavailability of high-quality data is a wide spread problem among practitioners. Ensuring the availability of high-quality historical data and managing sensor data stresses the importance of information management within firms. Nowadays, methods such as ‘big data analytics’ and ‘data mining’, require this high-quality (historical) data. Besides, from the case studies we can learn that installing sensors should not be seen as a ‘blind’ approach, a high level of contextual knowledge is required to determine the correct parameters to monitor. Besides, only looking at the available data can give a reduced picture of the truth (for example to distinguish between human error or normal wear and degradation).

Using data on the deterioration and operation of assets allows firms to apply a higher level of specialization, by for example using this data for outsourcing of maintenance (from a user perspective) or offering services (from an OEM perspective). This also introduces new challenges in firm’s business models (i.e. how to create value as a sub supplier who has a more distant relation with the end-user and cannot directly offer product related services).

Finally, a higher level of integration of specific sensors in the product could also imply changes to the original product design (facilitated from a design-for-maintenance perspective) and increased cooperation with suppliers. This is new for the maintenance function, which has often been seen as a cost center instead of an innovation center.

This thesis has argued (section 7.3) that the three proposed tools can be used in a sequential manner to conquer the main difficulties in navigating through the three main process steps of applying PdM: asset data acquisition, maintenance analytics, maintenance decision making. Therefore, one evident course for further research involves linking and applying the three proposed decision-support tools in industry.

Further, the exploratory part of this research has identified additional difficulties in using PdM that were not addressed within this dissertation. This dissertation only focused on the three main process steps and provides decision-support to navigate through this three-step process. Further, studying cases outside the Netherlands or within other industries where PdM is applied, i.e. oil and gas, telecom, automotive, agriculture, security, health, or civil and construction (Grubic et al. 2011), could lead to additional insights. The use of surveys could help to study a larger population of companies and draw more generalizable conclusions on the use of PdM within industry. The exploratory part of this research is a first step towards an overview of difficulties that practitioners experience in the use of PdM.

This thesis has provided structures to report on the choices made in the application of predictive maintenance and the pathways that are followed in the implementation of PdM. By mapping pathways that have been taken in practice, better conclusions can be drawn on feasible paths and their outcomes. Future research should therefore undertake more rigor in reporting the motivation of choices made in the application of predictive maintenance.

Finally, many scholars in the field seem to focus on the on the technical aspects of PdM only. Most research within the field of PdM excludes the organizational and managerial facets. This study however, shows that managerial difficulties such as implementing the analytics and justifying the investments are just as common and further research should include these difficulties. Moreover, many choices in the application of the analytics (e.g. the selection of methods and parameters to monitor) seem not well substantiated, which makes it difficult to appraise, compare and use the various methods.

# Dankwoord

Dit proefschrift is het slotstuk van vier jaar promotieonderzoek aan zowel de Universiteit Twente als de Nederlandse Defensie Academie. Dit was een mooie combinatie van een academische- en een defensieomgeving en gaf een brede blik op de verschillende toepassingen van – voorspellend – onderhoud. Het vertalen van de lessen uit beide werelden gaf dit onderzoek voor mij een extra dimensie. En maakte dit een intrigerende reis.

Daarnaast gaf dit onderzoek mij de mogelijkheid een kijkje achter de schermen te nemen bij veel bedrijven in verschillende industrieën. Ondanks dat de toepassingen en de specifieke problemen per bedrijf en per sector verschillen, zijn hier een aantal parallellen te trekken zoals ik uiteengezet heb in dit proefschrift. Dit gaf mij tegelijk een brede blik op het veld doordat ik de mogelijkheid had de uitdagingen bij het toepassen van voorspellend onderhoud inzichtelijk te maken en te bespreken.

Zoals de ondertitel van dit proefschrift al suggereert, is koers zetten naar voorspellend onderhoud een proces dat sturing vereist. Er zijn een aantal obstakels die overwonnen dienen te worden. Het schrijven van dit proefschrift was niet anders. Vele mensen hebben bijgedragen aan het koers zetten, maar ook aan het – mij – op koers houden tijdens dit promotieonderzoek. Ondanks dat ik lang niet een ieder die op enige wijze heeft bijgedragen aan mijn promotieonderzoek kan noemen, wil ik de voor mij belangrijkste personen in dit slotstuk danken.

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Allereerst zou dit proefschrift niet tot stand zijn gekomen zonder het Tools4LCM (Tools for Life Cycle Management) project, gefinancierd door het Ministerie van Defensie en het Netherlands Aerospace Centre NLR. Daarnaast heb ik de mogelijkheid gekregen veel van mijn werk uit te voeren in het MaSeLMA project (Maintenance and Service Logistics for Maritime Assets).

Dank aan alle consortiumleden en projectleden voor de verscheidene mogelijkheden mijn deelresultaten te presenteren, te spiegelen, te bediscussiëren en als proeftuin te fungeren. Deze manier van onderzoek doen heeft mij geholpen de aansluiting met de industrie – en misschien ook wel de werkelijkheid – te houden en tot praktisch toepasbare resultaten te komen welke ik in de praktijk kon uittesten.

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Wieger Tiddens<br>Heerenveen, juli 2018

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